We would like to express our sincere appreciation to the Reviewer #1 for the valuable and constructive suggestions, which have helped us improve the quality of this manuscript. We have addressed all these comments carefully and revised the manuscript accordingly. Following the Reviewer' comments in black, please find our point-to-point responses in blue. Hereafter, all new added or modified sentences are marked in blue and italic in this response.

Reviewer #1

Major comments:

1. While the paper demonstrates the benefit of using EMIT data in methodology, it would be helpful to provide a quantitative assessment of uncertainties introduced by the interpolation and assumptions in EMIT data processing (e.g., feldspar/quartz filling).

Response: We appreciate the reviewer's suggestion regarding the need for a more detailed quantitative assessment of uncertainties introduced by the interpolation and assumptions in EMIT data processing, particularly in relation to the filling of minerals like feldspar and quartz. We fully agree that understanding these uncertainties is crucial for a comprehensive evaluation of the methodology.

EMIT data processing involves spatial interpolation to create gridded maps of soil mineral composition. The primary interpolation method used is based on geographic mixing assumptions, where the spectral abundance of minerals detected at a given location is extrapolated to cover the grid cell. The uncertainty in this process arises from the assumption that the detected mineral signatures are representative of the entire grid cell. For minerals not directly measured by EMIT, such as quartz and feldspar, we use soil type conversion methods based on previous studies (e.g., Claquin et al., 1999; Journet et al., 2014) to estimate their contributions. These estimates are then used to fill in the remaining fraction of the soil composition.

We have revised Section 2.3 of the manuscript to include a quantitative assessment of uncertainties associated with the EMIT data processing as follow.

"*In contrast, the EMIT dataset (https://earth.jpl.nasa.gov/emit/data/data-products) required additional preprocessing, as it reports only normalized spectral abundances rather than mineral mass fractions. These spectral abundances were therefore recalculated to represent the normalized mass proportions of each mineral in each substrate. Furthermore, EMIT does not include data for feldspar and quartz, necessitating additional correction procedures described below.*

When the total mineral composition from EMIT summed to less than 100%, indicating missing mineral contributions, the residual fraction was assigned to quartz and feldspar based on their relative proportions in J2014 or N2012. Because EMIT reports illite and mica as a single category, their individual abundances were separated according to the ratios found in N2012 or J2014. For minerals that occur in both clay and silt fractions, EMIT values were partitioned following the relative contributions from N2012 or J2014.

For minerals not directly observed by EMIT (e.g., quartz and feldspar), their mass fractions were estimated using soil-type conversion methods from previous studies (Claquin et al., 1999; Journet et al., 2014). The spatial distributions of clay and silt were obtained from the global SoilW texture dataset (http://globalchange.bnu.edu.cn/research/soilw) at 1 km resolution and resampled to 0.5° to match EMIT data. Similarly, the J2014 and N2012 mineral datasets were resampled to 0.5° resolution. Major minerals extracted from EMIT L3 include calcite, dolomite, chlorite, goethite, gypsum, hematite, illite+muscovite, kaolinite, montmorillonite, and vermiculite. Notably, in the official EMIT L3B dataset (https://data.lpdaac.earthdatacloud.nasa.gov/lp-prod-protected/EMITL3ASA.001/EMIT_L3_ASA_001/EMIT_L3_ASA_001.nc), illite and muscovite are combined because they were jointly identified during the Tetracorder analysis of L2B data using mineral groups 1 and 2 and the corresponding band depths (https://github.com/nasa/EMIT-Data-Resources/blob/main/data/mineral_grouping_matrix_20230503.csv).

The EMIT mineral fractions were normalized so that their sum at each grid point *did not exceed unity. Any remaining fraction was attributed to quartz and feldspars according to their relative proportions in J2014 or N2012. To ensure consistency with the CHIMERE mineral representation, dolomite was merged into calcite, illite+muscovite was separated into illite and mica, and montmorillonite was treated as smectite. The mineral fractions were then converted to density-weighted values and renormalized at each grid point so that the total sum equaled one. Finally, each mineral was partitioned into clay and silt fractions based on the J2014 ratios, and the resulting fractions were normalized using Equations (1)–(4). The processed dataset was exported as a NetCDF file to serve as input for the CHIMERE model.*

To ensure mineral mass balance and model consistency, a normalization and partitioning procedure was applied as follows. Equation (1) defines the total mass fraction (MF_j) of mineral j as the sum of its contributions from the clay (MFC_j) and silt (MFS_j) fractions:

$$MF_j = MFC_j + MFS_j \ \ for\ all \in M_{CHIMERE} \tag{1}$$

Equation (2) enforces a normalization constraint so that the sum of all mineral mass fractions equals unity at each grid point.

$$1 = \sum_{j \in M_{CHIMERE}} MF_j \tag{2}$$

The normalized total fraction of each mineral (MF_j^*) was then redistributed between clay and silt according to their relative contributions in the reference dataset (J2014 or N2012), as shown in Equations (3) and (4):

$$MFS_j^* = MF_j^* \frac{MFS_j}{MFS_j + MFC_j} \tag{3}$$

$$MFC_j^* = MF_j^* \frac{MFC_j}{MFS_j + MFC_j} \tag{4}$$

Here, MFS_j^* and MFC_j^* represent the normalized mass fractions of mineral j in the silt and clay fractions, respectively. The weighting terms MFS_j and MFC_j preserve the clay–silt distribution patterns derived from the reference datasets while maintaining the normalized total (MF_j^*).”

