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Spatial and temporal characteristics of summer precipitation over Central Europe in a suite of high-resolution climate models

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ABSTRACT

15 High-impact, localized intense rainfall episodes represent a major socio-
16 economic problem for societies worldwide, and at the same time these events
17 are notoriously difficult to simulate properly in climate models. Here, the au-
18 thors investigate how horizontal resolution and model formulation influence
19 this issue by applying the HARMONIE regional climate model (HCLIM) with
20 three different setups; two using convection parameterization at 15 and 6.25
21 km horizontal resolution (the latter within the "grey-zone" scale), with lat-
22 eral boundary conditions provided by ERA-Interim reanalysis and integrated
23 over a pan-European domain, and one with explicit convection at 2 km reso-
24 lution (HCLIM2) over the Alpine region driven by the 15 km model. Seven
25 summer seasons were sampled and validated against two high-resolution ob-
26 servational data sets. All HCLIM versions underestimate the number of dry
27 days and hours by 20-40%, and overestimate precipitation over the Alpine
28 ridge. Also, only modest added value were found of "grey-zone" resolution.
29 However, the single most important outcome is the substantial added value in
30 HCLIM2 compared to the coarser model versions at sub-daily time scales. It
31 better captures the local-to-regional spatial patterns of precipitation reflecting
32 a more realistic representation of the local and meso-scale dynamics. Further,
33 the duration and spatial frequency of precipitation events, as well as extremes,
34 are closer to observations. These characteristics are key ingredients in heavy
35 rainfall events and associated flash floods, and the outstanding results using
36 HCLIM in convection-permitting setting are convincing and encourage fur-
37 ther use of the model to study changes in such events in changing climates.

38 1. Introduction

39 In August 2002 Central Europe experienced an extreme rainfall episode where a number of flash
40 floods led to record breaking rainfall amounts (locally up to 300 mm in 24 hours), caused several
41 rivers to overflow, and resulted in huge economical loss and a significant number of fatalities
42 (Ulbrich et al. 2003). In the past, Central Europe has frequently been affected by similar precipi-
43 tation events, often with large socio-economic impacts (Rotunno and Ferretti 2001; Kundzewicz
44 et al. 2005; Frei et al. 2000; Ruiz-Villanueva et al. 2012). There is also evidence that precipitation
45 extremes have become more common over recent decades (van den Besselaar et al. 2012), and,
46 despite large inter-model differences, there is suggestion of increases in the frequency and/or
47 intensity of extreme precipitation events in Europe in the future, both on daily (e.g. Feldmann
48 et al. 2013; Lenderink and van Meijgaard 2010; Frei et al. 2006; Ban et al. 2015) and sub-daily
49 timescales (e.g. Ban et al. 2015; Kendon et al. 2014). Estimates of future changes in extremes
50 of multi-hourly precipitation sums are critical for risk and impact assessment of changes in fre-
51 quency of flash floods and major flooding events. A correct representation of these heavy rainfall
52 events is an important (but not sufficient) condition to have confidence in projections for the future.

53
54 The concept of flash floods is underpinned by a simple, but important statement; *the heavi-*
55 *est precipitation occurs where the rainfall rate is the highest for the longest time.* Numerical
56 experiments and analysis of observed episodes of heavy rainfall in Central Europe reveal a number
57 of common key ingredients. The dynamical and thermodynamical interactions on synoptic to
58 local scale have been just right to enable sufficient moisture convergence and vertical updrafts,
59 and hence condensation and rainfall, as well as constraining convective systems to become
60 quasi-stationary (Doswell et al. 1996; Lin et al. 2001). In addition, airflow-orography interactions

may modify the development of precipitation-producing storms in critical ways by influencing the low-level stability and convergence patterns (Rotunno and Ferretti 2001). The main characteristics of a flash flood constitute a challenge for weather and climate models, as it requires an accurate representation of the local environment and storm dynamics.

A well-known source of error for the simulation of precipitation in numerical models is the parameterization of convection (Molinari and Dudek 1992; Hohenegger and Stevens 2013; O’Gorman and Schneider 2009). Individual moist convective updrafts and downdrafts have horizontal dimensions on the order of 0.1 – 10 km. Their role in re-stabilizing the lower atmosphere through production of clouds and precipitation are critical for a correct and physically sound representation of weather and climate. In large-scale models with mesh-grid sizes of $\mathcal{O}(100)$ km the statistical effects of convection on the grid scale are parameterized, but because of this, the convection scheme usually struggles to capture local and regional interactions, e.g. orographically forced convection in steep topography, as well as the detailed temporal evolution of convection at sub-daily time scales (e.g. Dai and Trenberth 2004; Dai 2006; Bechtold et al. 2004). Similar problems are seen also in regional climate models (RCMs) with parameterized convection (Liang 2004; Brockhaus et al. 2008). Generally, as the grid mesh becomes finer, the realism of precipitation patterns and intensities improves in models (e.g. Rauscher et al. 2010; Sharma and Huang 2012; Prein et al. 2015a; Gao et al. 2006), however, there are still errors in sub-daily precipitation statistics even at resolutions of ~ 10 km in models with an active convection scheme (Walther et al. 2013). Originally designed for coarser grids, convection schemes at ~ 10 km begin to violate the underlying statistical assumptions on which they are based, most importantly the assumption of scale-separation is no longer valid. At even finer resolution, entering the so called “grey-zone” resolution of ~ 3 -10 km, the issues of double

85 counting convective precipitation (parameterized and resolved) and excessive grid point stabiliza-
86 tion (Gerard 2007; Gerard et al. 2009) further degrade the model convective precipitation response.

