

Refining simulated mineral dust composition through modified size distributions: dual validation with mineral-specific and elemental observations

Sofía Gómez Maqueo Anaya¹, Sudharaj Aryasree², Konrad Kandler², Eduardo José dos Santos Souza¹, Khanneh Wadinga Fomba¹, Dietrich Althausen¹, Maria Kezoudi³, Matthias Faust¹, Bernd Heinold¹, Ina Tegen¹, Moritz Haarig¹, Holger Baars¹, and Kerstin Schepanski^{1,4}

¹Leibniz Institute for Tropospheric Research (TROPOS), Leipzig, Germany

²Institute of Applied Geosciences, Technical University of Darmstadt, Germany

³Climate and Atmosphere Research Centre (CARE-C), The Cyprus Institute, Nicosia, Cyprus

⁴Free University of Berlin, Berlin, Germany

Correspondence: Sofía Gómez Maqueo Anaya (maqueo@tropos.de)

Abstract. Two 2022 measurement campaigns in Cape Verde provided a unique opportunity to collect mineral dust aerosols from multiple Saharan source regions and characterize their composition. Mineral dust aerosols comprise a complex assemblage of minerals with distinct physico-chemical properties ~~-, leading to and~~ differentiated climatic impacts through interactions with radiation, cloud microphysics, and atmospheric chemistry. A crucial physical property governing these interactions is the particle size distribution (PSD), ~~which strongly influences~~ influencing aerosol optical properties, transport, and deposition. Although contemporary atmospheric models have begun integrating mineralogical data into their dust aerosol representations, implementation faces complications due to variations in dust emission parameterizations, making ~~some models more compatible with existing~~ compatibility with soil mineralogical databases ~~than others~~ model-dependent.

This work addresses the challenges encountered when incorporating mineralogical information into the COSMO5.05-MUSCAT atmospheric model, which employs ~~a dust emission scheme based on the~~ Marticorena and Bergametti (1995) dust emission scheme. We present an improved approach that refines the translation of mineralogical soil PSDs into emitted aerosol PSDs. ~~The revised implementation~~ This improved approach is evaluated using historical Saharan dust measurements and new mineralogical observations from the JATAC2022 and DUSTRISK2022 campaigns. Model performance is assessed using a dual validation framework considering both mineral-resolved and elemental composition. The elemental validation ~~approach provides complementary constraints that expose discrepancies in internal mixing assumptions and reveal limitations invisible to~~ provides additional constraints on model performance, exposing biases in composition that mineral-only comparisons may obscure due to the aggregate nature of mineral dust particles. Results indicate that the proposed modification substantially improves representation of phyllosilicates (illite, kaolinite, and smectite), quartz, and feldspar, while biases in iron, calcium, and magnesium highlight fundamental challenges in representing the heterogeneous internal structure of natural dust particles.

20 1 Introduction

Mineral dust aerosol is the most abundant atmospheric aerosol type by mass (Kinne et al., 2006) and exerts widespread influence on the Earth system. By scattering and absorbing solar and terrestrial radiation, dust modifies atmospheric heating rates, alters cloud microphysical processes, and perturbs the surface energy balance (Stocker et al., 2013; Kok et al., 2023). Despite this recognized role, large uncertainties remain in quantifying the net radiative forcing by dust. These uncertainties arise from the complex variability of dust properties during emission and transport, including particle size distribution (PSD), morphology, mixing state, and mineralogical composition (~~Huneus et al., 2011; Mahowald et al., 2014; Di Biagio et al., 2020~~) (Huneus et al., 2011; Mahowald et al., 2014, 2026; Di Biagio et al., 2020).

Mineralogical composition has emerged as a key factor in constraining dust–climate interactions. Different minerals govern how dust interacts with radiation, clouds, and other atmospheric constituents. For instance, small variations in the abundance of iron oxide-bearing minerals can strongly amplify shortwave absorption and alter dust’s radiative properties (Balkanski et al., 2007; Gómez Maqueo Anaya et al., 2025; Li et al., 2024; Miffre et al., 2023; Obiso et al., 2024; Sokolik and Toon, 1999; Zhang et al., 2024), while silicate minerals differ in their potential to act as ice-nucleating particles (INPs) or cloud condensation nuclei (CCN) under varying conditions (Chatziparaschos et al., 2023; Harrison et al., 2019; Kelly et al., 2007; Murray et al., 2012). Yet, most chemistry transport models treat dust as homogeneous with respect to its composition, neglecting the strong spatial and temporal variability of mineral fractions. This simplification introduces biases in estimates of dust absorption, cloud interactions, and downstream impacts such as nutrient deposition (Kok et al., 2023).

Incorporating mineralogical detail into models is therefore essential, but it depends critically on how the PSD of individual minerals in soils is represented. The PSD controls not only transport and deposition but also the mineral dust particles’ interaction with radiation. A central challenge is that the PSD of airborne dust does not directly reflect the PSD of the parent soil: during emission, processes such as soil texture effects, interparticle cohesion, wind friction velocity, and fragmentation and saltation dynamics reshape the particle size distribution (Marticorena and Bergametti, 1995; Kok, 2011). These nonlinear processes lead to size-dependent shifts in mineralogical composition, making the link between soil and atmospheric mineralogy far from trivial.

The particle size distribution of mineral dust fundamentally governs its atmospheric residence time and transport dynamics. Coarse-grained minerals such as quartz, feldspars, and calcite tend to be removed quickly by gravitational settling, resulting in higher concentrations near source regions. In contrast, finer clay-sized phyllosilicates, defined herein as the group of illite, kaolinite, and smectite, remain suspended for longer periods and thus constitute a major fraction of the dust transported to remote areas (Lawrence and Neff, 2009).

Despite the importance of these size-dependent dynamics, the Soil Mineral Atlases (SMAs), a generic term for databases describing the mineralogical composition of soils that are currently employed in atmospheric models, rely on a simplified classification of soil mineralogy into only two size fractions, clay (defined as particles with diameters up to 2.5 μm) and silt (particles with diameters between 2.5 to 50 μm) (diameter size ranges follow the convention used by Nickovic et al. (2012)). This framework introduces structural uncertainties and subsequent biases in model simulations. A notable consequence of this resolution limit is the representation of quartz; by assuming a constant mineral proportion across broad size ranges, models fail

to capture the size-dependent distributions observed in empirical studies (Kandler et al., 2007, 2009; Panta et al., 2023). This often results in a systematic overestimation of quartz mass fractions in coarser bins and a corresponding underestimation in finer fractions (Perlwitz et al., 2015a, b).

To mitigate these discrepancies, several models have moved toward mineral-specific PSD transformations based on the Brittle Fragmentation Theory (BFT) (Kok, 2011). This approach provides a semi-direct framework for predicting size-resolved emission fluxes (e.g., Gonçalves Ageitos et al., 2023; Seanza et al., 2015; Perlwitz et al., 2015a) (e.g., Gonçalves Ageitos et al., 2023; Menut et al., 2023). However, a significant number of models continue to rely on the parameterization scheme developed by Marticorena and Bergametti (1995). While robust for bulk soil properties, this scheme cannot directly provide mineral-specific fluxes, particularly when constrained by the incomplete mineralogical information inherent in standard SMAs. Assessing the implications of these contrasting emission strategies is essential for accurate mineral-resolved simulations, yet systematic evaluations of their impact remain limited.

In a previous study, Gómez Maqueo Anaya et al. (2024) implemented a mineralogical composition module for Saharan dust simulations within COSMO5.05–MUSCAT (Consortium for Small-scale MOdelling v5.05 - MUltiScale Chemistry Aerosol Transport). Building on that work, this article addresses a central methodological question: how should the transformation of the PSD from soil to atmosphere be represented within the COSMO5.05–MUSCAT dust emission framework to ensure a realistic reproduction of mineralogy-based dust properties? To this end, we evaluate two PSD transformation approaches based on the Marticorena and Bergametti (1995) emission scheme, coupled with the mineralogical database GMINER (Nickovic et al., 2012).

Specifically, we contrast two modeling schemes, hereafter referred to as the ‘original’ and ‘modified’ approaches. The ‘original’ scheme, following Gómez Maqueo Anaya et al. (2024), maps the mineral soil PSD directly onto the aerosol size distribution. While this method adequately represents clay-sized minerals, it shows marked discrepancies for silt-sized fractions when compared with observations. To improve this representation, the ‘modified’ scheme introduces refinements to the treatment of mineral soil PSD via a redistribution of mineral fractions informed by the application of the BFT. The details of this modification, along with the specific model configurations and experimental runs, are described in Section 2.

The performance of the two schemes is assessed against three observational datasets of complementary scope and resolution. First, a multi-level observational dataset. We first utilized a compilation of regional North African mineralogical measurements of in-situ aerosol samples to evaluate broad mineralogical patterns and enable a direct comparison between the implemented measurements is used to evaluate the geographical variability of mineralogical patterns across Saharan and Sahelian source and deposition regions, providing a broad-scale benchmark for comparing the two schemes. This is followed by a high-resolution comparison comparisons with concurrent in-situ observations from two campaigns in Cabo Verde: the Joint Aeolus Tropical Atlantic Campaign (JATAC, June 2022) and DUSTRISK (January–February 2022). JATAC 2022 provides vertically size-resolved measurements of both mineralogical composition and elemental mass concentrations -. Similarly, across multiple altitudes, while DUSTRISK 2022 offers size-resolved size-segregated elemental mass concentrations, allowing for a consistent enabling evaluation of the model’s chemical tracers -. The specific from surface sampling. The measurement methodologies, instrumentation for size-segregation, and associated uncertainties for these both campaigns are detailed in Section 3.

The strategy for model evaluation, including the metrics used for validation and the procedure for comparing grid-cell results to point measurements, is outlined in Section 4. Following this, the validation results are presented ~~through~~
90 ~~a tiered approach categorized by analytical scale, in two steps:~~ Section 5.1 ~~focuses on mineralogical comparisons~~addresses
mineralogical composition, beginning with the regional North African compilation and followed by a detailed assessment of the
JATAC 2022 results~~;~~ Section 5.2 then ~~provides a focused analysis of elemental composition, evaluating the model against the~~
evaluates elemental composition against both JATAC 2022 and DUSTRISK 2022 ~~campaigns, JATAC and DUSTRISK 2022.~~
~~This tiered approach campaigns. Together, these comparisons~~ allows us to assess whether the BFT-informed redistribution
95 effectively bridges the gap between soil mineralogy and airborne dust composition across different transport conditions and
measurement methodologies.

2 Model description and parametrizations

2.1 COSMO5.05-MUSCAT

The chemistry transport model used in this study is the MULTIScale Chemistry Aerosol Transport (MUSCAT) coupled online
100 with the Consortium for Small-scale MOdelling (COSMO) v5.05 model. COSMO, developed by the German Weather Service
(Deutscher Wetterdienst, DWD), is a non-hydrostatic regional weather prediction model that solves the fundamental equations
of atmospheric dynamics on a terrain-following grid (Baldauf et al., 2011). MUSCAT is the online-coupled chemistry transport
component, computing the atmospheric transport of aerosols through time-dependent mass balance equations driven by COSMO
meteorological fields (Heinold et al., 2011; Wolke et al., 2012). In this work, mineral dust aerosols are represented as passive
105 tracers, i.e., they are not subject to chemical aging or chemically reactive transformations.

The coupled atmosphere-aerosol model system, COSMO-MUSCAT, has been widely applied and evaluated for Saharan dust
studies. Previous validation efforts have demonstrated its capability to reproduce dust source activation, transatlantic transport,
and regional dust transport under different meteorological conditions (Heinold et al., 2011; Schepanski et al., 2009; Tegen
et al., 2013; Schepanski et al., 2016, 2017). The specific configuration used here has been further evaluated against atmospheric
110 dust loading observations for the North Africa region in Gómez Maqueo Anaya et al. (2024) and Gómez Maqueo Anaya et al.
(2025).

The atmospheric life cycle of dust aerosols in MUSCAT is represented through a set of physical parameterizations dynami-
cally coupled to COSMO meteorology and updated at every advection step. The main processes include: (1) dust emission,
parameterized following Tegen et al. (2002) with modifications to incorporate mineralogical soil fractions as described in Gómez
115 Maqueo Anaya et al. (2024); (2) aerosol transport, solved using a third-order upwind advection scheme with time-splitting
integration (Wolke and Knoth, 2000); and (3) aerosol deposition, accounting for both dry and wet removal processes. Dry
deposition is parameterized following the formulations of Seinfeld and Pandis (2016) and Zhang et al. (2001), while wet
deposition (including in-cloud scavenging or rainout, and below-cloud scavenging or washout) follows the approaches of Berge
(1997) and Jakobsen et al. (1997), with detailed implementation described in Heinold et al. (2011).

120 2.2 Dust emission scheme

Dust emission is a non-linear process initiated when near-surface wind velocity generate sufficient vertical shear stress at the soil surface to initiate particle mobilization. In COSMO-MUSCAT, threshold friction velocities are calculated following the parameterization of Marticorena and Bergametti (1995), which accounts for size-resolved soil particle mobilization and depends on soil texture, surface roughness, vegetation, and soil moisture.

125 Emission fluxes are then computed ~~interactively~~ iteratively using the scheme of Tegen et al. (2002), first implemented in COSMO-MUSCAT by Heinold et al. (2007). Fluxes scale with the cube of the wind friction velocity, derived from COSMO-simulated near-surface winds, and are further modulated by vegetation cover and soil moisture. Particle uplift occurs when the effective friction velocity exceeds the size-dependent threshold (U_t^*), which is controlled by the erodible particle diameter (D_p), the aerodynamic roughness length of the total surface (Z_0), and the smoother, erodible fraction roughness length (z_{0s}).

130 To account for the sheltering effect of roughness elements, a drag partitioning approach is utilized. This method defines an effective friction velocity (U_t^*), representing the total friction velocity required to mobilize size-dependent particles on a rough surface. It is related to the smooth-surface threshold friction velocity (U_{ts}^*), which is the threshold required for mobilizing the same particles under idealized, flat, conditions, via:

$$U_t^*(D_p, Z_0, z_{0s}) = \frac{U_{ts}^*(D_p)}{f_{\text{eff}}(Z_0, z_{0s})}, \quad (1)$$

135 where f_{eff} is the effective drag partition factor (ranging from 0 to 1). This factor accounts for the reduction in wind erosive potential due to surface roughness and it is calculated following Marticorena and Bergametti (1995) as:

$$f_{\text{eff}}(Z_0, z_{0s}) = 1 - \left[\ln \left(\frac{Z_0}{z_{0s}} \right) / \ln \left(0.35 \left(\frac{10}{z_{0s}} \right)^{0.8} \right) \right]. \quad (2)$$

For bare desert surfaces, the aerodynamic roughness length (Z_0) is prescribed as 0.001 cm, following the recommendation of Darnenova et al. (2009), while z_{0s} is obtained from global satellite-derived dataset (Prigent et al., 2005). The value of U_{ts}^* is calculated as a function of particle diameter (D_p), particle density, and air density (ρ_a), representing a balance between aerodynamic and gravitational forces.

The actual surface friction velocity exerted by the atmosphere (U^*) is estimated from COSMO's 10-meter wind speed components (u_{10} , v_{10}) and air density. These are combined to determine an effective wind speed at height Z , denoted as $U(Z)$. Assuming adiabatic conditions and a logarithmic wind profile within the boundary layer, U^* is calculated as:

145
$$U^* = \frac{U(Z)\kappa}{\ln \left(\frac{Z}{Z_0} \right)} \quad (3)$$

where $\kappa = 0.4$ is the Von Karman's constant, and Z represents the height of the first model layer.

Dust emission is triggered when this surface friction velocity exceeds the size-dependent threshold friction velocity ($U^* \geq U_t^*$). This process is further modulated by local soil conditions such as moisture, which is accounted by an additional coefficient in the threshold calculation, following Fécan et al. (1999).

150 Once the threshold is surpassed, the emitted flux is represented as the horizontal particle flux (G), which scales with the cube of the friction velocity and accounts for the soil particle size distribution:

$$G = \frac{\rho_a}{g} \cdot U^{*3} \cdot \sum_i \left[\left(1 + \frac{U_t^*(D_{pi}, Z_0, z_{0s})}{U^*} \right) \left(1 - \frac{U_t^{*2}(D_{pi}, Z_0, z_{0s})}{U^{*2}} \right) \cdot B_{rel-i} \right] \text{ for } U^* \geq U_t^*, \quad (4)$$

where g is gravitational acceleration, and B_{rel-i} represents the relative basal surface area of size fraction i . In MUSCAT, the soil is represented by 196 discrete size fractions.

155 Because the threshold friction velocity does not scale linearly with particle diameter, an accurate representation of the soil size distribution is required. In the Marticorena and Bergametti (1995) parametrization, the soil particle mass size distribution (PSD) is modeled using a multi-modal log-normal distribution:

$$\frac{dm(D_p)}{d \ln(D_p)} = \sum_{j=1}^n \frac{m_j}{\sqrt{2\pi \ln(\sigma_j)}} \exp \left(\frac{(\ln D_p - \ln MMD_j)^2}{-2 \ln^2 \sigma} \right). \quad (5)$$

where j denotes the size mode (clay, silt, sand in the present MUSCAT setup) m_j is the mass fraction of mode j , σ is the geometric standard deviation (set to 2.0 independent of the mode), and MMD_j are the mass median diameters, set to 2.0 μm (clay), 15.0 μm (silt), and 150.0 μm (sand), respectively.

To determine the basal (projected) surface area distribution, the PSD is transformed assuming spherical particles of uniform density:

$$dB_t(D_{pi}) = \frac{dm(D_{pi})}{\frac{2}{3}\rho D_{pi}}. \quad (6)$$

165 The total basal surface area (B_t) is obtained by integrating Eq. (6) across all particle sizes. Normalizing $dB_t(D_{pi})$ by B_t yields the relative basal surface area distribution B_{rel-i} , which is used in Eq. (4) to allocate the horizontal flux across particle sizes.

Saltation and particle bombardment processes (Marticorena and Bergametti, 1995) are incorporated by iteratively adjusting B_{rel-i} for each size class, accounting for the momentum transfer from saltating particles to finer dust grains. Following this adjustment, the total horizontal flux is computed.

170 The fraction of the horizontal flux that becomes airborne is parameterized as a vertical dust flux (F):

$$F = \omega \cdot A_{eff} \cdot G \cdot (1 - A_{snow}) \cdot I_\theta, \quad (7)$$

where ω is the sandblasting efficiency, prescribed per soil type based on the local clay, silt, and sand fractions (Tegen et al., 2002). A_{eff} denotes the erodible surface area, A_{snow} is the snow-covered fraction, and I_θ represents a soil moisture correction following Fécán et al. (1999). The vertical flux is then partitioned into five transport-relevant size bins (Table 1) to generate size-resolved dust fluxes for atmospheric injection.

The overall magnitude and spatial variability of emissions are determined by the interplay of these surface conditions. The influence of vegetation cover on A_{eff} is threshold-dependent. In desert regions, dust emission is inhibited once fractional vegetation cover exceeds 0.5; below this threshold, the erodible area is scaled linearly to account for the partial sheltering of the surface (Tegen et al., 2002). Similarly, I_θ reduces emissions linearly once soil moisture exceeds a critical threshold determined.

Table 1. Definition of MUSCAT five independent size classes for mineral dust aerosol transport. Their size limits are indicated.

Bin name	Diameter range
BIN 01	0.2 - 1 μm
BIN 03	1 - 3 μm
BIN 09	3 - 9 μm
BIN 26	9 - 26 μm
BIN 80	26 - 80 μm

180 While snow cover also inhibits dust emissions, its parametrization is deactivated in this model configuration given its negligible influence over the Sahara Desert. Together with the particle size distribution and surface roughness, these factors control the efficiency and spatial heterogeneity of dust emissions in the model.

2.3 Mineralogical composition modification

In the ‘original’ approach by Gómez Maqueo Anaya et al. (2024), mineralogical fractions are prescribed by directly mapping
185 the mineral soil particle size distribution (PSD) from GMINER (Nickovic et al., 2012) onto the mineral-resolved aerosol PSD as represented by the upper panel of Fig. 1. A key limitation of this approach is that the modifications to the bulk PSD caused by the emission process do not affect the mineral-resolved PSD. This overlooks the fact that the emission process explicitly alters the overall dust PSD, as predicted by dust emission theories (Kok et al., 2012; Marticorena and Bergametti, 1995; Shao et al., 2011).

This inconsistency stems from the structure of GMINER in combination with Marticorena and Bergametti (1995)’s emission
190 scheme, since GMINER provides mineralogical mass fractions only for the finest soil classes (silt and clay). These are assumed to represent the airborne dust range, given their capacity to remain suspended for several days. However, the emission scheme of Marticorena and Bergametti (1995) (Eqs. (5)–(6)) requires the full soil PSD to represent saltation and bombardment processes. Larger soil particles, although not staying airborne, are essential because their impacts release smaller fragments that otherwise could not overcome interparticle cohesion forces via wind induced friction velocity only (Marticorena and Bergametti, 1995;
195 Iversen and White, 1982).

