

1 Insights into microphysical and optical properties of
2 typical mineral dust within ~~urban industrial polluted~~
3 snowpack via wet/dry deposition in Changchun,
4 Northeastern China

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3 **Abstract.** This study presents the first compositional analysis of dust in snowpack from
4 a typical Chinese industrial city, utilizing utilizes the computer-controlled scanning
5 ~~electron microscope software IntelliSEM EPASTM~~, combined with K-means cluster
6 analysis and manual experience. The dust is predominantly, reports for the first time
7 that the dust in the snow accumulation from a typical industrial city in China is mainly
8 composed of kaolinite-like (36%), chlorite-like (19%), quartz-like (15%), illite-like
9 (14%), hematite-like (5%), and clay-minerals-like (4%), with minor contributions from
10 other components and other components. It was also found that the size distribution and
11 aspect ratio of the dust did not undergo significant changes during dry and wet
12 deposition, but they exhibited great variability among the different mineral composition
13 groups. Subsequently, these observed microphysical parameters were used to constrain
14 the optical absorption of dust, and the results showed that under low (high) snow grain
15 size scenarios, the albedo reductions caused by dust concentrations of 1, 10, and 100
16 ppm in snow were 0.007 (0.022), 0.028 (0.084), and 0.099 (0.257), respectively. These
17 results emphasize the importance of dust composition and size distribution
18 characteristics in constraining snowpack light absorption and radiation processes.

19

1 **1 Introduction**

2 Snow constitutes a crucial component of the terrestrial cryosphere, covering
3 approximately 40% of the global land area, with a maximum extent of around 45
4 million square kilometers (Hall et al., 1995; Lemke et al., 2007). It is predominantly
5 found in polar and high-latitude regions, as well as mountainous areas at mid-to-low
6 latitudes, exhibiting significant temporal and spatial variability due to seasonal changes
7 (Tan et al., 2019; Thackeray et al., 2016; Zhu et al., 2021). Current research indicates
8 that light-absorbing aerosols in the atmosphere (e.g. black carbon, brown carbon, and
9 dust) are eventually deposited on—various surfaces, the including snow surface or
10 glaciers through atmospheric diffusion, transport, and dry/wet deposition processes
11 (Doherty et al., 2010; Gilardoni et al., 2022; Kuchiki et al., 2015). This alters the single
12 optical properties of the snowfield, enhances the absorption of solar radiant energy, and
13 reduces the albedo of the snow and ice surface, thereby accelerating snowmelt and
14 altering the water cycle, and exerting a nuanced yet pivotal role in regional climate
15 dynamics (Hadley and Kirchstetter, 2012; Hansen and Nazarenko, 2004; Kang et al.,
16 2020; Skiles et al., 2018). Hence, it emerges as a critical determinant impacting both
17 regional and global climate change.

18 Extensive observational evidences highlighted significant reductions in the extent and
19 duration of snow cover across the Northern Hemisphere, particularly notable in high-
20 latitude and mountainous regions due to global warming (Bormann et al., 2018;
21 Derksen and Brown, 2012; Mote et al., 2018; Pulliainen et al., 2020; Zeng et al., 2018).
22 Currently, the duration of Northern Hemisphere snow cover is decreasing by

1 approximately 5-6 days per decade (Dye, 2002), with Arctic June snow cover
2 diminishing at a rate of 13.6% per decade (Derksen and Brown, 2012; Derksen et al.,
3 2017). Regions like the western Tibetan Plateau and Australia have experienced snow
4 cover retreat rates ranging from 11% to 30% per decade (Bormann et al., 2012;
5 Immerzeel et al., 2009), while the onset of snowmelt in the western United States has
6 advanced by 6-26 days since the mid-1970s (Hall et al., 2015). Dust, a prevalent aerosol
7 type in the Earth-atmosphere system, has garnered significant scientific attention due
8 to its role in accelerating ice and snow melt (Bryant et al., 2013; Dong et al., 2020;
9 Kaspari et al., 2015; Painter et al., 2012). Réveillet et al. (2022) reported an 8-12 day
10 earlier average snowmelt in the French Alps and the Pyrenees due to dust presence
11 during 1979-2018. Zhang et al. (2018) found that dust reduced snow albedo in the
12 southern Tibetan Plateau by approximately 0.06 ± 0.004 , equivalent to 30% of the
13 albedo reduction caused by black carbon. Sarangi et al. (2020) further demonstrated
14 dust's primary contribution to snow darkening above 4000 m altitude in the Tibetan
15 Plateau, surpassing that of black carbon in influencing regional ice and snow melt.

16 Whereas Xing et al. (2024) and Winton et al. (2024) –also highlighted the remarkable
17 contribution of dust events to the snow darkening of the Asian High Mountains and the
18 Southern Alps, respectively. Moreover, Hao et al. (2023) –projected a decrease in black
19 carbon deposition on ice and snow under future emission scenarios, and anticipated
20 thatwhile anticipating heightened dust emissions and deposition fluxes driven by
21 climate change-induced land use changes (Neff et al., 2008), frequent wildfires (Yu and
22 Ginoux, 2022), and increased drought (Huang et al., 2016). –Consequently, dust's

1 impact on ice and snow melt is expected to intensify markedly.

2 Previous studies have focused on investigating the concentration of dust in snow and

3 its related radiative effects, neglecting the impact of the microphysical properties of

4 dust on its optical absorption (Bryant et al., 2013; Reynolds et al., 2020; Xie et al.,

5 2018). In fact, the physical and chemical properties of mineral dust aerosols, including

6 their particle size distribution (PSD), composition, mixing state, and shape, determine

7 their optical properties (Chou et al., 2008; Colarco et al., 2014; Fountoulakis et al., 2024;

8 Haapanala et al., 2012; Shi et al., 2022b). Dong et al. (2020) compared the volume-size

9 distribution of dust deposition in ice and snow in western China and the Arctic, finding

10 significant differences in the median particle size of dust, and showing that the particle

11 size decreases with altitude in various remote regions except for the remote Arctic and

12 Antarctic regions. Wang et al. (2023) used intelligent scanning electron microscopy to

13 obtain typical PSD of dust in snow in Changchun. Additionally, related dust studies in

14 the atmosphere have confirmed the complex variability of dust mineral composition.

15 For example, in the case of dust aerosols from the Sahara Desert collected in Izana,

16 Spain, in the summer of 2005, it was found that they were mainly composed of silicates

17 (64%) and sulfates (14%), with small amounts of carbonaceous materials (9%), quartz

18 (6%), calcium-rich particles (5%), hematite (1%), and soot (1%) (Kandler et al., 2007).

19 In contrast, dust particles collected in Beijing, China, during an Asian dust storm were

20 primarily composed of clay minerals (35.5wt%, by weight percentage), quartz

21 (30.3wt%), and calcite (14.0wt%), followed by feldspar (8.7wt%), pyrite (1.0wt%), and

22 hornblende (0.4wt%), along with noncrystalline materials (10.1wt%) (Shi et al., 2005).

