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LESSONS report: Fine-scale representation of consecutive dry days

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Abstract. The number of consecutive dry days (CDD) is a widely used metric for assessing meteorological drought. This study investigates spatial CDD patterns over Germany during the drought year of 2018, comparing a convection-permitting model (CPM) at 3 km resolution with ERA5 reanalysis at 31 km, gauge-based interpolated observations at 1 km, and radar measurements at 1 km. The analysis reveals a *surprise*: high-resolution CPM and radar data produce strikingly heterogeneous, "brushstroke-like" spatial structures that differ fundamentally from the smooth fields of reanalysis and gridded observations. Our report confirms that these sharp spatial discontinuities are not computational artifacts but a physical consequence of the sensitivity to the fixed daily dryness threshold of the CDD metric. We find that the CPM can well reproduce these fine-scale patterns that are also detected by radar measurements, which is quantified by a spatial autocorrelogram and the radially averaged power spectral density.

While averaging CDD over multiple years smooths out the brushstroke patterns, such temporal averaging does not resolve the underlying *shortcoming*: multi-year CDD is built upon individual annual CDD values that are, as shown here, highly variable and strongly dataset-dependent. A statistic whose single-year realizations are dominated by threshold-crossing noise provides an unstable foundation for climatological analysis regardless of the aggregation period applied. As a *lesson* learnt, we recommend caution when applying CDD in any context — including drought monitoring, impact assessment, and climate model evaluation. This study reports on the surprising fine-scale spatial patterns and resulting shortcomings of the CDD metric and is therefore submitted as a LESSONS report, a paper category dedicated to documenting Limitations, Errors, Surprises, Shortcomings, and Opportunities for New Science.

1 Introduction

Droughts are one of the most expensive hazards, potentially triggering a wide range of ecological, economic, and societal risks (AghaKouchak et al., 2023). Meteorological droughts defined as the absence of rainfall can thereby induce a cascade towards agricultural, surface water and groundwater droughts (Liu et al., 2023). Various indices exist to assess meteorological droughts (Kchouk et al., 2022), where the number of consecutive dry days (CDD) is a simple and widely used metric defined by the Expert Team on Climate Change Detection and Indices (ETCCDI; Zhang et al., 2011).

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While droughts are typically considered as a large-scale phenomenon, drought indices may show spatial fine-scale variability (Gebrechorkos et al., 2023). Recent global analyses of kilometre-scale models confirm that the spatial sub-grid variability of ETCCDI extreme indices — including consecutive wet days, the wet-day counterpart of CDD — is largely lost at the coarse resolution of conventional global climate models (Brunner et al., 2025). Here, we aim to explore the spatial patterns of CDD in high-resolution data sets including a convection-permitting model (CPM) simulation. CPMs at resolutions of less than 4 km explicitly resolve convective processes instead of using a parametrization (Lucas-Picher et al., 2021), which is considered a "step change" in understanding local climate and impacts compared to conventional regional climate models (Kendon et al., 2021). CPMs better capture complex topography and land surface heterogeneities (Gutowski et al., 2020) and are found to improve representation of temperature over complex terrain (Karki et al., 2017). CPMs resolve storms and improve the representation of clouds and solar radiation (Hentgen et al., 2019), the daily cycle of precipitation (Lind et al., 2020), the frequency and intensity of precipitation (Ban et al., 2021), topography effects on extreme precipitation (Dallan et al., 2023; Poschlod and Koh, 2024), wind systems (Molina et al., 2024), snow depth (Monteiro et al., 2024; Poschlod and Daloz, 2024), and droughts (Akinsanola et al., 2024). For the representation of spatial CDD patterns, we here compare a CPM simulation to ERA5 reanalysis, gridded observations, and bias-adjusted radar measurements over Germany. We find a surprising spatial pattern providing lessons for future model evaluation and the use of the CDD metric.

2 Data and Methods

We use four different precipitation data sets over Germany: 1) ERA5 reanalysis (Hersbach et al., 2020) at 0.25° equalling ~ 31 km, 2) convection-permitting simulations of COSMO-CLM driven by boundary conditions of ERA5 at 3 km (Brienen et al., 2022; Rybka et al., 2023), 3) gridded observations of quality-checked rain gauge measurements (HYRAS) at 1 km (Rauthe et al., 2013), and 4) the radar-based precipitation reanalysis RADKLIM. RADKLIM consists of quality-checked and artifact-corrected radar measurements at 1 km, where the intensity is adjusted with the observed precipitation from rain gauges (Winterrath et al., 2017). In this short report, we mainly focus our analysis to the year 2018, reflecting severe drought conditions over Europe (Blauhut et al., 2022). We aggregate all data sets to daily resolution and calculate CDD following the ETCCDI, counting the largest number of consecutive days with precipitation below 1 mm within one year. CDD are calculated using the package *xclim* (Bourgault et al., 2023) in Python 3.8.

