

Response to Referee #1

The authors look at the primarily at the controls on the relationship between AOD and cloud effective radius (CER), both meteorological parameters and other cloud properties. Concentrating on two regions (over land and ocean near China), this study also introduces the geographical detector method (GDM) to the study of aerosol-cloud interactions. They also look at the impact of meteorological properties on the relationship between AOD and cloud properties more generally.

The introduction of the GDM to this study is novel and of interest to the readers of ACP. With some extra explanation, I think this paper would make a really useful introduction to the method for others in atmospheric science. However, I have a number of concerns about the paper as a whole that would have to be addressed before I would recommend publication.

The authors are grateful to Referee #1 for the valuable time spent on thorough reading our manuscript and providing expert views to guide us for improving the manuscript with the main and specific points and the references. We have taken notice of all comments, listed below in black, and made many changes to the manuscript to address these, together with the comments from the other referees. We address each of your comments below and refer to our responses in the revised manuscript and provide line numbers and copy text in “quotes”.

To ensure that the data used only included single layer liquid clouds and nonprecipitating cases, the filtering criteria described by Saponaro et al. (2017) were applied. It is noted that all the figures have been updated throughout the revised manuscript.

Main points

1. The introduction of the GDM method is a really nice aspect of this study. However, I feel it could be explained and examined in more detail, as there are a number of factors that are unclear to someone meeting this method for the first time. For example, the impact of the explanatory variables in Tables 4 and 5 sum to over 100%. This is not what I would have expected. Similarly, I am not familiar with the 'interaction detector' or the 'interactive q-values'. What do these mean? How should they be interpreted? Likewise, the term 'nonlinear enhancement of the influence of the independent parameters' on L456 is not straightforward to someone new to this method.






Answer: In statistics, the q-value is a measure used to evaluate the explanatory power of variables on the dependent variable. When multiple independent variables are considered separately, it is indeed possible for the sum of the q-values of multiple X variables to exceed 100%. When they are considered together, this is referred to as 'interaction q-value'. This situation is quite common and similar to the issue in multiple linear regression. The main reason for this is the presence of correlation among the X variables, indicating that these variables are not independent. Consequently, multiple independent variables may contribute to the dependent variable in a similar manner, leading to a sum of q-values over 100%.

To better explain this and clarify “interaction detector” and “interaction q-values”, we have replaced the text below figure 2 (lines 354-373) with “The interaction detector can be used to test for the influence of interaction between different influencing factors, e.g., x_1 and x_2 , on the dependent factor (y) and whether this interaction weakens or enhances the influence of each

of x_1 or x_2 on the dependent variable, y , or whether they are independent in influencing y . For example, Figure 3(a) shows the spatial distribution of the dependent variable, y . The factors x_1 and x_2 both vary across the study region, but in different ways, and for each factor different sub-regions can be distinguished by application of the Jenks classification method described above to each factor separately. This is illustrated in Figures 3(b) and 3(c) where, as an example, three different sub-regions are considered for each factor. Usually, the dependent variable y is influenced by several different factors x_i (Figure 3) and the combined effect of two or more factors may have a weaker or stronger influence on y than each of the individual factors. The q values for the influences of factors x_1 and x_2 on y , obtained from the application of the factor detector method (Eq. 2), may be represented as $q(x_1)$ and $q(x_2)$. Hence, a new spatial unit and subregions may be generated by overlaying the factor strata x_1 and x_2 , written as $x_1 \cap x_2$, where \cap denotes the interaction between factor strata x_1 and x_2 as illustrated in Figure 3(d). Thus, the q value of the interaction of $x_1 \cap x_2$ may be obtained, represented as $q(x_1 \cap x_2)$. Comparing the q value of the interaction of the pair of factors and the q value of each of the two individual factors, five categories of the interaction factor relationship can be considered which are summarized in Table 2. If $q(x_1 \cap x_2) > q(x_1) + q(x_2)$, this is referred to as a nonlinear enhancement of two variables. And if $q(x_1 \cap x_2) > \text{Max}[q(x_1), q(x_2)]$, this is referred to as a bilinear enhancement of two variables. The occurrence of nonlinear enhancement and bilinear enhancement are indicated with the q values in Table 2 and in the caption of Figure 7.”.

The occurrence of nonlinear enhancement is indicated with the q values in Table 1 (Table 2 in the revised manuscript) and in the caption of Figure 7 in the revised manuscript.

Table 1. Interaction categories of two factors and the interaction relationship

Illustration	Description	Interaction
	$q(x_1 \cap x_2) < \text{Min}[q(x_1), q(x_2)]$	Weakened, nonlinear
	$\text{Min}[q(x_1), q(x_2)] < q(x_1 \cap x_2) < \text{Max}[q(x_1), q(x_2)]$	Weakened, unique
	$q(x_1 \cap x_2) > \text{Max}[q(x_1), q(x_2)]$	Enhanced, bilinear
	$q(x_1 \cap x_2) = q(x_1) + q(x_2)$	Independent
	$q(x_1 \cap x_2) > q(x_1) + q(x_2)$	Enhanced, nonlinear

2. The AOD-CER relationship is difficult to interpret as the Twomey effect, especially where LWP is not controlled for (McComiskey and Feingold, 2012). Several previous studies have also investigated the potential controls on the AOD-CER relationship (e.g. Tan et al, 2017; Yuan et al, 2008; Myhre et al, 2007; Tang et al, 2014; Andersen and Cermak, 2015). There should be a clearer distinction around what is added by this work (which can be the GDM).

Answer: We have taken notice of the references provided and added them to the revised manuscript where appropriate. McComiskey and Feingold (2012) discuss effects of unconstrained LWP, which in the revised manuscript is mentioned in Section 4.2 (lines 442-444): “Note however, that no selection was made for LWP and the condition of constant LWP was not fulfilled. This will be further discussed in Section 4.3.” In section 4.3 and Discussions (lines 757-777) we discuss the effect of LWP on S in detail. McComiskey and Feingold (2012) also discuss the spatial separation of satellite observations of cloud and aerosol is addressed in

Section 2.2 (lines 225-229) and a reference to McComiskey and Feingold (2012) has been added: “Aerosol retrieval is only executed in clear sky conditions whereas cloud properties can only be retrieved in cloudy skies. Hence, it is not possible to obtain co-located aerosol and cloud data from satellite. For satellite-based aci studies it is assumed that, following, e.g., Jia et al. (2022), aerosol properties are homogeneous enough to be representative for those in adjacent cloud areas. Consequences of this assumption were discussed by McComiskey and Feingold (2012).”.

Potential controls on the CER-AOD relationship and confounding meteorological effects are discussed in the Introduction, supported with many references (lines 129-160): “Meteorological conditions are important factors determining ... promote the formation of thicker and higher clouds” and in Discussions (lines 778-798): “The above results were obtained by using traditional statistical methods where relationships were derived from scatterplots of CER versus AOD, stratified in two different AOD regimes and five different LWP regimes, as discussed above. The data were also analyzed by using the GDM to determine which factors influence aci and identify how interactions between different parameters influence the results of the aci analysis, i.e. the sensitivity and resulting adjustments. In particular, the GDM provides information on the extent to which the effect of individual factors is influenced by other factors. As shown in Section 4.6.1, the effect of individual factors may be overestimated when confounding effects of other factors are not accounted for. The interaction detector analysis (Section 4.6.2) shows a more realistic estimate of the effects on aci when different factors are analyzed together. The factor detector analysis (Section 4.6.1) shows that over the ECS, AOD has the largest influence on cloud parameters, as indicated by the large and statistically significant q values. Among the meteorological factors, PVV has more influence on the variations of the cloud parameters than RH and LTS. Over the YRD, AOD has the largest influence on COT, with large and significant q values. Among the meteorological factors, the effect of LTS on CF is greater than that of RH and PVV. However, the q-values may sum up to over 100% when the variables are not independent, i.e. the explanatory power of such variables is too high. The evaluation of the effects of interaction between different factors on aci corrects these clearly unrealistic situations. The analysis in section 4.6.2 shows that the interactive q-statistic values derived in this study are larger than any of the values for single variables, i.e. the explanatory power of a combination of factors is higher than that of individual factors, but less than 100%. However, although the GDM provides evidence of the effects of aerosol and meteorological factors and their interactions on cloud properties and quantify the relative contributions to aci, it cannot quantify the absolute contributions with confidence.”.

