Referee #5

As a new reviewer of this round of review, I found the manuscript is in good shape with important science questions, sound method, and convincing results. I also read the authors' responses to the previous comments, and they all seem well addressed. Meanwhile, I have some clarification questions on the Structural Equation Model (SEM) used to quantify the interactions between the various factors and light precipitation: 1) Are the targeted relationships assumed to be linear in this framework? 2) How does the model handle crossing correlation? E.g., both RH and TCLW contribute positively to light rain, but RH is also correlated with TCLW. This information is important for readers to understand Fig. 10 which so far nicely summarizes the key messages of the study.

Re: We thank the reviewer for the valuable comments, which we have addressed in the revised manuscript or responded as follows,.

1. Yes, the standard SEM framework we employed, which articulates hypotheses "in the form of a series of regression equations" (as stated in the revised Methods section, Line183), inherently models the relationships as linear. This is a common and powerful approach for quantifying the strength and significance of direct and indirect pathways within a complex system, providing clear, interpretable path coefficients (e.g., the r = -0.29 for $PM_{2.5}$'s direct effect in Fig. 10). While the atmosphere exhibits complexities, the linear SEM served our goal of identifying and quantifying the dominant mechanistic pathways behind the observed decadal trends.
2. Regarding how does the model handle the crossing correlation), actually, this is a fundamental and powerful feature of SEM. The SEM framework can simultaneously estimate all the relationships in the hypothesized model. For example, when it calculates the path coefficient from RH to Light Rain, it does so while holding the influence of TCLW constant. In statistical terms, it provides the direct effect of RH, after accounting for or "partialling out" the variation in RH that is common with TCLW (and vice versa).

   In essence, the path coefficients in Fig. 10 (e.g., r = 0.41 for TCLW) represent the independent contribution of each variable, already disentangled from the correlations with other variables in the model.

We have also revised the main text accordingly, please refer to lines186-189 in the revised manuscript:

"… One of the most important advantages of SEM is its capacity to disentangle complex interdependencies among multiple parameters. This is achieved by estimating the independent (direct) effect of each variable while simultaneously accounting for its correlations with other variables in the model….."

Referee #3

Thank you for the thorough revisions. Most of my previous comments have been adequately addressed, and the manuscript has improved substantially in clarity, structure, and analytical rigor. The authors' efforts to refine the methodology and strengthen the discussion are appreciated. However, there remain a few additional comments and suggestions that should be considered to further enhance the quality and completeness of the manuscript.

1. Justification of 2013 as a turning point: It is difficult to identify 2013 as the turning point in the national average light rain trends based on the blue line in Figure 1. The year 2007 appears to be a more reasonable inflection point for the nationwide average. However, I agree that 2013 serves as a meaningful transition year for both aerosol and light rain in the six selected regions. Additionally, Figure 1 (right) indicates that some regions do not exhibit clear increasing or decreasing trends. Please use caution when generalizing these findings to the national scale, and consider emphasizing they primarily reflect the characteristics of the selected regions.

Re: We thank the reviewer for this nuanced comment.. According to the comment, we have revised the manuscript and included several statements to avoid vague and broad statements and conclusions. See lines 213-219, lines131-134, or as follows,

"…. Note that, before 2013, the national average annual light rain days showed significant interannual fluctuations, with the lowest number of light rain days recorded in 2007 (Fig. 1a). This makes it seem as if 2007 was a turning point where the trend of light rain frequency shifted from decreasing to increasing. However, when the analysis is focused on specific different regions, it is found that the turning point of light rain frequency still occurred in 2013 (Fig. 2).

Considering the variation trend of PM2.5 comprehensively, this study divides the research period into two phases of 2001–2013 and 2013–2022…..”

“…Moreover, the frequency of light rain in most regions of China, especially those heavily affected by human activities, also showed a change pattern of first decreasing and then increasing before and after 2013 (Fig. 1, Fig. 2)…”

2. Justification of Selected Factors in XGBoost Model: Thank you for providing a clear physics-based rationale for the selected variables. I suggest considering the inclusion of additional potentially relevant parameters, such as geopotential height and vertical velocity (omega). Using the XGBoost model’s Gini importance scores, you could then identify the top ~10 most influential variables. This would help demonstrate whether the chosen factors indeed capture the dominant contributions.