For a further analysis of spatial variability of CDD fields, we remap the finer-resolution observational daily precipitation data from 1 km to the coarser 3 km grid of COSMO-CLM using bilinear interpolation (*remapbil* in CDO; Schulzweida, 2026) and re-calculate the CDD. We compute global Moran's I across a range of spatial scales by defining neighbourhoods as all grid cells within a circle of radius r, for r = 3 to 99 km, yielding a spatial autocorrelogram for scale-dependent comparison of CDD patterns between the three high-resolution datasets. Further, we calculate the radially averaged power spectral density (RAPSD; Sinclair and Pegram, 2005) by applying a 2-D fast Fourier transform to the CDD fields, constraining the analysis to the largest rectangle of valid CDD values (~500 km × 300 km) to avoid artefacts from no-data gaps. The spatial mean is

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subtracted prior to the transform to suppress the zero-frequency component, and the resulting power spectrum is averaged radially in wavenumber space using the package *pysteps* (Pulkkinen et al., 2019). RAPSD is commonly used to evaluate the spatial structure of precipitation fields across scales (Ravuri et al., 2021) and complements Moran's I by decomposing total variance continuously across wavelengths, allowing dataset differences to be attributed to specific spatial scales.

3 Spatial patterns of consecutive dry days

The spatial distribution of CDD for 2018 is shown in Fig. 1 for all four datasets at their native resolution. CDD values span a wide range of 7–100 days across the datasets. ERA5 exhibits a smooth, coarse-grained pattern reflecting its comparatively low spatial resolution (Fig. 1a), whereas the convection-permitting simulation COSMO-CLM at 3 km produces a strikingly heterogeneous field with elongated, anisotropic, brushstroke-like structures (Fig. 1b).

The gridded observational dataset HYRAS displays a slightly smoother pattern with quasi-circular, blob-like anomalies ("bull's-eyes") of alternating higher and lower CDD values superimposed (Fig. 1c). The radar-based RADKLIM product closely resembles the fine-scale spatial variability of COSMO-CLM (Fig. 1d). We note that a direct evaluation of CDD magnitudes is not the focus of this study, as the reanalysis and convection-permitting simulation are freely evolving atmospheric models that — despite being constrained by observed boundary conditions — will not reproduce observed precipitation at the correct locations due to internal climate variability. Rather, our interest lies in the characteristics of the spatial fine-scale structure of the CDD patterns.

The spatial pattern visible in Fig. 1b was initially unexpected for a hydro-climatic variable, prompting us to verify the CDD calculation. The pattern was confirmed to be robust across multiple years and an independent convection-permitting simulation using the WRF model (Collier and Mölg, 2020; see Fig. S1), and independent CDD implementations (CDO; Python code only based on *xarray* and *numpy* (Harris et al., 2020; Hoyer and Hamman, 2017)).

We therefore rule out computational artefacts and proceed to investigate the physical origin of the brushstroke-like structures. Figure 2 shows zoomed-in excerpts of two locations in Fig. 1b where neighbouring grid cells exhibit abrupt CDD transitions. Inspection of the underlying daily precipitation time series reveals that adjacent cells are generally in close agreement, but isolated precipitation events marginally exceeding the 1 mm d^{-1} threshold at one cell — but not its immediate neighbour — are sufficient to interrupt the CDD sequence and produce the sharp spatial discontinuities. This sensitivity to the threshold is an inherent characteristic of the CDD metric rather than a model artefact; applying alternative thresholds (0.1 mm d^{-1}; 2 mm d^{-1}) yields qualitatively similar spatial patterns (see Fig. S2).

Given that ERA5 lacks the resolution to represent such fine-scale CDD variability, the remainder of the analysis focuses on the three high-resolution datasets. To objectively quantify the spatial heterogeneity suggested by Fig. 1, the analysis is restricted to the common spatial extent of COSMO-CLM, HYRAS, and RADKLIM. The spatial autocorrelogram (Fig. 3a) and the RAPSD (Fig. 3b) confirm the visual impression from Figs. 1b–d: COSMO-CLM and RADKLIM exhibit a similar autocorrelation and variance structure, while HYRAS shows consistently higher spatial autocorrelation across all scales and

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lower variance especially below wavelengths of 20 km, consistent with the smoother, interpolation-driven pattern seen in Fig.
95 1c.

