

We provide detailed responses to all comments below; the responses are shown in blue, and all revisions in the manuscript are highlighted in red.

Comment to “Vertical structure and controlling factors of cloud condensation nuclei activation over eastern China: Insights from aircraft measurements and interpretable machine learning”

This manuscript presents a valuable observational study investigating the vertical distribution of cloud condensation nuclei (CCN) and their controlling factors over eastern China, using aircraft measurements combined with interpretable machine learning techniques (Generalized Additive Models, GAM, and SHapley Additive exPlanations, SHAP). The topic is highly relevant to aerosol–cloud–climate interactions, and the integration of aircraft observations with explainable AI methods represents a timely and scientifically sound approach. The writing is generally clear. I would like to recommend its acceptance for publication with necessary modifications.

We sincerely thank the reviewer for the positive and constructive assessment of our manuscript. We greatly appreciate the recognition of the scientific value of our aircraft observations and the application of interpretable machine learning techniques to investigate the vertical structure and controlling factors of CCN activation over eastern China. We also appreciate the reviewer’s positive comments on the clarity of the manuscript. We have carefully considered all of the reviewer’s comments and have made corresponding revisions and clarifications throughout the manuscript to further improve its scientific rigor, clarity, and completeness.

General comments

As most aircraft observation based studies, the sample size is too limited. The analysis is based on only four aircraft flights conducted over a single week in March 2018 over eastern China. While the authors acknowledge this limitation, the restricted temporal and spatial coverage raises concerns about the generality of the findings. Seasonal variations, different synoptic regimes, and regional differences across eastern China are not captured.

We thank the reviewer for this important comment regarding the limited temporal and spatial coverage of the aircraft observations. We fully agree that four flights conducted within a single week in March 2018 cannot capture the full seasonal variability, diversity of synoptic regimes, or regional heterogeneity across eastern China. Accordingly, the results of this study should not be interpreted as being universally representative of CCN characteristics over eastern China.

Nevertheless, the aircraft measurements provide vertically resolved, high-temporal-resolution observations of aerosols, CCN, meteorological variables, and cloud microphysical properties that are difficult to obtain from surface-based measurements. Although the

observational period was limited, the four flights sampled different atmospheric conditions, including both clear-sky and cloudy environments and a relatively broad range of altitudes and meteorological conditions. This variability allows us to investigate the statistical relationships between CCN, aerosol vertical structure, and environmental factors under the conditions sampled during the campaign.

In response to the reviewer's comment, we have revised the manuscript to more explicitly acknowledge this limitation and have moderated statements that could imply broad regional or seasonal representativeness. We now emphasize that the identified relationships are specific to the atmospheric conditions sampled during these aircraft observations. We have also added a statement in the Conclusions noting that additional aircraft observations covering different seasons, synoptic conditions, and regions are required to assess the generality of the present findings.

Line 133: Against this background, the present study utilizes aircraft observations to investigate CCN activation characteristics under different aerosol vertical structures and environmental conditions sampled over eastern China. Interpretable statistical modeling is further employed to identify the major environmental factors associated with variations in CCN number concentration. The results provide vertically resolved observational evidence for understanding CCN variability under the atmospheric conditions sampled during the campaign and offer useful constraints for future studies of aerosol–cloud interactions.

Line 599: Second, the analyses were based on four aircraft flights conducted within a limited observational period in March 2018. Therefore, the present dataset cannot fully capture seasonal variability, different synoptic regimes, or regional heterogeneity across eastern China. The relationships identified in this study should consequently be interpreted as representative of the atmospheric conditions sampled during these flights rather than as universally applicable characteristics of eastern China. Future studies incorporating aircraft observations from different seasons, synoptic conditions, and regions, together with numerical simulations, are needed to further evaluate the generality of these findings and the underlying physical mechanisms.

The CCNC cycled through five supersaturation levels sequentially (5 minutes each) rather than measuring them simultaneously. As the authors note, this creates a partial coupling between altitude and SS because the aircraft changed altitude during the 25-minute measurement cycles. This complicates the interpretation of vertical profiles and may introduce artifacts in the composite statistics.

We thank the reviewer for highlighting this important limitation of the CCNC measurement strategy. We agree that, because the five supersaturation (SS) levels were measured sequentially rather than simultaneously, the aircraft could change altitude during each 25-min measurement cycle. Consequently, altitude and SS are partially coupled, and the vertical differences observed among different SS levels cannot be interpreted as being controlled solely by altitude or supersaturation.

In our analysis, measurements at each SS level were therefore treated separately, based on

the altitude at which they were actually obtained, rather than assuming that all five SS levels represented simultaneous observations at the same altitude. The vertical profiles shown in the manuscript should thus be interpreted as composite statistics constructed from the observations available at each SS level, rather than as strictly altitude-controlled comparisons across SS levels.

Following the reviewer's suggestion, we have clarified this sampling limitation in both the Methods and Results and Discussion sections and have further moderated the corresponding interpretations. In particular, we now explicitly state that comparisons among different SS levels may contain some influence from differences in sampling altitude and flight trajectory, and therefore should be interpreted with appropriate caution.

Despite this limitation, the sequential SS measurements still provide useful information on CCN variability over a range of supersaturation conditions sampled during the flights. Future aircraft campaigns employing simultaneous multi-SS CCN measurements, or flight strategies specifically designed to maintain nearly constant altitude during SS scanning, would help further reduce this source of uncertainty.

Line 168: Because these supersaturation levels were measured sequentially rather than simultaneously, the aircraft altitude could change during a complete measurement cycle, resulting in partial coupling between sampling altitude and supersaturation. Therefore, measurements at each supersaturation level were analyzed according to the altitude at which they were actually obtained, and comparisons among different supersaturation levels were interpreted with caution.

Line 315: It should be noted that the CCNC operated sequentially across different supersaturation levels during each flight, resulting in partial coupling between altitude and supersaturation. Therefore, the vertical variations presented here represent composite statistics based on the observations available at each SS level rather than strictly altitude-controlled comparisons among supersaturation conditions. Accordingly, differences among SS levels may partly reflect variations in sampling altitude and flight trajectory and should be interpreted with appropriate caution.