2. The manuscript often mentions ACI (aerosol-cloud interaction), yet the modeling focuses on ARI only. Please clarify this distinction earlier in the Introduction and reduce any ambiguity about what has or has not been included.

Response: The Introduction of manuscript has been revised to clarify this distinction as follows.

"*Since the aerosol nucleation processes (ACI effects) of specific mineral components are not represented in the current two-way coupled WRF–CHIMERE framework, the present study concentrates on the ARI effects of dust minerals. This focus ensures a clear and robust assessment of how mineralogical composition influences radiative processes, without introducing additional uncertainties arising from incomplete cloud-related parameterizations. In this study, we employ a two-way coupled WRF–CHIMERE model with three mineralogical databases to investigate how dust composition influences radiation and meteorology in North China during a severe dust storm. Section 2 describes the model configuration and data sources, Section 3 presents the simulations with emphasis on ARI-induced impacts on meteorology and air quality, and Section 4 summarizes the main findings*."

3. The SSR and PM_{10} comparisons are robust, but more details on the performance metrics (bias, RMSE, etc.) across multiple sites and time periods would strengthen the validation claims.

Response: Additional details on the model evaluation have been included. In the revised manuscript, we now provide site-specific performance metrics (bias, RMSE, correlation coefficient) for both SSR and PM_{10} across multiple observational sites and time periods. These results are summarized in Table 1 and Figure 2 and discussed in Section 3.1.

"*The model demonstrates strong overall performance, with correlation coefficients (R) between observed and simulated values reaching approximately 0.7 for SSR and WS10, and up to 0.93 for T2. These results indicate the model's ability to capture key atmospheric patterns and variability across the simulation domain.*

Nevertheless, systematic biases are apparent, particularly in North China, where the model tends to overestimate SSR and WS10 by 60.69%–68.92% and 17.06%–17.52%, respectively, while underestimating T2 by 0.48%–0.58%. The overestimation of SSR likely results from uncertainties in cloud development associated with planetary boundary layer and convection parameterizations (Alapaty et al., 2012). The systematic overestimation of 10-m wind speed under low-wind conditions commonly observed in weather models mainly stems from outdated geographic data and coarse spatial resolution (Gao et al., 2024)."

"*The models show relatively high correlations for PM_{10}, with R values ranging from 0.61 to 0.89 and NMBs from −73.8% to −0.9%. In contrast, their performance for O_3 is notably poorer.*"

These additions strengthen the robustness of the validation and support the reliability of the modeling results.

4. The influence of mineralogy on PM_{10} and O_3 is clearly demonstrated, but more discussion of the physical mechanisms (e.g., specific reactions, photolysis suppression) would help interpret the observed changes.

Response: We agree that elaborating on the physical mechanisms will improve the interpretation of the results. In the revised manuscript, we have expanded the discussion (Section 3.3) to describe the processes by which mineral dust composition influences both PM_{10} and O_3.

"*These reactions would be related to the adsorption and catalytic decomposition of ozone on the surface of mineral dust particles, as well as the potential for dust to alter the concentration of reactive species in the atmosphere through heterogeneous chemistry (Cwiertny et al., 2008). For example, the presence of adsorbed water on dust particles can compete with ozone for reactive sites, reducing the overall uptake and decomposition of ozone (Usher et al., 2003). Additionally, the photochemical reactions involving dust particles, such as the photolysis of nitrate ions, can produce reactive* *radicals that further influence the atmospheric chemistry of ozone (Ma et al., 2021).*"

"*The photochemical reactions involving dust particles, such as the photolysis of nitrate ions, can produce reactive radicals that further influence the atmospheric chemistry of ozone (Ma et al., 2021).*"

5. The results show that quartz and feldspar dominate dust mass, while hematite dominates radiative effects. This contrast deserves more discussion in both the Results and Conclusion sections.

Response: We have expanded both the Results and Conclusion sections to emphasize the contrast between dust mass and radiative importance among minerals. Specifically, the revised text highlights that "*Within the scope of this study, the results indicate that overall dust mineralogical composition, rather than dust mass alone, plays a decisive role in ARI effects, with hematite exerting a dominant influence despite its minor abundance, although the radiative effects of individual mineral species were not separately quantified.*". The new discussion clarifies why mass-dominant minerals do not necessarily drive radiative forcing and why trace absorptive minerals can play an outsized role.

6. The model bias discussion (Section 3.1) is helpful but could be deepened by exploring possible reasons for the underestimation of PM_{10} at high dust sites.