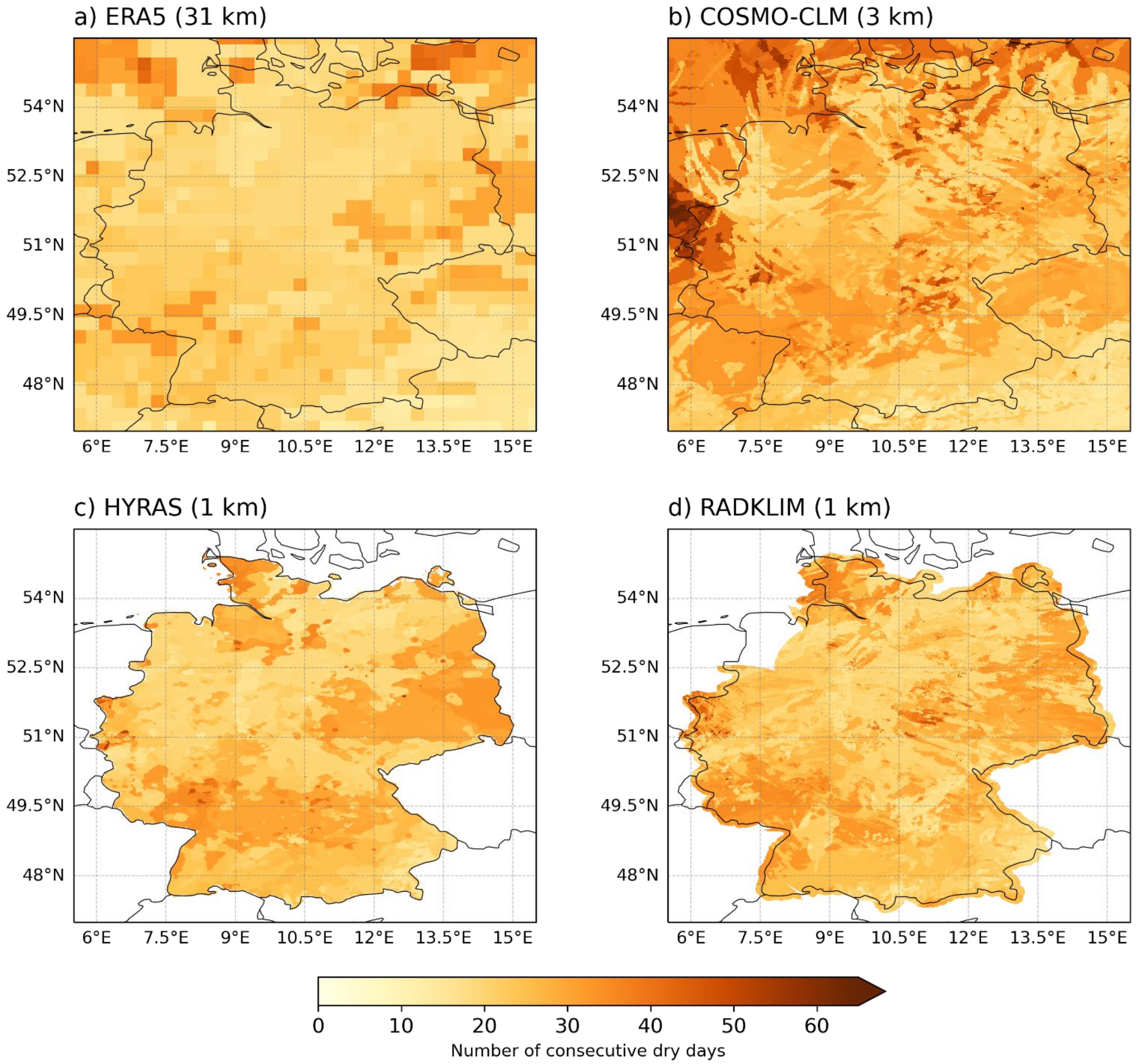

Figure 1: Number of consecutive dry days in 2018 for ERA5 reanalysis (a), convection-permitting simulations of COSMO-CLM (b),
100 **HYRAS gridded observations (c), and intensity-adjusted radar measurements of RADKLIM (d).**