Consequently, a consistent application of the Marticorena and Bergametti (1995) scheme is not possible with GMINER alone, since the database lacks information on the coarser soil fractions. Figure 2 illustrates this limitation for a representative Saharan grid cell, highlighting the substantial portion of the soil PSD that is missing when mineral fractions are restricted to only the two finest classes.

200 The emission scheme inherently favors silt-sized particles, which require relatively low wind stress for entrainment and are small enough to remain airborne, as illustrated by the threshold friction velocity function (in Fig. 1 of Marticorena and Bergametti (1995)). This aerodynamic preference becomes problematic when GMINER assigns minerals exclusively to silt or clay size classes. Treating these mineral-resolved PSDs as representative of the full soil PSD within the Marticorena and Bergametti (1995) framework introduces systematic biases: clay-sized minerals experience artificially suppressed emissions due to high

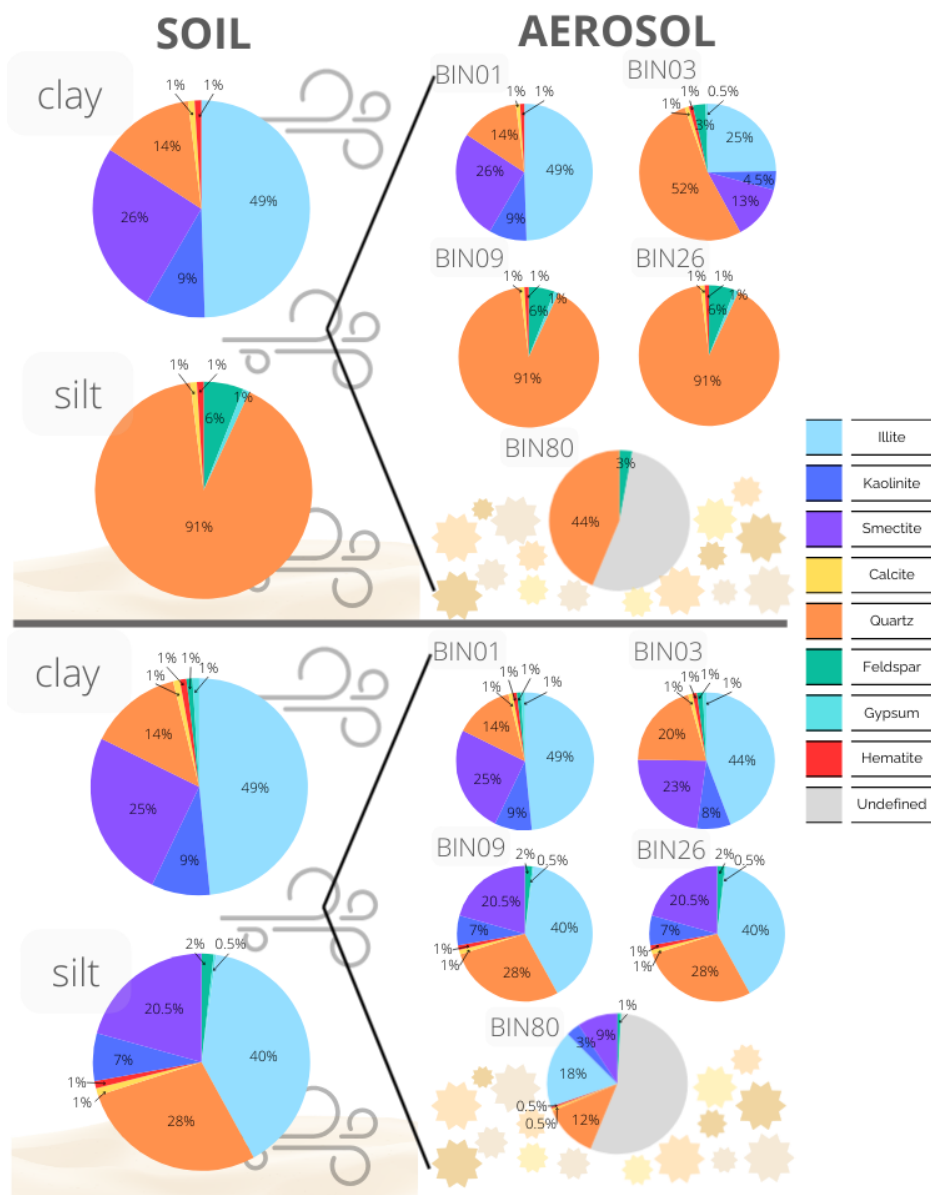


Figure 1. Mineralogical composition of soil and emitted dust particles. Larger pie charts represent the mineral fractions in the soil distribution, where clay is defined as particles with diameters below $2.5 \mu\text{m}$ and silt particles between $2.5 \mu\text{m}$ and $50 \mu\text{m}$. Smaller pie charts represent the mineral fractions of aerosols per size bin as classified in MUSCAT (Table 1). Particles exceeding $50 \mu\text{m}$ diameter are not classified by mineral component and are labeled as "undefined". The upper panel shows the 'original' mineral soil PSD as obtained by GMINER and the subsequent mineral fractions in the aerosol bins mimicking that distribution. The lower panel shows the modifications to the soil mineralogy distribution and resulting aerosol fractions following the parametrizations of Perlwitz et al. (2015a) and Gonçalves Ageitos et al. (2023).

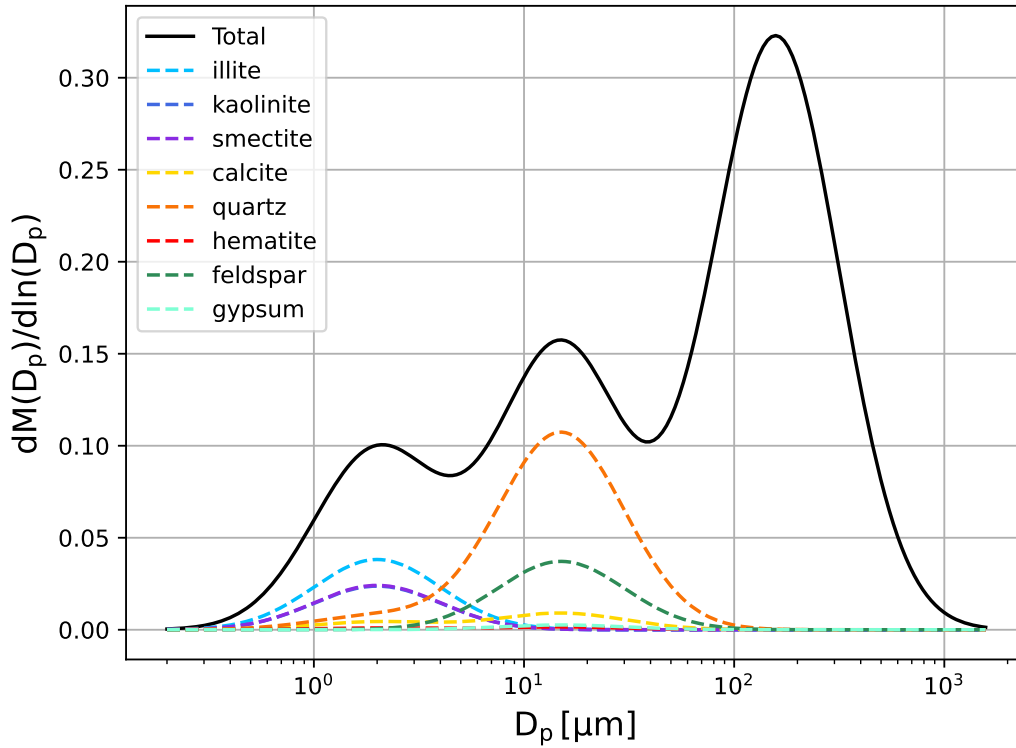


Figure 2. Mass size distribution of soil particles at a representative Saharan grid cell (22.45°N, 20.9°E). The black solid line represents the total distribution obtained from the SoilGrids database (Poggio et al., 2021), exhibiting three distinct modes corresponding to clay, silt and sand fractions. Dashed colored lines indicate the mineral specific mass size distributions as described by the GMINER database. Figure from Gómez Maqueo Anaya (2025)

205 cohesion thresholds that rely on larger saltating particles to be broken, while silt-sized minerals are prone to overestimation in the absence of coarser, non-erodible grains. Accurate dust emission calculations therefore require a complete soil PSD, where larger particles mobilize finer fractions via saltation bombardment (Kok et al., 2012; Marticorena and Bergametti, 1995). This issue is compounded by the methodology used to construct GMINER: wet sieving mechanically disaggregates soil samples, increasing the apparent fraction of clay-sized particles relative to undisturbed soils (Perlwitz et al., 2015a). While airborne
 210 clay-sized fractions generally match source soils and are preserved during transport (Caquineau et al., 1998; Lafon et al., 2004), silt-sized mineral distributions show poorer agreement, partly due to biases introduced by wet-sieving (Perlwitz et al., 2015a).

To address these issues, several modeling studies have incorporated mineral-specific transformations from soil to aerosol PSDs (e.g., Perlwitz et al., 2015a, b; Gonçalves Ageitos et al., 2023; Pérez García-Pando et al., 2016; Scanza et al., 2015; Li et al., 2021). These approaches build on the Brittle Fragmentation Theory (BFT) of Kok (2011), which posits that for the finest

215 particles, the emitted size distribution is largely independent of soil properties and wind speed. BFT conceptualizes emission as a sequence of energetic collisions between saltating aggregates, producing fragments that predominantly fall below a characteristic size threshold. The resulting particle number concentration N is inversely proportional to the square of the particle diameter D_p , modulated by an exponential cutoff controlled by a characteristic aggregate diameter D_c , as expressed in the following relation:

$$\frac{dN}{d\ln D_p} \propto \frac{1}{D_p^2} \exp \left[- \left(\frac{D_p}{D_c} \right)^3 \right] \text{ for } D_p > D_s, \quad (8)$$

220 where D_s represents a scalar diameter within the "indivisible" size range. Particles at or below this scale are considered primary grains resistant to further fragmentation due to inherent particle cohesion. Following Kok (2011), the probability of finding such indivisible grains at a specific size D_s is dictated by the PSD of the fully dispersed, wet-sieved soil. Incorporating this distribution, the emitted number size distribution is formalized as:

$$\frac{dN}{d\ln D_p} = \frac{1}{c_N D_p^2} \exp \left[- \left(\frac{D_p}{D_c} \right)^3 \right] \int_0^{D_p} p(D_s) dD_s, \quad (9)$$

225 where c_N is a normalization factor, and $p(D_s)$ represents the probability density function derived from the wet-sieved PSD. In this integral, D_s serves as the scalar integration variable representing the diameters of the constituent primary grains. This formulation captures the physical constraint that an emitted aggregate of size D_p can only be composed of indivisible components smaller than or equal to itself $D_s \leq D_p$. The integral term (the cumulative distribution function of the soil minerals) thus reduces the emission of small particles if the soil lacks sufficient fine indivisible grains, while the exponential cutoff suppresses the
230 emissions of very large diameters.

The BFT posits that the emitted number concentration of small dust particles is largely independent of the undispersed soil size distribution, with ~~the characteristic aggregate diameter (D_c)~~ estimated at $12 \pm 1 \mu\text{m}$ (Kok, 2011). In this framework, the PSD of emitted aggregates is skewed toward larger diameters compared to wet-sieved soil, consistent with observations by Kandler et al. (2009) and Enete (2012), which indicate that saltation-driven fragmentation preserves a greater fraction of
235 mass in the silt-size range than suggested by wet-sieved samples. Perlwitz et al. (2015a) further show that roughly 45% of the silt-sized emitted mass originates from aggregated indivisible particles that would be classified as clay-sized in wet-sieved soils. To reconcile this discrepancy, they proposed an empirical correction that reallocates a fraction of clay-sized minerals from wet-sieved soils to the silt fraction, particularly phyllosilicates (illite, kaolinite, and smectite), which are categorized in GMINER exclusively in clay size classes but contribute to silt-sized emissions in reality.

240 This adjustment is quantified using Equation (9) to derive a generalized ratio of emitted clay- to silt-sized particles, assumed to be spatially invariant and independent of local soil conditions. This simplifying assumption has been adopted in several modeling studies (Albani et al., 2014; Perlwitz et al., 2015a, b; Scanza et al., 2015; Pérez García-Pando et al., 2016; Gonçalves Ageitos et al., 2023). However, it applies only to particles below $20 \mu\text{m}$, as larger particles are more sensitive to site-specific emission factors such as wind speed, soil properties, and surface roughness. Since GMINER defines the silt class up to $50 \mu\text{m}$, a further
245 adjustment is needed for particles in the $20\text{--}50 \mu\text{m}$ range. Perlwitz et al. (2015a) addressed this by scaling the clay contribution using measurements from Kandler et al. (2009), which provided empirical data on the coarse-mode mineral distribution of

freshly emitted dust. Using Equation (9), they estimated a clay-to-silt ratio of 0.05 for diameters below 20 μm . When integrated over the full 0-50 μm range and volume-normalized to account for the coarser fraction, this corresponds to approximately 1.3% of the total emitted mass being attributed to the clay mineral fraction.

250 This methodology rests on two critical assumptions. First, it assumes that the PSD measured at Tinfou by Kandler et al. (2009) is representative of other dust source regions. While this may not hold universally, the observed increase in silt fraction with particle diameter is consistent with the physical principle that the threshold friction velocity for emission decreases with particle size (Marticorena and Bergametti, 1995; Iversen and White, 1982). The approach also assumes that the emitted PSD is primarily determined by mineral-specific fragmentation, neglecting wind speed variations. This assumption is reasonable
255 for particles below 20 μm , where Eq. (9) offers a reliable approximation, but becomes less reliable for coarser particles where emission dynamics are more sensitive to environmental conditions. Second, the model neglects modifications to the PSD caused by gravitational settling during transport to the Tinfou observation site. This simplification is justified by focusing only on measurements taken during high-concentration dust events, which are presumed to reflect recently emitted aerosols with minimal transport-induced size sorting.

260 This methodology is implemented here as the ‘modified’ approach, in which the dispersed soil size distribution from the GMINER SMA is adjusted to more realistically represent the aerosol size distribution observed in atmospheric dust. The formulation follows Perlwitz et al. (2015a), based on BFT. From GMINER, the mass fraction of each mineral k in the conceptual clay (0-2.5 μm) and silt (2.5-50 μm) size categories is denoted by $m_k^c(s_t)$ and $m_k^s(s_t)$, respectively. It should be noted that these two broad categories are used for the mineralogical reallocation process and are distinct from the five discrete aerosol
265 transport bins defined in Table 1. ~~These~~ These fractions are normalized for each soil type s_t (arid soil type provided by FAO74) such that:

$$\sum_{k=1}^8 m_k^c(s_t) = 1 \text{ and } \sum_{k=1}^8 m_k^s(s_t) = 1, \quad (10)$$

with 8 minerals considered. To better reflect the emitted PSD, the BFT-based method distributes all minerals across both size categories, including those originally classified exclusively as clay- or silt-sized in GMINER.

270 To assign mineral fractions to the actual aerosol size categories, soil texture information from the SoilGrids database (Poggio et al., 2021) is incorporated. Let $m^c(s_x)$ and $m^s(s_x)$ denote the soil mass fractions of clay- and silt-sized particles, normalized such that:

$$m^c(s_x) + m^s(s_x) = 1. \quad (11)$$

The combined soil mineral mass fraction in each size category at each location is then computed by weighting the GMINER
275 mineral fractions by the local soil texture proportions:

$$m_k^c(s_t, s_x) = m^c(s_x) m_k^c(s_t), \quad m_k^s(s_t, s_x) = m^s(s_x) m_k^s(s_t). \quad (12)$$

This ensures that the total soil mineral mass fraction across both reallocation size classes sums to unity:

$$\sum_{k=1}^8 (m_k^c(s_t, s_x) + m_k^s(s_t, s_x)) = 1. \quad (13)$$

In this formulation, soil mineral mass fractions vary spatially according to two factors: the arid soil type (s_t), which governs mineralogical composition, and the soil texture class (s_x), which determines the relative abundance of clay- and silt-sized particles.

Once the soil mineral fractions are obtained from Eq. (12), the next step is to derive the emitted mass fraction of each mineral in the clay and silt size SMA categories. Denote by ϕ^c and ϕ^s the total emitted mass fractions of clay- and silt-sized aerosols, constrained by:

$$\phi^c + \phi^s = 1. \quad (14)$$

These totals are composed of contributions from all minerals k . Let ϕ_k^c and ϕ_k^s represent the emitted clay- and silt-sized fractions attributable to mineral k . They satisfy:

$$\phi^c = \sum_{k=1}^8 \phi_k^c \text{ and } \phi^s = \sum_{k=1}^8 \phi_k^s, \quad (15)$$

and consequently:

$$\sum_{k=1}^8 (\phi_k^c + \phi_k^s) = 1. \quad (16)$$

Thus, the emitted mineral mass fractions across all species and size classes sum to unity. Following the BFT-based formulation, the global clay-sized emission fraction is prescribed as $\phi^c=0.013$, constant across all locations. The contribution of mineral k to clay-size emissions is therefore:

$$\phi_k^c(s_t) = \phi^c m_k^c(s_t), \quad \phi^c = 0.013, \quad (17)$$

meaning that the proportion of emitted clay-sized dust mirrors the clay mineral fractions of the fully dispersed soil. In this context, the fully dispersed soil represents a theoretical, maximally dispersed state, a conceptual limit where all aggregates are broken down into their primary, indivisible constituents.

With ϕ^c prescribed, the total silt-sized fraction follows implicitly as:

$$\phi^s = 1 - \phi^c = 0.987. \quad (18)$$

For each mineral, the emitted silt-sized fraction ϕ_k^s has two sources: (1) particles originally present in the soil in the silt-size range, and (2) primary clay minerals that are emitted within larger silt-sized aggregates during the saltation-driven fragmentation of the parent soil. To account for this, the model performs an empirical reallocation where a fraction of the soil's clay mineral mass is transferred into the silt-sized aerosol population. This is expressed as:

$$\phi_k^s = \vartheta (\gamma_k m_k^c(s_t, s_x) + m_k^s(s_t, s_x)). \quad (19)$$

where γ_k is a mineral-specific reaggregation coefficient quantifying the clay-to-silt transfer, and ϑ is a normalization constant ensuring that the sum of all ϕ_k^s equals ϕ^s .

For simplicity, γ_k is assumed constant across minerals, with the exception of feldspar, gypsum, and quartz. Feldspar is typically overrepresented in the silt fraction due to its fragmentation behavior, while gypsum is soluble and exhibits distinct disaggregation and spatial patterns (Perlwitz et al., 2015a). Quartz, which dominates the coarse end of the size spectrum and shows little evidence of disaggregation, is prescribed with $\gamma_{\text{quartz}}=0$.

Notably, feldspar and gypsum require special treatment since they are present in both clay and silt fractions of atmospheric aerosols (e.g., Enete, 2012) but are absent from the clay fraction in the GMINER SMA. Consequently, Eq. (17) cannot be applied directly. Instead, their clay-size fractions are estimated following the approach of Gonçalves Ageitos et al. (2023), which uses proxy minerals and scaling ratios: for feldspar, the extension into the clay fraction is scaled according to the quartz clay-to-silt ratio:

$$m_{\text{feldspar}}^c(s_t) = m_{\text{feldspar}}^s(s_t) * \frac{m_{\text{quartz}}^c(s_t)}{m_{\text{quartz}}^s(s_t)}, \quad (20)$$

and for gypsum, the calcite clay-to-silt ratio is used:

$$m_{\text{gypsum}}^c(s_t) = m_{\text{gypsum}}^s(s_t) * \frac{m_{\text{calcite}}^c(s_t)}{m_{\text{calcite}}^s(s_t)}. \quad (21)$$

To conserve the total clay-size mass balance (Eq. 10), the phyllosilicate fractions in the clay category are proportionally reduced by soil type.

Once these database gaps are addressed, the emitted silt-sized fraction of mineral k is expressed based on Eqs. (12) and (19) as:

$$\phi_k^s(s_t, s_x) = \vartheta(s_t, s_x) [\gamma_k m^c(s_x) m_k^c(s_t) + m^s(s_x) m_k^s(s_t)]. \quad (22)$$

In this formulation, γ_k acts to suppress the silt-size emissions of minerals such as quartz, while extending the contribution of clay-rich species (e.g., phyllosilicates) into the silt range. This redistribution reflects the contrasting aggregation behaviors of different minerals: quartz remains largely intact during saltation, whereas clay-mineral constituents are emitted as part of larger silt-sized aggregates rather than as fully dispersed fine particles.

A schematic representation of the ‘modified’ approach is shown in the lower panel of Fig. 1. In this framework, a substantial reduction of the quartz fraction is introduced, along with a redistribution of minerals across size classes. Specifically, phyllosilicates are incorporated into the silt fraction, while feldspar and gypsum are extended into the clay fraction. The application of Eqs. (22)–(21) thereby entails a relative decrease of feldspar and gypsum within the silt-size range, resulting from the additional contribution of phyllosilicates.

