The role of dust mineral composition in atmospheric radiation and pollution in North China: new insights from EMIT and two-way coupled modeling

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Abstract

Mineral dust is a major atmospheric aerosol influencing Earth's energy balance through aerosol-radiation (ARI) and aerosol-cloud interactions (ACI). While homogeneous dust effects have been studied, the impact of mineralogical composition on regional meteorology and air quality remains underexplored, limiting accurate forecasting of dust storm impacts, especially in dust belt regions. In this study, we used a two-way coupled WRF-CHIMERE model with three mineralogical dust atlases (Nickovic et al. (2012) (N2012), Journet et al. (2014) (J2014), and a new dataset, Li et al. (2024) (L2024), from the Earth Surface Mineral Dust Source Investigation (EMIT)) to evaluate ARI effects during the March 2021 dust storm in North China. Results showed significant spatial variations in radiative forcing due to mineralogical differences. Bulk dust (without considering mineralogy) caused an average shortwave radiative forcing of −5.72 W/m², while mineral-specific forcings increased this by up to +0.10 W/m². Integrating EMIT data reduced PM_{10} biases by over 15% in high-concentration regions and improved ozone predictions, with localized changes of −2.46 to +3.52 μg/m³. Hematite's strong absorption and quartz's reflective properties were key in altering radiative and air quality outcomes. Compared to scenarios of bulk dust, the consideration of ARI effects of mineralogical compositions can increase PM_{10} concentration by up to 1189.48 μg/m³ in dust source regions. Future research perspectives on the utilization of high-resolution EMIT data in two-way coupled meteorology and air quality models for investigating the ACI effects of

mineralogical dust on cloud microphysics are proposed.

1 Introduction

Mineral dust, a dominant component of global atmospheric aerosols, primarily originates from wind erosion in arid and semi-arid regions (Schepanski, 2018; Shao et al., 2011). It can affect the Earth's energy balance through direct scattering and absorption of solar, i.e. aerosol-radiation interaction (ARI), as well as indirect effects on cloud properties by acting as cloud condensation nuclei and ice nuclei, i.e., aerosol-cloud interaction (ACI) (Choobari et al., 2014; Kok et al., 2023). By altering biogeochemical cycles, atmospheric chemistry and visibility, and air quality, transported mineral dust can exacerbate economic losses, and health risks (Adebiyi et al., 2023; Cwiertny et al., 2008; Duniway et al., 2019; Maher et al., 2010; Tong et al., 2023). Accurate forecasting of mineral dust events is crucial to mitigate these adverse impacts.

Numerous studies have demonstrated that the magnitude of dust ARI and ACI effects is significantly influenced by its mineralogical composition. For instance, iron oxides, particularly hematite and goethite, have been identified as key components responsible for dust absorption of solar radiation, as evidenced by both observational and modeling studies (Alfaro et al., 2004; Gómez Maqueo Anaya et al., 2024; Lafon et al., 2006; Li et al., 2022; Obiso et al., 2024; Scanza et al., 2015; Song et al., 2024). Concurrently, a growing body of research has explored the impact of various dust mineral compositions, including hematite, corundum, kaolinite, mica, montmorillonite, quartz, calcite, illite, amorphous silicon, aluminum silicate, and potassium feldspar, on ice nucleation processes. Among these, potassium feldspar has emerged as a crucial component for dust nucleation activation (Harrison et al., 2016; Kumar et al., 2018). However, a notable gap exists in our understanding of how specific mineral compositions impact meteorology and air quality through ARI and ACI effects. Prior research has predominantly focused on homogeneous dust aerosols, assuming globally uniform composition and optical properties. However, this assumption introduces regional inaccuracies in estimating the impacts of dust aerosols,

which remain poorly understood due to uncertainties in dust composition (Ke et al., 2022; Klingmüller et al., 2019; Kok et al., 2017).

Many efforts have been directed to improve simulations of dust mineralogy and its representation in numerical models (Balkanski et al., 2021; Gómez Maqueo Anaya et al., 2024; Gonçalves Ageitos et al., 2023; Li et al., 2021, 2022, 2024; Li and Sokolik, 2018; Menut et al., 2020; Obiso et al., 2024; Scanza et al., 2015; Solomos et al., 2023b, a; Song et al., 2024). Most of the above are offline models, with only two studies conducting two-way feedback simulations with only WRF-Chem (Li and Sokolik, 2018) and WRF-CHIMERE (Menut et al., 2020) being applied. However, both of these studies are derived from artificially generated data and lack effective ground-based validation, as discussed in Claquin et al. (1999), Nickovic et al. (2012) (N2012 hereafter), and Journet et al. (2014) (J2014 hereafter). These validations predominantly focus on agricultural regions rather than the arid and semi-arid areas that are major sources of dust emissions (Green et al., 2020). EMIT instrument provides a new approach to invert and obtain the surface soil mineral composition and further assess the ARI and ACI effects of dust minerals (Connelly et al., 2021). To the best of our knowledge, no prior research has investigated the impact of dust on regional meteorology and air quality while considering its mineral speciation using two-way coupled models with three different mineralogical dust atlases.

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.

2 Methodology and data

2.1 Model configurations and data sources

The two-way coupled WRF model version 3.7.1 and CHIMERE model version 2020r3 were employed to simulate the ARI and ACI effects of mineralogical dust particles on meteorology and air quality over North China from March 12 to March 15, 2021, as shown in Fig. A1. The exchanges between meteorological and air quality variable are accomplished through the OASIS coupler (Briant et al., 2017). The simulation was conducted at a horizontal resolution of 27 km, with 165 grid cells in the east-west direction and 87 in the north-south direction, and the study domain is depicted in Fig. A1. The model has 33 vertical levels from surface to 50 hPa with 13 layers in the bottom 1km and the bottom thickness being 24.5 m. The Rapid Radiative Transfer Model for General circulation models (RRTMG) shortwave and longwave radiation schemes were employed to investigate the ARI effects (Briant et al., 2017). Additionally, the Thompson cloud microphysics scheme was utilized to assess the impacts of ACI (Tuccella et al., 2019). The initial and boundary conditions (ICs and BCs) for non-dust aerosols are prescribed by the LDMZ-INCA model, while those for dust aerosols are determined by the GOCART model. The options of other physics and chemistry schemes are presented in Table A1. The dry depositions are treated as described in Zhang et al. (2001). The parameterizations for the removal of dust particles below clouds by raindrops and snow are based on the methods proposed by Willis & Tattelman (1989) and Wang et al. (2014), respectively. Inline mineral dust emissions, incorporating mineralogy, are computed using a u* threshold and a dust production model for saltation (Kok et al., 2014; Shao and Lu, 2000). The model accounts for the impact of soil moisture on suppressing mineral dust emissions (Fécan et al., 1998). To minimize meteorological bias, a spectral nudging approach is applied (Menut et al., 2024).

For the calculations of ARI effects in WRF-CHIMERE, refractive indices corresponding to these mineralogical species are provided in Table 2 of Menut et al. (2020). Concerning shortwave (SW) radiation, the aerosol optical properties, encompassing single scattering albedos and asymmetry factors at 400 and 600 nm, as well as the aerosol optical depth (AOD) at 300, 400, and 999 nm, calculated using Fast-JX, were interpolated or extrapolated to obtain values at 14 SW intervals (Briant et al., 2017; Gao et al., 2022). AOD at 16 longwave (LW) intervals ranging from 3400 to 55600 nm are directly used to calculate LW radiation.

To evaluate the performance of the WRF-CHIMERE model with and without mineralogical dust emissions, we compiled a comprehensive set of environmental observations. Hourly PM_{10} and O_3 concentrations (132 observations) were obtained from https://quotsoft.net/air/, which aggregates official monitoring data from the Ministry of Ecology and Environmental Protection of China. Shortwave radiation (SSR) data (59 hourly measurements) were obtained from Tang et al. (2019), with the original measurements sourced from the China Meteorological Administration. Hourly surface meteorological data (844 observations) were also obtained from the China Meteorological Administration (https://data.cma.cn). All datasets were subjected to quality control procedures, including checks for outliers, unit consistency, and temporal alignment, to ensure reliability and integrity.

2.2 Mineral dust atlases

Accurate soil composition data are essential for partitioning dust emission fluxes into contributions from individual minerals. Mineral density and refractive index data were obtained from Menut et al. (2020). Three global mineralogical composition datasets (N2012, J2014, and EMIT) provide information on 12 mineral species (Table 1) at different spatial resolutions (1 km × 1 km and 0.5° × 0.5°).

To ensure a consistent spatial framework and facilitate cross-dataset integration, the N2012 dataset (originally provided at 1 km × 1 km resolution and available at

http://www.seevccc.rs/GMINER30) was resampled to 0.5° × 0.5°. The J2014 dataset, widely employed in the WRF–CHIMERE modeling framework, includes 12 mineral species distributed across the clay and/or silt fractions (see Table 2 in Menut et al., 2020). 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:

$$MF_j = MFC_j + MFS_j \;\; for\ all \in M_{CHIMERE} \quad (1)$$

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

$$1 = \sum_{j \in M_{CHIMERE}} MF_j \quad (2)$$

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):

$$MFS_j^* = MF_j^* \frac{MFS_j}{MFS_j + MFC_j} \quad (3)$$

$$MFC_j^* = MF_j^* \frac{MFC_j}{MFS_j + MFC_j} \quad (4)$$

Here, MFS_j^* and MFC_j^* represent the normalized mass fractions of mineral j in the

195 silt and clay fractions, respectively. The weighting terms MFS_j and MFC_j preserve the
196 clay–silt distribution patterns derived from the reference datasets while maintaining the
197 normalized total (MF_j^*).

198 Table 1. Mineralogical compositions in different datasets.

Mineral	Clay		Silt		EMIT
	N2012	J2014	N2012	J2014	
Smectite	✓	✓	×	×	✓
Illite	✓	✓	×	×	✓†
Hematite	✓	✓	✓	×	✓
Feldspar	×	✓	✓	✓	×
Kaolinite	✓	✓	×	×	✓
Calcite	✓	✓	✓	✓	✓
Quartz	✓	✓	✓	✓	×
Gypsum	×	×	✓	✓	✓
Vermiculite	×	✓	×	×	✓
Chlorite	×	✓	×	✓	✓
Goethite	×	×	×	✓	✓
Mica	×	×	×	✓	✓†
Resolution	1km	0.5°	1km	0.5°	0.5°

199 † indicates the content of illite + mica

200

201 **2.3 Scenario set up**

202 Ten parallel WRF-CHIMERE simulations were performed to investigate the influence
203 of mineralogical dust on meteorology and air quality in China, employing three distinct
204 mineralogical atlases, as illustrated in Figs. 1 and A5-A7. Each simulation was conducted
205 both with and without enabling ARI effects, as detailed in Table 2, to isolate and compare
206 the effects of mineralogical dust under different modeling conditions.