87

88 In "convection-permitting" models (1-4 km mesh size) there is a much better description
89 of precipitation processes, such as the initiation and organization of convection, orographic
90 enhancement and small-scale storm characteristics (Prein et al. 2015b). In numerical weather
91 prediction (NWP), convection-permitting models (CPMs) are now routinely delivering signifi-
92 cantly improved accuracy in quantitative precipitation forecasts (e.g. Weusthoff et al. 2010; Lean
93 et al. 2008; Roberts et al. 2009; Roberts and Lean 2008). In particular, Roberts and Lean (2008)
94 showed that the spatial frequency of precipitation was significantly improved in kilometer-scale
95 simulations compared to coarser ones, particularly for localized, heavy precipitation events. In
96 an excellent review on the use of CPMs in the climate modelling community, Prein et al. (2015b)
97 discuss at length the success in improving the simulation of various aspects of precipitation and
98 other meteorological variables referencing a multitude of studies. Recently, Kendon et al. (2012)
99 demonstrated an improved representation of duration and spatial extent of precipitation extremes
100 in a convection-permitting climate model (CPCM) compared to a coarser scale RCM. Using the
101 same model simulations, but focusing on the statistical behaviour of precipitation extremes, Chan
102 et al. (2014) showed that the CPCM was superior to the coarser model in representing summer
103 hourly and multi-hourly precipitation extremes. Furthermore, the typical deficiencies of a too
104 early onset and decay of diurnal convective precipitation, as well as too low peak intensities,
105 in RCMs with parameterized convection have been shown in several studies to be significantly
106 reduced when using CPCM (Prein et al. 2013; Ban et al. 2014).

107

108 Here, we sample a set of summer seasons over Europe and the Alps using different setups

109 with a new regional climate model, HARMONIE Climate (Lindstedt et al. 2015). Three model
110 configurations were applied; two integrated at 15 km and 6.25 km horizontal resolution using a
111 convection scheme particularly designed for resolutions within the "grey-zone". The third setup
112 employs a physics package designed for convection-permitting resolutions and is run at 2 km
113 resolution. With this suite of simulations, we aim to investigate the quality of each model version
114 in terms of the spatial and temporal characteristics of summer precipitation in the Alpine region on
115 daily and sub-daily time scales. Specifically, does the 2 km model behave differently concerning
116 precipitation extremes and capture intensities, durations and frequencies of precipitation spells
117 better than the coarser models using a convective parameterization? Also, do we benefit from
118 using HARMONIE Climate at 6.25 km resolution compared to 15 km, i.e. is there added value
119 already at this intermediate resolution compared to its coarser version?

120 **2. Experiment setup**

121 *a. Models*

122 HARMONIE (Hirlam Aladin Regional Mesoscale Operational NWP In Europe) is a seamless
123 NWP model framework developed jointly between several European national meteorological
124 services. The model system provides flexibility as it contains a suite of different physics packages,
125 each adapted for different horizontal resolutions. Here we have applied two different model
126 setups using the cy37h1.2 climate model version of HARMONIE (HCLIM) ; 1) a setup with the
127 ALARO (Gerard 2007; Gerard et al. 2009; Piriou et al. 2007) physics applying the 3MT (Modular
128 Multi-scale Microphysics and Transport) (Piriou et al. 2007; Gerard et al. 2009) convection pa-
129 rameterization (CP) scheme, applied at two horizontal resolutions, 15 and 6.25 km (hereon called
130 HCLIM15 and HCLIM6 respectively); 2) a setup with the AROME (Seity et al. 2011) physics

131 package. AROME is specifically developed to be run at convection-permitting resolutions resolv-
132 ing deep convection explicitly, and is here applied to a resolution of 2 km (hereon called HCLIM2).

133

134 In HARMONIE, irrespective of physics package, the ALADIN-NH provides the non-hydrostatic
135 dynamical core (Bénard et al. 2010), solving the fully compressible Euler Equations using a two
136 time level, semi-implicit, semi-Lagrangian discretization on an Arakawa A grid. Here, HCLIM15
137 and HCLIM6, with ALARO physics, used the hydrostatic version of the dynamical core. The
138 surface parameterization framework is SURFEX [Surface externalise (Masson et al. 2013)],
139 originating from the ISBA (Interactions Soil-Biosphere-Atmosphere) surface scheme (Noilhan
140 and Planton 1989). A more thorough description of SURFEX is found in Le Moigne (2012).

141

142 Differences between ALARO and AROME appears primarily in the atmospheric physics.
143 In ALARO, radiation is parameterized using the two-stream scheme developed by Ritter and
144 Geleyn (1992) with optical cloud properties following Mäsek (2005). Deep convection in
145 ALARO is not explicitly resolved and uses the 3MT parameterization scheme. In standard
146 parameterizations, separate schemes are used for deep convection and for "non-convective" (i.e.
147 resolved large-scale) clouds, with microphysical conversion to precipitation treated separately in
148 each scheme. However, at ever-higher resolution, the risk of double counting convective processes
149 (both through resolved and parameterized parts) increases and 3MT handles this by formally
150 separating the two different contributions (Lindstedt et al. 2015). The microphysical processes
151 handle five prognostic water phases, where autoconversion and evaporation are computed level
152 by level (Gerard et al. 2009). The turbulence parameterization is a pseudo-prognostic Turbulent
153 Kinetic Energy (pTKE) scheme which is an extension of the Louis type vertical diffusion scheme
154 (Louis 1979).

155

156 AROME parameterizes radiation using a two-stream approximation in model columns and
157 the effects of surface slopes accounted for. Short and long wave spectral computations follow
158 Fouquart and Bonnel (1980) and Mlawer et al. (1997) respectively, and cloud optical properties
159 for liquid clouds are derived from Morcrette and Fouquart (1986) and from Ebert and Curry
160 (1992) for ice clouds. AROME uses a mixed-phase microphysics scheme, the ICE3 scheme (Pinty
161 and Jabouille 1998), wherein cloud water and ice as well as rain, snow and graupel are prognostic
162 variables. Hail is assumed to behave as large graupel particles. The turbulence parameterization
163 was developed by Cuxart et al. (2000) and is based on a prognostic TKE equation combined with
164 a diagnostic mixing length L .