After constructing the adjusted mineral soil PSD, which better represents the composition of mineral aerosols at larger sizes, it is incorporated into the COSMO5.05-MUSCAT emission scheme. The underlying emission algorithm remains unchanged from the implementation described by Gómez Maqueo Anaya et al. (2024): the vertical emission flux in each MUSCAT size bin is scaled by the corresponding soil mineral fraction, with each mineral assigned to its own bin within the respective size category (see Table 1). In the revised configuration, the mineralogical SMA is updated to reflect the modified PSD, and additional bins are introduced to represent minerals that now occur simultaneously in both clay and silt size ranges.

To verify the ‘modified’ mineral approach, the scheme was compared against the MONARCH reference for Haplic Xerosols in the northwestern Sahara (Gonçalves Ageitos et al., 2023). Despite differences in bin resolution and emission parameterizations, both models demonstrate a consistent redistribution pattern, specifically, the shifting of phyllosilicates toward silt-sized categories and a proportional reduction in quartz. The resulting mineralogical shift from soil to emitted aerosol for this soil type is illustrated in Fig. B1.

2.4 Input files and simulation setup

Mineralogical dust simulations were conducted using a consistent COSMO5.05–MUSCAT physical configuration. The experimental design varied across two primary dimensions: the simulation period and the mineralogical scheme. To match the observational campaigns, simulations were performed for January–February 2022 (DUSTRISK) and June–July 2022 (JATAC). For each of these periods, the two distinct mineralogical composition approaches, the ‘original’ and ‘modified’ schemes, were applied. The simulation experiments are summarized in Table 2.

Table 2. Summary of simulations used for measurement comparison. Domain and all input files remain consistent across model runs. For a detailed description of the differences between mineralogy schemes, refer to Section 2.3

Simulation	Time frame	Mineralogy scheme
DUST-CM-01	January-February 2022	original
DUST-CM-02	January-February 2022	modified
JAT-CM-01	June-July 2022	original
JAT-CM-02	June-July 2022	modified

The COSMO5.05-MUSCAT model domain is set up to cover the majority of the Sahara Desert and extend westward over the Atlantic Ocean to include the Cape Verde archipelago. The domain is bounded by 30.75°W to 39.32°E and 38.49°N to 0.38°S as represented in Fig. 3. Simulations are conducted at a horizontal resolution of 0.25° (approximately 28 km), with a vertical discretization of 40 layers. The lowest, surface level, model layer has a thickness of 20 m.

~~Summary of simulations used for measurement comparison. Domain and all input files remain consistent across model runs. For a detailed description of the differences between mineralogy schemes, refer to Section 2.3~~ **Simulation Time frame Mineralogy scheme** DUST-CM-01 January-February 2022 originalDUST-CM-02 January-February 2022 modifiedJAT-CM-01 June-July 2022 originalJAT-CM-02 June-July 2022 modified

Meteorological initial and boundary conditions for COSMO5.05-MUSCAT are provided by the DWD in the form of 3-hourly meteorological fields. To maintain realistic atmospheric conditions, the model is re-initialized every 48 hours using overlapping cycles. Each 48-hour cycle begins with a 24-hour spin-up phase, during which only the COSMO5.05 meteorological model is active. Following this spin-up, MUSCAT is coupled to COSMO5.05 for the remaining 24 hours to simulate aerosol transport and interactions. Only the output from these second-day simulations, when both COSMO5.05 and MUSCAT are fully coupled, is used for analysis. Continuity between cycles is ensured by starting each new COSMO5.05 run 24 hours prior to the end of the

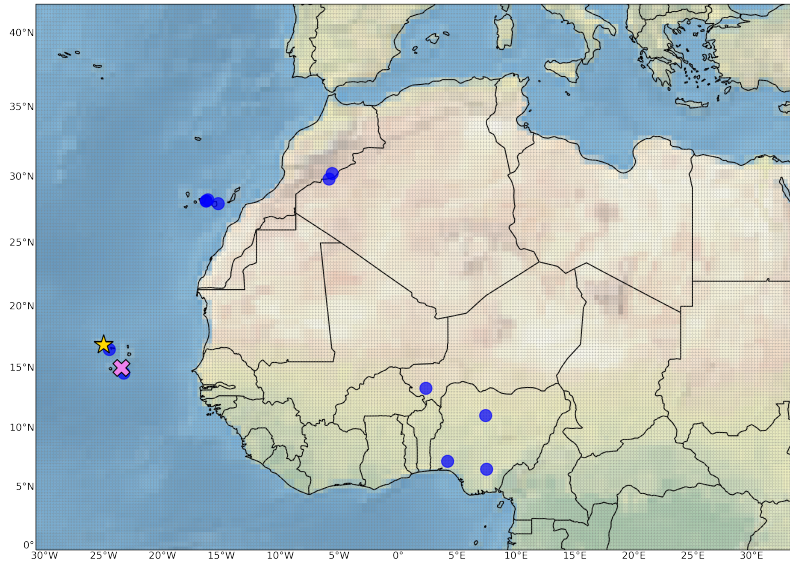


Figure 3. Simulation domain for COSMO5.05-MUSCAT, featuring a 0.25° resolution grid in gray dotted lines. The yellow star identifies São Vicente (Cabo Verde), the site of the JATAC 2022, while the violet X indicates Praia (Santiago, Cabo Verde), where the DUSTRISK 2022 measurements were conducted. Blue dots show the locations of a measurement compilation utilized for a broader model validation.

previous MUSCAT simulation, while MUSCAT continues using its own prognostic fields from the preceding cycle as initial
 365 conditions. The entire simulation period is preceded by a 15 day initial spin-up, and results are outputted at 1 hour intervals.

The MUSCAT dust emission scheme is controlled by external soil-related datasets. Vegetation cover is prescribed using the FCOVER product from the Copernicus Global Land Service (Fuster et al., 2020), which provides fractional green vegetation coverage. Soil moisture input is taken from ERA5-Land hourly reanalysis data (Muñoz Sabater and Copernicus Climate Change Service, 2019), specifically utilizing the volumetric soil water content of the 7 cm uppermost soil layer. Soil texture
 370 ~~expressed in terms of clay, silt, and sand fractions, is and mineralogical composition are~~ provided by the SoilGrids ~~database~~
~~(Poggio et al., 2021), while aerodynamic and GMINER databases (Poggio et al., 2021; Nickovic et al., 2012), respectively, and~~
~~implemented via the two distinct modeling approaches detailed in Sect. 2.3. Aerodynamic~~ roughness lengths are provided
 through the dataset ~~by of~~ Prigent et al. (2005).

These datasets, combined with the model's spatial constraints, restrict dust activation exclusively to continental source regions.
 375 ~~Furthermore~~~~Furthermore~~, the spatial distribution of active dust emission sources is constrained by the MSG-SEVIRI dust source
 activation frequency map by Schepanski et al. (2007). ~~Finally, the mineralogical composition is represented by the GMINER~~
~~SMA (Nickovic et al., 2012) implemented via the two distinct modeling approaches detailed in Sect. 2.3.~~

3 Cape Verde measurement campaigns: in-situ aerosol measurements

3.1 JATAC 2022

380 During the JATAC 2022 campaign, in-situ recollection of mineral dust aerosols were performed using Unmanned Aerial Vehicles (UAVs) over São Vicente, Cape Verde, (indicated by the yellow star in Fig. 3) throughout June 2022. The Cyprus Institute conducted 25 UAV flights, each equipped with Optical Particle Counters (OPCs) for fine- and coarse-mode height-resolved PSD observations. Dust particles were collected from the atmospheric layers using onboard impactor samples (Marinou et al., 2023), with a Giant Particle Collector (GPac) capable of capturing particle diameters from nanometers up to tens of micrometers
385 (Kezoudi et al., 2025, 2021). The GPac's upper size limit depends on airspeed, pressure, and temperature; as a reference, during the SAMUM-2 campaign, particles up to 28.5 μm were successfully collected (Lieke et al., 2011).

Two OPCs were mounted on each UAV. The Universal Cloud and Aerosol Sounding System counted aerosols with diameters from 0.28 to 17.0 μm , while the Printed Optical Particle Spectrometer measured number concentrations in the 0.14–3 μm range (Kezoudi et al., 2021). OPC measurements were used to validate PSDs derived from collected dust samples, following the
390 methodology of Panta et al. (2023).

Aerosol chemical composition and single-particle characteristics were analyzed using a scanning electron microscope coupled with Scanning Electron Microscope-Energy Dispersive X-ray spectrometry (SEM-EDX) to determine particle size, shape, and elemental composition. Back-scattered images were used to study particles with projected area diameters (PAD) $>0.5 \mu\text{m}$, where PAD ($D_p = \sqrt{4A_p/\pi}$, with A_p as the particle area) closely approximates aerodynamic diameter for dust (Aryasree et al., 2024;
395 Kandler et al., 2018). SEM-EDX provides normalized atomic percentages for elements including: F, Na, Mg, Al, Si, P, S, Cl, K, Ca, Ti, V, Cr, Mn, Fe, Zn, and Pb. This method allows detection of particles up to 30 μm , with measurement precision for major compounds within 2% relative standard deviation (RSD), while minor compounds range from 10–20% for particles $>3 \mu\text{m}$, and can exceed to 100% for the smallest particles. Diameter measurement uncertainty decreases with size, from $\sim 1.5\%$ RSD at 2 μm to $<1\%$ for particle diameters $>3 \mu\text{m}$ (Kandler et al., 2018).

400 Impactor sampler collected 18 samples, and analyzed size, shape and elemental composition for 25000 single particles during the measurement period. Samples with a low number of particles (<500) were discarded to ensure reliable statistics while counting/grouping each particle group. This screening protocol resulted in a final validation dataset comprising 17 high-quality samples.

~~In this study, one of the main objectives is to accurately represent the aerosol dust mineralogy in future modeling studies using measurement data. Hence, we adopt a classification scheme for mineral dust aerosols representative of the soil database as used in the model.~~
405 To enable a consistent comparison between measurements and model output, the observed minerals are classified following the same mineral groupings used in the GMINER soil database. This ensures that the measured and simulated mineral categories are directly comparable, avoiding ambiguities arising from differences in mineral nomenclature or aggregation between observational and modeling frameworks. Size-segregated chemical compositions (same as Table 1)
410 ~~chemical composition of major dust aerosols~~ were determined for the primary dust aerosol minerals: illite, kaolinite, smectite, quartz, feldspar, calcite, gypsum and hematite were derived by defining ideal elemental compositions for ~~the modeled minerals~~

in the elemental space. The used composition in terms of mass compositions are shown in each modeled mineral, accounting for common impurities associated with each mineral phase (Table A. This classification scheme assigns the single particles to the closest ideal composition. Counting). Individual measured particles are then matched to the nearest ideal composition, and counting statistics for each particle-mineral group are used to estimate uncertainty by generating via two-sided 95% confidence intervals under a binomial assumption.

For iron oxide minerals such as hematite, the ratio reported in Table A reflects the iron oxide content from a single-particle perspective. However, a significant fraction of iron in dust occurs within the crystal lattice of other minerals (Lafon et al., 2004; Zhang et al., 2015), necessitating an alternative approach to estimate total iron oxide content.

Following Aryasree et al. (2024), we use two parameters: (i) the total iron oxide percentage ($F_{e_{oxides}}$), which accounts for iron present either as pure oxy-hydroxides (e.g., hematite, goethite) or incorporated within mineral lattices, and (ii) the total Fe index, defined as the atomic ratio of Fe to the sum of all quantified elements. The total iron oxide percentage is calculated as:

$$F_{e_{oxides}} = \left(\frac{m_{Feox\%}}{m_{Fe\%}} \right) * \left(\frac{M_{Fe}}{M_{dry}} \right) * 100, \quad (23)$$

where $m_{Feox\%}$ and $m_{Fe\%}$ are the mass fractions of iron oxides and elemental iron relative to the total dust mass, respectively, obtained from Table 3 in Di Biagio et al. (2019) for different Saharan source regions. M_{Fe} is the estimated Fe mass within a single particle from SEM-EDX measurements, and M_{dry} is the particle's dry mass.

Using this formulation, mass percentages for both total iron oxide and hematite are derived. For hematite specifically, hematite mass fraction from Di Biagio et al. (2019) is used to substitute $m_{Feox\%}$ in Eq. (23). The uncertainty arising from the representative ratio of iron oxide content from 19 desert dust types given by Table 3 in Di Biagio et al. (2019) which is generally less than 15%. For us, this is a systematic error, as we apply the same ratio to all samples.

Additionally, elemental mass concentrations are provided for the species most commonly associated with mineral dust, including Si, Al, Fe, Ca, K, Mg and S. Both mineralogical and elemental data are partitioned into the MUSCAT size bins up to BIN26.

3.2 DUSTRISK 2022 campaign

The DUSTRISK 2022 campaign took place in the Cape Verde archipelago during January and February 2022. Particulate matter was sampled at two distinct sites, referred to as inflow and outflow, on the island of Santiago (Cabo Verde). The inflow site (14°54'32" N, 23°30'54" W, indicated by the violet X in Fig. 3) was positioned in the city of Praia, on the northeastern coast, directly facing the ocean.

The sampling site was strategically positioned to intercept air masses dominated by the prevailing northeast trade winds, which transport Saharan mineral dust directly from the African continent. Located upwind of both the urban center of Praia and the island's interior, the site is well-situated to ensure that collected aerosols represent long-range continental transport with minimal interference from local island soils. Although minor anthropogenic contributions from nearby urban areas cannot be entirely discounted, the site's orientation ensures that local influences remain negligible, as corroborated by previous studies (Cardoso et al., 2018; Fomba et al., 2025). In contrast, the outflow site is positioned downwind of the major metropolitan

445 area and is significantly more susceptible to local anthropogenic and local dust emissions (Bredeck et al., 2024; Souza et al., 2025). To ensure direct comparability with model simulations that represent only continental dust sources, this analysis focuses exclusively on measurements from the inflow site.

Particulate matter (PM) samples were collected using Digital DHA-80 high-volume samplers (Walter Riemer Mess Technik, Germany) operating at an average flow rate of 500 L min⁻¹. At each site, separate ~~PM_{2.5} and PM₁₀~~ PM_{2.5} and PM₁₀ samplers
450 were deployed. Sampling typically occurred over 24-hour periods (noon to noon); however, during pronounced dust events, sampling duration was shortened to capture peak concentrations. All samples were collected on Ahlstrom micro-quartz fiber filters (MK 360) (Bredeck et al., 2024; Souza et al., 2025).

Elemental concentrations were determined using Total reflection X-Ray Fluorescence (TXRF) spectroscopy, following the methodology described by Fomba et al. (2020). Filter samples of 1.5 cm² area were prepared by digesting three 8 mm spots per
455 filter in a HCl/HNO₃ mixture (0.375 mL and 1.125 mL, respectively) using a microwave digester (Mars 6, CEM, Germany). Internal standards (Sc/Co at 10 µL) were added to the digested solutions, which were then applied to siliconized quartz carriers, dried at 80°C, and analyzed using a Bruker S4 T-STAR instrument. This procedure determined concentrations of Al, Ti, Ca, K, Mg, S, Si, Cr, Mn, and Fe. To ensure precision and account for potential sample heterogeneity, each carrier was analyzed at two rotational positions (0° and 90°). Measurement uncertainty was quantified by calculating the relative error between these
460 replicates, revealing a dependency on mass loading: uncertainties reached up to 15% for samples with very high dust load (> 150 µg/m³) while remaining below 6% for samples with low dust concentrations typically below 38 µg/m³. These variations are attributed to instrumental limitations previously characterized in (Fomba et al., 2020).

Notably, blank silicon measurements for the filters and TXRF sample carriers showed significant, non-reproducible variations due to inconsistent filter densities and surface reflectance. The resulting uncertainties were too high for a meaningful comparison;
465 therefore, silicon was excluded from the analysis. To isolate the mineral dust signal from the background aerosol, the total mineral dust mass concentration was reconstructed from the remaining elemental data following the procedure of Souza et al. (2025). In this approach, the concentrations of key crustal elements (Al, Fe, Ca, Ti) are adjusted for their common oxide forms to estimate the total mineral mass. The dust concentrations were quantified using the stoichiometric relationship for crustal elements following Deabji et al. (2021); Souza et al. (2025):

$$470 \quad MD = 1.16 \times ((1.90 \times Al) + (23.3 \times Ca) + (2.09 \times Fe) + (1.67 \times Ti)). \quad (24)$$

Following established classification for mineral dust events in the Cabo Verde region (Souza et al., 2025), a mineral dust mass concentration threshold of $\geq 38 \mu\text{g}/\text{m}^3$ was applied. The threshold was chosen based on long-term analysis of PM₁₀ concentrations at the CVAO sampling site, during which dust concentrations were consistently high. This threshold, combined with air mass back-trajectory analysis, serves to distinguish significant long-range transported dust events from maritime
475 background or ~~localized-local~~ localized-local aerosols. This screening resulted in a final validation set consisting of ~~33-PM_{2.5} and 47-PM₁₀~~ 33-PM_{2.5} and 45-PM₁₀ filter samples.

4 Model comparison framework

4.1 Evaluation methodology

To ensure a robust comparison between COSMO5.05-MUSCAT simulations and in-situ observations, the model output is spatio-temporally sampled to align with the specific characteristics of each measurement campaign. Spatially, model variables were extracted from the grid cells corresponding to the geographic coordinates of the sampling sites. Temporally, hourly model outputs were averaged over the specific integration times of the filter samples. This alignment accounts for varying sampling durations, ranging from the high-frequency UAV cycles during JATAC 2022 to the day-long ground-based periods of the DUSTRISK 2022 campaign. To ensure temporal concurrency, a rounding convention is applied: if a sampling interval began or ended within 30 minutes of a full hour, the nearest hourly model timestep is used to define the averaging window. For example, a sampling period from 10:00 to 12:15 is matched with the model average from 10:00 to 12:00, while a period from 10:10 to 12:36 is matched with the 10:00 to 13:00 simulated average.

For the compilation of North African mineralogical measurements, where exact temporal matching is often not possible due to the lack of concurrent simulated data, the time dimension is constrained by selecting observations from the same seasons as the simulation period. Furthermore, the comparison is restricted to sites and dust trajectories similar to those simulated, ensuring that the emission sites to measurement place pathways in the model are representative of the taken measurements, as detailed in the following section.

It is important to note that the ‘original’ mineralogy scheme (Gómez Maqueo Anaya et al., 2024) possesses structural constraints regarding the simulation-to-measurements comparisons. Specifically, phyllosilicates are restricted to the clay and fine-silt fractions (BIN01 and ~~1/2~~ BIN03), while minerals such as feldspar and gypsum are defined with no mass in the clay-sized fraction (BIN01). These inherent model configurations limit the scope of certain comparisons where observations report these minerals in size fractions not supported by the scheme’s internal mapping.

Beyond these structural constraints, the definition of the simulated mineral mass concentrations also requires clarification. The simulated mineral mass fraction is defined as the ratio of a given mineral’s mass to the total dust mass fraction within the size range used for comparison. For example, for bulk comparisons, this ratio is computed by summing the mineral mass across all size bins in which it is simulated and dividing by the total dust mass summed across all size bins. Importantly, this definition is applied consistently even when a mineral is not represented across the full size spectrum; in such cases, the denominator still comprises the total dust mass over all size bins. This approach implicitly assumes that the simulated minerals collectively account for the entirety of the dust mass. However, it should be noted that additional minerals present in the observations but not represented in the model also contribute to the measured total dust mass. Since these non-simulated minerals cannot be quantified within the modeling framework, their contribution introduces an inherent but unquantifiable offset between the simulated and observed mineral mass fractions.

The agreement between simulated (S_y) and observed (O_x) mineralogical and elemental concentrations is quantified using the Mean Bias (MB) and the Pearson correlation coefficient (r). ~~In this framework,~~ and an orthogonal distance regression. ~~The correlation coefficient r is utilized serves~~ as a measure of spatial ~~correlation-to-evaluate agreement, evaluating~~ the model’s

ability to replicate the geographical variability and regional distribution of mineral dust signatures across the study domain. The Pearson correlation coefficient is defined as:

$$r = \frac{\sum_{i=1}^n (S_i - \bar{S})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (S_i - \bar{S})^2 \sum_{i=1}^n (O_i - \bar{O})^2}} \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (x_i - \bar{x})^2}}, \quad (25)$$

where $\bar{S}$ and $\bar{O}$ represent the mean values of the simulated and observed datasets, respectively, and n is the number of paired spatial samples. ~~Complementary to this, the~~

To account for uncertainties inherent to the baseline measurements (x), the linear model is fitted using an orthogonal distance regression rather than ordinary least squares, which minimizes residuals in both axes simultaneously and thereby prevents attenuation bias in the slope estimation. The linear model takes the form:

$$y = mx + b, \quad (26)$$

where m is the slope and b is the intercept, obtained by minimizing the weighted sum of squared orthogonal residuals:

$$\min_{m,b} \sum_{i=1}^n w_{x,i} \left[\left(x_i - \frac{y_i - b}{m} \right)^2 \right], \quad (27)$$

where $w_{x,i} = 1/\sigma_{x,i}^2$ are weights inversely proportional to the observational variance $\sigma_{x,i}^2$ of each measurement.