207 Simulations without ARI effects (Dust_NO, N2012_default_NO, N2012_EMIT_NO,
208 J2014_default_NO, J2014_EMIT_NO) were specifically designed to identify the direct
209 impact of mineralogical dust on meteorology and air quality, independent of the radiative

feedbacks induced by aerosols. These No_ARI simulations served as a baseline for assessing how mineralogical compositions affect meteorology and air quality in the absence of aerosol-radiation feedback mechanisms.

In contrast, simulations with ARI enabled (Dust_ARI, N2012_default_ARI, N2012_EMIT_ARI, J2014_default_ARI, J2014_EMIT_ARI) were used to quantify the additional effects arising from aerosol-radiation interactions. By comparing simulations with and without ARI for each mineralogical atlas (e.g., N2012_default_ARI − N2012_default_NO), the differential impact of ARI effects on meteorology and air quality for various dust compositions could be identified. This approach highlights how mineralogical properties of dust influence the strength and nature of ARI effects, thereby modulating key atmospheric processes such as radiation balance, temperature profiles, and pollutant distributions.

To evaluate the discrepancies in ARI effects among the mineralogical atlases, differences in the ARI impacts between EMIT-derived and default dust compositions were analyzed for both N2012 and J2014 datasets. For example, comparisons such as (N2012_EMIT_ARI − N2012_EMIT_NO) versus (N2012_default_ARI − N2012_default_NO) provide insight into the extent to which higher-resolution, satellite-derived mineralogical data influence ARI effects relative to default atlas-based representations. Similar comparisons were performed for the J2014 dataset.

Table 2. Summary of dust emission scenarios and aerosol feedback configurations for different simulation settings.

Scenario	Emission	Online choice	Coupling type	Aerosol feedback
Dust_NO	Bulk dust + anthropogenic emissions	[online] = 1	[cpl_case] = 1	No feedbacks
Dust_ARI		[online] = 1	[cpl_case] = 2	ARI effects
N2012_default_NO	N2012_default dust + anthropogenic emissions	[online] = 1	[cpl_case] = 1	No feedbacks
N2012_default_ARI		[online] = 1	[cpl_case] = 2	ARI effects
N2012_EMIT_NO	N2012_EMIT dust + anthropogenic emissions	[online] = 1	[cpl_case] = 1	No feedbacks
N2012_EMIT_ARI		[online] = 1	[cpl_case] = 2	ARI effects
J2014_default_NO	J2014_default dust + anthropogenic emissions	[online] = 1	[cpl_case] = 1	No feedbacks

J2014_default_ARI		[online] = 1	[cpl_case] = 2	ARI effects
J2014_EMIT_NO	J2014_EMIT dust + anthropogenic emissions	[online] = 1	[cpl_case] = 1	No feedbacks
J2014_EMIT_ARI		[online] = 1	[cpl_case] = 2	ARI effects

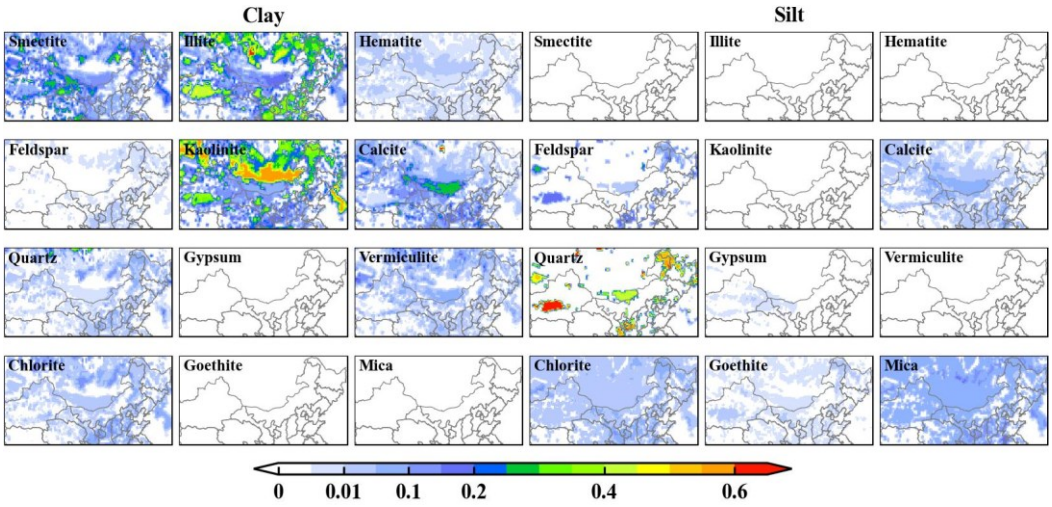

Figure 1. Spatial distribution of content for the different mineral dust species in the silt and clay fraction of the soil for original J2014 mineralogical data.

3 Results and discussion

3.1 Evaluation of meteorology and air quality

Table 3 presents the evaluation results for observed and simulated surface shortwave radiation (SSR), 2-meter temperature (T2), and 10-meter wind speed (WS10) from various scenario simulations conducted using the WRF-CHIMERE modeling system. 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).

A comparative analysis of the two configurations, N2012 and J2014, reveals that WRF-CHIMERE with N2012 generally outperforms J2014 in simulating SSR and T2, suggesting that the N2012 parameterization better captures radiative and thermodynamic processes in the region. Conversely, J2014 exhibits improved accuracy in simulating WS10, implying potential strengths in its representation of near-surface wind dynamics. These findings highlight the sensitivity of model performance to parameterization schemes and the need for tailored configurations for specific meteorological variables. The inclusion of detailed dust mineralogical compositions, while informative for certain applications, introduces additional complexities that reduce the overall accuracy of simulations. Specifically, while these compositions help mitigate the overestimation of SSR and the underestimation of T2, they exacerbate the overestimation of WS10. The integration of EMIT satellite data provides a significant boost to model performance, highlighting the value of incorporating high-resolution, real-time observational data to refine the simulation of atmospheric variables. EMIT data, with its detailed characterization of aerosol and dust properties, reduces the positive biases in SSR and WS10 while simultaneously minimizing the negative biases in T2.

When comparing the ARI effects of the defaulted mineralogical compositions in N2012 and J2014 with simulations that implement EMIT satellite data, the latter shows a clear advantage. Incorporating EMIT data further reduces the positive biases in SSR and WS10, while simultaneously minimizing the negative biases in T2. This suggests that EMIT data provides a more precise representation of dust properties and atmospheric conditions, enhancing the overall reliability of the model.

Table 3. Statistics analysis of daily averaged SSR, 2-meter temperature (T2) and 10-meter wind speed (WS10) from different scenario simulations and ground observations in North China including correlation coefficient (R) and normalized mean bias (NMB).

Scenario	SSR	T2	WS10

	R	NMB (%)	R	NMB (%)	R	NMB (%)
Dust_NO	0.70	68.92	0.93	–0.58	0.71	17.06
Dust_ARI	0.72	60.69	0.94	–0.48	0.72	17.46
N2012_default_NO	0.70	68.92	0.93	–0.58	0.71	17.06
N2012_default_ARI	0.71	61.80	0.94	–0.48	0.72	17.53
N2012_EMIT_NO	0.70	68.92	0.93	–0.58	0.71	17.06
N2012_EMIT_ARI	0.72	60.88	0.94	–0.48	0.72	17.44
J2014_default_NO	0.70	68.92	0.93	–0.58	0.71	17.06
J2014_default_ARI	0.71	61.68	0.94	–0.48	0.72	17.51
J2014_EMIT_NO	0.70	68.92	0.93	–0.58	0.71	17.06
J2014_EMIT_ARI	0.72	61.22	0.94	–0.48	0.72	17.48

To assess the ability of each scenario simulation to replicate regional PM_{10} and O_3 temporal patterns, Figure 2 presents hourly time series of simulated and in situ PM_{10} and O_3 concentrations at four North China sites: Ordos, Kalgan, Beijing, and Tianjin. These locations represent key dust aerosol transport pathways, which play a crucial role in the region's air quality dynamics due to frequent dust storms and anthropogenic emissions. The time series plots regarding PM_{10} and O_3 in Figures 2 and A2 allow for a direct comparison of model simulations with observed data, revealing important insights into model performance across different environmental conditions and geographical settings, respectively. The models exhibit 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 weaker, with R values between 0.25 and 0.63 and NMBs from +10.9% to +84.2%. Among the simulations, N2012 with EMIT data and ARI effects provides the best performance for PM_{10}, while N2012 with EMIT data without aerosol effects performs best for O_3 concentrations. All models accurately captured the peak PM_{10} and O_3 concentrations observed during the March 12 event in North China, which was characterized by significant dust emissions and high pollutant levels. This event serves as a key test case for evaluating the models' responsiveness to extreme atmospheric conditions. However, despite the overall agreement in peak concentration timings, simulations overestimated O_3 and underestimated PM_{10} at sites with high dust loads, such as Ordos and Kalgan. This

discrepancy highlights the challenge of simulating the complex interactions between dust aerosols, precursor gases, and photochemical reactions, particularly in regions with high dust deposition and frequent air pollution episodes. Additionally, the models tended to extend the period of elevated PM_{10} concentrations beyond the observed time frame, suggesting that the processes controlling dust aerosol removal or dispersion were not fully captured. CHIMERE simulations using J2014 mineralogical data generally outperformed those using J2012 data, with significant reductions in PM_{10} negative NMBs for three of the four cities, indicating the importance of accurate mineralogical characterization of dust for improving model predictions. When considering the ARI effects of bulk dust aerosols, the underestimation of PM_{10} was alleviated, whereas the overestimation of O_3 was amplified, which suggests that incorporating ARI effects helps to better represent the impact of dust on local radiative forcing and air quality. Moreover, incorporating ARI effects from the default dust mineralogical atlas further enhanced these trends, underscoring the need for refined aerosol property data in enhancing model performance. Finally, using Earth-observing systems such as the EMIT satellite data led to substantial reductions in PM_{10} negative bias at Kalgan, Beijing, and Tianjin, demonstrating the value of remote sensing data in improving model accuracy, particularly for regions with high aerosol concentrations and complex emission sources. 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).

