



1 Local impact analysis of climate change on precipitation 2 extremes: are high-resolution climate models needed for 3 realistic simulations?

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14 **Abstract.** This study explores whether climate models with higher spatial resolution provide higher accuracy for
15 precipitation simulations and/or different climate change signals. The outputs from two convection-permitting
16 climate models (ALARO and CCLM) with a spatial resolution of 3-4 km are compared with those from the coarse
17 scale driving models or reanalysis data for simulating/projecting daily and sub-daily precipitation quantiles. The
18 high-resolution ALARO and CCLM models reveal an added value to capture sub-daily precipitation extremes
19 during summer compared to the driving GCMs and reanalysis data. Further validation of historical climate
20 simulations based on design precipitation statistics derived from intensity–duration–frequency (IDF) curves shows a
21 better match of the convection-permitting model results with the observations-based IDF statistics. Results moreover
22 indicate that one has to be careful in assuming spatial scale independency of climate change signals for the delta
23 change downscaling method, as high-resolution models may show larger changes in extreme precipitation. These
24 larger changes appear to be dependent on the climate model, since such intensification is not observed for the
25 ALARO model.

26 1 Introduction

27 It becomes evident that climate change will increase the frequency and intensity of extreme events (IPCC, 2007,
28 2013). Therefore, the impacts of climate change on hydrological extremes such as heavy precipitation events have to
29 be considered when designing and optimizing water infrastructures. The future projection of climate change impact
30 on precipitation usually relies on the simulation results of General Circulation Models (GCMs). However, these
31 results need to be validated against historical precipitation observations prior to any use for local impact studies of
32 climate change. When GCM results are validated based on observations, sometimes large biases are observed
33 especially for extreme precipitation values (van Pelt et al., 2012; van Haren et al., 2013; Tabari et al., 2015),
34 imposing an uncertainty to the GCM projections for the future. The biases in the coarse-resolution GCMs come



1 from the fact that they disregard some governing features of precipitation at local scale, next to the scale differences
2 when comparing GCM results with local observations (Maraun et al., 2010; Willems et al., 2012). Some previous
3 studies that attempted to assess GCM skill as a function of resolution showed that the performance of GCMs is
4 independent of their resolution (Johnson et al., 2011; Masson and Knutti, 2011). However, given that deep
5 convective phenomena are sufficiently resolved only at spatial resolutions down to less than about 4 km, such
6 dynamical downscaling is expected to be one of the solutions for decreasing the systematic biases and narrowing the
7 gap between GCM outputs and needs for fine-scale precipitation in hydrological and water engineering studies.

8 One of the methods to dynamically downscale GCM outputs is to drive a Regional Climate Model (RCM) using
9 GCM as initial and boundary conditions. RCMs usually provide an improved description of surface features
10 (topographical, land cover, etc.) and more complex description of atmospheric processes compared to GCMs. This
11 often results in more realistic representation of precipitation variability and of climate feedback mechanisms (IPCC,
12 2001; Mearns et al., 2004; Christensen and Christensen, 2007; Mayer et al., 2015). Whatever climate models are
13 used, verification of their results under the current climate is needed, because some high-resolution RCMs fail to
14 adequately describe local-scale surface processes (especially in inhomogeneous regions with complex topography)
15 due to the convective parameterization scheme or the characteristics of the GCM they are nested in (Hohenegger et
16 al., 2008; Willems et al., 2012).

17 High-resolution (convection-permitting resolutions) climate models are of great added value to simulate large
18 convective storms and mesoscale organization (Kendon et al., 2014; Prein et al., 2015). At these resolutions, deep
19 convection is partly resolved and does not need to rely entirely on parameterizations. The representation of the daily
20 cycle in precipitation, extreme events and spatial variability strongly improves for convection-permitting models
21 (Kendon et al., 2012; Prein et al., 2013a, 2013b, 2015; Brisson et al., 2015; Ban et al., 2014, 2015, Fossier et al.,
22 2015). However, their simulation for long time scales is restricted due to high computational costs. They are
23 consequently mainly applied for numerical weather prediction (Done et al., 2004; Baldauf et al., 2011; Tang et al.,
24 2013). First simulations for decadal time periods using convection-permitting models point to a stronger increase in
25 extremes compared to coarser resolution integration, but the number of climate change impact studies with these
26 models is limited so far (Hohenegger et al., 2008; Kendon et al., 2012, 2014; Prein et al., 2015).

27 The use of regional climate models for local impact studies of climate change on precipitation (totals or
28 extremes) has been increased in recent years (e.g. Willems and Vrac, 2011; Olsson et al., 2012; Mearns et al., 2013;
29 Rajczak et al., 2013). Nevertheless, in some studies, climate scenarios have been based on a broad set of coarse-
30 resolution GCM results (Deng et al., 2013; Rana et al., 2014; Sun et al., 2015). Now, the question is whether high-
31 resolution climate models truly improve extreme precipitation simulations, and if so, to what extent. This study
32 intends to answer this research question by comparing high-resolution models (RCMs with resolutions between 40
33 and 3 km) with their driving GCM or reanalysis data for simulating sub-daily and daily precipitation quantiles.
34 Further comparisons are performed for simulating design precipitation statistics derived from intensity–duration–
35 frequency (IDF) curves.

36 Second research question considered, in case the high resolution climate models show improved extreme
37 precipitation results, is whether this improvement in absolute precipitation values also significantly changes the



1 relative climate change signal. Hydrological applications of climate change impact analysis often assume that the
2 change factors, defined as the relative change from historical to future climate conditions, can be obtained from
3 GCM or RCM simulations and applied for impact analysis at finer spatial scales. This is the case for any delta
4 change or perturbation based statistical downscaling method (e.g. Ntegeka et al., 2014; Sunyer et al., 2015). In this
5 study, the validity of this hypothesis is investigated by comparing the climate change signals on IDF statistics
6 between the high and coarse scale resolution models. Central Belgium is considered as the study location.

7 **2 Climate models**

8 **2.1 ALARO model**

9 The ALARO-0 model is a high-resolution regional climate model developed by the Royal Meteorological Institute
10 (RMI) of Belgium based on the numerical weather prediction model called Aire Limitee Adaptation Dynamique
11 Developpement International (ALADIN). Hereafter, ALARO is used as shorthand name for the ALARO-0 model
12 described in De Troch et al. (2013). The ALADIN model is the limited area model (LAM) version of the Action de
13 Recherche Petite Echelle Grande Echelle Integrated Forecast System (ARPEGE-IFS). The physics parameterization
14 package of the ALARO model was designed specifically for running at resolutions between 3 and 8 km. The
15 specific characteristics of the Modular Multiscale Microphysics and Transport (3MT) convection scheme used in the
16 ALARO model lead to a good multiscale performance, particularly in convection-permitting resolutions (De Troch
17 et al., 2013). The ALARO simulations for the present climate conditions over Belgium were performed for the
18 periods 1961-1990 and 1981-2010 at resolutions ranging from 40 km down to 4 km, both using a set of simulations
19 forced with ERA-40 or ERA-Interim reanalysis as well as with the CNRM-CM3 GCM for the historical control run
20 (Table 1). For the future climate projections (2071–2100), the CNRM-CM3 GCM under the A1B scenario was used
21 to force the ALARO model (Hamdi et al., 2014).

22 **2.2 CCLM model**

23 The other high-resolution climate model used in this study is the COSMO-CLM (CCLM) model. The CCLM is a
24 non-hydrostatic limited area climate model developed by the climate limited-area modeling (CLM) community. The
25 CCLM model is based on the COSMO model (Steppeler et al., 2003), designed by the Deutsche Wetterdienst
26 (DWD) for operational weather prediction. In order to perform climate simulations with the COSMO model, the
27 CLM community provided extensions such as dynamic surface boundaries, a more complex soil model and the
28 possibility to use various CO₂ concentration values (Böhm et al., 2006; Rockel et al., 2008).