The slope and intercept derived from this fit are reported alongside the Mean Bias (MB) in the results tables. The MB identifies systematic over- or underestimations and is ~~calculated as:~~ defined as:

$$MB = \frac{1}{n} \sum_{i=1}^n (S y_i - O x_i). \quad (28)$$

4.2 Compilation of North Africa mineralogical measurements

~~To evaluate the improvements introduced by the modified mineralogy scheme, we compared the Model outputs from DUST-CM-01 and DUST-CM-02 model outputs (see Table 2 for the list of the model experiments) are compared~~ against a compilation of in-situ aerosol mineralogical measurements. ~~This~~ The simulated period (January-February 2022) was specifically selected ~~to facilitate for two reasons. First, it enables~~ a direct comparison with the original mineralogy scheme presented by Gómez Maqueo Anaya et al. (2024). ~~By maintaining this temporal window, we ensure that, ensuring that any~~ differences in model performance ~~are attributable can be attributed~~ to the updated mineralogical parametrization rather than to variations in meteorological forcing ~~across different years.~~ Second, although an additional modeling period covering Northern Hemispheric (NH) summer conditions is available, it was not employed here since the measurement campaigns most representative of NH summer dust transport were already matched to source regions and transport pathways compatible with the January–February period through our classification methodology, rendering the additional period unnecessary for the present evaluation.

The core of this compilation is based on the global dataset of Perlwitz et al. (2015b). ~~As an initial step, the primary global datasets were subset, subsetted~~ to include only locations within the modeling domain, ~~and further expanded with one additional~~

dataset from the Atlas Mountains region in Morocco (Panta et al., 2023). Measurements predating the 1980s were excluded, as
540 the absence of satellite imagery prior to this period prevents reliable identification of dust emission events and source regions.
This expanded dataset is publicly available via the zenodo repository (<https://doi.org/10.5281/zenodo.21132304>), and the
corresponding measurement locations are represented by blue dots in Fig. 3.

The subsequent systematic processing is illustrated in Figure 4, which delineates the pathways for both in-situ obser-
vations (gray arrows) and COSMO5.05-MUSCAT simulation results (green arrows). The ~~datasets from both observations~~
545 ~~and modeling results are represented by yellow boxes with slanted corners.~~ Following the observational pathway, the data
undergoes a seasonal filter to retain only measurements representative of Northern Hemisphere (NH) winter months. This
step, represented by the first blue hexagon (decision point) in Figure 4, ensures the observational dataset closely matches the
simulation period.

This seasonal constraint is critical, as Saharan dust emissions and transport pathways exhibit pronounced intra-annual
550 variability (Barkan et al., 2004; Schepanski et al., 2009). Specifically, different dust source regions are active during NH winter
versus summer, resulting in distinct mineralogical signatures at the receptor sites. By restricting the compilation to the NH
winter season, we ensure that the dust sources activated within the model's simulation are representative for the measurement
comparison.

Schematic representation of the workflow used to select and compare in-situ mineral dust measurements with COSMO5.05-MUSCAT
555 simulations. Primary datasets are displayed in yellow boxes with slanted corners and bold text. The analysis pathway for
simulated mineralogy is depicted by green lines and arrows, while the in-situ measurement selection process is indicated by
gray lines and arrows. Decision points are represented by blue hexagons, procedural steps by blue octagons, supplementary
datasets by yellow rectangular boxes, and final outcomes by lavender octagons.

The second decision point in Fig. 4 determines the specific simulation data utilized for the comparison based first decision
560 step depends on the number of distinct dust events captured by each dataset. Measuring campaigns that sampled more than two
distinct dust events are categorized as long-term campaigns. ~~For these cases, for which~~ average mineral mass fractions ~~for the~~
~~measurement locations at the measurement location~~ grid cell are computed over the entire DUST-CM's simulation period and
compared directly against ~~the observed measurements~~ observations. This approach was applied to the datasets of Adedokun
et al. (1989); Enete (2012); Formenti et al. (2008); Kandler et al. (2009, 2011); Møberg et al. (1991) and Panta et al. (2023).

565 In contrast, shorter campaigns covering two or fewer dust events required a more detailed matching procedure, initiating the
"dust event analysis" workflow illustrated in Fig. 4. This methodology integrates HYSPLIT back trajectories (Stein et al., 2015)
with satellite-derived dust emission records from the MSG-SEVIRI Dust RGB product (EUMETSAT) to identify probable
source regions, following the approach of Schepanski et al. (2007), recently applied in Souza et al. (2025).

To ensure a like-to-like-like-for-like comparison, simulated dust plumes were selected only when their transport pathways
570 and source regions were consistent with the specific observed events. ~~For these cases, the comparison was performed using~~
, with model output extracted from the grid cell corresponding to the geographic coordinates of ~~the each~~ measurement site.
The "dust event analysis" workflow, illustrated in Figure 4, begins by identifying the probable source region of the observed
sample using HYSPLIT back-trajectories (Stein et al., 2015) intersected with dust emission records from the MSG-SEVIRI

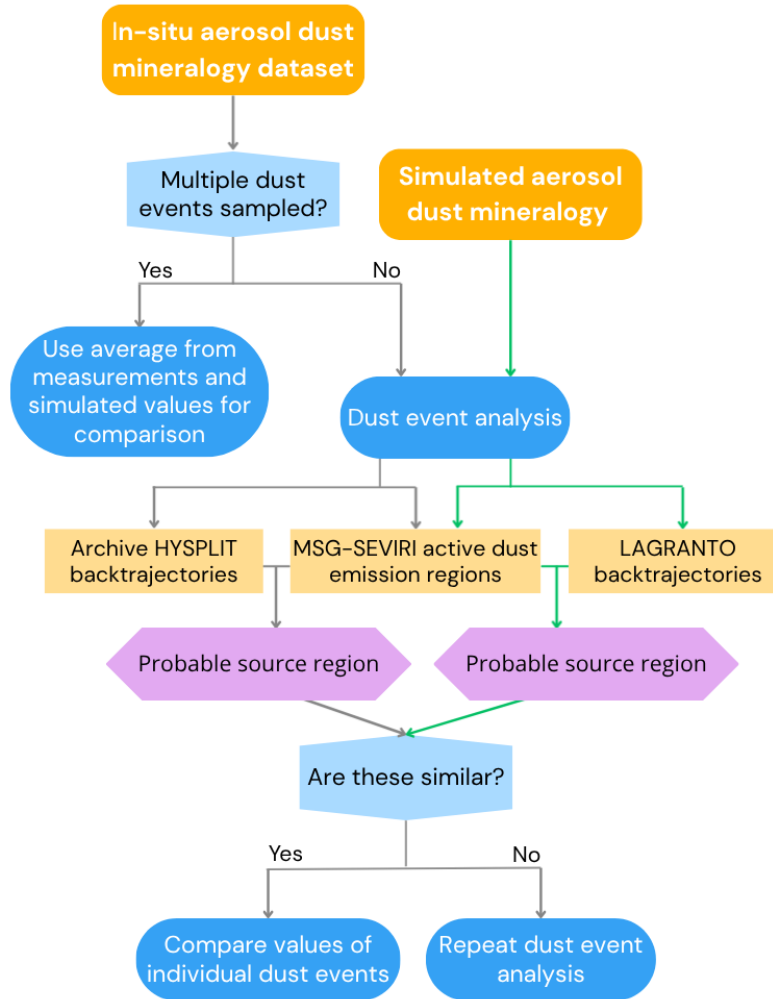


Figure 4. Schematic representation of the workflow used to select and compare in-situ mineral dust measurements with COSMO5.05-MUSCAT simulations. Primary datasets are displayed in yellow boxes with slanted corners and bold text. The analysis pathway for simulated mineralogy is depicted by green lines and arrows, while the in-situ measurement selection process is indicated by gray lines and arrows. Decision points are represented by blue hexagons, procedural steps by blue octagons, supplementary datasets by yellow rectangular boxes, and final outcomes by lavender octagons.

Dust RGB product. Simultaneously, backward trajectories for simulated dust events were computed using the LAGRANTO tool
575 (Miltnerberger et al., 2013), driven by COSMO5.05 meteorological fields. Comparison with measurements proceeded only when
the simulated and observed plumes originated from the same dust source region, thereby allowing for the direct matching of
individual plume signatures with high-resolution model outputs.

Three campaigns required this rigorous event-based matching procedure: Alastuey et al. (2005), Jeong and Achterberg (2014),
and Kandler et al. (2007). For Alastuey et al. (2005), which predates the MSG-SEVIRI record, Meteosat-7 natural color imagery
580 was utilized to track the specific plume transported from southern Algeria to Tenerife on 29 July 2002. For the remaining
campaigns, observed plumes were individually matched to simulated events by ensuring that both the HYSPLIT (observational)
and LAGRANTO (model) back-trajectories intersected with the same active MSG-SEVIRI dust emission areas.

~~The final dataset was further expanded with additional North African measurements not considered in the original Perlwitz et al. (2015b) compilation. This expanded dataset is publicly available via the zenodo repository ([https://zenodo.org/record/1000000](#)), and the corresponding measurement~~
585 ~~locations are represented by blue dots in Fig. 3. It should be noted that several historical measurements from the 1970s included in the Perlwitz et al. (2015b) study could not be reliably traced using this meteorological and satellite-based framework; consequently, these samples were excluded from the comparison to maintain the integrity of the spatio-temporal matching.~~
The resulting compilation spans multiple seasons and years; while Saharan dust transport pathways exhibit pronounced seasonal variability (Barkan et al., 2004; Schepanski et al., 2009), the event-based matching procedure applied to the NH summer measurements
590 ensures that the simulated and observed plumes originate from the same source region, mitigating potential biases introduced by seasonal differences in dust emission patterns.

To ensure a robust comparison between varying measurement techniques and model outputs, size-matching was performed
based on the reported diameter ranges. For each comparison, the simulated mineral mass fraction was calculated by integrating
the mass of a specific mineral across the relevant model bins and dividing this sum by the total simulated dust mass within those
595 same bins. Minerals absent from a given size bin in the model are excluded from the comparison at that size, meaning that differences in mineral implementation between schemes affect the number of available data points. For campaigns reporting
bulk measurements, model values were integrated across all available size bins (BIN01 through BIN80). For measurements
classified as "clay," the mass fraction was derived from BIN01 + ~~1/2~~1/2 BIN03, while "silt" classifications were compared to
the average of ~~1/2~~1/2 BIN03 + BIN09 + BIN26 + BIN80. For the campaign reporting high-resolution size distributions (Panta
600 et al., 2023), model bins were matched to the closest reported diameter ranges: 0—1 μm is compared to BIN01; 1—2 μm to
BIN03; 4—8 μm to BIN09; 8—16 μm to BIN26; and 32—64 μm to BIN80.

~~Following these spatio-temporal and~~ For the evaluation metrics, measurement sites are grouped by geographical region to
reflect the commonality of dust sources and transport pathways. Group 1 comprises sites in the Sahel, specifically Niger and
Nigeria; group 2 covers the receptor islands of the Canary Islands and Cabo Verde, and group 3 gathers sites surrounding
605 the Atlas Mountains in Morocco. Given the limited number of data points within each group, the linear fit and correlation
coefficient do not provide statistically meaningful information, and only the mean bias is reported for these grouped comparisons.

Following these size-matching and spatio-temporal constraints, the final size selected mineral mass fraction comparison is performed using the model output from the specific grid cell corresponding to each measurement site. While measurement
610 uncertainties were not consistently reported across all original studies, they have been included in the comparison with simulated data whenever available.

Despite these rigorous criteria, inherent uncertainties remain. Meteorological anomalies or atypical seasonal transport patterns in the historical data may not be fully captured by the January–February 2022 simulation period. Furthermore, several sites are located near major dust sources where local emissions may dominate the observed mineralogy in ways the model’s spatial
615 resolution cannot fully resolve (e.g., Formenti et al., 2008; Kandler et al., 2009; Møberg et al., 1991; Panta et al., 2023).

Finally, inconsistencies in particle size classification across datasets, such as varying definitions for "bulk," "clay," and "silt" fractions, introduce additional uncertainty. While model bins were mapped to these categories as previously described, the sensitivity of these boundaries (e.g., 2.0 vs 2.5 μm) highlights the necessity for high-resolution, well-characterized, and concurrent datasets, such as those obtained during the DUSTRISK 2022 and JATAC 2022 campaigns.

620 4.3 Application to Cape Verde measurement campaigns

4.3.1 Mineralogy comparison

Within the Cape Verde campaigns, mineralogical measurements were exclusively available from the JATAC 2022 dataset. For this evaluation, simulated mineral mass fractions from the JAT-CM-01 and JAT-CM-02 experiments were compared against the in-situ observations by extracting model variables from the grid cells corresponding to São Vicente. To ensure temporal and
625 vertical alignment, the model output is averaged over the specific sampling intervals and the documented altitude ranges of the UAV flights.

In terms of particle size, the JATAC 2022 observations are inherently compatible with the MUSCAT bin definitions, requiring no additional size-matching adjustments. However, BIN80 (32–64 μm) is excluded from the assessment due to the analytical detection limits of the substrate composition methodology (see Sec. 3). Consequently, each specific mineral mass fractions
630 ~~measurements derived~~ from the validated samples ~~are is~~ directly matched to its corresponding simulated mass ~~fraction to value~~
up to BIN26 to evaluate the model’s mineralogical representation.

4.3.2 Elemental comparison

Elemental compositions were evaluated for both the DUSTRISK and JATAC 2022 campaigns. To ~~facilitate a enable~~ direct comparison with the filter-based measurements, simulated mineral mass concentrations were converted into elemental mass
635 fractions using the stoichiometric percentages defined in Table 3. For each ~~specific~~ element, the total simulated mass is calculated by summing the contributions from all relevant minerals, which is then normalized by the total simulated dust mass to yield an elemental mass fraction. We focus our analysis on Fe, Si, Al, Mg, K, Ca, and S, as these elements serve as key tracers for mineral identification and source attribution in Saharan dust studies (Kandler et al., 2018; Formenti et al., 2011; Panta et al., 2023).

It should be noted that certain mineral groups, specifically feldspar and smectite, exhibit significant natural variability in their elemental ratios. For this study, the stoichiometric coefficients for these species were selected to reflect the chemical signatures most commonly observed in the North African and Saharan regions (e.g., Kandler et al., 2007; Formenti et al., 2014; Scheuvens et al., 2013). The spatio-temporal extraction followed the protocols described in Section 4, with size-matching adjusted according to the specific sampling characteristics of each campaign:-

- **DUSTRISK:** Observational elemental masses from inflow sites were normalized by the total measured mass. To match the reported size fractions, model outputs were aggregated into PM2.5 (BIN01 + 1/2 BIN03) and PM10 (BIN01 + BIN03 + BIN09).
- **JATAC:** No size-matching adjustments were required, as the measurement characteristics align directly with the MUSCAT bin definitions.

Table 3. Mass percentage of key elements found in the COSMO5.05-MUSCAT simulated minerals. The smectite group is represented by the end-member montmorillonite, and feldspar is groups are represented by a 1:1 average averages of nontronite and montmorillonite, in the case of smectite and of microcline (K-feldspar) and albite (Na-feldspar) for feldspar. This selection is based on common mineralogical assemblages observed in Saharan dust aerosols (Scheuvens et al., 2013; Formenti et al., 2011, 2014).

Mineral	Fe [%]	Si [%]	Al [%]	Mg [%]	K [%]	Ca [%]	S [%]
Hematite	69.94	-	-	-	-	-	-
Illite	1.43	25.25	9.01	1.87	6.03	-	-
Kaolinite	-	21.76	20.90	-	-	-	-
Smectite	-11.26	20.46-18.73	9.83-7.64	-	-	0.73-0.37	-
Quartz	-	46.80	-	-	-	-	-
Feldspar	-	30.89	10.23	-	14.05-7.03	0.76	-
Gypsum	-	-	-	-	-	23.28	18.62
Calcite	-	-	-	-	-	40.04	-

Feldspar and smectite exhibit significant natural variability in their elemental ratios; their stoichiometric coefficients were therefore selected to reflect the chemical signatures most commonly observed in the North African and Saharan source regions. For smectite, an average of nontronite and montmorillonite was applied. Although Mg-rich smectites are also present in the Sahara, their sources, such as ancient lake basins, are located far from Cabo Verde and would require an uncommon transport pathway to reach the archipelago, making a significant contribution unlikely. For feldspar an average of microcline and albite was selected to represent the K- and Na-feldspars characteristic of Saharan dust (e.g., Kandler et al., 2007; Formenti et al., 2014; Scheuvens et al., 2013).

It should be noted that the values in Table 3 are derived from the stoichiometric formulae of the respective minerals, whereas the identification criteria in Table A additionally incorporate characteristic elemental tracers for each mineral group. Alternative

tracer selections have been employed in other modeling studies (Menut et al., 2020; Mahowald et al., 2026); the tracers used here were hand-selected to best reflect the mineralogical signatures expected for Saharan dust reaching the Cabo Verde receptor site.

The size-matching procedure is adjusted to reflect the specific sampling characteristics of each campaign:

- **DUSTRISK:** Observational elemental masses from inflow sites were normalized by the total measured mass. To match the reported size fractions, model outputs were aggregated into $PM_{2.5}$ (BIN01 + 1/2 BIN03) and PM_{10} (BIN01 + BIN03 + BIN09).
- **JATAC:** No size-matching adjustments were required, as the measurement characteristics align directly with the MUSCAT bin definitions from BIN01 to BIN26.

5 Model validation

5.1 Mineralogy

To evaluate the performance of the ‘modified’ mineralogical scheme, we compare the simulated dust composition against two distinct observational benchmarks. First, we assess the model’s ability to capture the general characteristics of North African mineral dust using a comprehensive compilation of historical aerosol measurements from across the region as described in Section 4.2. This provides a statistically-robust-baseline for regional performance. Second, we evaluate the scheme’s precision during a specific transport event using high-resolution mineralogical data from the JATAC 2022 campaign. Together, these comparisons offer-a-multi-scale-provide a complementary validation of the model’s capacity to represent both climatological means-and-episodic-variability-in-the broad regional characteristics and the episodic variability of dust mineralogy.

5.1.1 Compilation of North Africa aerosol mineralogical measurements

~~Two simulations were performed for~~ The two simulations covering the DUSTRISK 2022 period ~~to assess the~~, CM-DUST-01 (‘original’ scheme) and DUST-CM-2 (‘modified’ schemes (DUST-CM-01 and DUST-CM-02, respectively)). These runs are compared with historical North African observations from locations and seasons with consistent transport pathways (Section 4.2). Performance metrics, including mean bias and spatial correlations, are synthesized in ~~the~~ scheme), are evaluated here. Only mean biases are reported per site group, as sample sizes preclude a statistically meaningful correlation analysis (Table 4 ~~and~~); the full per-mineral dataset is shown in Fig. 5, where yellow stars denote ~~the modified scheme~~). Error bars in Fig. 5 represent the observational uncertainties when reported in the original experimental studies.

The differences between the two simulations are consistent with the structural changes described for the modified approach. Comparing the two simulations directly DUST-CM-02 and error bars represent observational uncertainties where available. As expected from the structural changes introduced in the modified scheme (Section 2.3), the transition from the original to the modified approach DUST-CM-01 to DUST-CM-02 results in a fundamental redistribution of mass among the mineral species.

Table 4. Mean bias (MB) of the mineral mass fractions for the ‘original’ (DUST-CM-01, [abbreviated CM-01](#)) and ‘modified’ (DUST-CM-02, [abbreviated CM-02](#)) schemes. ~~The MB is calculated, evaluated~~ against the North African measurement compilation. [Results are organized by geographical group as defined in Section 4.2: group 1 \(Sahel: southern Niger and Nigeria\), group 2 \(receptor islands: Canary Islands and Cabo Verde\), and group 3 \(Atlas Mountains region, Morocco\).](#) The number of observation points used for each comparison is indicated in the parentheses ~~(n)~~^{superscript (n)}.

