

## Response to Reviewer #1 (RC1)

Manuscript egusphere-2026-4014: "LESSONS report: Fine-scale representation of consecutive dry days"

Benjamin Poschlod, Lukas Brunner and Jana Sillmann

We thank Dr Jonathan Wille for a constructive and openly signed review, which helped us to sharpen the main lesson. Following the reviewer's advice, we have (i) refined the lesson so that it is centred on the resolution at which CDD is computed and on what CDD then measures, (ii) aggregated the COSMO-CLM precipitation to ERA5-like and CMIP6-like grids before computing CDD and repeated the Moran's I analysis, (iii) compared CDD with other indices derived from the same daily precipitation field, and (iv) quantified, for all neighbouring grid cells, which precipitation events separate dry spells of very different length. As the main text is close to the length limit of LESSONS Reports, each new analysis is documented in the Supplement and summarised in the main text in at most two sentences.

Reviewer comments are reproduced in dark red italics. New or revised manuscript text is quoted in blue; line numbers refer to the initial preprint. LESSONS Reports are limited to about 2000 words in the main text.

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### General assessment

*This report presents a case for taking caution when using the longest number of yearly consecutive dry days (CDD) for analyzing drought behavior. Using a combination of radar and station rainfall observations and comparing them with ERA5 and kilometer-scale regional climate models, the authors make a convincing argument that the interpretation of CDD becomes different when measured at a higher resolution.*

*This discussion does open an important conversation about what CDD is actually measuring when used in hydro-climate studies. My opinion is that CDD has traditionally been used in studies using coarser-grid climate models where simulated precipitation occurrence is stretched across a larger grid cell, thus reducing spatial variability and leading to the drizzle bias as this study noted. This artificially reduces the noise in CDD, making it easier to analyze, and draw conclusions about broad precipitation patterns over a large geographic area. The analysis in Petrova et al. (2024) is a good example of using CDD at the CMIP GCM scale to identify broad regions where dry spells are projected to change in the future.*

*Kilometer-scale models are essentially simulating precipitation in a scale that feels more realistic to the average person on the ground. As this study highlights, kilometer-scale models can simulate rainfall patterns similar to radar measurements which is a tool we use to often perceive weather at the local scale. For example, imagine during a dry summer, you can watch a convective storm bring heavy rainfall to one half of your city while missing your home in the other half of the city, thus leaving your garden more yellow and parched compared to those who saw the rain. A coarse climate model would likely simulate that a light rain happened over the whole city and that the dry spell ended over your home while a kilometer-scale model would*

*simulate that the dry spell continues for half the city. For you and your dry garden, the continued dry spell more accurately describes your situation.*

*The point of this long and confusing example is that CDD at a higher resolution is measuring something different than CDD at a lower resolution. At a higher resolution, CDD may become less reliable to convey average precipitation patterns over a particular location, but it does become better at expressing the spatial variability of precipitation in a larger region. Especially as a warmer climate is expected to make precipitation more spatially concentrated and more convective, studying the future change in CDD with a kilometer-scale model can be useful for expressing how spatial distribution of precipitation becomes more scattered in the future. A higher variability in CDD across a region conveys that precipitation becomes more scattered or stochastic which has real consequences for agriculture as rainfall becomes less reliable.*

*Thus, the current text states to recommend caution when using CDD for drought evaluation, however I feel the analysis is pointing towards a different conclusion that is centered around the resolution at which CDD is being analyzed. The lesson could be refined to say that the intention of using CDD depends on the context and deserves caution depending on which resolution is being used and which precipitation characteristic is being analyzed.*

*Overall, I feel this report is well written and the analysis is robust and timely. I would support publication after a revision of the main lesson and the following comments are addressed*

**Response:** We agree with the reviewer's central argument that CDD computed at the kilometre scale measures something different from CDD computed on the grid of a global climate model. We will try to quantify this with a new analysis: When the daily COSMO-CLM precipitation is averaged to coarser grids before CDD is computed, the mean number of wet days ( $\geq 1$  mm) over Germany in 2018 increases from 94 at 3 km to 101 at 30 km and 111 at 99 km, and the mean CDD decreases accordingly from 26.8 to 24.5 and 23.0 days. A coarse-grid CDD is thus the longest dry spell of the area-mean precipitation, which is by construction shorter than the dry spells at most locations inside the grid cell. This is exactly the reviewer's garden: the coarse model ends the dry spell for the whole city, the kilometre-scale model does not.