29 The model settings are based on a previous study by Brisson et al. (2015), which provide recommendations for
30 performing climate simulations at convection permitting scale. The one-moment microphysical parameterization
31 includes a representation of graupel hydrometeors. In addition, the domain size of this simulation (192x175
32 gridpoints) is large enough to ensure that the analysis is not affected by the spatial spin-up described in Brisson et al.
33 (2015). A three-step nesting strategy was applied with the driving data, either from ERA-Interim reanalysis data or
34 the EC-EARTH GCM, forcing a CCLM at 25 km grid mesh size, which in turn forces a CCLM at 7 km grid mesh



1 size, and next at the final 2.8 km grid mesh size. Model simulations were performed for the period 2001-2010, and a
2 thorough evaluation of decadal statistics of precipitation, temperature and cloud characteristics was recently
3 performed (Brisson et al., 2016). The CCLM driven by EC-EARTH was performed for the period 2000-2010 and
4 2060-2069 using the RCP4.5 emission scenario (Table 1). Hereafter, the driving GCM or reanalysis dataset is shown
5 as subscript to the name of the RCM. As the control run of the EC-EARTH GCM ends in 2009, its data for the
6 period 2000-2009 were used for comparing with the driven CCLM simulations.

7 **3 Methodology**

8 In this study, simulations of sub-daily and daily precipitation quantiles from the climate models are analyzed. For
9 the future climate analysis, the climate change signals are obtained as relative changes of precipitation intensities
10 calculated as the ratios of precipitation quantiles derived from each climate model scenario simulation over those
11 from the corresponding climate model control simulation with same non-exceedance probability or return period.
12 This methodology has been applied in several recent climate change studies, e.g. on the basis of statistical
13 downscaling applying quantile mapping or quantile perturbations (Willems and Vrac, 2011; Gudmundsson et al.,
14 2012; Maraun, 2013; Ntegeka et al., 2014; Rana et al., 2014; Sunyer et al., 2015) and also a similar procedure for
15 analyzing decadal precipitation anomaly (Willems, 2013; Tabari et al., 2014; Tabari and Willems, 2016). Extreme
16 precipitation is defined in this study as precipitation with return period (T) higher than 1 year and the return period is
17 calculated empirically based on the rank of precipitation values (n/i , where n and i are the length of the study period
18 and rank, respectively; $i = 1$ for the highest value).

19 In addition to the quantile analysis, the historical simulations of the climate models are validated based on
20 precipitation intensity–duration–frequency (IDF) curves which are typically used for design storm calculations and
21 related designs, e.g., urban drainage systems and hydraulic structures. The IDF curves for 1-month, 1-year and 10-
22 year return periods and for durations from 10-15 minutes up to one month are developed for the control runs of the
23 climate models as well as the observations. The IDF curves are derived based on Peak Over Threshold (POT)
24 extreme value statistics after calibration of two-component exponential distributions, following Willems (2000). In
25 this paper, the precipitation intensities of given return periods are referred to as design precipitation quantiles.

26 For the climate models, precipitation data are extracted for the model grid cell covering Uccle station in Central
27 Belgium. This station is selected because it has high quality 10-min observations recorded with same instrument
28 since 1898 (Demarée, 2003). In addition to the 10-min station observations, daily E-OBS gridded data (v12.0,
29 Haylock et al., 2008) for 27.8 km and 55.7 km are used. These gridded data are aggregated to larger pixels of 167
30 km and 334 km to be consistent with the grid mesh size of the driving GCMs and reanalysis data.

31 **4 Validation of precipitation simulations**

32 The capability of the climate models to simulate the present-day precipitation is evaluated before investigating
33 future precipitation changes. The validation of the daily precipitation quantiles simulated by the ALARO and the
34 CCLM convection-permitting models and their boundary conditions based on the point and pixel interpolated Uccle



1 observations for the summer season (June-July-August: JJA) is shown in Fig. 1. This is done for the historical model
2 simulation periods 1961-1990 for ALARO and 2001-2010 for CCLM. The results reveal that the ALARO_{ERA40}
3 model overestimates the observed summer extremes. The extreme simulations of the ALARO_{CNRM-CM3} model with 4
4 km resolution are in between the point observations and the gridded ones with a grid size of 27.8 km which shows
5 good accuracy of these simulations. The CNRM-CM3 GCM and ERA40 reanalysis data used as the boundary
6 conditions of the ALARO model show a systematic underestimation especially for the higher return periods. This
7 confirms the finding that higher resolution results in more extreme precipitation in climate models (Jacob et al.,
8 2014).

9 As for the CCLM model (Fig. 1), the simulations of summer extremes for 2.8 km resolution are nearly unbiased
10 for the events with $T > 2$ years. The increasing skill of RCMs with increasing model resolution for simulation of the
11 spatio-temporal characteristics of summer precipitation has also been found by using the high-resolution models,
12 although limited in application (Rauscher et al., 2010; Kendon et al., 2012). For $T < 2$ years, the CCLM model tends
13 to underestimate the summer precipitation extremes particularly for the runs with coarser resolutions. These
14 underestimations for lower T appear to be explained by underestimations in the EC-EARTH GCM and ERA-Interim
15 reanalysis rather than in the CCLM model itself.

16 As the difference between climate model outputs and observations may be partly attributed to the spatial scale
17 difference, the extreme precipitation (averaged over the extreme events with $T > 1$ year) simulations of the climate
18 models versus spatial scale for both summer and winter seasons are shown in Fig. 2. Taking the spatial scale
19 difference into account and averaging the extreme values with $T > 1$ year, the ALARO_{ERA40} simulations are closer to
20 the observations compared with the ALARO_{CNRM-CM3} model. Decrease in systematic biases in the large-scale climate
21 in reanalysis-driven RCM simulations was also reported by Maraun et al. (2010). They also pointed out that these
22 RCMs are capable of reproducing the actual day-to-day sequence of weather events. The great ability of the CCLM
23 model, large underestimations of CNRM-CM3, EC-EARTH and ERA40, and slight overestimation of ERA-Interim
24 data for summer precipitation extremes are also obvious from these plots. As expected, the percentage bias of the
25 climate models decreases as the time scales get larger (i.e., weekly and monthly).

26 The validation of the climate model simulations for the summer season in terms of IDF statistics is shown in Fig.
27 3 for time scales in the range between 10-15 minutes and 30 days. The IDF curves are plotted with reference to
28 design precipitation intensities from the station and E-OBS pixel data over the Uccle location (Central Belgium).
29 Comparing the hourly simulations of the ALARO_{ERA40} model with different resolutions shows the greater intensities
30 for finer resolutions. In terms of accuracy, most of the ALARO runs underestimate the station observations and
31 overestimate the gridded observations (extrapolated). Regarding 3- and 6-hourly time scales, the ALARO model
32 simulates more intense precipitation of 10-year return period in comparison to both the station and gridded
33 observations. The model underestimates (overestimates) design storms of 1-year return period and 3- and 6-hourly
34 durations when compared with the station (gridded) observations. For larger time scales, design precipitation is still
35 overestimated by most of the ALARO runs.

36 The CCLM model simulates less intense 15-min precipitation of 10-year return period (Fig. 3). However, this
37 underestimation changes to overestimation for larger sub-daily aggregation levels. For the sub-daily design storms



1 of 1-year return period, the CCLM model generally underestimates the station observations, while both over- and
2 underestimations are seen in comparison with the gridded observations. However, the EC-EARTH GCM extremely
3 underestimates both the gridded and raingauge observations. This supports the recent findings for underestimation of
4 heavy hourly precipitation during summer by large scale climate models and more accurate simulations of
5 convection-permitting models (Chan et al., 2013, 2014; Ban et al., 2014; Fossier et al., 2015). In the case of daily to
6 monthly durations which are less important for urban drainage and hydraulic structure design, the precipitation
7 intensities are both overestimated and underestimated by the CCLM model.

