Response to Referee #2

This study uses correlation and the geographical detector method (GDM) to study relationships between aerosol optical depth (AOD), meteorological indicators, and cloud properties, contrasting a heavily polluted region in mainland China to a cleaner region of the Pacific Ocean influenced by transported pollution. The authors find different signs of the AOD-cloud effective radius relationships and find that AOD explains a very large fraction of variability in cloud properties, especially in the cleaner region.

The manuscript is well written, and the Figures and Tables illustrate the results and discussion well. But I have a mixed opinion about the study. On the one hand, there are innovative aspects, such as the application of the GDM to the aerosol-cloud problem. On the other hand, the study uses large-scale, time-averaged correlations of aerosols and clouds that have been shown to say little about aerosol-cloud interactions. And the impact of AOD on cloud variability that results from the GDM is so large that it would require a strong case to bring confidence in the method and results. On balance, I suggest major revisions to give the authors the chance to justify their results.

The authors thank Referee #2 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 other comments. 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 comments:

1. Recent papers, and especially Gryspeerdt et al. (2023, 10.5194/acp-23-4115-2023) and Arola et al. (2022, 10.1038/s41467-022-34948-5), have seriously challenged the usefulness of correlating aerosol and cloud parameters as done in the present study. Cloud variability and retrieval errors are such that correlations between aerosol optical depth and cloud properties (CNDC, CER, LWP) can in fact be spurious. That means that a large fraction of past literature on aerosol-cloud interactions (including the studies cited lines 86-107) needs to be look at again critically. Attempts to minimise retrievals uncertainties (lines 172-175) will not address parts of the issues. I think the present study remains interesting (especially the GDM analysis), but the authors need to acknowledge the possibility that the correlations they find do not say much about aerosol-cloud interactions.

Answer: Gryspeerdt et al. (2023) discuss aci in terms of N_d rather than CER and emphasize the importance of the susceptibility β of N_d to aerosol. The main interest of their study is to determine RF_{aci} and the importance of accurate determination of β. The variation in β is responsible for much of the uncertainty in ERF_{aci} in climate models and β is central to the strength of cloud adjustments. Gryspeerdt et al. point out that uncertainties and differences occur with low aerosol conditions where satellite derived values of β are uncertain due to retrieval assumptions and separation of the (weak) aerosol signal from the surface reflectance. In high aerosol conditions, the (stronger) aerosol signal is relatively larger than the surface reflectance rendering more accurate aerosol retrieval in polluted conditions than in clean conditions. The larger uncertainty in clean condition reduces the correlation between CCN and the retrieved AOD due to regression dilution and thus reduces the magnitude of β in clean conditions. In the discussion, Gryspeerdt et al. argue that, for observational studies, the aerosol-N_d relationship is non-linear and the value of β determined for high aerosol conditions is not necessarily "a good guide" for β in low aerosol conditions. Furthermore, they argue that β in high conditions is more likely an underestimate.

In our study we used CER rather than N_d, for reasons discussed in the Introduction (see lines 177-183 in the revised manuscript): "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.", and we stratified by aerosol regime. We acknowledge the findings of Gryspeerdt et al. (2023) and possible consequences to our results with the following text added in Section 5, Discussion (lines 747-756):

"It is noticed that in recent papers (e.g., Gryspeerdt et al., 2023; Arola et al., 2022) the usefulness of correlating aerosol and cloud parameters has been seriously challenged because cloud variability and retrieval errors are such that correlations between AOD and cloud properties (N_d, CER, LWP) can be spurious. Gryspeerdt et al. (2023) discussed aci in terms of the susceptibility β of Nd to aerosol rather than the sensitivity S of CER to aerosol (see the discussion in the Introduction on the use of N_d vs CER), and the problem arises with low aerosol conditions due to larger aerosol retrieval uncertainty due to surface correction (larger surface effect on the radiance at the top of the atmosphere), which applies equally to β and S. In the current study we did not consider the lowest aerosol conditions by limiting the data to situations with AOD ≥ 0.1, as discussed in Section 4.2. Furthermore, we stratified the analysis for moderate (0.1 ≤ AOD < 0.3) and high (0.3 ≥ AOD) aerosol regimes, based on the data."

