Evaluation and improvement of CAMS-derived CCN number concentrations using in-situ measurements

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Author's response to comments by referee 1 (Christina Williamson, 2026)

In the following, we respond to the referee's comments (**black**) with our statements in **blue** and the adapted text from the revised manuscript in **orange**.

Major comments

The paper addresses two relevant scientific modelling questions that are relevant to GMD, namely the performance of CAMS derived CCN number concentrations with respect to in-situ ground-station observations and possible corrections to improve that performance. Both the evaluation against a large set of ground-station observations from varied environments, and the proposed correction are novel and present important advances for the field.

The authors thank Christina Williamson for carefully reading the manuscript and acknowledging the significance of our study. We appreciate their valuable suggestions and useful comments.

Discussion on agreement between CAMS and observations

While the evaluation against in-situ observations is very valuable and well documented, the level of agreement between CAMS and observations is overstated as follows:

- Line 227 states that "simulated temporal variability agrees well for the majority of sites" (line 227), but R is less than 0.5 for almost half the evaluated stations for monthly averages.
  Indeed this seems as we have overestimated the initial results, but you need to consider the significance of these results. After careful consideration we rewrote this section as following:
  "Using daily 0-UTC medians, only 5 out of 23 stations with significant correlation coefficients show R values above 0.5 indicating at least moderate correlation of day-to-day fluctuations. This is a poor result considering that the CCN data are derived from a reanalysis in which the underlying aerosol fields are constrained by observations. Diurnal variations which might impact bias and correlation coefficient cannot fully be evaluated here only using 0-UTC CAMS data. Hence, applying 3-hourly CAMS CCN data could be very beneficial to account for these effects. However, in the current dataset by Block (2023), this temporal resolution is not available yet. A more detailed analysis on short-term variability of selected sites is given in Anders et al. (2025).

  Applying an 11-day running median on both datasets largely removes variability shorter than the synoptic scale, thereby improving temporal clarity of the time series at most stations. This filtering increases the correlation coefficient of 17 stations, compared to the daily medians, and thus, enhances the confidence that the CAMS-derived Nccn captures variability on synoptic time scales. Still, only 10 of 21 stations yielding significant result show R values larger than 0.5, which is about half of all stations. Correlation coefficients increase again for 8 stations when using monthly medians, especially for NOT, FIK and JFJ the increase is quite drastic.

However, only for 11 of the 25 stations significant correlation coefficients are found. Here, R values range from $+0.558$ to $+0.911$ within all remaining 11 stations across all environments and pollution regimes."

- Line 230 states that "CAMS Nccn reproduces observed variability very well on seasonal and annual time scale and is well suited for climatologies", but the seasonal and annual agreement with in-situ observations are not directly assessed in the manuscript, only the 11 day and monthly agreement.
  Yes, indeed the observational data of most stations are too sparse to produce any significant correlations with CAMS. We have therefore elaborated as such:
  "The results of Tab. 2 are further illustrated in Fig. 2 showing multi-year 11-day running medians, and Fig. A2 showing multi-year monthly medians of Nccn ($s = 0.4\,\%$) for all stations. Even though a correlation analysis of seasonal and annual medians does not produce significant results, as the available measurement periods are not long enough, we can visually judge the simulated temporal variability over several months indicating a yearly cycle from Fig. 2 and Fig. A2. From those 18 stations with at least 10 months of continuous observations available, 13 agree with CAMS in the yearly distribution of CCN, featuring e.g. correct differences in summer/wintertime CCN (SEO, SMR, SGP or JFJ), spring/autumn CCN (ATT, CES or FKB) or the double summer peak for VAV. Furthermore, at stations featuring wet and dry seasons, such as ATT, FIK, NIM and SEO (Galy-Lacaux and Modi, 1998; Kouvarakis et al., 2000; Pöhlker et al., 2016; Schmale et al., 2018), the increase in observed dry season Nccn is well captured by CAMS-derived Nccn (Fig. A3).

  From this we conclude that CAMS-derived Nccn mostly reproduces the observed variability on monthly and seasonal time scales and therefore is suitable to be used for climatological applications and studies focusing on these timescales."