Mineral	MB [%] ⁽ⁿ⁾					
	1		2		3	
	DUST-CM-01 CM-01	DUST-CM-02 CM-02	CM-01	CM-02	CM-01	CM-02
illite	4.3 (9) 16.3 (3)	9.4 (13) 20.7 (3)	-9.8 (5)	-1.2 (5)	5.1 (4)	8.2 (8)
kaolinite	-5 (12) -4.9 (4)	1.2 (17) 2.3 (5)	-9.6 (4)	-0.9 (4)	-0.3 (4)	1.5 (8)
feldspar	-0.1 (11) 15.6 (3)	-5.3 (13) 1.0 (5)	-1.9 (2)	-6.7 (2)	-2.5 (7)	-6.4 (8)
calcite	-1.9 (16) -2.1 (2)	-2.4 (16) -3.3 (2)	-0.7 (6)	-1.1 (6)	-2.7 (8)	-3.1 (8)
hematite	-0.2 (9)	-0.2 (9)	0.4 (2)	0.4 (2)	-0.3 (7)	-0.3 (7)
quartz	27.4 (21) 1.3 (5)	1.8 (21) -20.2 (5)	29.5 (7)	3.7 (7)	40.4 (9)	12.6 (9)

~~Specifically, DUST-CM-02 produces higher mineral species, with higher simulated~~ mass fractions for illite and kaolinite and lower ~~mass~~ fractions for quartz and feldspar~~compared to the DUST-CM-01 run.~~

690 When evaluated against the North African measurement compilation (Fig. 5), the redistribution of mineral mass in DUST-CM-02 leads to ~~varying impacts on model skill~~[mixed results across mineral species and measurement groups \(Table 4\)](#). The most ~~significant improvements are observed for kaolinite, where increased~~ striking improvement is observed for quartz, where the ~~reduced~~ simulated mass fractions ~~reduce the systematic underestimation seen for the~~ in DUST-CM-02 substantially decrease ~~the systematic overestimation present in DUST-CM-01 run.~~ As shown in Table 4, kaolinite ~~shifts from an underestimation~~
695 ~~(-5%) to a slight overrepresentation (+1.2~~. For groups 2 and 3, the MB drops from 29.5% to 3.7% and from 40.4% to 12.6%, respectively, representing a considerable reduction in bias. For group 1, however, the modest overestimation in DUST-CM-01 (1.3%) becomes a notable underestimation in DUST-CM-02 (-20.2%), ~~while also being the only mineral to show~~ suggesting that quartz content in those measurement points may be higher than captured by the modified scheme, possibly reflecting proximity to quartz-rich source regions where quartz is measured before significant deposition or long-range transport has
700 ~~occurred.~~

For illite, DUST-CM-02 shows a clear improvement ~~in spatial correlation (r_p).~~ ~~While illite exhibits a marginal correlation improvement, its overestimation is amplified in DUST-CM-02.~~ This ~~discrepancy is for group 2, notably the group where measurements are predominantly from long-range transport, reducing the MB from -9.8% to -1.2%.~~ For groups 1 and 3, the already positive biases increase slightly, from 16.3% to 20.7% and from 5.1% to 8.2%, respectively. The increase in data
705 ~~points for group 3, from $n=4$ to $n=8$ is due to the modified scheme extending the size range over which illite is simulated, enabling comparisons previously excluded due to the absence of simulated illite at those sizes.~~ Notably, the overestimation

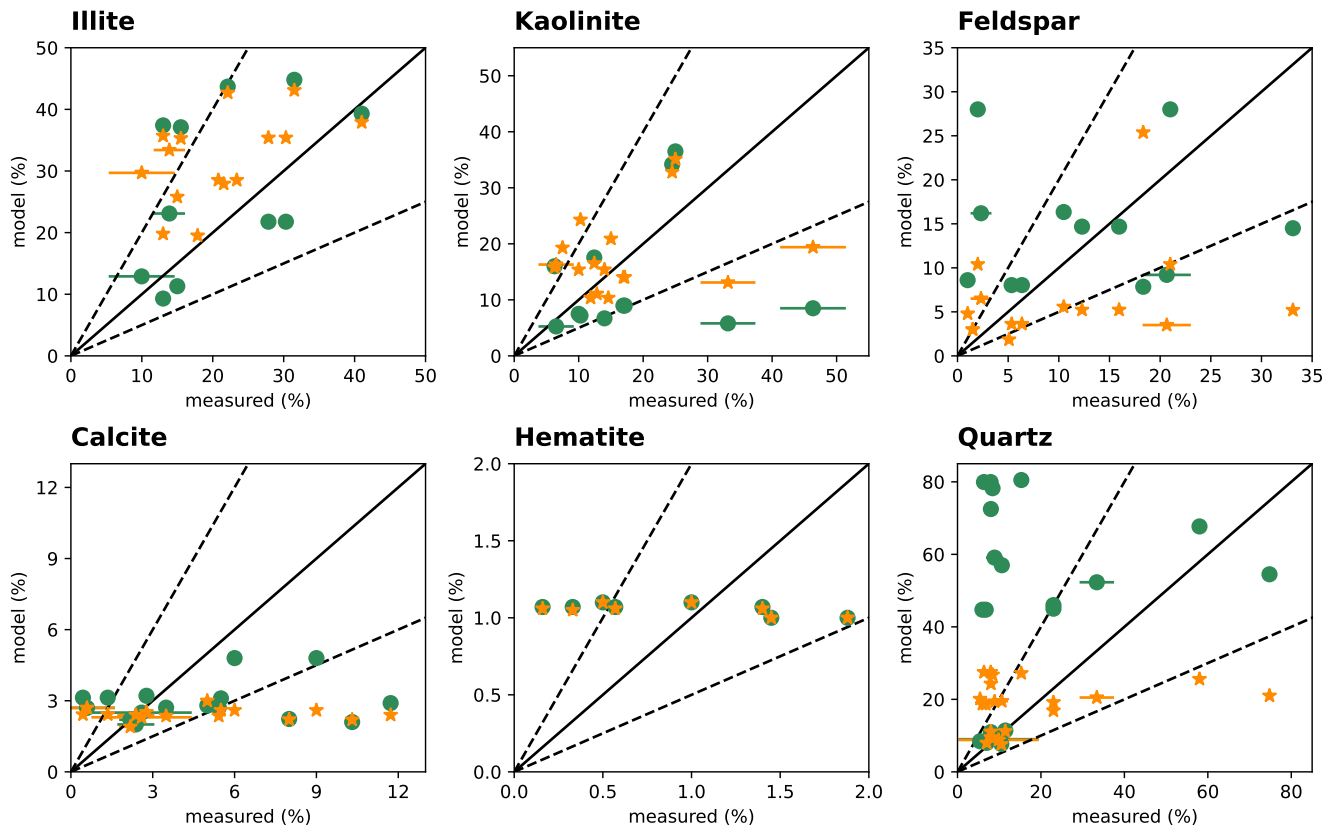


Figure 5. Scatterplots of mineral mass percentages of illite, kaolinite, feldspar, calcite, hematite and quartz measured vs. simulated values. Results from the ‘original’ simulation (DUST-CM-01) are shown as green solid dots, while the ‘modified’ approach (DUST-CM-02) is illustrated by yellow solid stars. The dashed lines represent the 1:2 and 2:1 ratios between simulated and observed values. Error bars indicate observational uncertainties as reported in the original studies; where no error bars are present, uncertainties were not provided in the source data. The comparison includes both bulk and size-segregated measurements, with model bins aggregated to match reported diameter ranges as detailed in Section 4.2. **Pearson correlation coefficients (r_p) for each approach are shown in the legend.**

does not increase proportionally to the added points, suggesting that the newly included size bins do not systematically worsen the bias. The persistent overestimation in groups 1 and 3 may partially reflect localized emissions from areas with relatively low illite content, including the southern Niger region of the Sahel and southeastern region off the Atlas Mountains (Nickovic et al., 2012). These discrepancies must be partly attributed to the broad mineralogical definition of illite groups, which complicates unique identification (Rieder et al., 1998, and references therein). **Notably, however, illite remains the only mineral species among those compared to demonstrate a moderate spatial correlation.**

Regarding the non-phyllosilicates minerals, quartz shows the most striking quantitative improvement; its *MB* is reduced from a $\sim 30\%$ overestimation in the original scheme to only 1.8% in the modified version, significantly enhancing overall

715 ~~model-observation agreement~~. Conversely, while the ~~Kaolinite follows a broadly similar pattern, with~~ DUST-CM-02 ~~run~~
~~improves the evaluation scope by including feldspar in reducing underestimation across all groups and yielding the closest~~
~~overall agreement with observations in the compilation. As with illite, the finest size fraction (Eq. 20), a 49% reduction in its~~
~~simulated mass exacerbates the existing model-observation discrepancy, leading to a larger negative MB (Table 4). increase~~
~~in data points in groups 1 and 3 reflects the extended size coverage of the modified scheme.~~

720 ~~Despite these shifts in mass loading, the spatial correlations (r_p) for both quartz and feldspar remain largely unaffected~~
~~between the two modeling approaches. This stability suggest that for r_p , even though the underlying soil mineralogy distribution~~
~~changed, the transport patterns remain similar enough to not enact changes on it. Moreover, the impact of the~~ For feldspar,
~~DUST-CM-02 scheme on correlation is evident when considering the expanded observational scope. For illite and kaolinite,~~
~~the inclusion of previously unrepresented size fractions allowed for a more comprehensive validation against a larger pool~~
725 ~~of data points (Table 4), resulting in a notable and positive shift in r_p . While a similar size-range expansion was applied~~
~~to feldspar, produces a marked improvement for group 1, reducing the MB from 15.6% to 1%, while also expanding the~~
~~number of available data points. Group 1 is located in region of relatively low feldspar content (Nickovic et al., 2012), and~~
~~since high quartz abundance is generally associated with lower feldspar content (Scheuvens et al., 2013), the addition of two~~
~~observational points was insufficient to yield a statistically significant change in its correlation~~ reduction in simulated feldspar
730 ~~mass in DUST-CM-02 is most consistent with the mineralogical characteristics of this regions. In contrast, groups 2 and 3 show~~
~~a notable increase in model negative biases indicating that modified scheme does not adequately represent feldspar content in~~
~~regions where higher abundances are expected, nor along the long-range transport pathways that connect these source areas to~~
~~the receptor sites.~~

~~The representation of calcite and hematite remains a challenge. Despite moderate increases in their simulated mass fractions~~
735 ~~(12% and 17%, respectively from DUST-CM-01 to~~ Calcite shows a consistent but modest increase in underestimation across
~~all groups in DUST-CM-02), calcite remains underestimated ($MB \simeq -2\%$) and hematite correlations remain poor with negative~~
 ~~r_p values. Interestingly, for the same number of observation points, the two minerals showed diverging trends in spatial skill:~~
~~hematite r_p improved from -0.35, with the MB shifting from -2.1% to -0.18, while calcite correlation degraded from 0.17~~
~~to -0.04. The shift in hematite -3.3% for group 1, from -0.7% to -1.1% for group 2 and from -2.7% to -3.1% for group 3.~~
740 ~~Notably, the largest absolute bias occurs in Group 1, where low calcite content is expected from the surrounding soil mineralogy~~
~~(Nickovic et al., 2012), suggesting that even small reductions in simulated calcite mass are sufficient to generate a discernible~~
~~bias in low-abundance regions. While the changes are small in absolute terms, their systematic direction suggests that the mass~~
~~redistribution in DUST-CM-02 partially corrected previous spatial mismatches, making the model "less wrong" regarding its~~
~~distribution, even if a negative correlation persists. These discrepancies likely stem from inherent uncertainties in hematite~~
745 ~~quantification, which occurs both as discrete particles and within other mineral lattices (Lafon et al., 2004; Zhang et al., 2015)~~
~~. Furthermore, the fact that these domain averaged mass increases are not strongly reflected in the site-specific comparisons~~
~~of Fig. 5 suggest that the modified mass allocation may have introduced new spatial biases by reducing calcite particles~~
~~which could result in an incorrect emission calculation for this mineral. the modified scheme reduces calcite representation by~~
~~reallocating emission mass towards phyllosilicates. Hematite biases, on the other hand, remain unchanged between schemes~~

750 with non-negligible MB values across available groups. The insensitivity of the scheme change is expected, as hematite is not directly reallocated; nonetheless, the persistent biases and limited variability in the simulated values raise questions about the model's ability to accurately capture the spatially variable hematite content characteristic of Saharan dust sources.

~~Potential biases in the measurement dataset~~ Spatial scale mismatches between point observations and model grid-cell averages should also be considered ~~. For instance, the inclusion of the FRAGMENT campaign when interpreting these results. The FRAGMENT campaign (Panta et al., 2023), which added ~40% more data to the reference set (Fig. 5 in Gómez Maqueo Anaya et al. (2024)). These measurements, reported by Panta et al. (2023), were collected~~, was conducted in the Drâa Valley, Morocco, near active dust source regions ~~. Such localized influences may not be captured by the model, as its where small-scale convective emission events can produce highly local mineralogical signatures that the model's at 28 km spatial resolution represents grid-cell averages and does not resolve small-scale convective events. Likewise cannot resolve. Similarly,~~
760 several other ~~campaigns included in the comparison~~ measurement campaigns in the compilation were conducted close to dust sources, reflecting local emissions rather than regional ~~transport observations. Consequentially, these point observations may not fully represent the broader mineral fraction distributions that transported mineral fractions~~ the model is designed to simulate. Seasonal coverage also plays a role: while some campaigns spanned transitional months with shifts in dominant source regions, the simulations are restricted to NH winter (January–February), potentially missing these seasonal variations
765 (Gebauer et al., 2026). ~~Ultimately, while the scale mismatch between point measurement and grid-cell average persists, the Nonetheless, DUST-CM-02 framework~~ provides a more robust baseline for mineralogical validation ~~. By than its predecessor, and by identifying where temporal and spatial representativeness limit our correlations, this approach the model-observation agreement, this analysis~~ clarifies the specific observational constraints needed to further reduce uncertainty in mineral dust modeling.

770 5.1.2 Comparison with JATAC 2022

The ~~comparison between in-situ mineral dust aerosol measurements from the JATAC 2022 campaign and COSMO5.05-MUSCAT simulations is illustrated across several figures: Fig. 6 presents results for individual and grouped phyllosilicates (labeled provides size-resolved mineralogical measurements that allow a detailed evaluation of both the original (JAT-CM-01; Gómez Maqueo Anaya) and modified (JAT-CM-02; Sect. 2.3) schemes across individual mineral species. Results for phyllosilicates (individually and~~
775 grouped as “clay minerals”) are presented in Fig. 6, while Fig. 7 ~~show shows~~ the comparisons for quartz, calcite, feldspar, and gypsum, and ~~gypsum and~~ Fig. 8 ~~show shows~~ the comparison for hematite. ~~For this evaluation, we contrast the original mineralogical scheme (JAT-CM-01; Gómez Maqueo Anaya et al., 2024) with the modified approach (JAT-CM-02; Sect. 2.3). As detailed in the evaluation methodology (The summary of the statistical metrics, including the mean bias (MB) and the slope and intercept of the uncertainty-weighted linear fit, is provided in Table 5 for all mineral species and size bins. The~~
780 size-matching procedure follows the methodology described in Sect. 4.3), ~~measurements were~~, with measurements binned to match the COSMO5.05-MUSCAT size categories (BIN01 through BIN26).

~~For the grouped phyllosilicates~~ The first notable feature in Fig. 6 is that the observational uncertainties reported for BIN26 are too large to support any meaningful model diagnostic from these data. For the grouped phyllosilicates, the model generally

Table 5. Mean bias (MB) of the mineral mass fractions. Statistical metrics for the ‘original’ (JAT-CM-01) and ‘modified’ (JAT-CM-02) model schemes. The MB is calculated against the JATAC 2022 mineral measurements: mean bias (MB), and the slope (m) and intercept (b) of the observational uncertainty weighted linear fit ($mx + b$). The default number of observation data points used for each comparison is $n = 17$; deviations are indicated in the parentheses (n) by a superscript.

Mineral	MB [%]							
	mx + b							
	JAT-CM-01				JAT-CM-02			
	BIN01	BIN03	BIN09	BIN26	BIN01	BIN03	BIN09	BIN26
clay minerals	-4.2 (17) <u>$0.41x + 36.2$</u>	-42.2 (17) <u>$0.16x + 20.3$</u>	– <u>–</u>	– <u>–</u>	-6.7 (17) <u>$0.4x + 34.2$</u>	-23 (17) <u>$0.24x + 33.5$</u>	-32.4 (17) <u>$-0.84x + 104.5$</u>	-32.8(17) <u>$-0.14x + 63.7$</u>
illite	-21.6 (17) <u>$0.22x + 18.4$</u>	-43.7 (17) <u>$0.002x + 14.7$</u>	– <u>–</u>	– <u>–</u>	-22.6 (17) <u>$0.22x + 17.5$</u>	-34.5 (17) <u>$0.001x + 24$</u>	-35.8 (17) <u>$-0.5x + 47.5$</u>	-42.2(17) <u>$-0.09x + 30.7$</u>
smectite	12.5 (17) <u>$1.3x + 11.1$</u>	2.3 (17) <u>$-0.03x + 8.6$</u>	– <u>–</u>	– <u>–</u>	11.8 (17) <u>$1.31x + 10.5$</u>	7.5 (17) <u>$-0.07x + 14.1$</u>	0.3 (17) <u>$0.02x + 11$</u>	2.9(15) ⁽¹⁵⁾ <u>$-0.02x + 14.1$</u>
kaolinite	4.9 (17) <u>$0.13x + 15.7$</u>	-1.2 (17) <u>$0.08x + 7.8$</u>	– <u>–</u>	– <u>–</u>	4.1 (17) <u>$0.12x + 15$</u>	3.9 (17) <u>$0.13x + 12.4$</u>	3 (17) <u>$0.09x + 10.3$</u>	4.5(16) ⁽¹⁶⁾ <u>$-0.1x + 13.6$</u>
quartz	1.6 (17) <u>$0.71x + 3.1$</u>	25.2 (17) <u>$2.2x + 18.6$</u>	46.1 (17) <u>$0.15x + 53.8$</u>	62.3(14) ⁽¹⁴⁾ <u>$0.94x + 62.8$</u>	1.6 (17) <u>$0.71x + 3.1$</u>	6.7 (17) <u>$0.75x + 8.1$</u>	9.2 (17) <u>$0.16x + 16.8$</u>	15.7(14) ⁽¹⁴⁾ <u>$0.09x + 22.3$</u>
calcite	-1.6 (17) <u>$0.05x + 1.7$</u>	-4 (17) <u>$-0.04x + 2.6$</u>	-4.2 (18) <u>$-0.03x + 3.1$</u>	1.1(9) ⁽⁹⁾ <u>$-0.07x + 3.3$</u>	-1.6 (17) <u>$0.05x + 1.7$</u>	-4.3 (17) <u>$-0.03x + 2.3$</u>	-4.8 (17) <u>$-0.02 + 2.4$</u>	0.5(9) ⁽⁹⁾ <u>$-0.04x + 2.7$</u>
feldspar	– <u>–</u>	2.5 (17) <u>$-0.46x + 9.5$</u>	9.9 (17) <u>$0.14x + 14.5$</u>	14.3(15) ⁽¹⁵⁾ <u>$-0.01x + 19.5$</u>	-1.9 (17) <u>$-0.08x + 1.8$</u>	-1.3 (17) <u>$-0.23x + 4.5$</u>	0.3 (17) <u>$-0.12x + 6.4$</u>	2.2(15) ⁽¹⁵⁾ <u>$0.001x + 7.3$</u>
gypsum	– <u>–</u>	-6.3 (17) <u>$-0.01x + 0.5$</u>	-2.7 (17) <u>$0.02x + 0.9$</u>	-3.2(14) ⁽¹⁴⁾ <u>$0.01x + 1.2$</u>	-7.8 (17) <u>$-0.01x + 0.9$</u>	-6.2 (17) <u>$-0.01x + 0.6$</u>	-3.3 (17) <u>$0.001x + 0.3$</u>	-4(14) ⁽¹⁴⁾ <u>$0.005x + 0.4$</u>
hematite	-0.9 (17) <u>$-0.43x + 1.7$</u>	-0.5 (17) <u>$-0.13x + 1.1$</u>	-0.1 (17) <u>$-0.35x + 1.3$</u>	0.1 (17) <u>$0.03x + 1.1$</u>	-0.9 (17) <u>$-0.43x + 1.7$</u>	-0.4 (17) <u>$-0.11x + 1.2$</u>	0.1 (17) <u>$0.48x + 0.6$</u>	0.1 (17) <u>$0.04x + 1$</u>

