



Future projections of wet and dry spells in southern Sweden: The impact of climate model resolution

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ABSTRACT

This study evaluates how well five Regional Climate Model (RCM) projections at resolutions from 44 km to 3 km reproduce wet and dry spells compared with observations at six locations in Scania, southern Sweden. Future changes in general and extreme wet and dry signals were also analyzed under RCP8.5 to the end of the 21st century. Convection-permitting climate models (CPMs), operating at resolutions fine enough to explicitly resolve convective processes (< 4 km), are widely recognized to simulate precipitation characteristics more accurately than coarser models. Our results confirm that CPM AROME (3 km), outperforms coarser RCMs in representing both wet and dry spells. Future projections across all resolutions indicate increases in wet spells to the end of the century, with average daily precipitation increasing by 8–12 %. The number of wet events, their average depth, and duration also projected to increase to varying degrees. For dry spells, the annual number of dry days shows a slight increase (0–3 %). The number of dry events is projected to decrease while both the average duration and the annual maximum consecutive dry days increase. Extreme value analysis shows that extreme precipitation intensities at various accumulating durations increase over 5- to 50-year return periods, as implied by the Wet Climate Factor (WCF). The Dry Climate Factor (DCF) indicates shorter annual maximum consecutive dry days in the near future, but prolonged at the end of the century by 3–9 %. These findings corroborate with previous research and improve understanding of systematic biases across RCMs resolutions. They further suggest that CPMs offer improved reliability in projecting future variability in wet and dry conditions, with important implications for regional climate services.

1. Introduction

One of the major concerns of ongoing climate change is the increasing occurrence of extreme hydrometeorological events, such as floods and droughts (Easterling et al., 2000), which pose significant challenges to society, the economy, and agriculture. The Sixth Assessment Report of Intergovernmental Panel on Climate Change (IPCC) concluded that the frequency and intensity of heavy precipitation events have likely increased across most land areas globally, with Europe being particularly affected. In addition, the risk of more frequent agricultural and ecological droughts is also increasing with global warming (Grillakis, 2019; Rodell and Li, 2023). Extremes, in the form of floods or drought, have significantly affected Europe in recent decades (Kreibich

et al., 2022). This includes floods in northern Italy, France, and Switzerland (2000), the UK (2007), Germany and France (2016), and Belgium and Germany (2021), as well as intense heat waves and droughts in 2003, 2018, and 2022. These extreme events have had substantial consequences and cascading effects. For instance, the 2011 Copenhagen cloudburst and the 2014 Malmö one caused extensive damage (Mobini et al., 2021; Sörensen and Mobini, 2017), while the 2018 drought in northern Europe, connected to persistent high temperatures, led to wildfires and water shortages (Hari et al., 2020; Peters et al., 2020). Therefore, understanding and quantifying changes in the intensity and frequency of these extremes, including both wet and dry spells, is crucial for mitigating the impacts of climate change.

Climate models are essential tools for simulating climate variations

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and evaluating the impacts of global warming on precipitation patterns. Extensive efforts have been devoted to the development and application of both global climate models (GCMs) and regional climate models (RCMs) to improve our understanding of climate change impacts. Basharin et al. (2016) highlighted that the selected CMIP5 GCMs effectively reproduced historical precipitation variability and provided robust projections of future precipitation and temperature changes over Europe. Ruosteenoja et al. (2018) showed that climate projections derived from multiple GCMs within the CMIP5 project indicated significant decreases in soil moisture across southern and central Europe, accompanied by increasingly frequent extreme drought episodes under future climate scenarios. Heinrich and Gobiet (2012) used RCMs to project future variations in wet and dry conditions across Europe. Their results indicated a pronounced trend toward drier conditions in the southernmost subregions of Europe, while the northernmost subregions exhibited a shift toward wetter conditions. Rajczak and Schär (2017) demonstrated that multi-model ensembles from EURO-CORDEX suggested intensifications of precipitation extremes across Europe, particularly highlighting increases in heavy rainfall in winter and autumn despite overall summer decreases. Similarly, Spinoni et al. (2018) using bias-adjusted high-resolution RCM simulations, projected significant increases in the frequency and severity of droughts, particularly over the Mediterranean region, under moderate and high-emission scenarios. These studies underline the critical role of GCMs and RCMs in advancing the understanding of precipitation and drought patterns at regional scales.

Climate models differ in spatial (horizontal and vertical) as well as temporal resolution. Precipitation characteristics, such as amount, frequency, intensity and duration, are highly sensitive to model resolution. Projections from higher-resolution models generally indicate increased precipitation intensity but reduced frequency and duration, compared with those from coarser-resolution models (Chen and Dai, 2018, 2019). Wehner et al. (2010) demonstrated that enhanced model resolution improves the simulation of atmospheric dynamics and boundary conditions, leading to a more accurate representation of regional climate variability, particularly for extreme events (Demory et al., 2020; Olsson et al., 2015; Sunyer et al., 2015). However, the benefits of higher resolution for broader seasonal averages are often limited (Kotlarski et al., 2014; Yao et al., 2017). When examining the effect of model resolution on precipitation characteristics, Eggert et al. (2015) found it depends strongly on the spatio-temporal nature of the events themselves: stratiform precipitation of large scale shows little sensitivity, while small-scale convective precipitation is highly sensitive to resolution changes.

Regional climate models (RCMs) with high spatial and temporal resolution, known as Convection-Permitting Models (CPMs), has been developed to explicitly resolve deep convection processes. CPMs represent deep convection directly and require parameterization only for shallow convection, thereby addressing limitations of traditional GCMs and RCMs (Kendon et al., 2014). CPMs significantly enhance the simulation of precipitation characteristics, particularly peak hourly intensity and the diurnal cycle of precipitation (Prein et al., 2015; Lucas-Picher et al., 2021; Médus et al., 2022). Studies have shown that CPMs can reduce biases in short-duration extremes, reproducing heavy precipitation events with spatial scales and intensities comparable to the observed ones, such as the 2014 Malmö event (Olsson et al., 2021), and improve projections of daily and sub-daily precipitation across Fennoscandia (Lind et al., 2020). Furthermore, extremely high-resolution CPMs (e.g. 750 m) outperform coarser-resolution models in simulating precipitation extremes (Thomassen et al., 2023). Overall, CPMs represent a significant advancement by providing more accurate simulations of localized convective precipitation and improving the assessment of extreme weather events.

Previous research has provided valuable insights into the role of spatial resolution in capturing climate extremes, particularly in relation to wet spells. However, relatively limited attention has been paid to addressing both wet and dry spells, even though analyzing both can

yield a more comprehensive understanding of model performance. Panthou et al. (2018) showed that higher-resolution RCMs capture dry spell characteristics more accurately than their coarser counterparts, and Berthou et al. (2019) further demonstrated a clear advantage of a CPM at 4.5 km resolution over lower-resolution RCMs in representing both wet and dry spells in West Africa. As emphasised by Giorgi et al. (2019), more meaningful assessments of hydroclimatic extremes require going beyond mean precipitation fields and incorporating higher-order statistics, in order to capture the full range of processes shaping wet and dry events.

When analyzing future projections across different model resolutions, the imbalance in attention to wet versus dry spells becomes more evident. Many studies have investigated the added value of higher-resolution models in projecting future rainfall extremes, particularly by comparing CPMs with other RCMs with coarser resolutions. For example, Kendon et al. (2014) compared a CPM at 1.5 km with another RCM at 12 km and found that the CPM projected more substantial changes in precipitation extremes. Lind et al. (2023) showed that a CPM at 3 km projected a significantly stronger increase in summer hourly precipitation extremes compared to an RCM with 12 km resolution. Dyrreid et al. (2023) found notable variability among CPM simulations, with one CPM driven by EC-Earth projecting changes close to the EURO-CORDEX ensemble median, whereas another CPM driven by GFDL-CM3 predicted significantly higher changes, exceeding the EURO-CORDEX median by about 20–40 % in several parts of southern Scandinavia. Rybka et al., 2023 reported that a CPM (COSMO-CLM, 3 km) projected an approximately 30 % increase in the intensity of daily precipitation extremes under a high-emission scenario by the end of the 21st century. However, it did not project further intensification of sub-daily high-intensity rainfall, contrary to coarser-resolution RCMs, which generally projected stronger intensification at sub-daily scales. Additionally, studies addressing future changes in both wet and dry spells across multiple RCM resolutions remain limited. Although studies such as Chan et al. (2014) and Gadian et al. (2018) have explored both types of spells, they are limited to comparisons between two sets of resolutions (1.5/12 km and 3/12 km). With climate change, the risks posed by uneven spatial and temporal distribution of precipitation are intensifying, making it particularly important to take both wet and dry spells into consideration when evaluating the model performances. Comprehensive multi-resolution analyses, as suggested by Tölle et al. (2018), are essential for bridging this gap and advancing the understanding of how model resolution affects projections of extreme events under future climate scenarios.

To address these issues, we examine the bias in both wet and dry spells using five RCMs with resolutions ranging from ~44 km down to ~3 km (including one CPM) for the Scania region in Sweden, by comparing model projections and observations. It should be noted that the bias analysis in this study is based on GCM-driven RCM simulations in the historical period 1996–2005, complementing the reanalysis-driven RCM simulations evaluated in Olsson et al. (2021). Furthermore, we assess how model resolution influences projected future changes in wet and dry spells until the end of 21st century. This study addresses two main scientific questions: (1) How does RCM resolution, particularly CPM and non-convection-permitting models (non-CPMs), influence the accuracy of wet and dry spell representations during the historical period? (2) How consistent are the projected future changes in wet and dry spells, including extremes, across CPMs and non-CPMs at different resolutions? These results provide valuable insights for interpreting results from regional and global hydrological climate services. This is particularly relevant given the current EURO-CORDEX standard of 12.5 km (Jacob et al., 2014), but also as coarser resolutions are still widely applied. Our multi-resolution comparison clarifies the added value and potential limitations of moving toward convection-permitting scales (~3 km) compared with the existing standard, informing future decisions that balance computational feasibility with essential spatial detail for hydrological impact assessment and adaptation planning.