We have added the references provided by Referee#1 with a brief summary of the findings reported in these references. In Section 6 Conclusions, we have added (lines 807-809): “These results may be influenced by confounding effects of meteorological parameters. The study further shows that over the ECS the CER is larger for higher LTS and RH but lower for higher PVV. Over the YRD, there is no significant influence of LTS on the relationship between CER and AOD.

However, the main comment of Referee #1 is about the question “what is added by this work” and the answer is indeed that it is the GDM as was already mentioned in the Introduction at lines 164-172 in the revised manuscript: “In the current study the geographical detector method (GDM) is applied as a complementary tool to quantify the relative importance of the effects of nine parameters on S. The GDM is explained in detail in Section 3.2. In brief, a set of statistical methods is used to detect the spatial variability of aerosol and cloud properties, which are

spatially differentiated, and evaluate the occurrence of correlations in their behaviour and the driving forces behind these correlations (Wang and Hu, 2012; Wang et al., 2016). The basic idea of the GDM is that the spatial distributions of two variables tend to be similar if these two variables are connected (Zhang and Zhao, 2018). The method is used in this study to analyse the relative importance of different factors, and interactions between them, influencing aci .”

Furthermore, we have changed the first sentence of Section 3.2 (lines 312-313) to “The geographical detector method (GDM) is introduced to analyze which factors influence the aci and identify possible correlations between different factors” and the text below Figure 2 has been changed (see also response to comment 1).

And in the conclusions we have added the text cited above (lines 810-819): “The GDM has been applied to determine which factors influence S and cloud parameters and the interaction detector analysis has been used to determine the combined effect of different parameters on cloud parameters. The results from the GDM interaction detector analysis clearly show the enhancement of the interaction q -values over the q -values for the individual factors. In other words, the explanatory power of the combined effects of aerosol and a meteorological parameter is larger than that of each parameter alone. Thus, the GDM provides an alternative way to obtain information on confounding effects of different parameters. We conclude that aerosol and meteorological conditions significantly influence cloud parameters and that combined effects of different factors are often more important than the effect of each individual factor. The relative importance of each factor differs significantly over the ECS and YRD.”

3. The majority of more recent studies have used N_d for calculation of the ACI , rather than CER (Quaas et al, 2008; Gryspeerd et al, 2017; McCoy et al, 2018; Hasekamp et al, 2019). There are also useful studies that investigate the susceptibility (AOD - N_d relationship) and the impacts on this value (Jia et al, 2022). This avoids the LWP - CER issue prevalent in previous work and presents a cleaner separation of the Twomey and adjustments. It could be worth including a section on why CER is used and might be something to consider for future work in this area.

Answer: We address the use of CER rather than N_d with the following text, added to the Introduction (lines 177-186): “It is noted that RF_{aci} is formulated in terms of N_d , whereas studies on the Twomey effects often use CER instead of N_d . CER is readily available as a satellite retrieval product, although in particular over land the reliability is questioned (Grandey and Stier, 2010), whereas N_d is derived from CER and the cloud optical thickness (COT) (e.g., Grandey and Stier, 2010; Arola et al., 2022). This implies that N_d is subject to the same retrieval errors as CER , including a possible relation between CER and LWP . The comparison of global maps of the sensitivities of CER and N_d to AOD by Grandey and Stier (2010) exhibits very similar patterns. In this study, the CER sensitivity to AOD is stratified by LWP , which however poses problems in the evaluation of RF_{aci} . However, the current study focuses on understanding effects of different parameters on CER sensitivity to aerosol rather than the application to determine RF_{aci} .”.

4. Previous studies have shown that it is difficult to interpret correlations over large regions as an aerosol effect due to the impact of meteorological confounders (Grandey and Stier, 2010). Correlations between AOD and cloud properties are also fraught with potential confounding effects (Quaas et al, 2010; Boucher and Quaas, 2012; Gryspeerd et al, 2014). Does the GDM method address these issues? If so how? If not, this study should be much clearer about the claims of causality it puts forward.

Answer: Thank you for this comment. We have added the references provided in the introduction with a brief summary of the findings of each of them. This comment addresses two issues: large regions and confounding effects. As regards large regions: Grandey and Stier (2010) recommend $4^{\circ}\times 4^{\circ}$ as the largest size and “if data exist at higher gridded resolution the possibility of analyzing data at this higher resolution should be seriously considered.” In this study we have followed this recommendation: we have considered two large study regions (YRD and ECS) for the initial evaluation of CER-AOD relationships. Based on these results, we have selected data ranges for which a clear ACI relationship occurs and for these conditions we have refined this study to smaller scales using $1^{\circ}\times 1^{\circ}$ grid cells and the results are presented in Figure 6 and discussed in Sections 4.2 and 4.3 in the revised manuscript.

We have also considered the size of the study area, or grid size, when using the GDM. In the GDM, the y data are recorded in a raster grid, over a total study area of $9^{\circ}\times 9^{\circ}$, as illustrated in Figure 1 (Figure 2 in the manuscript). The data in the raster grid is transformed into dot files, each dot containing a value for y and for one of the influencing parameters x. The dependent (y) and influencing (x) parameters are separated into 2 layers with the same grid. As the resolution of MYD 08 data used in this study is $1^{\circ}\times 1^{\circ}$, the data transformed into dot files is based on raster grid $1^{\circ}\times 1^{\circ}$. Here, 15-year averaged distributions of clouds (y, 5 layers) and aerosols/meteorological conditions (x, 4 layers) are used as input in the GDM. Tables 2 and 3 show the q values for factors which may influence cloud parameters over the ECS and YRD in different regions sizes, evaluated for data collected in the period from 2008-2022. The data in Tables 2 and 3 show that for regions smaller than $9^{\circ}\times 9^{\circ}$, the GDM result is not significant and that the results become more significant when the area is getting larger (for example $9^{\circ}\times 9^{\circ}$, $10^{\circ}\times 10^{\circ}$, $11^{\circ}\times 11^{\circ}$, $12^{\circ}\times 12^{\circ}$). In future research, higher resolution data can be used for GDM by controlling the size of the study area to be less than $4^{\circ}\times 4^{\circ}$.

The problem of large regions and the effect of possible meteorological confounders was also addressed by Arola et al. (2022) and in response to a comment by Referee#2 we have added the following text to Section 5 (Discussion, lines 757-777): “Arola et al. (2022) addressed the susceptibility of N_d to changes in aerosol and the adjustment of LWP (using satellite observations), and confounding factors, in particular co-variability of N_d and LWP induced by meteorological effects. They show how errors in the retrieved CER and COT or spatial heterogeneity in cloud fields influence the N_d - LWP relation. However, both N_d and LWP are not retrieved but derived from CER and COT. Using Eq. 1 and Eq. 2 in Arola et al. (2022), the N_d -LWP relationship can be shown to have a highly non-linear dependence on CER and thus it is no surprise that any error in CER strongly affects the relation between N_d and LWP. Their experiments, i.e. using smaller scales ($5^{\circ} \times 5^{\circ}$) to reduce spatial meteorological variability, or using snapshots to remove meteorological variability in time, did not lead to a conclusion whether the N_d - LWP variability is due to spatial heterogeneity in the cloud fields or due to retrieval errors. The main message from this part of the study (using satellite data) by Arola et al. (2022) is “the spatial variability of CER introduces a bias which moreover becomes stronger in conditions where the CER values are lower on average”. Experiments with simulated measurements show that “the main cause of the negative LWP vs N_d slopes is the error in CER”. Arola et al. emphasize that the spatial cloud variability and retrieval errors in CER and COT are similar sources for negative bias in LWP adjustment and that these sources could not be separately assessed in their simulations. The implication of the findings of Arola et al. (2022) on the adjustment of LWP for the results of the current study on the sensitivity of CER to aerosol (or CCN, using AOD as proxy) is that the assumption of constant LWP may be violated. This would affect the results presented in Section 4.3 where LWP was stratified and S was

found to vary with LWP. In view of the LWP adjustment to changes in aerosol, the variation of CER sensitivity with LWP may be somewhat different from that reported in section 4.3.”