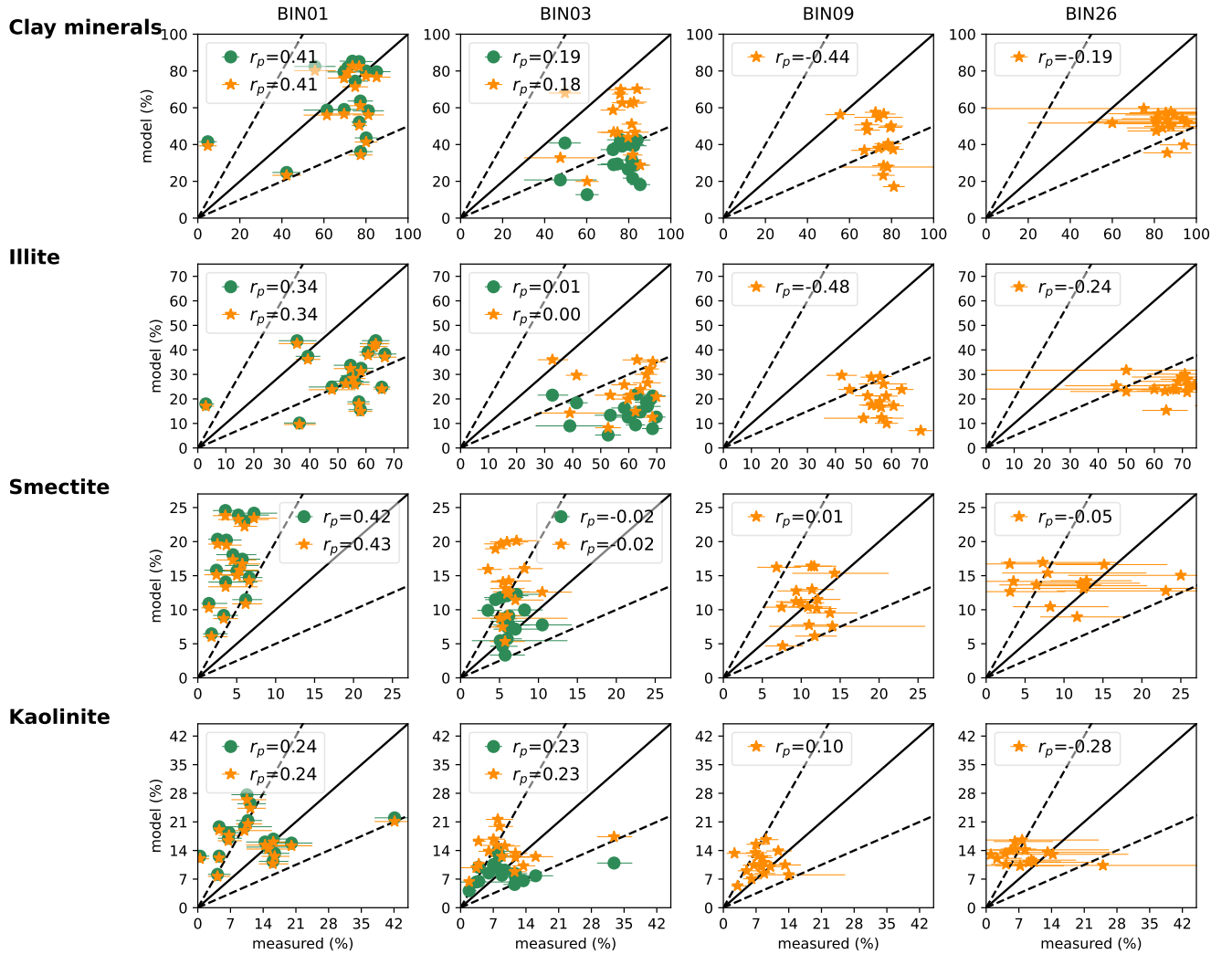


Figure 6. Scatterplots of minerals mass percentages of-for the grouped "clay minerals", illite, smectite, and kaolinite vs. simulated by COSMO5.05-MUSCAT. 'original' mineral emission scheme (JAT-CM-01) in green solid dots while the 'modified' version (JAT-CM-02) is shown in yellow solid stars. The titles of the columns are size classifications from COSMO5.05-MUSCAT, the diameter ranges they represent are described in Table 1. The dashed lines represent the ratios of 2:1 and 1:2 between the simulated and observed mineral percentages. The error bars represent the lower and upper limits of the confidence intervals (between 2.5% and 97.5%). [Uncertainty-weighted linear fits are reported in Table 5 but omitted from the figure for clarity, as the limited dynamic range in several size bins renders them visually uninformative.](#)

~~underestimating underestimates~~ the total mass fraction across all size ranges. A key functional improvement of the ‘modified’
 785 scheme (JAT-CM-02) is the redistribution of these minerals into coarser size bins, enabling a direct comparison beyond the
 sub-2.5 μm fraction where the ‘original’ scheme was restricted~~and therefore no direct comparison between schemes can be~~
~~made~~. In the finest fraction (BIN01), both approaches show a similar underrepresentation with MB values of -4.2% for
 JAT-CM-01 and -6.7% for JAT-CM-02. However, in BIN03, JAT-CM-02 reduces the underestimation by half compared to
 JAT-CM-01 (~~-23% vs. -42-2%~~), suggesting that the ‘modified’ scheme more accurately captures the mass distribution in coarser
 790 fractions. Within the expanded comparison size range, the model underestimation remains consistent across ~~both coarse the~~
~~coarser~~ size bins (Table 5). ~~Notably, the highest spatial~~ Regarding the linear fit, the slope in BIN01 is similar between schemes
 ($0.41x + 36.2$ for JAT-CM-01 and $0.40x + 34.2$ for JAT-CM-02; Table 5), reflecting the concentration of most measured values
 around the 80% mass fraction (Fig. 6) which limits the dynamic range available for regression at this size. Spatial correlations
 (r_p) ~~for the phyllosilicates grouped comparison are moderate and found are highest~~ in BIN01, ~~showing little sensitivity to the~~
 795 ~~structural differences between the two schemes (nonetheless, and similarly insensitive to the scheme differences (Fig. 6). In~~
 BIN03, the slope improves with the modified scheme (from $0.16x + 20.3$ to $0.24x + 33.5$), consistent with the reduction in
 MB , suggesting that JAT-CM-02 better captures the spatial variability of the phyllosilicate mass fractions at this size despite
 the persistent underestimation, an improvement not reflected in r_p value. (Table 5 and Fig. 6).

Regarding individual species, measured illite fractions during JATAC 2022 were notably high, falling above the typical
 800 ranges in the North African compilation (Fig. 5). This ~~localized observational trend leads to a systematic underestimation in~~
~~both model versions. Such discrepancies partly reflects the known challenges in identifying these specific mineral groups in~~
~~SEM-EDX measurements (Rieder et al., 1998), introducing uncertainties in both~~ likely reflects the aggregate nature of mineral
 dust aerosols, which are predominantly composed of Si- and Al-rich mineral particles, making phyllosilicates, and illite in
 particular, readily identifiable but difficult to distinguish unambiguously in the ~~observations and the reference mineralogical~~
 805 ~~databases~~ single-particle SEMD-EDX analysis (Rieder et al., 1998). Furthermore, while illite is formally classified as a clay
 mineral, airborne dust measurements have consistently reported illite fractions well above what clay-size constraints would
 suggest (e.g., Panta et al., 2023), a discrepancy that partly arises from the wet-sieving methodology used to characterize soil
 mineralogy, as discussed in Section 2.3. The presence of illite in coarser size fractions is further explained by its tendency
 to form stable platelets and aggregates that survive natural wind-driven disaggregation, whereas mechanical and chemical
 810 treatment in soil analyses is more likely to break up such structures. SEM images of coarse illite-bearing particles collected
 during JATAC 2022 (Fig. C1) illustrate the variety of shapes these particles exhibit, including platelet-like morphologies,
 highlighting that illite can be transported in large aggregated forms. These platelet-shaped particles are assigned to the large
 size bin based on their measured dimensions; however, their actual volume is substantially smaller than that of a sphere of
 equivalent bin diameter as assumed in the model. As a result, the equivalent-volume sphere of such a platelet would fall into
 815 a smaller size bin, meaning that the measurement and the model are not directly comparable for these coarse, non-spherical
 particles, introducing an additional source of uncertainty for the comparison at these sizes.

Notwithstanding these complexities, both schemes systematically underestimate illite across all size bins. In BIN01, the MB
 values are similar between schemes, and the slopes of the linear fit are likewise nearly identical, indicating that the modified

scheme introduces no meaningful change at this size. In BIN03, JAT-CM-02 reduces the underestimation from MB values of -43.7% to -34.5%, though the near-zero slopes in both cases ($0.002x + 14.7$ and $0.001x + 24$) suggest that neither scheme captures the spatial variability of illite at this size, with the intercept dominating the fit. Within the expanded size range enabled by JAT-CM-02, the underestimation remains substantial and increases with particle size, with negative slopes for the coarser bins indicating an inverse relationship between simulated and observed values (Table 5). The Pearson correlation coefficient (r_p) confirms this in BIN09 and remain insensitive to the choice of scheme for smaller size bins, with the strongest correlations and lowest mean biases occurring in BIN01. While JAT-CM-02 reduces the bias for BIN03, significant underestimation persists and scales with increasing particle size (Fig. 6 and Table 5).

Conversely, smectite and kaolinite are generally overestimated across the simulations. Both minerals show a performance improvement under JAT-CM-02 in terms of reduced mean biases for both simulations. For smectite, the MB in BIN01 shows little change between schemes, with nearly identical slopes, indicating that JAT-CM-02 further exacerbates the overestimation in the coarser introduces no meaningful change at this size. In BIN03: for kaolinite, it shifts a slight underestimation toward a more pronounced overestimation, while for smectite, the overestimation grows. Among the individual phyllosilicates, the strongest the overestimation increases from 2.3% to 7.5% under JAT-CM.02, with near-zero slopes in both cases, suggesting that neither scheme captures the spatial variability of smectite at this size. Within the expanded size range, BIN09 shows near-neutral biases and negative r_p values are consistently found in BIN01, regardless of the scheme employed. While kaolinite exhibits weak but stable correlations across both, indicating that the model reproduces the mean smectite fraction reasonably well at coarser sizes but without spatial skill. For kaolinite, the MB improves slightly in BIN01 and, with slopes and r_p values remaining low and stable between schemes. In BIN03, spatial correlations for the coarser sizes of both minerals remain weak or negative (JAT-CM-02 over corrects, shifting a slight underestimation (-1.2%) to an overestimation (3.9%), though the slope improves modestly; notably, kaolinite is the only individual phyllosilicate that retains weak but stable spatial correlation at this size bin. In BIN09, kaolinite remains moderately overestimated (3%) (Fig. 6 and Table 5).

As expected, the spatial correlations for the grouped phyllosilicate category exhibits r_p values are similar to those of the individual species, as this metric is inherently tied to the mineral distribution within since r_p is primarily governed by the geographical distribution of minerals in the parent soil. Notably, nearly all spatial correlations, which is unchanged between schemes. While the modified scheme redistributes emitted mineral mass across size bins, it does not alter the underlying source patterns, and spatial correlations would therefore be expected to remain stable if the PSD redistribution scaled uniformly across the domain. However, nearly all r_p values for the coarser size bins are negative. This suggests that shifts in the mineral PSD do not necessarily align with the composition of the parent soil. Such statistical decoupling is significant, given that illite and kaolinite distributions vary distinctly across the North African desert (Formenti et al., 2008, 2014; Scheuven et al., 2013). This discrepancy may stem from uncertainties in the source maps that define these regional signatures. Alternatively, it may arise from the methodological assumption that phyllosilicates identified in the clay-sized fraction, suggesting that the redistribution might be introducing spatially variable shifts in mineral mass that are inconsistent with observations. Notably, the strongest negative correlation in the entire dataset occurs for illite in BIN09 ($r_p = -0.48$), indicating that the model systematically places coarse illite mass in locations where observations suggest it should be low, and vice versa (Fig. 6). This likely reflects the

855 constraining transport behavior between the model and reality: the model treats minerals as discrete spherical particles subject to gravitational settling, whereas in reality, coarse illite is predominantly transported as aggregates and within a variety of shapes (Fig. C1), enabling longer travel distances than an equivalent single spherical particle would achieve. Small errors in simulated emission locations or transport pathways are therefore amplified in the spatial distribution at receptor sites. Additionally, the redistribution of mass into coarse bins is derived from fine-fraction soil data via wet-sieving
~~are similarly present in coarser fractions, despite being undetectable by those specific measurement techniques and one measurement campaign,~~
 860 which may systematically overestimate coarse illite in certain source areas and underestimate it in others. Finally, while the model's dust transport performance has been evaluated against AERONET AOT observations for this period and shows reasonable agreement (Gómez Maqueo Anaya et al., 2025), day-to-day shifts in circulation patterns not fully resolved by the meteorological driver, partly due to its spatial resolution, could result in incorrect source-receptor attribution for individual measurement events, introducing spatial mismatches independent of the mineralogical scheme.

865 These findings ~~build upon the work of Gonçalves Ageitos et al. (2023) who noted~~ are consistent with those of Gonçalves Ageitos et al. (2023), ~~who showed~~ that the GMINER SMA (Nickovic et al., 2012) generally outperforms Journet et al. (2014) SMA in reproducing the spatial distribution of phyllosilicates, despite a tendency to overestimate kaolinite and smectite while underestimating illite across the Sahara. Their analysis further showed that for fine clay-sized fractions, illite is often overestimated near sources but underestimated during long-range transport, whereas coarser silt-sized illite is ~~typically underestimated. Our comparison with~~
 870 ~~JATAC 2022 measurements corroborates these trends, showing a persistent underestimation of illite across all simulated size bins. This suggests~~ systematically underestimated. Together, these results suggest that while the ~~JAT-CM-02 mass redistribution aims for greater accuracy, it may be amplifying existing uncertainties inherent in regional phyllosilicates source functions~~ mass redistribution introduced by JAT-CM-02 improves the size representation of phyllosilicates, and some mass biases, it may also amplify existing uncertainties in the regional source functions, particularly for illite, where the limitations of the underlying
 875 ~~soil mineralogical database remain the dominant source of error.~~

For the non-phyllosilicates minerals shown in Fig. 7, ~~the JAT-CM-02 run significantly reduces quartz overestimation, particularly produces the most substantial improvements for quartz and feldspar, while calcite and gypsum remain largely unchanged between schemes. Quartz is strongly overestimated in JAT-CM-01 from BIN03 onward. Mean biases decrease from~~, with *MB* values of 25.2%, 46.1%, and 62.3% ~~in the JAT-CM-01 run~~ for BIN03, BIN09, and BIN26, respectively,
 880 ~~accompanied by a slope of 2.2x in BIN03 indicating that the model greatly amplifies the observed spatial variability at that size. JAT-CM-02 substantially reduces these biases to 6.7%, 9.2% and 15.7% in JAT-CM-02, with the slope of BIN03 returning to a more physically plausible 0.75x. In BIN01, both schemes produce identical results, confirming that the modification does not affect its finest fraction (Table 5). Despite these substantial quantitative improvements, overestimations remain high relative to measured values, and the spatial correlations (r_p) exhibit high variability across size bins. Similar to the phyllosilicate results,~~
 885 ~~the two smallest size fractions show no difference between modeling schemes, maintaining weak but consistent correlations. In contrast, the improvements, overestimation persists across all size bins in JAT-CM-02, and spatial correlations remain weak and highly variable. The correlation for BIN09 improves modestly under JAT-CM-02, though it remains statistically insignificant, while the correlation but decreases importantly for BIN26 worsens~~ (Fig. 7). The sharp decline in quartz correlation for the

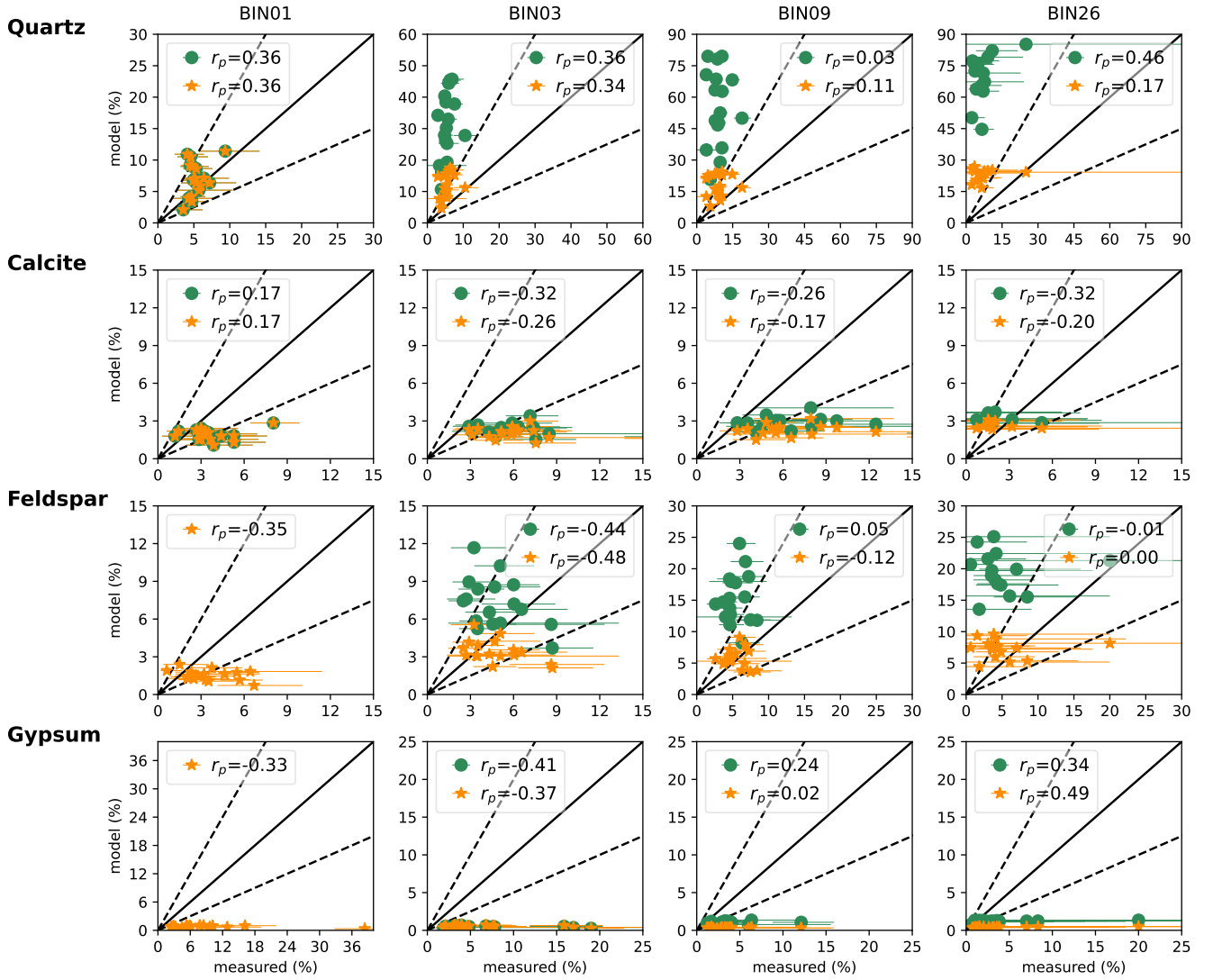


Figure 7. As in Fig. 6 but for quartz, calcite, feldspar, and gypsum. Note: Axis scales vary between panels to optimize the visibility of the fine fractions for quartz, feldspar and gypsum

coarsest fraction (BIN26), likely results from the significant likely reflects the reduction in simulated coarse-mode mass in the JAT-CM-02 scheme. While this reduction successfully corrects the previous mass overestimation, while this correction brings the mass bias closer to observations, it simultaneously weakens the spatial signal of the quartz plume. ~~As the absolute mass loading in the coarsest bins approaches more realistic, the correlation coefficient becomes~~, making the correlation increasingly sensitive to localized transport mismatches and the ~~potential 'wash-out'~~ preferential deposition of coarse particles ~~before they reach distant observational~~ on a discrete spherical particle simulation scheme before reaching distant measurement sites.

Similarly, feldspar shifts from strong overestimation in JAT-CM-01, ~~particularly in the coarser size bins, significantly less biased results across sizes ($\pm 1-2\%$)~~ with MB values of 2.5%, 9.9% and 14.3% for BIN03, BIN09, BIN26, respectively, to near-neutral biases across all sizes in JAT-CM-02 (-1.9%, -1.3%, 0.3%, 2.2% for BIN01 throughout BIN26), representing one of the most consistent quantitative improvements of the modified scheme (Table 5). Interestingly, this ~~localized success during the JATAC 2022 contrasts~~ contrast with the broader North African compilation, where the ~~mass reduction exacerbated existing discrepancies~~ same mass reductions exacerbated existing underestimations in groups 2 and 3 (Table 4). ~~Furthermore, these quantitative improvements in mass magnitude~~, highlighting the regional dependence of the scheme's performance. The worsening in group 2 is particularly noteworthy given that it includes Cabo Verde measurements, suggesting that the observational dataset or sampling conditions underlying that group may differ in other ways that resulted in higher concentration of feldspar measured than what was measured during JATAC 2022. Regardless, the quantitative improvements at JATAC are not reflected in the spatial correlations, which show no ~~improvement across any of the size ranges~~ meaningful change across any size bin; as with most other minerals, the large observational uncertainties in BIN26 further limit the spatial diagnostic at that size (Fig. 7).

~~In contrast, calcite~~ Calcite and gypsum remain consistently underestimated across all size fractions, ~~with these tendencies in both schemes, with biases~~ generally worsening under the JAT-CM-02 scheme. For calcite, ~~these results align the MB values~~ are nearly identical between schemes across all bins, with near-zero slopes throughout, indicating that neither scheme captures any spatial variability in calcite distribution (Table 5). These results are consistent with previous findings for 2–20 μm particles (Gonçalves Ageitos et al., 2023) and with the broader North African measurement compilation comparison (Fig. 5). Correlation coefficients for calcite either remain ~~stable or improve marginally under~~ negative for the majority of the sizes, with only slight improvements for JAT-CM-02, yet they remain negative. Gypsum underestimation is ~~further~~ similarly persistent, with near-zero slopes across all bins reflecting an absence of spatial skill in both schemes. The underestimation is slightly exacerbated in JAT-CM-02; ~~notably, the r_p for BIN09 degrades despite moderate agreement for~~, and it is particularly noteworthy in BIN01 ($MB = -7.8\%$). Interestingly, the highest correlation value is found for the modified scheme in BIN26, ~~where~~ but due to high uncertainties and gross underestimation, no conclusion can be made here. The highest correlation value in the dataset occurs for JAT-CM-02 ~~shows a meaningful improvement~~ in BIN26, though the combination of large observational uncertainties and gross underestimation at that size precludes any meaningful interpretation.