- Reproducing variability between Dry and Wet season evaluation is mentioned but has explicitly not been shown (line 236)
  We added a figure to the appendix, showing the distribution of CAMS-derived and observed Nccn during wet and dry season periods for the stations ATT, FIK, NIM and SEO. Further we write:
  "Furthermore, at stations featuring wet and dry seasons, such as ATT, FIK, NIM and SEO (Galy-Lacaux and Modi, 1998; Kouvarakis et al., 2000; Pöhlker et al., 2016; Schmale et al., 2018), the increase in observed dry season Nccn is well captured by CAMS-derived Nccn (Fig. A3)."

- Block et al 2024 is sited as evidence for good agreement (lines 233-234), but this uses only sites SGP, PVC, PGH, GRG, MAG, and only 2 out of these 5 sites have R>0.5
  Completely correct! We have deleted this sentence. Even though Block et al. (2024) shows yearly cycles of CCN (Fig. 6), this is not evaluated by observations.

Regarding the method of comparison between CAMS and observations, CAMS derived NCCN are at 0UTC only, but the full diurnal cycle of in-situ observations is used (Section 2.3 Data Treatment). It is worth questioning whether diurnal cycles in observed NCCN lead to a bias here. The approach of longer temporal averaging taken here is not sufficient to remove such a bias. If hourly observations are available from the stations, it should be straightforward to test this.

Thanks for this useful suggestion. We decided to redo the analysis but for observations around 0 UTC. We computed medians for the time from 22:00 UTC to 02:00 UTC because observation files only partly contain values at 0 UTC precisely, and in order to have enough data for statistical robustness.

For most of the observed datasets that workes fine as the instrument steps through all supersaturation levels within 1 hour, only for ATT a problem emerges while doing this subsampling. The instrument took several hours to step through one cycle of supersaturations, then jumped back to the starting point instead of stepping down slowly, and recycled. Therefore, it is impossible to receive hourly data for each supersaturation and e.g. for 0.4 %, which was not directly measured, it is also impossible to interpolate that value via Twomey power law over nearby supersaturation points as at least one of them is outside the selected time frame. Thus, as stated in the text, CCN measured at 0.47% is taken directly in the selected time frame around 0 UTC only for correlation purposes (Table 2), while for other analyses (e.g. bias estimates) or plots median numbers of ATT, CCN at 0.4 % supersaturation are derived via inter/extrapolation of nearby supersaturation points. For instance, in Fig. 2, 11-day running medians are computed for 0.2 % and 0.6 % supersaturation separately, and only afterwards the value of 0.4 % is derived via Equations 2 and 3, which then is finally plotted.

If not stated otherwise, all results of the revised version are now based on these 0-UTC medians. Accordingly, statistical values have changed throughout the entire manuscript, as selecting this subset of data is one of the first steps in this analysis. However, we are happy to note that the main conclusions remain untouched and are therefore robust.

Table 1 in this document illustrates the difference between comparing model data at 0 UTC to observations around 0 UTC versus comparing model data at 0 UTC to daily median observations (full day). Please note that this table is for the reviewers' eyes only, and not printed as such in the manuscript! When using 0 UTC data only, the bias is decreased for 10 stations, it is increased for 8 stations and for 7 stations it does not change more than 1 % in either direction. The correlation coefficient is increased only for 4 stations and decreased for 9 stations, excluding those for which there are insignificant results. For 6 stations the values don't change more than ± 0.05 and are mostly unchanged.

This shows that daily variability is not negligible and the comparison underlines your correct hypothesis that a daily cycle, or a negligence of such, can indeed lead to biased results. However, our results indicate that such biases are not one-sided but rather very variable. CAMS-derived CCN data at 0 UTC might be less representable for environments with large diurnal cycles of aerosol load while it may be better representable for locations with small diurnal cycles. Either way, using median values from both observations and CAMS-derived CCN data around 0 UTC, only 5 out of 25 stations show correlation coefficients above 0.5 which is a poor result considering that the CCN data are coming from a reanalysis. Assuming 0 UTC is representable for entire days and comparing this to daily median observations, only 7 of 25 stations show correlation coefficients above 0.5, while in our previous analysis considering daily means, not medians, we had a match of 11 out of 25.