The results from the GDM interaction detector analysis in Section 4.6.2 clearly show the enhancement of the interaction q-values over the q-values for the individual factors. In other words, the explanatory power of the combined effects of a meteorological parameter and aerosol is larger than that of each parameter alone. Thus, the GDM provides an alternative way to obtain information on confounding effects of different parameters.

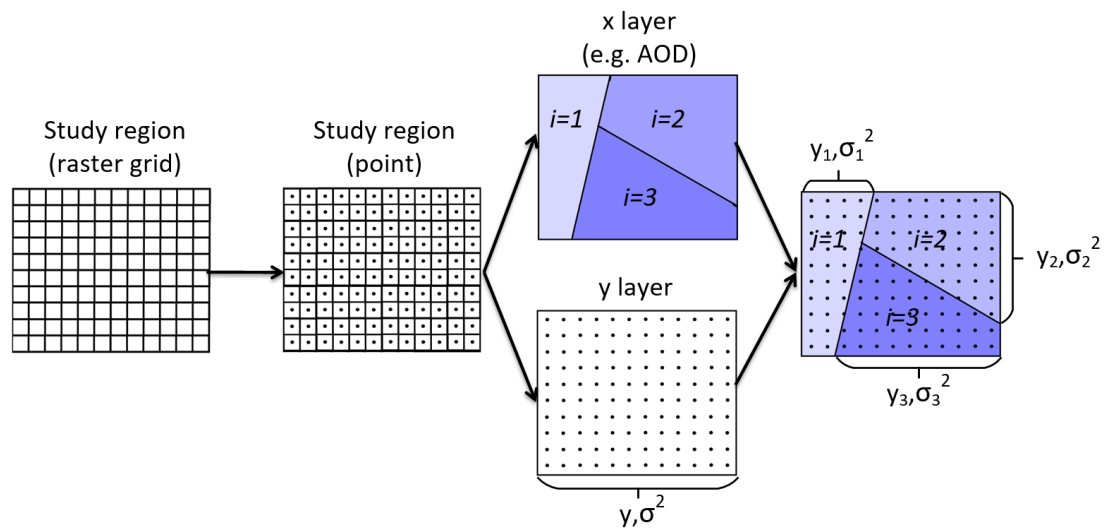


Figure 1. The principle of the geographical detector method. See text for explanation.

Table 2. q values for factors which may influence cloud parameters over the ECS in areas with different sizes, evaluated for data collected in the period from 2008-2022.

Region	Cloud	AOD	RH	LTS	PVV
4°x4°	CER	0.67	0.43	0.14	0.59
	COT	0.27	0.51	0.28	0.44
	LWP	0.72	0.25	0.09	0.53
	CF	0.68	0.29	0.11	0.28
	CTP	0.31	0.50	0.29	0.57
5°x5°	CER	0.79	0.42	0.40	0.72
	COT	0.54	0.41	0.25	0.48
	LWP	0.57	0.37	0.34	0.52
	CF	0.46	0.48	0.16	0.53
	CTP	0.49	0.45	0.25	0.31
6°x6°	CER	0.85**	0.47	0.49	0.54
	COT	0.62	0.62	0.37	0.56
	LWP	0.64	0.34	0.41	0.31
	CF	0.30	0.23	0.16	0.40
	CTP	0.46	0.47	0.22	0.45
7°x7°	CER	0.73***	0.36	0.39	0.63***
	COT	0.60	0.37	0.37	0.53**
	LWP	0.58	0.19	0.31	0.47
	CF	0.34	0.13	0.05	0.43**

	CTP	0.37	0.47	0.21	0.47
8°x8°	CER	0.86 ^{***}	0.48	0.57 ^{***}	0.63 ^{**}
	COT	0.72 ^{***}	0.50	0.54	0.65 ^{***}
	LWP	0.71	0.41	0.48	0.51
	CF	0.39	0.27	0.14	0.42 ^{**}
	CTP	0.48	0.56	0.56	0.56
9°x9°	CER	0.81 ^{***}	0.33 ^{***}	0.44 ^{***}	0.70 ^{***}
	COT	0.69 ^{***}	0.40	0.38	0.67 ^{***}
	LWP	0.68 ^{***}	0.23	0.43 ^{***}	0.49 ^{***}
	CF	0.46 ^{***}	0.20	0.09	0.47 ^{***}
	CTP	0.47	0.53	0.18	0.58
10°x10°	CER	0.86 ^{***}	0.46 ^{***}	0.54 ^{***}	0.62 ^{***}
	COT	0.71 ^{***}	0.55 ^{**}	0.52 ^{***}	0.67 ^{***}
	LWP	0.72 ^{***}	0.29	0.39 ^{***}	0.47 ^{***}
	CF	0.49 ^{***}	0.19	0.09	0.44 ^{***}
	CTP	0.53	0.58	0.29	0.66
11°x11°	CER	0.87 ^{***}	0.45 ^{***}	0.39 ^{***}	0.54 ^{***}
	COT	0.71 ^{***}	0.53 ^{***}	0.45 ^{***}	0.60 ^{***}
	LWP	0.73 ^{***}	0.73	0.26	0.44 ^{***}
	CF	0.48 ^{***}	0.13	0.04	0.29 ^{***}
	CTP	0.62	0.52	0.26	0.57
12°x12°	CER	0.84 ^{***}	0.42 ^{***}	0.31	0.55 ^{***}
	COT	0.66 ^{***}	0.46 ^{***}	0.37	0.52 ^{***}
	LWP	0.64 ^{***}	0.30	0.05	0.41 ^{***}
	CF	0.42 ^{***}	0.13	0.11	0.24 ^{***}
	CTP	0.53	0.49	0.27	0.54

Note: ^{***}indicates that the q value is significant at the 0.01 level ($p < 0.01$), ^{**}indicates that the q value is significant at the 0.05 level ($p < 0.05$).

Table 3. q values for factors which may influence cloud parameters over the YRD in areas with different sizes, evaluated for data collected in the period from 2008-2022.

Region	Cloud	AOD	RH	LTS	PVV
4°x4°	CER	0.47	0.64	0.04	0.27
	COT	0.75	0.62	0.37	0.55
	LWP	0.60	0.54	0.49	0.60
	CF	0.42	0.62	0.06	0.62
	CTP	0.85	0.59	0.53	0.77
5°x5°	CER	0.28	0.53	0.24	0.17
	COT	0.79	0.43	0.43	0.53
	LWP	0.69	0.49	0.44	0.38
	CF	0.46	0.42	0.33	0.51
	CTP	0.86	0.69	0.57	0.60
6°x6°	CER	0.17	0.14	0.18	0.11
	COT	0.75	0.30	0.27	0.41
	LWP	0.71	0.32	0.31	0.26
	CF	0.30	0.34	0.12	0.39
	CTP	0.81	0.53	0.40	0.54

7°x7°	CER	0.18	0.21	0.06	0.19
	COT	0.75	0.47	0.21	0.53
	LWP	0.43	0.44	0.52	0.33
	CF	0.36	0.26	0.13	0.23
	CTP	0.73	0.75	0.46	0.65
8°x8°	CER	0.31	0.24	0.34	0.17
	COT	0.66***	0.45	0.24	0.31
	LWP	0.21	0.43	0.60	0.38
	CF	0.28**	0.07	0.68***	0.05
	CTP	0.60	0.75	0.45	0.56
9°x9°	CER	0.31	0.25	0.13	0.18
	COT	0.61***	0.45***	0.12	0.29
	LWP	0.16	0.32	0.55***	0.18
	CF	0.30***	0.02	0.50***	0.07
	CTP	0.50	0.74***	0.32	0.56
10°x10°	CER	0.41	0.28	0.20	0.27
	COT	0.63***	0.50**	0.08	0.37
	LWP	0.21	0.36	0.51***	0.22
	CF	0.38***	0.06	0.48***	0.17
	CTP	0.50	0.78	0.31	0.60
11°x11°	CER	0.35	0.28	0.17	0.22
	COT	0.69***	0.40***	0.06	0.46
	LWP	0.35**	0.28	0.40	0.24
	CF	0.39***	0.06	0.47***	0.15
	CTP	0.48	0.72***	0.24	0.49
12°x12°	CER	0.32	0.19	0.19	0.16
	COT	0.50***	0.28***	0.07	0.47
	LWP	0.18**	0.25***	0.36***	0.26
	CF	0.37***	0.06	0.45***	0.12
	CTP	0.32	0.65***	0.25	0.35

Note: ***indicates that the q value is significant at the 0.01 level ($p < 0.01$), **indicates that the q value is significant at the 0.05 level ($p < 0.05$).