Line 592: First, CCN measurements at different supersaturation levels were conducted sequentially rather than simultaneously, resulting in partial coupling between altitude and supersaturation. Consequently, comparisons among different SS levels may also contain some influence from differences in sampling altitude and flight trajectory.

In aircraft based observations, temperature and altitude are physically correlated. Although the GAM/SHAP framework identifies temperature as the dominant predictor, the manuscript appropriately cautions that this reflects statistical association rather than direct causation. However, the discussion could benefit from a more explicit analysis of partial effects or sensitivity tests that decouple these variables.

We thank the reviewer for this insightful suggestion. We agree that temperature and altitude are strongly coupled in aircraft observations, and that this coupling should be explicitly

examined when interpreting the relatively high importance of temperature identified by the GAM/SHAP analysis.

To quantify this issue, we first analyzed the temperature–altitude relationship in the full cloud-free dataset. Temperature showed a strong negative correlation with altitude in all three aerosol vertical-structure categories as well as in the combined dataset. For the full dataset, the Pearson correlation coefficient was $r = -0.950$ and the Spearman rank correlation coefficient was $\rho = -0.954$, confirming a strong large-scale temperature–altitude dependence in the aircraft observations.

Following the reviewer’s suggestion, we then performed an additional sensitivity analysis using a quasi-level flight segment at approximately 5.8 km altitude. In this segment, the aircraft altitude remained nearly constant, with an altitude range of only 10–17 m depending on supersaturation level, while temperature still varied by about 0.9–2.3 °C. This subset therefore substantially reduces the influence of the large-scale vertical temperature gradient while retaining measurable temperature variability. We further evaluated the temperature–altitude correlations within this quasi-level subset separately for each supersaturation level and found that they were much weaker and no longer consistently negative, indicating that the original large-scale coupling had been greatly mitigated.

Among the five supersaturation levels, the $SS = 0.6\%$ subset was selected for the GAM/SHAP sensitivity analysis because it provided the largest sample size ($N = 506$) and the widest temperature range (2.27 °C), while the altitude variation remained very small (17 m). The sensitivity analysis showed that the relative SHAP importance of temperature decreased compared with that in the full-dataset analysis, indicating that part of the original temperature importance was indeed associated with the large-scale altitude–temperature gradient. Nevertheless, the SHAP dependence still showed an overall increasing trend with temperature, suggesting that the positive temperature–NCCN association persisted under near-constant-altitude conditions.

We emphasize that this additional analysis does not establish an independent causal effect of temperature on CCN concentration. Rather, it demonstrates that although altitude-related covariation explains part of the temperature importance in the full dataset, the temperature–NCCN statistical association is not entirely an artifact of the large-scale vertical temperature gradient under the sampled conditions. We have added this sensitivity analysis and the corresponding discussion to the revised manuscript and Supplementary Information.

Line 250: To assess the influence of temperature–altitude coupling inherent in aircraft observations, an additional sensitivity analysis was conducted. First, the temperature–altitude relationship was quantified for the full cloud-free dataset using Pearson and Spearman correlation coefficients, both for the combined dataset and for the three aerosol vertical-structure categories. Second, a quasi-level flight segment near 5.8 km altitude was selected, in which altitude remained nearly constant while temperature still varied measurably. Summary statistics of altitude, temperature, and CCN concentration were calculated separately for each supersaturation level. The temperature–altitude correlations within this subset were also evaluated for each supersaturation level. Among these subsets, the $SS = 0.6\%$ data were selected for a GAM/SHAP sensitivity analysis because they provided the largest sample size and the

widest temperature range while maintaining very small altitude variability. The results were compared with those obtained from the full dataset.

Line 504: Because temperature and altitude are physically linked in aircraft observations, we further evaluated the robustness of the temperature–NCCN relationship through a sensitivity analysis. In the full cloud-free dataset, temperature was strongly negatively correlated with altitude, with Pearson $r = -0.950$ and Spearman $\rho = -0.954$ (Fig.S30). Similar negative correlations were found within the Increase, Stable, and Decrease structure categories, although the correlation strength varied among them. These results confirm that the high importance of temperature in the full-dataset GAM/SHAP analysis must be interpreted with caution.

Line 511: To reduce the influence of the large-scale vertical temperature gradient, a quasi-level flight segment near 5.8 km altitude was selected. In this segment, the altitude range was only 10–17 m depending on supersaturation level, whereas temperature still varied by about 0.9–2.3 °C. The temperature–altitude correlations within this subset were much weaker and no longer systematically negative, indicating that the original large-scale coupling was substantially mitigated. Among the five supersaturation levels, the SS = 0.6% subset was used for the GAM/SHAP sensitivity analysis because it had the largest sample size ($N = 506$) and the widest temperature range (2.27 °C) while maintaining very small altitude variability. In this near-constant-altitude subset, the relative SHAP importance of temperature decreased compared with that in the full dataset (Fig. S32), but the SHAP dependence still showed an overall increase with temperature (Fig.S33). This suggests that altitude-related covariation explains part, but not all, of the temperature importance identified in the full dataset. Nevertheless, this result should still be interpreted as a statistical association rather than a direct causal temperature effect.

Line 576: A sensitivity analysis based on a quasi-level flight segment further showed that the importance of temperature decreased after substantially reducing altitude variability, although a positive temperature–NCCN association remained. This indicates that part of the temperature importance in the full dataset is related to altitude-associated covariation, while the remaining relationship should still be interpreted as a statistical association rather than a direct causal effect.