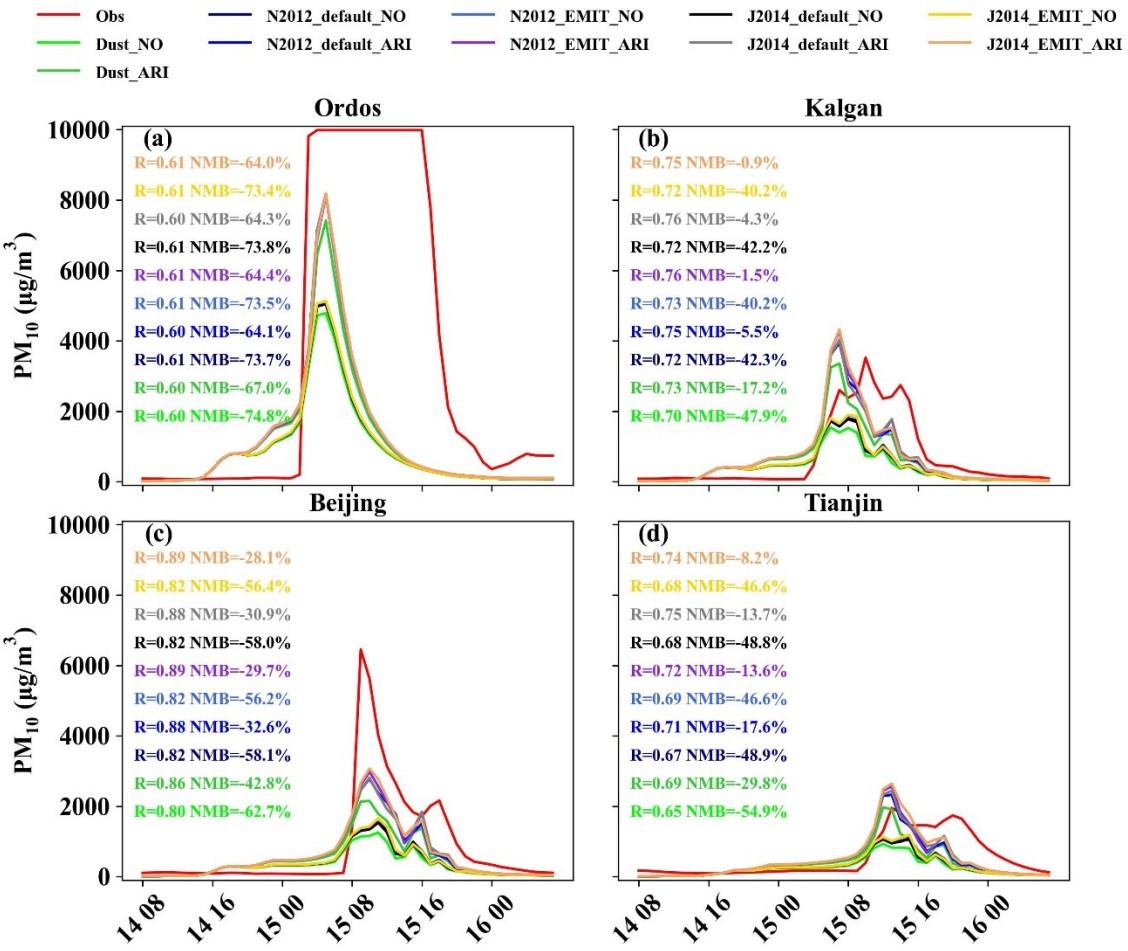

Figure 2. Statatiscal metrices between observated and simulated PM_{10} concentrations by different scenario simulations.

To evaluate the model performance in simulating the horizontal distribution and vertical profile of dust aerosol, Figure 3 presents the false RGB imagery of dust derived from Himawari-8 thermal infrared imagery, along with CALIPSO cross sections of 532 nm total attenuated backscatter and the vertical feature mask for the overpass of China. The figure also includes the corresponding spatial distributions of PM_{10} concentrations at 05:00 UTC on 15th March 2021, a time of significant dust transport in the region. This detailed comparison allows for a comprehensive assessment of how well the model captures both the horizontal and vertical characteristics of dust aerosol distribution. All six experiments display similar dust distributions in the atmosphere, consistent with observations from

Himawari-8 and CALIPSO. This suggests that the models effectively capture the general spatial patterns of dust transport. On March 15, 2021, the daily domain-averaged PM_{10} concentration was 533.81 μg m^{-3}, with a 95% confidence interval (CI) of 0.28–5962.95 (Table S1). Specifically, the false RGB imagery from Himawari-8 clearly indicates the presence of dust plumes in the atmosphere, with distinct thermal contrasts that help identify the dust layers. The CALIPSO data, which provide vertical profiles of aerosol backscatter, further validate the model's ability to capture the vertical extent and concentration of dust layers. These observations are critical for understanding the atmospheric processes governing dust dispersion and their impact on air quality. The close agreement between model simulations and satellite data across all six experiments also underscores the robustness of the model in representing dust aerosol distribution under different simulation conditions. This evaluation demonstrates that the models are capable of simulating the main features of dust aerosol transport, though further refinement in capturing the fine-scale variations and aerosol properties may still be necessary for more accurate predictions in future studies.

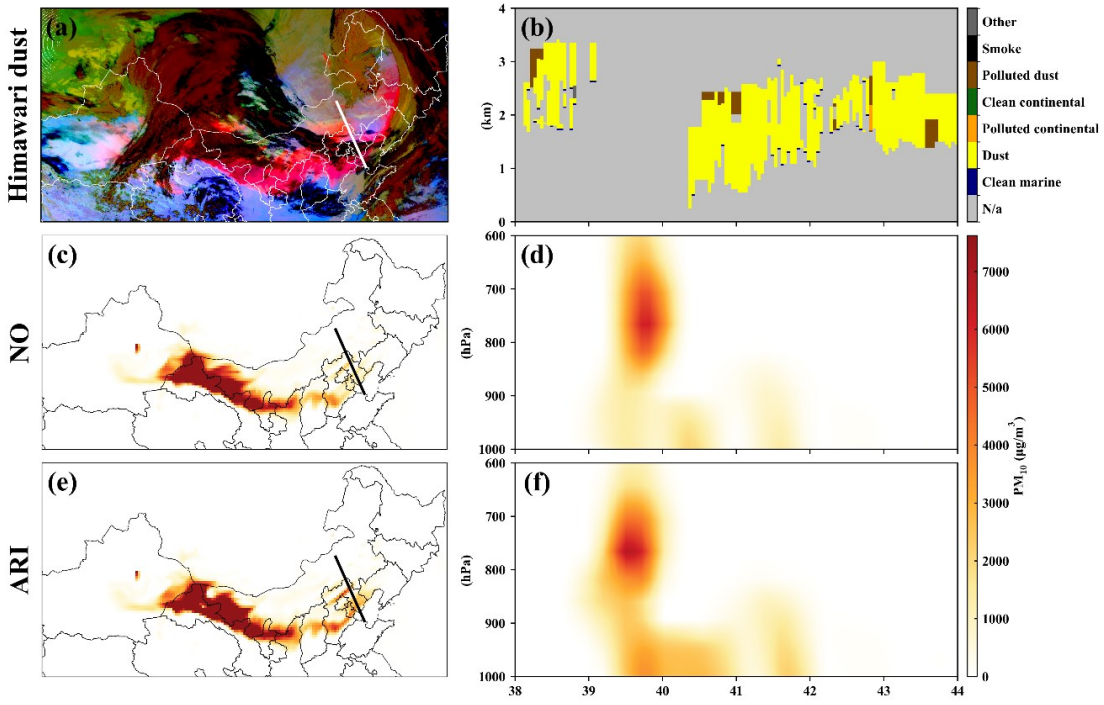

Figure 3. The false color imagery of dust from Himawari-8 thermal infrared imagery(a), CALIPSO

cross sections of 532 nm total attenuated backscatter and the vertical feature mask for the overpass of China on 13:00 (local time) 15th March 2021 (b), and corresponding horizontal (c and e) and vertical (d and f) distributions of PM_{10} concentrations.

3.2 Radiative effect on meteorology

To further investigate the impacts of dust radiation on energy balance, the spatial distributions of the average shortwave (SW), longwave (LW), and net (NET) radiative forcing induced by bulk dust on the surface (SFC), in the atmosphere (ATM), and at the top of the atmosphere (TOA) are presented during the dust episode shown in Figure 4. The radiative forcing values provide critical insights into the energy exchanges between dust aerosols and the atmosphere, and their subsequent effects on regional climate dynamics. For SW radiation forcings, dust aerosols produced cooling effects at all three layers: the surface, the atmosphere, and the top of the atmosphere. The average SW radiative forcing was about −5.72 W m^{-2} at the surface, −8.69 W m^{-2} in the atmosphere, and −2.97 W m^{-2} at the TOA, highlighting the significant reduction in solar radiation reaching these layers due to the scattering and absorption properties of the dust particles. Particularly in the dust source regions, the cooling effect at the surface exceeded −900 W m^{-2} (Figures 4a, 4d, and 4g), indicating the strong influence of dust on the regional energy budget in these areas. This is a result of the large dust concentrations and their optical properties, which effectively block solar radiation from reaching the Earth's surface. In contrast, the dust-induced LW radiative forcing warmed the surface and atmosphere, with average values ranging from 5.78 to 5.86 W m^{-2}. This warming effect is associated with the absorption of longwave radiation by dust particles, which then re-radiate heat, contributing to local warming. However, dust particles induced negative LW radiative forcing at the TOA, with values ranging from −461.88 to −379.95 W m^{-2}, reflecting the downward flux of longwave radiation absorbed by the aerosols, which reduces the amount of energy reaching the TOA. The NET radiative forcing, which represents the combined effect of both SW and LW forcings, was positive at the surface (about +0.15 W m^{-2}), negative in the atmosphere (about −2.91 W m^{-2}), and negative at the TOA (about −3.06 W m^{-2}), as shown in Figures 4c, 4f, and 4i. The positive NET radiative forcing at the surface suggests a slight net

warming effect at ground level, while the negative values in the atmosphere and at the TOA indicate an overall cooling effect at these higher altitudes.