1 Panta et al. (2023) conducted detailed field measurements using electron microscopy
2 in the Sahara Desert of Morocco, reporting the statistical characteristics of the single-
3 particle composition, size, mixing state, and aspect ratio of newly emitted mineral dust.

4 Kok et al. (2023) also highlight that dust-snow interactions generate a global annual-
5 mean radiative forcing of $+0.013 \text{ W m}^{-2}$ (90% confidence interval: $0.007\text{--}0.03 \text{ W m}^{-2}$),
6 with large uncertainties primarily attributed to variations in dust-snow mixing state,
7 particle size distribution, and chemical composition. To date, no studies have
8 comprehensively analyzed the composition, size, and morphology of dust in snow or
9 clarified the interrelationships among these characteristics. This lack of understanding
10 significantly limits accurate assessments of the optical properties and radiative effects
11 of dust in ice and snow (Flanner et al., 2021; He et al., 2024).

12 Based on a field snow observation experiment conducted in Changchun, northeastern
13 China, in November 2020, this study utilized intelligent scanning electron microscopy
14 with an energy-dispersive X-ray analyzer to investigate in detail the composition, size,
15 and morphological characteristics of dust during dry and wet deposition. These
16 statistically significant parameters were subsequently used to constrain the complex
17 refractive index and optical absorption inversion of dust, providing more accurate dust
18 optical parameter inputs for snow radiative transfer models, and enhancing the accuracy
19 of climate effect assessments of dust in snow.

20 **2 Methods**

21 **2.1 Snow sample collection and analysis**

1 Our previous study has detailed the snow field experiment conducted in Changchun
2 (Wang et al., 2023). The sampling site is located at the meteorological station of Lvyuan
3 District (43°88'N, 125°25'E), with no apparent sources of air pollution emissions in the
4 visual range. During and after a heavy snowfall from November 19 to December 17,
5 2020, we collected snow samples every two days, yielding a total of one fresh snowfall
6 sample (wet deposition) and 15 aged surface snow samples (dry and wet deposition).
7 This study selected five samples for measurement and analysis at intervals of 6-8 days,
8 including one wet deposition sample (D1) and four dry/wet deposition samples (D7,
9 D15, D23, and D29; "D" denotes days). Briefly, the selected snow samples were melted
10 at room temperature, and an appropriate volume of the snow solution was taken based
11 on the cleanliness of the snow sample (20 ml for D1 and 1 ml for the rest four samples).
12 The solution was filtered through a polycarbonate membrane with a diameter of 25 mm
13 and a pore size of 0.1 μ m to separate the particles. The membrane was then transferred
14 to a storage box and dried in a desiccator. Prior to analysis, a filter membrane
15 approximately 0.5 cm^2 was cut and gold-plated. The samples were placed in the electron
16 microscope sample chamber for vacuum processing, and data were collected and
17 analyzed using the Environmental Particle Analysis Software (IntelliSEM-EPASTM) of
18 the intelligent scanning electron microscope.
19 The IntelliSEM-EPASTM system automatically scans multiple matrix areas within the
20 field of view. By collecting backscattered signals from the scanning electron
21 microscope (TESCAN Mira3) and comparing the image signal intensity with preset
22 threshold levels, particles are detected. Upon detection, the system automatically

1 records the morphology images and positions of the particles on the polycarbonate
2 membrane and utilizes two Bruker XFlash 6|60 energy dispersive spectroscopy (EDS)
3 detectors-EDS technology to analyze the relative content of 24 chemical elements (C,
4 O, ~~F~~, Na, Mg, Al, Si, P, S, Cl, K, Ca, Ti, V, Cr, Mn, Fe, Co, Ni, Cu, Zn, ~~As, Br, Rh, Pd,~~
5 ~~Sn, Ag, Ba, SePt,~~ and Pb) in the particles. This process rapidly generates high-definition
6 images and energy spectrum data for each particle (thousands of particles per hour).
7 Additionally, IntelliSEM-EPASTM provides detailed measurements of the maximum
8 and minimum diameters, average diameter, particle projection area, roundness, and
9 aspect ratio of the particles-with the acquired particle SEM images based on a built-in
10 image processing module (Zhao et al., 2022). Compared to manually operated scanning
11 electron microscope experiments, the IntelliSEM-EPASTM system has the advantages
12 of intelligent control and fast analysis speed, allowing for the acquisition of a large
13 amount of environmental particle information in a short time, including detailed data
14 on particle concentration levels, morphology characteristics, and component content
15 across arbitrary size ranges, and were also comparable to the results from bulk analysis
16 (Peters et al., 2016; Wagner and Casuccio, 2014). The elemental concentrations
17 obtained by CCSEM show good consistency with bulk analysis results from atomic
18 absorption (AA), bulk X-ray fluorescence (XRF), proton-induced X-ray emission
19 (PIXE), and anion chromatography (IC) (Casuccio et al., 1983). Mamane et al. (2001)
20 also showed that 360 particles were sufficient to obtain representative results in
21 CCSEM analysis of particle types and size distributions, based on comparisons of 360,
22 734, 1456, and 2819 individual particles. Although CCSEM has a superior advantage

1 in high efficiency for measuring large quantities of particles, it encounters challenges
2 with certain types of particles that have complex morphologies, such as soluble salts
3 and soot (Peters et al., 2016). CCSEM-induced errors may include particle overlap,
4 contrast artifacts, sizing inaccuracies, and particle heterogeneity (Mamane et al., 2001).
5 Consequently, manual error correction is typically performed prior to data processing.
6 ~~thereby providing data support for big data analysis of particle micro-morphology~~
7 ~~characteristics and physicochemical properties.~~

8 **2.2 Dust microphysical properties derived from IntelliSEM-EPAS™**

9 Based on the IntelliSEM-EPAS™ system, this study obtained the geometric
10 information and energy spectrum data of about 4,000-5,000 particles in each sample,
11 aiming to reveal the statistical characteristics of the microphysical properties of
12 insoluble particles in snow. Specifically, according to Kandler et al. (2007), particles
13 with a relative mass proportion of C and O elements exceeding 95% were roughly
14 classified as carbonaceous particles. Then, for all remaining particles, the elemental
15 index of each element other than C and O was calculated. Based on single-particle
16 composition quantification, the elemental index of element X is defined as the atomic
17 ratio of the concentration of the considered element to the sum of the concentrations of
18 the quantified elements (Panta et al., 2023).

$$19 |X| = \frac{X}{(Na + Mg + Al + Si + P + S + Cl + K + Ca + Ti + V + Cr + Mn + Fe + Co + Ni + Cu + Zn + Sn + Ba + Pb)} \quad (1)$$

20 The elemental symbol indicates the relative contribution measured for each particle (in
21 atomic percent). Using the obtained elemental indices and combining K-Means
22 clustering algorithms and manual experience, these non-carbonaceous particles were

1 classified (Kandler et al., 2007; Panta et al., 2023; Zhao et al., 2022). The main principle
2 of the K-means clustering algorithm is to use the k-means algorithm to classify particles
3 with similar chemical compositions into 30 types based on the elemental index of each
4 element, and then, according to relevant research and manual experience classification
5 principles of EDS spectra (Panta et al., 2023), classify the 30 types into 12 mineral
6 phases by merging some similarly classified clusters, with particle categories named
7 after their most common chemical composition, including quartz-like, hematite-like,
8 rutile-like, kaolinite-like, chlorite-like, illite-like, hematite-like, clay-minerals-like etc.