Hematite (Fig. 8) ~~is underestimated by an average of 0.9% in~~ shows near-identical performance between schemes across all sizes, with both JAT-CM-01 and JAT-CM-02 producing MBs of -0.9% and identical slopes for BIN01 ~~under both modeling schemes, with mean biases decreasing in the larger size fractions~~. In BIN03, the ~~JAT-CM-02 run slightly reduces the bias~~

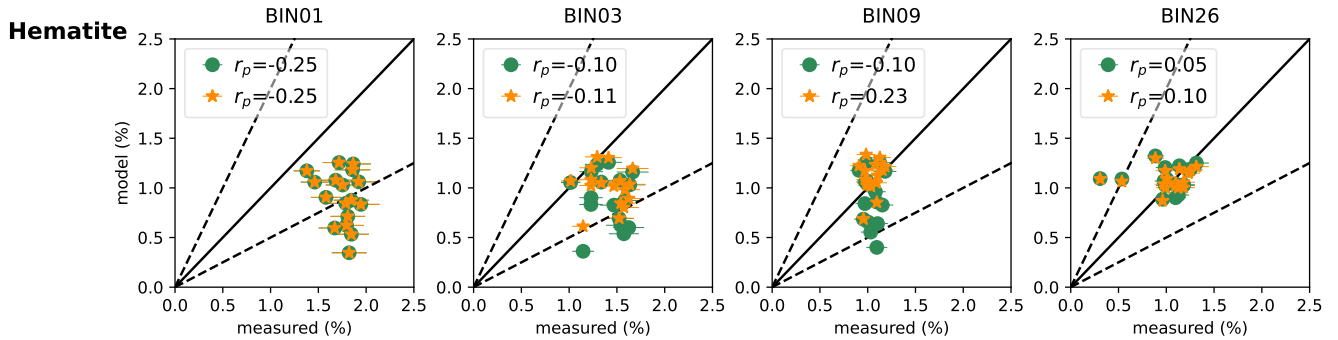


Figure 8. As in Figs. (6 & 7) but for hematite by following Eq. 23 replacing $w_{\text{Feox\%}}$ by $w_{\text{Hem\%}}$. Error bars represent 10% variation from the measurement.

while in BIN09 and BIN26, the two schemes diverge minimally, both yielding near-zero mean biases (0.1%). On average, hematite mass increases modestly by 5% bias reduces marginally from -0.5% to -0.4% and similarly small changes in the slope. The most notable difference between schemes occurs in BIN09, where the linear fit changes from $-0.35x + 1.3$ to $0.48x + 0.6$ in the modified scheme. While JAT-CM-02, accompanied by a change in r_p values remain similar in the finer size fractions, from -0.1 to 0.23. This sign reversal in both the slope and the correlation coefficient represents the only instance where the JAT-CM-02 framework shows a notable, albeit weak, improvement for the coarser bins (e. g., BIN09). This is the first instance in which the ‘modified’ scheme demonstrates a clear advancement in the spatial representation of hematite. Despite persistent biases, hematite produces a clear improvement in spatial representation. In BIN26, both schemes converge to near-zero biases and near-zero slopes, with no meaningful difference between them (Table 5 and Fig. 8). Overall, despite the persistent negative slopes in the finer fractions, likely reflecting the dual occurrence of hematite as discrete particles and within the lattice structure of other minerals (Lafon et al., 2004; Zhang et al., 2015), hematite shows encouraging agreement with observations, supporting the scheme’s robustness for applications sensitive to dust optical properties (e.g., Gómez Maqueo Anaya et al., 2025).

Averaged over the JATAC 2022 simulation period, the JAT-CM-02 produces substantial increases in phyllosilicates, phyllosilicate mass relative to JAT-CM-01, with illite, kaolinite, smectite, exhibiting collectively showing 130% more mass relative to JAT-CM-01, alongside, alongside a modest changes in hematite (+5%). Conversely, quartz (-61%), feldspar (-56%), and calcite (-14%), and gypsum (-17%) mass loadings all decline significantly.

Collectively, these results suggest that while mass redistribution effectively addresses the mass redistribution introduced by the modified scheme effectively reduces systematic magnitude biases for quartz and feldspar in this specific dataset, at the JATAC 2022 measurement sites, but spatial correlations remain limited primarily by uncertainties in the underlying soil mineralogy maps remain a primary source of uncertainty rather than by the emission scheme itself. The treatment of dust as discrete spherical particles further contributes to spatial misrepresentation, as it neglects the aggregate nature of mineral dust transport and the size-dependent settling behavior that arises from it. The persistent underrepresentation underestimation of calcite and gypsum, which seems to be independent of atmospheric model or dust emission parametrization

(e.g., Gonçalves Ageitos et al., 2023), indicates that spatial correlation is limited more by source-map uncertainties than by appears to be a common feature across different atmospheric models and dust emission parametrizations (e.g., Gonçalves Ageitos et al., 2023), further supports this interpretation, pointing to the wet-sieving methodology used to construct soil mineralogical databases as a structural source of bias that propagates independently of the emission scheme itself.

5.2 Elemental composition

Cape Verde serves as a critical receptor site for Saharan dust, making its observational record uniquely suited for evaluating the modified mineralogical scheme. In this section, we supplement our mineral-specific analysis with a validation of elemental mass fractions. By converting simulated mineral compositions into elemental abundances (via the relationships defined in Table 3), we establish a secondary, providing a complementary and independent metric for assessing evaluating model performance.

While size-resolved elemental comparisons provide a broader perspective on dust composition, they also introduce complexities inherent to field data. Neither modeling approach fully accounts for the observed elemental variability, as measured compositions frequently include non-dust constituents or minerals not simulated in the current framework.

broaden the assessment, they introduce additional uncertainties: despite filtering for dust-dominated samples, contributions from minerals outside the modeling framework cannot be fully excluded. This is particularly evident in relevant for the DUS-TRISK 2022 dataset; because these measurements were conducted, collected near the surface during the NH winter, they are more susceptible to where interference from local emissions and/or or Sahelian biomass burning plumes from the Sahel (Tesche et al., 2011). In contrast, is more likely (Tesche et al., 2011); the JATAC 2022 observations were performed within, made within the Saharan Air Layer, typically considered as pure dust during NH summer. However, are more representative of pure Saharan dust, though minor contamination during atmospheric transit remains possible. transport cannot be ruled out. It should also be noted that the simulated elemental compositions are sensitive to the assumed elemental fractions per mineral, for which different choices have been made across modeling studies (Menut et al., 2020; Mahowald et al., 2026); the compositions adopted here were selected as most representative of the mineralogical signatures expected at the Cabo Verde receptor site, as discussed in Section 4.3.

5.2.1 JATAC 2022

Figure 9 compares the observed and simulated concentrations of Si, Al, Fe, and Ca. For silicon (Si), the differences between the two schemes are negligible in the finest fraction (BIN01), with both producing near-identical MB values and slopes (Table 6). However, in the intermediate size ranges (In BIN03 and BIN09), the modified scheme (JAT-CM-02) shifts the model from an overestimation a slight overestimation (0.6%) to an underestimation. Notably, the magnitude of this underestimation exceeds the previous overestimation, (-4.5%), with the slope decreasing from $0.86x$ to $0.63x$. In BIN09, this underestimation grows further (-5.9%; Table 6), a result that initially seems to contradict the substantial quartz overestimation identified for these size categories (Table 5).

Since quartz is not the only contributor to Si mass (Table 3), this underestimation likely stems from reflects the compounded effect of stark reductions in feldspar and quartz both quartz and feldspar that are not fully compensated for by the increase in phyllosilicates. This supports a hypothesis that non-simulated ,high-Si minerals, such as those in the mica (e.g., muscovite) or chlorite groups ,may be missing from the model (Scheuven et al., 2013), while adding (Scheuven et al., 2013), contribute to the measured Si mass signal in ways the model cannot reproduce. In the coarsest bin (BIN26), while both schemes overestimate where observational uncertainties are relatively low for Si, JAT-CM-02 significantly mitigates this bias, reducing the mean bias from -14.1% to 0.9% substantially reduce the overestimation from 13.6% to 0.1% (Table 6). This improvement is directly attributable to the substantial reduction of quartz content in, directly mimicking the reduction in simulated coarse quartz mass. The improvement is reflected in the mean bias exclusively since the spatial correlation degrades modestly in BIN26 under JAT-CM-02 for this size category (Table 5). Ultimately, this demonstrates that refining (Fig. 9). This shows that redistributing mineral abundances can effectively improve elemental mass representation even when spatial correlations remain stagnant stagnate or degrade, a trend consistent with quartz comparisons across both the North African compilation the quartz comparison (Fig. 5) and the JATAC 2022 dataset (Fig. 7).

Aluminum exhibits a clear size-dependent improvement across the bin-resolved mean biases (Table 6). While no significant changes occur in in mean bias under JAT-CM-02. While there is no meaningful change between scheme for BIN01, all other size bins show a progressive reduction in underestimation. This from BIN03 onward, JAT-CM-02 progressively reduces the underestimation, from -6.7% to -5% in BIN03, from -9.1% to -5.3% in BIN09, and from -9.9% to -5.1% in BIN26 (Table 6). This progressive improvement directly reflects the redistribution of clay minerals into larger size fractions within the modified scheme, a shift that better captures, better capturing the aggregated state of phyllosilicates during emission and atmospheric transport. Persistent underestimation ,however, may be attributed to the presence of across all bins may be partly attributed to high-Al ,non-simulated minerals such as chlorite (Scheuven et al., 2013). This mass redistribution is particularly encouraging, as the resulting Al concentrations align more closely with observations than the The elemental perspective is particularly informative here: while the individual mineral comparisons might suggest suggest conflicting needs, more illite mass but less kaolinite and smectite (Table 5). Nonetheless, these and Fig. 6), the Al comparison more clearly indicates that a net increase in simulated Al-bearing mineral mass could improve the remaining bias, revealing an improvement direction that is partially obscured at the mineral level. These improvements in mass bias do not extend to the spatial correlation coefficients (r_p), which show a slight degradation in the under JAT-CM-02 scheme (Fig. 9). This suggests that while the mass balance is improved, the inherently weak correlation, likely driven by the influence of from BIN03 onward. The spatial correlation for Al is inherently weak, likely because non-simulated minerals ,is further exacerbated by the proposed mass redistribution ,introduce spatial variability in the observed Al signal that the model cannot capture. The mass redistribution in JAT-CM-02, while improving the overall mass balance, does not resolve this structural limitation and marginally exacerbates the spatial mismatch, consistent with the pattern observed for Si (Fig. 9).

Iron (Fe) content shows negligible sensitivity to the choice of emission scheme choice remains substantially underestimated across all size bins ,as evidence by the persistent and severe underestimation exhibited by the mean bias for both approaches in both schemes, though JAT-CM-02 produces meaningful reductions in bias from BIN03 onward. In BIN01, both schemes

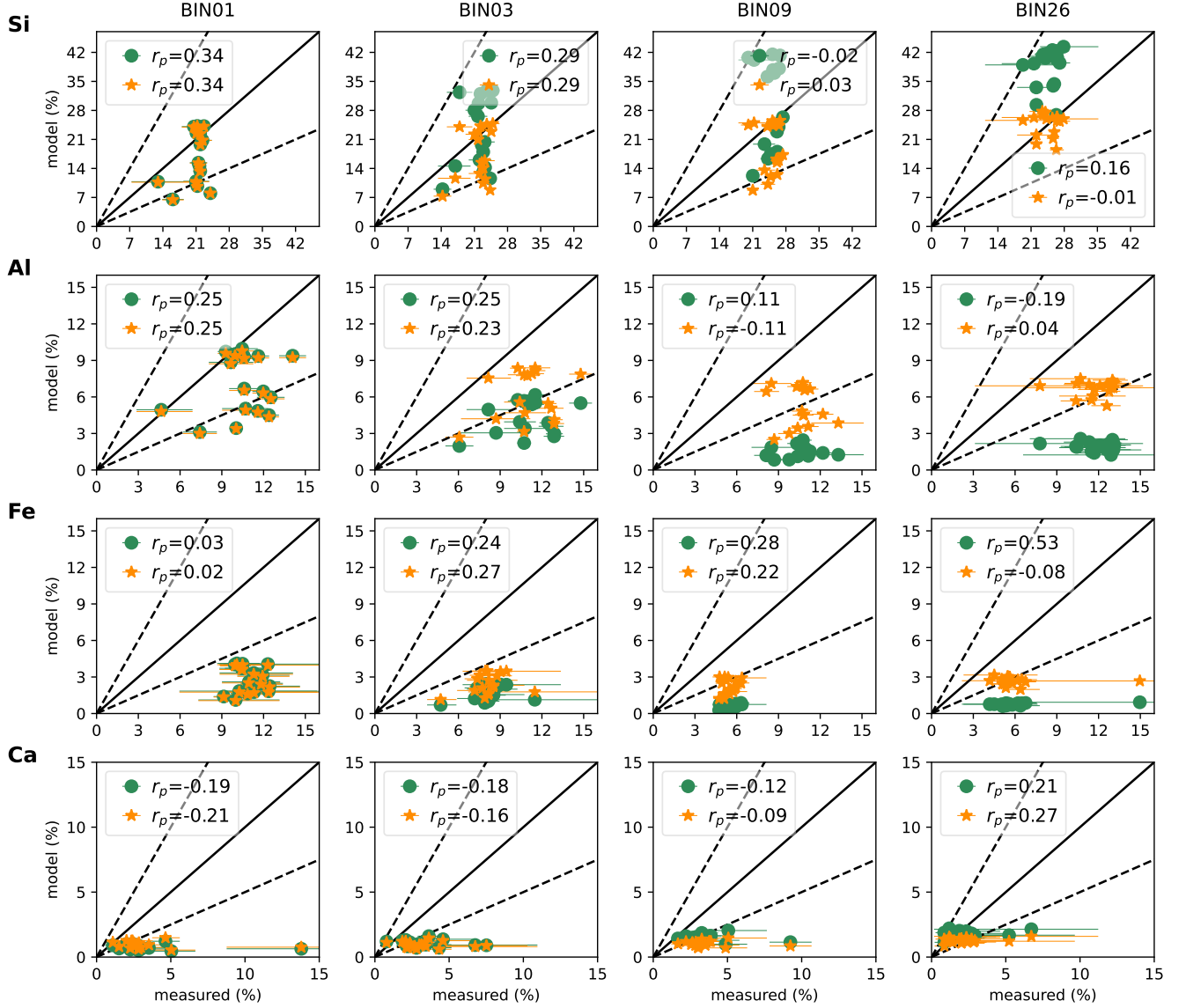


Figure 9. Scatterplots of observed elemental mass percentages of Si, Al, Fe, and Ca against simulated by COSMO5.05-MUSCAT. Simulated values were derived by multiplying modeled mineral mass by their respective elemental compositions (detailed in Table 3). Green solid circles indicate the ‘original’ mineral emission scheme (JAT-CM-01), while yellow solid stars represent the ‘modified’ version (JAT-CM-02). The titles of the columns are size classifications from COSMO5.05-MUSCAT (Table 1). The dashed lines represent the ratios of 2:1 and 1:2 between the simulated and observed mineral percentages. The error bars represent the lower and upper limits of the confidence intervals (between 2.5% and 97.5%). Uncertainty-weighted linear fits are reported in Table 6 but omitted from the figure for clarity, as the limited dynamic range in several size bins renders them visually uninformative.

Table 6. Mean-bias (MB) of the elemental mass fractions—Statistical metrics for the ‘original’ (JAT-CM-01) and ‘modified’ (JAT-CM-02) model schemes. The $\sim$ mean bias (MB is calculated against $\sim$), and the JATAC 2022 slope (m) and intercept (b) of the elemental measurements—observational uncertainty weighted linear fit ($mx + b$). The number of observation-data points used for each comparison is indicated in the parentheses (n) $n = 17$.

Mineral	MB [%]					
	JAT-CM-01				JAT-CM-02	
	BIN01	BIN03	BIN09	BIN26	BIN01	BIN03
Si	-3.6 (17) <u>-4.3</u>	0.4 (17) <u>0.6</u>	4.4 (17) <u>4.3</u>	14.1 (17) <u>13.6</u>	-3.7 (17) <u>-4.4</u>	-4.5 (17)
Al	-2.8 (17) <u>$-0.84x - 1$</u>	-6.5 (17) <u>$-0.86x + 3.7$</u>	-8.8 (17) <u>$-0.08x + 31.1$</u>	-9.4 (17) <u>$-0.33x + 30.1$</u>	-2.9 (17) <u>$-0.85x - 1.3$</u>	-4.6 (17) <u>$-0.63x + 3.5$</u>
Al	-3.4	-6.7	-9.1	-9.9	-3.5	-5 (17)
	<u>$0.29x + 4.1$</u>	<u>$0.17x + 2.4$</u>	<u>$0.04x + 1.1$</u>	<u>$-0.05x + 2.5$</u>	<u>$0.28x + 4$</u>	<u>$0.23x + 3.5$</u>
Fe	-10.3 (17) <u>-8.2</u>	-7.6 (17) <u>-6.5</u>	-6 (17) <u>-4.9</u>	-5.2 (17) <u>-5.3</u>	-10.3 (17) <u>-8.3</u>	-7.4 (17) <u>-5.7</u>
	<u>$0.03x + 2.5$</u>	<u>$0.11x + 0.8$</u>	<u>$0.11x - 0.01$</u>	<u>$0.02x + 0.6$</u>	<u>$0.03x + 2.4$</u>	<u>$0.16x + 1.1$</u>
Ca	-2.8 (17) <u>-2.6</u>	-2.3 (17)	-2.3 (17) <u>-2.1</u>	-1.2 (17) <u>-0.6</u>	-2.6 (17) <u>-2.4</u>	-2.4 (17)
K	-0.2 (17) <u>$-0.01x + 0.8$</u>	-0.4 (17) <u>$-0.03x + 1.1$</u>	0.1 (17) <u>$-0.02x + 1.5$</u>	0.1 (17) <u>$-0.04x + 1.7$</u>	-0.1 (17) <u>$-0.02x + 1$</u>	-0.3 (17) <u>$-0.03x + 1$</u>
K	-0.1 (17)	-0.7	-1	-1.3	-0.1 (17)	-0.4
	<u>$0.79x + 0.3$</u>	<u>$0.12x + 1.1$</u>	<u>$0.15x + 0.7$</u>	<u>$0.01x + 1.3$</u>	<u>$0.79x + 0.3$</u>	<u>$0.16x + 1.3$</u>
Mg	-1.2 (17) <u>-1.1</u>	-1.6 (17)	—	—	-1.2 (17) <u>-1.1</u>	-1.5 (17)
	<u>$-0.03x + 0.6$</u>	<u>$-0.01x + 0.3$</u>	—	—	<u>$-0.03x + 0.6$</u>	<u>$-0.01x + 0.4$</u>
S	—	-1.1 (17)	-0.4 (17)	-0.4 (17)	-1.3 (17) <u>-1</u>	-1.1 (17)
	—	<u>$-0.01x + 0.1$</u>	<u>$-0.02x + 0.2$</u>	<u>$0.01x + 0.2$</u>	<u>$-0.02x + 0.2$</u>	<u>$-0.01x + 0.1$</u>

produce near-identical results, and among the improved bins, BIN09 shows the most notable gain in both mass bias and spatial skill, with the MB improving from -4.9% to -3.2% and the linear fit slope changing from $0.11x - 0.01$ to $0.27x + 0.7$ (Table 6). From These improvements are consistent with the increased smectite mass in JAT-CM-02 results, spatial correlations increase (Table 5 and Fig. 6), given that smectite is the second largest contributor to the simulated Fe budget after hematite. A sensitivity study (not shown) in which smectite stoichiometry was replaced entirely by nontronite, the Fe-rich end-member, produced a consistent reduction in Fe underestimation across all size bins, in the order of 1.5%, confirming that the assumed smectite composition is a meaningful source of uncertainty in the simulated Fe budget, though insufficient to fully resolve the persistent underestimation. However, these improvements in mass bias are not reflected in the Pearson correlation coefficients, which show a modest improvement only for BIN03 and BIN09 but deteriorate further for under JAT-CM-02, while deteriorating

for the remaining bins. The most striking degradation occurs in BIN26, where r_p drops from 0.53 in JAT-CM-01 to -0.08 in JAT-CM-02, suggesting that the addition of phyllosilicates to this mode is reducing the mass reduction but worsening the spatial signal (Fig. 9). Notably, the mineral-specific hematite comparison (Figs. 8 & 5) does not show a comparable ~~underestimation~~ level of underestimation, exposing a critical difference between mineralogical and elemental validation: reproducing hematite mass fractions reasonably well does not preclude a substantial underestimation of total Fe, ~~and while not all Fe is found in hematite, it is still a major carrier from which this level of discrepancy is unexpected. Therefore this discrepancy exposes a critical difference between mineralogical and elemental validation metrics~~ a gap that cannot be fully compensated by the Fe contributions of other modeled minerals. This inconsistency reveals an inherent limitation of modeling frameworks that treat minerals as discrete particles with idealized uniform compositions, and underscores the value of elemental validation as a complementary diagnostic. Given iron ~~oxide's~~ pivotal role in dust-atmosphere interactions (Li et al., 2024, 2021; Song et al., 2024; Journet et al., 2008; Lafon et al., 2004; Li et al., 2024, 2021; Song et al., 2024; Zhang et al., 2024), this distinction carries significant implications for radiative and ~~bio-geochemical modeling. This inconsistency reveals an inherent limitation of modeling frameworks that treat minerals as discrete particles with uniform composition.~~ biogeochemical modeling.