5. Another important factor is the calculation of LWP that is used for binning in the ACI calculations. As the LWP depends on the CER, does this not lead to an implicit filtering by CER, which would affect the calculation of ACI?

Answer: Stratification of the data for LWP was applied by, e.g., Saponaro et al. (2017) and Ma et al. (2018) in an attempt to satisfy the conditions for the Twomey effect. Indeed, Ma et al. (2018) show that the variation of the CER vs AI (both stratified according to LWP) relation changes with changes in LWP. The data in Section 4.3 also show the variation of S with the LWP interval and likely this is a more continuous variation if smaller LWP intervals (quasi-constant LWP, Ma et al., 2018) would be used. So indeed the assumption of constant LWP is not truly satisfied and this indeed affects the calculation of ACI as can be deduced from the data in Table 4 below (Table 3 in the revised manuscript). We further note that Arola et al. (2022) and others show a clear LWP - N_d relationship, in agreement with other studies. And LWP and N_d are both calculated from CER and COT, so a relationship is expected. We have addressed the findings by Arola et al. (2022) and this text was copied in our response to

comment 4. We have added the following text in Section 4.3 (lines 528-534): “The variation of S with changes in LWP indicates that the condition of constant LWP is not truly satisfied: if the data would be stratified according to smaller LWP intervals (quasi-constant LWP, Ma et al., 2018), S would likely vary more smoothly with LWP. As mentioned in the Introduction, LWP is not directly retrieved but calculated from CER and COT and thus also the calculation of S is to some extent affected by LWP. We further note the results by Ma et al. (2018), i.e. the slope of CER versus AI (comparable to S in this paper) varies little with LWP, with positive values over land and negative values over ocean and thus behaves similar to the data in Table 4 (Table 3 in the revised manuscript) for YRD and ECS.”.

Table 4. Estimates of S, computed using Eq. (1), and correlation coefficients R between CER and AOD, stratified by LWP, over the ECS for $0.1 < \text{AOD} < 0.3$ and over the YRD for $\text{AOD} > 0.3$. Statistically significant data points are indicated with * (p value < 0.01).

LWP (g m^{-2})	ECS ($0.1 < \text{AOD} < 0.3$)		YRD ($\text{AOD} > 0.3$)	
	S	R	S	R
0-40	0.10	0.94*	0.08	0.63*
40-80	-0.19	-0.98*	0.10	0.81*
80-120	-0.38	-0.99*	0.06	0.57*
120-160	-0.41	-0.99*	-0.03	-0.11
160-200	-0.46	-0.98*	-0.14	-0.42*

6. Is there a reason for using AOD, rather than a product such as the aerosol index (Nakajima et al, 2001), which has a stronger link to the CCN concentration?

Answer: $\text{AI} = \text{AOD} * \text{AE}$, but AE retrieval over land from MODIS is problematic (Ma et al., 2018 refers to Sayer et al., 2013) and therefore is no longer provided as a MODIS product in C6! We cite Ma et al.: “using AOD instead of AI does not influence the conclusions. (next to their Table 1)”

Another argument may come from Gryspeerdt et al. (2023): “The larger relative error in the aerosol retrieval under clean conditions reduces the correlation between the CCN and the retrieved aerosol due to regression dilution (Pitkänen et al., 2016). This reduces the magnitude of β under clean conditions, as observed in Fig. 1a and b. This issue is particularly severe for AI, which is calculated using the ratio of aerosol optical depths at two wavelengths, resulting in a relative error which tends to infinity under clean conditions” ($\beta = d \ln N_d / d \ln A$, where A is the aerosol proxy AI or AOD). The problem occurs under clean aerosol conditions because the contribution of the surface to the TOA result in larger uncertainty in the retrieved AOD.

We have added the following text in the Introduction (lines 106-122): “In studies on S utilizing satellite data, which is the subject of the current study, the aerosol optical depth (AOD) is often used as a proxy for the aerosol concentration, which is justified by the correlation of AOD and CCN published by Andreae (2009). However, AOD is determined by all aerosol particles in the atmospheric column, including particles that do not act as CCN, depends on the relative humidity (RH) throughout the atmospheric column, does not provide information on chemical composition and may be influenced by aerosol in disconnected layers. The use of the Aerosol Index (AI), the product of AOD and the Ångström Exponent (AE; describing the spectral

variation of AOD), is suggested as a better indicator of CCN because AE includes information on aerosol size (e.g., Nakajima et al., 2001). However, the AE is determined from AOD retrieved at two or more wavelengths and the evaluation of the results versus ground-based reference data shows the large uncertainty in AE. Therefore, in recent MODIS product Collections, AE is not provided over land (e.g., Levy et al., 2013; Kourtidis et al., 2015). AE is also not well-defined for low AOD for which uncertainty is largest (Bellouin et al., 2020; Gryspeerdt et al., 2023). The issues associated with using AOD or AI as proxy for CCN were discussed by, among others, Rosenfeld et al. (2014) who do not recommend the use of AI while also concluding that no better proxy is available. Therefore, in this study, AOD is used as a proxy for CCN to study S. It is noted that in other studies, e.g., Jia et al., 2022, both AOD and AI have been used and the results show similar behaviour.”.

Specific points

1. The abstract mostly list results, rather than providing an overview of the paper and the conclusions. Is there an overall picture or aim of the study that could help to structure this?

Answer: We have revised the abstract substantially and added to following sentence upfront, to provide the overall picture “The sensitivity (S) of cloud parameters to the influence of different aerosol and meteorological parameters has in most previous aerosol-cloud interaction (aci) studies been addressed using traditional statistical methods. In the current study, relationships between cloud droplet effective radius (CER) and aerosol optical depth (AOD, used as a proxy for cloud condensation nuclei, CCN), i.e. the sensitivity (S) of CER to AOD, is investigated with different constraints of AOD and cloud liquid water path (LWP). In addition to traditional statistical methods, the geographical detector method (GDM) has been applied to quantify the relative importance of the effects of aerosol and meteorological parameters, and their interaction, on S.” Note that many other changes were made to the abstract in “track changes”.

2. L39 - Is this opposite effect just because the sign of the pressure vertical velocity is defined differently? I am not sure what opposite means in this context.

Answer: We can see that the CER decreases with increasing AOD over the ECS, which is consistent with the Twomey effect. The meteorological parameters do not change the trend of CER variation to the AOD. However, the CER is larger for higher LTS and RH but lower for higher PVV. We also reorganized the text with “The study further shows that over the ECS the CER is larger for higher LTS and RH but lower for higher PVV.” (see lines 32-33) in the revised manuscript.

3. L68 - The terms first and second indirect effect are less commonly used in more recent studies. I would suggest referring to adjustments instead (see IPCC AR5), as this more closely links in with the radiative forcing/effective radiative forcing distinction and aligns more closely with other recent work.

Answer: Thank you for this valuable comment. We have changed the terminology throughout the revised manuscript and used several key references to guide us, such as IPCC AR5, Gryspeerdt et al. (2023), Bellouin et al. (2020) and several others.

4. L81 - I would have said that satellites typically have a fairly poor temporal resolution (unless the authors are referring to geostationary satellites?)

Answer: In this paper we only use MODIS data. We have removed “and high spatial and temporal resolution”

5. L93 - Is there any reason for choosing these studies? They seem to be rather disjointed, with some looking at the Twomey effect directly and some considering adjustments. Some notable studies looking at the impact of meteorological parameters on potential adjustments (e.g. Koren et al, 2010) and the particularly Twomey effect (Jones et al, 2009; Jia et al. 2022) are left out.

Answer: We have reorganized the text and added the notable references looking at the impact of meteorological parameters on potential adjustments (e.g. Koren et al, 2010) and the particularly Twomey effect (Jones et al, 2009; Jia et al. 2022). See the text on pages 5-6 (lines 129-164) in the revised manuscript.

6. L96 - PVV is redefined here

Answer: Consistent notation has been used through the revised manuscript.