165

166 A suite of seven summers have been simulated; 1998, 2000, 2002, 2004, 2006, 2007 and
167 2010. All simulations were initialized in May of each year and run until the end of August, with
168 May omitted from subsequent analysis. HCLIM15 and HCLIM6 were applied over a domain
169 covering Europe (300x320 and 720x800 grid boxes respectively). Lateral boundary conditions
170 are provided by ERA-Interim (Dee et al. 2011) every 6 hours. HCLIM15 was then downscaled
171 by HCLIM2 over a domain covering the Alpine region (see Figure 1), consisting of 480x360 grid
172 boxes. In this downscaling the lateral boundaries were provided by HCLIM15 every 3 hours. All
173 HCLIM simulations have 65 levels in the vertical.

174 *b. Area of investigation*

175 The black rectangle in the left panel in Figure 1 depicts the investigated area in this study, which
176 covers the nested domain of HCLIM2. For analysis of sub-daily precipitation, only Switzerland
177 was considered (Fig. 1, right panel), as suitable observations were only available for this area.

178 Within the HCLIM2 domain, the most prominent characteristic is the arc-shaped mountain range
179 of the European Alps with an average height of ~ 2500 m, a length of 800 km and a width ranging
180 from about 100 to 300 km. The ridge is intersected by a series of deep valleys, dividing the
181 range into major mountain massifs. The mountain range has a significant influence on the large
182 scale atmospheric flow and on the generation of local to meso-scale circulation patterns, acting
183 as triggering mechanism for convection. With this topographical diversity, and its proximity to
184 several large scale climate regimes (e.g. Mediterranean and European continental climates), this
185 area is both meteorologically interesting and a challenge to simulate correctly.

186 *c. Evaluation data*

187 To account for the large spatial and temporal variability in precipitation, it is often necessary to
188 include multiple observations in model evaluation. In this study we use a number of observational
189 data sets that fulfil the conditions of having sufficient spatial coverage and high-enough temporal
190 resolution to investigate the statistical behaviour of convective precipitation in HCLIM on hourly
191 to daily time scales.

192 *EURO4M-APGD* (Isotta et al. 2013) (hereon EURO4M) is a gridded data set covering the Alps
193 and adjacent forelands. It consists of rain-gauge data from an average of 5500 daily measurements,
194 covering the time period 1971-2008. A distance-angular weighting method was used to interpolate
195 point measurements to daily time scale on a 5 km regular grid. Scales that are effectively resolved
196 are coarser, depend on station density and vary both in time and space. Inter-station spacing sets
197 and approximate lower limit of the effective resolution for daily totals, and in high-density areas
198 this is around 10-15 km (Isotta et al. 2013). The smoothing effect from the interpolation and
199 the inherent uncertainties in gauge measurements affect the quality of the end product. Although
200 gauge undercatch is most prominent in winter (Adam and Lettenmeier 2003), the localized and

intermittent nature of convective precipitation in summer causes systematic biases in the observations (Isotta et al. 2013; Rubel and Hantel 2001). Generally, in EURO4M, high intensities are underestimated and low intensities overestimated (Isotta et al. 2013).

To investigate hourly precipitation the *RdisaggH* data set is used (Wüest et al. 2010). Combining weather radar and daily precipitation totals, it consists of hourly precipitation estimates on a 1 km mesh grid over Switzerland for the years 2004-2010. The method involves disaggregating rain gauge data using radar and, therefore, the advantage of the high temporal resolution of radar can be utilized while reducing the impact of its quantitative biases. Validation, through a systematic comparison of *RdisaggH* at the location of 72 rain gauge stations in Switzerland, shows that errors in intensity and frequency are smaller than 25%, with larger errors in regions with deep valleys due to shielding of the radar beam (Wüest et al. 2010).

3. Methodology

To assess the realism of the simulated precipitation distribution and spell duration, a number of statistical methods have been adopted. Generally, statistical analysis of daily and sub-daily precipitation, whereby a significant part may or may not consist of zero-values (i.e. dry days, hours etc.) commonly involves thresholding the data. This sub-selection of data can have a significant impact on the resulting analysis (changing sample sizes) and therefore should be considered carefully. HCLIM demonstrates a clear underestimation of dry days and hours in the Alpine region. Compared to EURO4M (*RdisaggH*) HCLIM2, HCLIM6 and HCLIM15 underestimate the fraction of dry days (hours) by 35%, 19% and 23% (20%, 29%, 41%) over the Alpine region (Switzerland) respectively. The too frequent wet hours and days are spatially mostly associated with the steep topography of the Alps. This indicates that HCLIM, both with and without convection parameterization, too easily triggers precipitation producing processes in interaction with this strong surface

224 forcing. However, a definite explanation for this deficiency demands a more in-depth analysis
225 which is beyond the scope of this study. Keeping in mind these biases, the statistical methods used
226 in this study will mainly focus on when it actually rains, hence using, unless otherwise stated,
227 thresholds to extract wet days or hours. We employ thresholds of 1 mm per day and 0.1 mm per
228 hour for definition of wet events.