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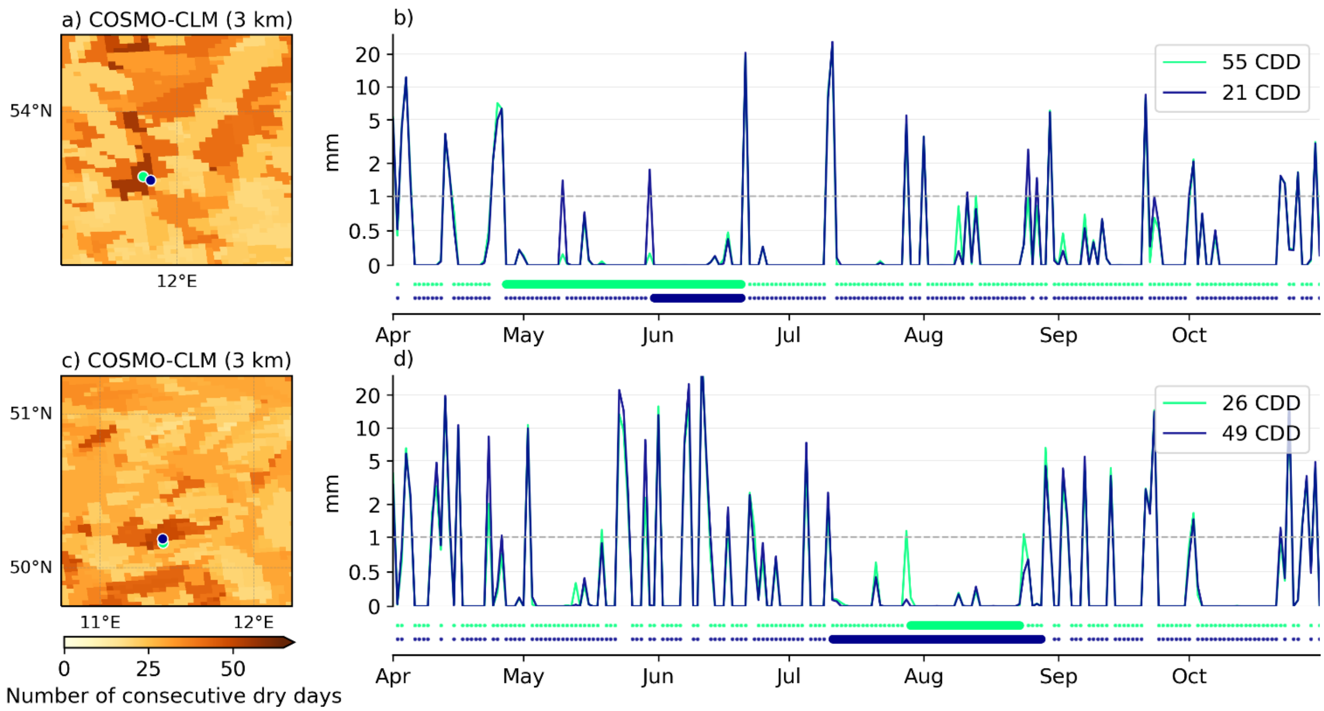

Figure 2: Number of consecutive dry days in 2018 for COSMO-CLM in two regions (a, c) and time series of daily precipitation (b, d) at the two neighbouring grid cells marked in (a) and (c). The dots in (b) and (d) mark dry days below the threshold of 1 mm, where the thick line highlights the longest spell of consecutive dry days. Note the scaling of the y-axis, which is linear below 1 mm and logarithmic above 1 mm.