7. L116 - There needs to be some discussion of how the GDM is affected by the results of Grandey and Stier (2010), who suggest that spatial correlations are unreliable. It may be that the results of GS10 are not applicable here, as the GDM method is capable of accounting for the co-variations that drive the results in GS10. If so, it would be good to have some evidence of this, as it would provide more significance to the results presented in this work.

Answer: Spatially-varying aerosol and cloud properties may contribute towards observed relationships between aerosol and cloud properties. This may affect the results of many of the aforementioned studies which analyze data on a relatively large regional scale. Aerosol type, cloud regime and synoptic regime may vary over such large spatial scales. If data are analyzed for the region as a whole, false correlations may be introduced. Grandy and Stier (2010) suggested that for region sizes larger than $4^{\circ}\times 4^{\circ}$, spurious spatial variations in retrieved cloud and aerosol properties can introduce widespread significant errors to calculation S. However, we can observe that at the regional scales of $8^{\circ}\times 8^{\circ}$ and $15^{\circ}\times 15^{\circ}$, although significant errors are introduced, the spatial distribution patterns of S (the sensitivities of CER and N_d to AOD) look very similar, as shown in Figure 2 of Grandy and Stier (2010).

GDM is a spatial statistical analysis method aimed at studying the degree of influence and spatial patterns of different factors on the changes in geographic phenomena. In the analysis, we can simultaneously consider the interactions and impacts among multiple factors, thus revealing the relationships of synergistic changes. Therefore, the geographic detector method can encompass the analysis of co-variations.

We have added the following text in the Sect 4.6.1 (lines 647 to 666): “Tables 5 and 6 list q values for individual factors, together with p showing the absence of statistical significance in many cases, especially over the YRD, and often the explanatory power is not high when the significance is low. These data show that cloud parameters are dominated by aerosol effects over the ECS but meteorological influences on cloud parameters predominate over the YRD, as was also concluded from the analysis from “traditional” statistical methods presented in Section 4.5 and these conclusions are consistent with the results published by Andersen and Cermak (2015). Among the meteorological parameters, we also find that PVV (with highest q in the three meteorological parameters) predominantly influences cloud parameters over the ECS. Jones et al. (2009) and Jia et al. (2022) reported that stronger aerosol cloud interactions

typically occur under higher updraft velocity conditions. In addition, we find that CTP is mainly affected by RH ($q = 0.74^{***}$) and PVV ($q = 0.56$) over the YRD, as suggested by Koren et al. (2010). Koren et al. reported that observed cloud top height correlates best with model pressure updraft velocity and relative humidity. To some extent, LTS influences CER ($q = 0.44^{***}$) and LWP ($q = 0.43^{***}$) over the ECS, while, in contrast, over the YRD LTS predominately influences CF ($q = 0.50^{***}$) and LWP ($q = 0.55^{***}$). Matsui et al. (2004) and Tan et al. (2017) reported that aerosol impact on CER is stronger in more dynamic environments that feature a lower LTS and argue that very high LTS environments dynamically suppress cloud droplet growth and reduce aci intensity. While strong correlations between AOD and cloud parameters have been previously observed, they are likely due to the swelling of aerosol particles in humid airmasses (Quaas et al, 2010), rather than an aerosol influence, which is in agreement with findings by, e.g., Myhre et al. (2007), Twohy et al. (2009) and Quaas et al. (2010).”

This study provides a general description of the sensitivity (S) of cloud parameters to the influence of different aerosol and meteorological parameters over the YRD and the ECS. Correlations between AOD and cloud parameters are found over the target regions, which can be attributed in part to the influence of general circulation. In general, there are many relations between the various parameters, both related to cloud microphysics and meteorology. Thus, establishing cause and effect relationships between parameters is difficult and must be made with care. It is not possible to completely separate meteorological influences from aerosol influences on clouds. This work can therefore only provide further evidence of the aerosol and meteorological effect on clouds and quantify the relative contributions and combined effects on clouds, but cannot quantify the absolute contributions with confidence.

In the current study, based on a regional scale of $9^{\circ} \times 9^{\circ}$, the GDM method is used to explore the relative importance of various factors on cloud parameters and identify possible correlations between different factors. In the future, aerosol cloud interactions can be studied on smaller regional scale ($<4^{\circ} \times 4^{\circ}$) using higher resolution source data.

8. L154 - Why only 2008 to 2022? The MODIS record runs back to 2002/3

Answer: There is no particular reason for the selection of 2008 as the starting year. Most other studies use a shorter period of time. Based on your comment and that of other referees, we have thought about shorter periods and realized that, in principle, periods were included when the AOD was at its maximum (2008-2014) and when the AOD was decreasing in response to implementation of emission reduction policy. We therefore split the data sets for these 2 periods and plotted CER vs AOD, see Figures 2 and 3 below. We noticed that over the ECS there was not a significant difference between the CER/AOD relations during these two periods. However, over the YRD, for the high AOD period, CER clearly decreased with increasing AOD for $0.1 < \text{AOD} < 0.3$ and for larger AOD the CER increased with $R=0.87$. For the second period, however, there was no clear correlation between CER and AOD for both AOD intervals. The data also show that over the YRD the CER for $\text{AOD} > 0.3$ increased to larger values during the first period than during the second period. We did not look for explanations of this difference, possibly the aerosol properties changed in response to emission reduction, or confounding meteorological factors played a role.

We also looked for shorter periods, considering each year between 2008 and 2022. The results show similar behavior for each year over both study areas with interannual variations between

the fits, and thus the value of S . However, the statistical significance is low (large p) due to the small number of samples.

These findings were briefly summarized in the Discussion (lines 733-746): “These results were obtained using data from a period of 15 years. During this period, the aerosol properties changed in response to expanding economy, resulting in the increase of the AOD until 2007, and the implementation of emission reduction policy resulting in the decrease of the AOD from 2014 which flattened from about 2018 (de Leeuw et al., 2021; 2022; 2023). To account for these changes, the sensitivity S was determined for the periods 2008-2014 and 2014-2022, without stratification for LWP (see Figures S1 and S2 in the Supplementary). The results for the ECS show no significant difference between the CER-AOD relations during these two periods. Over the YRD, however, the data for 2008-2014 show a clear decrease of CER with increasing AOD for $0.1 < \text{AOD} < 0.3$ and for larger AOD the CER increased, with a statistical significant correlation ($R=0.87$) and $S=0.10$ as compared to $S=0.08$ for the whole period. In contrast, the data for 2014-2022 show no clear correlation between CER and AOD for both AOD intervals over the YRD. A similar exercise for shorter periods, i.e. for each year between 2008 and 2022, show similar behavior as for the whole period 2008-2022, over both study areas, with interannual variations of the value of S . However, the statistical significance is low (large p) due to the small number of data samples in each year.”

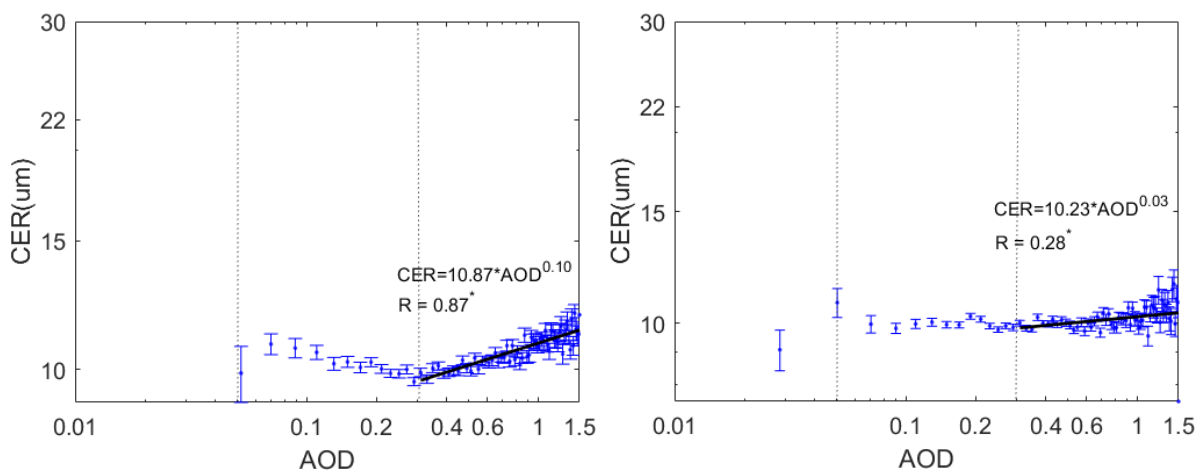


Figure 2. CER vs AOD over the YRD for the periods 2008-2014 (left) and 2015-2022 (right).