229 *a. Fractions Skill Score*

230 Roberts and Lean (2008) introduced a method, called *Fractions Skill Score* (FSS), that fits into
231 the neighbourhood verification category. This will be a short overview of the method, and for a
232 detailed description the reader is referred to Roberts and Lean (2008). The main purpose of FSS is
233 to provide an objective way to assess how the skill in high-resolution numerical models varies with
234 spatial scale. FSS gives information on realism in terms of spatial frequency, and, furthermore, the
235 smallest spatial scale where the simulations can be considered skillful. The computation of FSS
236 is performed in a two-step operation: First, a threshold is applied to grid points of model data and
237 observations, converting them into binary fields (1 above threshold, 0 otherwise). Secondly, the
238 fraction of pixels exceeding the threshold within a specified neighbourhood of each grid point is
239 then compared between model and observations. This set of operations is repeated for a number of
240 thresholds and neighbourhoods, ranging in sizes from a single pixel to the entire domain. Values
241 of FSS can range from 0, corresponding to no skill, to 1, perfect skill. FSS typically increases
242 from a minimum value for grid point scales to larger values as the neighbourhood area gets larger,
243 asymptotically reaching its maximum value for large neighbourhoods. The maximum value would
244 be 1 if no bias were present in the model, otherwise it asymptotes to a lower value. Roberts
245 and Lean (2008) defined a smallest neighbourhood size for which a sufficient skill is achieved;
246 when $FSS_u = 0.5 + f_o/2$ is obtained, where f_o is the observed wet area fraction in the domain.

247 The skill of a *random* forecast which has the same fractional coverage of precipitation over the
248 whole domain as observations is given by $FSS_r = f_o$, and sets a minimum level of skill. The FSS
249 calculation is performed for every time step chosen (e.g. hourly). Prior to this both observations
250 and model data must be interpolated to the same grid configuration. Here, we aggregate all data
251 on to the coarsest 15 km grid, and the domain is limited to the RdisaggH coverage, i.e. the area of
252 Switzerland.

253 *b. Event duration analysis*

254 A more complete analysis would encompass a temporal aspect as well. Therefore, we include
255 an analysis to address the realism of the simulated precipitation in terms of the duration of
256 precipitation spells, mainly following the methodology of Kendon et al. (2012). All grid points
257 covered by both models and RdisaggH observations, the area of Switzerland, are considered. We
258 use all seven summers of model data and all RdisaggH data, even though there is not a complete
259 overlap between these. A sensitivity test by using only overlapping data did not alter the results
260 significantly and we chose to use as much data as possible to increase the statistical robustness.
261 All data is aggregated to the HCLIM15 grid prior to analysis.

262
263 For each grid pixel, events are identified as occurrences of precipitation above a certain
264 threshold. The duration of an event consists of the number of coherent hours of precipitation
265 above the threshold. During a spell, the intensity of precipitation varies, and it varies differently
266 depending on the nature of the process, comparing for example a localized convective rainfall
267 event and a warm frontal passage. To assess this, we record the peak intensity of each identified
268 event. Further on, percentile thresholds are used in the analysis thereby avoiding the effect of
269 possible biases in model data. In particular, to focus on the upper tail of the precipitation distri-

270 butions, a number of high percentiles are used and are calculated for all grid points and all hours
271 (wet plus dry) within the domain for models and observations separately. The statistics assembled
272 through this methodology provide the basis for the computation of probability distributions of
273 spell duration and intensity.

274 The significance of model-observation differences are assessed using a block bootstrap method
275 (Efron and Tibshirani 1993). Auto-correlation of the data is considered by the use of blocks
276 and here the block size is set to the number of hours per summer season. 500 re-samplings are
277 generated for each pixel, and all these surrogate time series undergo the same statistical analysis as
278 described above, resulting in 500 probability distributions for duration and peak intensities. From
279 this we can calculate 500 differences between model and observations (or between different model
280 versions). If the 99% confidence interval of these differences does not include zero, the difference
281 is considered statistically significant at the 1% level.

282 *c. Statistical analysis of hourly extremes*

283 By the very nature of extremes, the rarity of events make the robustness of a direct analysis of
284 them weak, and one needs to apply statistical methods and models specifically designed for the
285 tail behaviour of distributions. In this study we employ the *Peak-over-Threshold* (PoT) method
286 which exclusively describes the characteristics of precipitation events that exceeds a high-enough
287 threshold (Coles 2001). PoT has recently been applied in several studies of extreme precipitation
288 at daily and sub-daily timescales (e.g. Früh et al. 2010; Feldmann et al. 2013; Chan et al. 2014).
289 The well-known asymptotic three-parameter *generalized Pareto distribution* (GPD) (Hosking and
290 Wallis 1987) is used to describe the behaviour of the PoT events, and the associated parameter es-
291 timation is performed using the method of *L-moments* (Hosking 1990). The latter is the preferred
292 method of estimation for small data samples, as is the case here, over other methods like maxi-

293 mum likelihood (Hosking and Wallis 1987). GP distributions are defined by α , k and ξ , which
 294 represent the scale (describing the dispersion), the shape (analogous to skewness) and the location
 295 (equivalent to the threshold for exceedances) respectively. The cumulative distribution function is
 296 then given by:

$$F_{(k,\xi,\alpha)}(x) = \begin{cases} 1 - \left[1 + \frac{k(x-\xi)}{\alpha}\right]^{-1/k} & k \neq 0 \\ 1 - \exp\left[-\frac{(x-\xi)}{\alpha}\right] & k = 0 \end{cases} \quad (1)$$

297 Use of PoT entails the sampling of data that exceeds a pre-defined threshold, a limit that should be
 298 high enough to ensure that the assumptions of the statistical model are justified, and low enough
 299 to capture a reasonable number of events. Recent literature suggest the use of a (wet) percentile
 300 threshold in the range of 90-95% (e.g. Chan et al. 2014; Feldmann et al. 2013; Tomassini and
 301 Jacob 2009), and we deploy in this study the 95th percentile of wet values ($> 0.1mm$). The un-
 302 derlying precipitation data is highly susceptible to serial correlation and to make sure that only
 303 distinct events are used, we apply an automatic de-clustering technique developed by Ferro and
 304 Segers (2003). Also, to increase robustness, the PoT analysis is applied to pooled grid points;
 305 the nearest neighbours of each grid point, i.e. a total of 9 grid points, are included in all separate
 306 calculations. We do this under the assumption that the threshold of the actual grid point is valid for
 307 all of the pooled members. However, in areas with very strong spatial gradients in precipitation
 308 (climatologically) this assumption may not be completely valid.