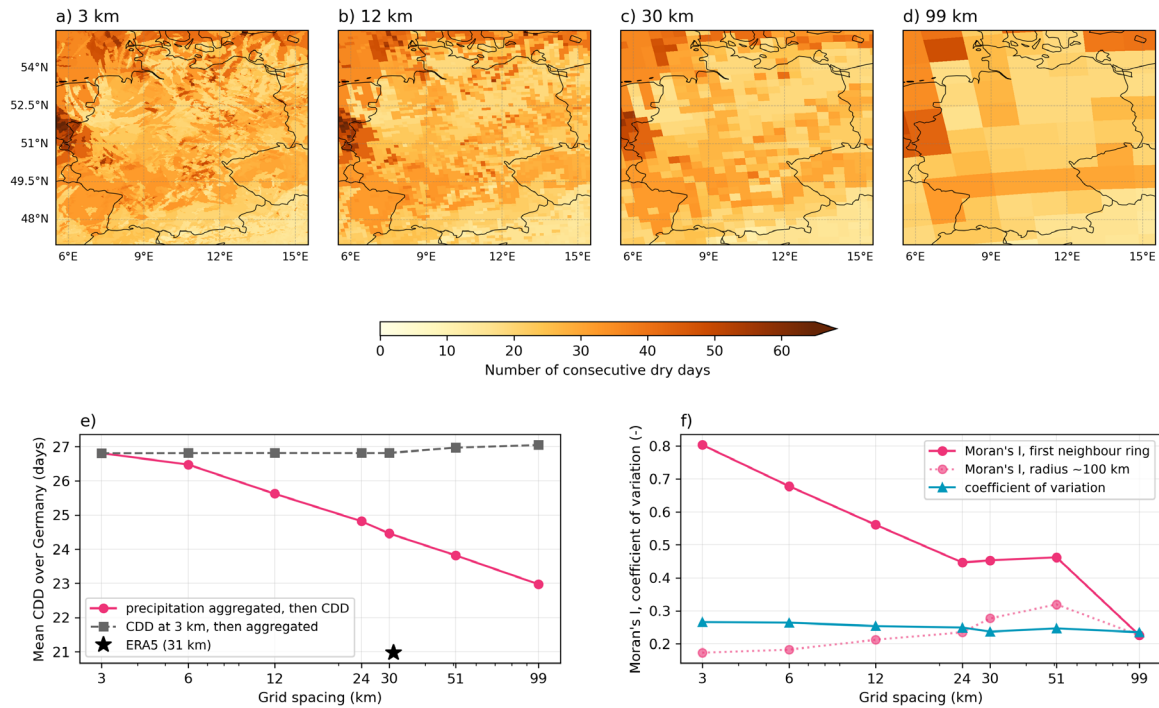
We therefore followed the reviewer's suggestion and refined the lesson around resolution: (i) CDD is not a resolution-independent property of the local climate and should only be compared between data sets of similar resolution; (ii) at the kilometre scale, the CDD of an individual grid cell or station is often decided by a single event close to the threshold and must be interpreted with caution; (iii) the spatial variability of kilometre-scale CDD is itself informative about the intermittency of precipitation. The last point is, in the sense of the LESSONS acronym, an opportunity for new science, for instance for studying changes towards more convective and spatially concentrated precipitation as the reviewer suggests. The abstract and the final paragraph of Section 4 will read:

**New text (tracked change, Abstract, replacing "As a lesson learnt, we recommend caution when applying CDD in any context ..."):**

"As a lesson learnt, CDD depends on the spatial resolution of the data and, at the kilometre scale, on single precipitation events close to the threshold; CDD should therefore only be compared between data sets of similar resolution and interpreted with caution at individual grid cells or stations, including in drought monitoring, impact assessment, and climate model evaluation."