2. Study area and data

2.1. Local precipitation observations

Precipitation data from six stations (located throughout the southern part of Sweden, Fig. 1) with 15 min time-step (Table 1) over the period 1996–2005 were collected from Swedish Meteorological and Hydrological Institute (SMHI). Precipitation data are collected at stations managed by SMHI utilizing GEONOR automated precipitation gauges equipped with windshields. It was pointed out that the impact for observation data from gauge undercatch, i.e., that the wind field around the gauge makes some of the precipitation miss the gauge, is small in southern Sweden (Nešpor and Sevruk, 1999). The instrument provides precipitation intensity data at a resolution of 0.1 mm/h and the average relative error of intensity measured by this gauge has been estimated to be within $\pm 2.5\%$ (Lanza and Vuerich, 2009). Following guidelines of the SMHI data distribution center, initial quality control was performed in order to treat erroneous negative precipitation amounts, which obviously arose from the electronic characteristics of the device, and these were set to missing records (e.g., Jeong et al., 2011).

2.2. Regional climate model projections

The GCM EC-Earth member r12i1p1 (Hazeleger et al., 2010, 2012) was selected for dynamical downscaling in this study, using Representative Concentration Pathway (RCP) RCP8.5, and three time slices: 1986–2005 (P1), 2041–2060 (P2), and 2081–2100 (P3). RCP8.5 is commonly referred to as the “worst-case” scenario in IPCC assessments. It assumes that greenhouse gas emissions will continue to rise throughout the 21st century without significant mitigation efforts, leading to a radiative forcing level of 8.5 W m^{-2} by the year 2100 (Moss et al., 2008). This scenario projects high levels of global warming and is associated with the most severe impacts on climate, including higher average global temperatures, more frequent and intense extreme weather events, and significant sea-level rise. While RCP8.5 is increasingly regarded as less likely given ongoing mitigation efforts (Hausfather and Peters, 2020), it remains crucial for comprehensively

Table 1

Precipitation observation stations.

Abbreviation	Name	Latitude	Longitude
SKI	Skillinge	55.49	14.31
HÖR	Hörby	55.86	13.67
HEL	Helsingborg	56.03	12.77
HAN	Hanö	56.01	14.85
HAV	Hallands väderö	56.45	12.55
MAL	Malmö	55.57	13.07

assessing climate risks and for planning adaptive and mitigating strategies.

The fourth version of the Rossby Centre Regional Atmospheric Climate Model (RCA4) represents a substantial advancement over its predecessor, RCA3, which was primarily tuned for European domains and involved a technically complex setup (Samuelsson et al., 2011). RCA4 was developed as a more versatile and transferable model, suitable for application across different global domains without extensive retuning, while also improving computational efficiency and user-friendliness. RCA4 was initially applied for downscaling over the European CORDEX domain (see <https://cordex.org/domains/cordex-regi-on-euro-cordex/>). In this study, we use RCA4 simulations driven by EC-Earth member r12i1p1 at horizontal resolutions of 0.44° ($\sim 50 \text{ km}$), 0.22° ($\sim 25 \text{ km}$), and 0.11° ($\sim 12.5 \text{ km}$).

HCLIM38 (Lindstedt et al., 2015; Lind et al., 2016; Belušić et al., 2020) is a regional climate model (RCM) system based on the ALADIN–HIRLAM numerical weather prediction (NWP) framework. It employs atmospheric physics packages from three NWP configurations, each designed for different horizontal resolutions. A key focus of HCLIM is convection-permitting climate modelling. In this study, two configurations of HCLIM38 are applied for downscaling the selected GCM: (1) HCLIM38-AROME, which is designed for convection-permitting scales ($< 4 \text{ km}$) and uses non-hydrostatic dynamics (Seity et al., 2011; Bengtsson et al., 2017; Termonia et al., 2018); (2) HCLIM38-ALADIN shares physical parameterizations with the global model ARPEGE and can be regarded as its limited-area version, typically applied at grid spacing $\geq 10 \text{ km}$. The boundary layer parameterization is based on the

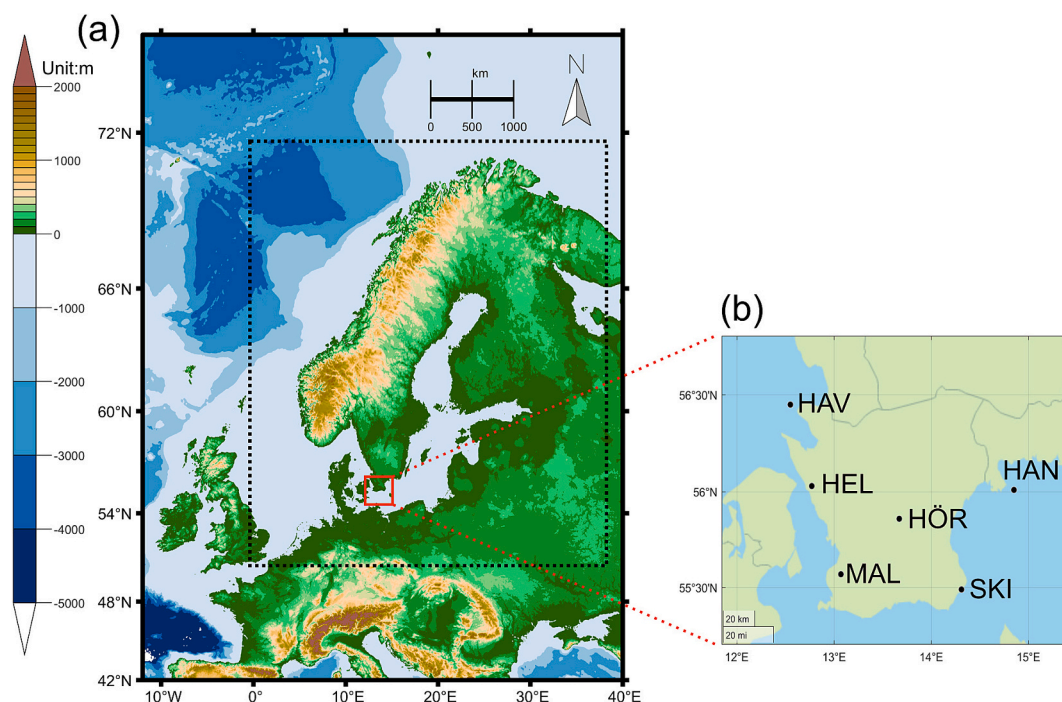


Fig. 1. (a) The model domains for AROME (outer rectangle with solid line) and ALADIN (inner rectangle with dashed line); (b) the locations of study region and observational stations.

Table 2
Regional climate model simulations.

RCM	Acronym	Gridding size	Temporal output resolution	Grids over domain
HCLIM38-AROME	AROME	~ 3 km	15 min	73 × 73
HCLIM38-AROME	AROME4x4	~ 12 km	15 min	/
HCLIM38-ALADIN	ALADIN	~ 12 km	1 h	19 × 19
RCA4-011 degree	RCA011	~ 12.5 km	1 h	21 × 21
RCA4-022 degree	RCA022	~ 25 km	1 h	11 × 11
RCA4-044 degree	RCA044	~ 50 km	1 h	5 × 5

prognostic equation of the turbulent kinetic energy (TKE) (Cuxart et al., 2000), which is also used in AROME, but in this case is associated with the shallow convection scheme (KFB) based on a CAPE closure (Bechtold et al., 2001). Both schemes are connected to the thermal production of TKE, computed by the KFB scheme and by a modification of the original mixing length from Bougeault and Lacarrere (1989) to account for shallow cloud in KFB. Deep convection is represented by an updated version of the mass-flux scheme based on a moisture convergence closure (Bougeault, 1985). Atmospheric convection is parameterized in HCLIM38-ALADIN, whereas in HCLIM38-AROME atmospheric deep convection is explicitly resolved.

In summary, five sets of model outputs with varying temporal and spatial resolutions were obtained by downscaling the same GCM using two different RCMs, as listed in Table 2. The spatial domains of the RCM outputs differ slightly due to variations in grid resolution, but all consistently cover the study area (Fig. 1b). The datasets were extracted from the grid cells covering the observation stations; hence the bias reported in Section 4.1 was calculated using gauge observations and data from their nearest grid points. To better compare the impact of grid size on wet and dry spell statistics, a time series of averaged values from AROME was aggregated to 4 × 4 grid (denoted as AROME4x4), so that its spatial resolution was expanded to ~12 km, comparable to ALADIN and RCA011. All grid cells within the domain were included in the future change estimates.

3. Methods

3.1. Event-based metrics

3.1.1. Wet spells

In this study, we employ a threshold-based method to detect and characterize individual precipitation (wet) events from hourly precipitation data. A precipitation event is defined to commence when the hourly precipitation exceeds 1 mm hour⁻¹ and continues as long as values remain above this threshold. An event ends when the precipitation falls below the threshold.

Based on all identified wet events, we calculated the following statistics: (1) number of wet events, (2) total depth of each wet event, and (3) duration of each wet event. Average values of these metrics were then calculated. In addition, average daily precipitation was calculated to assess the general wet conditions in three projection periods. Average daily precipitation P_{daily} is calculated as:

$$P_{daily} = \frac{\sum_{j=1}^N P_j}{N} \quad (1)$$

Where P_j is the daily precipitation on j th day, N is the total number of days for a specific study period.

3.1.2. Dry spells

A similar approach was applied to isolate and characterize dry periods. A dry event is defined to begin when daily precipitation falls below 1 mm day⁻¹ and to continue as long as consecutive daily precipitation remains below this threshold. In line with the Expert Team on Climate Change Detection and Indices (ETCCDI), the traditional Consecutive Dry Days (CDD) index is defined as the maximum number

of consecutive days with daily precipitation below 1 mm within a given period (e.g., one year; Alexander et al., 2006). In this study, we also apply the tradition CDD definition but extend the analysis by identifying and including all dry events, regardless of their length or interval. For each year, all consecutive dry events were identified, and the following metrics were calculated at each station or grid point: (1) number of dry events, (2) length of dry events, and (3) annual maximum length of dry events (corresponding to the CDD index). If a dry event extended beyond the end of the calendar year, it was terminated on the last day of that year and counted separately from any continuation into the following year. As the longest dry spells in the study region typically occur in summer, this approach is expected to have minimal influence on the statistics of dry or extreme dry events.

To assess the general characteristics of projected dry condition, we also calculated the average annual number of dry days DT_{year} (unit: days / year):

$$DT_{year} = \frac{\sum_{y=1}^Y T_{dry}(y)}{Y} \quad (2)$$

Where $T_{dry}(y)$ is the total number of dry days in the y th year, a dry day is defined as the daily precipitation no more than 1 mm. Y denotes the total number of years.