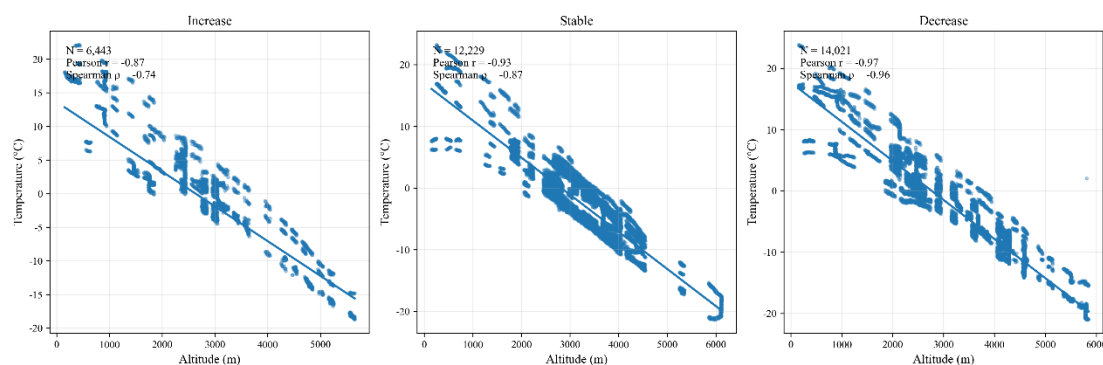


Fig.S30. Scatter plots of temperature versus altitude under different aerosol vertical structures, with the corresponding Pearson and Spearman correlation coefficients.

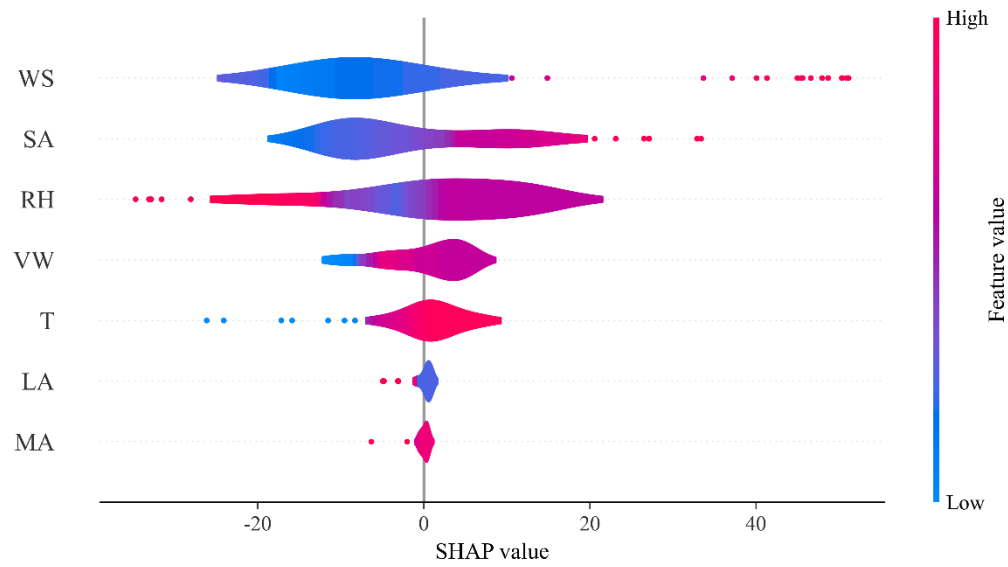


Fig.S31. SHAP violin summary plots from the near-constant-altitude sensitivity analysis.

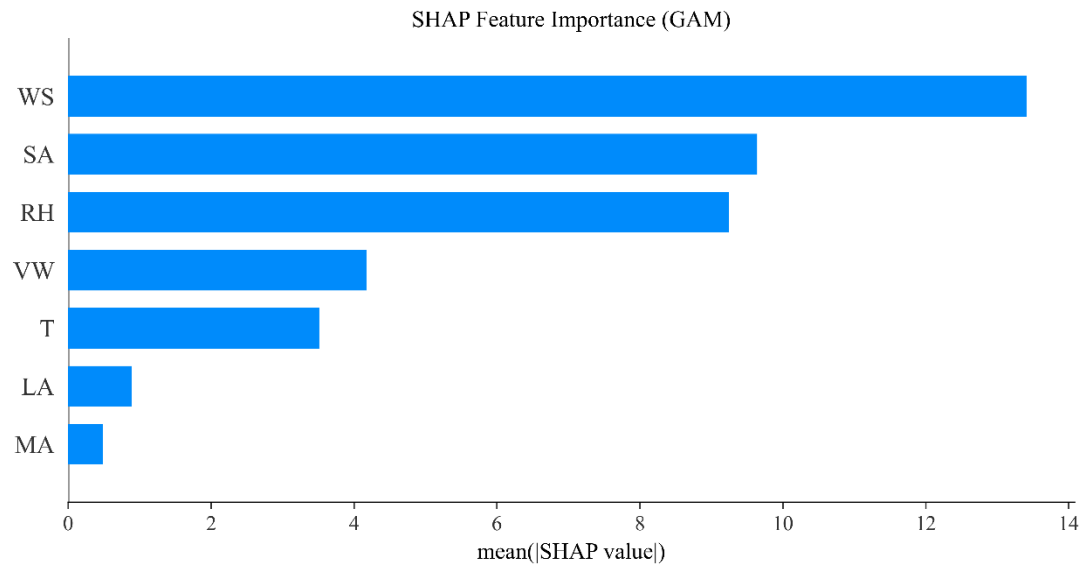


Fig.S32. Relative SHAP contributions and ranking of different predictors in the near-constant-altitude sensitivity analysis.