9 Figure S1 presents the percentage distribution of elemental indices (excluding C and O)
10 for 12 categories of mineral particles. Specifically, hematite-like, quartz-like, rutile-like,
11 apatite-like, and dolomite-like particles are predominantly characterized by Fe, Si, Ti,
12 Ca, and Mg, respectively. Kaolinite-like particles are enriched in Al and Si, while clay
13 mineral-like and Ca-rich silicate particles contain significant amounts of Al and Si,
14 along with notable Ca content, with the latter exhibiting a higher Ca concentration. In
15 contrast, illite-like, smectite-like, and chlorite-like particles, in addition to being
16 enriched in Al and Si, also contain varying amounts of K, Mg, and Fe, respectively.
17 Correspondingly, representative SEM images of particles are presented within each
18 mineral category panel.

19 The size distribution of different types of particles is described using a normal
20 distribution, specifically expressed as (Flanner et al., 2021; Li et al., 2021; Flanner et
21 al., 2021):

$$22 n_r = \frac{dN}{dr} = \sum_{i=1}^n \frac{N_i}{\sqrt{2\pi} r \ln(\sigma_i)} \exp \left\{ -\frac{1}{2} \left[\frac{\ln(r) - \ln(r_i)}{\ln(\sigma_i)} \right]^2 \right\} \quad (2)$$

1 where N_i is the total number of particles per unit volume in the i -th size mode, r_i is
 2 the mean radius, and σ_i is the geometric standard deviation. These parameters can be
 3 fitted from the measured data. Similarly, the aspect ratio (AR) of particles is also
 4 expressed as a normal distribution function (Panta et al., 2023):

$$5 \quad n_{AR} = \frac{dN}{dAR} = \sum_{i=1}^n \frac{N_i}{\sqrt{2\pi}AR\ln(\sigma_i)} \exp\left\{-\frac{1}{2}\left[\frac{\ln(AR)-\ln(AR_i)}{\ln(\sigma_i)}\right]^2\right\} \quad (3)$$

6 **2.3 Dust light absorption and snow albedo calculation**

7 Based on the proportion of different mineral phases in the dust, the effective volume
 8 refractive index (m_{eff}) of mineral mixtures in snow aerosols was calculated using the
 9 effective medium approximation (EMA) method. Specifically, for binary mixtures, the
 10 effective complex refractive index under EMA-Bruggeman approximation can be
 11 written as (Kahnert, 2015):

$$12 \quad m_{\text{eff}} = \sqrt{\frac{\frac{1}{4}[m_1^2(2-3f) + m_2^2(3f-1)] + \sqrt{\left[\frac{1}{16}[m_1^2(2-3f) + m_2^2(3f-1)]^2 + \frac{1}{2}m_1^2m_2^2\right]}}{14} \quad (4)}$$

15 where m_1 is the complex refractive index of the background matrix, m_2 is the complex
 16 refractive index of the inclusions, and f is the volume fraction of the inclusions. The
 17 effective complex refractive index for multicomponent mixtures can be obtained by
 18 repeating the above process. The refractive indices of different minerals used in this
 19 study were obtained from the spectral refractive index dataset of the main mineral
 20 components and chemical compositions provided by Zhang et al. (2024). For more
 21 detailed information about the dataset, refer to Zhang et al. (2024). Subsequently, using

1 the effective complex refractive indices of dust constrained by observations, size
2 distribution, and aspect ratio (AR) data, we calculated the mass absorption coefficient,
3 single scattering albedo, and asymmetry factor of different types of dust particles using
4 the MOPSMAP program package (Gasteiger and Wiegner, 2018). The MOPSMAP
5 model is a comprehensive aerosol optical property model combining T-matrix, Mie
6 scattering theory, and geometric optics, widely used in calculating complex aerosol
7 optical parameters (Kanngiesser and Kahnert, 2021; Shi et al., 2022b).

8 The simulation of snow albedo was executed by our team's developed the Spectral
9 Albedo Model for Dirty Snow (SAMDS) (Wang et al., 2017), which has been applied
10 in many studies and is applicable to semi-infinite snow depth scenarios (Shi et al., 2021;
11 Li et al., 2021). Its accuracy is also well validated, achieving an albedo accuracy of
12 ±0.02 compared to field spectroradiometer data (Wang et al., 2017). Specifically, the
13 albedo of a snow-covered field containing dust under clear sky conditions can be
14 expressed as:

$$15 \quad R_d(\lambda) = \exp \left(-4 \sqrt{\frac{8\pi B R_{ef} k(\lambda)}{9\lambda(1-g)} + \frac{2\rho_{ice} R_{ef}}{9(1-g)} MAC_{Dust} \cdot C_{Dust}} \cdot \frac{3}{7} (1 + 2 \cos(\nu_0)) \right) \quad (5)$$

16 where λ is the wavelength in μm ; ν_0 is the solar zenith angle; $k(\lambda)$ is the imaginary
17 part of the complex refractive index of ice. ρ_{ice} and R_{ef} represent the density and
18 effective radius of snow grains (in μm), respectively; g is the asymmetry factor of snow
19 grains (weighted average of the scattering angle cosine); B is a factor related only to
20 the shape of the snow grains. MAC_{Dust} is the mass absorption coefficient of dust, and
21 C_{Dust} is the concentration of dust particles in the snow. SAMDS uses 480 bands (0.2–
22 12

1 5.0 μm to resolve spectral albedo. Here we used $B = 1.27$ and $g = 0.89$ to characterize
2 spherical snow grains (Wang et al., 2017), SAMDS is also capable of simulating the
3 albedo of non-spherical snow grains, and our previous work has explored the albedo
4 variation induced by snow grain shape (Shi et al., 2022a), which will not be reiterated
5 here. Additionally, this study assumes dust-snow external mixing. However, it is worth
6 noting that some studies have indicated that internal mixing can further enhance the
7 dust-induced albedo reduction caused by 5%–30% (He et al., 2019; Shi et al., 2021).
8 Therefore, this assumption may underestimate the impact of dust on albedo.