Above metrics are calculated for both observational and model data across all study periods. The resulting statistics are utilized to evaluate model biases against observations during the historical period (1996–2005) and to compare future scenarios across various climate models in terms of absolute values and relative changes.

3.1.3. Cross-comparison and sensitivity test

The historical analysis was restricted to a 10-year period (1996–2005), in contrast to the 20-year future periods (P2 and P3). To enable a more comprehensive evaluation, we employed a cross-comparison approach by comparing model output from an earlier period (1986–1995) against observational data from 1996 to 2005. Because the GCM-driven simulations are not linked to specific years, apart from prescribed greenhouse gas concentrations, there is no one-to-one comparison of individual short periods. As a sensitivity test, we therefore compared a nearby period to explore robustness, essentially sampling natural variability.

When analyzing model biases relative to observations in the historical period, we use the term “bias” to encompass both model errors and statistical differences arising from varying spatial resolutions, since model outputs represent grid-cell averages while observations are point measurements. Acknowledging that spatial averaging can influence statistical measures, particularly threshold-based metrics, we complemented the analyses with additional sensitivity tests. Specifically, we evaluated wet and dry events using alternative thresholds (0.1, 0.5, and 1.5 mm). The analyses were performed on different temporal scales—hourly for wet events and daily for dry events—while maintaining consistent threshold values (mm/h and mm day⁻¹, respectively). For each threshold, all metrics described in 3.2.1 and 3.2.2 were calculated across models and compared with observations for 1996–2005.

3.2. Extreme value analysis and climate factor

3.2.1. Data preparation and precipitation maxima

We calculated annual maximum precipitation values at each model grid point and for observations at various accumulation durations: 15 min, 30 min, 1 h, 2 h, 3 h, 6 h, 12 h, and 24 h. For durations ≥ 1 h, a running window with a 1-h step was applied, while for the 30 min accumulation non-overlapping window was applied. The 15 and 30 min durations were only applicable to observations, AROME, and AROME4x4 due to the temporal resolution constraints. Although differences in windowing schemes may slightly influence extreme precipitation estimates, previous studies (e.g., Berg et al., 2019) suggest the impact is limited.

The annual precipitation maxima were calculated to enable comparison between RCMs and observations during 1996–2005. Besides, They were also derived for P1–P3 for each model, forming the basis for extreme value analysis and for subsequent climate factor estimation.

3.2.2. GEV fitting and return level estimation

The Generalized extreme value (GEV) distribution (Jenkinson, 1969) was applied to model annual extremes. The cumulative distribution function is defined using the standardized variable $\zeta = (x - \mu) / \sigma$,

$$F(\zeta; \xi) = \begin{cases} \exp\left(- (1 + \xi^* \zeta)^{-\frac{1}{\xi}}\right) & \xi \neq 0 \\ \exp(-\exp(-\zeta)) & \xi = 0 \end{cases} \quad (3)$$

where $\mu \in \mathbb{R}$ is a location parameter, $\xi \in \mathbb{R}$ is a shape parameter, and $\sigma > 0$ is a scale parameter. For $\xi > 0$, the expression is valid for $\zeta > -1/\xi$, while for $\xi < 0$, the expression is valid for $\zeta < -1/\xi$.

In probability theory, the GEV distribution forms a family of continuous probability distributions within extreme value theory, combining the Gumbel, Fréchet, and Weibull families corresponding to $\xi = 0$, $\xi > 0$, and $\xi < 0$, respectively. Parameters were estimated using the maximum likelihood method, with significance assessed at the 0.05 level.

For wet spells, the GEV was fitted to the annual maxima of precipitation at each grid point and accumulation duration. For dry spells, it was applied to the annual maximum consecutive dry days. Return levels were estimated for 5-, 10-, 20-, and 50-year return periods for both wet and dry spells. The suitability of the GEV for modelling extremes has been demonstrated in previous studies (e.g., Zhang et al., 2012; Zhang et al., 2017; Olsson et al., 2019). To verify goodness of fit, a one-sample Kolmogorov–Smirnov (K-S) test was applied at each grid point. The proportion of grid points showing statistically significant fits ranged from 79.3 % to 99.2 % across models and periods, with notably high proportions (over 95 %) for AROME and ALADIN, indicating robust overall performance.

3.2.3. Wet climate factor (WCF) and dry climate factor (DCF)

To quantify projected changes in extreme precipitation intensity, we calculated the Wet Climate Factor (WCF) following the method adopted in previous studies (Willems, 2012; Dyrddal et al., 2023). The WCF is defined as the ratio of future to historical extreme precipitation intensity:

$$WCF_{T,d} = \frac{P_{fut}(T, d)}{P_{hist}(T, d)} \quad (4)$$

where P_{fut} and P_{hist} are the precipitation return levels for a given return period (T) and duration (d) under future (P2 and P3) and historical (P1) conditions, respectively. WCF values were first derived for each grid point, after which spatial averages were computed across the domain for each duration and return period, yielding WCF–duration curves.

In addition to WCF, we introduce a Dry Climate Factor (DCF),

defined as the ratio of future and historical return levels of annual maximum consecutive dry days:

$$DCF_T = \frac{D_{fut}(T)}{D_{hist}(T)} \quad (5)$$

where D_{fut} and D_{hist} represent return levels for a given return period (T) in future and historical periods. Domain-averaged DCF values were computed for each return period and model.

It should be noted that wet and dry spells were analyzed at different temporal scales: wet extremes at hourly (sub-daily) scales and dry extremes at daily scales. This reflects the distinct research focus of the two analyses. Given the inclusion of high-resolution RCMs, the wet spell analysis emphasizes intense precipitation events by applying higher thresholds and evaluating short-term accumulations, while dry spell analysis prioritizes consecutive dry days, providing a generalized representation of drought conditions rather than intensity-based extremes.

4. Results

4.1. Historical analysis of wet and dry spells

4.1.1. Wet spell characteristics

The biases of RCMs relative to the observations during 1996–2005 are shown in Fig. 2. In terms of the number of wet events, AROME (AROME4x4) shows a slight underestimation at most stations, ranging from –6.8 % to 1.2 %. RCA011 consistently overestimate the number of events, with an average bias of 24.8 %. The biases of ALADIN, RCA022 and RCA044 are spatially heterogeneous, alternating between over- and underestimation depending on location. For the average total depth of wet events, most models show systematic negative biases across stations. RCA022 and RCA044 typically show the smallest biases, lying closest to zero, suggesting they capture total depth better than the other models. For average duration, AROME and AROME4x4 generally underestimate, while ALADIN, RCA022 and RCA044 tend to overestimate. RCA011 is closest to neutral, with an average bias of 2.1 %. Compared with AROME, AROME4x4 shows larger bias in the number of events, smaller bias in average duration, and similar bias in average depth.

The cross-comparison results (Supplementary Fig. S1a–c) basically confirmed the same overall tendencies, although with clear differences in magnitude. Several models retain their overall sign in bias; for example, AROME and AROME4x4 generally underestimate wet spells, while RCA011 tends to overestimate the number of wet events but shows much smaller biases for average depth and duration. RCA022 and RCA044 generally overestimate wet durations. Biases also vary across wet spell characteristics between decades: all models show stronger negative biases in number of events, while AROME and ALADIN maintain the same sign of bias in total depth across stations. In contrast, RCA011, RCA022 and RCA044 show opposite bias signs at some stations. The average duration of wet events (Supplementary Fig. S1c) shows larger variability. These results indicate that the intrinsic model bias characteristics are relatively robust over time, while shifts in bias magnitude suggest that natural variability and/or model non-stationarity play a role.

Recognizing that spatial averaging can influence statistical measures, particularly threshold-based metrics, we therefore complement part of the analyses with additional sensitivity tests. Supplementary Fig. S1d–l shows the deviations of model projections from observations during 1996–2005 when progressively higher thresholds of 0.1, 0.5 and 1.5 mm were applied to define wet events. Combined with Fig. 3 (using 1 mm threshold), the results show that models tend to overestimate the number of wet events at lower thresholds and gradually shift toward underestimation as the threshold increases. For total depth, all models generally underestimate, but the magnitude decreases as the threshold increases. For event duration, RCA022 and RCA044 consistently show overestimations of about 30 % across thresholds, whereas AROME

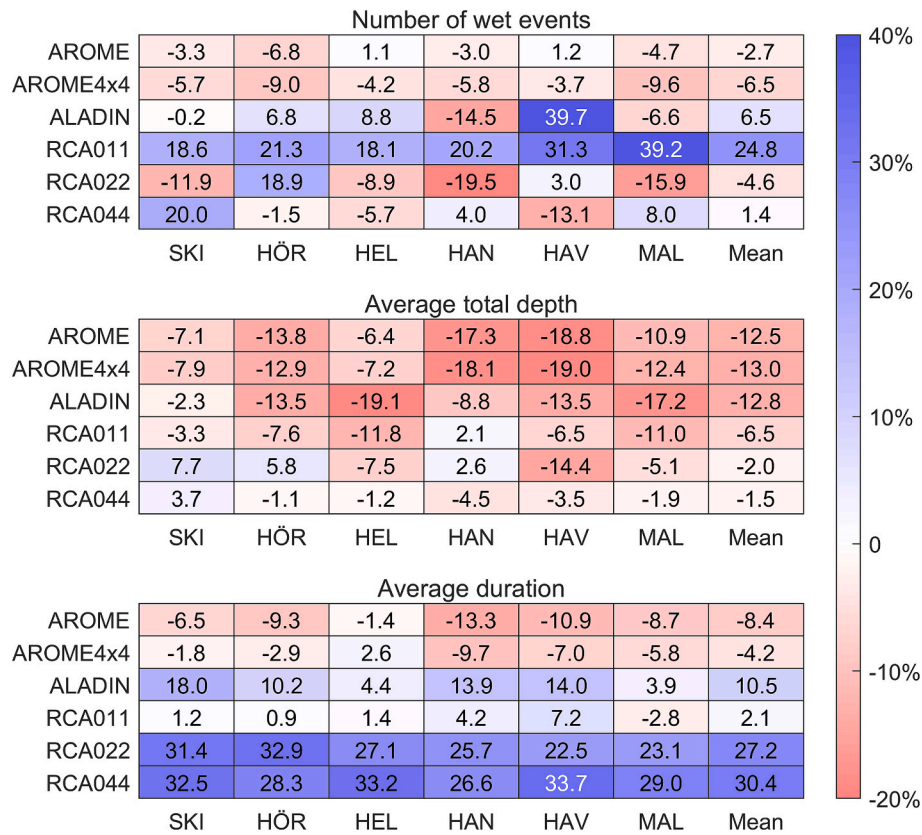


Fig. 2. Heat map of biases in percentage (%) of all models: total number, average depth, and average duration of wet events during a historical period (1996–2005). Darker colors denote larger bias; blue / red denotes positive / negative bias. Values are given for all stations individually as well as mean over all stations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