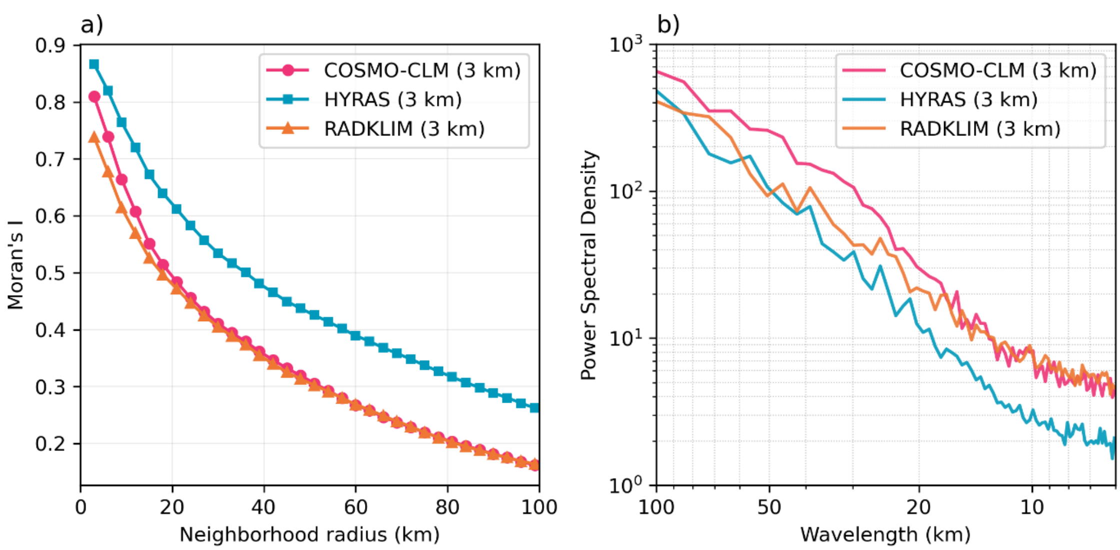

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Figure 3: Spatial structure of 2018 CDD fields for COSMO-CLM, HYRAS, and RADKLIM at 3 km resolution. a) Global Moran's I as a function of neighbourhood radius (3 – 99 km), where higher values indicate stronger spatial autocorrelation. b) Radially averaged power spectral density as a function of wavelength, where higher values indicate greater spatial variance at a given scale.

4 Lessons for the investigation of consecutive dry days

ERA5 is generally well-suited to reproducing the large-scale characteristics of droughts (Keune et al., 2025), whereas small-scale features such as storm tracks interrupting dry spells are not captured by ERA5 within the CDD metric. Coarse-resolution climate models are known to overestimate the frequency of low-intensity precipitation events — a phenomenon referred to as drizzle bias. Consistent with this, ERA5 has been shown to overestimate precipitation on nominally dry days (Lavers et al., 2022), resulting in an inflated number of wet days (Bandhauer et al., 2022) and a consequent underestimation of CDD. Although HYRAS is derived from several thousand rain gauges, the bull's-eye anomalies in CDD are attributed here to artifacts of the interpolation methodology: inverse distance weighting preserves measured daily precipitation amounts at gauge locations but is known to produce steep spatial gradients when surrounding values differ substantially (Cressie, 2010).