8 For the winter season (December-January-February: DJF), the results show overestimations of the ALARO and
9 CCLM models (Fig. 2). As winter precipitation over Belgium is mainly controlled by large scale circulation, an
10 improvement in the simulations of convection-permitting models in comparison to the parent large scale models is
11 less expected for the winter season. Although improved simulations of winter precipitation by convection-permitting
12 model have been reported for regions with complex topography (Ikeda et al., 2010; Rasmussen et al., 2011) due to
13 better resolved orography (Prein et al., 2015), this effect is less relevant for Belgium which is more flat.

14 Whereas winter daily precipitation extremes are systematically overestimated by the ALARO model, the driving
15 CNRM-CM3 GCM and ERA40 reanalysis data slightly underestimate the winter extremes (Fig. 2). Deficiency of
16 very high resolution climate models in simulation of winter precipitation extremes is because the fronts and synoptic
17 depressions that cause the dynamical processes driving winter precipitation events have scales of 10^2 - 10^3 km. This
18 deficiency has been demonstrated by Hong and Leetmaa (1999) and Chan et al. (2013). For the CCLM model, when
19 the CCLM_{EC-EARTH} 2.8 km simulations are compared with those of the CCLM_{ERA-Interim} 2.8 km for the winter
20 extremes, the overestimations of the earlier run is higher than the later one which can be attributed to a large
21 overestimation of the EC-EARTH GCM results taken as the boundary conditions.

22 After validation of design precipitation simulations by the convection-permitting models for summer and winter
23 seasons separately, further analysis was performed in the framework of IDF relationships, considering the extremes
24 for all seasons as usually done for developing design standards (Fig. 4). Based on this analysis, the ALARO_{ERA-Interim}
25 model underestimates hourly design precipitation derived from the IDF curves based on the station observations.
26 Although sub-daily gridded precipitation are not available, by imaginary extending the IDF curves for the daily
27 gridded data still a small underestimation of the ALARO_{ERA-Interim} simulated hourly design precipitation can be
28 noted. In the case of 3- and 6-hourly design precipitation, the ALARO_{ERA-Interim} model provides closer results to the
29 existing IDF curves and probably a slight overestimation in comparison with the gridded data. As for the daily time
30 scale, the ALARO_{ERA-Interim} simulates larger precipitation intensities compared to the ALARO_{CNRM-CM3} model and
31 the ERA-Interim reanalysis. For aggregation levels between 5 days and 1 month, the difference between the model
32 simulations is smaller except for the CNRM-CM3 GCM with a remarkable underestimation.

33 For the CCLM model, the 2.8 km run tends to underestimate the precipitation intensities at 15 and 30 minutes,
34 which are typically used for sewer and drainage system design. For instance, for a storm of 10-year return period
35 and 15-min duration, this underestimation can be up to 63 mm/h. Although this underestimation may be partially
36 due to spatial scale difference, in practice IDF curves based on station observations (and not gridded observations)
37 are typically used for the design of hydraulic structures. For sub-daily durations (hourly, 3-hourly and 6-hourly),



1 design precipitation intensities are underestimated by almost all the CCLM model runs except for some 2.8 and 7
2 km runs. In the case of daily to monthly durations, the precipitation intensities simulated by the models are very
3 close to each other. No improvements in the simulations of daily mean precipitation by the convection-permitting
4 models compared with large scale climate models were reported by Chan et al. (2013) and Fosser et al. (2015),
5 while some other researchers found improvements especially over mountainous areas (Prein et al., 2013b; Ban et al.,
6 2014), implying region and model dependency for simulation of daily mean precipitation. Nevertheless, it can be
7 concluded from the IDF plot (Fig. 4) that design precipitation intensities are overestimated by the driving ERA-
8 Interim reanalysis data and underestimated by the driving EC-EARTH GCM. The underestimation of sub-daily
9 precipitation by the EC-EARTH GCM is remarkable.

10 **5 Future precipitation changes**

11 To cope with the scale difference and the biases shown in the previous section, state-of-the-art climate change
12 impact analysis makes use of statistical downscaling. One of the popular downscaling methods is the delta change
13 method. Different versions exist for that method: from the simple basic method to more advanced methods such as
14 the quantile perturbation method. In this type of methods, the intrinsic assumption is made that the bias under future
15 climate conditions is identical to the bias in current climate conditions. This is implemented through the use of
16 “change factors” applied for historical precipitation quantiles. Another important assumption that is made by these
17 methods is that the change factors are spatial scale independent, such that the scale difference, although it is an issue
18 for the absolute precipitation intensity values, is less an issue for the delta change methods at which relative changes
19 are applied. The latter assumption is tested next. In this context, the relative changes in precipitation quantiles
20 between the future and historical simulations of climate model runs were calculated to compare the convection-
21 permitting models and their driving GCMs. These change factors were computed for winter and summer seasons as
22 sub-daily and daily precipitation quantiles from the scenario period divided by those from the control period with the
23 same return period (change factor equal to one means no change).

24 The change factors in precipitation extremes for winter and summer seasons computed by the ALARO_{CNRM-CM3}
25 model are shown in Fig. 5. The ALARO_{CNRM-CM3} projects an increasing signal in the range of 14% to 74% for
26 winter, implying a substantial wetter winter. A drier summer is expected from the ALARO_{CNRM-CM3} model
27 projections with a decreasing signal down to -23%. When the change factors computed for ALARO_{CNRM-CM3} are
28 compared with those obtained from the driving CNRM-CM3 GCM, more or less the same conclusion can be made:
29 an increasing signal for winter between 17% and 61% and a decreasing signal for summer which goes as low as -
30 18%. Generally, it can be inferred from the results that, at synoptic (daily) scale, the projections by the ALARO
31 model are consistent with those from the driving GCMs. De Troch et al. (2013) pointed out that an increase in
32 spatial resolution in the ALARO model is not as important as the parameterization scheme used for extreme
33 precipitation modeling at daily scale.

34 Fig. 6 shows change factors for daily and 3-hourly precipitation computed using the CCLM_{EC-EARTH} model with
35 different spatial resolutions for winter and summer seasons. The change factors for all extreme events with $T > 1$
36 year are shown in this figure. To simplify the interpretation of the results, the change factors for extreme



1 precipitation averaged over the extreme events with $T > 1$ year versus the models' spatial scale are presented in Fig.
2 7. For the winter season, the change factors for both daily and 3-hourly precipitation decrease as the model's
3 resolution increases. Nevertheless, the change factors for all the CCLM runs are higher than those for the driving
4 EC-EARTH GCM. A larger change is projected for 3-hourly precipitation compared with daily precipitation. For
5 summer, the change in 3-hourly precipitation obtained from the CCLM_{EC-EARTH} 2.8 km run is greater than that from
6 the CCLM_{EC-EARTH} 7 and 25 km runs, while the pattern for the daily time scale is similar to that of the winter season:
7 decreasing change factors with increasing the model's resolution. Similar to winter, the results show an
8 amplification of the future climate change signals for 3-hourly extremes in the CCLM 2.8 km model compared with
9 the driving EC-EARTH GCM (18% average relative changes for the CCLM_{EC-EARTH} 2.8 km run versus 6% change
10 for the EC-EARTH GCM). This amplification is not evident for the daily scale. Intensification of change in sub-
11 daily precipitation extremes that are not simulated by large scale models was also found by Kendon et al. (2014).
12 The results also reveal that sub-daily precipitation extremes during summer are expected to change at a higher rate
13 compared to daily extremes. Generally, it can be inferred that there is an increase in the change factors of sub-daily
14 precipitation when going from parameterized convection to the convection-permitting scale.