**New text (tracked change, Sect. 4, replacing l. 145–147):**

"Hence, as our lesson learnt, CDD is not a resolution-independent property of the local climate: coarse grids yield the shorter dry spells of area-mean precipitation, whereas kilometre-scale CDD at a single location is often decided by one event close to the threshold (Supplement Sects. S3 and S7). CDD should therefore only be compared between data sets of similar resolution and be interpreted with caution at individual locations in dry spell monitoring, drought impact and low-flow analyses, and climate model evaluation (e.g. ESMValTool; Weigel et al., 2021), whereas its spatial variability may serve as a diagnostic of precipitation intermittency."



Draft of new Fig. S3. CDD in 2018 from COSMO-CLM after averaging the daily precipitation to (a) 3 km (native), (b) 12 km, (c) 30 km and (d) 99 km. (e) Mean CDD over Germany as a function of grid spacing when the precipitation is aggregated before computing CDD (pink) and when the 3 km CDD is aggregated (grey); the star marks ERA5. (f) Moran's I for the first neighbour ring (8 directly adjacent grid cells) and for a radius of about 100 km, and coefficient of variation of the CDD field over Germany.

## Specific comment #1

### SC#1: Introduction

*Introduction: In the first paragraph, I recommend discussing why CDD is a popular drought metric used in important climate reports and studies. For instance, you can cite and discuss the results from (Petrova et al. 2024) which uses CDD to highlight the growing risk of drought in future climate projections. Of relevance for this report is that the study was done with coarser CMIP5/CMIP6 models and would have much different results with kilometer-scale models. It might be worth citing and discussing Wille et al. (2025) which showed that CDD decreases in*

*kilometer-scale models when interpolated to a coarser resolution, but with differences in whether the model had convection parameterization or no parameterization.*

**Response:** Thanks a lot for the recommended literature. We will add one sentence to the first paragraph of the Introduction that motivates the popularity of CDD with its use in the IPCC AR6, where CDD serves, together with the SPI, as the precipitation-based index of meteorological drought for observed trends and projections, with the recent global projections of Petrova et al. (2024), and that points to the resolution dependence shown by Wille et al. (2025):

**New text (tracked insertion, Introduction, after I. 29):**

"CDD is used to assess meteorological drought in the IPCC AR6 (IPCC, 2023) and in global projections of dry spells (Petrova et al., 2024), which rely on grids of about 100 km; kilometre-scale models yield shorter dry spells when remapped to such grids (Wille et al., 2025)."

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## Specific comment #2

### **SC#2: Discussion**

*Discussion: It could be interesting to give an example of a negative or incorrect conclusion of drought evaluation that could be reached when using CDD at the higher resolution.*