9 **3 Results**

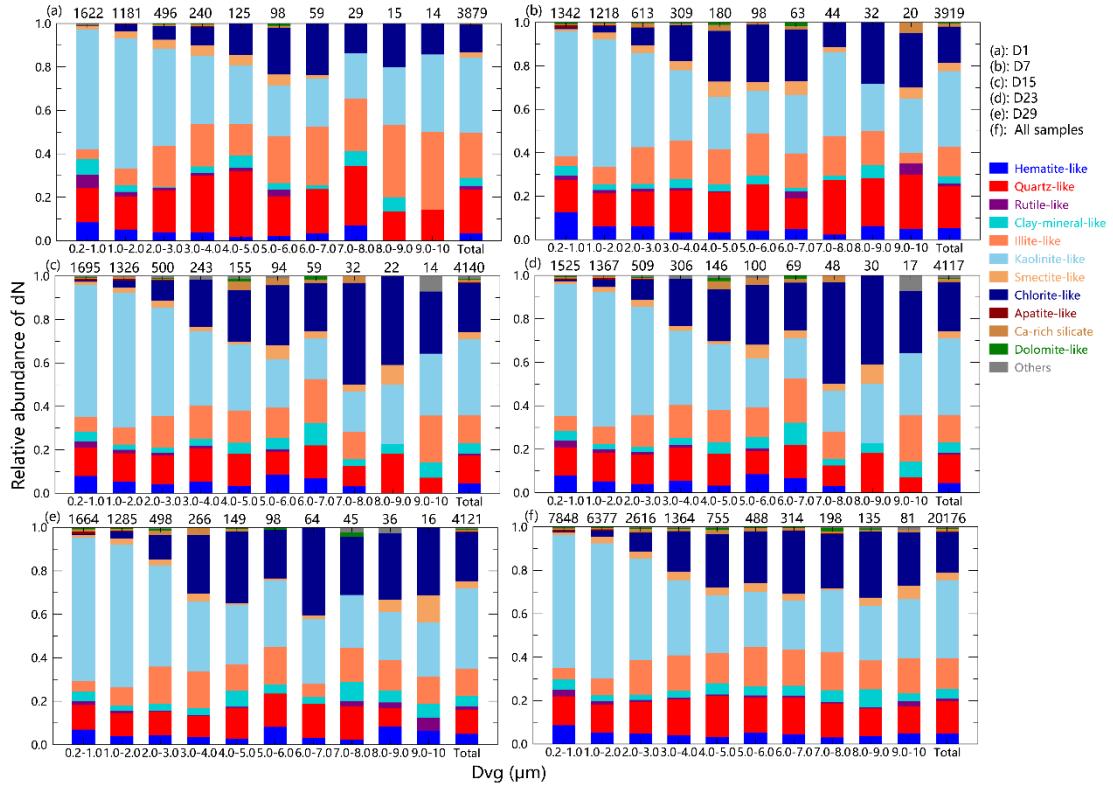
10 **3.1 The composition of dust in seasonal snow**

11 The composition of dust determines its complex refractive index, which is crucial for
12 studying the radiative effects of dust (Reynolds et al., 2020; Lee et al., 2020). This study
13 identified a total of 12 mineral components, including hematite-like, quartz-like, rutile-
14 like, clay-mineral-like, illite-like, kaolinite-like, smectite-like, chlorite-like, apatite-like,
15 Ca-rich silicates, domolite-like, and others. However, it is important to handle this
16 classification scheme with caution, as each particle may consist of different minerals,
17 which may have variable or ambiguous compositions. Therefore, the groups used
18 cannot uniquely identify minerals but rather indicate the most likely minerals matching
19 the particle composition. This is reflected in the suffix "-like" used in the group naming
20 scheme. Given the existence of other potential identification methods, each with its own
21 advantages and limitations, the complete dataset generated and used in this study can

1 be utilized for future research. Figure 1 (Figure S24) shows the number (mass) relative
2 proportions of different mineral components in dry and wet deposition snow samples
3 at different size resolutions, indicating significant trends observed among different
4 particle groups with changes in size categories. For all samples, kaolinite-like is the
5 most abundant, present in all size ranges, with its abundance decreasing with increasing
6 size. Quartz-like particles have nearly similar abundance in each size category
7 (approximately 10%-20%), which is higher than the values reported by Panta et al.
8 (2023) for dust from Morocco (approximately 5%). Similarly, clay-minerals-like are
9 evenly distributed across each size category, accounting for about 4% of the relative
10 abundance. Hematite-like exhibits similar relative abundances, but its contribution
11 decreases with increasing particle size, and its strong light-absorbing properties have
12 drawn widespread attention (Li et al., 2024; Zhang et al., 2015; Moteki et al., 2017). In
13 contrast, chlorite-like's relative contribution increases with increasing size, with an
14 average abundance of approximately 20%. It is noteworthy that the relative abundance
15 of illite-like is higher in wet deposition samples than in dry deposition samples, possibly
16 due to K-rich illite, considered one of the most effective ice nucleation sources found
17 among different mineral components in dust (Atkinson et al., 2013; Harrison et al.,
18 2022). Additionally, the relative abundance of quartz-like in dry deposition samples is
19 significantly lower than in wet deposition samples, which is closely related to the
20 migration process of quartz-like particles in snow. Table S1 provides the relative
21 proportions of different mineral components within the measured size range (0.2-10
22 μm). Overall, dust in Changchun snow is primarily composed of kaolinite-like (36%),

1 chlorite-like (19%), quartz-like (15%), illite-like (14%), hematite-like (5%), and clay-
2 minerals-like (4%) and other components. In comparison, Shi et al. (2005) reported
3 mineralogical properties of Asian dust primarily consist of clay minerals (35.5wt%, by
4 weight percentage), quartz (30.3wt%), and calcite (14.0wt%), followed by feldspar
5 (8.7wt%), pyrite (1.0wt%), and hornblende (0.4wt%). For the Middle East, Prakash et
6 al. (2016) reported relative mass abundances of clay minerals ranging from 45% to 75%,
7 plagioclase from 5% to 54%, and quartz from 0.1% to 10.2% as major components.

8 Considering that industrial activities (e.g., coal combustion, urban construction, and
9 road dust) emit quartz-rich particles, while long-range transport from arid regions (e.g.,
10 the Gobi Desert) contributes illite, which is consistent with the dust profile in Asia (Li
11 et al., 2021). The anthropogenic contribution (e.g., hematite-like particles) aligns with
12 the presence of nearby steel production facilities. Therefore, our results suggest that
13 dust is likely a mixture of local and long-range sources.



1

2 **Figure 1.** Size-resolved number abundance of different particle groups for D1 sample

3 (a), D7 sample (b), D15 sample (c), D23 sample (d), D29 sample (e), and All samples