These results clearly show that the methodology and preparation of the data plays a major role here. To not confound the reader of these varying results that solely depend on methodology, we decided to exclude any results that use mismatching temporal fields or means instead of medians to be more consistent throughout this study. Thus, we only note:

"Diurnal variations which might impact bias and correlation coefficient cannot fully be evaluated here only using 0-UTC CAMS data. Hence, applying 3-hourly CAMS CCN data could be very beneficial to account for these effects."

Table 1: Cluster (as defined by pollution regime and environment), Kling-Gupta efficiency KGE, bias B, correlation coefficients R and number of points # as derived from daily CAMS CCN data at 0 UTC and observational data from 22:00 UTC to 02:00 UTC for all 25 stations, sorted by KGE from highest to lowest. CCN are taken at $s = 0.4\,\%$, except for ATT where 0.4% was not available as such and instead 0.47% was applied here - which eventually might lead to a slightly decreased bias. R values in parentheses indicate not significant correlations (95 % confidence interval). The cluster names are abbreviated: clean continental as 'cle-con', polluted continental as 'pol-con', clean marine as 'cle-mar', polluted marine as 'pol-mar'. In comparison, the correlation of CAMS CCN data at 0 UTC against observed daily medians, using all available data over a day is presented.

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		0-UTC				full day		
ID	cluster	KGE	B [%]	R	#	B [%]	R	#
MHD	cle-mar	0.505	+ 14.09	0.669	188	+ 23.67	0.742	190
ATT	pol-con	0.493	+ 11.15	0.543	172	+ 3.11	0.625	227
PVC	pol-mar	0.406	− 11.36	0.455	142	− 12.53	0.253	153
FKB	pol-con	0.373	+ 25.19	0.506	266	+ 28.55	0.459	278
SMR	cle-con	0.279	− 38.47	0.321	746	− 38.18	0.469	809
ASI	cle-mar	0.164	+ 63.80	0.818	420	+ 62.15	0.790	430
NOT	pol-mar	0.155	− 5.30	0.214	233	− 13.98	0.289	258
VAV	cle-con	0.147	− 27.97	0.173	388	− 23.84	0.360	395
FIK	pol-mar	0.146	− 13.42	0.172	271	− 13.55	0.167	279
SGP	pol-con	0.084	− 38.46	0.174	3847	− 39.82	0.072	3948
CES	pol-con	0.075	− 40.60	0.287	560	− 32.35	0.542	565
JFJ	cle-con	0.066	− 42.31	0.385	548	− 48.63	0.513	594
AWR	cle-mar	0.023	+ 201.19	0.487	198	+ 215.42	0.557	201
GRW	cle-mar	− 0.016	+ 22.90	0.121	563	+ 29.45	0.103	575
NIM	pol-con	− 0.042	+ 99.45	0.243	262	+ 134.96	0.219	266
SEO	pol-con	− 0.097	+ 69.15	0.183	586	+ 72.50	0.353	634
OLI	cle-mar	− 0.126	+ 190.46	(0.019)	256	+ 195.34	0.048	278
MEL	pol-con	− 0.141	− 45.02	0.129	263	− 46.52	0.245	476
PYE	pol-mar	− 0.175	+ 93.13	0.282	178	+ 100.78	(0.077)	187
PGH	pol-con	− 0.201	+ 75.59	0.609	217	+ 28.87	0.439	265
ENA	cle-mar	− 0.207	+ 37.82	0.293	682	+ 33.11	0.171	706
NSA	cle-mar	− 0.230	− 38.95	0.146	1329	− 36.48	0.129	1371
COR	cle-con	− 0.240	− 68.71	(− 0.061)	184	− 61.77	− 0.168	192
MAO	pol-con	− 0.339	+ 48.74	0.441	83	+ 47.08	0.510	86
BRW	cle-mar	− 1.558	− 17.85	0.225	129	− 15.56	(0.093)	165