This text is followed by the discussion of the implications of the findings of Arola et al (2022) for our results (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° x 5°) 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."

2. The idea of using the GDM is interesting, but it is difficult to make physical sense of the results (Table 4 and 5). First, the q factors do not sum up to 1. What does that mean that AOD explains 87% of CER variability, while RH explains a further 36%? Then, the size of the q factors for AOD in Table 4, and to a lesser extent Table 5, stretches belief. If aerosols were that important in determining cloud properties, then estimating aerosol-cloud radiative forcing would have been very easy. Clearly, something goes wrong here. Is it perhaps that the four variables studied (AOD, RH, LTS, and PVV) are not independent? That the large q-values are simply a symptom of correlations caused by atmospheric circulation in the ECS and YRD? This is essentially what Figure 10 suggests. A strong discussion is needed to support the results.

Answer: A similar comment was made by Referee#1, i.e. that the q-values sum up to over 100% and about the interpretation of the q-values when the variables are not independent. Indeed, due to the interaction, the influence of a parameter may be strengthened or weakened and therefore the influence of different parameters need to be considered together. Therefore, our response is the same as that to Referee#1 Main point 1, while we also refer to the second part of our answer to your comment 3.

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 354-374) with "The interaction detector can be used to test for the influence of interaction between different influencing factors, e.g., x1 and x2, on the dependent factor (y) and whether this interaction weakens or enhances the influence of each of x1 or x2 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 x1 and x2 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 xi (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 x1 and x2 on y, obtained from the application of the factor detector method (Eq. 2), may be represented as q (x1) and q (x2). Hence, a new spatial unit and subregions may be generated by overlaying the factor strata x1 and x2, written as x1∩x2, where ∩ denotes the interaction between factor strata x1 and x2 as illustrated in Figure 3(d).

Thus, the q value of the interaction of x1∩x2 may be obtained, represented as q (x1∩x2). 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(x1∩x2) > q(x1) + q(x2), this is referred to as a nonlinear enhancement of two variables. And if q(x1∩x2) > Max[q(x1), q(x2)], 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.".

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, geographic detector can encompass the analysis of synergistic changes.

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) predominantely 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°x9°, 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°x4°) using higher resolution source data.

3. The GDM assumes that the spatial distributions of independent and dependent variables “should have evident similarities” [line 211]. But at what scale is that assumption true for aerosol-cloud interactions? One could expect the assumption to break down when going down to the scale of a cloud field because clouds evolve after their aerosol-influenced formation phase. Is that a problem?

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 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°x4°, 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°x8° and 15°x15°, 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, geographic detector can encompass the analysis of synergistic changes.

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In the current study, based on a regional scale of 9°x9°, 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°x4°) using higher resolution source data.

Other comments:

1. The name "ACI index" is vague. That quantity is really a sensitivity of cloud effective radius to changes in aerosol optical depth, in a similar way to beta_ln(N)-ln(tau) in Bellouin et al. (2020, doi: 10.1029/2019RG000660)

Answer: Following your suggestions below (in particular comment 5 referring to lines 55-78) we have changed the nomenclature and use sensitivity S (rather than β used in Bellouin et al. (2020)) and changed the title of Section 3.1 to "Sensitivity of cloud parameters to changes in aerosol concentrations" and used sensitivity throughout the manuscript. We also explained that we don't use cloud droplet number concentration (N_d) but cloud droplet effective radius (CER) and why we made this choice (see lines 175-186).

2. Lines 26 and 27: "significant" – is that in the statistical sense?

Answer: Yes, it is in the statistical sense and "significant" has been removed in order to make clear presentation.