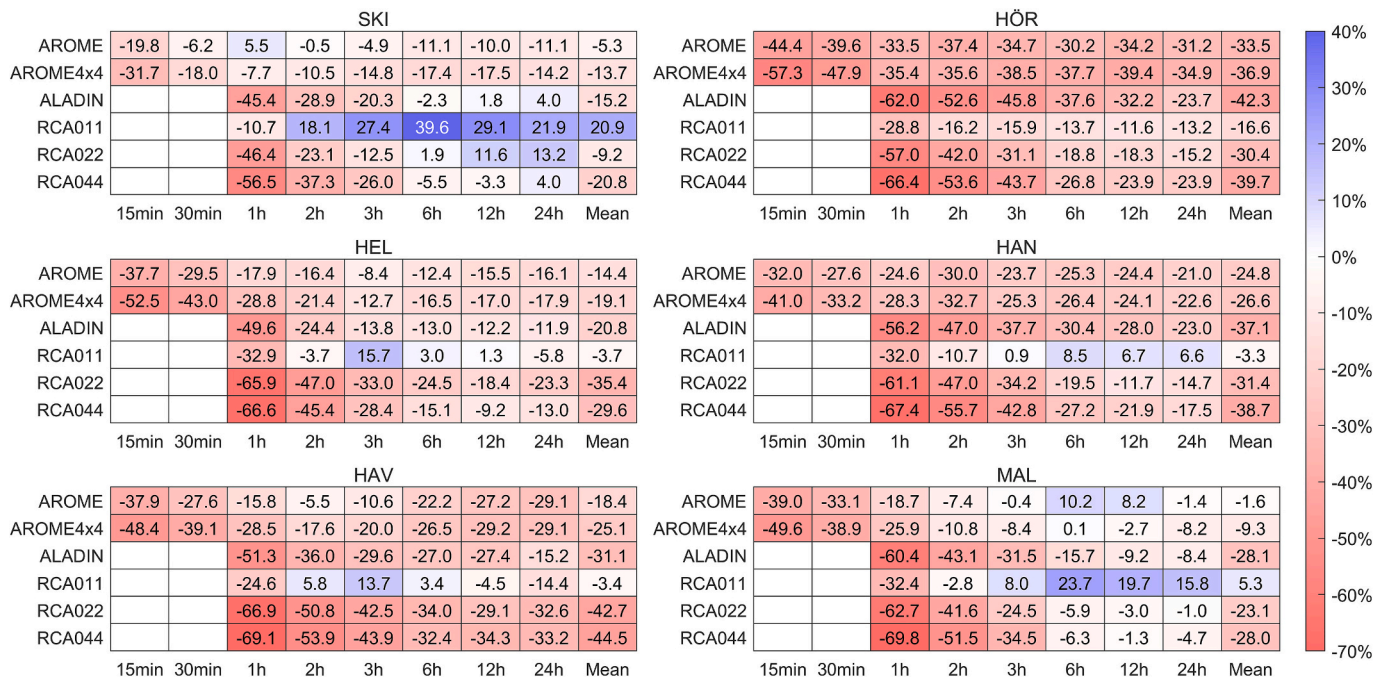


Fig. 3. The model biases the average annual maximum precipitation intensity (%) at various durations (15 min to 24 h). Darker colors denote larger bias; blue / red denotes positive / negative bias. For a better comparison, the mean values are calculated from 1 to 24 h for all models. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

exhibits increasingly large underestimations at higher thresholds. Among the three models at 12 km-resolution (AROME4 × 4, ALADIN, RCA011), the responses differ: AROME4x4 and ALADIN underestimate number of events at lower thresholds but overestimate at higher thresholds, while RCA011 starts with a large overestimation (+100 %) at the lowest threshold and diminishes toward zero with increasing threshold. All three models show comparable bias in average total depth at lower thresholds, but RCA011 approaches zero bias as thresholds increase. For durations, ALADIN consistently overestimates, while AROME4x4 and RCA011 remain within $\pm 6\%$ on average, with AROME4x4 showing modest underestimation at higher thresholds and RCA011 tending toward slight overestimation. Different metrics show varying sensitivity to threshold choice, largely explained by model resolution and spatial averaging effects.

4.1.2. Precipitation maxima across durations

Fig. 3 shows the relative biases of average annual precipitation maxima at different durations at all locations. The models generally perform better in reproducing precipitation maxima at accumulation durations of 6 h or longer. Overall, biases increase as the model resolution decreases. AROME and AROME4x4 cover sub-hourly output in this study. They tend to underestimate the observed precipitation intensity by up to -57.3% (HÖR), with the smallest bias in SKI. For durations longer than 1 h, AROME and RCA011 show smaller biases than the other models. AROME generally underestimates at all durations, while RCA011 overestimates intensity at durations longer than 3 h. ALADIN, RCA022 and RCA044 produce similar results across durations, showing general underestimation at all stations. Their biases are larger at shorter durations and decrease with increasing duration.

4.1.3. Dry spell characteristics

Fig. 4 presents the bias between observed and projected dry spells, including average number, length and annual maximum length of dry

events. A consistent pattern across models is an overestimation of the total number of dry events, coupled with underestimation of both the average and annual maximum lengths, except for the maximum CDD at HEL by AROME. AROME and AROME4x4 show smaller deviations from observations than other models across all metrics. AROME4x4 shows slightly larger biases than AROME due to averaging effects, but their overall performance in reproducing wet and dry spells remains comparable.

The cross-evaluation results (Supplementary Fig. S2a–c) indicate that the bias signs are generally consistent across decades, although the magnitude differ. The largest discrepancies occur for the annual maximum length, which displays substantial uncertainties and occasionally change the sign of the climate signal. These results suggest that systematic biases in dry spell characteristics are relatively robust, while their magnitudes are influenced by natural variability or model non-stationarity.

Sensitivity tests using different thresholds to define the dry spells (Supplementary Fig. S2d–l) reveal systematic patterns. For the number of dry events, all models underestimate at the lowest threshold (0.1 mm) but show positive biases at higher thresholds, with increasing in magnitude as the threshold increases. In contrast, both average and annual maximum length of dry events remain underestimated across all thresholds, with stronger underestimation at lower thresholds. These results also indicate that higher-resolution models generally produce smaller biases, while biases increase as the horizontal resolution decreases. An exception is RCA022, which exhibits comparable bias to higher-resolution ALADIN at larger threshold.

4.2. Future projections of wet and dry spells

4.2.1. Wet spell metrics: distributions and changes

To evaluate future changes in wet spells, Fig. 5 provides boxplots of wet spell characteristics and their relative differences across study

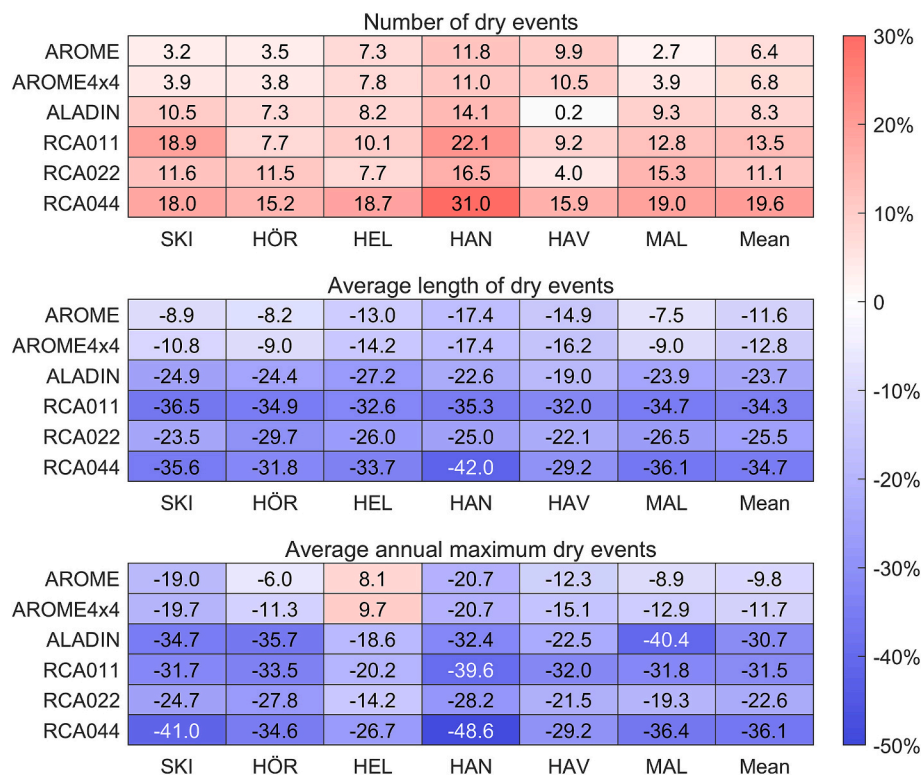


Fig. 4. Heat map of total number, average length and annual maximum length of CDD events during 1996–2005: observation and bias in percentage of all RCM projections (darker colors denote larger bias; green / red denotes positive / negative bias.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

