Dear Editors and Reviewers:

Thank you very much for your careful review and constructive suggestions with regard to our manuscript "The contribution of fires to $PM_{2.5}$ and population exposure in Asia Pacific" (Manuscript Number: egusphere-2025-598). Those comments are valuable and helpful for revising and improving our paper. We have studied these comments carefully and made changes in the manuscript according the reviewers' comments. The responses to the reviewer' comments are listed as follows.

RC2: This study investigated the contribution of forest and vegetation fires to $PM_{2.5}$ and public health across Pacific Asia. The fire-specific $PM_{2.5}$ was effectively isolated from the monitoring data using the trajectory-fire interception method (TFIM) in combination with the random forest method. Based on the reliable and timely dataset, the geographical disparities in population exposure to both $PM_{2.5}$ and fire-specific $PM_{2.5}$ were estimated. The topic is novel, and the findings provide valuable insights for $PM_{2.5}$-related public health. Moreover, this manuscript is well-structured and readable. However, several issues need to be clarified before it can be considered for publication. Below are specific comments:

Response: Thanks for recognition of novelty and value of our study. We appreciate the valuable comments and suggestions and have made necessary revisions of our manuscript as below.

Specific Comments

1. I suggest changing the regional abbreviations to Southeast Asia (SEA), Northeast Asia (NEA), East Asia (EA) and Central Asia (CA), respectively. And these key regions should be marked in Figure 1.

Response: Thank you for the suggestion. We have updated the regional abbreviations to Southeast Asia (SEA), Northeast Asia (NEA), East Asia (EA), and Central Asia (CA) to enhance clarity. Besides, we have added Figure 1(b), which provides specific scopes of each region. Please see Figure 1(b) and the corresponding text thorough the revised manuscript for the modifications.

2. To derive fire-specific $PM_{2.5}$ concentrations, a machine learning method was employed using aerosol variables, AOD, meteorological factors, land use, NDVI, and the GDP data. Ultimately, 15 of these variables were selected to fit $PM_{2.5}$ concentrations. In recent years, many Asian countries have implemented strict anthropogenic emissions reduction strategies to mitigate $PM_{2.5}$ pollution

(see lines 322-330 for details). Anthropogenic emissions play crucial role in $PM_{2.5}$, but they are not incorporated into the machine learning model. While some variables, such as GDP and population, can indirectly reflect changes in anthropogenic emissions, the relationship needs to be further clarified. Therefore, the authors should briefly describe the machine learning method and variables used, even in the supporting information.

Response: We appreciate the insight comment. It is indeed important to acknowledge the significant role of anthropogenic emissions in ambient $PM_{2.5}$ concentrations across Asian countries. To comprehensively account for anthropogenic aerosols in this study, we considered not only indirect reflection features, such as GDP and population, during the construction of machine learning model, but also various aerosol data that directly reflect anthropogenic sources. This includes black carbon, organic carbon, SO_2 surface mass concentrations and so on. These data are derived from the MERRA-2 reanalysis, which assimilates multiple aerosol remote sensing, emissions, and meteorological datasets using the Goddard Earth Observing System Model. With these advances, MERRA-2 aerosol products can provide reliable anthropogenic and natural aerosols (like dust). Therefore, we did not incorporate anthropogenic emissions during dataset construction. We have added related descriptions about the machine learning method and variable used. Please see Line 234-242 and 347-356 in the revised manuscript.

3. Section 3 Results: It is recommended that additional subheadings (e.g., 3.1, 3.2, 3.3, ...) be added to improve clarity. Furthermore, more attention should be given to key regions (SEA, EA, NEA and CA) during wildfires. Regions with extremely sparse stations (Figure 1), such as Mongolia and the Tibetan Plateau, may be masked out due to the large uncertainties in their results.

Response: Thank you very much for the valuable comment and suggestions.

(1) We have added subheadings in Section 3 Results to enhance clarity and facilitate reading. The subheadings are:

3.1 Estimating fire-specific $PM_{2.5}$

3.2 The spatial and temporal distributions of $PM_{2.5}$ and fire-specific $PM_{2.5}$

3.3 The fire-specific $PM_{2.5}$ exposure and health impact

3.4 Future trends of fire-specific $PM_{2.5}$ under climate change

The subheadings help structure the section more clearly and improve the overall readability.