3. Line 47: "in practice" in the atmospheric sciences. Other disciplines use the term more properly.

Answer: Thank you, we have changed "in practice" to "usually".

4. Lines 44-54: Those generalities on aerosols are not necessary, so that section could be shortened. In fact, the introduction could start directly from line 54: "Aerosol particles are important for climate…"

Answer: The manuscript discusses aerosol cloud interaction in contrasting regions as regards aerosol properties (high/low concentrations, composition). Therefore we feel that a short introduction on aerosols, their origin and their variability in space and time is appropriate. This short text also provides context for the description of the choice of study area (Section 2.1).

5. Lines 55-78: Note that many papers since Chapter 7 of the IPCC AR5 (Boucher et al. 2013) use the concept of aerosol-radiation and aerosol-cloud interactions and their respective adjustments (e.g., Bellouin et al. 2020, Quaas et al. 2022 10.5194/acp-22-12221-2022). The terms direct/1st indirect/2nd indirect remain in use in parts of the community, but it would be good to connect to the new terminology.

Answer: Thank you for this comment. Because the term "(in)direct" is still used quite often, also in recent publications, and in particular in the older literature, we had followed this terminology which is more common to us. However, we have of course also noticed the change and, although it was not easy to follow up on your comment, we have made an attempt and hope we have done it correctly, made no large mistakes, and done it everywhere where appropriate throughout the revised manuscript.

6. Lines 85-86: It should be said that using AOD as a proxy for aerosol concentrations when looking at aerosol-cloud interactions raises issues. See Section 6 of Bellouin et al. (2020).

Answer: Thank you for this comment. Indeed there are issues with the use of AOD and often AI (the product of AOD and the Ångström parameter, AE) is used. However there are also issues with AE from satellites and AE has even been withdrawn as a MODIS product from the more recent collections. The use of AOD in aci studies is discussed 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.".

7. Line 168: Andreae (2009) is often cited as justification for using AOD for looking at aerosol-cloud interactions, but ironically its Figure 1 shows that the correlation only exists across aerosol regimes. For a given regime (as done in the present study) there is essentially no correlation. I could not see why Kourtidis et al. (2015) justifies the use of AOD, but I may have missed it.

Answer: See our response to your comment 6 as regards using AOD as aerosol proxy. Specifically to this comment 7: Andreae (2009) plots AOD vs CCN for 4 aerosol types, which happen to be separated in two groups for low and high CCN and indeed the correlation was evaluated across these 4 aerosol regimes. However, it is noted that the number of data pairs is scarce but within each aerosol type the AOD increases with increasing CCN. This AOD-CCN relation may however vary between aerosol types (as would be expected for aerosol types with different composition and thus also hygroscopic properties), but the number of data points is too small to derive different relationships for different aerosol types. Furthermore, the aerosol types over each of the two study regions varies with season (seasonal emissions like desert dust in spring, biomass burning from different sources, domestic heating in winter) and large scale meteorological condition resulting in different transport pathways in different seasons.

We referenced Kourtidis et al. (2015) because these authors justify the use of AOD instead of AE based on personal communication with Lorraine Remer, as mentioned in our response to your comment 6.

8. Lines 169-170: That assumes that cloud contamination has a lesser impact on smaller AODs. Is that true?

In aerosol retrieval, cloud screening is a major source for over-estimation of the AOD, in particular in the vicinity of clouds which is important for aci. The impact of undetected clouds depends on the COD, and may be small (in an absolute sense) for thin Cirrus clouds, but also discrimination between high AOD and clouds is often a problem. The removal of cloud-contaminated pixels is not straightforward. A post-processing method shows the effect of removal of residual clouds on the AOD in both relatively clean and polluted areas (doi:10.5194/amt-10-491-2017). Alternative methods have been proposed such as setting a threshold for AOD < 0.6 proposed by Brendan et al. (2006) who used the MOD06 Collection 04 cloud product. Brendan et al. (2006) 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 (Varnái and Marshak, 2009) and the swelling of aerosols by higher relative humidity.” And “Varnái 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 ± (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.