Discussion on s-dependent k parameter

The method for deriving the correction factor is well justified in terms of justifying an s-dependent k parameter, and in using empirical fits of the Nccn-s spectrum to derive this. Limitations in this method being unable to use the full 3-hourly CAMS reanalysis data or change the underlying size distribution are well justified. However, aspects of the method seem unjustified and sensitivities to the large uncertainties involved not fully investigated. Details of these are as follows:

- The authors clearly note that CAMS derived CCN at latitudes above 70N and 70S are problematic because of the lack of data assimilation at these latitudes. The inclusion of these stations in the derivation of the global correction factor therefore seems poorly justified.
  The slope parameter k is calculated from the observations only. Under the assumption that

we trust observations from polar sites, it would be justified to use them in the derivation of k. However, to be more consistent in terms of applicability for CAMS CCN, we excluded these 4 stations both from the derivation of the new parametrization and the evaluation of the improved dataset. The here developed correction is however also applied to these stations for completeness (Fig. 7). But since they differ so much in the first place, the effect of correction is also inconsistent.

- The k parameter is derived by grouping together median continental, coastal/polar and remote marine stations to find average factors for each environment. However, the variability of Sbest within coastal/polar and continental environment groups is greater than between the different environments (Fig. 4). This suggests that the grouping is not valid for this purpose.
  Thank you for pointing this out. We again evaluated the categories based on environment and overall pollution level. Again we came to the conclusion that based on Sbest alone, the corrections are fundamentally better when such categories are applied rather than not recognizing any variation at all. Unfortunately, the sparse data coverage does not enable a robust clustering of pollution and environmental settings. However, we did change the definition of these categories. In our previous version, we only classified environmental regimes as this gave better results than classifying only by pollution level. Now, we decided a better way forward would be to combine both, environmental and pollution regimes, which reduces the variability within each regime. Therefore, we now have 4 categories: 1. clean marine, which includes remote marine, coastal and polar stations with Nccn (0.4 %) $<$ 500 cm^{-3}, 2. polluted marine, which includes remote marine, coastal and polar stations with Nccn (0.4 %) $\geq$ 500 cm^{-3}, 3. polluted continental, which includes inland only Nccn (0.4 %) $\geq$ 500 cm^{-3}, and 4. clean continental including inland only Nccn (0.4%) $<$ 500 cm^{-3}. As can be seen from Fig. 4, there still are varying levels of variability within the categories, but a tendency of increasing Sbest over categories can cleary be seen.

- The k factor is derived by averaging the median continental, coastal/polar and remote marine correction factors with equal weighting (line 333-335). While the authors are correct to try to account for the fact that the environmental distribution of stations with available observations does not accurately reflect the global distribution, there is no justification given for assuming that the global atmosphere is made of equal parts coast, ocean and continent.
  We changed the global average to a weighted mean of 70 % ocean and 30 % land. Coastal stations are attributed to the marine environment in the revised version, since we account for their different pollution regime (as described above).

  This new classification only changes little to the derivation and application of the k parameter.

  This is the original equation for k:

$$k(s) = \left\{ \begin{array}{ll} -1.371028\, s + 1.210104 & \text{for } s < 0.2\,\% \\ 0.355152\, s^{-0.619866} & \text{for } s \geq 0.2\,\% \end{array} \right\} . \tag{1}$$

  which now has changed to:
  "The global $k(s)$ parameterization can be written as:

$$k(s) = \left\{ \begin{array}{ll} -1.041286\, s + 1.069804 & \text{for } s < 0.2\,\% \\ 0.370341\, s^{-0.524598} & \text{for } s \geq 0.2\,\% \end{array} \right\} ." \tag{2}$$

  The description of the weighting has changed to:
  "To account for the uneven global distribution of continental (30 %) and marine environment (70 %), we perform a weighted average of these environment medians for each supersaturation, to obtain a global spectrum of observation-derived $k(s)$."

- There are large uncertainties/variability in the empirical fits for the k-factor (Fig. 4). Some understanding of how this uncertainty affects the resulting Nccn and the bias reduction is needed.