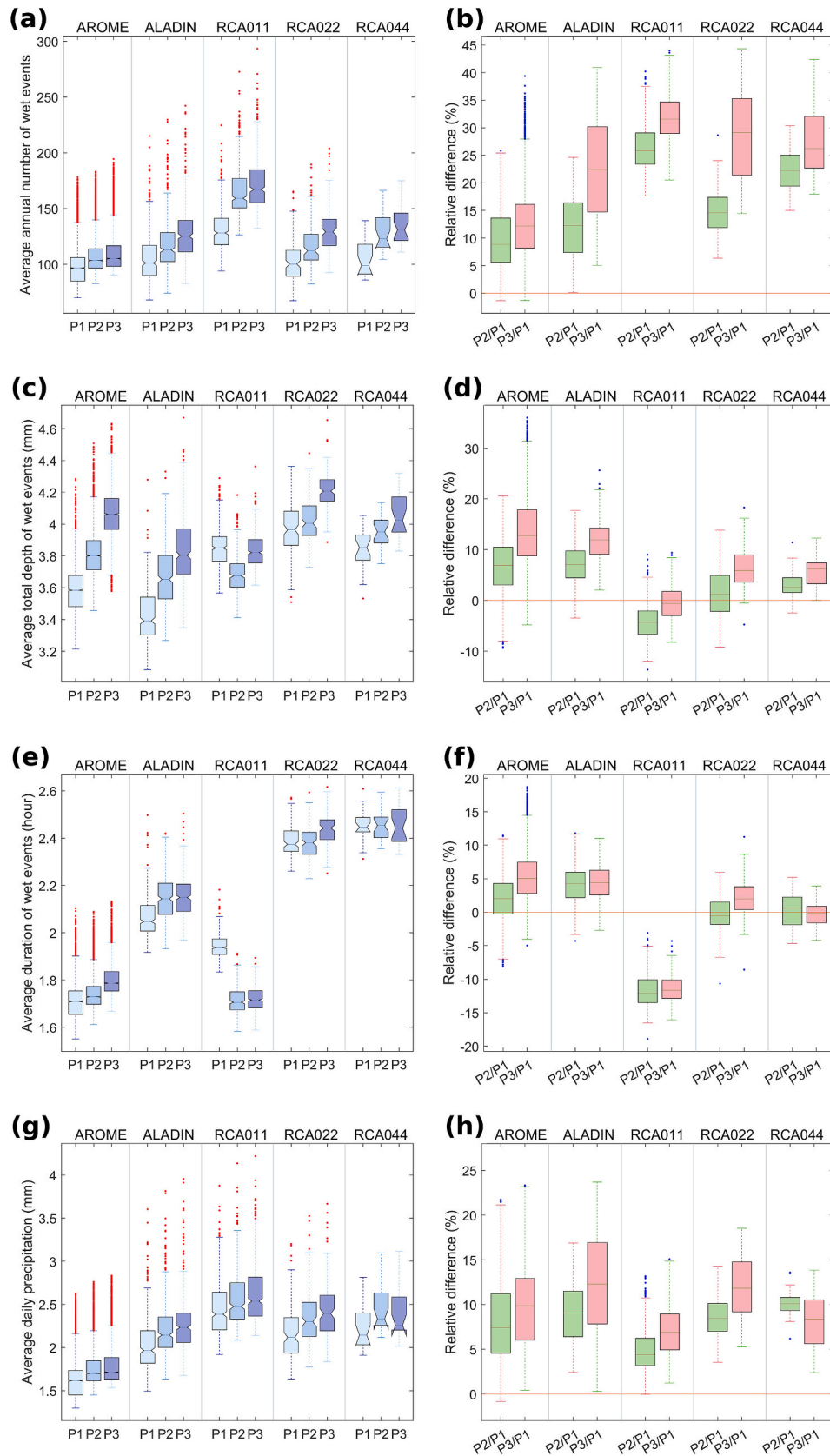


Fig. 5. Boxplots of wet spell metrics across the model domain for the three periods (P1–P3) and their relative changes. For each metric, the left panel shows the distribution of absolute values in P1, P2, and P3, while the right panel shows the relative differences (%) in P2 and P3 compared to P1. The four metric groups are: (a–b) average annual number of wet events; (c–d) average total depth of wet events; (e–f) average duration of wet events; and (g–h) average daily precipitation. P1: 1986–2005, P2: 2041–2060, P3: 2081–2100.

periods for all grid cells within the domains of five RCMs. A general assessment of average daily precipitation is shown in Fig. 5g-h. Most models project a gradual increase from the reference period (P1) to the near-future (P2) and the far-future period (P3). RCA044, however, shows a slight decreases in P3 compared to P2. Across the models, RCA011 produces the highest daily precipitation in all periods but indicates the smallest relative increase. In contrast, AROME, ALADIN, and RCA022 exhibit similar relative increase, with the medians between 5 and 10 % in P2, and exceeding 10 % in P3. ALADIN shows a noticeably larger increase than AROME, though its behaviour is more comparable to RCA022 than to RCA011.

Event-based analyses are shown in Fig. 5a-f. For the number of wet events (Fig. 5a-b), most models indicate a progressive increase from P1 to P3, reflected in positive and growing relative changes. AROME shows the smallest increase, whereas ALADIN projects a more pronounced rise,

particularly in P3. This increase is even more evident in the coarser-resolution models. Notably, although ALADIN has a similar resolution to RCA011, its projections are more consistent with RCA022, while RCA011 consistently produces the highest values among the models in both absolute value distributions and relative changes.

Fig. 5c-d illustrates the average total depth of wet events. AROME and ALADIN show comparable relative increases in both future periods. By contrast, RCA022 and RCA044 exhibit higher absolute values across all periods but smaller relative changes. RCA011 shows a marked decrease in P2 and only a slight increase in P3, remaining below P1 levels. Overall, AROME and ALADIN project clearer and larger increases than RCA models in total depth of wet events.

The average duration of wet events is shown in Fig. 5e-f. Similar to the results for average total depth, AROME and ALADIN indicate consistent increases in both future periods, with most grid values

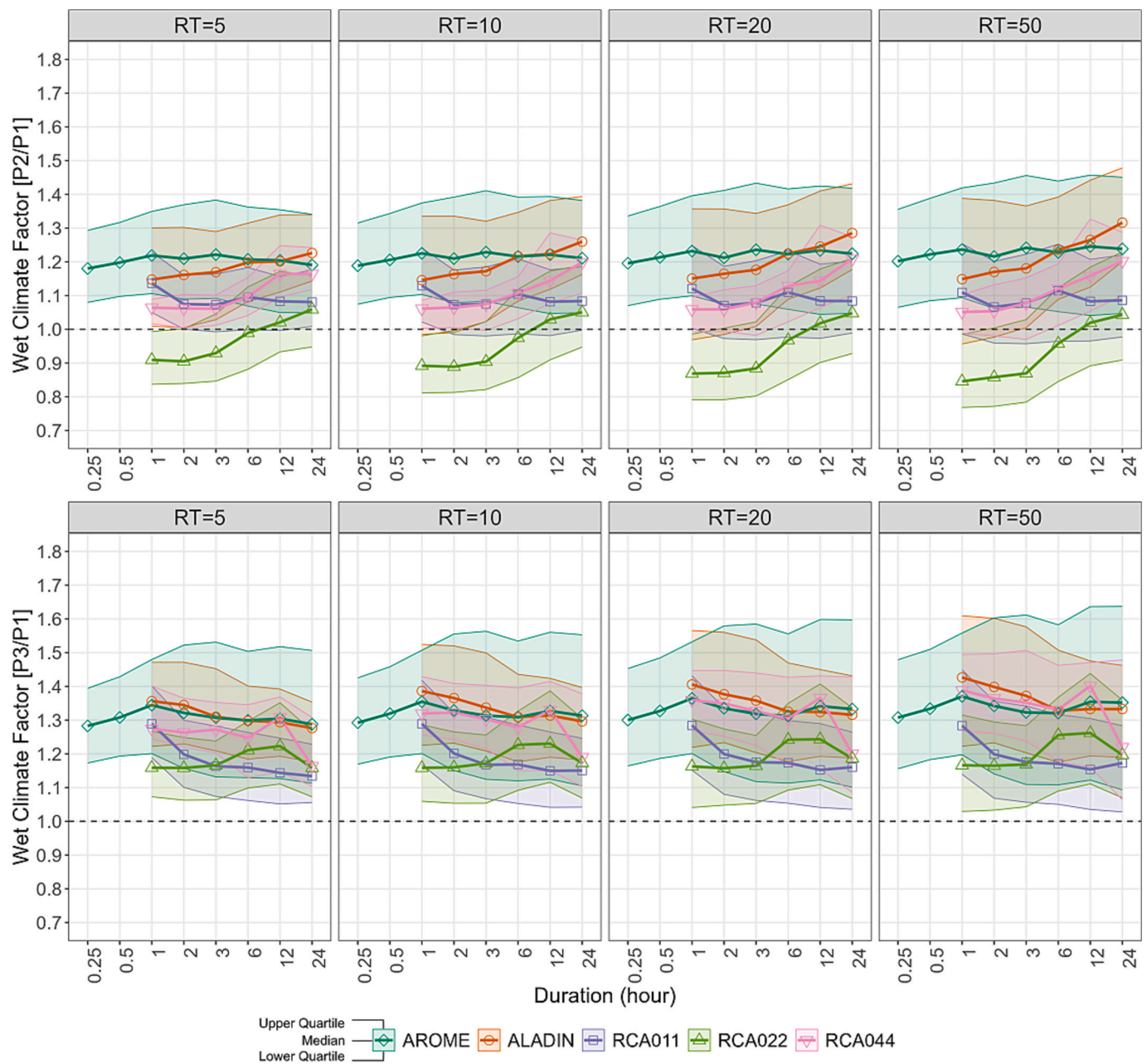


Fig. 6. Wet Climate Factor (WCF) between future periods (P2 and P3) and the historical period (P1) for all models across multiple accumulation durations. Return periods of 5-, 10-, 20- and 50-year were used when estimating extreme precipitation intensities. P1: 1986–2005, P2: 2041–2060, P3: 2081–2100. Solid lines with markers denote medians of all grids for each model. The shaded areas represent the interquartile range.

increasing by 0 % to 7.5 %. ALADIN shows almost no differences from P2 to P3. RCA011 project pronounced decreases (median > 10 %) in wet event durations from P1 to both P2 and P3. RCA022 and RCA044 show comparable ranges with only minor changes across periods, except for a modest increase in P3 for RCA022.

4.2.2. Wet climate factor (WCF)

Fig. 6 presents WCF as a function of event duration (0.25 to 24 h) for four return periods (RT = 5, 10, 20, and 50 years), providing an overview of the intensity-duration analysis conducted using the GEV method for annual maximum precipitation. Medians of all grids are shown as solid lines with markers for each model, while the shaded areas represent the interquartile range (Q25 lower to Q75 upper), indicating spatial variations among the grids.