309 4. Results and Discussion

310 *a. Spatial distribution and frequency analysis*

311 Figures 2 and 3 present the spatial distribution of daily and hourly precipitation statistics
 312 over the Alps and Switzerland respectively. Although HCLIM is generally able to represent the
 313 overall spatial distribution of summer mean daily precipitation, including the complex variability

314 within the Alps massifs, it clearly overestimates precipitation in mountainous areas, especially in
 315 HCLIM2 which has a strong correlation between wet biases and topographic features. A summer
 316 wet bias in the Alps compared to EURO4M has been seen in other RCMs and CPCMs (e.g.
 317 Ban et al. 2014), although not as large as in HCLIM. The wet biases over the Alpine peaks and
 318 crests are mostly due to too frequent precipitation events as clearly seen for hourly precipitation
 319 statistics over Switzerland (top panel in Figure 3) comparing models to RdisaggH observations. It
 320 is most notable in HCLIM6 and HCLIM15, while, interestingly, they concurrently underestimate
 321 the mean wet hour intensity (middle panel). In the southern Alpine regions fewer wet hours are
 322 observed, which is relatively well simulated by HCLIM2 but in HCLIM6 and HCLIM15 this is
 323 highly overestimated apart from southern Ticino. Interestingly, the observed mean intensity of
 324 wet hours has a distinct maximum in the Ticino area, thus this area is exposed to few but quite
 325 vigorous rain spell events (Isotta et al. 2013). This is also supported by considering the fraction
 326 of total precipitation received from intensities in the upper part of the distribution (bottom panel
 327 in Figure 3). This combined characteristic is much better simulated in HCLIM2 compared to the
 328 other HCLIM versions. In the northernmost part, on the other hand, HCLIM2 underestimates the
 329 frequency but overestimates the intensity of events, while in HCLIM6 and HCLIM15 it is the
 330 other way around. Note that in the south-eastern and to some extent in the south-western part of
 331 Switzerland, the quality of RdisaggH observations are relatively low primarily because of low
 332 radar data coverage and radar beam shielding effects due to steep topography (Wüest et al. 2010),
 333 and the interpretation of results in these areas should be done with caution.

334
 335 One major benefit of increased model resolution is expected to occur in mountainous re-
 336 gions as the finer mesh-grid provides a more detailed representation of orography and hence of
 337 surface forcing. In Figure 4 this expected behaviour is further explored. The rate of precipitation

338 as a function of altitude (top panel) in observations and HCLIM shows that RdisaggH and
339 HCLIM2 exhibit qualitatively similar behaviour for daily amounts with an increase in rates up to
340 around 1000 m. However, there is a clear underestimation of HCLIM6 and HCLIM15 for these
341 lower lying areas (see also Figure 2). Above this altitude, the patterns diverge; in all versions of
342 HCLIM the rates continues to increase until ~ 2000 m while EURO4M reaches a maximum just
343 below ~ 1500 m and then starts to decrease. It is worth mentioning that at the higher elevations,
344 EURO4M most likely underestimates precipitation amounts due to a lack of observations (Isotta
345 et al. 2013). Although HCLIM2 has distinctly larger absolute values, it does capture the overall
346 decrease at higher altitudes in closer agreement with EURO4M than the coarser simulations.
347 Over Switzerland, for the hourly precipitation rates, the dependence on altitude is also remarkably
348 similar between RdisaggH and HCLIM2. Differences between HCLIM6 and HCLIM15 are
349 generally small.

350 The observed trans-Alpine character of hourly averages (lower panel in Figure 4) exhibit a
351 shielding effect both in the eastern and western parts, manifest as minimum values at or close
352 to shallow valleys within the Alpine crest areas. This is well captured by the models. On the
353 northern slopes there is an observed increase in precipitation rate followed by decreases in the
354 flat areas further north, a pattern which is broadly seen also in HCLIM, however, HCLIM2
355 with greater realism than HCLIM6. Note the strong increase in precipitation from the crest and
356 southward, an area frequently subjected to meso-scale heavy precipitation events during summer
357 and fall (Isotta et al. 2013; Frei and Schär 1998), again well captured by HCLIM2 but weak and
358 erratic in HCLIM6.

359
360 Frequency-intensity distributions of daily and hourly precipitation totals are presented in
361 Figure 5. Only wet days and hours are considered in the analysis. On daily time scales, HCLIM

shows good agreement with EURO4M. HCLIM2 overestimates the moderate-to-strong events ($\sim 20\text{--}40\text{ mm day}^{-1}$) while HCLIM6 and HCLIM15 underestimate these. For the very extreme events, there is a good resemblance between HCLIM and EURO4M, most clearly seen in the inset figure, showing only the highest intensities, with models and observations on their native grid. Here, HCLIM6 shows an exceptionally close agreement with EURO4M, as does HCLIM2 but not to the same extent, while HCLIM15 systematically underestimates the probabilities. For the hourly estimates, the results are markedly different. The resolution and explicit/non-explicit convection dependencies becomes evident. With outstanding accuracy, HCLIM2 matches RdisaggH over almost the complete spectrum of intensities whereas HCLIM6 and HCLIM15 have statistically significant (as depicted by the 95% confidence interval) lower probabilities already for moderate intensities and then continuously for successively stronger intensities. HCLIM6 does, however, perform somewhat better than HCLIM15, which signifies some added value from the increased model resolution.