15 **6 Concluding remarks**

16 A comparative study between the convection-permitting climate models with a spatial resolution from 2.8 km up to
17 40 km and driving GCMs or reanalysis data was performed to check whether the models with higher resolution
18 provide more accurate precipitation simulations. Another analysis was performed to validate the spatial scale
19 independency assumption of climate change signals for the delta change downscaling method. The results show that
20 whereas winter daily precipitation extremes are generally overestimated by the ALARO and CCLM models,
21 improved (unbiased) results for summer precipitation extremes are observed. This suggests the added value of
22 convection-permitting climate models to simulate summer extremes because of either better representation of deep
23 convection or larger detail of the land surface. The results moreover indicate that the difference between the
24 convection-permitting models and the parent GCMs or reanalysis data decreases as the time scales get larger (i.e.,
25 weekly and monthly). Based on the precipitation statistics derived from IDF curves, the ALARO and CCLM models
26 mostly underestimate sub-daily precipitation, but still better simulate it compared with parent GCM or reanalysis
27 data when available. For summer IDFs, higher precipitation intensities are simulated by finer resolution models as a
28 result of better representation of small-scale convective precipitation by these models.

29 To investigate whether or not the climate change signals from the convection-permitting models are more or less
30 the same as those from the large scale driving GCMs, the relative changes were computed for precipitation extremes
31 during summer and winter. For the ALARO model, it can be concluded that, at synoptic (daily) scale, the change
32 factors for the ALARO model are comparable with the ones from the driving CNRM-CM3 GCM. In the case of the
33 CCLM model, the results reveal an intensification of climate change signals for the CCLM model compared with
34 the driving EC-EARTH GCM, for both 3-hourly and daily time scales for winter and sub-daily scale for summer. In
35 a similar pattern, the change factors of 3-hourly summer precipitation extremes for the CCLM_{EC-EARTH} 2.8 km run



1 are larger than those from the 7 and 25 km runs. Comparing change factors for 3-hourly and daily precipitation, a
2 larger change is projected for 3-hourly precipitation for both winter and summer seasons.

3 In summary, because the results of this study indicate that the summer extreme precipitation simulations of the
4 high-resolution climate models are closer to the observations, their future projections are expected to be more
5 accurate than those of the driving GCMs. These climate change signals obtained from the high-resolution models
6 may differ from the ones based on the coarse-resolution models. However, the resulting precipitation change from
7 these high-resolution climate models should not be interpreted as an exact number because of their limited number.
8 More runs with high-resolution models are required to check the consistency among models. In the same way as an
9 ensemble approach on climate models provides uncertainty estimates on the climate change signals, an ensemble of
10 the high-resolution models provides uncertainty estimates on the difference between the climate change signals of
11 fine versus coarse scale as a result of improved representation of complex landscape and land surface processes,
12 which may provide more realistic statistics of precipitation including extremes for regional hydrological modeling.
13 Also, the statistical significance of the difference in climate change signals at fine versus coarse scale can be tested
14 in such approach. From the comparison in this study, the results of the CCLM_{EC-EARTH} model indicate an increase in
15 the change factors in summer when going from parameterized convection to the convection-permitting scale. This is
16 different for the ALARO model, where the higher resolution models show changes in the same range as the coarse
17 resolution models. Different procedures for convection parameterization in the CCLM and ALARO models and
18 different boundary conditions (the first one is nested in the EC-EARTH model from CMIP5 and the later in the
19 CNRM-CM3 model from CMIP3) might explain the discrepancy between the results of the two models.

20
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22 Institute of Belgium (RMI) by R. De Troch, O. Giot, R. Hamdi and P. Termonia. The CCLM climate model was
23 implemented by S. Saeed, E. Brisson and N. Van Lipzig in the Earth and Environmental Sciences Department of
24 KU Leuven. H. Tabari and P. Willems developed the methodology and performed the analyses. The paper was
25 prepared by H. Tabari and P. Willems with substantial contributions from all co-authors.

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30 **References**

- 31 Baldauf, M., Seifert, A., Förstner, J., Majewski, D., Raschendorfer, M., and Reinhardt, T.: Operational convective-
32 scale numerical weather prediction with the COSMO model: Description and sensitivities, *Mon. Weather Rev.*,
33 139(12), 3887–3905, doi:10.1175/MWR-D-10-05013.1, 2011.
- 34 Ban, N., Schmidli, J., and Schar, C.: Evaluation of the convection-resolving regional climate modeling approach in
35 decade-long simulations, *J. Geophys. Res.-Atmos.*, 119, 7889–7907, doi:10.1002/2014JD021478, 2014.



- 1 Ban, N., Schmidli, J., and Schär, C.: Heavy precipitation in a changing climate: Does short-term summer
2 precipitation increase faster?, *Geophys. Res. Lett.*, 42, 1165–1172, doi:10.1002/2014GL02588, 2015.
- 3 Böhm, U., Kücken, M., Ahrens, W., Block, A., Hauffe, D., Keuler, K., Rockel, B., and Will, A.: CLM – The
4 Climate Version of LM : Brief Description and Long-Term Applications, *COSMO Newsletters*, 6, 225-235,
5 2006.
- 6 Brisson, E., Demuzere, M., and van Lipzig, N. P. M.: A study on modelling strategies for performing convective
7 permitting climate simulations using the COSMO-CLM over a mid-latitude coastal region, *Meteor. Z.*, doi:
8 10.1127/metz/2015/0598, 2015.
- 9 Brisson, E., Van Weverberg, K., Demuzere, M., Devis, A., Saeed, S., Stengel, M., and van Lipzig, N. P. M.: How
10 well can a convection-permitting climate model reproduce decadal statistics of precipitation, temperature and
11 cloud characteristics?, *Climate Dynam.*, doi: 10.1007/s00382-016-3012-z, 2016.
- 12 Chan, S. C., Kendon, E. J., Fowler, H. J., Blenkinsop, S., Ferro, C. A. T., and Stephenson, D. B.: Does increasing
13 the spatial resolution of a regional climate model improve the simulated daily precipitation?, *Climate Dynam.*,
14 41, 1475–1495, doi: 10.1007/s00382-012-1568-9, 2013.
- 15 Chan, S. C., Kendon, E. J., Fowler, H. J., Blenkinsop, S., Roberts, N. M., and Ferro, C. A.: The value of high-
16 resolution met office regional climate models in the simulation of multi-hourly precipitation extremes, *J. Clim.*,
17 27(16), 6155–6174, doi:10.1175/JCLI-D-13-00723.1, 2014.
- 18 Christensen, J. H., and Christensen, O. B.: A summary of the PRUDENCE model projections of changes in
19 European climate by the end of this century, *Climatic Change* 81, 7–30, doi:10.1007/s10584-006-9210-7, 2007.
- 20 Demarée, G. R.: Le pluviographe centenaire du plateau d’Uccle: son histoire, ses données et ses applications, *La*
21 *Houille Blanche*, 4, 95–102, doi:10.1051/lhb/2003082, 2003.
- 22 Deng, H., Luo, Y., Yao, Y., and Liu, C.: Spring and summer precipitation changes from 1880 to 2011 and the future
23 projections from CMIP5 models in the Yangtze River Basin, China, *Quatern. Int.*, 304, 95–106,
24 doi:10.1016/j.quaint.2013.03.036, 2013.
- 25 De Troch, R., Hamdi, R., Van De Vyver, H., Geleyn, J.-F., and Termonia, P.: Multiscale performance of the
26 ALARO-0 model for simulating extreme summer precipitation climatology in Belgium, *J. Climate*, 26, 8895-
27 8915, doi:10.1175/JCLI-D-12-00844.1, 2013.
- 28 Done, J., Davis, C. A., and Weisman, M.: The next generation of NWP: Explicit forecasts of convection using the
29 Weather Research And Forecasting (WRF) model, *Atmos. Sci. Lett.*, 5(6), 110–117, doi: 10.1002/asl.72, 2004.
- 30 Fosser, G., Khodayar, S., and Berg, P.: Benefit of convection permitting climate model simulations in the
31 representation of convective precipitation, *Climate Dynam.*, 44, 45-60, doi:10.1007/s00382-014-2242-1, 2015.
- 32 Gudmundsson, L., Bremnes, J. B., Haugen, J. E., and Engen-Skaugen, T.: Downscaling RCM precipitation to the
33 station scale using statistical transformations – a comparison of methods, *Hydrol. Earth Syst. Sc.*, 16, 3383-3390,
34 doi:10.5194/hess-16-3383-2012, 2012.
- 35 Hamdi, R., Van de Vyver, H., De Troch, R., and Termonia, P.: Assessment of three dynamical urban climate
36 downscaling methods: Brussels’s future urban heat island under an A1B emission scenario, *Int. J. Climatol.*, 34,
37 978–999, doi:10.1002/joc.3734, 2014.