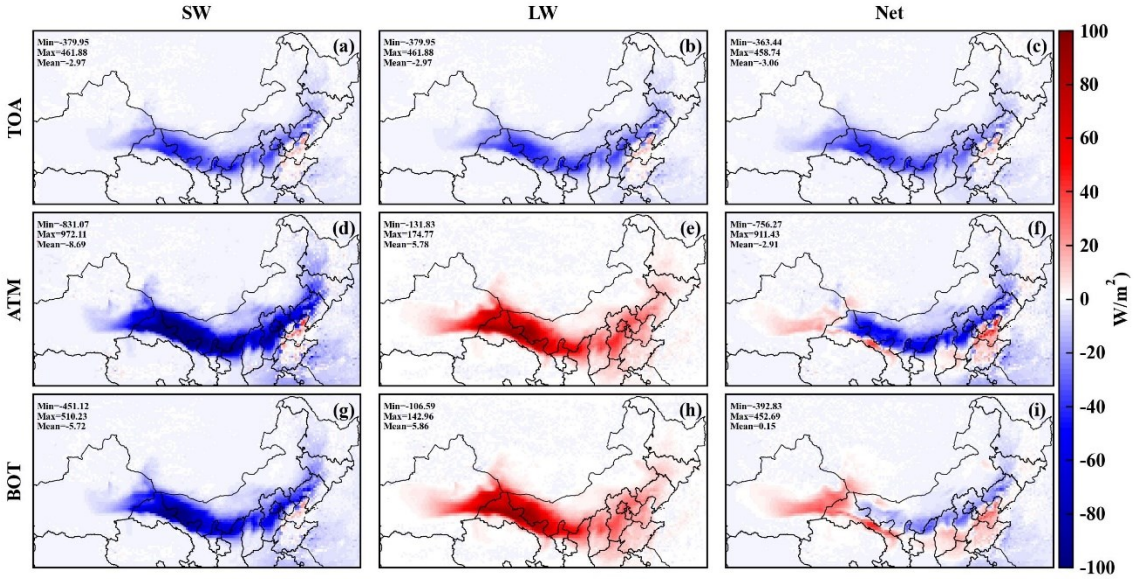

Figure 4. Radiation forcings due to bulk dust enabling ARI effects.

To assess the impact of dust mineralogical composition on radiative forcings, Figure S6 illustrates the spatial distribution of radiative differences, considering the ARI effects of bulk dust and comparing them to the default N2012 mineralogy atlas. This comparison provides valuable insights into how variations in the mineralogical composition of dust particles can influence the energy balance in the atmosphere. Compared to the ARI effects of bulk dust, the mineralogical composition of dust aerosols can lead to increases in SW radiation forcings at the surface and in the atmosphere, ranging from +0.10 to +0.82 W m^{-2}. This increase reflects the different optical properties of dust mineral types, which can affect the scattering and absorption of solar radiation. These variations in the SW radiation forcings are particularly important for understanding how different dust types modulate the amount of solar radiation reaching the Earth's surface and atmosphere. At the TOA, however, the mineralogical composition resulted in a decrease of about −0.72 W m^{-2} in SW radiation forcing, suggesting that certain mineralogical types may be more efficient at

reflecting solar radiation back into space. Similar to SW radiation forcings, net radiation forcings at the surface and in the atmosphere increased, ranging from +0.02 to +0.63 W m^{-2}, while at the TOA, net radiation forcings decreased by about −0.65 W m^{-2}. The increase in net radiation at the surface and in the atmosphere reflects the combined effect of increased SW absorption and the potential changes in longwave (LW) radiative properties. For LW radiation forcings, the mineralogical composition of dust led to decreases in the radiative forcing across different layers, ranging from −0.72 to −0.12 W m^{-2}. This decrease suggests that certain dust mineral types are more efficient at absorbing and emitting longwave radiation, which can contribute to cooling effects in the atmosphere and at the surface.

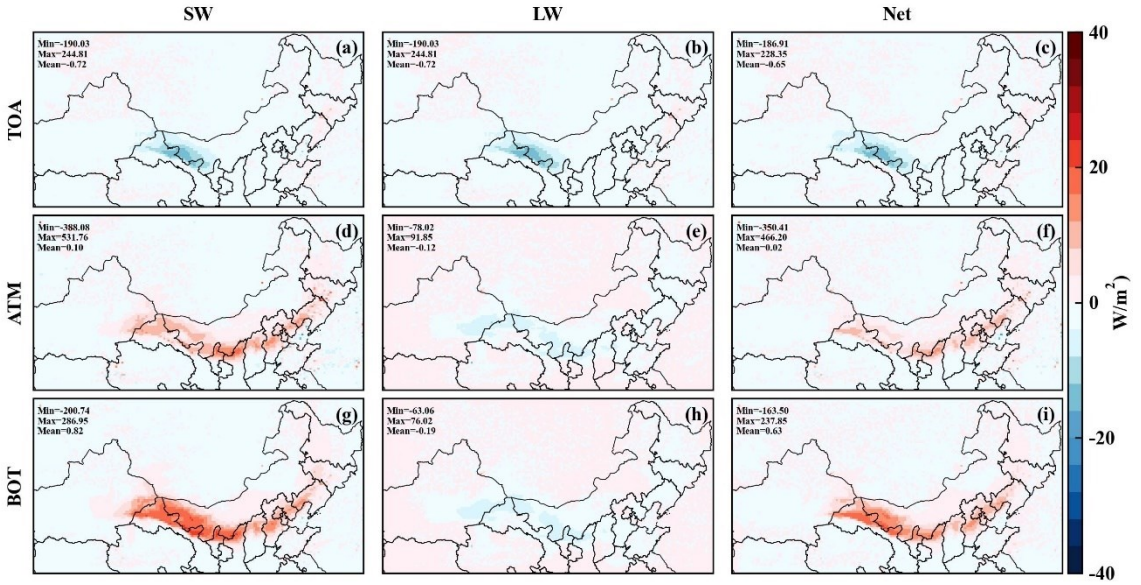

Figure 5. Difference between TOA, ATM and BOT radiation forcings with considering bulk dust and mineralogical dust compositions (i.e., N2012_default) enabling ARI effects.

As demonstrated in Figure A3, the selection of the soil mineralogy dataset and the modeling approach significantly influences the calculated dust radiative forcings. When comparing shortwave dust radiative effects (DRE) from WRF-CHIMERE simulations using the default N2012 and J2014 mineral atlases, we observe a minor discrepancy in the DRE amplitude, particularly for shortwave and net radiation forcing at the surface. This

discrepancy suggests that the choice of mineralogical dataset can influence the magnitude of radiative forcings, especially under varying atmospheric conditions. Previous research has highlighted the distinct optical properties of hematite and goethite in the shortwave spectrum (Lafon et al., 2006; Sokolik and Toon, 1999). These differences contribute to variations in the dust's radiative properties and, in turn, its effect on energy transfer in the atmosphere. Incorporating both minerals in dust production results in a flatter spectral single scattering albedo (SSA), as goethite's less pronounced dependence on shortwave wavelengths reduces the overall absorption in the shortwave spectrum (Formenti et al., 2014). This effect is particularly noticeable when comparing the radiative forcings from the different mineralogy datasets, as the presence of goethite alters the absorption and scattering characteristics of the dust particles.

As depicted in Figure 6, the distinct day-night variations in shortwave radiation forcing (SWRF) induced by ARI effects have been thoroughly demonstrated when considering different mineralogical atlases compared to bulk dust. These variations reflect the different impacts that dust aerosols have on solar radiation during the day and night, with a clear difference in the magnitude of the effects between the two periods. Notably, SWRF variations were more pronounced during the daytime than at night, which can be attributed to the stronger interaction between dust aerosols and incoming solar radiation during daylight hours. The presence of dust aerosols alters the reflection, absorption, and scattering of sunlight, leading to significant changes in the radiation balance, especially during the day when solar energy is at its peak.

Incorporating default dust mineralogical compositions into the simulations led to an increase in daytime SWRF at the surface and within the atmosphere, ranging from 1.60 to 3.74 W m^{-2}. This increase suggests that the specific mineralogy of dust aerosols contributes to greater absorption and scattering of solar radiation, amplifying the cooling effect at the surface and the atmosphere. However, at the top of the atmosphere (TOA), the SWRF decreased by approximately 2.00 W m^{-2}, which could be indicative of increased reflection

of shortwave radiation back into space due to the dust particles' optical properties. This shift in radiative forcing at the TOA highlights the role of dust in altering the energy fluxes across different atmospheric layers.

When comparing simulations using default dust mineralogical compositions to those employing Earth-observing EMIT satellite data within the WRF-CHIMERE model, notable differences in SWRF were observed. Daytime SWRF at the surface was reduced for the N2012 mineralogy dataset (−1.88 W m^{-2}) and J2014 mineralogy dataset (−1.37 W m^{-2}) when using EMIT data, compared to the default dust mineralogy compositions. This reduction could be due to more accurate mineralogical characterization, which alters the dust's optical properties and reduces its ability to absorb and scatter sunlight. Conversely, SWRF was enhanced in the atmosphere (N2012: +1.44 W m^{-2}, J2014: +0.84 W m^{-2}) when using the EMIT data, indicating that the updated mineralogical information leads to a different interaction with solar radiation in the atmospheric layer, possibly due to changes in dust composition that affect scattering and absorption properties at higher altitudes.

Furthermore, SWRF at the TOA transitioned from negative to positive in simulations using the EMIT data. For the N2012 dataset, the SWRF varied from −1.73 to +1.59 W m^{-2}, and for the J2014 dataset, it ranged from −2.14 to +0.07 W m^{-2}. This shift suggests that more accurate dust mineralogy data, particularly from satellite observations, can have a significant impact on the amount of solar radiation reflected back to space, thereby influencing the radiative balance at the TOA. The transition from negative to positive forcing at the TOA emphasizes the importance of incorporating realistic mineralogical information to enhance the accuracy of dust-related radiative forcing calculations and better understand their role in climate systems.