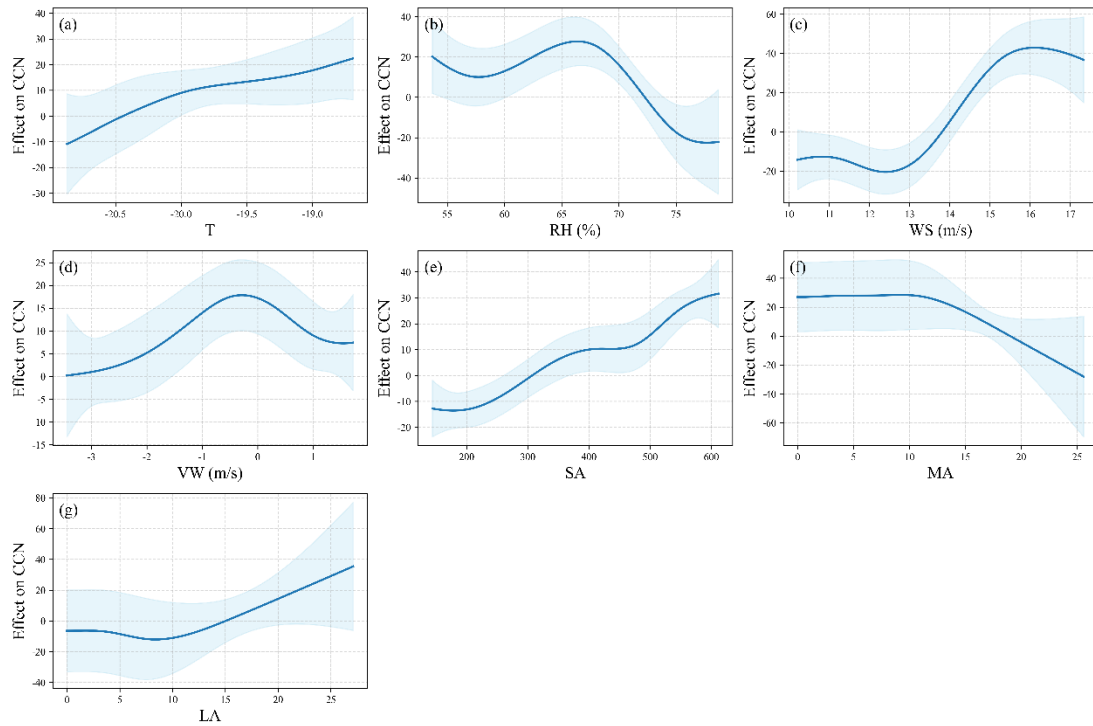


Fig.S33. SHAP dependence plots for different predictors in the near-constant-altitude sensitivity analysis.

Provide confidence intervals or bootstrap estimates for the SHAP contribution percentages to better convey the robustness of the factor rankings.

We thank the reviewer for this helpful suggestion. To quantify the uncertainty in the SHAP-based relative contribution percentages and assess the robustness of the feature-importance patterns, we performed a nonparametric bootstrap analysis using the sample-level SHAP values retained from the original analysis.

For each aerosol vertical-structure and supersaturation scenario, observations and their corresponding SHAP-value vectors were resampled with replacement 1,000 times. For each bootstrap replicate, the mean absolute SHAP value of each predictor was recalculated and normalized by the sum of the mean absolute SHAP values across all predictors to obtain its relative SHAP contribution percentage. The 2.5th and 97.5th percentiles of the resulting bootstrap distributions were used as the lower and upper bounds of the 95% confidence intervals.

The bootstrap results have been added to the Supplementary Information (Table.S1). Overall, the confidence intervals for the major predictors were relatively narrow, indicating that the estimated contribution percentages were generally stable. T, SA, RH, and WS remained among the major contributors across most scenarios. However, predictors with similar contribution percentages showed overlapping confidence intervals in several cases. For example, under the Increase structure at $SS = 0.4\%$, SA contributed 29.74% (95% CI: 27.50%–32.24%) and T contributed 29.66% (27.27%–32.14%). Similarly, under the Increase structure at $SS = 0.2\%$, the confidence intervals of SA and WS substantially overlapped. These results

indicate that the broader feature-importance pattern is robust, whereas small differences in the exact rankings of similarly important predictors should not be overinterpreted.

Accordingly, we have revised the manuscript to report the bootstrap-derived confidence intervals and to place greater emphasis on the overall feature-importance patterns rather than strict predictor rankings.

Line 261: To quantify the uncertainty in the SHAP-based relative contribution percentages, a nonparametric bootstrap analysis was further performed using the sample-level SHAP values from the original analysis. For each aerosol vertical-structure and supersaturation scenario, observations and their corresponding SHAP-value vectors were resampled with replacement 1,000 times. For each bootstrap replicate, the mean absolute SHAP value of each predictor was recalculated and normalized by the sum across all predictors. The 2.5th and 97.5th percentiles of the resulting bootstrap distributions were taken as the lower and upper bounds of the 95% confidence intervals, respectively.

Line 478: Bootstrap-derived 95% confidence intervals further indicate that these broad feature-importance patterns are generally robust, although the intervals overlap for several predictors with similar contributions, suggesting that small differences in their exact rankings should not be overinterpreted (Table.S1).

Structure	SS (%)	T	RH	WS	VW	SA	MA	LA
Increase	0.2	20.25	39.67	16.74	1.34	16.83	2.07	3.10
		(18.57–21.95)	(38.05–41.20)	(15.04–18.34)	(0.94–1.84)	(15.37–18.28)	(1.29–3.13)	(2.05–4.36)
Increase	0.4	29.66	18.92	8.46 (7.14–9.76)	4.45	29.74	4.30	4.46
		(27.27–32.14)	(17.75–20.20)		(3.63–5.44)	(27.50–32.24)	(3.84–4.81)	(3.97–5.02)
Increase	0.6	19.22	15.65	31.76	3.65	22.04	4.02	3.67
		(17.81–20.52)	(12.55–18.58)	(29.73–33.73)	(3.02–4.38)	(20.36–23.77)	(2.89–5.54)	(3.01–4.49)
Increase	0.8	38.19	12.25	12.86	3.08	30.30	1.18	2.14
		(36.66–39.75)	(11.24–13.43)	(12.02–13.61)	(2.45–3.85)	(28.48–32.07)	(0.99–1.39)	(1.67–2.73)
Increase	1.0	30.40	9.50 (8.22–10.90)	7.78 (6.69–9.02)	2.35	44.94	3.81	1.22
		(28.35–32.40)			(1.96–2.81)	(41.47–48.19)	(3.21–4.48)	(0.92–1.75)
Stable	0.2	29.02	23.57	15.34	6.16	21.05	2.58	2.28
		(26.56–31.75)	(21.65–25.55)	(14.37–16.37)	(5.61–6.78)	(19.42–22.80)	(2.32–2.87)	(1.99–2.62)
Stable	0.4	38.16	14.94	13.22	2.70	26.21	3.05	1.72
		(36.00–40.45)	(13.34–16.50)	(12.38–14.09)	(2.39–3.09)	(23.40–28.98)	(2.47–3.78)	(1.18–2.50)
Stable	0.6	34.34	14.73	10.65	5.64	31.13	2.22	1.29