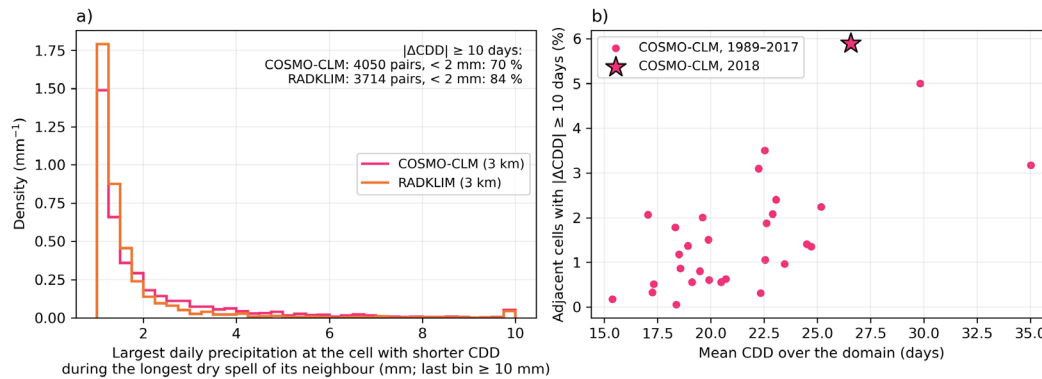
**Response:** Thank you, this is a very useful suggestion, and the example is already contained in Fig. 2. A drought assessment based on CDD would conclude that the two neighbouring cells in Fig. 2b (4.3 km apart) experienced meteorological droughts of very different severity, 55 versus 21 days. Yet both cells received almost the same water input: 143 and 149 mm from April to October, with a correlation of 0.99 between their daily series. During the 55-day spell (27 April to 20 June), the first cell received 2.3 mm and its neighbour 5.0 mm, and the dry period of the neighbour was interrupted only by two events of 1.39 mm (10 May) and 1.75 mm (30 May). The second pair (Fig. 2d, 3.1 km apart) is even more counter-intuitive: the cell with the longer CDD (49 versus 26 days) received more precipitation from April to October (307 versus 273 mm), and the shorter spell was cut by events of 1.14 and 1.07 mm.

To show that these are not hand-picked cases, we repeat this diagnosis for all 68,759 pairs of adjacent COSMO-CLM grid cells in the common domain of COSMO-CLM and RADKLIM. In 2018, 5.9 % of these pairs differ by at least 10 days in CDD. For these pairs, the largest daily precipitation at the cell with the shorter CDD during the longest dry spell of its neighbour has a median of 1.4 mm; it is below 2 mm in 70 % and below 5 mm in 94 % of the pairs, typically on a single wet day, and the median additional precipitation over the whole spell is 1.0 mm. The radar product shows the same behaviour: in RADKLIM on the same 3 km grid, the separating event is below 2 mm for 84 % of the corresponding pairs.

Such sharp jumps are most frequent in dry years: among the 30 years 1989–2018, 2018 has the highest share of adjacent pairs with CDD differences of at least 10 days (5.9 %, median of all years 1.4 %), and the share increases with the mean CDD of the year (Spearman  $\rho = 0.60$ ). The noise is therefore largest exactly when CDD is consulted most. We will add the following sentences after I. 141:

**New text (tracked insertion, Sect. 4, after l. 141):**

"For instance, the two neighbouring cells in Fig. 2b differ by 34 days in CDD, although they received 143 and 149 mm from April to October. In COSMO-CLM and RADKLIM, 70 % and 84 % of the adjacent cells whose CDD differ by at least 10 days are separated by events below 2 mm, and such jumps are most frequent in dry years (Supplement Sect. S7)."



Draft of new Fig. S7. (a) Largest daily precipitation at the cell with the shorter CDD during the longest dry spell of its neighbour, for all adjacent pairs of 3 km grid cells in the common domain of COSMO-CLM and RADKLIM with CDD differences of at least 10 days in 2018. (b) Share of adjacent COSMO-CLM cell pairs with CDD differences of at least 10 days versus the mean CDD over Germany for each year 1989–2018.

### Specific comment #3

**SC#3: Moran's I at coarser resolutions**

*I really like the analysis of Moran's I in Figure 3. One small additional analysis that could be interesting is to interpolate the COSMO-CLM to a couple coarser resolutions (like the ERA5 and CMIP6 level resolutions) and repeat the analysis. I would expect the spatial autocorrelation to increase with higher resolution which would strengthen the argument that CDD becomes more stochastic at the higher resolution.*

**Response:** Thank you, we will include this analysis in the Supplement (Figure shown already above). When averaging the daily COSMO-CLM precipitation conservatively (block means of  $2 \times 2$  to  $33 \times 33$  grid cells) to grid spacings of 6, 12, 24, 30 (ERA5-like), 51 and 99 km (CMIP6-like) and recomputing CDD on each grid, the results over Germany are:

- **Spatial autocorrelation:** At a fixed distance, Moran's I increases with coarser grid spacing. Moran's I of the first neighbour ring (8 directly adjacent cells) decreases from 0.80 to 0.45 between 3 and 30 km, because the distance between neighbours grows with the grid spacing.
- **Magnitude:** The mean CDD decreases from 26.8 days at 3 km to 24.5 days at 30 km and 23.0 days at 99 km, while the number of wet days increases from 94 to 101 and 111, consistent with Wille et al. (2025). About 40 % of the difference between COSMO-CLM (26.8 days) and ERA5 (21.0 days) is therefore explained by the grid spacing alone.
- **Noise:** The coefficient of variation of the CDD field changes little (0.27 at 3 km, 0.24 at 30 km, 0.23 at 99 km), and the 12 and 30 km maps still show jumps between adjacent cells. The order of operations therefore matters: a coarse-grid CDD is not the average of the local CDD, which reinforces the refined lesson.

In the main text, we will summarise this in one sentence after l. 116:

**New text (Sect. 4, after l. 116):**

"Part of this difference stems from the grid spacing: averaging the COSMO-CLM precipitation to 30 km before computing CDD reduces its mean over Germany from 26.8 to 24.5 days, compared with 21.0 days in ERA5 (Supplement Sect. S3)."

**Two further checks of Fig. 3.** While extending the analysis, we re-examined the code behind Fig. 3 and report two points for transparency.

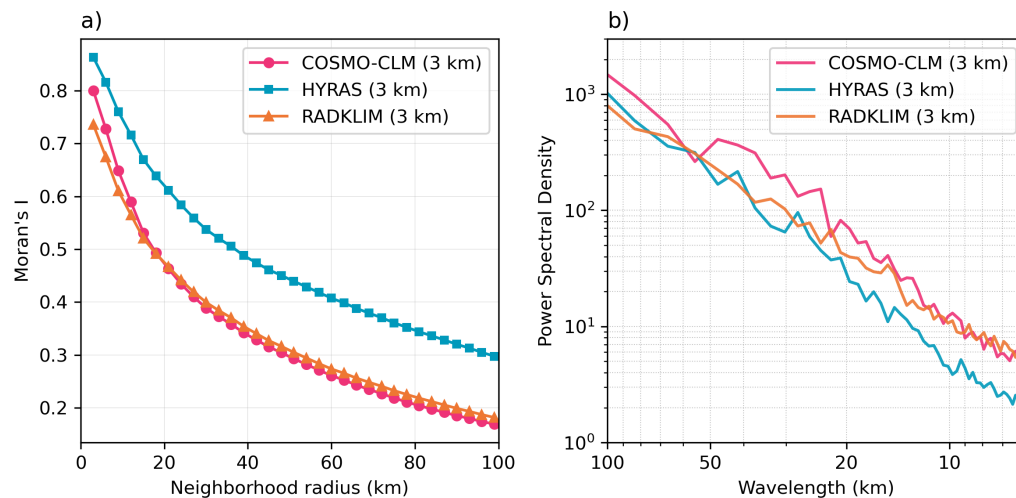
(1) Our Moran's I uses the  $k$  nearest valid grid cells, with  $k$  equal to the number of cells within radius  $r$ , so that cells at the edge of the valid domain draw some neighbours from beyond  $r$ . We will update this by a strict radius-based neighbourhood. This will change Moran's I by at most 0.04 at any radius and leaves the ranking of the three data sets unchanged.

(2) The RAPSD routine of pysteps assigns radial wavenumbers in index units, which is exact only for *square* fields, whereas we applied it to a *rectangle* of 507 km  $\times$  288 km. Recomputing the spectra with wavenumbers on the largest *square* of common valid grid cells (333 km  $\times$  333 km), gives qualitatively the same picture.

We will therefore also revise Fig. 3: Fig. 3a now uses the strict radius-based neighbourhood, and Fig. 3b shows the RAPSD computed with pysteps on the largest square of common valid grid cells (333 km  $\times$  333 km). The conclusions drawn from Fig. 3 are unchanged, and the Methods will be adapted accordingly:

**New text (Sect. 2, l. 60–61):**

"... constraining the analysis to the largest square of valid CDD values (333 km  $\times$  333 km) to avoid artefacts from no-data gaps."