Response: The discussion of model bias in Section 3.1 has been expanded. In particular, we now examine potential reasons for the underestimation of PM_{10} at high-dust sites. Possible explanations include "*Although considerable progress has been made in dust modeling, notable uncertainties remain. The parameterization of threshold friction velocity and soil texture in emission schemes can still result in underestimated emissions under strong winds (Zuo et al., 2024). Similarly, simplifications in coarse particle size distributions may lead to enhanced deposition and transport losses. In addition, incomplete knowledge of local soil mineralogical composition continues to limit the accurate simulation of both emission fluxes and heterogeneous chemistry*

(Pang et al., 2024).". We have added this discussion in Section 3.1, noting that these factors collectively contribute to the underestimation of PM_{10} peaks in dust-dominated regions.

Minor comments:

1. Line 137: Please specify how missing EMIT data (quartz/feldspar) are estimated — a numeric assumption or spatial filling?

Response: We have clarified the treatment of missing EMIT data at Line 137. Specifically, gaps in quartz and feldspar fractions are addressed using a spatial filling approach rather than applying a single numeric assumption. The missing values are filled by interpolating from neighboring valid EMIT pixels within the same dust source region, constrained by the relative proportions observed in the reference mineralogical dataset. This procedure ensures spatial consistency and preserves regional mineralogical characteristics. The revised text in Section X.X now explicitly describes this method.

"*When the total mineral composition from EMIT summed to less than 100%, indicating missing mineral contributions, the residual fraction was assigned to quartz and feldspar based on their relative proportions in J2014 or N2012.*"

2. Line 187–198: The bias in SSR is discussed, but no mention is made of possible causes (e.g., aerosol loading or model radiation scheme limitations).

Response: We thank the reviewer for this valuable suggestion. We have now expanded the discussion of possible causes of the SSR bias (Lines 187–198) as follow.

"*The overestimation of SSR likely results from uncertainties in cloud development associated with planetary boundary layer and convection parameterizations (Alapaty et al., 2012).*"

3. Line 194: The overestimation of SSR and WS10 could be more quantitatively discussed. Is this bias consistent with other dust studies in this region?

Response: We appreciate the reviewer's constructive suggestion. We have revised the text around Line 194 to provide a more quantitative discussion of the overestimation of SSR and WS10.

"*Nevertheless, systematic biases are apparent, particularly in North China, where the model tends to overestimate SSR and WS10 by 60.69%–68.92% and 17.06%–17.52%, respectively, while underestimating T2 by 0.48%–0.58%. The overestimation of SSR likely results from uncertainties in cloud development associated with planetary boundary layer and convection parameterizations (Alapaty et al., 2012). Likewise, the systematic overestimation of 10-m wind speed under low-wind conditions commonly observed in weather models mainly stems from outdated geographic data and coarse spatial resolution (Gao et al., 2024).*".

Previous study evaluating the modeling performance of two-way coupled WRF–CMAQ, WRF–Chem, and WRF–CHIMERE systems in simulating meteorology and air quality over eastern China have also reported overestimations of SSR and WS10 (Gao et al., 2024).

4. Line 213–214: "minimizing the negative biases in T2" — perhaps "reducing the magnitude of negative biases" is clearer.

Response: We thank the reviewer for this helpful wording suggestion. We have revised the text at Lines 213–214 to "reducing the magnitude of negative biases in T2," which we agree is clearer and more precise.

5. Line 250: "Positive O_3 biases increased" is unclear — do you mean O_3 concentrations were overestimated?

Response: We appreciate the reviewer's comment. Our intent was to indicate that the model overestimated O_3 concentrations during that period. To improve clarity, we have revised the wording at Line 250 to "*the underestimation of PM_{10} was alleviated, whereas the overestimation of O_3 was amplified*" instead of "positive O_3 biases increased."

6. Line 305: "-900 W m^{-2}" seems unusually large for surface shortwave cooling. Please double-check this value.

Response: Thank you for raising this point. We rechecked the model diagnostics and confirm that the value -900 W m^{-2} reported on line 305 is correct.

7. Line 584: Suggest shortening this part of the conclusion and moving satellite technical details into Data/Methods.

Response: We thank the reviewer for this constructive suggestion. We have shortened the text in the Conclusion (Line 584) to focus on the key findings, and we have moved the technical details regarding satellite data (sensor specifications, retrieval algorithms, and processing steps) into the Data/Methods section.

"*Dust mineral composition plays a vital role in regulating atmospheric radiation and air quality, yet its effects remain poorly constrained in current atmospheric models. Understanding these impacts is particularly important for North China, where severe dust storms frequently affect regional climate and pollution. This study investigates how variations in mineral composition influence aerosol–radiation interactions and their implications for meteorology and air quality during a major dust storm event.*

The findings revealed significant spatial variations in radiative forcing due to differences in dust mineralogy. Compared to the ARI effects of bulk dust, the mineralogical composition of dust aerosols can increase SW radiation forcing at the surface and in the atmosphere by +0.10 to +0.82 W m^{-2}, while simultaneously causing a decrease of approximately -0.72 W m^{-2} in SW radiation forcing at the TOA. Integrating EMIT data into the model reduced PM_{10} biases by over 15% in high-concentration regions and improved ozone predictions, with localized changes ranging from -2.46 to +3.52 μg m^{-3}. Specifically, the ARI effects of these mineralogical compositions led to a notable increase in PM_{10} levels, reaching up to 1189.48 μg m^{-3} in dust source regions, when compared to bulk dust scenarios.