- 1 Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., and New, M.: A European daily high-
2 resolution gridded dataset of surface temperature and precipitation, *J. Geophys. Res (Atmospheres)*, 113,
3 D20119, doi:10.1029/2008JD10201, 2008.
- 4 Hohenegger, C., Brockhaus, P., and Schar, C.: Towards climate simulations at cloud-resolving scales, *Meteor. Z.*,
5 17, 383–394, doi:10.1127/0941-2948/2008/0303, 2008.
- 6 Hong, S. Y., and Leetmaa, A.: An evaluation of the NCEP RSM for regional climate modeling, *J. Climate*, 12, 592–
7 609, doi:10.1175/1520-0442(1999)012<0592:AEOTNR>2.0.CO;2, 1999.
- 8 Ikeda, K., et al.: Simulation of seasonal snowfall over Colorado, *Atmos. Res.*, 97(4), 462–477,
9 doi:10.1016/j.atmosres.2010.04.010, 2010.
- 10 IPCC: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the
11 Intergovernmental Panel on Climate Change [Houghton, J.T., et al. (eds.)], Cambridge University Press,
12 Cambridge, United Kingdom and New York, NY, USA, 881 p, 2001.
- 13 IPCC: IPCC Fourth Assessment Report (AR4), Cambridge University Press, Cambridge, 2007.
- 14 IPCC: Summary for Policymakers. Climate Change 2013: The Physical Science Basis, Contribution of Working
15 Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, In: Stocker, T. F.,
16 Qin, D., Plattner, G.-K., Tignor, M., Allen, S. KBoschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M.
17 (Eds.), 2013.
- 18 Jacob, D., et al.: EURO-CORDEX: new high-resolution climate change projections for European impact research,
19 *Reg. Environ. Change*, 14, 563–578, doi:10.1007/s10113-013-0499-2, 2014.
- 20 Johnson, F., Westra, S., Sharma, A., and Pitman, A. J.: An assessment of GCM skill in simulating persistence across
21 multiple time scales, *J. Climate*, 24(14), 3609–3623, doi: 10.1175/2011JCLI3732.1, 2011.
- 22 Kendon, E. J., Roberts, N. M., Fowler, H. J., Roberts, M. J., Chan, S. C., and Senior, C. A.: Heavier summer
23 downpours with climate change revealed by weather forecast resolution model, *Nature Climate Change*, 4, 570–
24 576, doi:10.1038/nclimate2258, 2014.
- 25 Kendon, E. J., Roberts, N. M., Senior, C. A., and Roberts, M. J.: Realism of rainfall in a very high-resolution
26 regional climate model, *J. Climate*, 25, 5791–5806, doi: 10.1175/JCLI-D-11-00562.1, 2012.
- 27 Maraun, D.: Bias correction, quantile mapping, and downscaling: revisiting the inflation issue, *J. Climate*, 26: 2137–
28 2143, doi:10.1175/JCLI-D-12-00821.1, 2013.
- 29 Masson, D., and Knutti, R.: Spatial-scale dependence of climate model performance in the CMIP3 ensemble, *J.*
30 *Climate*, 24, 2680–2692, doi: http://dx.doi.org/10.1175/2011JCLI3513.1, 2011.
- 31 Maraun, D., et al.: Precipitation downscaling under climate change: Recent developments to bridge the gap between
32 dynamical models and the end user, *Rev. Geophys.*, 48, RG3003, doi:10.1029/2009RG000314, 2010.
- 33 Mearns, L. O., Giorgi, F., Whetton, P., Pabon, D., Hulme, M., and Lal, M.: Guidelines for use of climate scenarios
34 developed from regional climate model experiments. Data Distribution Centre of the Intergovernmental Panel on
35 Climate Change, 2004.
- 36 Mearns, L. O., et al.: Climate change projections of the North American Regional Climate Change Assessment
37 Program (NARCCAP), *Climatic Change*, 120, 965–975, doi:10.1007/s10584-013-0831-3, 2013.



- 1 Ntegeka, C., Baguis, P., Roulin, E., and Willems, P.: Developing tailored climate change scenarios for hydrological
2 impact assessments, *J. Hydrol.*, 508, 307–321, doi:10.1016/j.jhydrol.2013.11.001, 2014.
- 3 Olsson, J., Willén, U., and Kawamura, A.: Downscaling extreme Regional Climate Model (RCM) precipitation for
4 urban hydrological applications, *Hydrol. Res.*, 43, 341–351, doi: 10.2166/nh.2012.135, 2012.
- 5 Prein, A. F., Gobiet, A., Suklitsch, M., Truhetz, H., Awan, N. K., Keuler, K., and Georgievski, G.: Added value of
6 convection permitting seasonal simulations, *Climate Dynam.*, 41, 2655–2677, doi:10.1007/s00382-013-1744-6,
7 2013a.
- 8 Prein, A., Holland, G. A., Rasmussen, R. M., Done, J., Ikeda, K., Clark, M. P., and Liu, C. H.: Importance of
9 Regional Climate Model Grid Spacing for the Simulation of Heavy Precipitation in the Colorado Headwaters, *J.*
10 *Climate*, 26, 4848–4857, doi:10.1175/JCLI-D-12-00727.1, 2013b.
- 11 Prein, A.F., et al.: A review on regional convection-permitting climate modeling: demonstrations, prospects, and
12 challenges, *Rev. Geophys.*, doi: 10.1002/2014RG000475, 2015.
- 13 Rockel, B., Will, A., and Hense, A.: The Regional Climate Model COSMO-CLM (CCLM), *Meteor. Z.*, 17, 347–
14 348, doi:10.1127/0941-2948/2008/0309, 2008.
- 15 Rajczak, J., Pall, P., and Schär, C.: Projections of extreme precipitation events in regional climate simulations for
16 Europe and the Alpine Region, *J. Geophys. Res.-Atmos.*, 118, 3610–3626, doi:10.1002/jgrd.50297, 2013.
- 17 Rana, A., Foster, K., Bosshard, T., Olsson, J., and Bengtsson, L.: Impact of climate change on rainfall over
18 Mumbai using Distribution-based Scaling of Global Climate Model projections, *J. Hydrol. Reg. Stud.*, 1, 107–
19 128, doi:10.1016/j.ejrh.2014.06.005, 2014.
- 20 Rauscher, S. A., Coppola, E., Piani, C., and Giorgi, F.: Resolution effects on regional climate model simulations of
21 seasonal precipitation over Europe, *Climate Dynam.*, 35, 685–711, doi: 10.1007/s00382-009-0607-7, 2010.
- 22 Rasmussen, R., et al.: High-resolution coupled climate runoff simulations of seasonal snowfall over Colorado: A
23 process study of current and warmer climate, *J. Clim.*, 24(12), 3015–3048, 2011.
- 24 Steppeler, J., Doms, G., Schättler, U., Bitzer, H. W., Gassmann, A., Damrath, U., and Gregoric, G.: Meso-gamma
25 scale forecasts using the nonhydrostatic model LM, *Meteor. Atmos. Phys.*, 82, 75–96, doi:10.1007/s00703-001-
26 0592-9, 2003.
- 27 Sun, Q., Miao, C., and Duan, Q.: Projected changes in temperature and precipitation in ten river basins over China in
28 21st century, *Int. J. Climatol.*, 35, 1125–1141, doi: 10.1002/joc.4043, 2015.
- 29 Sunyer, M. A., et al.: Inter-comparison of statistical downscaling methods for projection of extreme precipitation in
30 Europe, *Hydrol. Earth Syst. Sc.* 19, 1827–1847, doi:10.5194/hess-19-1827-2015, 2015.
- 31 Tabari, H., AghaKouchak, A., and Willems, P.: A perturbation approach for assessing trends in precipitation
32 extremes across Iran, *J. Hydrol.*, 519, 1420–1427, doi:10.1016/j.jhydrol.2014.09.019, 2014.
- 33 Tabari, H., Taye, M.T., and Willems, P.: Water availability change in central Belgium for the late 21st century,
34 *Global Planet. Change*, 131: 115–123, doi:10.1016/j.gloplacha.2015.05.012, 2015.
- 35 Tabari, H., and Willems, P.: Daily precipitation extremes in Iran: decadal anomalies and possible drivers, *J. Am.*
36 *Water Resour. As.*, doi:10.1111/1752-1688.12403, 2016.