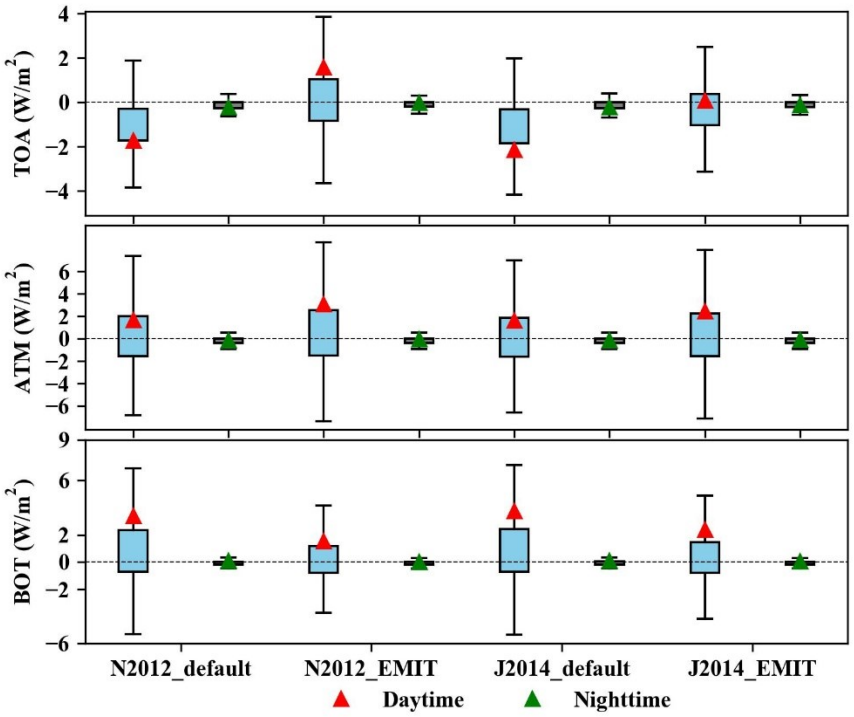

Figure 6. Day-night changes of TOA, ATM and BOT shortwave radiation forcings from simulations using different composition atlases (N2012_default, N2012_EMIT, J2014_default and J2014_EMIT) compared to bulk dust.

3.3 Radiative effect on air quality

Aerosol effects not only gave rise to changes in meteorological variables but also had a significant impact on air quality. As shown in Figure 7 and Table S2, the inclusion of bulk dust aerosol feedbacks in the WRF-CHIMERE model resulted in substantial increases in PM_{10} concentrations, with an average increase of 119.48 μg m^{-3} with a 95% CI of −27.63 to 1408.39 μg m^{-3}. This rise in particulate matter highlights the important role of dust aerosols in contributing to local and regional air pollution, especially in regions that are susceptible to dust storms. Along with these increases in PM_{10} concentrations, O_3 concentrations slightly decreased, with an average reduction of −46.52 μg m^{-3}. This reduction in ozone can be attributed to the complex interaction between dust particles and ozone precursor gases, where dust aerosols can act as both a sink for ozone and influence the photochemical processes that govern its formation and degradation. 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 most pronounced increases in PM_{10} concentrations occurred in the Badain Jaran Desert, a well-known dust source region, where peak values exceeded 1200 μg m^{-3}. This reflects the large dust emissions typical of desert environments, where strong winds mobilize vast quantities of particulate matter. Downwind regions, including Ningxia, Shaanxi, and Beijing, also experienced significant PM_{10} elevations, with concentration differences reaching approximately 600 μg m^{-3} compared to baseline levels. The inclusion of speciated dust influences long-range transport and can substantially affect PM_{10} concentrations. Comparison of the subfigures in Fig. 8 reveals pronounced regional differences in PM_{10} predictions arising from the use of different mineralogical databases. Incorporating detailed mineralogical data enhances the accuracy of dust composition representation and its associated effects on PM_{10}, highlighting the critical role of mineral speciation in dust modeling and regional air quality assessment.

Ozone changes along transport pathways were generally smaller than the surrounding concentrations, typically ranging from −60 to −40 μg m^{-3} with a mean value of −46.52 μg m^{-3} (95% CI: −63.38 to −31.74) as shown in Table S2. These smaller changes in O_3 concentrations reflect the fact that dust aerosols have a more localized and complex effect on ozone formation and destruction, with significant variability depending on the regional and temporal context. In particular, dust-induced reductions in ozone are likely to be influenced by the local presence of other atmospheric constituents. The photochemical reactions involving dust particles, such as the photolysis of nitrate ions, can produce

519 reactive radicals that further influence the atmospheric chemistry of ozone (Ma et al., 2021).

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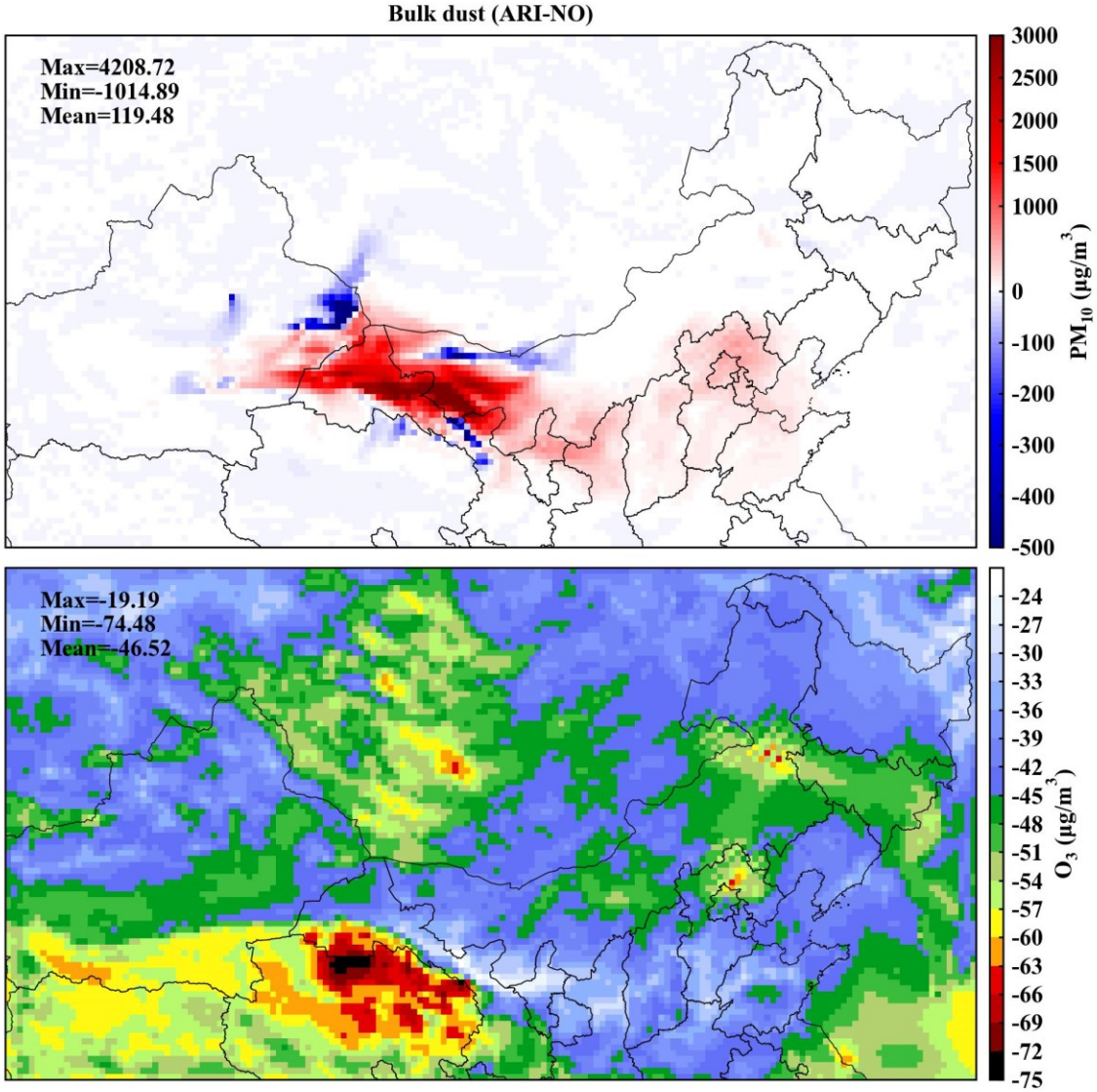

522

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

525

526 The spatial differences in PM_{10} and O_3 concentrations simulated by WRF-CHIMERE
527 with different mineralogy atlases compared to bulk dust, enabling ARI effects, are depicted
528 in Figures 8 and A4. These comparisons reveal substantial changes in the PM_{10} and O_3
529 concentrations across the different mineralogical compositions, including N2012_Default,

530 N2012_EMIT, J2014_Default, J2014_EMIT, and bulk dust. This suggests that the
531 normalization of the 12 minerals from these atlases significantly modifies meteorological
532 conditions, further influencing the relative abundances of dust particles and their
533 subsequent effects on air quality and atmospheric composition.

534 When compared to bulk dust, reduced PM_{10} concentrations were primarily observed
535 in the Taklimakan Desert, with decreases of around 60 μg m^{-3}, while increases in PM_{10}
536 concentrations occurred in the Badain Jaran Desert and its downwind regions, with
537 concentrations rising up to 1000 μg m^{-3}. These regional variations indicate that different
538 dust mineralogical compositions can impact the emission and transport of dust, with certain
539 mineral types leading to more efficient scattering or absorption of radiation, which may
540 alter the local meteorological conditions and dust dispersion patterns.

541 For O_3 concentrations, reductions and enhancements were mainly observed in the
542 Horqin sandy land and North China Plain, with changes up to 4 μg m^{-3}, respectively. This
543 highlights the complex interaction between dust aerosols and ozone chemistry, where dust
544 can either enhance or reduce ozone concentrations depending on the region. Dust aerosols
545 can influence ozone levels by acting as a surface for heterogeneous chemical reactions or
546 by modifying the photochemical processes that control ozone formation and destruction.

547 When considering the EMIT data, PM_{10} concentrations were reduced in dust source
548 regions and enhanced in downwind regions, with reductions of up to −1567.16 μg m^{-3} and
549 increases of +218.26 μg m^{-3}. This suggests that more accurate mineralogical data can
550 influence dust transport patterns, leading to greater reductions in PM_{10} at the source regions
551 and increased dust concentrations in the downwind areas. These findings further emphasize
552 the role of mineralogical composition in modulating dust aerosol behavior and distribution.

553 For O_3, enhancements appeared in source regions, while reductions were observed in
554 downwind regions, with changes ranging from −2.46 to +3.52 μg m^{-3}. These trends suggest
555 that more accurate dust speciation can influence regional ozone levels in different ways,
556 with possible implications for local air quality and atmospheric chemistry. Notably, the

impacts on PM_{10} concentrations from N2012_EMIT compared to N2012_Default were larger than those observed from J2014_EMIT versus J2014_Default, while the impacts on O_3 concentrations followed the opposite trends. This indicates that the choice of dust mineralogical dataset has a differential impact on PM_{10} and O_3 concentrations, underscoring the importance of considering mineral composition in aerosol modeling to more accurately predict air quality and climate effects.