(2) Regarding the emphasis on key regions (SEA, EA ,NEA and CA) during fires, we have provided Figure 8, 9 and S1, along with analysis in the text, revealing spatial and temporal distributions of fire-specific $PM_{2.5}$ in the key regions during fire season. Additionally, we have showed and discussed the population exposure and health impact of fire-specific $PM_{2.5}$ in key regions during fire season.

(3) As for the regions with extremely sparse stations, like Mongolia and Tibetan Plateau. We think the sparsity of stations will not increase the uncertainty in the calculations for the specific stations. There are two key steps in estimation of fire-specific $PM_{2.5}$ at a station using TFIM method.

First, determine whether a station was exposed to fire smoke at a specific time based on back trajectory calculations and satellite fire point data. The fire point distribution monitoring by satellite is not influenced by distribution of ground monitoring stations, and reflects exposure conditions at the station accurately. Subsequently, extract non-smoke $PM_{2.5}$ employing machine learning method. In this process, we correspond data of different resolutions to station data based on the nearest distance principle. The model was constructed through point-to-point comparisons.Both these key processes remain unaffected by the distribution of stations.

In areas with sparse stations, while the calculation results may not accurately reflect the fine spatial distribution within the region, using these averages to represent the regional mean is still relatively reasonable.

We have added some explanations regarding calculation and representative of fire-specific $PM_{2.5}$ in regions with sparse stations. Please see subheadings in Result, Figure 8, 9 and S1 and Line 400-403 of the revised manuscript.

4. Figure 10 and 11: To my knowledge, the Health Impact Function (HIF) exhibits large uncertainty due to the relative risk (RR). Additionally, the Integrated Exposure-Response (IER) equation varies by region and population, resulting in a confidence interval in the estimated number of premature deaths. Although these key parameters are from Burrett et al. (2014) and Song et al. (2017) (please note that the citation of Song is missing in the reference list) in this study, they should still be explicitly provided.

Response: We appreciate the insightful comment and apologize for the missing information in the reference list. We have included the confidence intervals in estimated number of premature deaths, as the key parameters from Burrett et al. (2014) and Song et al. (2017) provide necessary confidence intervals for these values. Additionally, the parameters used in this study have been updated in the Supplemental Information, and the missing citation for Song et al. (2017) has been added to the reference list. Please see Line 23-28, 264-265, 440-447, 528-533 and 752-753 in the revised manuscript, and Table S1 in the Supplemental Information.

5. Figure 12: The results related to vaper pressure deficit (VPD) appear some what disconnected from the main body of this manuscript.

Response: Thanks for the comment. We provide variations of VPD in Figure 12 is due to its common use as a climate indicator to establish the relationship between climate change and fire occurrence or emissions (Abatzoglou and Williams, 2016; Burke et al., 2023). In this study, we analyzed historical data and found the positive relationship existing between VPD and fire-specific $PM_{2.5}$ across different regions of Asia Pacific (Figure 12a). Based on this, we can roughly infer future trend in fire-specific $PM_{2.5}$ through examining the VPD future trends (Figure 12b), assuming that relationship between future VPD and fire-specific $PM_{2.5}$ continues to exist. The analysis is important because because they allow us to associate fire-specific $PM_{2.5}$ with climate change, and explore future changes in fire-specific $PM_{2.5}$. Through discussion, we can examine the necessity of addressing climate change and air pollution in a coordinated manner. Of course, studying the future trends of fire-specific $PM_{2.5}$ will require integrating more data and methods for a more precise analysis, which is a direction for our future research. We have added more descriptions about this in the manuscript. Please see Line 557-563 in the revised manuscript.

Technical Corrections

1. Normally, references are sorted alphabetically rather than chronologically.

Response: Thank you for the careful comment. We have re-sorted the references to ensure they are sorted as alphabetically. Please see Reference in the revised manuscript.

2. Line 230: “in this study” instead of “is this study”

Response: We apologize for the clerical error and have modified it in Line 270 of the revised manuscript.

3. Figure 8: Please add the unit.

Response: We feel sorry for the neglect and have added the unit in the figure. Please see Figure 8 in the revised manuscript.

4. The manuscript contains minor spelling and grammatical errors that should be corrected.

Response: Thanks for the valuable comment. We have carefully review the text and make corrections to ensure clarity and accuracy. Please see throughout the revised manuscript.

Best regards,

Authors