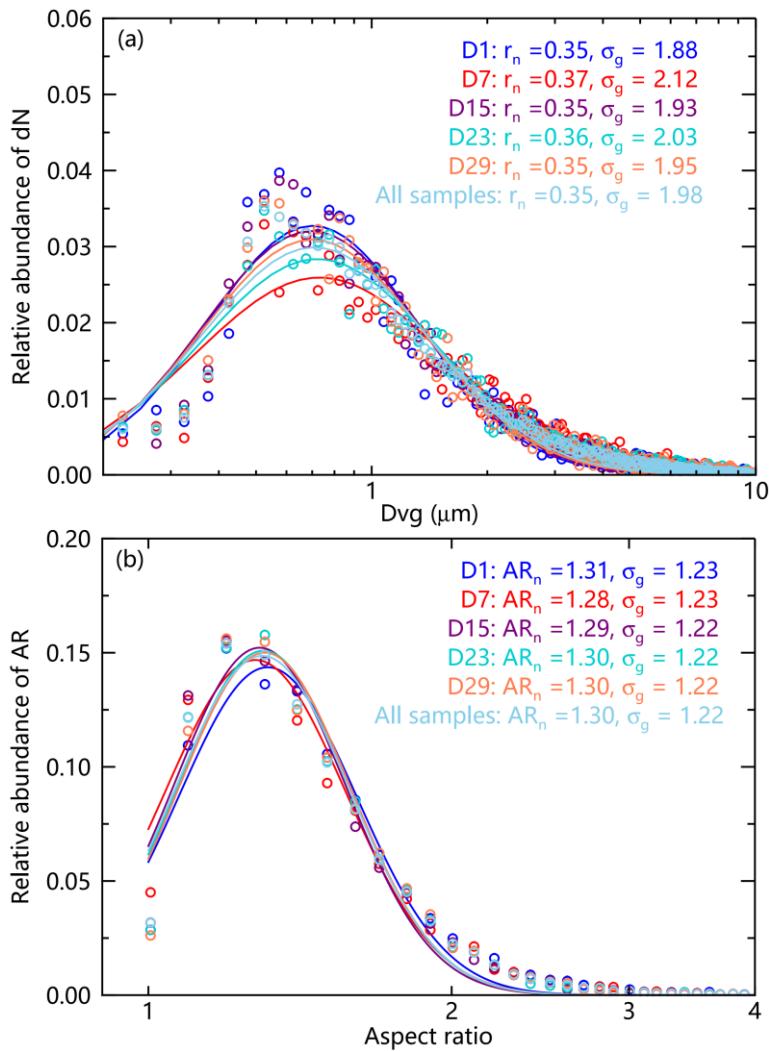
4 (f). The numbers on top represent total particle counts in the given size bin.

5 **3.2 Size distribution and aspect ratio of dust in seasonal snow**

6 Particle size is a key factor influencing the light-absorbing properties of dust, which has
 7 received widespread attention in field observations, numerical models, and satellite
 8 remote sensing (Castellanos et al., 2024; González-Flórez et al., 2023; Song et al.,
 9 2022). Figure 2a illustrates the size distribution characteristics of dust particles
 10 collected from snow samples at different periods, indicating that the peak particle size
 11 of dust during dry deposition did not vary significantly. All samples exhibited similar
 12 size distributions, with geometric mean radii ranging from 0.35 to 0.37 μm and
 13 geometric standard deviations from 1.88 to 2.12, comparable to findings reported in

1 other studies (Kok, 2011; Di Mauro et al., 2015; Kok et al., 2017). Interestingly,
2 significant differences in size spectra were observed among different mineral
3 components (Figure S2-S3 and Table S2), considering only the cases where the fitted
4 values passed significance tests. Chlorite-like particles exhibited the coarsest size
5 spectrum (median radius = 1.32 μm), nearly double that of smectite-like particles (0.57
6 μm), likely due to their tendency to aggregate during atmospheric transport (Formenti
7 et al., 2014). Illite-like particles displayed the widest size range (0.38-0.59 μm) across
8 different snow samples, possibly reflecting multiple source regions or differential
9 atmospheric processing. The dominant kaolinite-like and quartz-like particles shared
10 similar size distributions centered around 0.36 μm , consistent with their common origin
11 in soil fragmentation (Kok, 2011), though kaolinite exhibited slightly less size
12 variability. Together these components represented 51% of particles and primarily
13 determined the overall dust size characteristics. Particularly noteworthy were hematite-
14 like particles, which despite being the smallest at 0.29 μm characteristic of iron oxide
15 condensation formation, disproportionately influenced radiative properties due to their
16 exceptional light absorption (Formenti et al., 2014; Go et al., 2022). Chlorite-like
17 showed the largest size spectrum, with a median radius reaching 1.32 μm , significantly
18 higher than smectite-like, the second largest with a median radius of 0.57 μm . Illite-like
19 exhibited a broader range of sizes across different snow samples, ranging from 0.38 to
20 0.59 μm . Kaolinite-like and quartz-like particles had similar size distributions, with
21 median radii of approximately 0.36 μm , although the geometric standard deviation of
22 the former was slightly lower than that of the latter. These two components, due to their

1 high proportions, largely determine the overall size distribution characteristics of dust.
 2 Despite hematite having the smallest size ($0.29 \mu\text{m}$), its study is of significant interest
 3 due to its strong light-absorbing properties (Formenti et al., 2014; Ge et al., 2022).



5 **Figure 2.** Relative abundances of (a) logarithmic dust size number distributions $dN/d\log D_p$ and (b) logarithmic dust AR number distributions $dN/d\log AR$ for different
 6 snow samples. D_{vg} : particle diameter of dust in snow, r_n : the number median radius,
 7 σ_g : the geometric standard deviation.

9 Aspect ratio (AR) is another critical geometric parameter of dust particle that affects
 10 their light-absorbing properties (Botet and Rai, 2013; Haapanala et al., 2012; Huang et

1 al., 2023). Figure 2b describes the spectral distribution of aspect ratios of dust particles
2 in dry and wet deposition samples. Similar to the size results, the aspect ratio of dust
3 particles during dry and wet deposition did not show significant variations, with all
4 samples displaying similar spectral distributions. The geometric mean values ranged
5 from 1.28 to 1.31, with geometric standard deviations from 1.22 to 1.23. These results
6 are slightly lower than those reported in atmospheric dust studies, such as
7 measurements of dust from Morocco and Asia with AR values of 1.46 and 1.40,
8 respectively (Kandler et al., 2009; Okada et al., 2001). During the Fennec campaign in
9 central Sahara, a median AR of 1.3 was found (Rocha-Lima et al., 2018), and
10 measurements of dust particles collected in the Sahara air layer and marine boundary
11 layer during the AERosol Properties-Dust (AER-D) period showed median AR values
12 of 1.30–1.44 for particles ranging from 0.5 to 5 μm and 1.30 for particles from 5 to 10
13 μm , and 1.51 for particles from 10 to 40 μm (Ryder et al., 2018). Furthermore, we also
14 explored the spectral characteristics of aspect ratios of different mineral components
15 (Figure [S3](#)[-S4](#) and Table S3). Unlike the size distribution, although there are differences
16 in aspect ratios among different components, the variation range is not large. Most
17 mineral component groups have similar median AR values of 1.30, except for
18 [goethite](#)[hematite](#) and clay minerals, which have the lowest median AR of 1.275 and the
19 highest median AR of 1.37, respectively. The AR of the same mineral component group
20 shows no significant differences among different samples. Additionally, we found that
21 AR is generally independent of particle size and type (Figure [S4](#)[-S5](#)), consistent with the
22 results of Panta et al. (2023).

3.3 Dust light absorption and its effects on snow albedo

The refractive index of various mineral components exhibits significant variation.

Figure [S5-S6](#) illustrates the complex refractive indices (both real and imaginary parts)

of the eight principal mineral component groups identified in this study. The imaginary

parts, indicative of absorption, vary by up to six orders of magnitude. Hematite shows

the highest imaginary part of the complex refractive index, indicating the strongest

light-absorbing properties, while quartz displays the smallest, indicating the weakest.