The models AROME and ALADIN show consistently higher WCF for extreme precipitation, compared to the RCA models. In the near-future period (P2), median WCF of AROME ranges between 1.2 and 1.3 consistently across all durations, with slightly elevated values for durations of 1 to 6 h. These factors correspond to the changes in precipitation from P1 to P2, for example, from 9.1 mm to 10.9 mm in 15 min duration, from 21.7 mm to 26.8 mm in 1 h, from 37.0 mm to 45.2 mm in 6 h and from 49.6 mm to 59.7 mm in 24 h. For ALADIN, RCA022, and RCA044, the climate factors tend to increase as the duration gets longer, with similar values for the 1 to 3-h range and a clear increase observed from 6-h durations onward, suggesting a larger increase in extreme precipitation at longer durations during the near-future period. RCA011, however, shows relatively high climate factors for 1-h durations, then stabilizing around 1.1 for the longer durations. Patterns of WCF in period P2 across different return periods are generally similar, with larger spatial variations reflected by the interquartile range.

In the far-future period (P3), some shifts in these patterns are observed, with variations across durations and models. Across all return periods and different models, the median WCF and the interquartile ranges are consistently above 1, indicating an overall intensification signal for extreme precipitation from P1 to P3. AROME and ALADIN project higher WCFs with larger spatial variability especially at the longer durations, while RCA011 and RCA022 display lower medians in some durations. RCA044 lies in between, with a notable drop of WCF at the 24 h duration. Despite model differences, the overall pattern across return periods remains broadly similar, with larger spatial variability emerging at longer return periods. Notably, the patterns across different durations can reverse when compared with P2. For example, RCA044 and ALADIN display higher WCF for longer durations, this trend reverses in P3, where higher values now appear for shorter durations (less than 6 h). This indicates a substantial increase in return levels for shorter-duration extreme precipitation events in the far future. On the other hand, AROME still exhibits a stable pattern of WCF in both P2 and P3 across accumulation durations.

While this study primarily focuses on relative changes in future extremes of wet spells, we also compared absolute values of maximum precipitation at the 10-year return period to evaluate how different

models reproduce the magnitudes of extreme precipitation (Table 3). The CPM (AROME) shows superior performance across all durations, particularly for short-term convective events (15 min–3 h), where its explicit representation of convection reduces biases present in parameterized models such as ALADIN. In contrast, the coarser models (RCA011–RCA044) exhibit systematic biases, with RCA011 tending to overestimate and RCA044 showing substantial underestimation. These biases likely result from spatial averaging effects associated with lower spatial resolution and, in some cases, from the absence of convective parameterization schemes. Overall, the results highlight the importance of model resolution and explicit convection in accurately capturing precipitation extremes (Berg et al., 2019). The consistent performance of AROME in simulating absolute values also reinforces the credibility of its estimates for future changing signals.

4.2.3. Dry spell metrics: distribution and changes

Similar to the analysis of wet spells in Fig. 5, we assess the characteristics of dry spells and compare future periods with the reference period to evaluate projected changes across the five RCMs, summarized in Fig. 7.

A notable pattern in the analysis of dry spells is the consistency across models in both the direction and the relative magnitude of projected changes, in contrast to the larger variability observed for wet spells in Fig. 5. The average annual dry days (Fig. 7g–h) indicate a general decrease in the near-future period (P2) across most models, ranging from 0 % to –4 %, whereas the far-future period P3 projects an increase of 0 % to 4 %. Among the models, AROME produces more dry days overall, but with fewer dry events (Fig. 7a) and longer durations (Fig. 7c), suggesting a tendency toward longer, continuous dry periods.

In terms of annual dry event numbers (Fig. 7a–b), all models project a similar pattern: an increase of approximately 5 % in P2, followed by a comparable decrease in P3 relative to P1. This implies a significant reduction in the number of dry events during P3. At the same time, the average durations of dry events decrease in P2 but increase in P3 (Fig. 7c–d), indicating a compensatory relationship between frequency and duration. Specifically, the near-future is characterized by more frequent but shorter dry events, while the far-future tends to have fewer events of longer duration. The annual maximum dry event (Fig. 7e–f) declines in P2 across all models, with reductions up to 20 %, but increase in P3, with some models projecting rises of around 10 %.

4.2.4. Dry climate factor (DCF)

Fig. 8 shows the DCF between the future periods and the historical baseline for different return periods. In the near-future period (Fig. 8, P2/P1), median DCF ranges mostly between 0.8 and 1, which suggests an overall decrease in CDD (annual maximum consecutive dry days). The main exception is RCA022 at the 50-year return period, which gives a median higher than 1 together with a large spatial variability indicated by the wide interquartile range. Conversely, the far future (Fig. 8, P3/P1) shows an increase in terms of CDD, with DCF median ranging between 0.9 and 1.3. This suggests mixed possibilities of increasing or

Table 3

Extreme precipitation (mm) over various accumulation periods at 10-year return period derived from observation and five climate models.*

Duration	Observation (AVG)	AROME	ALADIN	RCA011	RCA022	RCA044
15 min	12.9	<u>8.5</u> / 10.1 / 11.0	—	—	—	—
30 min	16.4	<u>14.0</u> / 17.0 / 18.5	—	—	—	—
1 h	20.2	<u>20.1</u> / 24.8 / 27.1	9.9 / 11.3 / 13.6	15.9 / 18.1 / 20.6	9.9 / 8.9 / 11.5	3.0 / 3.4 / 4.1
2 h	23.7	<u>26.1</u> / 32.1 / 35.1	16.6 / 19.0 / 22.7	26.7 / 28.8 / 32.3	18.1 / 16.3 / 20.9	4.3 / 4.6 / 5.7
3 h	27.6	<u>29.2</u> / 36.1 / 38.8	21.1 / 24.4 / 28.5	33.2 / 35.6 / 39.4	24.2 / 22.3 / 28.0	6.3 / 6.6 / 8.3
6 h	34.3	<u>34.4</u> / 41.9 / 45.4	29.0 / 34.9 / 38.1	42.9 / 46.6 / 50.0	33.8 / 33.7 / 40.8	11.7 / 12.4 / 15.3
12 h	43	<u>39.7</u> / 47.8 / 53.0	36.3 / 45.3 / 47.4	51.4 / 55.1 / 59.1	<u>41.5</u> / 43.3 / 51.6	16.6 / 17.7 / 21.4
24 h	48.3	<u>46.3</u> / 55.4 / 61.0	44.4 / 51.7 / 57.4	59.4 / 64.5 / 68.0	<u>49.8</u> / 52.4 / 58.9	26.9 / 29.6 / 33.9

* Observed values are calculated for the period 1996–2005, which is within the P1 period (1986–2005). Model results are shown as values for P1 / P2 / P3. Bold values indicate model estimates for the P1 period. Underlined values indicate the model result closest to the observed value for each duration. ‘—’ indicates that data are not available for the corresponding model-duration combination.

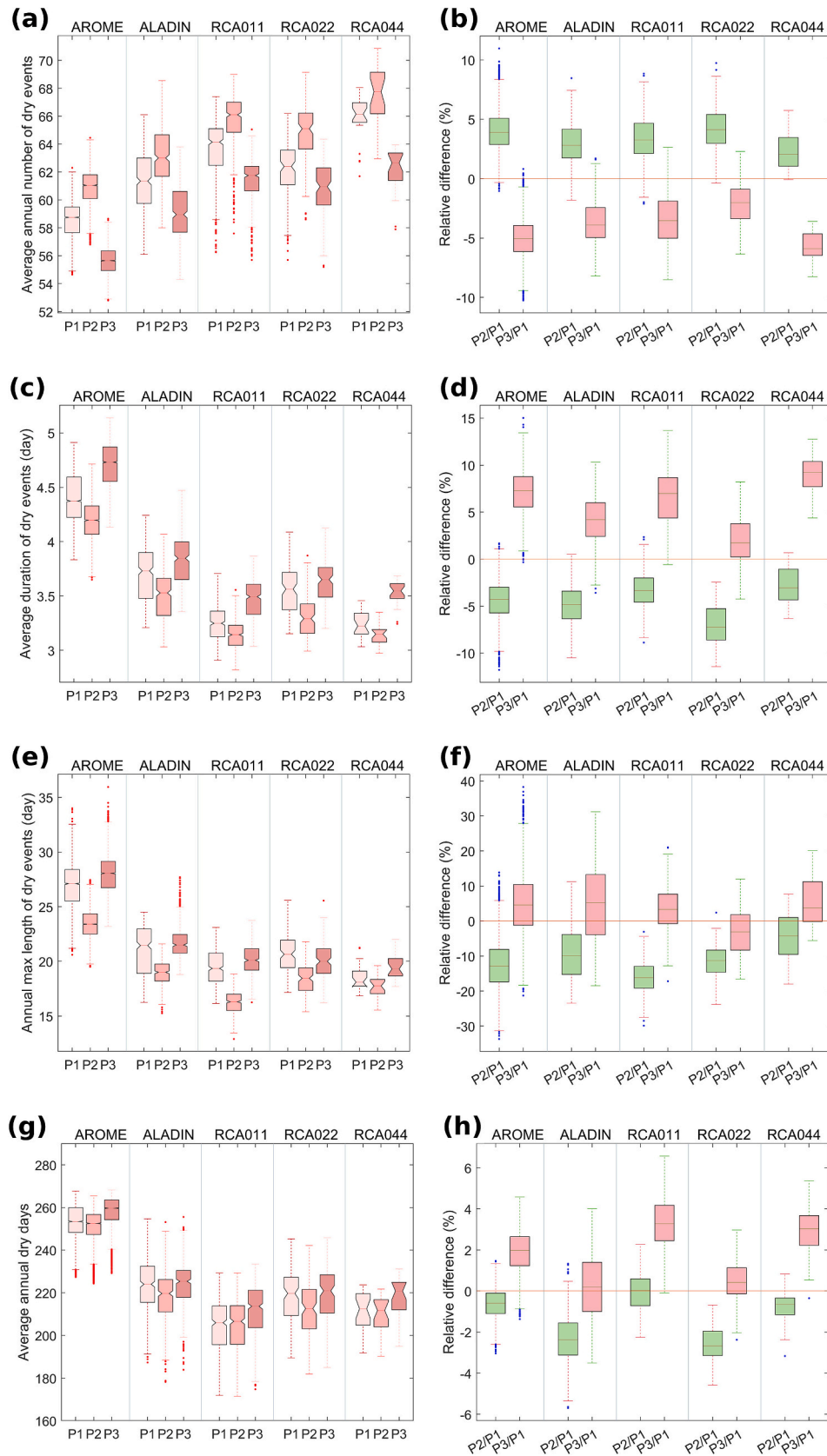


Fig. 7. Boxplots of dry spell metrics across the model domain for the three periods (P1–P3) and their relative changes. For each metric, the left panel shows the distribution of absolute values in P1, P2, and P3, while the right panel shows the relative differences (%) in P2 and P3 compared to P1. The four metric groups are: (a–b) average annual number of dry events; (c–d) average duration of dry events; (e–f) average of annual maximum duration; (g–h) average annual dry days (DT_{year}). P1: 1986–2005, P2: 2041–2060, P3: 2081–2100.