Structure	SS (%)	T	RH	WS	VW	SA	MA	LA
Stable	0.8	(32.42–36.33)	(13.77–15.66)	(9.72–11.60)	(5.06–6.28)	(29.05–33.31)	(2.04–2.40)	(1.18–1.42)
		46.36	20.16	12.65	2.40	11.72	3.78	2.93
		(43.62–49.31)	(18.12–22.13)	(11.29–14.07)	(2.13–2.73)	(10.87–12.52)	(3.47–4.07)	(2.40–3.76)
Stable	1.0	37.09	11.59	6.42	5.58–6.86	29.38	4.23	4.43
		(35.00–39.10)	(10.77–12.43)	(5.80–7.37)	(5.80–7.94)	(27.75–31.11)	(3.84–4.66)	(4.03–4.84)
		45.22	13.58	15.66	5.58	16.18	2.48	1.31
Decrease	0.2	(43.22–47.18)	(12.72–14.54)	(14.58–16.71)	(5.07–6.11)	(14.92–17.38)	(1.92–3.47)	(0.73–2.45)
		56.51	16.24	5.60	4.98–4.14	12.00	2.53	2.99
		(54.33–58.24)	(14.97–17.72)	(6.32)	(3.40–5.11)	(11.09–13.00)	(2.17–3.09)	(2.25–4.20)
Decrease	0.6	52.70	19.76	7.82	7.15–1.94	14.82	2.04	0.91
		(50.98–54.20)	(18.50–21.14)	(8.55)	(1.51–2.43)	(13.34–16.41)	(1.74–2.51)	(0.79–1.08)
		55.71	13.72	18.80	1.82	8.61	0.95	0.39
Decrease	0.8	(54.07–57.43)	(12.19–15.28)	(17.94–19.61)	(1.58–2.09)	(7.66–9.57)	(0.85–1.07)	(0.18–0.80)
		52.46	18.18	3.48	3.13–3.63	15.98	3.42	2.85
		(48.97–55.20)	(16.47–20.02)	(3.84)	(3.06–4.26)	(14.69–17.17)	(2.11–5.10)	(1.34–4.74)

Table.S1.Values are relative SHAP contribution percentages (%), with bootstrap-derived 95% confidence intervals shown in parentheses. Confidence intervals were obtained from 1,000 nonparametric bootstrap resamples of the sample-level SHAP values.

Detailed comments

Line 33-34, Regarding the aerosol impacts, recent review studies could serve as important supporting references, such as Zhao et al. (2024, doi: 10.1016/j.scib.2024.03.014) and so on.

We thank the reviewer for this helpful suggestion. We agree that recent review studies provide important context for the complex effects of aerosols on clouds and precipitation. We have therefore added the recommended review by Zhao et al. (2024), which summarizes recent observational evidence and mechanisms of aerosol effects on precipitation, and have revised the corresponding text in the Introduction to better reflect the current understanding of aerosol–cloud–precipitation interactions.

Line 46: However, aerosol effects on clouds and precipitation are highly complex and depend on aerosol properties, cloud and precipitation regimes, the vertical distribution of aerosols, and meteorological conditions. Recent observational syntheses further indicate that

aerosol perturbations may either suppress or enhance precipitation depending on the environmental and cloud dynamical context (Zhao et al., 2024).

Reference:

Zhao, C., Sun, Y., Yang, J., Li, J., Zhou, Y., Yang, Y., Fan, H., Zhao, X., 2024. Observational evidence and mechanisms of aerosol effects on precipitation. *Science Bulletin* 69, 1569–1580. <https://doi.org/10.1016/j.scib.2024.03.014>

Line 37-39, Regarding this point, Negative Aerosol-Cloud re Relationship from Aircraft Observations over Hebei has been found, which is worthy to mention.

We thank the reviewer for this helpful suggestion. We agree that aircraft observations over Hebei provide important regional evidence for aerosol–cloud interactions over northern China. We have therefore added the study of Zhao et al. (2018), which reported a robust negative relationship between aerosol loading and cloud droplet effective radius based on aircraft observations over Hebei. This result is particularly relevant because it differs from some previously reported positive aerosol–cloud effective-radius relationships derived from satellite observations over eastern China, further illustrating the dependence of aerosol–cloud relationships on observational platform and atmospheric conditions. The corresponding discussion has been added to the Introduction.

Line 40: Consistent with this classical response, aircraft observations over Hebei, China, have reported a negative relationship between aerosol loading and cloud droplet effective radius, with smaller droplets observed under more polluted conditions (Zhao et al., 2018).

Reference:

Zhao, C., Qiu, Y., Dong, X., Wang, Z., Peng, Y., Li, B., Wu, Z., Wang, Y., 2018. Negative Aerosol-Cloud re Relationship From Aircraft Observations Over Hebei, China. *Earth and Space Science* 5, 19–29. <https://doi.org/10.1002/2017EA000346>

Line 39-40, In addition to the decrease of precipitation, aerosol invigoration effect on precipitation should also be briefly introduced for fair.

We thank the reviewer for this important suggestion. We agree that aerosol effects on precipitation should be described in a balanced manner rather than only in terms of precipitation suppression. In the revised Introduction, we now explicitly state that aerosol perturbations may either suppress or enhance precipitation depending on the environmental and cloud dynamical context, supported by the recent review of Zhao et al. (2024).