The results so far confirm the commonly stated conclusion from multiple other studies that RCMs at meso-gamma horizontal resolution with convection parameterization schemes may be able to reproduce observed frequency-intensity distributions of daily accumulated precipitation, however, on the sub-daily time scales, they are generally outperformed by CPCMs (e.g. Ban et al. 2014; Fosser et al. 2014). Precipitation extremes and associated high impact events such as flash-floods most often involve convective processes with life time spans of a few hours (Ulbrich et al. 2003; Doswell et al. 1996). This highlights the importance of the sub-daily time evolution of precipitation, especially during summer with rainfall of predominantly convective origin, and how it is represented in climate models (Kendon et al. 2012). It is important to note that there is generally better agreement between HCLIM2 and RdisaggH on hourly time scales than on

386 daily (where RdisaggH is in agreement with EURO4M, not shown), suggesting that analysis is
387 sensitive to thresholding of data. In addition, small hourly biases accumulate to larger (relative)
388 values when aggregated to daily intensities (Fig. 3).

389 *b. Extremes*

390 How are hourly precipitation extremes represented in HCLIM? Due to the inherent uncertainty
391 associated with extremes (very low frequency) and the relatively short-term simulations in this
392 study, we address this question by extending the basic validation (Figs. 3 and 5) with extreme
393 value analysis, adopting the Peak-over-Threshold (PoT) statistical model (Sec. 3c). This provides
394 a much more complete analysis of the statistical distribution of extreme rainfall events.

395 The parameters that define the extreme value distributions over Switzerland in HCLIM and
396 RdisaggH are shown in Figure 6. For brevity only HCLIM2 and HCLIM6 are included in the fig-
397 ure, showing analysis made on the 6 km grid resolution. An analysis performed on the 15 km grid
398 showed that HCLIM15, at best, showed similar but mostly less accurate results than HCLIM6.
399 The scale (α) and shape (k) parameters are diagnostics of the dispersion (analogue to standard
400 deviation) and skewness ("thinness"/"thickness" of the tail) of the distribution respectively (Sec.
401 3c). The spatially averaged scale parameter is somewhat overestimated in HCLIM2, mostly due
402 to the larger estimates in northern Switzerland, but otherwise is in good agreement. Conversely,
403 HCLIM6 has too "narrow" extreme value distributions reflected in the lower estimates in most
404 parts of the domain. The highest values are observed in Ticino which is consistent with the few
405 but vigorous events seen in this area (Fig. 3). HCLIM2 is able to reproduce this maximum but
406 this is much lower in HCLIM6 (barely perceptible in HCLIM15, not shown). HCLIM has trouble
407 reproducing the skewness; HCLIM2 has overall a somewhat thin tail and HCLIM6 has better
408 spatial mean but larger regional differences. Interestingly, HCLIM2 (HCLIM6) underestimate

(overestimate) the skewness in Ticino. The threshold for exceedances (location, defined here by the 95th percentile of wet hours) is well captured by HCLIM2, with a similar spatial average as in RdisaggH but for example too high estimates in the north. In HCLIM6 the location is clearly underestimated throughout the domain.

413

These parameters form the basis from which one may extrapolate the behaviour of extreme precipitation beyond the considered time scale. Return levels z , defined as the (high) quantile value of the GPD distribution which is exceeded, on average, once every T years, the return period. Using the quantile function, which is the inverse of (1), and the estimated crossing rate λ (i.e. the expected number of events exceeding the threshold per year or season), the return level is given by:

$$z(T|\xi, \alpha, k) = \begin{cases} \xi + \frac{\alpha}{k} [(\lambda T)^k - 1] & k \neq 0 \\ \xi + \alpha \ln(\lambda T) & k = 0 \end{cases} \quad (2)$$

where ξ , α and k are the GPD parameters. Estimates of z as a function of $\log_{10}(T)$ are shown in Figure 7, the lines representing the domain average values. We again only consider HCLIM2 and HCLIM6 because HCLIM15 severely underestimates all return levels (not shown). In addition to hourly return levels, the data has been aggregated in time to 6 and 12 hours respectively to investigate the sensitivity to the temporal evolution of events (in a statistical sense). As only seven seasons have been sampled, the uncertainty for return levels of large T is large. In Figure 7 return levels for $T > 20$ years have therefore been partially "shaded" to emphasize this uncertainty. For all accumulations HCLIM underestimates the return levels for the full range of recurrence intervals T , however with clear differences between HCLIM2 and HCLIM6. At hourly accumulations, the former is rather close to RdisaggH, especially for shorter return periods. Conversely, HCLIM6 significantly underestimates the return levels across all return periods, which is due to the clearly

430

too low values of the threshold (ξ) and scale (α) parameters (Fig. 6). Despite this, in both model
 and observations there is a similar quasi-linear increase of z with $\log(T)$, reflecting the near-zero
 values of the shape (k) parameter (Fig. 6). HCLIM2 has a lower mean value than HCLIM6 and
 RdisaggH and thus also have the smallest rate of increase of z with $\log(T)$. The slight underesti-
 mation in both HCLIM2 and HCLIM6 in this rate of increase compared to observations leads to
 negative biases becoming larger for larger T .