We have added the following text to Section 2.2 (lines 252-260): “The choice of this threshold, rather than 0.6 used by Brendan et al. (2006), who used MOD06 Collection 04 products, is based on reports by Christenson et al. (2017) and (Varnái 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 (Varnái and Marshak, 2009) and the swelling of aerosols by higher relative humidity.” Varnái 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)."

9. Line 207: "intermittently" Probably not the correct word. Interchangeably?

Answer: Thank you for this suggestion, we have changed "intermittently" to "Interchangeably"

10. Line 231: Does q sum up to 1 for all factors considered? Is it also able to quantify an unexplained fraction that could suggest the need for more factors?

Answer: This comment is similar to a comment made by Referee#1 and was addressed in our response to your comment 2. Because the contribution of each independent variable (each factor) is calculated separately according to Eq. (2), the contributions of some factors (if needed) that are not considered can also be calculated separately according to Eq. (2).

11. Figure 3: What does that Figure tell the reader? It's impossible to say from its caption or from lines 241-245. The discussion needs to cover each of the panels in turn.

Answer: To better explain the Figure and clarify "interaction detector" and "interaction q-values", we have replaced the text below figure 2 (see lines 354-374 in the revised manuscript) with "The interaction detector can be used to test for the influence of interaction between different influencing factors, e.g., x1 and x2, on the dependent factor (y) and whether this interaction weakens or enhances the influence of each of x1 or x2 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 x1 and x2 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 xi (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 x1 and x2 on y, obtained from the application of the factor detector method (Eq. 2), may be represented as q (x1) and q (x2). Hence, a new spatial unit and subregions may be generated by overlaying the factor strata x1 and x2, written as $x1 \cap x2$, where $\cap$ denotes the interaction between factor strata x1 and x2 as illustrated in Figure 3(d). Thus, the q value of the interaction of $x1 \cap x2$ may be obtained, represented as q ($x1 \cap x2$). 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 $q(x1 \cap x2) > q(x1) + q(x2)$, this is referred to as a nonlinear enhancement of two variables. And if $q(x1 \cap x2) > Max[q(x1), q(x2)]$, 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.".

12. Lines 251-252: "for several different purposes". Give examples based on the papers cited.

Answer: Examples based on the GDM have been added in the revised manuscript below Table 2 (lines 383-387): "The geographical detector method has been used to detect influencing factors for several different purposes (e.g., Wang et al., 2018; Zhang and Zhao, 2018; Zhou et al., 2018). For example, the GDM was used to detect the influence of annual and seasonal factors on the spatial-temporal characteristics of surface water quality (Wang et al., 2018). Other examples are the application of the GDM to examine factors influencing regional energy-related carbon emissions (Zhang and Zhao, 2018) and to examine effects of socioeconomic development on fine particulate matter (PM2.5) in China (Zhou et al., 2018)."

13. Line 265: "averaged over the years 2008-2022". Does the study use 14-year averaged distributions, or a less dramatic averaging (e.g., multi-annual monthly means)? How can correlation of distributions averaged over such a long period still inform about the physical correlation between clouds and aerosols?

Answer: In Figure 4 we provide and overview of the data as averages over the whole study period (2008-2022). However, in the text we indicate that individual data pairs are used in the research, e.g., in Section 3.2. (lines 338-339) "In this study, multi-years of mean values of influencing factors (x) and dependent factors (y) were calculated for each raster grid" and in Section 4.2. (lines 429-431) "To investigate S, we used correlated data pairs for 15 years and the data was binned in AOD intervals with a bin width of 0.02, and the CER data in each AOD bin were averaged."