These findings highlight the importance of incorporating dust mineralogical data to improve simulations of radiative forcing and air quality impacts. Within the scope of this study, the results indicate that overall dust mineralogical composition, rather than *dust mass alone, plays a decisive role in ARI effects, with hematite exerting a dominant influence despite its minor abundance, although the radiative effects of individual mineral species were not separately quantified. Systematic biases in surface radiation, near-surface winds, and temperature persist, reflecting challenges in simulating dust–atmosphere interactions and uncertainties in mineralogical datasets. Future research should focus on coupling mineral-specific dust with cloud processes and leveraging higher-resolution soil and satellite data to refine dust emission simulations and reduce model biases.*"

8. Figure 1: Please include a scale bar and clear region names to help interpret mineral distributions.

Response: We appreciate the reviewer's helpful suggestion. We have revised Figure 1 to include a scale bar and have added region names to facilitate interpretation of the mineral distributions. The updated figure improves geographic clarity and makes it easier for readers to contextualize the results.

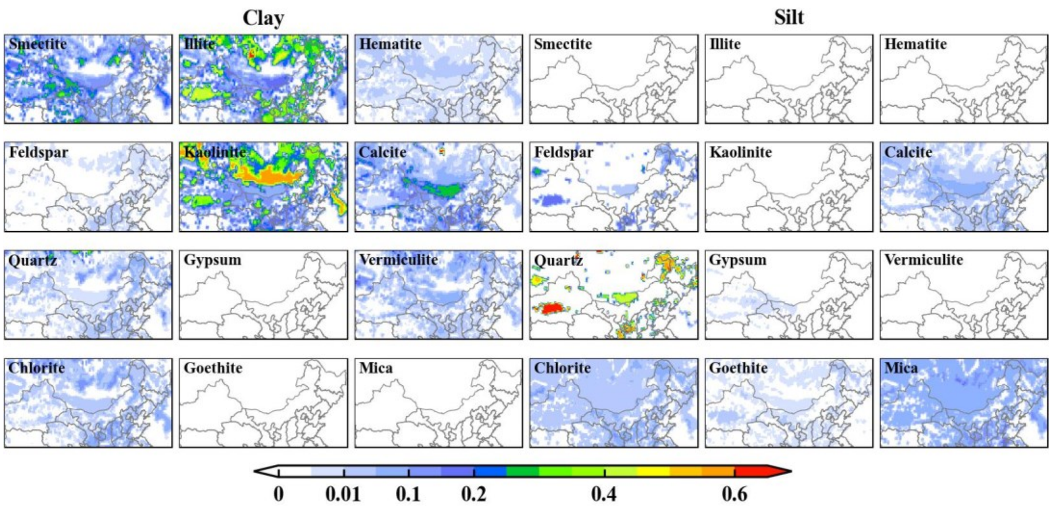

Figure 1. Spatial distribution of content for the different mineral dust species in the silt and clay fraction of the soil for original J2014 mineralogical data.

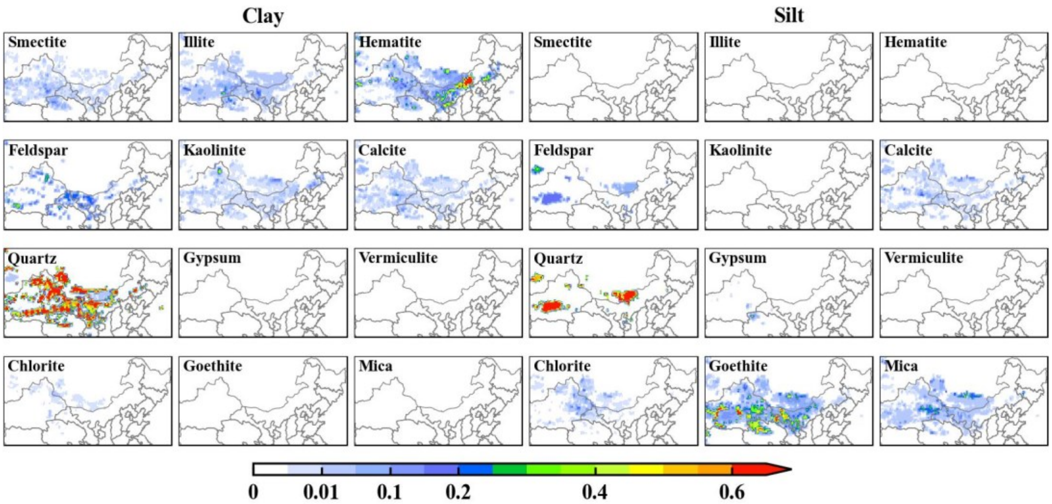

Figure A5. Spatial distribution of content for the different mineral dust species in the silt and clay fraction of the soil for J2014 with EMIT satellite data.