Similar behaviour is seen for the 6 hour accumulations (and also for 3 hour accumulations, al-
 though here HCLIM2 match RdisaggH almost perfectly for all T , not shown) which indicates an
 insensitivity to accumulation periods of a few hours. However, there is a sharp shift in the results
 for 12-hour accumulations. Both model versions significantly underestimate the return levels and
 their rate of increase. A closer examination reveals that the differences in z are mainly attributed
 to much higher values in RdisaggH in the western part of Switzerland, an area with relatively low
 frequency of rain spells which on average are moderate or weak (Fig. 3). Hence, the non-extreme
 nature of precipitation in this area may not be adequately described by the GP distribution. Chan
 et al. (2014) performed a similar extreme value analysis for southern UK using a regional climate
 model at 12 and 1.5 km resolution, the latter treating deep convection explicitly. In accordance
 with our results, the high-resolution model outperformed the RCM with CP and coarser grid in
 the summer season. Even though the convection-permitting model tended to overestimate return
 levels, the coarser model had difficulties representing the rate of increase of z with T because of
 an overestimated shape parameter. Here, HCLIM6 is actually able to realistically represent this
 statistical behaviour, but struggles with the intensity of extremes thereby reducing the realism.

c. *Spatial frequency of precipitation*

Figure 8 depicts two-dimensional representations of Fractions Skill Score (FSS) over Switzerland, with threshold along the ordinate and the horizontal scale on the abscissa. The typical behaviour, seen in the leftmost panel, is that FSS values increase for larger horizontal scales and decreases for higher thresholds. We choose to show results for 3-hourly accumulations to increase the signal for the higher thresholds, however, the main results do not change for other accumulation times. It is evident from the figure that at higher intensities, HCLIM2 has larger FSS values (more reddish color on the right hand sides), signifying better spatial frequency of high-intensity events in HCLIM2 compared to HCLIM6 and HCLIM15. It should be noted that for the highest thresholds, the signal is weak (i.e. few events) which undermines the robustness of the results. Furthermore, there is no clear difference between HCLIM6 and HCLIM15, at least on these spatial scales. Figure 9 presents FSS as a function of horizontal scale for a few selected thresholds, namely 0.5, 2, 5 mm hour⁻¹ and 15 mm per 3 hours respectively. Already at the lowest threshold, HCLIM2 generates higher FSS than the coarser simulations, and differences become increasingly evident the higher the intensity threshold (although the significance of the differences is, as mentioned, low for the higher intensity thresholds). For 2 and 5 mm hour⁻¹ intensity limits, HCLIM2 reaches random skill faster than HCLIM6 and HCLIM15, at approximately 15-30 km smaller horizontal scales, and the upper skill is passed at ~30-60 km shorter scales. For the highest rate, upper skill is achieved at around 200 km in HCLIM2, almost 150 km earlier than HCLIM6, not being reached at all in HCLIM15. Similar results have been achieved elsewhere; for example, in a suite of CPCM and RCM simulations at 3-10 km resolutions over the Alps region, Prein et al. (2013) showed that the CPCMs performed better with higher FSS values and skills reached for much smaller spatial scales than the coarser RCMs.

475 It is worth re-emphasizing that the FSS analysis does not directly diagnose particular physical
 476 aspects of the simulated precipitation processes such as areal extent or intensity. However, another
 477 important property of precipitation is the frequency of exceeding a critical threshold, which can be
 478 interpreted as the probability for a severe event, and in this respect FSS provide valuable informa-
 479 tion. Furthermore, we have used absolute threshold values in the analysis, and therefore, positive
 480 results tend to bias towards higher-resolution models for higher thresholds as they in general have
 481 larger probabilities for occurrences of such events (assuming no severe deficiencies in the model
 482 physics such as the convection parameterization). Nonetheless, the purpose of this study is to ex-
 483 amine and quantify the added value using a CPM version of HCLIM compared to the version with
 484 parameterized convection, especially in terms of realism. Therefore, we find it preferable in the
 485 FSS analysis to use absolute thresholds instead of relative (percentile) thresholds. The results show
 486 that HCLIM2 surpasses both skill limits faster than HCLIM6 and HCLIM15, most evidently for
 487 stronger intensity thresholds, hence, there are strong indications of a higher realism of the spatial
 488 frequency of heavy rainfall events in HCLIM2.

489 *d. Spell duration analysis*

490 Apart from accurate spatial distributions (e.g. where it rains), the temporal aspect of precipita-
 491 tion events is also important, as the duration has large impact on the total amount of accumulated
 492 precipitation at a specific location. In this last section we explore the duration of precipitation
 493 events over Switzerland in RdisaggH and to what extent HCLIM can reproduce this temporal
 494 characteristic. For this, an Eulerian framework is adopted, whereby the duration of events is cal-
 495 culated for each grid point separately. Figure 10 presents the probabilities of rain spell durations
 496 for different percentile thresholds used to define the start (and end) of an event. Each row represent
 497 a probability distribution of spell durations (x-axis) for a given threshold (y-axis). The leftmost

panel shows the observed probabilities for different percentile thresholds (top row) and peak intensities (bottom row). Typically, for the highest percentile thresholds, the duration of rainfall tend to be short, probabilities decreasing quickly for durations of more than a couple of hours. Intuitively, and what is also observed, for lower thresholds there is an increase in the probabilities for events to last longer (e.g. a larger chance of neighbouring time steps being included in a single rain event). The observed dependency of peak intensity of the complete rain spells (i.e. using a very low threshold of 0.1 mm hour^{-1}) on the duration of events indicates that low peak intensities are usually associated with short-lived events and moderate-to-strong peak intensities, between $\sim 2\text{-}10 \text{ mm hour}^{-1}$, are embedded in spells with a greater range of durations, that is, even for more persistent events (6-12 hours), the probabilities remain relatively high. For the most intense peak values, there are few events (Fig. 5) that are distributed evenly across the event durations. The models have similar behaviour but there are significant differences in the probability distributions as seen in Figure 10, especially for the coarser HCLIM runs. The latter clearly underestimates the frequency of very short 1-3 hourly events and overestimates the longer lasting spells. This deficiency is particularly pronounced for the heaviest rain spells (percentiles $\geq p99$). Furthermore, HCLIM6 too frequently produces multi-hour rain spells with low peak intensities and underestimates the occurrence of short-duration low-to-moderate peak intensity events. These kind of deficiencies have been noted in other RCMs (e.g. Kendon et al. 2012), and is most probably related (at least in part) to the use of a convective parameterization. This bias pattern is consistent with a problem seen in many climate models; the too early onset of diurnally forced convection, prohibiting the build-up of convective available potential energy and often resulting in a lower late afternoon maximum in convective precipitation rate than observed (e.g. Brockhaus et al. 2008; Kendon et al. 2012; Prein et al. 2013; Ban et al. 2014). For both the duration probabilities and peak intensities, HCLIM6 shows better agreement with observations than HCLIM15 (mostly sta-