The complex refractive indices of kaolinite, illite, chlorite, and smectite present

relatively similar values, suggesting minimal variation in their light-absorbing

properties. Based on the complex refractive index database of mineral component

groups and combined with volume relative proportions under observational constraints,

an effective medium approximation method is used to obtain the effective complex

refractive index of dust in snow. Additionally, to assess the impact of different mineral

component groups on the effective complex refractive index, we adjusted the initial

volume proportions of hematite, kaolinite, chlorite, and illite by factors of 1.25, 1.50,

1.75, and 2.0, respectively, while keeping the relative proportions of other components

unchanged, and finally normalizing the proportions of all components. Figure 3

illustrates the variation in the effective complex refractive index of dust with

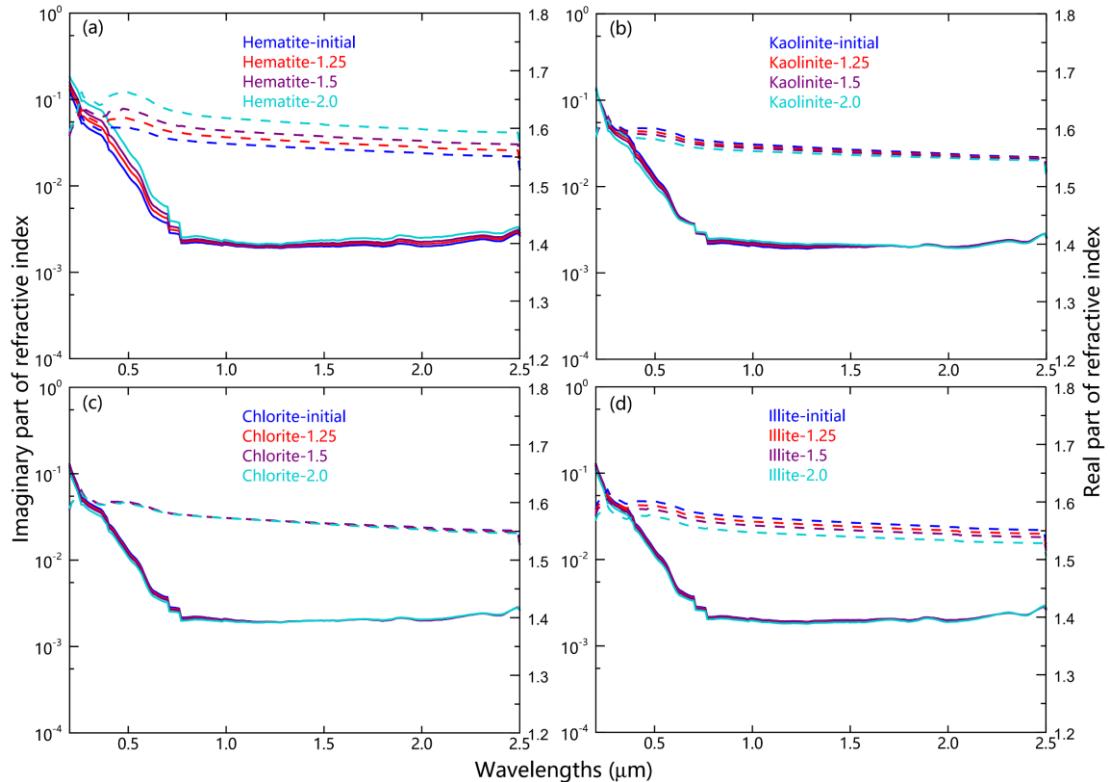
wavelength under these scenarios, focusing on the imaginary parts related to absorption.

Overall, k_{dust} is distributed within a narrow range (~0.001–0.01), gradually decreasing

with increasing wavelength in the UV and VIS bands, and then stabilizing in the NIR

band, comparable to values reported in other literature. Notably, an increase in the

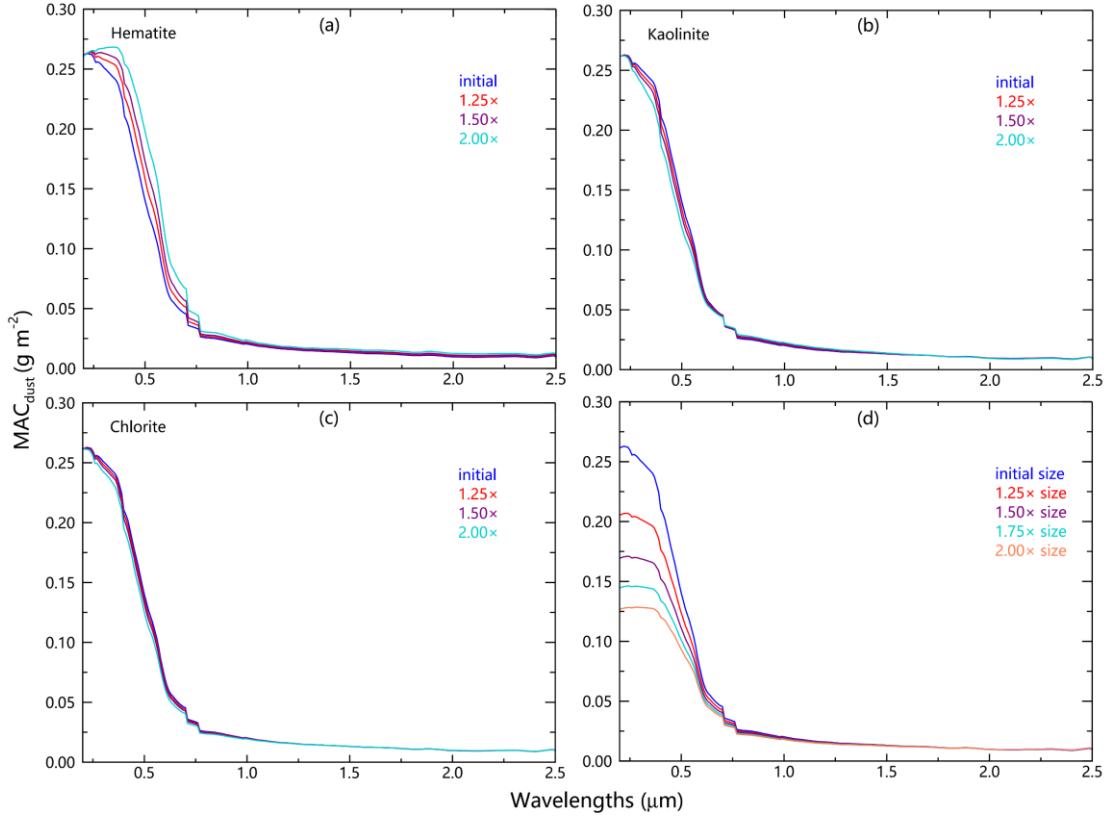
1 relative proportion of hematite leads to a significant rise in k_{dust} , especially in the visible
 2 spectrum. Conversely, increases in the relative proportions of kaolinite, chlorite, and
 3 illite cause a slight decrease in k_{dust} , due to the reduced relative proportion of hematite
 4 after normalization.