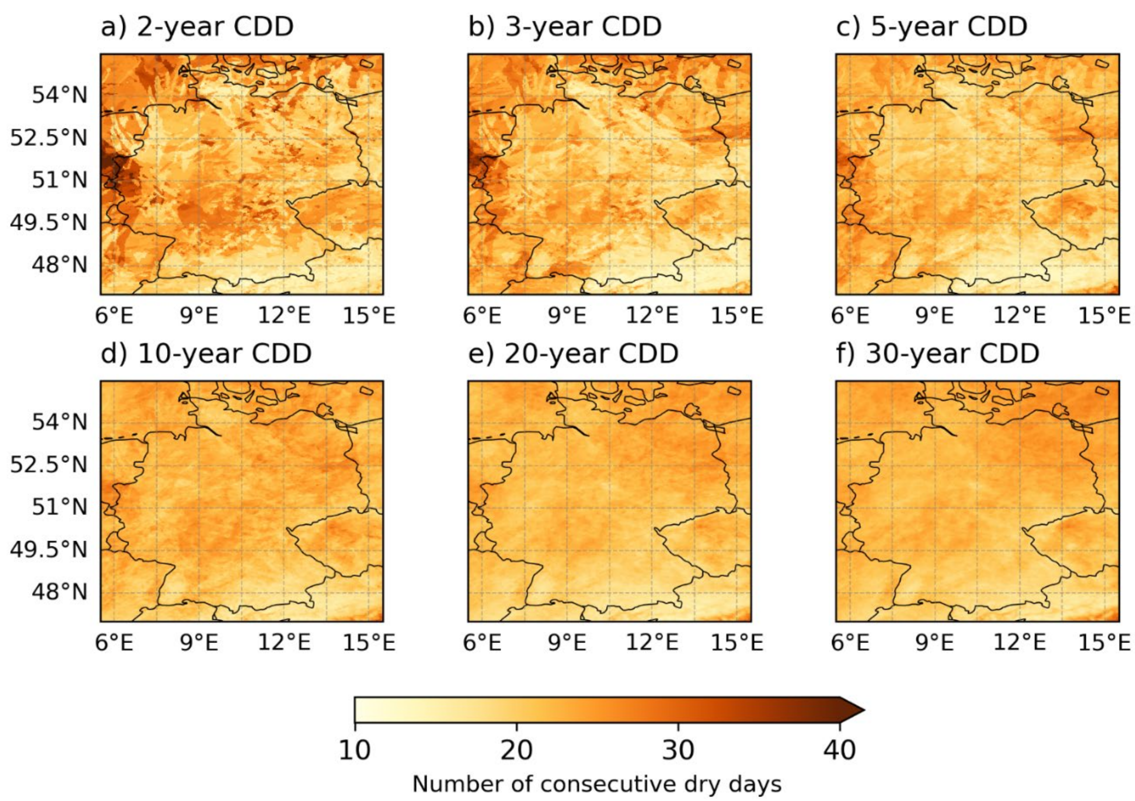

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Figure 4: CDD from the COSMO-CLM simulation based on 2 (a), 3 (b), 5 (c), 10 (d), 20 (e), and 30 (f) years. Years are selected as 2017 – 2018, 2016 – 2018, 2014 – 2018, 2009 – 2018, 1999 – 2018, and 1989 – 2018, respectively. Note that the colour scaling is narrower than in Figures 1 and 2.

As a radar-based product, RADKLIM provides spatially consistent coverage, though it is subject to uncertainties and errors inherent to indirect measurement approaches (Kreklow et al., 2020). In a comparison with rain gauges, Kreklow et al. (2020) found that RADKLIM underestimates the frequency of low-intensity precipitation events, owing to overcorrection of low-reflectivity signals during clutter removal and to shading effects, whereby the radar beam is blocked or attenuated by intervening areas of more intense rainfall. Nevertheless, spatial patterns are generally well reproduced.

We argue that the brushstroke pattern in CDD arises from precipitation events and convective storm tracks exceeding the 1 mm d^{-1} threshold that are resolved by both radar observations and convection-permitting simulations. We therefore assume that CPMs are capable of reproducing the fine-scale spatial characteristics of CDD. While this is a positive finding regarding the capabilities of CPMs, the spatial analysis reveals an issue that leads us to advise caution against applying CDD for the purpose of drought evaluation. When CDD are averaged over multiple years (Fig. 4), the chaotic brushstroke patterns diminish, and the dominant spatial structure reflects large-scale climatic gradients as well as finer-scale topographic influences (Fig. 4f). Nevertheless, multi-year CDD metrics are built upon annual CDD values, which — as demonstrated here — can differ substantially across datasets and are dominated by whether a threshold-exceeding precipitation event happened to occur at a given location in a given year. This is not merely a problem of short averaging windows: a metric whose individual realisations are governed by the stochastic occurrence of near-threshold events provides a fundamentally unstable foundation for climatological analysis, regardless of the temporal aggregation applied. Furthermore, this noise does not vanish when CDD is directly derived from point-scale rain gauge records — which is what the ETCCDI were originally designed for: station-based CDD entirely misses the fine-scale spatial variability documented here, and the apparent (dis-)agreement between station records and gridded CDD may be coincidental rather than physically meaningful.

Hence, as our lesson learnt, we recommend caution when applying CDD in any context — including dry spell monitoring, drought impact assessment, drought propagation and low-flow analyses, and climate model evaluation (e.g. with CDD as part of the ESMValTool; Weigel et al., 2021).

Code and data availability

The data (CDD of 2018 derived from the four data sets) and code for this study are openly available on Zenodo (Poschlod, 2026). ERA5 reanalysis data is available from Copernicus CDS (https://doi.org/10.24381/cds.4991cf48). HYRAS and RADKLIM are available from the German Weather Service via https://opendata.dwd.de/climate_environment/CDC/grids_germany/daily/hyras_de/precipitation/ and

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https://opendata.dwd.de/climate_environment/CDC/grids_germany/hourly/radolan/reproc/2017_002/netCDF/. The COSMO-CLM simulations are openly available at https://doi.org/10.5676/DWD/HOKLISIM_V2022.01.

Author contributions

BP and JS had the idea to assess CDD in convection-permitting simulations. BP conceptualized the study. BP prepared data and software. BP created the figures and prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that there is no conflict of interests.

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Review statement

The review statement will be added by Copernicus Publications listing the handling editor as well as all contributing referees according to their status anonymous or identified.

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