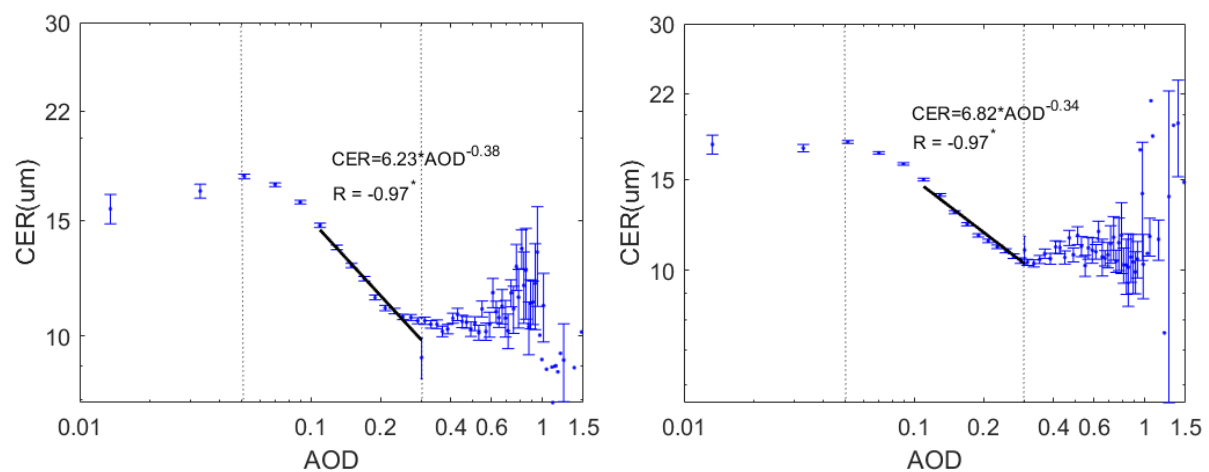


Figure 3. CER vs AOD over the ECS for the periods 2008-2014 (left) and 2015-2022 (right).

9. L159 - The aerosol and cloud retrievals are necessarily conducted in different regions of the 1x1 degree gridbox (aerosol retrievals are only conducted in clear sky), meaning that they are not coincident. This may not affect the results if the regions are non-precipitating. Jia et al (2022) showed that wet scavenging can have a considerable impact on the susceptibility.

Answer: The use of non-collocated aerosol and cloud data is addressed in Section, 2.2. (lines 225-229): “Aerosol retrieval is only executed in clear sky conditions whereas cloud properties can only be retrieved in cloudy skies. Hence, it is not possible to obtain co-located aerosol and cloud data from satellite. For satellite-based aci studies it is assumed that, following, e.g., Jia et al. (2022), aerosol properties are homogeneous enough to be representative for those in adjacent cloud areas. Consequences of this assumption were discussed by McComiskey and Feingold (2012).”

We have filtered the data (exclude precipitating clouds) following the method used in Ma et al. (GRL2018) and Saponaro et al. (2017) (see lines 265-267 in the revised manuscript): “To ensure that the data used only included single layer liquid clouds and nonprecipitating cases, the filtering criteria described by Saponaro et al. (2017) were applied.”. This issue is shown throughout the revised manuscript (all the figures were changed/modified in this respect).

10. L153 - I would suggest referencing Platnick et al (2016), given the authors are using MODIS collection 6.1.

Answer: We have added the following text to Section 2.2. (lines 236-245): “The MODIS Collection 6.1 AOD product over China has been validated by, e.g., Che et al. (2019) and globally over land and ocean by Wei et al. (2019). MODIS C6.1 cloud products were evaluated by Platnick et al. (2017). The validation of CER and LWP, the primary cloud products used in this paper, was described by Painemal and Zuidema (2011), who compared MODIS C5 with in situ data (aircraft), and likewise the MODIS C6.1 CER product was evaluated by Fu et al. (2022) by comparison with airborne measurements. Fu et al. (2022) concluded that their “validation, along with in situ validation of MODIS CER from other regions (e.g., Painemal and Zuidema, 2011; Ahn et al., 2018), provides additional confidence in the global distribution of bias-adjusted MODIS CER reported in Fu et al. (2019).” It is noted that COT and CER are retrieved whereas LWP is secondarily derived (e.g., Painemal and Zuidema, 2011).”

11. L169 - Brendan et al (2005) suggests that cloud contamination becomes an issue when the AOD is larger than 0.6. Why is a larger threshold used here?

Answer: The conclusion of Brendan et al. (2005) applies to the MOD06 Collection 04 cloud product and these authors conclude with “The cloud masking technique in the recently updated Collection 05 cloud retrieval algorithm has been improved, and the Collection 05 cloud products available in the near future will largely eliminate the aerosol contamination effect”. Christenson et al. (ACP 2017) used MOD06 C6 data (1km x1km) and reported that “large aerosol optical depths remain in the MODIS-observed pixels near cloud edges, due primarily to 3-D effects (Varnáí and Marshak, 2009) and the swelling of aerosols by higher relative humidity.” And “Varnáí and Marshak (2009) also noted that beyond 15 km contamination effects were minimized in MODIS data (1km x1km).” Therefore Christensen et al. only used data pairs beyond the 15 km length scale in their aci study.

In our study we use MODIS L3 collection 6.1 with a spatial resolution of 1°x1°. Comparisons with surface-based sun photometer data revealed that Collection 6 should improve upon

Collection 5, and overall, 69.4% of MODIS Collection 6 AOD fell within an expected uncertainty of $\pm (0.05 + 15\%)$ (Levy et al., 2013; Tan et al., 2017). In this study, to eliminate 1° by 1° scenes in which the aerosol distribution is heterogeneous, retrievals with a standard deviation higher than the mean values are discarded (Saponaro et al., 2017; Jia et al., 2022). In addition, many previous researches do not set a threshold of AOD when using MODIS L3 C6 data (Grandey and Stier, 2010; Tang et al., 2014; Saponaro et al., 2017; Tan et al., 2017; Ma et al., 2018; Jia et al., 2022). Based on these findings, we used the larger threshold of 1.5.

These explanations have been summarized in the text added to section 2.2 (lines 252-260): “The choice of this threshold, rather than 0.6 used by Brennan et al. (2006), who used MOD06 Collection 04 products, is based on reports by Christenson et al. (2017) and (Varnáí and Marshak, 2009). Christenson et al. (2017) used MOD06 C6 data (1km x1km) and reported that “large aerosol optical depths remain in the MODIS-observed pixels near cloud edges, due primarily to 3-D effects (Varnáí and Marshak, 2009) and the swelling of aerosols by higher relative humidity.” Varnáí and Marshak (2009) noted that beyond 15 km contamination effects were minimized in MODIS data (1km x1km). Furthermore, we discarded scenes (1° by 1°) in which the aerosol distribution is heterogeneous, i.e. with a standard deviation higher than the mean value (Saponaro et al., 2017; Jia et al., 2022).”

12. L172 - Why is 200gm^{-2} used as a threshold for the LWP?

Answer: In the text we added (line 261): “LWP larger than 200 g m^{-2} is excluded to avoid deep convective clouds (Wang et al., 2014)”.

13. L184 - I would suggest putting the URL links in the references or acknowledgements

Answer: Although it is nowadays quite common to provide url + last accessed data as a reference in the text, we have followed this suggestion.

14. L187 - ERA5 and ERA Interim both seem to be mentioned at different points in this work. I suggest using only one (preferably ERA5)

Answer: Indeed we used ERA-5 and have corrected this throughout the text.

15. L190 - I am not sure this is the definition of the first indirect effect as all of these properties also vary with cloud adjustments.

Answer: In response to your comments and those from other reviewers, we have changed the terminology to the terminology recommended in IPCC AR5 (see also our response to your specific point 3). As a result, we have change the title of Section 3.1 to “Sensitivity of cloud parameters to changes in aerosol concentrations” and the first sentence now reads “Changes in aerosol loading lead to an adjustment of cloud optical or microphysical parameters (COT, CER, etc.)”, together with many other changes throughout the revised manuscript.