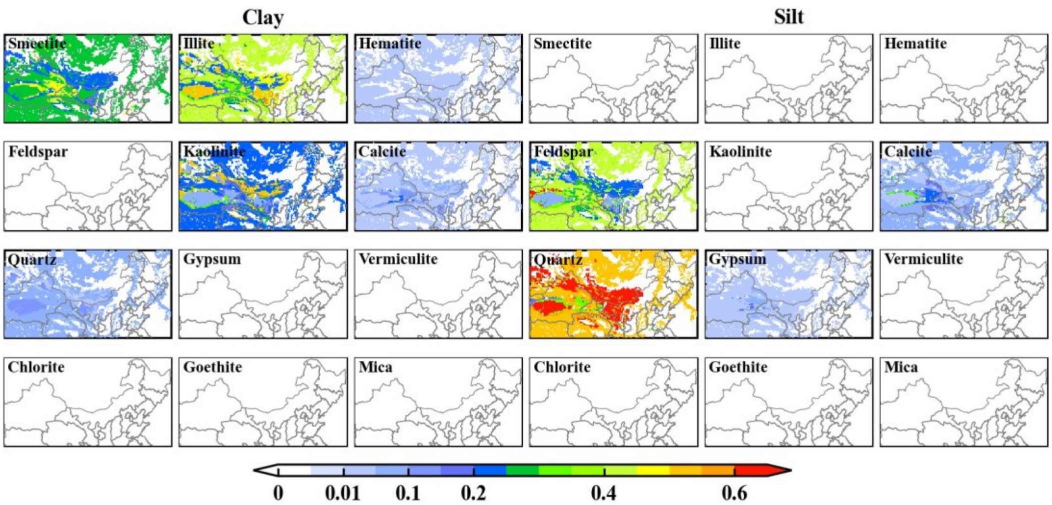

Figure A6. Spatial distribution of content for the different mineral dust species in the silt and clay fraction of the soil for original N2012 mineralogical data.

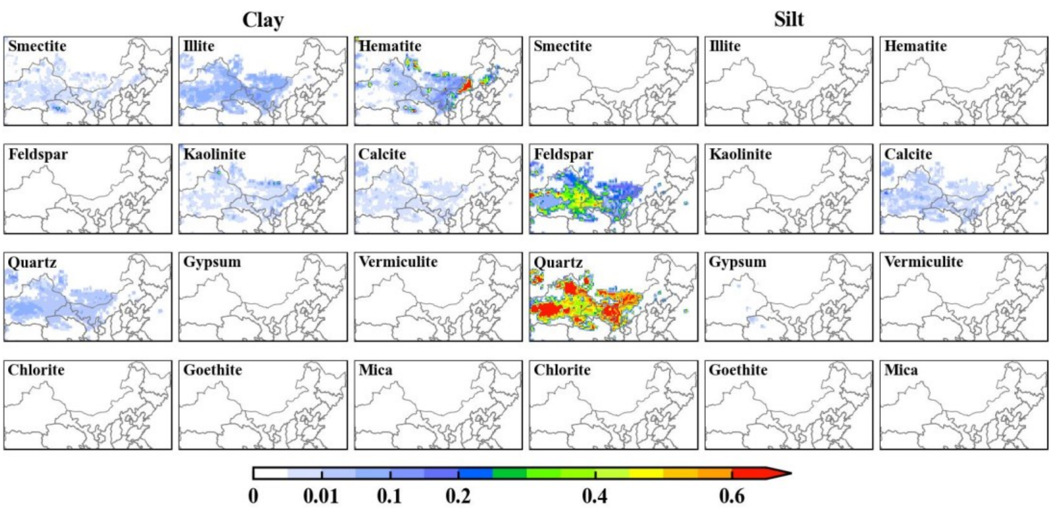

Figure A7. Spatial distribution of content for the different mineral dust species in the silt and clay fraction of the soil for N2012 with EMIT satellite data.

9. Figure 2: Consider including error bars or confidence intervals for observed values, “Statatiscal metrices” → should be “Statistical metrics” in its caption.

Response: We thank the reviewer for this valuable suggestion. We have revised Figure 2 to include error bars representing the standard deviation (or 95% confidence intervals) of the observed values, thereby providing a clearer indication of observational uncertainty.