The use of multi-year averages is not uncommon in aci studies, e.g. Ma et al. (GRL 2018) use 2003-2016. Such large samples allow for large numbers of data pairs. However, with hindsight we agree that 15 years is very long. 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 the Figures 1 and 2 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<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 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<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."

In the GDM, the y data are recorded in a raster grid, over a total study area of 9°x9°, as illustrated in Figure 3 (Figure 2 in the revised 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 MYD08 data used in this study is 1°x1°, the data transformed into dot files is based on raster grid 1°x1°. Thus, 15-year averaged distributions of clouds (y, 5 layers) and aerosols/meteorological conditions (x, 4 layers) are used as input in the GDM. This is specified in the text on page 13 of the revised manuscript (see lines 338-341): "In this study, multi-years of mean values of influencing factors (x) and dependent factors (y) were calculated for each raster grid. Then, we classified the influencing factors (e.g. AOD and meteorological parameters) into 5 sub-regions by the Jenks natural breaks classification method (Brewer and Pickle, 2002).".

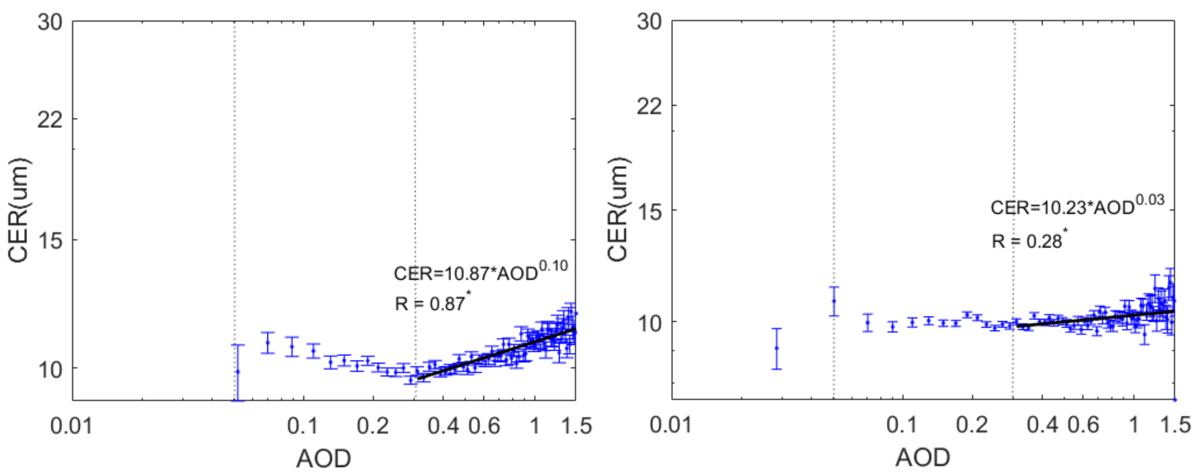

Figure 1. CER vs AOD over the YRD for the periods 2008-2014 (left) and 2015-2022 (right).