5
 6 **Figure 3.** Complex spectral refractive indices of dust mixtures in scenarios with
 7 different composition group percentages. The solid and dashed lines in the diagram
 8 represent the imaginary and real parts, respectively. The default average volume
 9 fraction of each mineral group is 35.6% Kaolinite, 19.4% Chlorite, 15.2% Quartz, 14.6%
 10 Illite, 4.5% Hematite, 3.1% Smectite, and 1.1% Rutile. (a), (b), (c), and (d) represent
 11 the effects of changes in the proportion of hematite, kaolinite, chlorite, and illite,
 12 respectively.

13 Furthermore, incorporating observed dust size distribution and AR spectra

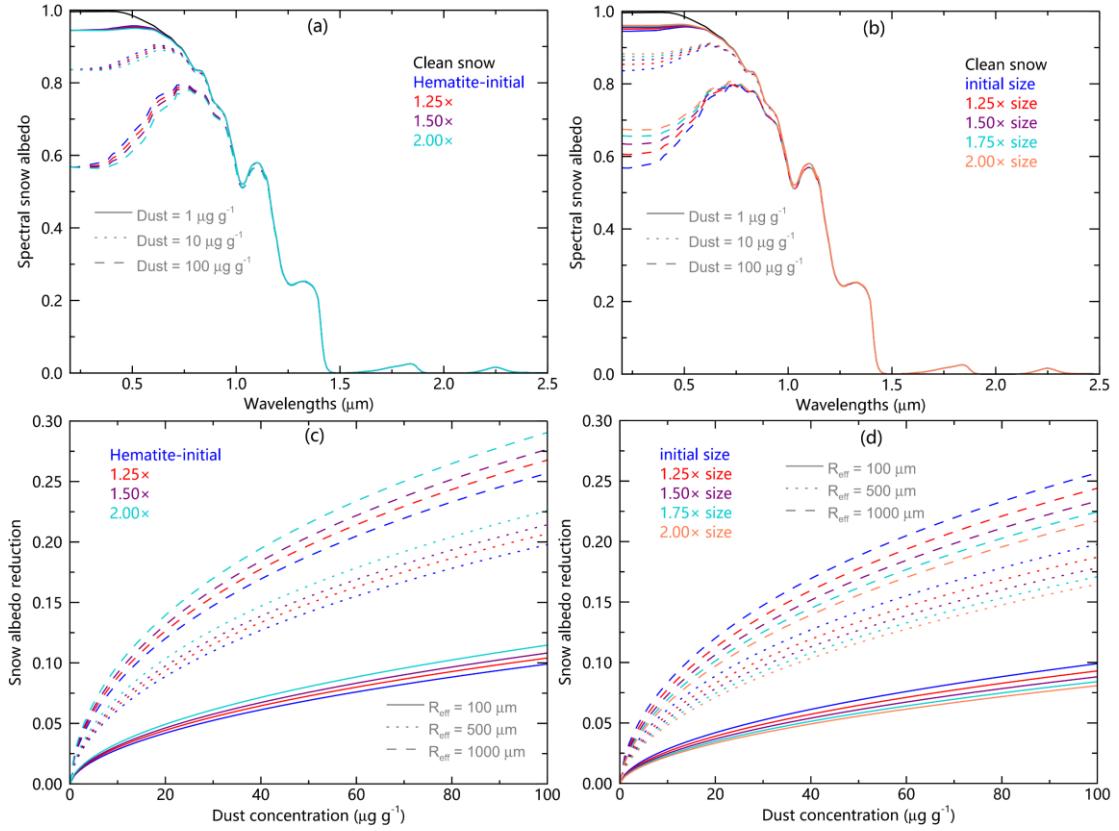
1 characteristics, we calculated the mass absorption cross-section (MAC_{dust}), as shown in
2 Figure 4. Similar to k_{dust} , MAC_{dust} is distributed within a narrow range ($\sim 0\text{--}0.3 \text{ m}^2/\text{g}$),
3 gradually decreasing with increasing wavelength in the UV and VIS bands, and
4 approaching stability (~ 0) at wavelengths greater than 1000 nm. An increased relative
5 proportion of hematite enhances MAC_{dust} in the visible spectrum. For instance,
6 doubling the relative proportion of hematite raises MAC_{dust} at 500 nm from 0.14 m²/g
7 to 0.19 m²/g. However, changes in the relative proportions of kaolinite and chlorite have
8 minimal effects on MAC_{dust}, consistent with the results for k_{dust} . Additionally, an
9 increase in R_{dust} significantly reduces MAC_{dust} in the UV and VIS bands, weakening its
10 spectral dependence. For example, when R_{dust} is increased by factors of 1.25, 1.5, and
11 2.0, MAC_{dust} at 300 nm decreases by 20% (0.20 m²/g), 33% (0.17 m²/g), and 48% (0.13
12 m²/g), respectively, and at 500 nm, it decreases by 12% (0.12 m²/g), 21% (0.11 m²/g),
13 and 34% (0.09 m²/g). Overall, the measured MAC_{dust} values (0—0.3 m²/g) show
14 regional variations that reflect compositional differences: while comparable to Saharan
15 dust (0.1—0.25 m²/g, Balkanski et al., 2007), they are significantly lower than Tibetan
16 Plateau dust (0.3—0.5 m²/g, Li et al., 2021) and slightly higher than Colorado (San Juan
17 Mountains) dust (0.05—0.15 m²/g, Skiles et al., 2017). This pattern correlates with
18 hematite content, decreasing from 8—12% in Tibetan Plateau dust to 5% in our samples
19 and just 2—3% in Greenland dust. The distinct quartz-rich signature in our samples (15%
20 vs <5% in other regions) may reflect unique industrial emission sources in northeastern
21 China.



1 **Figure 4.** Spectral variations in the dust mass absorption cross-sections (MACs) for
2 different simulation scenario: (a) Hematite, (b) Kaolinite, (c) Chlorite, and (d) Size.
3 Here the dust aspect ratio is fixed at 1.3.