16. L192 - Ice nuclei are usually referred to as "ice nucleating particles" (INP) - Vali et al (2015)

Answer: Thank you for this suggestion: this has been changed here and elsewhere in the revised manuscript.

17. L204 - Do the authors mean CCN here (as in Andreae, 2009)

Answer: In the original formulation by Feingold et al (2001), α is the AOD. This relation was derived assuming that the cloud droplet number concentration N_d varies with the aerosol number as $N_d \propto N_a^{a_1}$ (their eq. 5), with $a_1=0.7$. Following Andreae (2009) there is a power law relation between AOD and CCN. We changed the sentence below eq. 1 (see lines 300-301 in the revised manuscript) to “Where r_c represents the CER and α represents the AOD. Following Andreae (2009), AOD and CCN are correlated and AOD varies with CCN following a power law relationship.”, while also changes were made to the rest of this paragraph.

18. L216 - An explicit list of these parameters, perhaps in the diagram, could be useful for others trying to replicate this study.

Answer: Thank you for this comment. We have added this information in Table 5 (Table 1 in the revised manuscript).

Table 5. Parameters used in the present study, together with the sources, time periods and spatial resolutions.

Source	Time period	Resolution	Parameters
MYD08	Jan 2008-Dec 2022	Daily, 1°x1°	AOD at 550 nm COT at 2.1 μ m CER at 3.7 μ m and 2.1 μ m Cloud-top temperature Cloud-top pressure LWP at 2.1 μ m Cloud Fraction Solar zenith angle Sensor zenith angle Cloud multi-layer flag Cloud phase flag
ERA5	Jan 2008-Dec 2022	hourly, 0.25°x0.25°	Temperatures at 700 and 1000 hPa Relative humidity at 750 hPa Vertical velocity at 750 hPa

19. L221 - I have not used the Jenks method before, but from what I understand, you have to specify the number of regions/regimes? How is this done and does the number of regions chosen affect the results?

Answer: The geographic detector model requires the input independent variable to be a type variable. The Jenks natural breaks classification method is one of many discretization methods and is commonly used in literature. The Jenks natural breaks classification method (Brewer and Pickle, 2002), aiming to minimize the variance within the group and maximize the variance between groups, was applied to categorize the whole region into n subregions. For example,

AOD needs to be classified into 5 levels using the Jenks natural breaks classification method, and the AOD source data needs to be reclassified into 1-5 natural numbers from small to large, and then counted into the grid. Therefore, the input of the independent variable AOD is a type variable. However, it should be noted that the GDM also has unstable characteristics. On the one hand, it is due to the MAUP (Modified Area Unit Problem) variable area unit problem, which can be understood as the influence of "scale effect". Due to the limitation of data resolution used in this study, the spatial statistical unit is $1^{\circ} \times 1^{\circ}$. On the other hand, the methods used for data discretization can also have an impact. This study attempts to determine the optimal number of classifications by examining the impact of different classification numbers (3-8) on the GDM output results (as shown in Tables 6 and 7 below). The data shows that the classification number of regions does not affect the relative importance of cloud factors on the cloud. Here we classify the values of each cloud factor into 5 levels during the period of 2008-2022.

Table 6. q values for factors which may influence cloud parameters over the ECS ($9^{\circ} \times 9^{\circ}$) in different number of classification levels (3~8) (see text) using Jenks natural breaks classification method, evaluated for data collected in the period from 2008-2022.

cloud parameters	number of classification levels	AOD	RH	LTS	PVV
CER	3	0.80 ^{***}	0.33 ^{**}	0.42 ^{***}	0.69 ^{***}
	4	0.81 ^{***}	0.40 ^{***}	0.43 ^{***}	0.67 ^{***}
	5	0.81 ^{***}	0.33 ^{**}	0.44 ^{***}	0.70 ^{***}
	6	0.85 ^{***}	0.41	0.52 ^{***}	0.73 ^{***}
	7	0.83 ^{***}	0.37	0.44	0.74 ^{***}
	8	0.84 ^{***}	0.40	0.48 ^{**}	0.70 ^{***}
COT	3	0.66 ^{***}	0.43	0.42 ^{**}	0.64 ^{***}
	4	0.69 ^{***}	0.45	0.43	0.66 ^{***}
	5	0.69 ^{***}	0.40	0.38	0.67 ^{***}
	6	0.72 ^{***}	0.47	0.50	0.72 ^{***}
	7	0.75 ^{***}	0.49	0.43	0.71 ^{***}
	8	0.75 ^{***}	0.48	0.46	0.68 ^{***}
LWP	3	0.68 ^{***}	0.18	0.34 ^{***}	0.57 ^{***}
	4	0.67 ^{***}	0.25	0.37 ^{**}	0.48 ^{***}
	5	0.68 ^{***}	0.23	0.43 ^{***}	0.49 ^{***}
	6	0.72 ^{***}	0.27	0.44	0.55 ^{***}
	7	0.71 ^{***}	0.30	0.36	0.59 ^{***}
	8	0.75 ^{***}	0.26	0.45	0.58 ^{***}
CF	3	0.42 ^{***}	0.19	0.05	0.46 ^{***}
	4	0.46 ^{***}	0.18	0.07	0.44 ^{***}
	5	0.46 ^{***}	0.20	0.09	0.47 ^{***}
	6	0.47 ^{***}	0.22	0.07	0.50 ^{***}
	7	0.49 ^{***}	0.19	0.08	0.56 ^{***}
	8	0.49 ^{***}	0.22	0.09	0.50 ^{***}
CTP	3	0.47	0.48	0.24	0.60
	4	0.44	0.56	0.21	0.58
	5	0.47	0.53	0.18	0.58
	6	0.51	0.56	0.36	0.69
	7	0.50	0.57	0.27	0.66

8 0.51 0.58 0.26 0.65

Note: ***indicates that the q value is significant at the 0.01 level ($p < 0.01$), **indicates that the q value is significant at the 0.05 level ($p < 0.05$).

Table 7. q values for factors which may influence cloud parameters over the YRD (9°x9°) in different number of classification levels (3~8) (see text) using Jenks natural breaks classification method, evaluated for data collected in the period from 2008-2022.

cloud parameters	number of classification levels	AOD	RH	LTS	PVV
CER	3	0.22	0.14	0.01	0.12
	4	0.32	0.19	0.05	0.14
	5	0.31	0.25	0.13	0.18
	6	0.33	0.17	0.17	0.23
	7	0.34	0.25	0.17	0.15
	8	0.38	0.27	0.19	0.23
COT	3	0.52***	0.47**	0.08	0.19
	4	0.53***	0.52***	0.10	0.31
	5	0.61***	0.45	0.12	0.29
	6	0.56**	0.45	0.11	0.28
	7	0.60***	0.49	0.12	0.28
	8	0.59	0.54	0.15	0.32
LWP	3	0.17	0.35	0.52***	0.16
	4	0.17	0.34	0.54***	0.00
	5	0.16	0.32	0.55***	0.18
	6	0.18	0.34	0.55	0.21
	7	0.18	0.38	0.54**	0.18
	8	0.23	0.37	0.55	0.20
CF	3	0.30***	0.01	0.34***	0.04
	4	0.37***	0.02	0.45***	0.03
	5	0.30***	0.02	0.50***	0.07
	6	0.39***	0.03	0.50***	0.09
	7	0.36***	0.05	0.58***	0.06
	8	0.38***	0.04	0.56***	0.10
CTP	3	0.49	0.72**	0.26	0.48
	4	0.46	0.74***	0.35	0.52
	5	0.50	0.74***	0.32	0.56
	6	0.52	0.75	0.32	0.56
	7	0.55	0.79	0.38	0.57
	8	0.50	0.79	0.36	0.56

Note: ***indicates that the q value is significant at the 0.01 level ($p < 0.01$), **indicates that the q value is significant at the 0.05 level ($p < 0.05$).

20. Eq2 - I am not familiar with this method, so might need a bit more explanation. Is sigma here the variance of y within the specified region/regime?

Answer: Sigma σ here is the standard deviation of y within the specified region/regime and σ^2 is the variance of y within the specified region/regime. This is specified in the text on page 13 of the revised manuscript (see lines 334-335): “and σ_i^2 and σ^2 denotes variance of samples in the subregion i and the total variance in the entire study area, respectively.”.