- 1 Tang, Y., Lean, H. W., and Bornemann, J.: The benefits of the met office variable resolution NWP model for
2 forecasting convection, *Meteorol. Appl.*, 20(4), 417–426, doi:10.1002/met.1300, 2013.
- 3 van Haren, R., van Oldenborgh, G. J., Lenderink, G., and Hazeleger, W.: Evaluation of modeled changes in extreme
4 precipitation in Europe and the Rhine basin, *Environ. Res. Lett.*, 8, 014053, doi:10.1088/1748-9326/8/1/014053,
5 2013.
- 6 van Pelt, S. C., Beersma, J. J., Buishand, T. A., van den Hurk, B. J. J. M., and Kabat P.: Future changes in extreme
7 precipitation in the Rhine basin based on global and regional climate model simulations, *Hydrol. Earth Syst. Sci.*,
8 16, 4517–4530, doi: 10.5194/hess-16-4517-2012, 2012.
- 9 Willems, P.: Compound IDF-relationships of extreme precipitation for two seasons and two storm types, *J. Hydrol.*,
10 233: 189–205, doi:10.1016/S0022-1694(00)00233-X, 2000.
- 11 Willems, P.: Multidecadal oscillatory behaviour of rainfall extremes in Europe, *Climatic Change*, 120, 931–944,
12 doi:10.1007/s10584-013-0837-x, 2013.
- 13 Willems, P., Arnbjerg-Nielsen, K., Olsson, J., and Nguyen, V.-T.-V.: Climate change impact assessment on urban
14 rainfall extremes and urban drainage: Methods and shortcomings, *Atmos. Res.*, 103, 106–118,
15 doi:10.1016/j.atmosres.2011.04.003, 2012.
- 16 Willems, P., and Vrac, M.: Statistical precipitation downscaling for small-scale hydrological impact investigations
17 of climate change, *J. Hydrol.*, 402, 193–205, doi:10.1016/j.jhydrol.2011.02.030, 2011.

**Table 1** The convection-permitting model runs used in this study.

Climate model	Driving GCM/reanalysis	Spatial scale (km)	Temporal scale	Control period	Scenario period	Data coverage
CCLM	ERA-Interim	2.8	hourly	2001-2010	-	whole year
	ERA-Interim	7	hourly	2001-2010	-	whole year
	ERA-Interim	25	hourly	2001-2010	-	whole year
	EC-EARTH	2.8	15 min ¹	2001-2010	2060-2069	whole year
	EC-EARTH	7	hourly	2001-2010	2060-2069	whole year
	EC-EARTH	25	3 hourly	2001-2010	2060-2069	whole year
ALARO	ERA-Interim	4	hourly	1981-2010	-	whole year
	ERA40	4	daily	1961-1990	-	whole year
	CNRM-CM3	4	daily	1961-1990	2071-2100	whole year
	ERA40	4	hourly	1961-1990	-	summer
	ERA40	10	hourly	1961-1990	-	summer
	ERA40	40	hourly	1961-1990	-	summer

¹ CCLM_{EC-EARTH} 2.8 km data for the scenario period are available for hourly time scale.

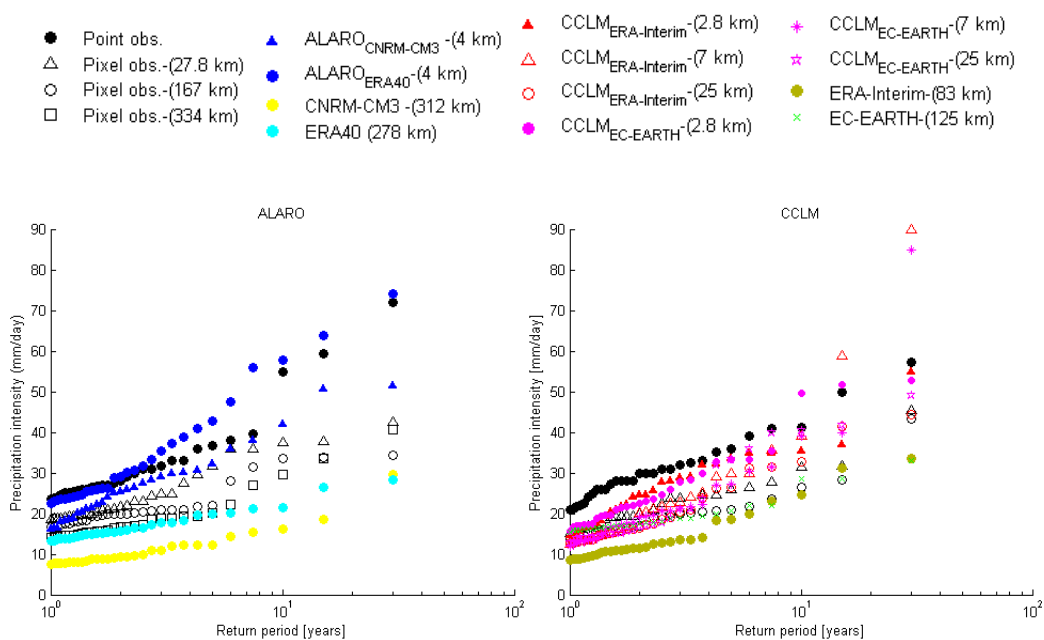


Figure 1. Validation of the daily precipitation quantiles for the ALARO (left) and CCLM (right) models and their driving GCMs or reanalysis data based on point and pixel interpolated Uccle observations, for summer season (historical climate: 1961-1990 for ALARO and 2001-2010 for CCLM).