  Fig. 4 shows Sbest for each station, while we think Fig. 6 is what you are referring here to. For better clarification, we changed Fig. 6, so it now shows $k(s)$ which is purely obtained from observations for each individual station in each category, except for polar ones as they are not applied to CAMS CCN data. In addition we changed previous Fig. A3 to now Fig. A4 to better depict how each k or $k(s)$, depending on definition, affect the correction of the bias of CAMS CCN over supersaturation, exemplary showing one station per cluster. Additionally we rewrote this section for better clarification and elaborated as follows:

  "We also explored other possible derivations of a k-s spectrum, by treating each regime/environment/cluster individually instead of a global mean. In Fig. A4, we show a comparison of these approaches at SMR, SGP, ENA and FIK, which are the stations with the highest number of points in their respective cluster.

  For the constant k parameterizations, we apply Eq. 3 with $s_1 = 0.1\,\%$ and $s_2 = 1.0\,\%$ for each individual station, resulting in one single-value k per station. For applying a correction with a constant global k, we group these k values by environment and perform a weighted average of the median of all continental stations (30 % weight) and median of all marine stations (70 % weight). Thus, we use one single-value k globally. The correction with a constant cluster k is done similarly but with grouping by cluster before applying the median single-value k in the respective cluster.

  Additionally, bias corrections are performed with four different $k(s)$ parameterizations in comparison. First, an s-dependent spectrum of $k(s)$ is calculated for each station. For applying a correction using a global mean $k(s)$ on all stations, we group these station spectra by environment and perform a weighted average of the median of all continental stations (30 % weight) and median of all marine stations (70 % weight). The resulting global average $k(s)$-spectrum is fitted, as described above. Thus, we use one global $k(s)$-spectrum for each station. The parameterization with a regime dependent $k(s)$ is done by grouping the station spectra by regime and fit the regime-median $k(s)$. This fitted spectrum is used for each station of the respective regime. Parameterizations using the environment dependent $k(s)$ and the cluster dependent $k(s)$ are done similarly, but by grouping first by environment or by cluster, respectively.

  All Nccn parametrizations are then retrieved from Eq. 2 with the respective k or $k(s)$ and the cluster-specific reference supersaturation s_i (clean continental: 1.0 %, polluted continental: 0.6 %, clean marine: 0.2 %, polluted marine: 0.4 %.)

  For most stations the differences between group-specific (regime, environment, cluster) and global $k(s)$ are not very large (as at ENA and FIK in Fig. A4), thus it would be unnecessary to distinguish between clusters (or environments/regimes), as we did for the definition of s_i. This simplifies applications on a global scale in any future developments or use cases. However, another reason why we prefer the parameterization with a globally weighted mean $k(s)$ is that the bias correction produces the most balanced biases for low and high supersaturations, as can also be seen in Fig. A4 for SMR and SGP. Please note that all 25 stations behave differently, which is why the chosen parametrization is not necessarily the best fit at each station. It is rather a tradeoff between the individual stations and the applicability on a global scale. For completeness, all group-specific $k(s)$ parameterizations are listed in Table A3."

- The PGH site is excluded from the derivation of k(s) because they lead to negative values. This is only noted in the caption for Fig. 6, and no physical justification is given for excluding these data. This is especially problematic given that PGH is the only site from southern Asia. That these data lead to an unphysical k(s) seems motivation to reevaluate aspects of the method used for this correction.

In previous Fig. 3, for which all observations over a day at a certain supersaturation were used to compute daily medians, you could see that at PGH median Nccn (0,8 %) was lower than Nccn (0.6 %). This feature did not appear at any other station and was leading to a negative $k(s)$ in this case. This is indeed unphysical behavior and could originate from biased measurements at high supersaturation. However, this problem disappeared when using only data within the 22 - 2 UTC time frame to construct 0-UTC daily medians as is shown now in the revised version. We have therefore decided to include this data to construct $k(s)$ just like the other stations (see Fig. 6). However, we recommend to carefully treat CCN data from this station and additionally check them against measurements of total aerosol number concentration when using this data for validation purposes.

