We sincerely thank the reviewers for their thoughtful comments, insightful questions, and constructive suggestions. Their feedback has greatly helped us clarify our ideas, strengthen our arguments, and improve the overall quality of the manuscript. Our responses are in blue text.

Major Comments.

1) Readability: The new statistical approach is meticulously written, but it is often hard to read due to various statistical jargon that is unfamiliar to atmospheric scientists like me. Can you clearly define these terms at the beginning? For example, define it like this in the table.

Confounder: a variable that affects both the dependent and independent variables in a study, causing an association that may not be accurate. (parameters include ….)

Exposures: Any factor that may be associated with an outcome of interest. (parameters include ….)

Probably these terms are common in epidemiology, but not in atmospheric science.

We thank the reviewer for this suggestion. It would indeed be helpful for the reader to be acquainted with these terms earlier in the manuscript. We have added a table and a few sentences about these variables to the introduction where the g-computation model is first introduced. This information is provided to the reader again in Section 3 where the g-computation analysis begins.

We added these sentences to Line 99 in the original manuscript: "In general, g-computation requires the identification of three types of variables for causal analysis: the exposure variable, the outcome variable, and the confounder variable(s). These variables are described in Table 1 and further explained in Section 3."

Table 1. Explanations of each term in the g-computation model with examples.

Terms	Explanations	Examples
Exposure variable / Independent variable	It is a variable whose causal effect on another variable (outcome) is being investigated. It represents the condition being manipulated or analyzed in hypothetical scenarios.	Aerosol number concentration, CCN number concentration
Outcome variable / Dependent variable	It is the variable of interest for which we aim to estimate the causal effect of an exposure. By applying g-computation, potential outcomes under varying exposure levels can be simulated, allowing for the assessment of differences between exposure scenarios.	Convective cloud 30-dBZ echo top height

Confounder / Confounding variable	They are variables, other than the one being studied (the exposure), that are associated with both the outcome and the exposure. They can distort or mask the true effect of the exposure on the outcome, leading to inaccurate conclusions about the relationship between the two.	Convective Available Potential Energy, Environmental Lapse Rate

2) New and traditional approach: At the end of the manuscript, the authors mentioned quite significant statements "Nevertheless, this study pioneers the use……….. scientific questions". To be honest, I still wonder why this new method is so novel compared to the previous old approach because there's no comparison between the new and traditional statistical approaches. For example, here is one of the earliest aerosol-deep convection manuscripts.

Lin, J. C., Matsui, T., Pielke, R. A., & Kummerow, C. (2006). Effects of biomass-burning-derived aerosols on precipitation and clouds in the Amazon Basin: A satellite-based empirical study. Journal of Geophysical Research: Atmospheres, 111(D19). https://doi.org/10.1029/2005JD006884

In this paper, DCC properties (precipitation, cloud top height, and cloud fraction) are related to aerosol optical depth for a given meteorological parameter (cloud work function in that study). Can you compare your novel approach with this traditional approach (simple statistics stratified by meteorological parameters)? Do you think the old approach leads to significant biases in understanding the aerosol-DCC relationship? Can you prove or briefly explain?

We first thank the reviewer for providing the reference. (We added it to the introduction.)

In Lin et al. (2006), they relied on bivariate correlations, which do not account for basic confounding effects. In contrast, our method extends previous capabilities and attempts to control for confounding using known or potentially confounders.

We are not denying the fact that linear regression or correlation can be used for causal inference, but only under ideal circumstances where individual values are *randomly assigned* to groups. This condition, however, is not applicable to our observational study or similar types of studies in atmospheric science. Fundamentally, whether linear regression can infer causal relationship depends on how the data was collected. See the first few paragraphs of the introduction in Chatton et al. (2020) for more information.