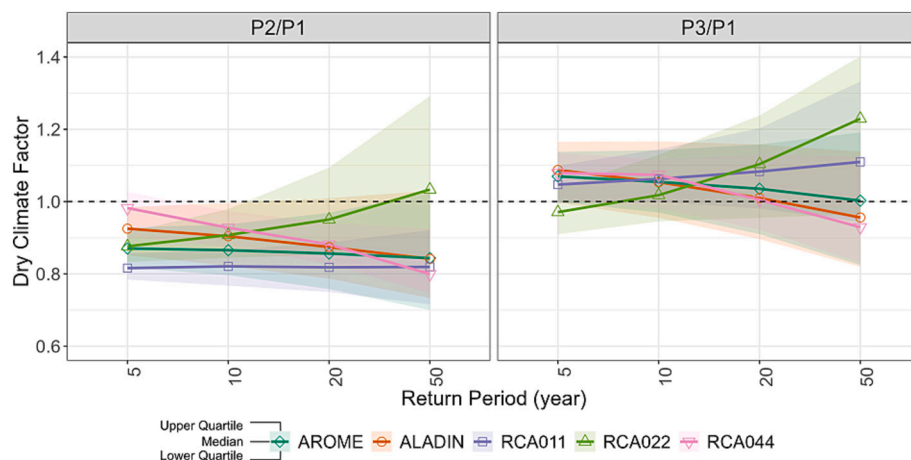


Fig. 8. Dry Climate Factor (DCF) between future periods (P2 and P3) and the historical period (P1) for all models across multiple return periods. P1: 1986–2005, P2: 2041–2060, P3: 2081–2100. Solid lines with markers denote medians of all grids for each model. The shaded areas represent the interquartile range.

decreasing CDD depending on the model, with differences among the models becoming more pronounced for longer return periods, indicating the growing uncertainty. Patterns between models are very different. For both periods, AROME and ALADIN behave similar in DCF across different return periods. RCA044 also joins AROME in the far-future period. RCA022, however, shows a distinct increase in DCF under both future periods as the return period extends. RCA011 produces the lowest DCF among the models in P2, indicating a substantial reduction in CDD. Overall, this highlights potential challenges associated with varying extreme dry spells by the end of the century, as well as the large uncertainty of future change across the models.

5. Discussion

5.1. Bias in analysis of historical wet and dry spells

Given the mismatch in spatial scales between gridded model outputs and point-based observations, we agree with [Chen and Knutson's \(2008\)](#) that model precipitation should be interpreted as areal means rather than point estimates. Differences in spatial resolution can significantly influence comparative studies, coarser grids tend to smooth local variations and extreme precipitation values, highlighting the impact of spatial averaging. [Pavlovic et al. \(2016\)](#) proposed addressing these differences using Areal Reduction Factors (ARFs). However, such adjustments would introduce additional uncertainty, and resolving this issue is beyond the scope of the present study. We therefore followed the approach of earlier studies ([Olsson et al., 2021](#); [Lind et al., 2023](#)) and did not apply such corrections.

During the historical period, model outputs of annual precipitation extremes matched observations more closely as the accumulation duration increased; while biases generally enlarged with decreasing spatial resolution. These findings are consistent with [Olsson et al. \(2021\)](#), who evaluated CPMs and RCMs driven by reanalysis. For wet spells, AROME and AROME4x4 systematically underestimate most metrics, whereas coarser models showed less consistency across stations. RCA022 and RCA044 reproduce total depth most accurately, but both systematically overestimated the duration of wet events, indicating that the coarser models tend to depict wet events as longer-lasting but less intense. RCA011 was notable for its nearly neutral bias in duration. The behaviour of high-resolution models can be explained by their ability to represent localized precipitation heterogeneity: many grid cells remain dry while intense precipitation is concentrated in a few cells. In contrast, larger grid cells tend to represent precipitation more uniformly, leading to higher areal totals. As noted by [Olsson et al. \(2021\)](#), the overestimation in coarser models was mainly caused by the overestimation

of weak to moderate precipitation, often referred to as the 'drizzle effect'. Sensitivity test (Supplementary Fig. S1d, 1 g, 1j) further supporting this interpretation, showing that models overestimate the number of wet events at lower thresholds but shift toward underestimation at higher thresholds. For dry spells, all models overestimated the total number of dry events while underestimating the average and annual maximum length of dry events. Substantial improvements were observed with increasing resolution across all dry spell metrics. These results confirm the potential of CPMs in providing close correspondence to observational data, demonstrating the importance of explicit convection in estimating future precipitation extremes. It should also be noted that some of the identified biases in the RCMs may originate from their driving GCM, as part of the large-scale precipitation signal is inherited through the boundary conditions. [Lind et al. \(2020\)](#) showed that RCMs with parameterized convection often reproduce the same types of precipitation biases as their GCM drivers, including overall weak precipitation intensity and errors in the diurnal cycle of convective rainfall, while convection-permitting models were able to reduce such biases and provide added value over Fenno-Scandinavia. In a more recent study, [Lind et al. \(2023\)](#) found that EC-Earth, the driving GCM used for all RCMs in this study, systematically underestimates seasonal mean precipitation compared to ERA5, with the strongest negative bias in summer (JJA), whereas the downscaled RCMs achieved better agreement with reanalysis and captured more robust changes in extremes.

The models exhibit distinct behaviours in the number of wet and dry spells. AROME and AROME4 × 4 exhibit the smallest and most coherent biases: they slightly underestimate the number of wet spells and slightly overestimate the number of dry spells, reflecting a relatively accurate alternation between wet and dry conditions. RCA011 consistently overestimates the number of both wet and dry spells, indicating that it divides wet and dry periods into shorter and more discrete events. The remaining models (ALADIN, RCA022 and RCA044) show spatially heterogeneous biases in wet spells, alternating between over- and underestimation depending on location, however, consistently overestimate the number of dry spells.

The robustness of the historical evaluation was further assessed by cross-comparing two separate 10-year model periods against the same 10-year observations record. Such a comparison is relevant because the climate model projections are not constrained to the natural variability cycles of the actual historical climate, and regional natural variability can be stronger than climate change induced by anthropogenic over short time periods. The analysis shows that the identified biases are mostly consistent in sign across both periods, although magnitude can vary substantially, especially for extremes. We acknowledge that the relatively short 10-year historical evaluation period may not fully

capture climatological statistics. Longer periods (e.g., 20 years) would provide a more robust reference, as also suggested by the cross-comparison. Nevertheless, preliminary checks indicate that the main findings would remain unchanged.

The sensitivity of the results to the choice of threshold for defining wet or dry events was also investigated. A clear tendency shows that with increasing threshold from 0.1 to 1.5 mm, models shift from overestimating to underestimating wet events, while the opposite pattern is seen for dry events. Several reasons may explain this behaviour. Coarser resolution can reduce precipitation intensities through spatial averaging, and many models are prone to excessive low-intensity drizzle. Although these processes are not investigated in detail here, we conclude that the results are substantially sensitive to the applied threshold, which affects the magnitude of biases but not necessarily the direction of the projected climate change signal.

5.2. Future change in wet and dry spells

A comparison across all models (Fig. 5a–f) provides insights into future patterns of wet events. Both AROME and ALADIN project a substantial general trend toward wetter conditions, indicated by increases in number of wet events and longer durations, resulting in more frequent and prolonged wet spells with higher total precipitation depth. RCA011 shows gradual increases in wet event numbers but decreases in durations and inconsistent changes in total depth, suggesting a tendency toward more frequent but less intense events by the end of the century. All models provide a gradual increase in average daily precipitation from P1 to P3. Although AROME produces the smallest absolute values, all models show comparable relative increases in P2 and P3. Consistent with these findings, Lind et al. (2023), using a larger domain (Fennoscandia), reported increases in average daily precipitation under RCP 8.5, particularly during winter (DJF).

By the end of the century (P3/P1), the models with convective schemes (AROME and ALADIN) project stronger changes in extreme precipitation intensity, especially at duration 1–3 h (WCF = 1.30–1.40). This is consistent with the predominance of convective precipitation in summer (JJA) in the study region, as noted by Olsson et al. (2021). RCA011 projects smaller increases (WCF $\approx$ 1.1 for P2 and 1.2 for P3), in line with Coppola et al. (2021), who reported similar projected changes using EURO-CORDEX ensembles at the same resolution. These results challenge existing Swedish guidelines for urban drainage design, which have historically questioned the reliability of RCMs for short-duration rainfall due to coarse resolution (Svenskt Vatten, 2011). That report, based on the RCAO-E model at 50×50 km resolution under scenario A2, suggested climate factors of 1.3–1.4 for rainfall within 30 min, equivalent to ~ 1.5 when adjusted to point precipitation for 2071–2100 relative to 1961–1990. For southern Sweden, however, it recommended lower climate factor of 1.1–1.2. More recently guidance (Svenskt Vatten, 2016; Svensson et al., 2020) recommends climate factors of 1.25 (<1 h) and 1.20 (>1 h) under RCP4.5 and RCP8.5. The ability of CPMs to explicitly represent convective processes underpins their advantage in capturing short-duration extremes, though other factors such as topography and large-scale circulation must also be considered (Li et al., 2019; An et al., 2023). Dyrddal et al. (2023), applying a similar approach, reported WCF values of 1.31–1.65 for 15-min precipitation extremes, and 1.36–1.68 for 1 h extremes in AROME, depending on the driving GCM. Differences with our results likely reflect variations in domain (southern Sweden vs. all of Sweden) and return periods adopted analyses. Their findings also shows that CPMs dominate changes across durations, while the overall magnitude of WCF is strongly influenced by the driving GCM, providing a context for interpreting inter-model differences in Fig. 6.