Minor comments

More minor comments are as follows:

- The abstract fails to state the result of the evaluation of CAMS Nccn.
  Yes, we added the main results and revised the abstract as follows:
  "Cloud condensation nuclei (CCN) are key components of aerosol-cloud interactions (ACI). Thus, a precise knowledge about their number concentrations (Nccn) is crucial for climate models and ACI studies. This study presents a comprehensive evaluation of the recently published CAMS-derived total Nccn using direct observations from 25 ground-based sites. The evaluation focuses on the representation of temporal variability, the applicability of CAMS-derived Nccn across different environments and pollution regimes and in particular, the sensitivity of CCN to supersaturation. At a mid-range supersaturation of $s = 0.4\,\%$ the CAMS-derived Nccn reproduces monthly and seasonal variability well, with monthly median Pearson correlation coefficients ranging from +0.558 to +0.911, while the representation of day-to-day variability is considerably weaker, with significant daily correlations ranging from +0.121 to +0.818. No systematic dependence of model performance on environment or pollution regime is found for this level of supersaturation. The dataset therefore appears well suited for climatological applications and studies focusing on variability beyond synoptic timescales. The analysis further reveals a bias shift in simulated Nccn with increasing supersaturation. This feature correlates to the ratio of the two dominant CCN species, likely reflecting assumptions in the underlying size distributions and/or emissions fractions. To address this issue, we developed an observation-based parameterization using a modified power law with an s-dependent k spectrum that modifies the supersaturation dependence of total Nccn without altering aerosol size distributions or species concentrations. This is applied to modeled Nccn which are grouped by environment and pollution regimes yielding different levels of best fitting supersaturations. Overall, this correction substantially reduces the median bias by 30.1 % at 0.1 % supersaturation and by 43.3 % at 1.0 % supersaturation, improving agreement of the modeled Nccn with observations at most sites. These results further enhance the applicability of the dataset for global aerosol–cloud interaction studies, leading the way to an improved version of CAMS-derived Nccn."
- Line 218 "temporal presentability" - unclear terminology
  This is changed to:
  "Using the advantage of the CAMS-derived Nccn dataset as a continuous multi-year time series, a qualitative assessment of its ability to reproduce temporal variability is performed."

- Section 2.2 Observed Data - While the number of stations and different environments included in the evaluation is high, and reflects well what is available, it is of note that available observations are still biased toward Europe and North America, with Africa and Australasia remaining particularly underrepresented. This is not a fault of this study, but it would be helpful to note this bias and its' potential implications in the manuscript.
  We added:
  "As can be seen from Fig. 1, available observational sites are concentrated in Europe and North America, while Africa, Australasia and large parts of central and northern Asia remain particularly underrepresented. Furthermore, effectively only two sites (ENA/GRW, ASI) are available to represent remote oceanic environments. This uneven spatial coverage can introduce distortions when observations from different sites are combined to derive global estimates. Therefore, oceanic and continental contributions are weighted separately in subsequent analyses, as described in Section 3.2.2."

- The conclusions sections states both that there is no dependence of model performance on environment nor pollution but also that more polluted sites show a positive bias (lines 392-395). These are contradictory.
  Yes, we agree with this point. After recomputing using 0-UTC medians and changing the environment-pollution classes we had to revise the latter statement - now focusing on the bias, instead of KGE. It now reads:
  "Block et al. (2024) made the comment, based on PGH data only, that very polluted sites might be overestimated by CAMS CCN. To further evaluate this feature we examined the bias of the most polluted sites available in our observations. Observations at SEO, MEL, CES, NOT, FIK and PGH all show median $\mathrm{CCN_O} > 1000\,\mathrm{cm^{-3}}$ for $s = 0.4\,\%$, outranging all other observations. But only SEO and PGH are overestimated by CAMS, while the other 4 stations are underestimated. Thus we cannot confirm that heavily polluted sites are high biased in general. However, examining data from other megacities, such as in Asia and Africa, might be necessary, as our list of stations only included one (SEO)."

- Why do the R values for the daily comparisons with SGP, PVC and PGH differ from those presented in Block et al 2024 (see table below)?