In the case of aerosol-convection interactions, it is *impossible* to erase the background aerosol state and randomly inject specific amounts of cloud condensation nuclei (CCN) into naturally formed convective clouds with current technologies. The CCN concentration at a particular location on a given day can be a result of other factors, such as humidity, wind direction, and/or pre-existing convection. These hidden factors (confounders) could themselves be the true causes of changes in convective intensity. As long as CCN concentrations cannot be randomly assigned, bivariable correlation coefficients cannot accurately infer causal effects. In some cases, bivariate correlations can lead to more bias compared with g-computation results as discussed in Snowden et al. (2011).

In our method, we control the aerosol state through a "forced" experiment, which, though less ideal than a fully randomized experiment, involves adjusting certain variables while others are held constant or randomized to minimize their confounding effects. In our case, we forced the aerosol number concentration to be 1 as a polluted condition and 0 as a clean condition. Our identified confounders were kept constant in these two scenarios.

Additionally, g-computation offers a more flexible framework. While we currently use linear regression as our Q-model in the first step, it can support more complex methods, such as machine learning regression, to accurately capture nonlinear relationships. In contrast, correlation analysis is limited to detecting linear relationships.

3) Potential biases in radar-based approach: Authors use threshold NEXRAD radar parameters to define DCC. However, if DCC has a much smaller amount of raindrops due to a large number of background aerosols, this cell may not be counted as DCC due to larger concentrations of small-size droplets, which won't increase S-band reflectivity. Alternatively, if you use cloud optical depths and top height, the DCC sampling can include such cells. This is a NEXRAD-based cell tracking approach, so you cannot change your approach. However, it is important to discuss potential sampling biases using the NEXRAD radar.

We thank the reviewer for pointing this out. We agree that using fixed thresholds on radar reflectivity for tracking cells may introduce potential uncertainties in sample selection.

To address this, we have added the following sentences to Section 2.1 in the manuscript: "Note that using fixed thresholds may potentially influence the selection of DCCs investigated in the study, particularly in conditions where DCCs contain fewer raindrops due to the presence of a large number of background aerosols."

Minor Comments.

Line 87: Please remove parenthesis "(either invi…..)".

Agreed

Line 120-121: "exclude the presence of shallow convection" sounds like removing the sampling during shallow stages. So I suggest just re-write as "exclude the shallow convection cells".

Agreed

Line 179: Please define the threshold of diameters of “ultrafine aerosols”.

Done

Line 274: “buoyancy-driven DCCs”. Well, all DCCs are driven by buoyancy over the flat terrain. So you may re-write this as “locally driven DCCs”.

Agreed

Line 294: “30-dBZ ETH/15-dBZ ETH” should be “30-dBZ ETH and15-dBZ ETH”.

Done

Line 303-306: We won’t be able to measure supersaturation directly within the convective storms. However, you can infer the required supersaturation in order to activate all aerosols (including ultrafine). For this case, can you describe roughly how much supersaturation is required to support your argument?

The exact supersaturation required to activate all aerosol particles in a particular environment is challenging to estimate without appropriate instrumentation. The actual supersaturation values may depend on meteorological conditions, including atmospheric instability, moisture content, and updraft strength. A SS value of 1% does not yield a statistically meaningful effect of Nccn on DCC ETH in our study (Figure 8 in the manuscript). We hypothesize that a higher SS (> 1%) may be necessary to activate more particles and effectively influence DCCs in the Houston region. However, we have refrained from adding this discussion of hypothetical SS values needed to activate additional aerosols within the manuscript. This is because the values remain speculative and are not based on actual observations of SS within the convective clouds.

Fig. 4: Why is there no correlation between thermodynamics and Nccn? It seems to be more important?

The black hatch lines indicate non-significant R-values on Figure 4, meaning these values are not statistically significant. Basically, there are no significant correlations between most of the environmental variables and Nccn in Houston.

Line 547: “30-dBZ ETH/15-dBZ ETH is 1.1 km/1.0 km,” should be “30-dBZ ETH and15-dBZ ETH is 1.1 km and 1.0 km, respectively.”

Agreed