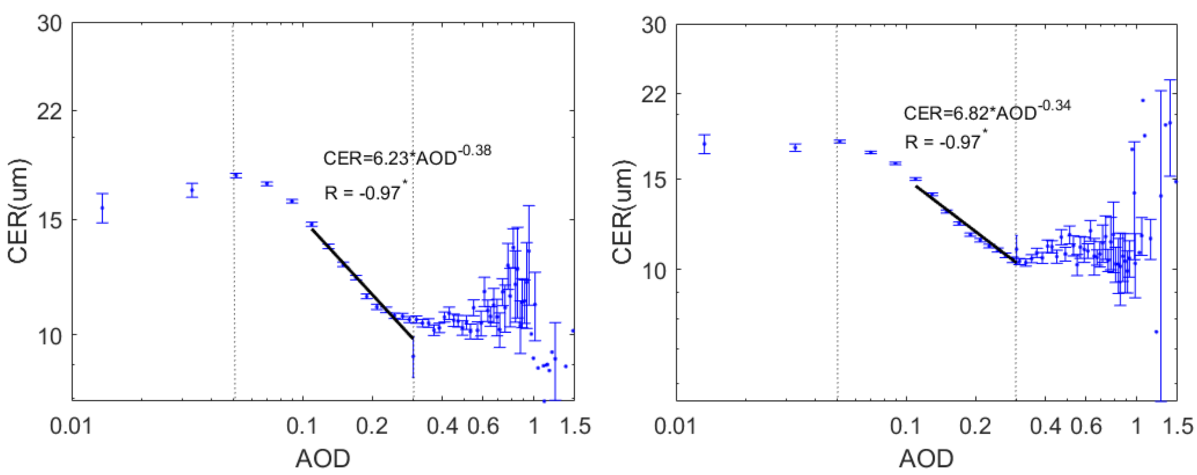

Figure 2. CER vs AOD over the ECS for the periods 2008-2014 (left) and 2015-2022 (right).

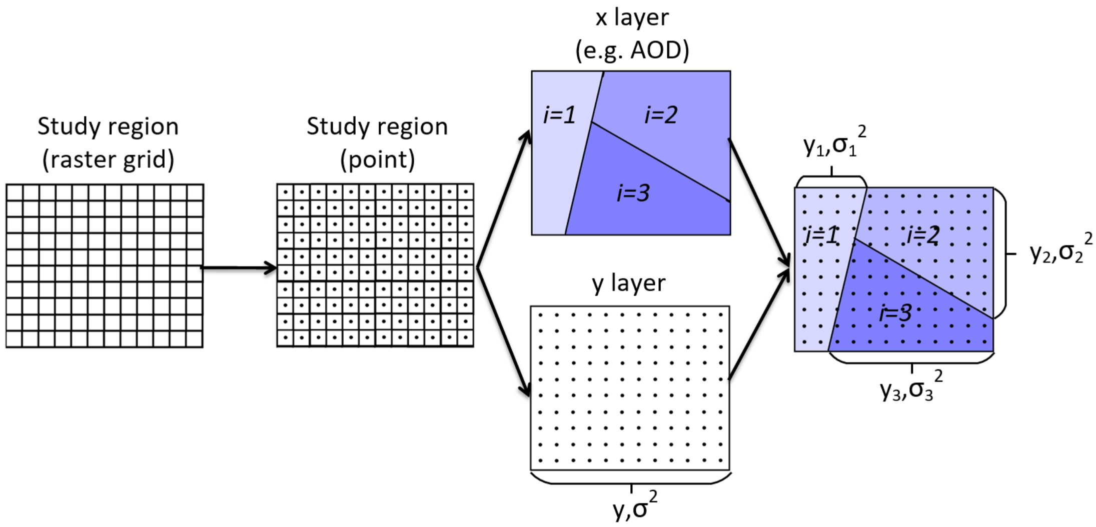

Figure 3. The principle of the geographical detector method. See text for explanation.

14. Lines 285-286: Or it could be due to meteorological factors.

Answer: In this section we describe the observations based on Figure 4 in the revised manuscript. We note that over ocean the aerosol properties are different than over land and certainly sea spray aerosol is abundant, while over land other aerosol types dominate. In the next Section we notice that the sensitivity of CER to AOD is larger over ocean than over land, which confirms the observations in lines 285-286 (now lines 421-422 in the revised manuscript). Certainly, meteorological factors influence the aci too and the interactive q-factors presented and discussed in Section 4.6.2 show that the combined effect has a larger influence than the effect of one factor alone. However, we prefer to structure the paper and go step by step through the different aspects. To explain this, we have added the following text above Figure 4 (lines 422-424): "The influence of different factors on the sensitivity of cloud parameters to aerosol and the adjustments are discussed in the following sections, based on both statistical methods and the application of the GDM."

15. Line 373: Missing word: "in the range of"

Answer: Thank you for this comment: corrected.