	Daily	11day	month	Block2024 (daily)
SGP	0.069	0.133	0.709	0.24
PVC	0.296	(0.098)	(0.360)	0.66
PGH	0.532	0.623	(0.480)	0.41

  Thanks for pointing this out. There are several reasons for these differences: For SGP, other data products have been used in addition to AOSCCNAVG and the observed time period has expanded, such that we have 3873 days available (now using 0-UTC data only: 3847 days) instead of the 264 days used in Block et al. (2024). For PVC and PGH the same data product and time periods have been used, but the data processing has changed such that more days have become available for analysis. In Block et al., 2024, only data retrieved for at least four of the seven s bins with a minimum total of 96 measurements per day (1/3 of maximum possible data coverage) were taken into account. This was done to ensure that each daily mean consisted of enough data points to be representable. Here we ignored these limitations to keep as many data points as possible. Even if a day of observed CCN measured less than 4 hourly cycles (of max. 12 cycles), we now take this data into our analysis. Meanwhile, we slightly adjusted the data processing as described in lines 148 – 165, e.g. by directly using data within a 0.05 % supersaturation range or simply averaging within a 1 % supersaturation range. The Twomey-interpolation was only used here, when no CCN were found within a

1 % supersaturation range, while in Block et al. (2024), this was applied every time a specific supersaturation was not represented in the data. Additionally, we took care of the correct measurement height and compared this to the corresponding model level (l. 129), which was not considered in Block et al. (2024). This is especially important e.g. for the PGH station which is located at 1936 m above sea level. Now, in the revised version, the additional limitation in time (22 - 2 UTC) has added even more differences. As stated earlier, data preparation and methodology can have huge impacts on the results.

- Line 219 typo "andcorrelations"
  Thanks for noticing. We also updated this sentence in regard to the new averaging metrics. The revised sentence now reads as follows:
  "Tab. 2 compares R values for each station distinguishing daily medians, running medians with windows of 11 days and monthly medians, all based on 0-UTC time periods."

- Fig A3 legend hard to distinguish between station and environment specific
  We updated this figure entirely, aiming also for better readability. It is now Fig. A4.

- Line 245 "$\mathrm{CCN_O}$ are significantly overestimated" – does this means observations>CAMS or other way round? Similar at line 265
  After careful investigation, we have decided to rewrite the entire paragraph to:
  "Block et al. (2024) made the comment, based on PGH data only, that very polluted sites might be overestimated by CAMS CCN. To further evaluate this feature we examined the bias of the most polluted sites available in our observations. Observations at SEO, MEL, CES, NOT, FIK and PGH all show median $\mathrm{CCN_O} > 1000\,\mathrm{cm^{-3}}$ for $s = 0.4\,\%$, outranging all other observations. But only SEO and PGH are overestimated by CAMS, while the other 4 stations are underestimated. Thus we cannot confirm that heavily polluted sites are high biased in general. However, examining data from other megacities, such as in Asia and Africa, might be necessary, as our list of stations only included one (SEO)."
  Furthermore, for better understanding we have rephrased the other sentence to:
  "As depicted from Fig. 2, CCN are overestimated by CAMS at some stations (e.g., AWR, NIM or ASI), while underestimation is present at others (e.g., MEL, JFJ or SGP)."

- Line 247 "Most stations fall in the respective pollution regime category as defined by observations" unclear – I think the authors mean the pollution categorization from CAMS matches that from observations in most cases - needs to be stated more clearly.
  As part of our revision, we simplified our classification (clean/polluted, marine/continental). The new clustering is entirely based on CAMS-derived Nccn, as this is necessary for the application of the improved parametrization. We also added a comparison of the regimes as defined by a) observations and b) CAMS-derived Nccn to Tab. A2. Lastly, we rephrased the paragraph as part of the necessary update:
  "For most stations, the pollution regime as identified by $\mathrm{CCN_C}$ ($s = 0.4\,\%$) matches the regime it would have if regimes were defined by the observational $\mathrm{CCN_O}$ ($s = 0.4\,\%$). A comparison of both definitions is part of Tab. A2. Only 4 stations deviate as a result of their bias, and thus would fall into a different category. Due to their negative bias, SMR, VAV and COR are classified in $\mathrm{CCN_C}$ as clean regimes instead of polluted ones. Meanwhile, PYE is classified as polluted instead of clean due its positive bias. A decrease in absolute bias would lead to a correction of pollution regime identification."