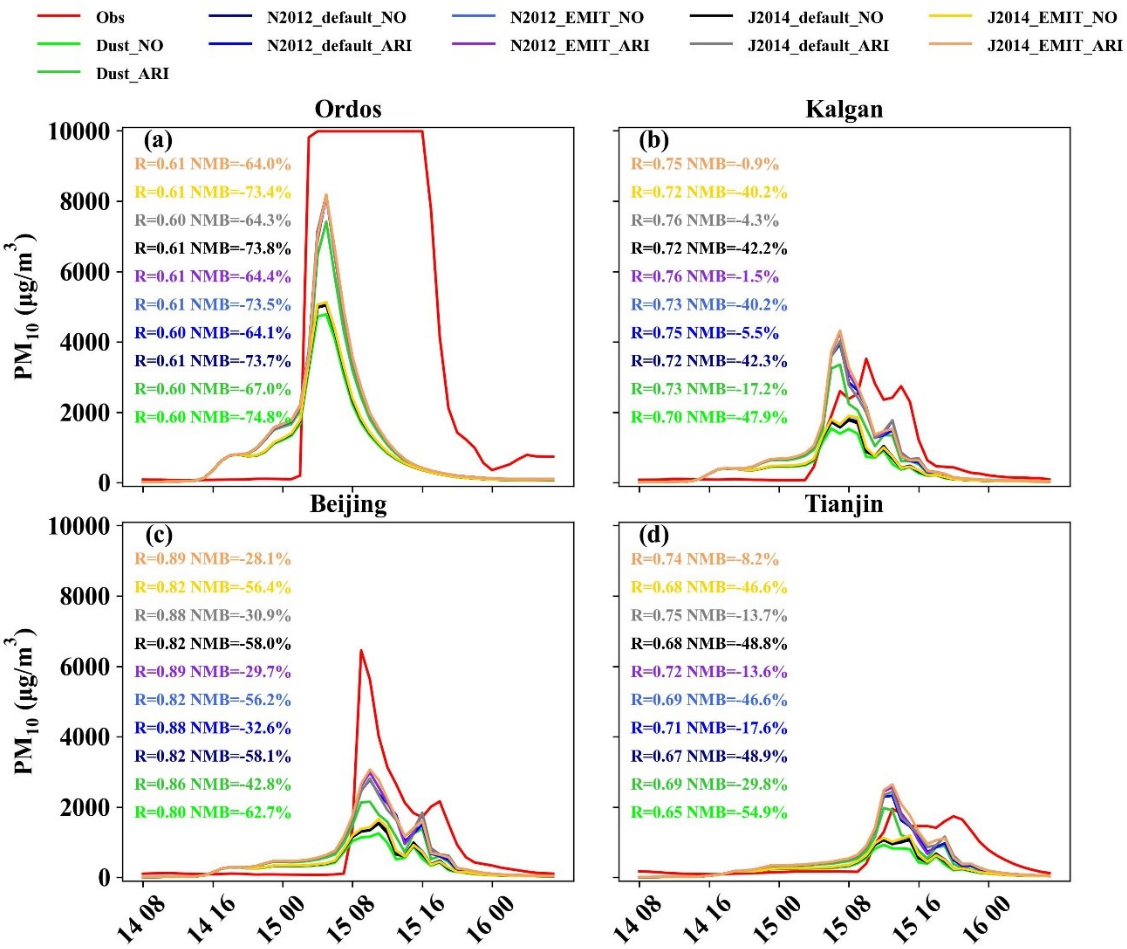

Figure 2. Statatiscal metrices between observated and simulated PM_{10} concentrations by different scenario simulations.

In addition, we have corrected the typographical error in the caption, changing “Statatiscal metrices” to “Statistical metrics.”

10. Figure quality could be improved — e.g., Figures 2 and 7 would benefit from enhanced color contrast and labeled axes for clarity.

Response: We thank the reviewer for this helpful suggestion. We have improved the quality of Figures 2 and 7 by enhancing the color contrast to better distinguish data ranges and by adding clearly labeled axes with units where applicable. These improvements enhance readability and ensure that the figures convey the data more effectively.