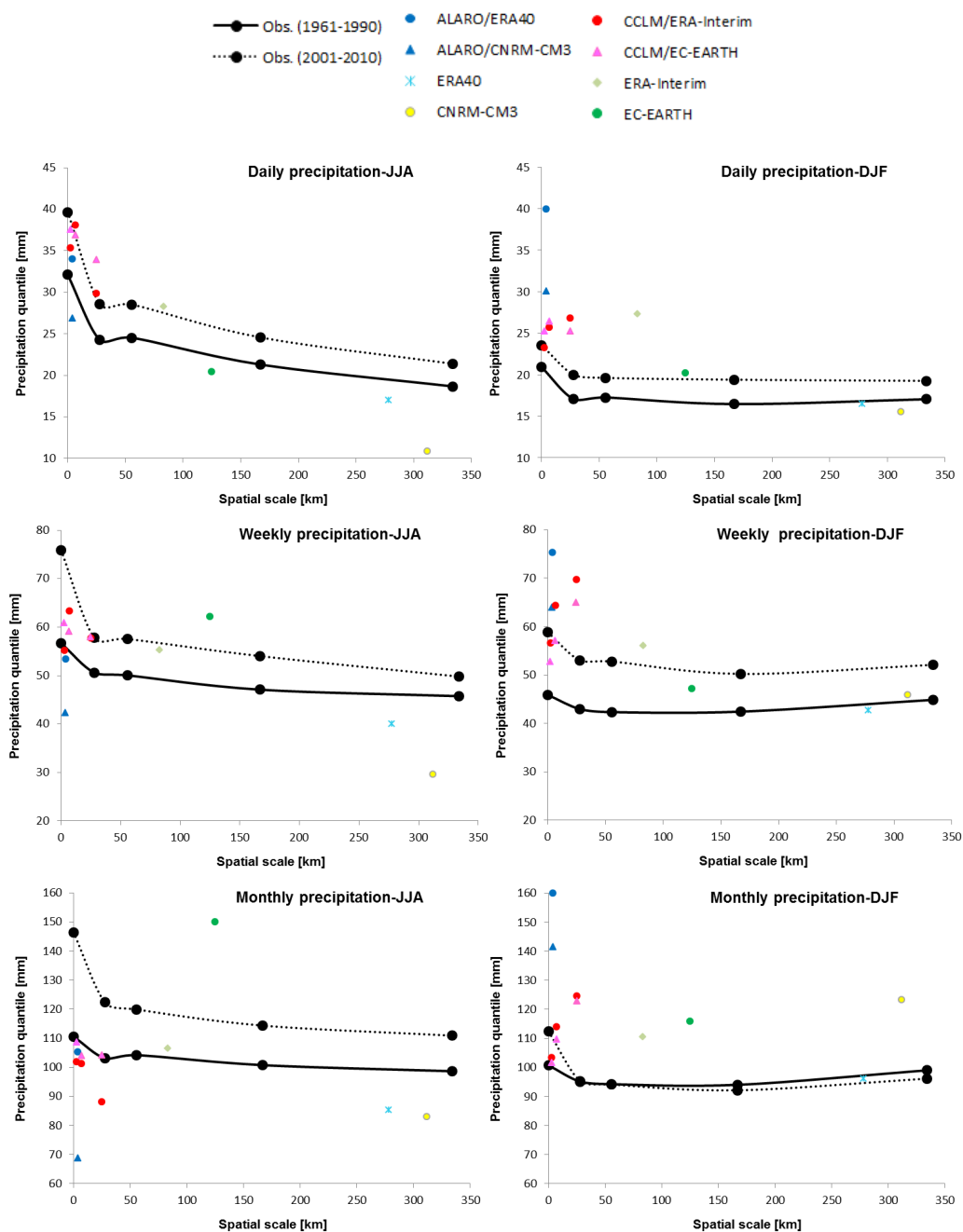


Figure 2. Validation of the extreme precipitation (averaged over the extreme events with $T > 1$ year) simulations for the ALARO, CCLM and the driving GCMs or reanalysis data based on point and pixel interpolated Uccle observations for summer (left) and winter (right) seasons, versus the models' spatial scale.

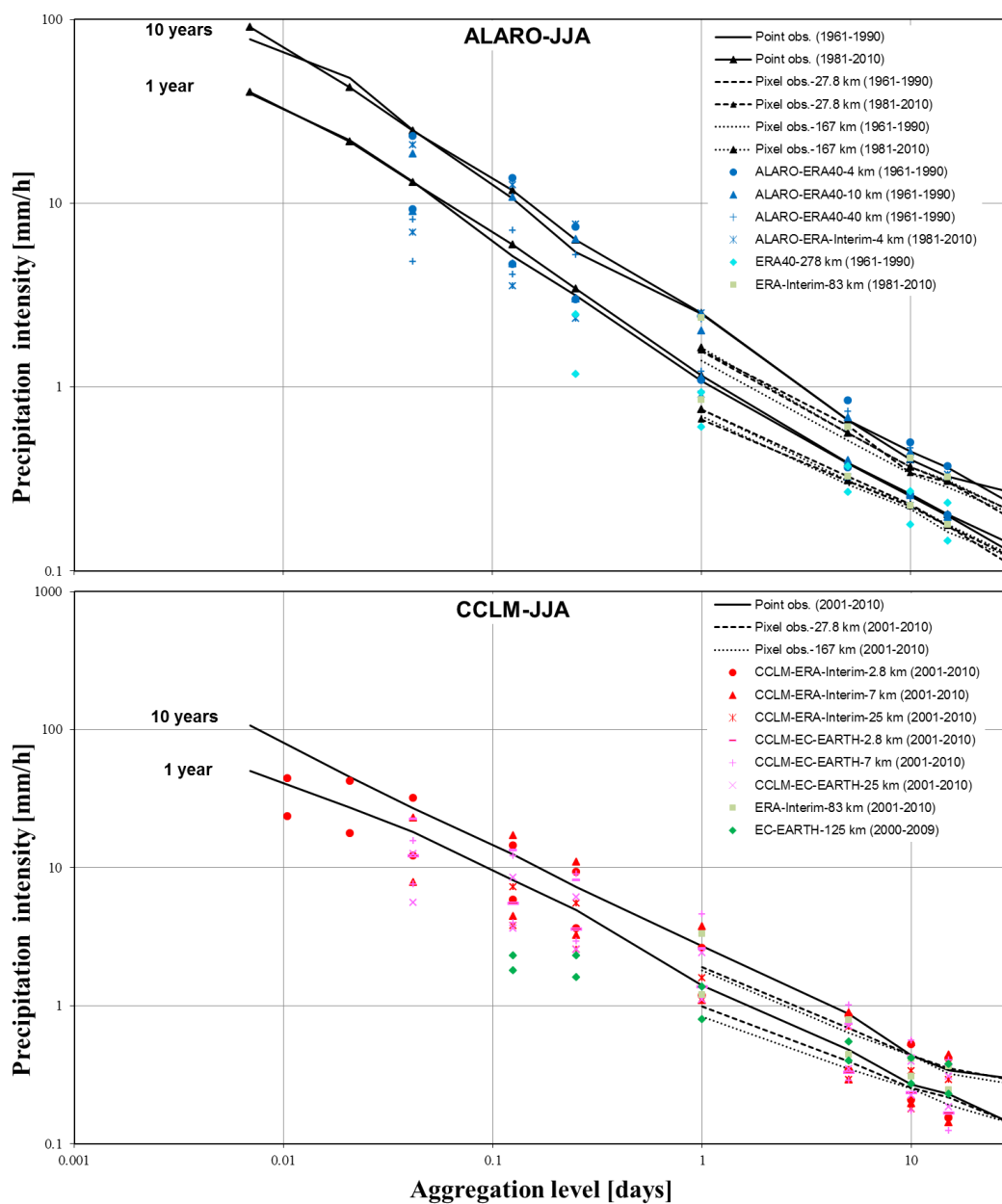


Figure 3. Comparison of historical IDF-relationships based on point and pixel interpolated Uccle observations, with the CCLM, ALARO and the driving GCM or reanalysis results for summer season.