21. Eq2 - How does this method compare to a more common correlation measure for non-linear relationships, such as Spearman's Rank?

Answer: Spearman's Rank analysis and GDM are two different statistical methods used to study the correlation and degree of influence between variables.

Spearman's Rank analysis is a non-parametric statistical method used to measure the correlation between two variables. It assesses the monotonic relationship between variables by only calculating the rank order of the variables.

GDM is a spatial statistical analysis method mainly used to study the spatial correlation and influencing factors between geographical phenomena. It can identify the dominant role, interaction, and non-linear effects of different factors on the spatial distribution of geographical phenomena. It not only accounts for the rank order of the variables but also spatial information.

The results of Spearman's Rank analysis are shown in Table 8 and Table 9 below. Over the ECS, the correlation coefficient ρ between dependent a y variable (CER, COT, LWP) and an independent x variable (AOD, RH, LTS and PVV) are highest for AOD and following by PVV, LTS and RH. For CF and CTP, the correlation coefficient ρ is highest for PVV, followed by AOD, RH and LTS. The orders of correlation coefficient ρ are consistent with that of GDM q values (Table 5 in the revised manuscript). Over the YRD, for the CF the orders of correlation coefficient ρ are different from that of GDM q values (Table 6 in the revised manuscript). It shows that the correlation coefficient ρ is lowest for LTS but the GDM q value is highest for LTS. It may be attribute to that GDM not only accounts for the rank order of the variables as determined by the Spearman's Rank method but also spatial information.

Table 8. Statistics of Spearman's Rank analysis between x (AOD and meteorological conditions) and y (cloud parameters) over the ECS during 2008-2022. Statistically significant data points are indicated with * (p value < 0.01)**

Cloud parameter	AOD	RH	LTS	PVV
CER	-0.92***	0.61***	0.65***	-0.83***
COT	0.85***	-0.63***	-0.63***	0.83***
LWP	-0.85***	0.48***	0.59***	-0.71***
CF	0.65***	-0.46***	-0.23**	0.71***
CTP	-0.70***	0.73***	0.37***	-0.81***

Table 9. Statistics of Spearman's Rank analysis between x (AOD and meteorological conditions) and y (cloud parameters) over the YRD during 2008-2022. Statistically significant data points are indicated with * (p value < 0.01)

Cloud parameter	AOD	RH	LTS	PVV
CER	0.40***	-0.36***	-0.09	0.25**
COT	-0.76***	0.63***	-0.19	-0.42***
LWP	-0.35***	0.59***	-0.63***	-0.44***
CF	-0.49***	0.30***	0.26**	-0.32***
CTP	0.72***	-0.85***	0.48***	0.71***

22. L379 - The p-value for testing here is quoted as 0.01, but elsewhere it appears that 0.1 (a fairly lax criteria) is used.

Answer: Done. We have made unified standards that the p-value for testing here is quoted as 0.01 through the revised manuscript.

23. L422 - The high explanatory power of AOD for CF variations suggests that this method is not actually identifying causal relationships. While strong correlations between AOD and CF have been previously observed, they are likely due to aerosol humidification (Quaas et al, 2010), rather than an aerosol influence. It seems likely the same effect is being observed here, so care should be taken in the presentation of the results not to mis-attribute causality (unless applicable).

Answer: This study provides a general description of the sensitivity (S) of cloud parameters to the influence of different aerosol and meteorological parameters over YRD and ECS. Correlations between AOD and cloud parameters are found over the target regions, which can be attributed in part to the influence of general circulation. In general, there are many relations between the various parameters, both related to cloud microphysics and meteorology. It is not possible to completely separate meteorological influences from aerosol influences on clouds. This work can therefore only provide further evidence of the aerosol and meteorological effects on clouds and quantify the relative contributions and combined effects on clouds, but cannot quantify the absolute contributions with confidence. Thus, establishing cause and effect relationships between parameters is difficult and must be made with care.

We have added the following text in the Sect 4.6.1 (lines 647 to 666): “Tables 5 and 6 list q values for individual factors, together with p showing the absence of statistical significance in many cases, especially over the YRD, and often the explanatory power is not high when the significance is low. These data show that cloud parameters are dominated by aerosol effects over the ECS but meteorological influences on cloud parameters predominate over the YRD, as was also concluded from the analysis from “traditional” statistical methods presented in Section 4.5 and these conclusions are consistent with the results published by Andersen and Cermak (2015). Among the meteorological parameters, we also find that PVV (with highest q in the three meteorological parameters) predominantly influences cloud parameters over the ECS. Jones et al. (2009) and Jia et al. (2022) reported that stronger aerosol cloud interactions typically occur under higher updraft velocity conditions. In addition, we find that CTP is mainly affected by RH (q = 0.74***) and PVV (q = 0.56) over the YRD, as suggested by Koren et al. (2010). Koren et al. reported that observed cloud top height correlates best with model pressure updraft velocity and relative humidity. To some extent, LTS influences CER (q = 0.44***) and LWP (q = 0.43***) over the ECS, while, in contrast, over the YRD LTS

predominately influences CF ($q = 0.50^{***}$) and LWP ($q = 0.55^{***}$). Matsui et al. (2004) and Tan et al. (2017) reported that aerosol impact on CER is stronger in more dynamic environments that feature a lower LTS and argue that very high LTS environments dynamically suppress cloud droplet growth and reduce aci intensity. While strong correlations between AOD and cloud parameters have been previously observed, they are likely due to the swelling of aerosol particles in humid airmasses (Quaas et al, 2010), rather than an aerosol influence, which is in agreement with findings by, e.g., Myhre et al. (2007), Twohy et al. (2009) and Quaas et al. (2010).”.

We have also added the following text in the Sect 4.6.2 (lines 652 to 655 and lines 695-699): “Among the meteorological parameters, we find that the combined effect of AOD and PVV predominately influences on cloud parameters over the ECS. The result is in accord with the finding of Jones et al. (2009) and Jia et al. (2022) that stronger aerosol cloud interactions typically occur under higher updraft velocity conditions.” and “The results from the GDM interaction detector analysis clearly show the enhancement of the interaction q -values over the q -values for the individual factors. In other words, the explanatory power of the combined effects of aerosol and a meteorological parameter is larger than that of each parameter alone. Thus, the GDM provides an alternative way to obtain information on confounding effects of different parameters.”.

24. L469 - After the introduction of the GDM, sections 4.5 and 4.6 appear to go back to more 'traditional' methods as used by previous paper. I am not sure I really see how these section support the paper in determining the cause of the different ACI values in these regions. It would be good to have a clearer link to the other work performed and how it supports the overall aim and conclusions of the paper.

Answer: In the revised version, we have moved Sections 4.5 (now 4.4.) and 4.6 (now 4.5) before Section 4.4 (now 4.6). Thus, we first discuss findings from “traditional” methods, followed by findings using the GDM. We have also added Section 5 (Discussion) and Section 6 (Conclusions) where we discuss the different findings using “traditional” methods and GDM, with more emphasis on the added value of GDM.

25. L601 - Could the authors be more specific on how this study will help improve model parametrisations?

Answer: Aerosol particles, acting as cloud condensation nuclei, affect the number and size of cloud droplets. The link between aerosol and the formation and properties of clouds could better simulate changes in cloud parameters. By comparing with observational data of aerosols and clouds, the model's ability to simulate changes in cloud parameters can be evaluated. Meteorological factors are key influencing parameters for the formation and evolution of clouds, and a more accurate description of the relative contribution of meteorological factors can improve the parameterization scheme of the model. Therefore, by more accurately simulating and predicting the impact of aerosols and meteorological parameters on clouds, parameterization schemes will be adjusted and improved, which further improve the simulation ability and accuracy of climate models for cloud parameter changes.

The text in the Conclusion has been reorganized as “By comparison with aerosol and cloud observations, the regional climate model’s ability to simulate changes in cloud parameters can be evaluated. A more accurate description of the relative contribution of meteorological factors

can improve the parameterization scheme of the model over eastern China.” in the revision manuscript (lines 821-824).

References

We thanks referee#1 for providing these excellent references. They have been used in the manuscript and most of them have been quoted or summarized when appropriate. We have added some more references in the reference list of the revised manuscript.

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