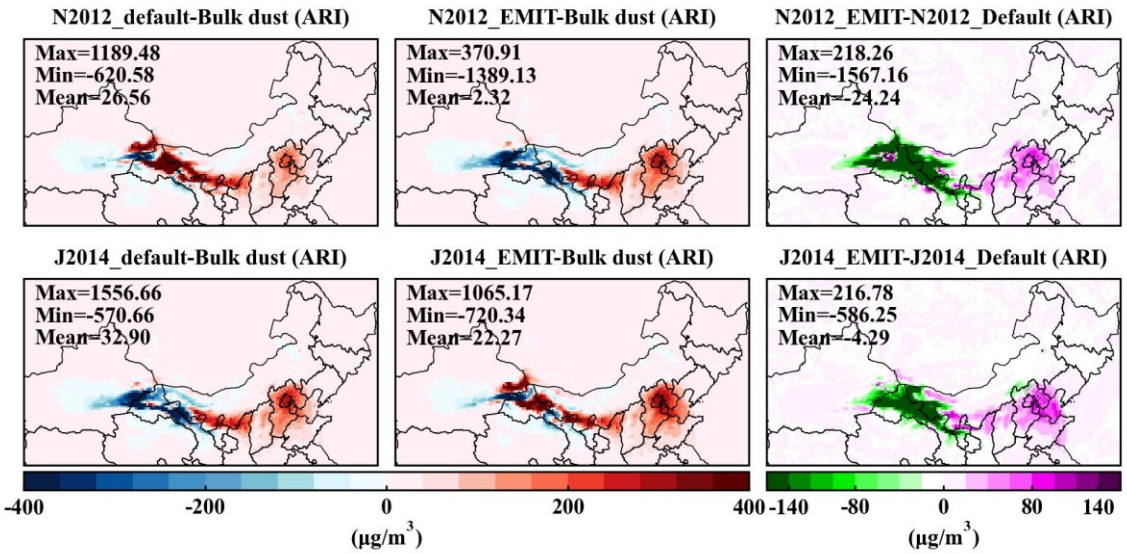

Figure 8. Difference in PM_{10} concentrations considering bulk dust and various dust mineralogy atlases that enable ARI effects.

Figure 9 shows the percentage changes in surface concentrations of mineral dust with and without considering ARI effects. These results provide valuable insight into how the inclusion of ARI effects modifies the composition and radiative properties of dust aerosols, depending on the mineralogical dataset used. For the N2012_default and N2012_EMIT data, quartz and feldspar accounted for a substantial portion of the total dust, ranging from approximately 51.7% to 57.4% for quartz and 18.6% to 19.8% for feldspar. This indicates that quartz and feldspar are the dominant mineral components in the dust modeled with the N2012 dataset.

In contrast, for the J2014_default dataset, the mineral composition was more

diversified, with calcite, quartz, and mica contributing about 26.3%, 24.0%, and 20.0%, respectively, to the total dust composition. This shift in mineral proportions reflects the differences in the mineralogical characterization between the N2012 and J2014 datasets, with J2014 incorporating a broader range of dust minerals. For J2014_EMIT, the mineral composition shifted further, with quartz and mica making up approximately 46.8% and 27.5% of the dust, respectively. This highlights the importance of using accurate mineralogical data, such as that from EMIT satellite observations, to better represent the composition of dust aerosols in simulations.

The inclusion of EMIT data led to an increase in the absorption percentage of hematite by about 8% for N2012 and 6% for J2014. Hematite is a highly absorbing mineral, especially in the shortwave spectrum, and its increased presence enhances the dust's ability to absorb solar radiation, thereby affecting the DRE in the shortwave spectrum. This increase in hematite absorption is significant, as it directly impacts the radiative effects of dust, potentially contributing to a greater cooling effect on the atmosphere by modifying the shortwave radiation balance.

While quartz constitutes the largest portion of the dust in both the N2012 and J2014 datasets, its DRF effects are relatively limited, as noted in Li et al. (2021). Quartz is known for its high reflectivity in the shortwave spectrum, and while it makes up a large fraction of the total dust mass, it has a less pronounced effect on radiative forcing compared to more absorbing minerals like hematite or mica. This suggests that, despite its dominance in dust composition, quartz plays a smaller role in modifying the energy balance of the atmosphere through direct radiative effects.

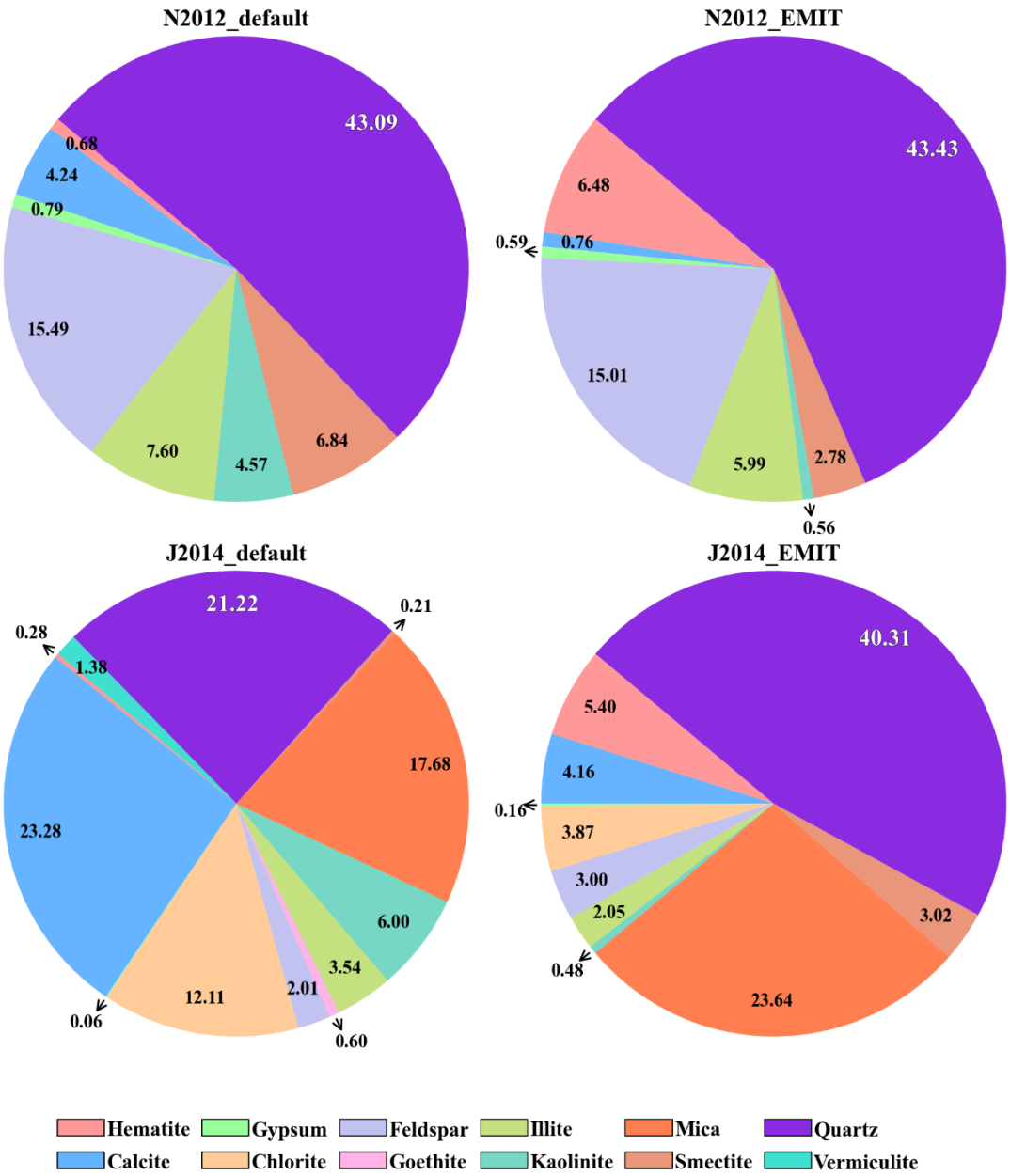

Figure 9. Contributions of different mineralogical compositions using N2012_default, N2012_EMIT, J2014_default, and J2014_EMIT, considering ARI effects, compared to the scenario without enabling aerosol feedbacks.

3.4 Limitations and uncertainties for aerosol feedbacks of mineralogical dust

The accuracy of simulated dust emission is intricately linked to soil properties, such as soil texture and moisture, which primarily influence the threshold friction velocity required for dust particle mobilization (Kim and Choi, 2015; Su and Fung, 2015). These

610 factors play a critical role in determining the magnitude and spatial distribution of dust
611 emissions, underscoring the need for precise and high-resolution soil data in dust modeling.
612 While the current EMIT L3 data offers a spatial resolution of 0.5° × 0.5°, real-time higher
613 spatial resolution datasets, such as the 60 m × 60 m EMIT L2B mineral atlas
614 (https://earth.jpl.nasa.gov/emit/internal_resources/282), can provide a more detailed
615 representation of soil mineralogy, thereby enhancing the fidelity of dust emission
616 simulations.

617 The uncertainty associated with dust mineralogical datasets is being actively
618 addressed by NASA's EMIT. This initiative has deployed a hyperspectral imaging
619 spectrometer aboard the International Space Station to deliver global retrievals of soil
620 mineral compositions with unprecedented spatial detail. The spectrometer captures spectral
621 absorption features within the UV to near-infrared range (0.38–2.5 μm), offering critical
622 insights into the distribution and variability of soil minerals (Castellanos et al., 2024;
623 Connelly et al., 2021). In addition to satellite-based observations, ground-based stations
624 play a vital role in measuring dust mineralogical compositions using stationary instruments,
625 which provide localized and highly accurate data. Complementing these measurements,
626 aircraft-based instruments offer the capability to sample dust particles along specific flight
627 tracks, providing valuable vertical and spatial profiles of speciated dust properties (e.g.,
628 size and mixing state, Panta et al., 2023; Ryder et al., 2015). Together, these observational
629 platforms form a robust foundation for validating and improving dust models.