5 Figure 5a illustrates the impact of changes in the relative proportion of hematite on the
6 spectral snow albedo, considering scenarios with low, medium, and high dust loads in
7 snow, assuming a snow particle size of 500 μm (medium scenario). It can be observed
8 that changes in spectral albedo due to variations in dust concentration and composition
9 proportions generally occur in the visible light spectrum, while the near-infrared (NIR)
10 spectrum is primarily influenced by the microphysical properties of snow particles
11 themselves (Gardner and Sharp, 2010; He and Flanner, 2020), thus unaffected by dust
12 concentration and composition proportions. Specifically, spectral albedo decreases in
13 the UV and visible light (UV-Vis) bands with increasing dust concentration, with a

1 further decrease observed with rising proportions of hematite. Similar to Figure 5a,
2 Figure 5b describes changes in spectral albedo of snow under different dust particle
3 sizes, showing that increasing dust particle size can mitigate the decline in spectral
4 albedo in the visible light spectrum, which is more pronounced in high dust load
5 scenarios. For example, doubling the dust particle size increases the spectral albedo
6 (300 nm) from 0.946, 0.840, and 576 to 0.961, 0.882, and 0.673 for dust concentrations
7 of 1, 10, and 100 ppm in snow, respectively. Figures 5c and 5d respectively illustrate
8 the effects of changes in the relative proportion of hematite and dust particle size on the
9 reduction in snow albedo, considering three snow particle size scenarios. Specifically,
10 the reduction in albedo increases with increasing dust concentration and snow particle
11 size, further exacerbated by an increase in the proportion of hematite, especially in high
12 dust concentration and snow particle size scenarios. Conversely, an increase in dust
13 particle size reduces the reduction in albedo, and increases in dust concentration and
14 snow particle size can further amplify this effect. For instance, in low (high) snow
15 particle size scenarios, increasing the proportion of hematite increases the reduction in
16 albedo caused by dust concentrations of 1, 10, and 100 ppm in snow from 0.007 (0.022),
17 0.028 (0.084), and 0.099 (0.257) to 0.008 (0.026), 0.033 (0.098), and 0.115 (0.291).
18 Conversely, increasing the dust particle size reduces the reduction in albedo caused by
19 dust concentrations of 1, 10, and 100 ppm in snow to 0.005 (0.017), 0.022 (0.066), and
20 0.081 (0.217). These results emphasize the complex effects of dust composition,
21 particle size, concentration, and snow particle size on snow albedo.



1 **Figure 5.** (a) Spectral snow albedo in the wavelength range of 0.2–2.5 μm for different
2 dust concentrations and hematite percentages, with assumed snow radii of 500 μm . (b)
3 Spectral snow albedo for different dust concentrations and sizes. (c) Broadband snow
4 albedo reduction as a function of dust concentration for different hematite percentages
5 and snow snow-grain radii (100, 500, and 1,000 μm). (d) Similar to (c), but hematite
6 percentage is replaced with dust size.

8 **4 Summary and discussion**

9 This study employed CCSEM technology to quantitatively analyze insoluble
10 particulate matter in snow in Changchun, ranging from 0.2 to 10 μm , and identified 12
11 mineral component groups through K-means cluster analysis and empirical
12 identification. The findings indicate that the dust in Changchun snow primarily
13 comprises [kaolinite-like \(36%\), chlorite-like \(19%\), quartz-like \(15%\), illite-like \(14%\),](#)

1 hematite-like (5%), and clay-minerals-like (4%)~~clay aggregates (48%), quartz (22%),~~
2 ~~plagioclase (11%), calcite (6%), and orthoclase (5%)~~, with no significant changes in the
3 proportions of different mineral components during dry deposition processes. In
4 contrast, wet deposition samples contain higher proportions of illite and quartz, which
5 may be attributed to illite as an effective source of ice nuclei and the dynamic migration
6 of quartz in snow. The study also found that the size and aspect ratio (AR) of dust follow
7 normal distribution characteristics, with geometric means and standard deviations of
8 $0.35 \pm 0.37 \mu\text{m}$, 1.88 ± 2.12 for size, and 1.28 ± 1.31 , 1.22 ± 1.23 for AR, respectively.
9 Although there were no significant changes in the size and AR of dust during dry and
10 wet deposition processes, significant variability was observed among different mineral
11 component groups in terms of size and AR. Subsequently, based on statistically derived
12 characteristics of dust components, size, and AR under observational constraints, we
13 analyzed the light absorption characteristics of dust. The mass absorption cross-section
14 (MAC_{dust}) was found to be distributed within a narrow range ($\sim 0\text{--}0.3 \text{ m}^2/\text{g}$). An increase
15 in the relative proportion of hematite was observed to increase MAC_{dust} , while an
16 increase in dust particle size decreased MAC_{dust} by a specific percentage ($10\% \pm 50\%$).
17 Finally, the study discussed the complex effects of dust composition, particle size,
18 concentration, and snow particle size on snow albedo. The results indicate that an
19 increase in the relative proportion of hematite further enhances the reduction in snow
20 albedo caused by dust, whereas an increase in dust particle size mitigates this reduction.
21 Additionally, increases in dust concentration and snow particle size can further amplify
22 these effects.

1 Compared with bulk sample collection and other techniques, we emphasize that
2 CCSEM technology provides an innovative approach to detect the statistical
3 characteristics of mineral composition, size distribution, and shape (AR) of dust in snow,
4 significantly enhancing the accuracy of dust radiative forcing in model simulations.

5 However, it is worth noting that although mineralogy provides strict definitions for
6 mineral phases based on composition and crystal structure, atmospheric dust particles
7 typically consist of heterogeneous mixtures. Currently, the scientific community lacks
8 standardized protocols for classifying the mineralogical components of such complex
9 particulate assemblages~~there is currently no strict set of criteria in the scientific~~
10 ~~community for classifying dust mineral components~~, making it difficult to compare dust
11 composition reported in different literature, severely limiting research on dust chemical
12 composition in different regions globally (Castellanos et al., 2024; Zhang et al., 2024).
13 Therefore, we call for the establishment of strict criteria for distinguishing mineral
14 components as soon as possible, which will also support high-spectral projects and
15 space programs developed and implemented by international societies and aerospace
16 institutions to enhance understanding of mineral composition in terrestrial dust source
17 regions (Green et al., 2020; Guanter et al., 2015). On the other hand, there is still a lack
18 of understanding of the basic mineralogical and physical properties of dust particles,
19 including key minerals such as hematite and goethite's spectral refractive indices.
20 Measurements of hematite refractive indices currently vary widely, hindering attempts
21 to calculate dust optical properties and forcing changes (Zhang et al., 2024). In addition,
22 the irregular shapes of dust particles cannot be represented by simple mathematical

1 models, and the lack of comprehensive and realistic shape models is a prominent issue
2 in dust optical modeling, distinguishing it from other aerosol types (Huang et al., 2023;
3 Ito et al., 2021). Overall, the greatest limitation lies in the lack of detailed, region-
4 specific, statistically representative information on the microphysical properties of base
5 dust particles — size distribution, morphology, complex refractive index spectra,
6 heterogeneity of internal structures, and resulting optical characteristics.

7 **Supporting Information**

8 Figures S1–S~~6~~⁵.

9 Tables S1-S3

10 **Data availability statement**

11 The data used for analysis are available via a Zenodo archive, which can be found in
12 the references (<https://zenodo.org/doi/10.5281/zenodo.14633496>, last access: 12 Jan
13 2025).

14 **Author contributions**

15 X.W. and J.W. designed the study and evolved the overarching research goals and aims.
16 T.S. wrote the first draft with contributions from all co-authors. T.S., Z.W., Y.Z. and
17 W.P. collected snow samples and performed sampling analyses. T.S. and J.C. applied
18 formal techniques such as statistical, mathematical and computational to analyze study
19 data. Y.B. and Z.H. provided the majority of the methodology and software. The other
20 authors provided technical guidance. All authors contributed to the improvement of
21 results and revised the final paper.

1 **Competing interests**

2 The authors declare that they have no conflict of interest.

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