Line 63: However, aerosol effects on clouds and precipitation are highly complex and depend on aerosol properties, cloud and precipitation regimes, the vertical distribution of aerosols, and meteorological conditions. Recent observational syntheses further indicate that aerosol perturbations may either suppress or enhance precipitation depending on the environmental and cloud dynamical context (Zhao et al., 2024).

Reference:

Zhao, C., Sun, Y., Yang, J., Li, J., Zhou, Y., Yang, Y., Fan, H., Zhao, X., 2024. Observational evidence and mechanisms of aerosol effects on precipitation. *Science Bulletin* 69, 1569–1580. <https://doi.org/10.1016/j.scib.2024.03.014>

Line 42, Citation format is not right, which should be corrected (also other citations).

We thank the reviewer for pointing this out. We have carefully checked the citation formatting throughout the manuscript and corrected the inconsistent or incorrect citation styles, including spacing, punctuation, and the placement of author–year citations. The reference citations have now been standardized throughout the revised manuscript according to the journal format.

Line 68: For example, Prabhakaran et al. (2025) found that under a warming climate, aerosol perturbations influence the stratocumulus-to-cumulus transition (SCT) over the northeastern Pacific; during the non-precipitating stratocumulus stage, the cloud radiative effect (CRE) responds more strongly to climate change than to aerosols, whereas aerosol effects become more important after cloud breakup.

Line 45-50, Actually, different even opposite findings regarding aerosol-cloud interactions have been demonstrated by previous studies, which should be briefly introduced.

We thank the reviewer for this important comment. We agree that previous studies have reported diverse and, in some cases, contrasting aerosol–cloud responses. In the revised Introduction, we have therefore added a more balanced discussion emphasizing that aerosol effects on clouds and precipitation depend strongly on aerosol properties, cloud regime, vertical aerosol distribution, and meteorological conditions. We now explicitly note that aerosol perturbations may either suppress or enhance precipitation and provide examples from previous studies showing contrasting responses in cloud radiative effects, droplet growth, and precipitation-related microphysical processes (Borys et al., 2003; Khatri et al., 2022; Prabhakaran et al., 2025; Zhao et al., 2024).

Line 63: However, aerosol effects on clouds and precipitation are highly complex and depend on aerosol properties, cloud and precipitation regimes, the vertical distribution of aerosols, and meteorological conditions. Recent observational syntheses further indicate that aerosol perturbations may either suppress or enhance precipitation depending on the environmental and cloud dynamical context (Zhao et al., 2024). With the advancement of research, different and even contrasting aerosol–cloud responses have increasingly been reported. For example, Prabhakaran et al. (2025) found that under a warming climate, aerosol perturbations influence the stratocumulus-to-cumulus transition (SCT) over the northeastern Pacific; during the non-precipitating stratocumulus stage, the cloud radiative effect (CRE) responds more strongly to climate change than to aerosols, whereas aerosol effects become more important after cloud breakup. Khatri et al. (2022) reported that increased aerosol loading may enhance droplet collision–coalescence under certain conditions, leading to larger cloud

droplets. Borys et al. (2003) observed that high anthropogenic aerosol concentrations substantially modified the microphysical structure of lower “feeder” layers in orographic clouds, suppressing or even inhibiting the riming growth of snow particles and thereby reducing snow water equivalent precipitation rates. These contrasting responses highlight the strong dependence of aerosol–cloud interactions on cloud type, aerosol characteristics, and environmental conditions. Therefore, a thorough understanding of CCN activation processes and the factors associated with their variability is crucial for improving our understanding of aerosol indirect climate effects.

Reference:

Borys, R.D., Lowenthal, D.H., Cohn, S.A., Brown, W.O.J., 2003. Mountaintop and radar measurements of anthropogenic aerosol effects on snow growth and snowfall rate. *Geophysical Research Letters* 30. <https://doi.org/10.1029/2002GL016855>

Khatri, P., Hayasaka, T., Holben, B.N., Singh, R.P., Letu, H., Tripathi, S.N., 2022. Increased aerosols can reverse Twomey effect in water clouds through radiative pathway. *Sci Rep* 12, 20666. <https://doi.org/10.1038/s41598-022-25241-y>

Prabhakaran, P., Myers, T.A., Hoffmann, F., Feingold, G., 2025. Aerosol-Cloud Interactions in Marine Low-Clouds in a Warmer Climate. *EGUsphere* 1–26. <https://doi.org/10.5194/egusphere-2025-2935>

Zhao, C., Qiu, Y., Dong, X., Wang, Z., Peng, Y., Li, B., Wu, Z., Wang, Y., 2018. Negative Aerosol-Cloud re Relationship From Aircraft Observations Over Hebei, China. *Earth and Space Science* 5, 19–29. <https://doi.org/10.1002/2017EA000346>

Line 56, based on Köhler theory, not only aerosol size, but also aerosol chemical composition affects the CCN activity.

We thank the reviewer for this important comment. We agree that, according to Köhler theory, CCN activation is controlled not only by aerosol particle size but also by particle hygroscopicity, which is closely related to chemical composition. We have therefore revised the corresponding text in the Introduction to explicitly emphasize the joint roles of aerosol size and chemical composition in determining the critical supersaturation and CCN activation characteristics.

Line 85: According to Köhler theory, the critical supersaturation of an aerosol particle is closely related to its size and hygroscopicity, which is strongly influenced by chemical composition; therefore, both aerosol size distribution and chemical composition are key determinants of CCN number concentration and activation characteristics.

Line 61-62, There are also laboratory experimental characterizations.

We thank the reviewer for this helpful comment. We agree that laboratory experiments represent an important approach for characterizing CCN activation under controlled conditions.

We have therefore revised the Introduction to include laboratory experiments together with ground-based observations, satellite retrievals, and aircraft measurements, and briefly clarified their complementary role in investigating the effects of aerosol physicochemical properties on CCN activation.