In contrast to wet spells, projected changes in dry spells are relatively consistent across models. Fig. 7 g–h reveals a slight decrease in the number of dry days from P1 to P2, followed by an increase in P3. Conversely, Fig. 7a–b show an increase in the number of dry spells in P2, implying that fewer dry days are clustered into longer spells. This

suggests that the driving GCM controls the background conditions of dry spells, while both ALADIN and AROME respond similarly to those conditions. Despite its higher spatial resolution (73×73 grid points compared with 5×5 in RCA044), AROME shows no larger spatial variability, indicating better consistency in its projections. With regard to future dry signals, our results suggest that annual number of dry days will remain largely unchanged (≤ 4 days in difference by 2100), consistent with Strandberg et al. (2015) and Cardell et al. (2020). This corresponds to 0–3 % changes across models and no more than 10 days (Fig. 8h). Previous studies found a reduction in maximum CDD in northern Sweden by the late 21st century (Eklund et al., 2015; Coppola et al., 2021), but little change in the south. With targeting southern Sweden, all models project a slight increase in maximum CDD, which is less than +5 % in the median, except RCA022 which shows a decrease of –3 % (Fig. 8f).

However, the non-monotonic behaviour between near-future (P2/P1) and far-future (P3/P1) changes in dry spells remains without a definitive physical explanation. The conceptual framework of Baumberger et al. (2017) suggests that long-term projection adequacy depends not only on empirical accuracy and robustness, but also on the support from background physical knowledge. Further investigation into mid-century external forcings and internal variability is therefore required to better interpret this projected transition.

5.3. Impact of spatial resolution in hydrometeorological characteristics

Numerous studies have demonstrated the added value of CPMs in representing high-intensity precipitation compared with coarser-resolution RCMs. Kendon et al. (2014) and Chan et al. (2014) showed that projections of winter precipitation changes over the UK are robust across resolutions, whereas deficiencies in convective parameterization schemes in coarse-resolution models strongly affect summer precipitation projections. By contrast, relatively few studies have investigated CPM performance in projecting future dry spells. Gadian et al. (2018), for example, found that an RCM with parameterized convection produced larger increases in summer dry duration over eastern UK for 2031–2036 compared with a higher-resolution CPM. Our study suggests that RCM resolution has a greater influence on projected wet spell characteristics than on dry spells. This implies that higher resolution and explicit convection primarily improve the representation of localized, intense precipitation processes, whereas the large-scale drivers of dry periods (e.g. circulation patterns and soil-moisture feedback) are already captured reasonably well by driving GCMs. In this study, the CPM (AROME) demonstrated superior performance in reproducing both wet and dry spell intensities during the historical period, attributable to its explicit representation of convection and finer-scale atmospheric dynamics. This improved historical performance provides a stronger confidence in CPM projections of future wet and dry signals compared with coarser models.

A comparison of three models at 12 km resolution: AROME4 $\times$ 4 (explicit convection), ALADIN (parameterized convection) and RCA011 (no convection scheme), illustrates how differences in convection treatment affect wet spell biases. RCA011, lacking a convective scheme, produces pervasive light drizzle, leading to a large overestimation at low thresholds, which diminish as the thresholds increase. ALADIN suppresses much of this drizzle but consistently overestimates wet spell duration across thresholds. AROME4 $\times$ 4 explicitly resolves convection and better constrains the number of light wet spells, though aggregation introduces averaging effects that increase biases compared with AROME. In contrast, dry spell characteristics show a clearer hierarchy: AROME displays the smallest biases, ALADIN intermediate, and RCA011 the largest. These threshold-dependent behaviours indicate that even at identical spatial resolution, the treatment of convection substantially affects the representation of wet and dry signals. Overall, CPMs provide a more reliable representation, particularly in capturing the number and duration of events.

5.4. Limitations, assumptions and uncertainties

In this study, we compared CPM grid cells with co-located high-resolution observations to evaluate the added value of explicit convection. Because CPMs can resolve the fine-scale meteorological structures that drive high-intensity, short duration precipitation, direct comparison at the station scale provides a rigorous test of their performance. One limitation, however, is the relatively small domain of CPM, constrained by computational cost and data volumes. A larger domain would likely reveal additional benefits. Our approach parallels [Olsson et al. \(2021\)](#), who evaluated AROME and ALADIN in simulating an extreme sub-daily precipitation event (> 122 mm in 6 h, Malmö, Sweden). Both models underestimated accumulations relative to observations, but AROME produced higher value than ALADIN, reflecting the advantage of explicit convection. Another limitation is that the comparison analysis in a historical period relied on a 10-year period (1996–2005). While sufficient for model intercomparison, longer observational periods (e.g., 20 years) may increase the robustness of analysis and represent better climatological statistics.

Many previous studies have identified wet spells at daily scale ([Zolina et al., 2010](#); [Vaittinada Ayar and Mailhot, 2021](#)). In this study, we adopted an hourly scale to better capture sub-daily, high-intensity events, which is essential when including CPMs. This choice, however, may introduce uncertainties. Specifically, excluding precipitation below 1 mm hour^{-1} means that light precipitation is not reflected in the statistics, which may be more relevant in regions dominated by persistent, low-intensity precipitation. To address this, we conducted sensitivity tests using different thresholds for wet and dry events during the historical period. For dry events, we applied 1 mm day^{-1} following the ETCCDI definition ([Alexander et al., 2006](#)). A deeper analysis of the mismatch between grided model output and point-based observations could apply the methodology of [Haerter et al. \(2015\)](#), which bridges the spatial gap by temporal averaging. We also set the minimum inter-event time (MIT) to one time step, i.e., 1 h for wet spells and 1 day for dry spells, to maximize events identification. [Dunkerley \(2008\)](#) claimed that the selection of MIT can significantly affect event-based analysis, requiring a balance between the independence of events and their intra-event characteristics.

Previous studies suggested that the annual maximum lengths of wet and dry events have increased in southern Sweden over recent decades (e.g., [Breinl et al., 2020](#)), although this trend has been reported to vary seasonally ([Zolina et al., 2013](#)). This indicates the importance of future analyses at seasonal scales to provide more representative and nuanced results, particularly in understanding the temporal and climatic factors influencing these patterns. [Thomassen et al. \(2023\)](#), consistent with our findings, confirmed that high-resolution CPMs better reproduce precipitation intensity than coarser RCMs over Denmark. They also demonstrated that while a 750 m CPM outperformed its 3 km counterpart, the limited added value highlights the need for thorough evaluation of sub-kilometer CPMs to balance improved performance with computational feasibility. How to analyze, interpret and utilize the benefits of CPMs still requires further investigation.

6. Conclusions

This study investigated the impact of regional climate model (RCM) resolution on wet and dry signals in southern Sweden, with a focus on the performance of high-resolution convection-permitting model (CPM) compared to coarser-resolution RCMs. By analyzing both historical and future periods, we quantified changes in wet and dry conditions, including extremes, and assessed the role of model resolution in describing these changes. Our findings provide insights into the representation of wet and dry spells across different RCMs and highlight the added value of CPM for regional climate services. The main findings are:

- In the historical period, higher resolution improves the representation of dry spell characteristics, while results for wet spells vary more strongly with resolution.
- High-resolution models better capture precipitation maxima, particularly at short durations.
- Future wet spell changes are more sensitive to model resolution: higher-resolution models project fewer and shorter wet spells but larger total depths, with the CPM projecting stronger increases in sub-daily precipitation extremes across study periods.
- Future dry spell changes show weaker dependence on model resolution, with similar patterns across models. The DCF indicates only minor changes in the length of dry extremes by the end of the century.

The comparison of model projections with station observations for 1996–2005 shows that the CPM (AROME) provides the most consistent representation across metrics, particularly for sub-daily extremes (≤ 3 h) and wet spell characteristics at all thresholds. Biases generally increase with decreasing resolution. The CPM therefore offers stronger reliability for regional climate projections, although scale mismatches between areal model outputs and point observations remains a consideration, particularly in areas with complex topography. In future periods, AROME projects moderate increases in wet spells and more pronounced intensification in extremes, with WCF median values above 1.20 (P2) and 1.30 (P3), which is the highest among all models. Coarser RCMs project smaller changes with larger inter-model variability. The explicit representation of convective processes in AROME allows it to capture finer-scale features, such as localized extremes, while coarser models tend to overestimate light precipitation and underestimate extremes. Thus, resolution influence not only the magnitude of projected wet spell changes but also their spatial and temporal distribution.

For dry events, AROME also demonstrates the most coherent performance across metrics. In the historical period, all models overestimate the number of dry spells and underestimate their duration, but the model performance improves with higher resolution. In future periods, higher-resolution models tend to project fewer drought events but with longer durations. Overall, projected changes in dry spells are modest: durations increase slightly by the end of the century, while the number of dry spells decrease. A novel contribution of this study is the introduction of the Dry Climate Factors (DCF), which extends the established WCF concept to extreme dry spells. In P2, all model project a decrease in lengths of extreme dry spells (DCF 0.8–1.0), followed by a slight increase in P3 (DCF > 1.0). Although DCF shows little dependence on resolution, AROME exhibits the most consistent behaviour across return periods, whereas coarser models show greater variability. This stability reflects the reduced uncertainty associated with CPMs in assessing future extreme dry spells.

These findings carry important implications for global and regional climate services. RCMs at 10–50 km remain widely used due to their balance between computational cost and representation of key regional climate features, such as storm tracks and heatwaves ([Kjellström et al., 2016](#); [Iles et al., 2020](#)). Our results confirm the added value of CPMs in representing regional wet and dry spells including extreme signals, indicating the potential of providing further improvements by better reproducing local-scale phenomena, particularly those influenced by topography and convection. For coarser-resolution RCMs, users must remain cautious about their limitations in representing extreme and small-scale spatial variability when interpreting results for policy and planning.

Future work should aim to improve convective parameterization in non-CPM RCMs (e.g., ALADIN), extend analyses to regions with different climatic conditions to further clarify the role of model resolution in capturing wet and dry spells, and evaluate a broader set of extreme climate events such as heatwaves, cold spells, windstorms, and compound extremes. Investigating wet and dry spells at seasonal scales could provide more comprehensive understanding of variability and

model skill. Further, exploring sensitivity of projections to different emission scenarios and validating model outputs against high-resolution observational datasets would help strengthen the reliability and applicability of regional climate projections.

CRedit authorship contribution statement

Dong An: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Jonas Olsson:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Yiheng Du:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Johanna Sörensen:** Writing – review & editing, Validation. **Cintia B. Uvo:** Writing – review & editing, Conceptualization. **Peter Berg:** Writing – review & editing, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.atmosres.2025.108547>.

Data availability

The authors do not have permission to share data.

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