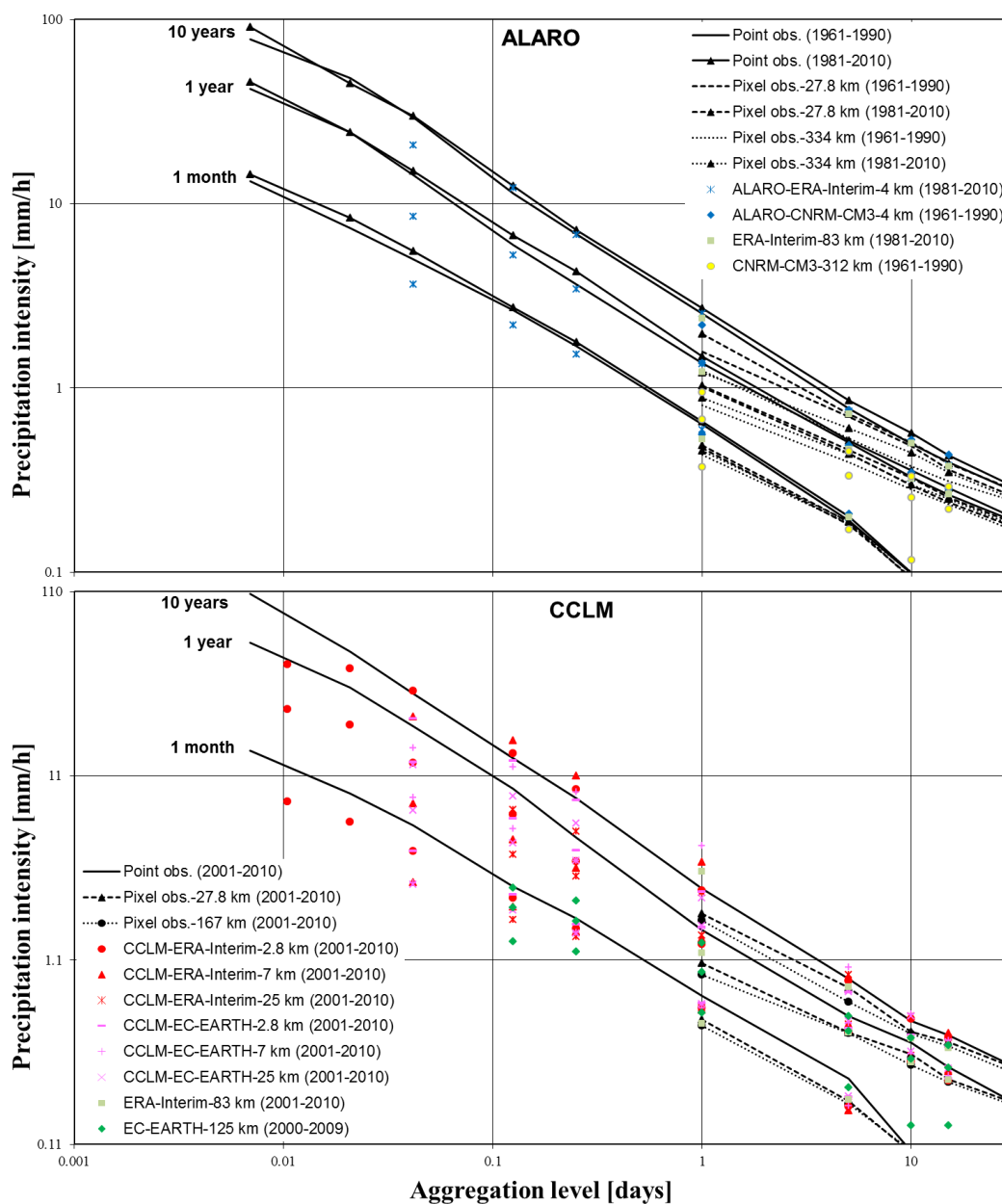


Figure 4. Comparison of historical IDF-relationships based on point and pixel interpolated Uccle observations, with the CCLM, ALARO and driving GCM or reanalysis results.

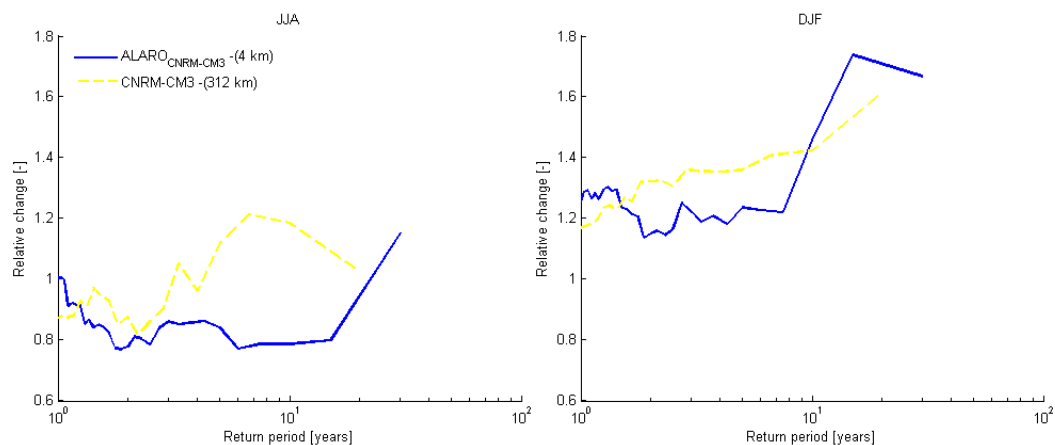


Figure 5. Change factors for daily precipitation quantiles computed using the ALARO_{CNRM-CM3} 4 km and the driving CNRM-CM3 (A1B) for summer (left) and winter (right) seasons.

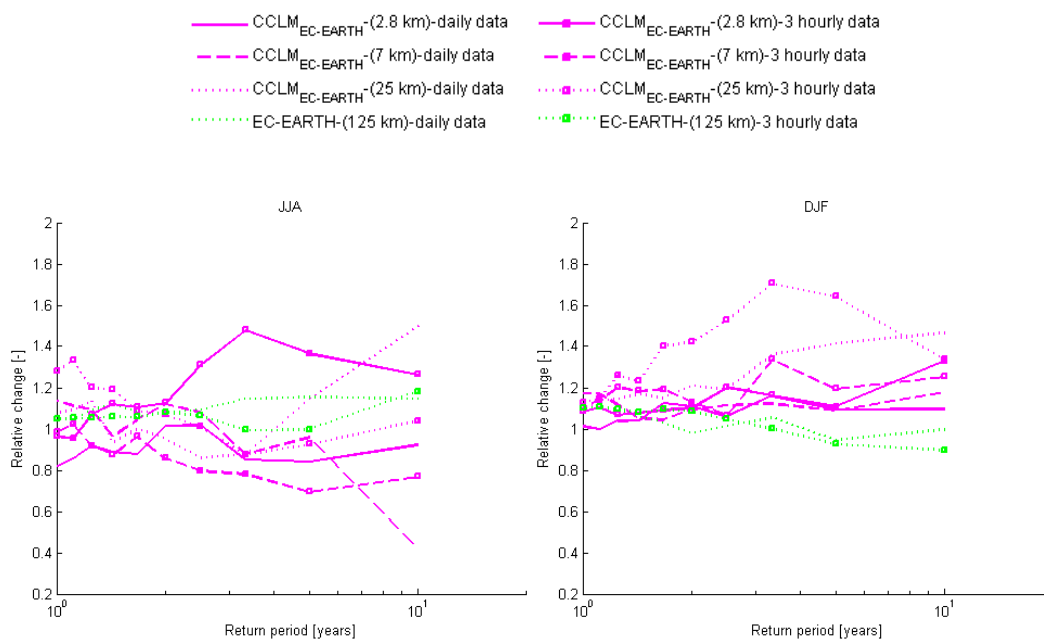


Figure 6. Change factors for daily and 3-hourly precipitation quantiles computed using the CCLM_{EC-EARTH} 2.8, 7, 25 km for summer (left) and winter (right) seasons.

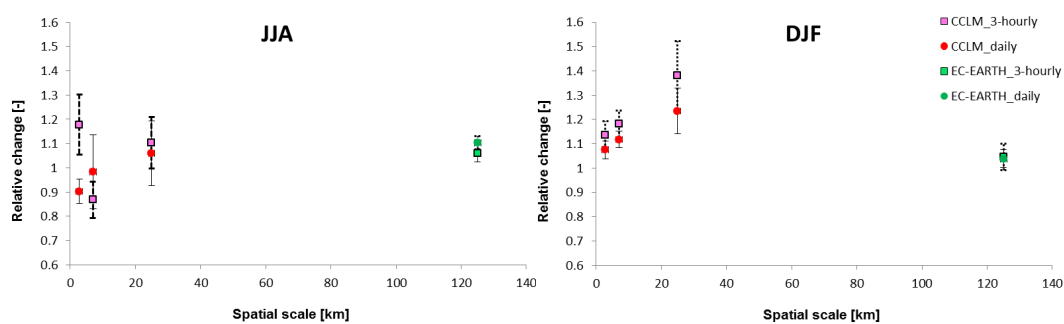


Figure 7. Change factors for extreme daily and 3-hourly precipitation (averaged over the extreme events with $T > 1$ year) computed using the CCLM_{EC-EARTH} 2.8, 7, 25 km and the driving EC-EARTH GCM for summer (left) and winter (right) seasons, versus the models' spatial scale (vertical bars show the 95% confidence intervals calculated using t test).