Line 91: Current studies on CCN characteristics rely on a combination of ground-based observations, laboratory experiments, satellite retrievals, and aircraft measurements. Laboratory experiments provide controlled conditions for examining CCN activation as a function of aerosol size, chemical composition, hygroscopicity, and mixing state, whereas field observations are essential for characterizing CCN behavior under complex atmospheric conditions.

Line 62-64, For fair, the limitation of aircraft observations should be also discussed.

We thank the reviewer for this important suggestion. We agree that the advantages of aircraft observations should be presented together with their limitations. We have therefore revised the Introduction to note that, although aircraft measurements provide unique vertically resolved information on aerosols, meteorological conditions, and cloud microphysical properties, their temporal and spatial coverage is usually limited by operational constraints. Consequently, individual campaigns may not fully capture seasonal variability, different synoptic regimes, or broader regional representativeness.

Line 97: However, aircraft campaigns are generally limited in temporal and spatial coverage because of operational constraints, and individual flights may not fully capture seasonal variability, different synoptic regimes, or broader regional representativeness.

Line 74-75, Supporting evidence should be given for this claim.

We thank the reviewer for pointing this out. We agree that the original statement was too strong because machine learning does not necessarily reduce uncertainty in all cases. We have therefore revised the sentence to more specifically describe the demonstrated strengths of ML in handling high-dimensional datasets and identifying nonlinear relationships among multiple covarying aerosol, cloud, and meteorological variables, supported by Chen et al. (2022). This revision avoids overstating the ability of ML to reduce uncertainty relative to conventional statistical approaches.

Line 117: In aerosol–cloud interaction studies, ML methods have been increasingly used to identify complex and nonlinear relationships among aerosol, cloud, and meteorological variables, particularly when multiple covarying environmental factors are involved (Chen et al., 2022). Their ability to handle high-dimensional datasets and nonlinear dependencies provides a useful complement to conventional statistical approaches.

Reference:

Chen, Y., Haywood, J., Wang, Y., Malavelle, F., Jordan, G., Partridge, D., Fieldsend, J., De Leeuw, J., Schmidt, A., Cho, N., Oreopoulos, L., Platnick, S., Grosvenor, D., Field, P., Lohmann,

U., 2022. Machine learning reveals climate forcing from aerosols is dominated by increased cloud cover. *Nat. Geosci.* 15, 609–614. <https://doi.org/10.1038/s41561-022-00991-6>

Line 79-80, What do the authors mean “CCN research”?

We thank the reviewer for pointing out this ambiguous wording. By “CCN research,” we intended to refer specifically to studies of CCN number concentration and activation characteristics, including the prediction of NCCN and the analysis of relationships among aerosol physicochemical properties, meteorological conditions, and CCN activation. We have revised the sentence accordingly to make the scope more explicit.

Line 121: In studies of CCN number concentration and activation characteristics, ML methods have been applied to predict NCCN using aerosol physicochemical properties and meteorological variables, and to explore the relationships among aerosol composition, size distribution, and CCN activation (Ren et al., 2025; Nair et al., 2021).

Line 81, Ren et al. 2025 is not listed in the reference list.

We thank the reviewer for pointing out this omission. The reference information for Ren et al. (2025) was inadvertently omitted from the reference list. We have now added the complete bibliographic information to the revised manuscript and have also rechecked the correspondence between all in-text citations and the reference list to avoid similar inconsistencies.

Line 751: Ren, J., Zou, S., Xu, H., Liu, G., Wang, Z., Zhang, A., Zhao, C., Hu, M., Shang, D., Tang, L., Huang, R.-J., Sun, Y., Zhang, F., 2025. Machine learning significantly improves the simulation of hourly-to-yearly scale cloud nuclei concentration and radiative forcing in polluted atmosphere. *EGUsphere* 1–32. <https://doi.org/10.5194/egusphere-2025-1483>

More background information about the aircraft observations should be given, particularly over east China regions.

We thank the reviewer for this valuable suggestion. We agree that additional background on previous aircraft observations over China, particularly eastern China, helps place the present study in a clearer regional context. We have therefore expanded the Introduction to summarize previous aircraft-based investigations of CCN vertical distributions over the North China Plain and southern China, including the reported influences of thermodynamic structure, air-mass origin, anthropogenic emissions, boundary-layer processes, and vertical transport. We also clarified that, despite these advances, systematic comparisons of CCN activation under different aerosol vertical-structure regimes remain limited.

Line 101: Aircraft observations over different regions of China have revealed pronounced vertical heterogeneity in CCN and aerosol properties. For example, Zhang et al. (2022) found that over the North China Plain, the vertical distribution of NCCN was jointly influenced by

temperature(T) structure, air-mass origin, anthropogenic emissions, and topography. Xu et al. (2022) reported that in southern China, NCCN initially increased with altitude, peaked at approximately 1.3 km, and then decreased rapidly at higher levels. Liu et al. (2025) further showed that CCN vertical distributions were closely associated with boundary-layer structure, air-mass transport, and thermodynamic conditions, with aerosols at different altitudes potentially contributing to cloud droplet formation through vertical transport. These studies demonstrate the strong vertical variability of CCN over eastern and southern China and highlight the value of aircraft observations for resolving such structures. However, most previous studies have focused on overall vertical profiles or general statistical relationships, while systematic investigations of how different aerosol vertical structures, such as increasing, decreasing, or relatively stable profiles with altitude, influence CCN activation remain limited.

Line 108-134, Uncertainties in the instrument measurements should be briefly introduced.

We thank the reviewer for this important comment. We agree that the measurement uncertainties of the instruments should be briefly described. We have therefore added a short discussion in Section 2.2 summarizing the main uncertainty sources of the CCNC, PCASP, CDP, and CIP, including supersaturation calibration, particle sizing, refractive-index assumptions, and imaging/sampling artifacts, with support from relevant instrument-characterization studies.