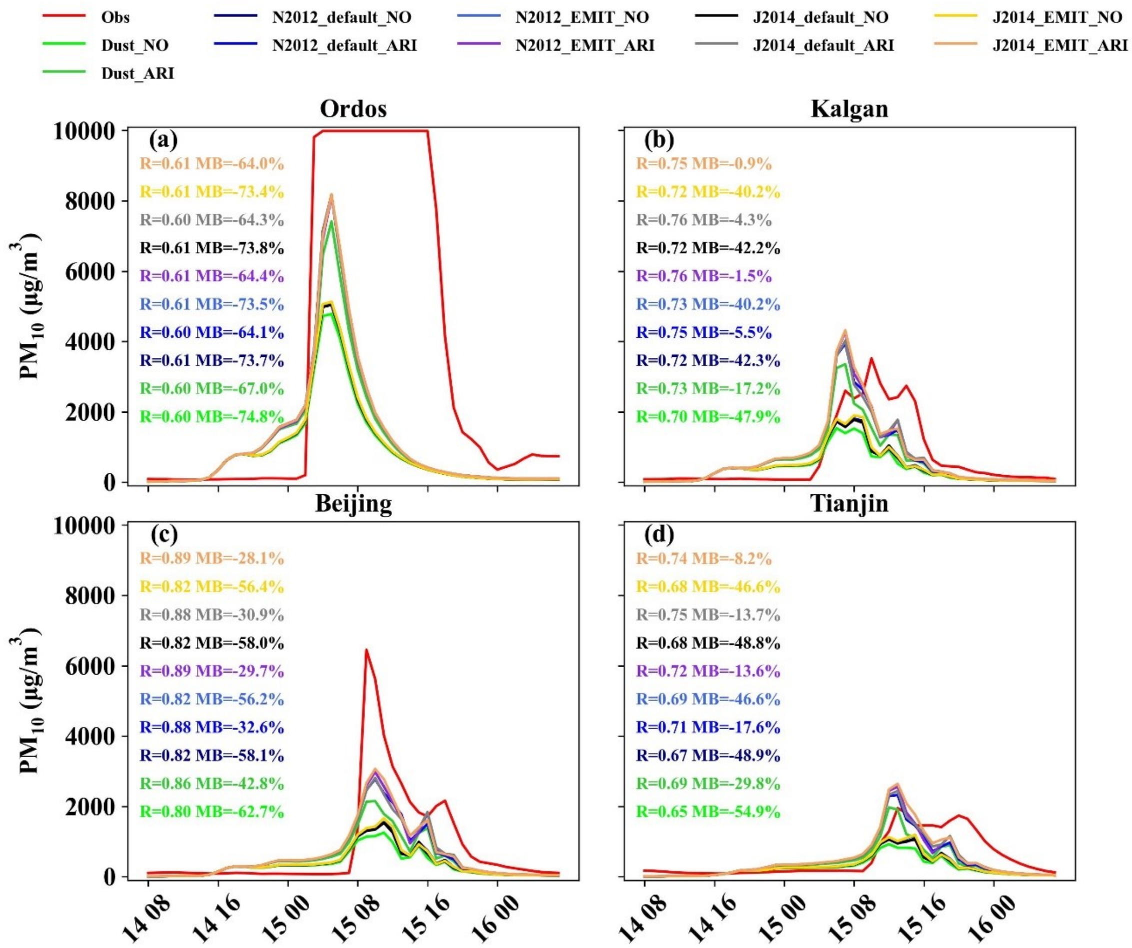

Figure 2. Statatiscal metrices between observated and simulated PM_{10} concentrations by different scenario simulations.

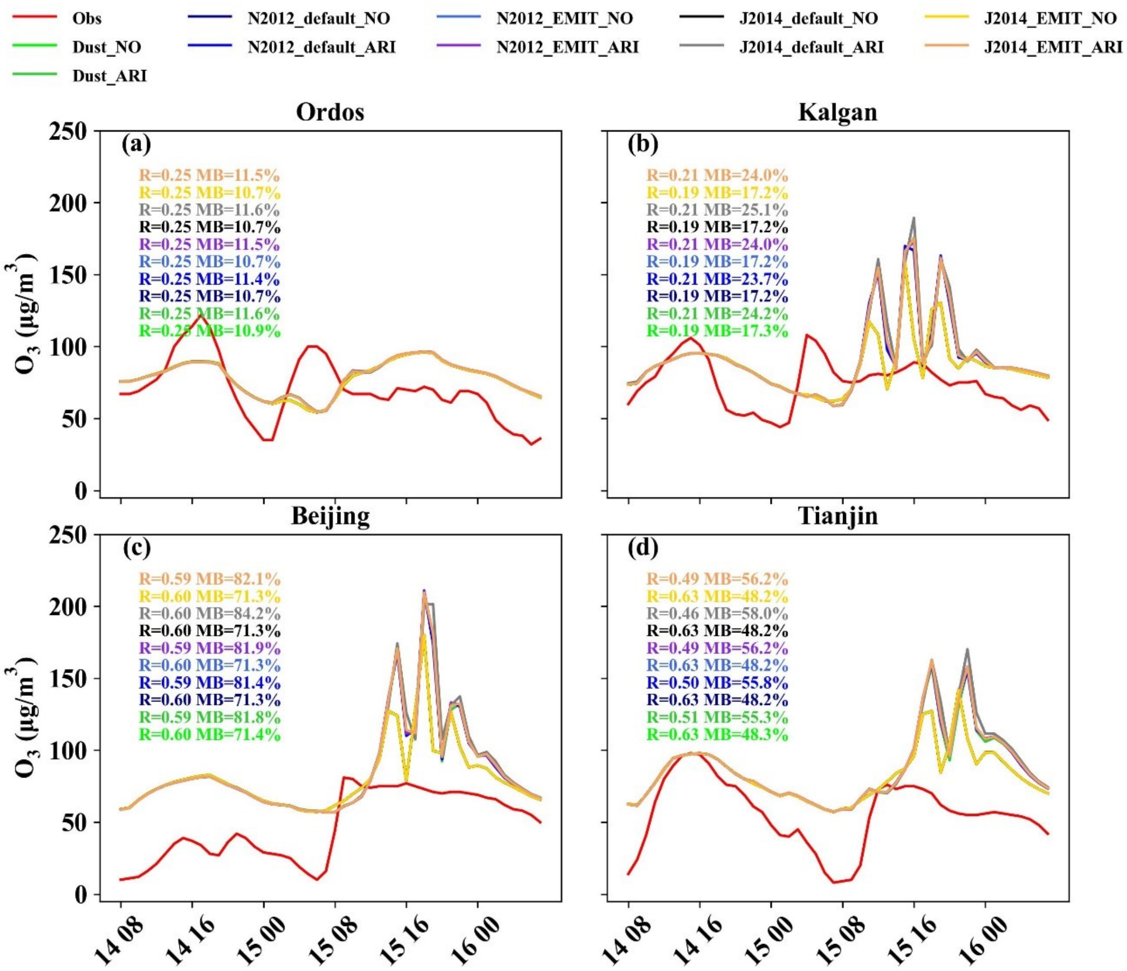

Figure A2. Statatiscal metrices between observated and simulated O_3 concentrations by different scenario simulations.