630 Aerosol-cloud interactions involving speciated dust are another critical aspect of dust-
631 climate interactions that require further investigation, especially for feldspar and quartz
632 (Atkinson et al., 2013; Chatziparaschos et al., 2023). Incorporating these interactions into
633 two-way coupled WRF-CHIMERE models can provide a more comprehensive
634 understanding of the feedback mechanisms between dust aerosols and cloud microphysics.
635 Such implementations are currently a focus of ongoing work, aiming to refine the
636 representation of dust-induced radiative and microphysical effects in regional and global

637 models. These efforts will not only improve model accuracy but also enhance our ability
638 to predict the impacts of dust on weather, air quality, and climate.
639
640 **4 Conclusion**
641 Dust mineral composition plays a vital role in regulating atmospheric radiation and
642 air quality, yet its effects remain poorly constrained in current atmospheric models.
643 Understanding these impacts is particularly important for North China, where severe dust
644 storms frequently affect regional climate and pollution. This study investigates how
645 variations in mineral composition influence aerosol–radiation interactions and their
646 implications for meteorology and air quality during a major dust storm event.
647 The findings revealed significant spatial variations in radiative forcing due to
648 differences in dust mineralogy. Compared to the ARI effects of bulk dust, the mineralogical
649 composition of dust aerosols can increase SW radiation forcing at the surface and in the
650 atmosphere by +0.10 to +0.82 W m^{-2}, while simultaneously causing a decrease of
651 approximately −0.72 W m^{-2} in SW radiation forcing at the TOA. Integrating EMIT data
652 into the model reduced PM_{10} biases by over 15% in high-concentration regions and
653 improved ozone predictions, with localized changes ranging from −2.46 to +3.52 μg m^{-3}.
654 Specifically, the ARI effects of these mineralogical compositions led to a notable increase
655 in PM_{10} levels, reaching up to 1189.48 μg m^{-3} in dust source regions, when compared to
656 bulk dust scenarios.
657 These findings highlight the importance of incorporating dust mineralogical data to
658 improve simulations of radiative forcing and air quality impacts. Within the scope of this
659 study, the results indicate that overall dust mineralogical composition, rather than dust mass
660 alone, plays a decisive role in ARI effects, with hematite exerting a dominant influence
661 despite its minor abundance, although the radiative effects of individual mineral species
662 were not separately quantified. Systematic biases in surface radiation, near-surface winds,
663 and temperature persist, reflecting challenges in simulating dust–atmosphere interactions
664 and uncertainties in mineralogical datasets. Incorporating meteorological spectral nudging

in future simulations could provide a more realistic representation of ARI-induced dust perturbations under different mineralogical compositions. Coupling this approach with higher-resolution soil and satellite data, as well as additional observational constraints, would further refine dust emission simulations and reduce model biases, particularly in regions frequently affected by severe dust events.

Data and software availability

The meteorological ICs and BCs, Chemical ICs and BCs and emission data used for WRF–CHIMERE and all data used to create figures and tables in this study are provided in an open repository on Zenodo (https://doi.org/10.5281/zenodo.14728874, Gao et al., 2025a). Himawari and CALIPSO satellite data are available at ftp://ftp.ptree.jaxa.jp/jma/netcdf and https://subset.larc.nasa.gov/calipso, respectively.

The source codes of the two-way coupled WRFv3.7.1–CHIMERE v2020r3 models are obtained from https://www.lmd.polytechnique.fr/chimere. The related source codes, configuration information, namelist files and automated run scripts of these three two-way coupled models are archived at Zenodo with the following associated DOI: https://doi.org/10.5281/zenodo.14729124 (Gao et al., 2025b).

Author contributions

CG, XZ, HY and LH carried out the data collection, related analysis, figure plotting, and paper writing. HZ, SZ, and AX were involved with the original research plan and made suggestions for the paper writing.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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Appendix

Table A1. Model setups and inputs for the WRF-CHIMERE model.

		WRF-CHIMERE
Domain configuration	Horizontal grid spacing	27 km (165 × 87)
	Vertical resolution	33 levels
Physics parameterization	Shortwave radiation	RRTMG
	Longwave radiation	RRTMG
	Cloud microphysics	Thompson
	PBL	YSU
	Cumulus	Grell-Freitas
	Surface	Monin-Obukhov
	Land surface	Noah LSM
	Icloud	Xu-Randall method
Chemistry scheme	Aerosol mechanism	SAM
	Aerosol size distribution	Sectional (10 bins)
	Aerosol mixing state	Core-Shell
	Gas-phase chemistry	MELCHIOR2
	Photolysis	Fast-JX with cloud effects
Emission	Dust emission	Kok
Input data	Meteorological ICs and BCs	FNL
	Chemical ICs and BCs	LMDZ-INCA

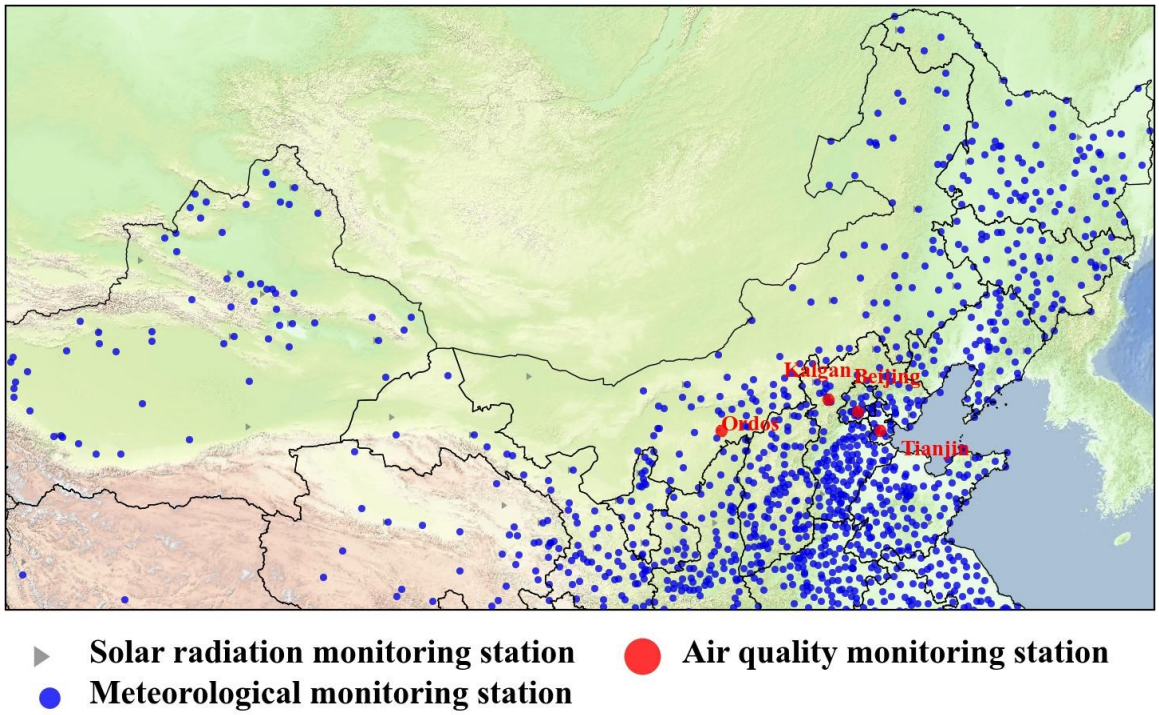


Figure A1. Simulation domain and locations of meteorology and air quality monitoring stations.

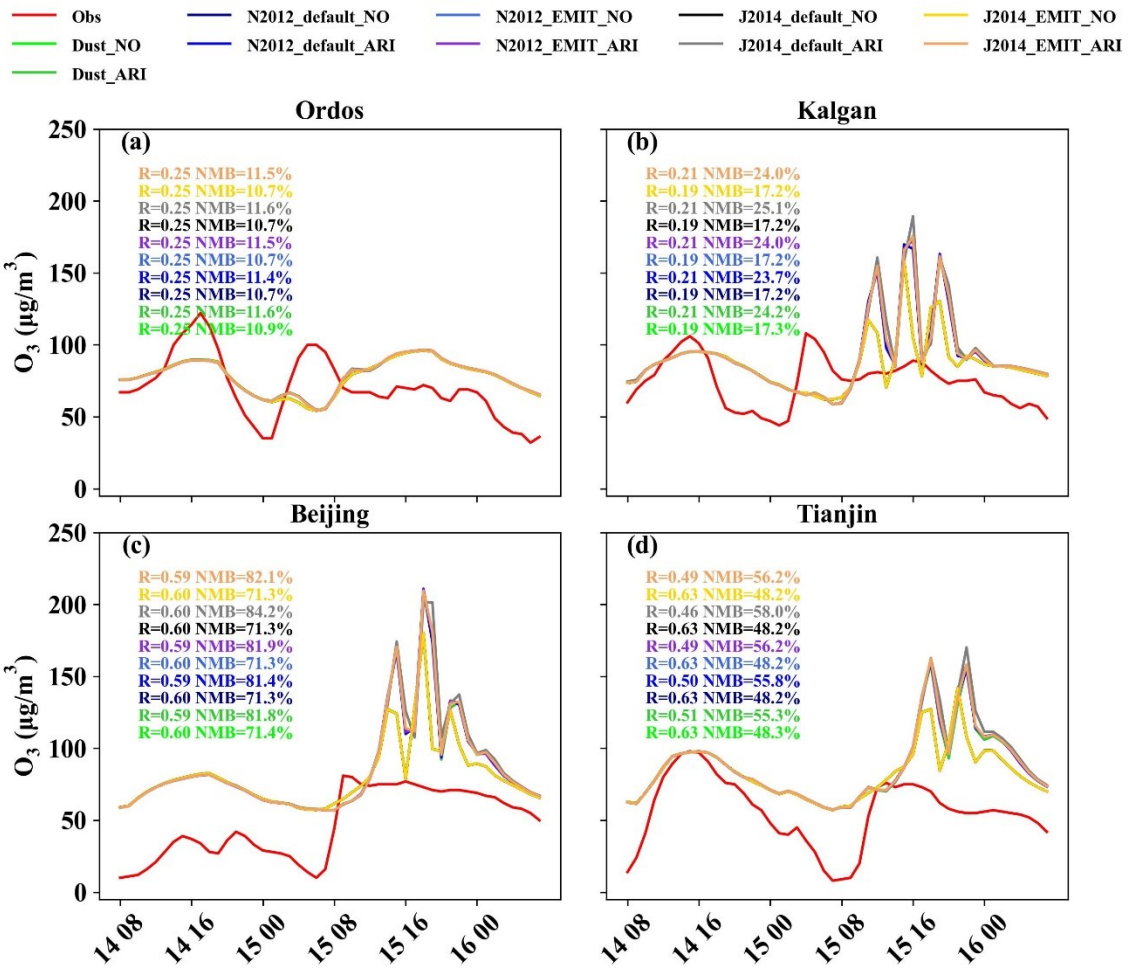


Figure A2. Statatiscal metrices between observated and simulated O_3 concentrations by different scenario simulations.