522 tistically significant), most clearly for spell durations ≤ 6 hours (rightmost panels in Figure 10). In
523 stark contrast to these results, HCLIM2 does a much better job at simulating the observed char-
524 acteristics, signified by the much smaller differences in the probabilities compared to RdisaggH.
525 This largely resembles the results and conclusions of Kendon et al. (2012), although for a different
526 region and model. HCLIM2 does show some overestimation of the occurrence of 1-hourly events
527 for the higher percentiles and slight underestimation for multi-hourly events, the differences being
528 statistically significant. For the peak intensities, HCLIM2 display similar behaviour to HCLIM6
529 but with a much reduced bias, and overall there is a significant improvement in the use of HCLIM2
530 compared to HCLIM6 and HCLIM15.

531 **5. Conclusions**

532 Accurate model projections of precipitation distribution, especially the frequency and intensity
533 of wet extremes, still remains one of the largest challenges in the climate model community. Com-
534 monly, models have errors due to inadequate representation of local and regional forcing and to
535 unresolved processes important for correct storm evolution. Recently, the introduction and ap-
536 plication of convection-permitting climate models (CPCMs) at the kilometer-scale resolution has
537 resulted in a marked increase in accuracy and realism of small-scale, convective precipitation
538 events (e.g. Kendon et al. 2012; Prein et al. 2015b; Ban et al. 2014) and its extremes (e.g. Chan
539 et al. 2014). However, it still is computationally very expensive to run these models, and the ex-
540 periments are usually confined to short time periods and/or small domains using a single model.
541 In absence of any large multi-CPCM ensembles to study uncertainties and robustness associated
542 with model differences, introducing new CPCMs in separate experiments and testing for repro-
543 ducibility of results adds important information for future applications. Furthermore, the question

544 of cost versus benefit is becoming more and more important to answer within the regional climate
545 modelling community.

546 In this study we have employed the HCLIM RCM at various resolutions; at 15, 6.25 and 2 km re-
547 spectively over the Alpine region. Seven summers have been sampled and the validation of the in-
548 tensities, durations and frequencies of precipitation spells have been studied using high-resolution
549 gridded observations, based on synoptic as well as radar measurements. In contrast to HCLIM2,
550 HCLIM15 and HCLIM6 uses a hydrostatic dynamical core and convection parameterization. Our
551 results show HCLIM in general has some problems in the simulation of precipitation distributions.
552 For example, HCLIM underestimates dry days and hours by $\sim 20\text{-}40\%$ compared to observations,
553 making the statistical analysis sensitive to thresholding of the data. Also, there is a clear overes-
554 timation of precipitation in connection to the Alps crest areas. Despite these issues, we conclude
555 that HCLIM2 is able to represent spatial and temporal (duration) characteristics of sub-daily pre-
556 cipitation, including extremes, with a considerable larger realism than its coarser counterparts that
557 uses a convection parameterization scheme. For example, at an intensity of 15 mm per 3 hours,
558 HCLIM2 attains a pre-defined level of skill in the simulation of spatial frequency of events at a
559 horizontal scale 36% shorter than HCLIM6, at 220 and 345 km respectively. The increased re-
560 alism in HCLIM2 support findings in other similar studies using CPCMs (e.g. Prein et al. 2013;
561 Ban et al. 2014; Kendon et al. 2012; Fosser et al. 2014; Chan et al. 2014), and further points to a
562 distinct advantage of using CPCMs in modeling of sub-daily precipitation, particularly in regions
563 where and seasons when deep convection is dominant and also in areas with strong topographi-
564 cal heterogeneity. These are all characteristics that have been shown important in past flash-flood
565 events in Europe (e.g. Ulbrich et al. 2003; Lin et al. 2001). With respect to future projections of
566 extreme precipitation using CPCMs, it is worth pointing out that these models, although skillful in

567 representing precipitation processes, are dependent on driving large-scale models to provide good
568 large-scale circulation within which the CPCMs will operate.

569 With regards to the benefit of "grey-zone" resolution, no clear improvement has been shown
570 here in HCLIM6 compared to HCLIM15. HCLIM6 do however show larger probabilities for
571 high-intensity events, statistically significantly at hourly time scales, in better agreement with
572 observations. Furthermore, HCLIM6 statistically significantly reduce biases in the duration and
573 peak intensity of rain spells, particularly for shorter 1-6 hours events, and also has a somewhat
574 better skill in the spatial frequency as shown by the FSS analysis. In summary, HCLIM6 shows
575 an improvement compared to HCLIM15, however not always beyond uncertainties associated
576 with the analysis and not near the improvement seen in HCLIM2. It is worthwhile to consider
577 differences in computational cost. HCLIM6 is more than ~ 5 times as expensive as HCLIM15
578 to run, thus it may be more reasonable to use a resolution of ~ 10 -15 km on the scale of Europe
579 which is then downscaled by a CPCM, skipping the intermediate resolution. Finally, the use of a
580 CP scheme in RCMs limits the models ability to simulate convective events correctly. There are
581 similar issues in this version of HCLIM as well, even though HCLIM uses a scale-independent
582 (down to a few kilometers) scheme. However, no clear conclusions in this matter can really be
583 drawn in this study, and further investigations are needed.

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