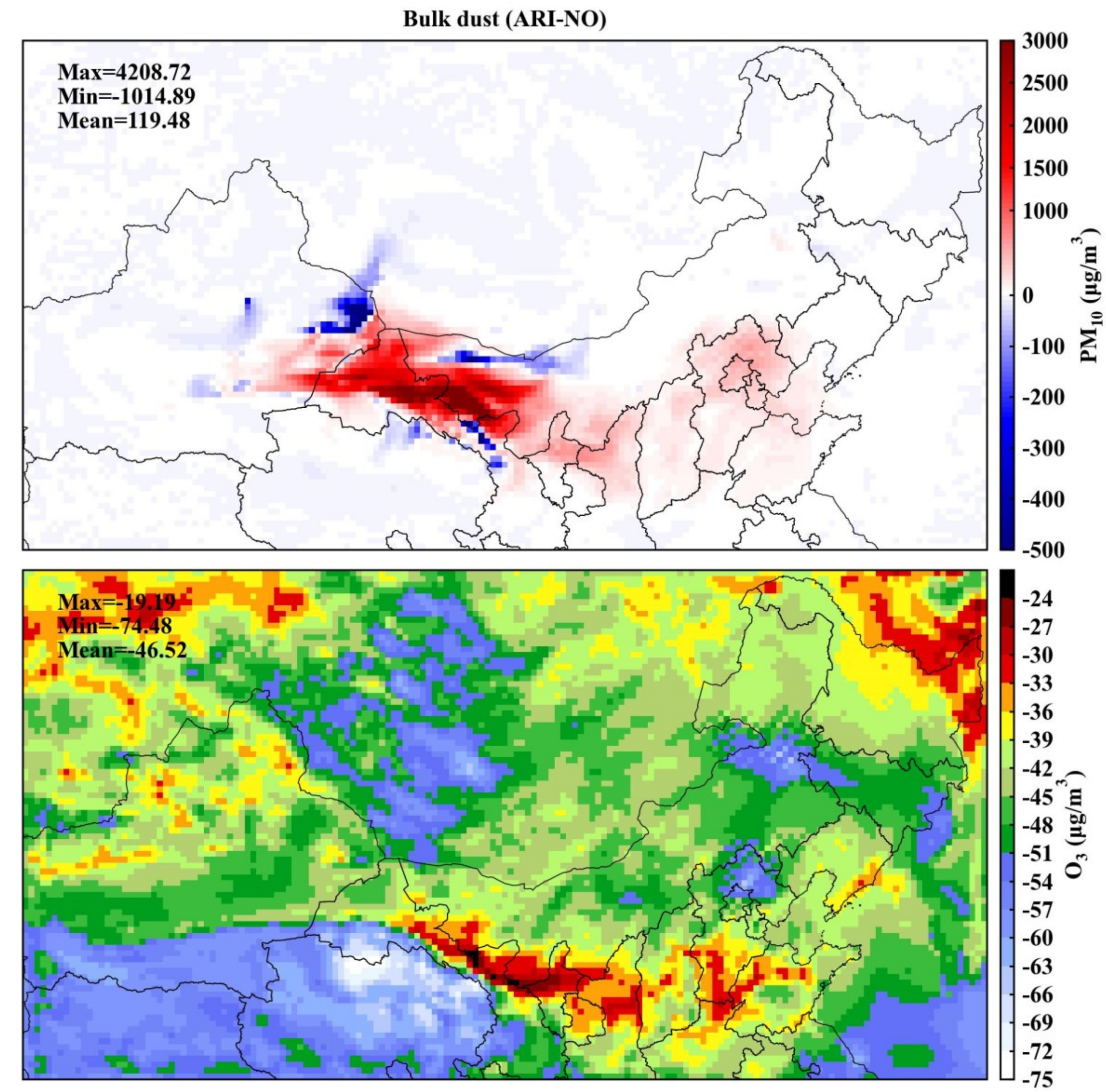

Figure 7. Changes in PM_{10} and O_3 concentrations resulting from bulk dust-induced ARI effects, compared to the scenario without aerosol feedbacks.

11. Reference format is mostly consistent, but some recent references (e.g., Panta et al., 2023) are missing DOIs.

Response: We thank the reviewer for noting this. We have carefully checked all references and added missing DOIs, including for Panta et al. (2023) and any other recent studies where applicable. The reference list is now complete and consistent with the journal's formatting requirements.

Panta, A., Kandler, K., Alastuey, A., González-Flórez, C., González-Romero, A., Klose, M., Querol, X., Reche, C., Yus-Díez, J., and Pérez García-Pando, C.: Insights into the single-particle composition, size, mixing state, and aspect ratio of freshly emitted mineral dust from field measurements in the Moroccan Sahara using electron microscopy, Atmospheric Chemistry and Physics, 23, 3861–3885, https://doi.org/10.5194/acp-23-3861-2023, 2023.

Green, R. O., Mahowald, N., Ung, C., Thompson, D. R., Bator, L., Bennet, M., Bernas, M., Blackway, N., Bradley, C., and Cha, J.: The Earth surface mineral dust source investigation: An Earth science imaging spectroscopy mission, 2020 IEEE aerospace conference, 1–15, https://doi.org/10.1109/AERO47225.2020.9172731, 2020.

At last, many thanks for the Reviewer's helpful for comments and suggestions to improve the quality of our manuscript.