Line 186: Measurement uncertainties were considered in the interpretation of the observations. For the CCNC, the main uncertainty is associated with supersaturation calibration (Rose et al., 2008). For the PCASP and CDP, particle sizing may be affected by calibration and refractive-index assumptions (Rosenberg et al., 2012; Faber et al., 2018), while CIP measurements may additionally be influenced by ice-particle shattering and image-processing uncertainties (Lawson, 2011).

Line 135-140, How do the authors solve the measurement issues in the first or second bins, along with the shattering of ice crystals?

We thank the reviewer for raising this important issue. We agree that the first one or two size bins of the CIP are subject to relatively large uncertainties and that ice-particle shattering may artificially increase the concentration of small particles.

In our data processing, the first two CIP size bins were excluded when calculating ice crystal number concentration (Ni) in order to reduce the influence of uncertainties associated with the smallest particle sizes. The resulting Ni was then used primarily to support the identification of in-cloud periods rather than to quantitatively analyze the detailed ice-particle size distribution.

We acknowledge that no dedicated ice-shattering correction was applied to the present CIP dataset, and therefore some residual influence of shattering cannot be completely excluded. However, because the smallest two bins were removed and the CIP data were used mainly as an auxiliary indicator for cloud identification, rather than as a central variable in the subsequent CCN analysis, we expect this uncertainty to have a limited influence on the main conclusions.

We have clarified these processing procedures and limitations in the revised Methods section.

Line 199: To reduce the uncertainty associated with the smallest particle sizes, the first two CIP size bins were excluded when calculating N_i . The CIP-derived N_i was used primarily to support in-cloud identification rather than to analyze detailed ice-particle size distributions. No dedicated shattering correction was applied, and the potential influence of residual shattering artifacts is therefore acknowledged.

Line 145, How reliable for this cloud identification method? Or how sensitive are the results to threshold values?

We thank the reviewer for this important comment. We agree that the reliability of the cloud-identification method should be further clarified. The criteria used in this study were based on cloud-phase identification methods commonly adopted in previous airborne cloud-microphysical observations.

Specifically, liquid clouds are commonly identified when the cloud droplet number concentration (N_c) is $\geq 10 \text{ cm}^{-3}$, a threshold widely used in aircraft observations to distinguish cloud droplets from the ambient aerosol background (Hobbs and Rangno, 1998; Lance et al., 2010; Fu et al., 2022). Ice clouds can be identified using a combination of cloud droplet concentration, ice crystal concentration, and temperature ($N_c \leq 1 \text{ cm}^{-3}$, $N_i > 1 \text{ L}^{-1}$, and $T \leq -5 \text{ }^\circ\text{C}$), while mixed-phase clouds can be identified when $N_c \geq 10 \text{ cm}^{-3}$, $N_i > 1 \text{ L}^{-1}$, and $T \leq 0 \text{ }^\circ\text{C}$.

However, the purpose of cloud identification in the present study was not to distinguish among liquid, ice, and mixed-phase clouds, but to exclude observations potentially affected by cloud particles from the subsequent CCN analysis. Therefore, based on the above established criteria, we combined the liquid- and ice-particle indicators and adopted a more inclusive screening criterion: an observation was considered in-cloud when either $N_c \geq 10 \text{ cm}^{-3}$ or $N_i > 1 \text{ L}^{-1}$. All samples satisfying the more restrictive cloud-phase criteria are therefore also excluded by this screening criterion, while some additional observations showing evident liquid-droplet or ice-particle signals may also be removed. Consequently, this treatment retains fewer potentially cloud-affected samples and provides a more conservative exclusion of in-cloud observations, thereby reducing the possible influence of cloud particles on the CCN analysis.

Line 204: Based on previous airborne cloud microphysical studies (Hobbs and Rangno, 1998; Hou et al., 2021; Lance et al., 2010) and operational experience from weather-modification aircraft observations in China, a conservative in-cloud screening criterion was adopted. Because the purpose of cloud identification in this study was not to distinguish cloud phase but to exclude observations potentially affected by cloud particles, a measurement was considered in-cloud when either $N_c \geq 10 \text{ cm}^{-3}$ or $N_i > 1 \text{ L}^{-1}$.

Reference:

Hobbs, P.V., Rangno, A.L., 1998. Microstructures of low and middle-level clouds over the Beaufort Sea. *Q. J. R. Meteorol. Soc.* 124, 2035–2071. <https://doi.org/10.1002/qj.49712455012>

Lance, S., Brock, C.A., Rogers, D., Gordon, J.A., 2010. Water droplet calibration of the Cloud

Droplet Probe (CDP) and in-flight performance in liquid, ice and mixed-phase clouds during ARCPAC. *Atmospheric Meas. Tech.* 3, 1683–1706. <https://doi.org/10.5194/amt-3-1683-2010>

Fu, D., Di Girolamo, L., Rauber, R.M., McFarquhar, G.M., Nesbitt, S.W., Loveridge, J., Hong, Y., Van Diedenhoven, B., Cairns, B., Alexandrov, M.D., Lawson, P., Woods, S., Tanelli, S., Schmidt, S., Hostetler, C., Scarino, A.J., 2022. An evaluation of the liquid cloud droplet effective radius derived from MODIS, airborne remote sensing, and in situ measurements from CAMP2 Ex. *Atmospheric Chem. Phys.* 22, 8259–8285. <https://doi.org/10.5194/acp-22-8259-2022>

Line 205, UTC time or Beijing time?

We thank the reviewer for pointing this out. The times reported in this study are in Beijing Time (BJT, UTC+8). We have clarified this information in the revised manuscript.

Table1. Detailed Information of Aircraft Flight Missions

Flight	Aircraft Modle	Date	Takeoff Time(UTC+8)	Cloud Phase	0°C Level Height	Departure Location
1	B-3726	2018-3-21	21:44	Clear-sky	-	-
2	B-3435	2018-3-23	20:48	Mixed-phase	3500m	Zhengzhou
3	B-3435	2018-3-24	13:55	Mixed-phase	2600m	Xinzheng Airport
4	B-3435	2018-3-26	16: 00	Mixed-phase	3100m	Xinzheng Airport