Re: We thank the reviewer for this constructive suggestion regarding the inclusion of additional meteorological parameters.

The variables selected for our XGBoost model (CAPE, RH, T, TCLW, LCC, $PM_{2.5}$, E, and WS) were chosen to specifically represent the key thermodynamic and microphysial processes through which aerosols influence light rain. $PM_{2.5}$ represents the aerosol loading and its potential for cloud microphysical modulation; CAPE, RH, and T describe the thermodynamic environment for convection triggering and condensation; TCLW and LCC reflect cloud microphysical and macro-physical structures directly relevant to precipitation formation; and E and WS represent surface moisture supply and horizontal transport, respectively.

We agree with the reviewer that parameters such as geopotential height and vertical velocity (omega) indeed influence precipitation by controlling large-scale synoptic conditions and vertical motion. However, it is important to note that the influence of these dynamic factors is indirectly captured by our selected variable set. Vertical velocity is closely related to CAPE, RH, TCLW, and LCC, as enhanced upward motion is often associated with greater instability, moisture, and cloud liquid water. Geopotential height influences the patterns of temperature, humidity, and wind fields, thereby indirectly affecting the distributions of CAPE, T, and WS. Therefore, even without the explicit inclusion of geopotential height and omega, their physical effects are represented within our current modeling framework.

3. Figure1: The added black dots are difficult to discern in regions of deep blue and dark red. Please consider adjusting their color, size, or outline to improve visibility and contrast.

Re: We thank the reviewer for pointing out the visibility issue of significance markers in Figure 1. The revised figure is included below and updated in the manuscript on line 220.

Revised Figure 1:

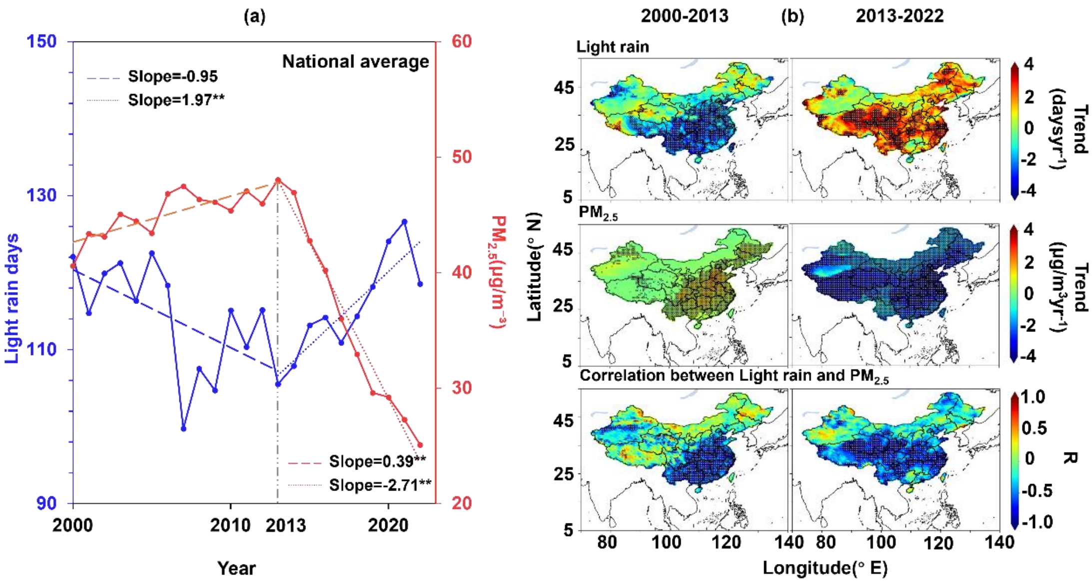

Figure 1. National trend and spatial patterns of light rain and PM2.5. (a) Nationally averaged time series of light rain days (blue lines) and PM2.5 mass concentration (red lines) from 2000 to 2022. The dashed lines represent the piecewise linear trends for the periods 2000–2013 and 2013–2022, with the slopes indicated. Trends significant at the 95% confidence level are marked with **. (b) Spatial distribution of the trends of light rain, PM2.5 and spatial correlation between PM2.5 and light rain days in 2000–2013 and 2013–2022. This map of China is created based on same-origin data provided by the Tianditu Platform (www.tianditu.gov.cn). (black dots indicate passing the 95% significance test).