- 6a Impossible to see which datapoints belong to the same station except at the edges, so impossible to see if k does decrease with s for each station as stated at line 320-323. Solid lines for environment specific medians not very visible in 6a either.

We replaced this figure to break down the $k(s)$-spectra at each station and to show the differences and similarities between all four clusters.

- ATT station is used as an example of how the method works (Fig. A3) with some acknowledgement that the global average approach does not improve the predicted Nccn for all stations (lines 344-352). However, ATT has s-best in the middle of the range of all stations, and therefore is likely a case where the global average works best. It would be more justifiable to illustrated also cases that work less well.
  We replaced this figure with Fig. A4 showing the biases of different approaches at the example of one station per cluster (SMR, SGP, ENA, FIK). Each of them is the station with the longest time frame available in their own cluster. This figure shows advantages and deficiencies of our chosen method compared to other possible approaches.

- Fig A1 – legend and caption unclear.
  We clarified the meaning of this figure in the caption.

References

Anders, Y., K. Block, and J. Quaas (2025). “Validation of CAMS derived CCN variability with in-situ observations”. In: *Meteorologische Arbeiten (XXX) und Jahresbericht 2024 des Instituts für Meteorologie der Universität Leipzig*, pp. 11–26. URL: https://nbn-resolving.org/urn:nbn:de:bsz:15-qucosa2-1001574.

Block, K. (2023). “Cloud condensation nuclei (CCN) numbers derived from CAMS reanalysis EAC4 (Version 1)”. Version 1. In: *World Data Center for Climate (WDCC) at DKRZ*. DOI: 10.26050/WDCC/QUAERERE_CCNCAMS_V1. URL: https://www.wdc-climate.de/ui/entry?acronym=QUAERERE_CCNCAMS_v1.

Block, K. et al. (2024). “Cloud condensation nuclei concentrations derived from the CAMS reanalysis”. In: *Earth System Science Data* 16.1, pp. 443–470. ISSN: 1866-3516. DOI: 10.5194/essd-16-443-2024. URL: https://essd.copernicus.org/articles/16/443/2024/.

Christina Williamson (2026). “Comment on egusphere-2026-1404”. peer review. peer review. DOI: 10.5194/egusphere-2026-1404-RC1. URL: https://egusphere.copernicus.org/preprints/2026/egusphere-2026-1404#RC1 (last access: 04/30/2026).

Galy-Lacaux, C. and A. I. Modi (1998). “Precipitation Chemistry in the Sahelian Savanna of Niger, Africa”. In: *Journal of Atmospheric Chemistry* 30.3, pp. 319–343. ISSN: 1573-0662. DOI: 10.1023/A:1006027730377. URL: https://doi.org/10.1023/A:1006027730377.

Kouvarakis, G. et al. (2000). “Temporal variations of surface regional background ozone over Crete Island in the southeast Mediterranean”. In: *Journal of Geophysical Research: Atmospheres* 105.D4, pp. 4399–4407. DOI: https://doi.org/10.1029/1999JD900984. URL: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/1999JD900984.

Pöhlker, M. L. et al. (2016). “Long-term observations of cloud condensation nuclei in the Amazon rain forest – Part 1: Aerosol size distribution, hygroscopicity, and new model parametrizations for CCN prediction”. In: *Atmospheric Chemistry and Physics* 16.24, pp. 15709–15740. DOI: 10.5194/acp-16-15709-2016. URL: https://acp.copernicus.org/articles/16/15709/2016/.

Schmale, J. et al. (2018). “Long-term cloud condensation nuclei number concentration, particle number size distribution and chemical composition measurements at regionally representative observatories”. In: *Atmospheric Chemistry and Physics* 18.4, pp. 2853–2881. DOI: 10.5194/acp-18-2853-2018. URL: https://acp.copernicus.org/articles/18/2853/2018/.