Revised Fig. 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). b) Radially averaged power spectral density on the largest square of common valid grid cells (333 km  $\times$  333 km) as a function of wavelength.

## Minor comments

*Line 57: Please briefly define what Moran's I is for the readers who are not familiar with this term.*

**Response:** Added. The sentence now continues: "... yielding a spatial autocorrelogram for scale-dependent comparison of CDD patterns between the three high-resolution datasets; Moran's I correlates the value of each grid cell with those of its neighbours, from about -1 (dispersed) via 0 (random) to 1 (clustered)."

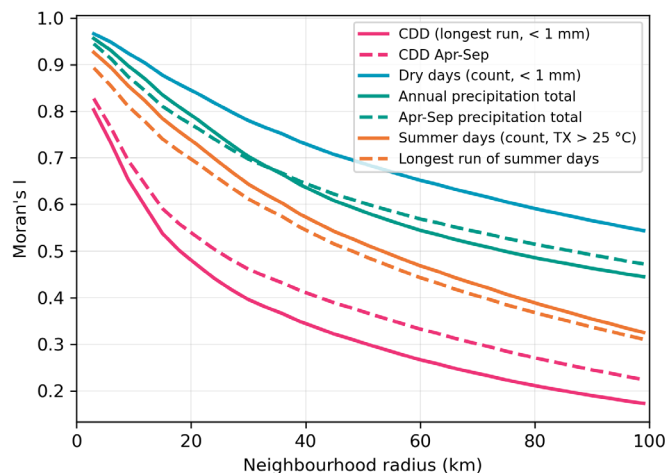
*Line 139: You can bolster your argument here by saying that other threshold dependent climate indices, like days above a certain temperature threshold, have a higher spatial autocorrelation and are less stochastic, even at a higher resolution. Thus, CDD is uniquely problematic given its high spatial variability when examined at a high resolution.*

**Response:** Thank you for this nice and illustrative idea. We will show that with temperature and precipitation indices computed from COSMO-CLM in 2018. Temperature behaves as you suggested: the number of summer days (daily maximum temperature above 25 °C) has a Moran's I of 0.93 for adjacent cells and 0.33 at 99 km, compared with 0.80 and 0.17 for CDD.

Looking at the draft of Fig S4, comparing CDD to the number of dry days shows that the noise is mostly caused by the run-length (maximum) operator combined with the dryness threshold, which makes CDD uniquely sensitive, as you suggested. We will add one sentence after l. 139:

**New text (Sect. 4, after l. 139):**

"This sensitivity stems from the run-length definition combined with the threshold as the numbers of dry days are much smoother (Supplement Sect. S4)."



Draft of new Fig. S4. Moran's I as a function of neighbourhood radius for indices computed from the COSMO-CLM simulation of 2018 over Germany (daily precipitation and daily maximum temperature).

## References added to the manuscript

Petrova, I. Y., Miralles, D. G., Brient, F., Donat, M. G., Min, S.-K., Kim, Y.-H., and Bador, M.: Observation-constrained projections reveal longer-than-expected dry spells, *Nature*, 633, 594–600, <https://doi.org/10.1038/s41586-024-07887-y>, 2024.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., and Zhou, B.: Weather and Climate Extreme Events in a Changing Climate, in: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by: Masson-Delmotte, V., Zhai, P., Pirani, A., et al., Cambridge University Press, Cambridge, UK and New York, NY, USA, 1513–1766, <https://doi.org/10.1017/9781009157896.013>, 2021.

Wille, J. D., Koch, R., Becker, T., and Fischer, E.: Extreme precipitation depiction in convection-permitting Earth System Models within the nextGEMS project, *J. Adv. Model. Earth Sy.*, 17, e2024MS004840, <https://doi.org/10.1029/2024MS004840>, 2025.