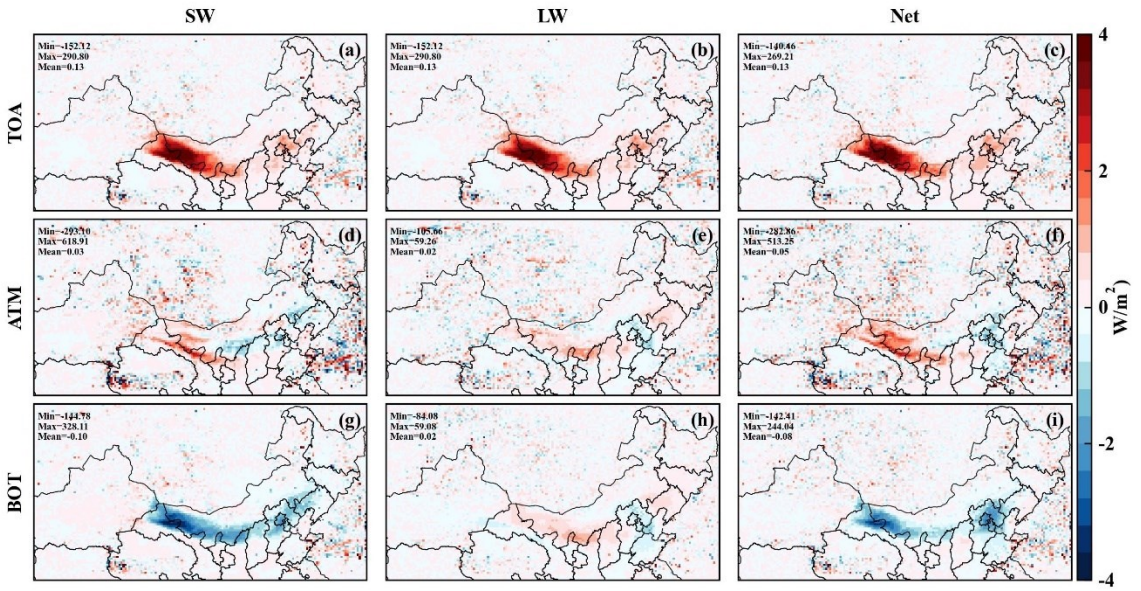


Figure A3. Difference between TOA, ATM and BOT radiation forcings with considering J2014 and N2012 mineralogical dust compositions (i.e., N2012_default) enabling ARI effects.

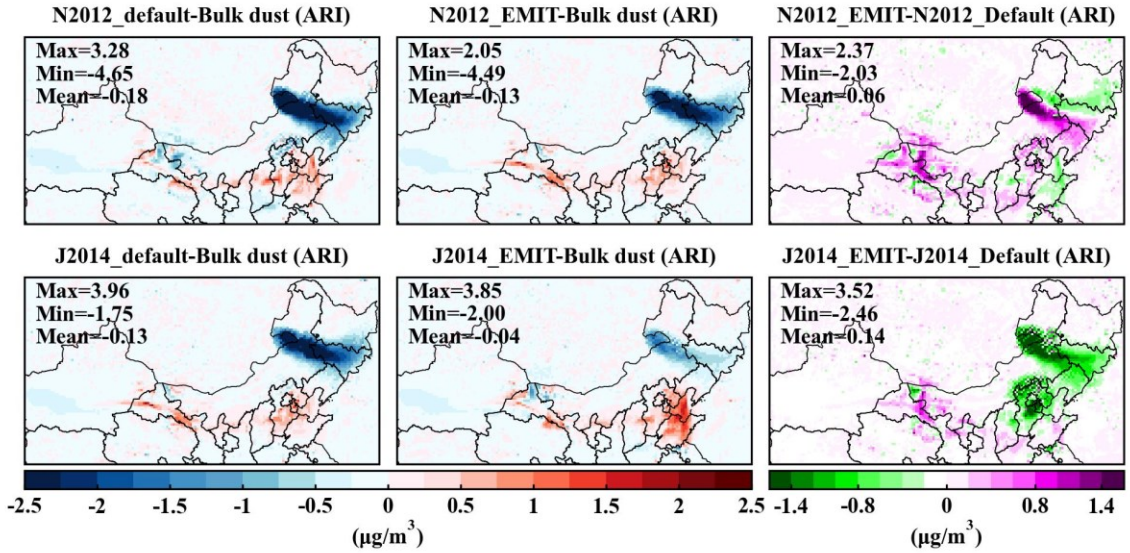
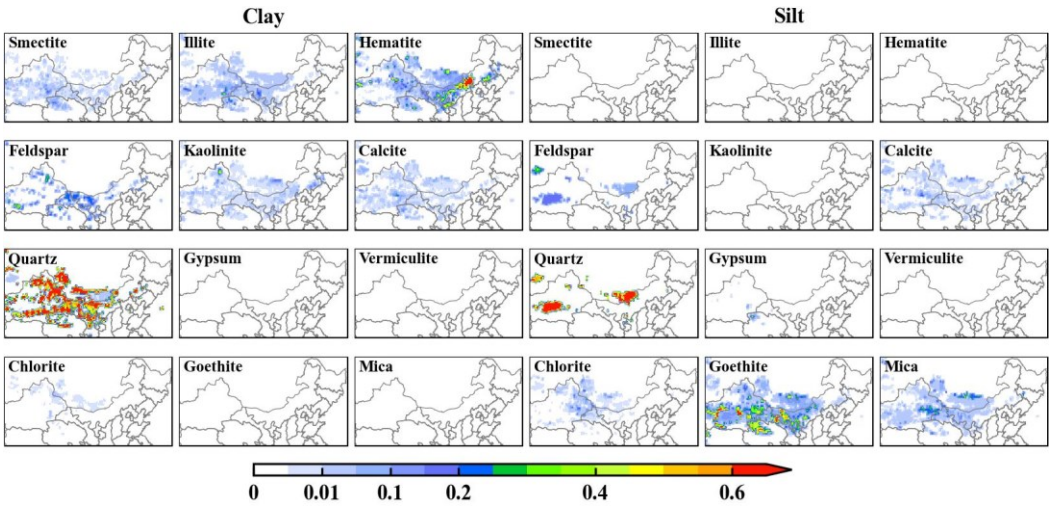


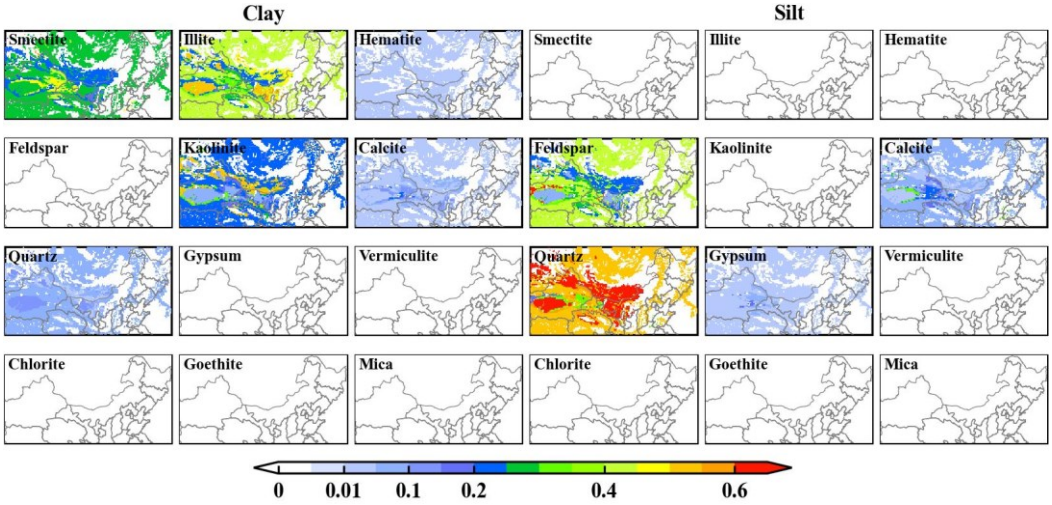
Figure A4. Difference in O_3 concentrations considering bulk dust and various dust mineralogy atlases that enable ARI effects.



926

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

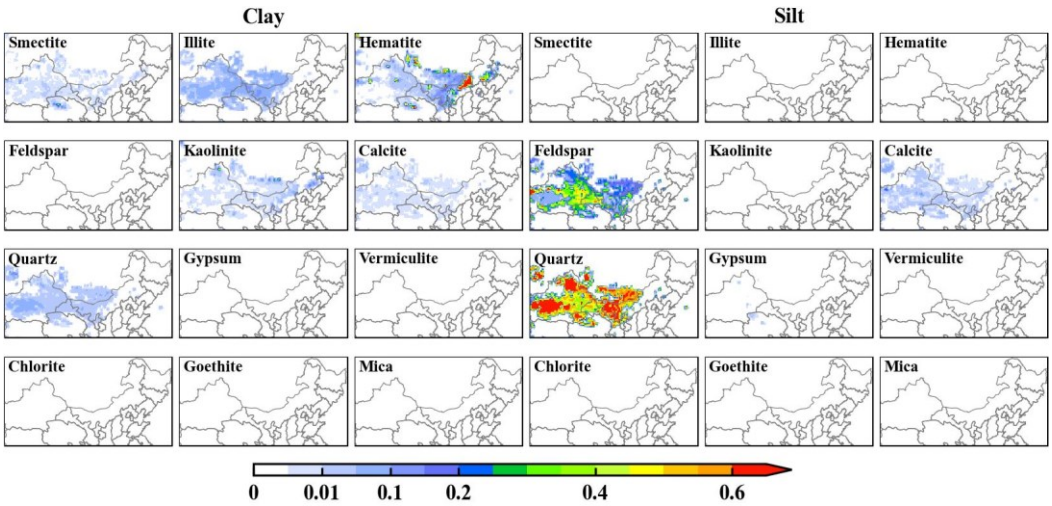
929



930

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

933



934

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

937