The calcium (Ca) comparison in Fig. 9 reveals ~~an increased underestimation in the JAT-CM-02 scheme~~ a consistent underestimation across all size ~~fractions~~ bins in both schemes, with JAT-CM-02 showing a marginal increase in underestimation relative to JAT-CM-01. The MB values remain stable across bins, ranging from -2.6% to -0.6% in JAT-CM-01 and from -2.4% to -1.1% in JAT-CM-02, with near-zero or slightly negative slopes throughout both schemes, indicating that neither captures any meaningful spatial variability in Ca distribution (Table 6). This result is consistent with the JATAC 2022 mineralogical analysis, where both schemes significantly underestimate the concentrations of calcite and gypsum, the primary Ca-bearing minerals currently simulated (Fig. 7). ~~This~~ The bias is further exacerbated by the exclusion of dolomite, a major Ca-rich mineral in the Sahara (Formenti et al., 2014), not accounted for in the model simulations. ~~Interestingly, while the spatial correlation increases for the coarsest fraction (Spatial correlations remain low or negative across most size bins, with no meaningful improvement under JAT-CM-02. A very slight improvement is observed in BIN09 and BIN26), this may be, though given the near-zero slopes and the known limitations of the Ca representation discussed above, these marginal gains are unlikely to reflect a genuine improvement in spatial skill and are more probably an artifact of the sampling distribution ; the remaining size bins show low or even negative correlations, with no discernible trend of improvement under the modified scheme.~~ (Fig. 9).

Figure 10 presents the scatterplots comparing ~~the~~ simulated and measured content of K, Mg, and S. ~~In the bin-resolved analysis for~~ For potassium (K), JAT-CM-02 reduces the underestimation from BIN03 onward, with MB values remaining near-neutral across all bins. The most notable improvement occurs in BIN09, where the slope increases from $0.15x + 0.7$ to $0.51x + 0.5$, indicating considerably better spatial sensitivity under the 'modified' scheme (JAT-CM-02) ~~shows an improvement in both~~ Table 6). Spatial correlations remain unchanged between schemes for BIN01 and BIN03, ~~resulting in lower mean biases. In contrast, but improve meaningfully for BIN09 and BIN26~~ transition from an overestimation in JAT-CM-01 to an underestimation of comparable magnitude in JAT-CM-02 (Table 6).

, consistent with the explicit inclusion of illite in these coarser fractions, though the BIN26 improvement should be interpreted with caution given the large observational uncertainties at that size (Fig. 10). Interestingly, while the mineral-specific feldspar

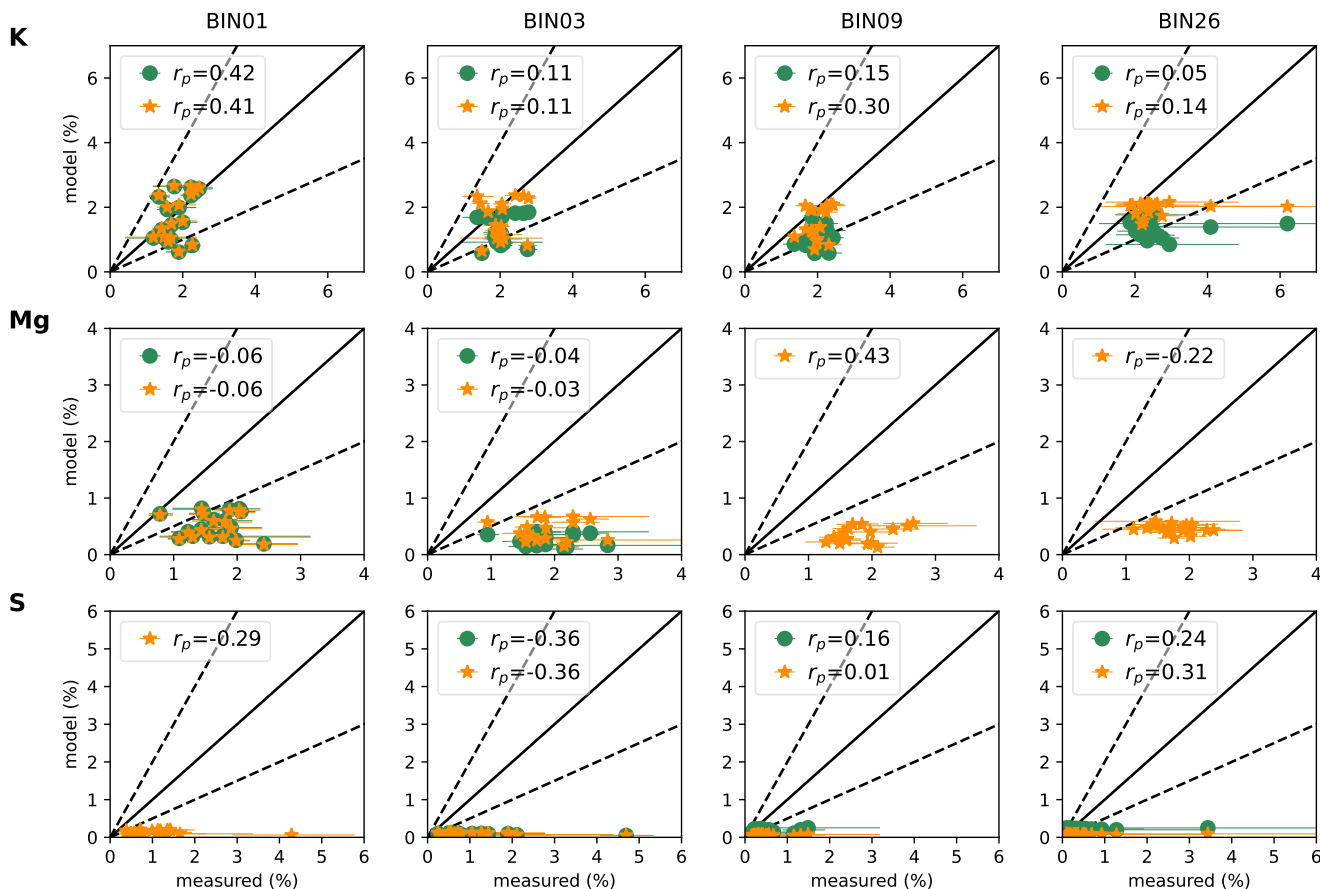


Figure 10. As in Fig. 9 but for K, Mg, and S.

comparison showed improved mean biases values but no meaningful gain in spatial skill under JAT-CM-02 (Fig. 7) also showed a uniform improvement across all sizes for JAT-CM-02, the reduction in bias between schemes was more striking for feldspar than for elemental K. This suggests that potassium partitioning is influenced by factors beyond feldspar size distribution alone; specifically, both illite and feldspar contribute to the K budget, alongside, the elemental K response is more robust in both MB and spatial skill, likely because K receives contributions from both feldspar and illite, as well as non-simulated minerals such as white mica. Nevertheless, the mean biases indicate a reasonable agreement between simulated and observed K mass. The increase in r_p values for the two largest size categories in JAT-CM-02 is encouraging, suggesting that the explicit inclusion of illite in these fractions provides a more representative spatial and mass distribution. This stands in contrast to the spatial correlation coefficients. This contrasts with the weak to negative correlations seen for feldspar and illite, which oscillate between weak and negative, (Fig. individually (Figs. 7)). These discrepancies highlight the value of elemental-level validation in assessing modifications to mineralogical emission schemes, as changes that appear modest in mineral-specific comparisons

may produce clearer signals when evaluated through their elemental signatures. & 6), and suggests that K serves as a more integrative diagnostic for assessing the combined redistribution of these two mineral groups.

Both emission schemes underestimate magnesium (Mg) in the size-resolved analysis, with no significant differences between the measured mean bias for across all size bins, with near-identical results between JAT-CM-01 and JAT-CM-02 in BIN01 and BIN03 and near-zero slopes throughout, indicating an absence of spatial skill at these sizes (Table 6). This persistent underestimation mirrors the results for illite, the sole Mg-bearing mineral currently simulated, which exhibits a dramatic underrepresentation by the model is dramatically underrepresented across all size bins (Fig. 6). Interestingly, while the underestimation for illite intensifies in illite underestimation intensifies in the coarser size categories, this trend is not observed for Mg. This divergence suggests two possibilities: either the, suggesting either that illite is being misclassified in the measurements, a common hurdle challenge in complex mineralogical assemblages (e.g., Rieder et al., 1998), or the Mg content assigned to illite in Table 3 is insufficient. Notably, the that contributions from Mg-rich minerals absent from the model, such as dolomite (Formenti et al., 2014), partially offset the illite signal in the observations. JAT-CM-02 extends the comparison to BIN09 and BIN26, where the MB remains small and the moderate r_p values found for value in BIN09, supported by the highest slope of the Mg comparison, further supports the conclusion that the inclusion of including illite in larger size fractions is a more physically representative approach to simulating this mineral's distribution. However, the low correlation values in the remaining bins likely reflect the absence of additional Mg sources in the model such as the high-Mg mineral dolomite (Formenti et al., 2014) representative approach (Table 6 and Fig. 10).

Sulfur is consistently and substantially underestimated by the model across all size bins in both emission schemes in the bin-resolved comparison, with near-zero slopes and similar MB values ranging from -0.4% to -1.1% (Fig. 10 and Table 6). This deficiency directly reflects the earlier gypsum-specific. The negligible differences between schemes and the absence of any spatial skill in either confirm that the modified scheme does not meaningfully alter the S budget, consistent with the limited changes observed for gypsum in the mineral comparison (Fig. 7 and Table 5) and is. This persistent underestimation is directly attributable to the well-documented underrepresentation of gypsum content in SMAs (Gonçalves Ageitos et al., 2023) in soil mineralogical databases (Gonçalves Ageitos et al., 2023), as discussed above.

Overall, the transition to the modified scheme demonstrates that refining mineralogical size distributions, specifically the aggregation of phyllosilicates and the reduction of coarse-mode quartz, significantly improves the model's ability to replicate observed elemental mass balances elemental validation reveals improvements in mass balance for Si, Al, and K. However, these improvements are not uniformly reflected in the spatial correlation coefficients (with the modified scheme that are not always apparent from the mineral-level comparison alone, underscoring the added diagnostic value of this approach. However, spatial correlations (r_p), which remain sensitive to the inherent limitations of the current modeling framework.

A notable discrepancy persists for iron; while simulated hematite shows reasonable agreement with observations, total elemental Fe remains severely underestimated across both schemes. This inconsistency underscores a critical disconnect between discrete mineral modeling and the chemical complexity of natural dust. These discrepancies point to a compounded effect of remain limited across most elements and size bins, reflecting the combined influence of source map uncertainties, missing mineral phases (e.g., dolomite, muscovite, and chlorite) and the presence of "hidden" elements within nanoscale

oxide coatings and silicate aggregates (Kandler et al., 2009; Lafon et al., 2004; Scheuvens et al., 2013). Consequently, while the mass redistribution in JAT-CM-02 moves toward a more physically representative simulation of dust chemistry, a complete elemental closure will likely require the inclusion of these non-simulated minerals and, for Fe, a shift away from assuming uniform mineral compositions across all size fractions, and transport errors.

5.2.2 DUSTRISK 2022 campaign

Table 7. Mean Statistical metrics: mean bias (MB), slope (m) and intercept (b) for the linear fit of the simulated elemental mass fractions for using the ‘original’ (DUST-CM-01) and ‘modified’ (DUST-CM-02) schemes. The MB is These are calculated against the DUSTRISK 2022 elemental measurements. The baseline number of observation points used for each comparison is $n = 34$ for $PM_{2.5}$, and $n = 45$ for PM_{10} , unless indicated in the otherwise by superscript parentheses(n).

Element	MB [%]			
	mx + b			
	DUST-CM-01		DUST-CM-02	
	PM2.5	PM10	PM2.5	PM10
Al	6.6 (34) <u>6.1</u> <u>$-0.17x + 10.8$</u>	-4.6 (45) <u>-4.8</u> <u>$0.02x + 4.3$</u>	4.7 (34) <u>4.3</u> <u>$0.09x + 7.9$</u>	-1.2 (45) <u>-1.6</u> <u>$0.03x + 7.5$</u>
Fe	-2 (34) <u>0.6</u> -2.2 (34) <u>$0.15x + 3.5$</u>	-1.7 (45) <u>-0.7</u> -4.8 (45) <u>$0.06x + 1.8$</u>	-2.1 (34) <u>0.2</u> <u>$0.1x + 3.3$</u>	-1.4 (45) <u>0.6</u> <u>$0.13x + 2.9$</u>
Ca <u>Ca</u>	-2.3 (34) <u>$0.02x + 1.1$</u>	-4.8 (45) <u>$0.01x + 1.2$</u>	-2.4 <u>$0.02x + 1$</u>	-4.9 <u>$0.01x + 1.1$</u>
K	2.3 (34) <u>1.6</u> <u>$0.05x + 3.1$</u>	0.9 (45) <u>0.2</u> <u>$0.15x + 1.4$</u>	1 (34) <u>0.8</u> <u>$-0.03x + 2.5$</u>	1.1 (45) <u>0.8</u> <u>$0.09x + 2.1$</u>
Mg	0.1 (33) ⁽³³⁾ <u>$0.08x + 0.7$</u>	-0.6 (40) ⁽⁴⁰⁾ <u>$0.02x + 0.3$</u>	-0.1 (33) ⁽³³⁾ <u>$0.03x + 0.7$</u>	-0.3 (40) ⁽⁴⁰⁾ <u>$0.04x + 0.6$</u>
S	-0.7 (34) <u>$0.05x + 0.1$</u>	-0.8 (45) <u>$0.005x + 0.1$</u>	-0.7 (34) <u>$0.1x + 0.05$</u>	-0.8 (45) <u>$0.003x + 0.1$</u>

The scatterplots in Fig. 11 demonstrate marked differences in performance between the ‘original’ (DUST-CM-01) and ‘modified’ (DUST-CM-02) mineral emission schemes when evaluated schemes across elemental composition and particle size categories (mean biases detailed in Table 7).

The For aluminum (Al), DUST-CM-02 approach shows a better representation for aluminum, resulting in higher concentrations and greater variability in PM10 compared to PM2.5. For the PM2.5, the modest reduction in phyllosilicate mass under improves the representation across both size fractions, though the nature of the improvement differs. In PM_{2.5}, the original scheme

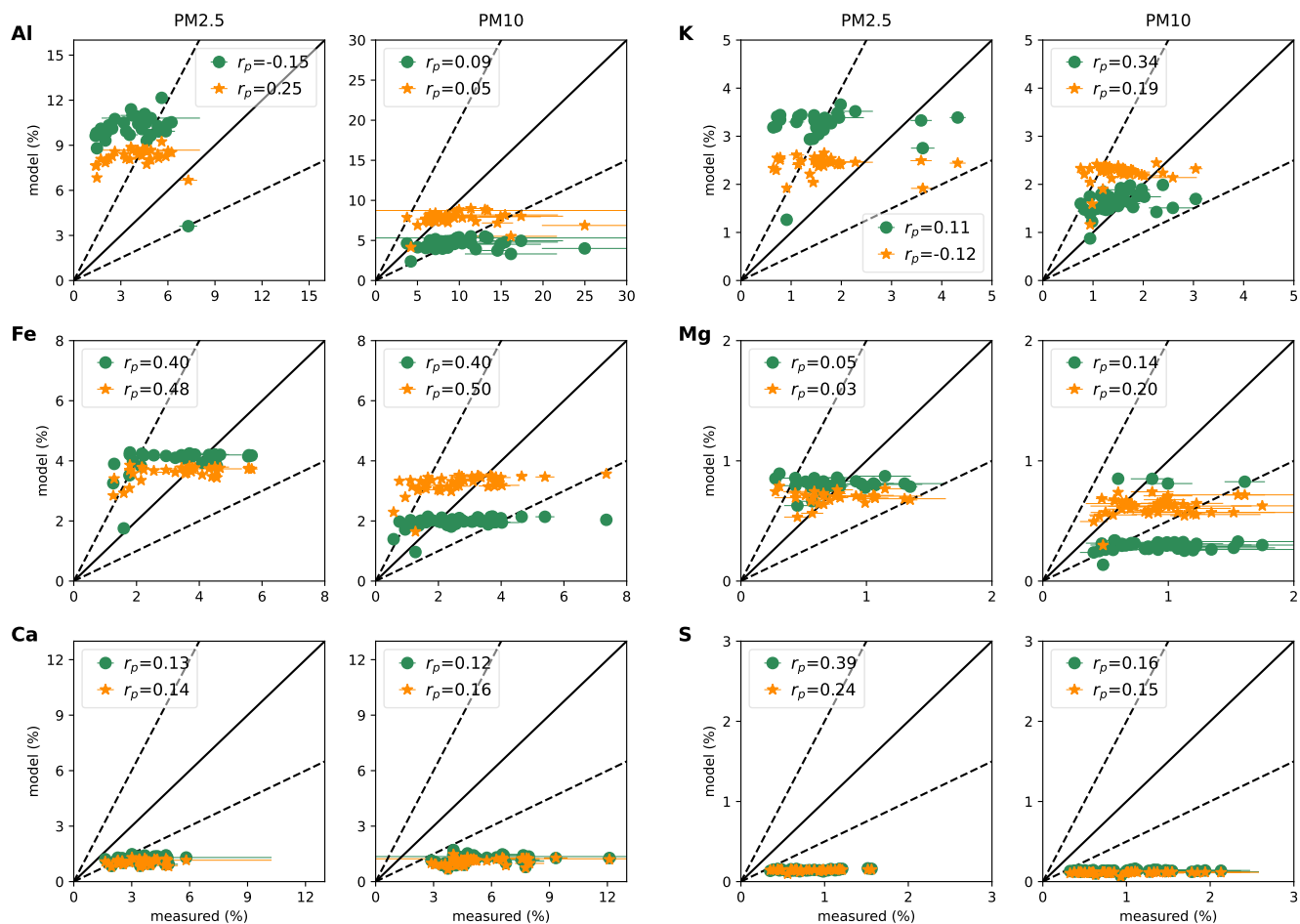


Figure 11. Scatterplots comparing observed elemental mass percentages of Al, Fe, Ca, K, Mg, and S against simulated values from COSMO5.05-MUSCAT. Simulated values were derived by multiplying modeled mineral mass by their respective elemental compositions (detailed in Table 3). Green solid circles indicate the ‘original’ mineral emission scheme (DUST-CM-01), while yellow solid stars represent the ‘modified’ version (DUST-CM-02). Column headers denote size classifications based on in-situ filter measurements: PM_{2.5-2.5} and PM₁₀₋₁₀. The error bars represent the measurements’ standard deviation. Dashed lines mark the 2:1 and 1:2 ratios between simulated and observed mineral percentages. Note: Axis scales vary between PM_{2.5-2.5} and PM₁₀₋₁₀ panels for Al to optimize the visibility. [Uncertainty-weighted linear fits are reported in Table 7 but omitted from the figure for clarity, as the limited dynamic range in several size bins renders them visually uninformative.](#)

overestimates Al ($MB=6.1\%$; $-0.17x + 10.8$), with the negative slope indicating an inverse relationship between simulated and observed values. DUST-CM-02 ~~mitigates model overestimation~~ reduces the overestimation ($MB=4.3\%$) and corrects the slope ($0.09x + 7.9$), with a notably improved spatial correlation at this size (Table 7 and Fig. 11). In PM_{10} , ~~with mean biases improving from 6.6% to 4.7%. Conversely, increased phyllosilicate concentrations in the PM_{10} fraction, reduces the previous underestimation from -4.6% to -1.2% (Table 7)~~ DUST-CM-01 underestimates Al ($MB=-4.8\%$), which DUST-CM-02 reduces to -1.6%, consistent with the increased phyllosilicates mass in the coarser fraction. Near-zero slopes in both schemes for PM_{10} indicate limited spatial skill, reflected as well in the r_p values regardless of the scheme. This size-dependent pattern complicates the interpretation of the phyllosilicates simulation: the overestimation in $PM_{2.5}$ is consistent with the individual smectite and kaolinite comparisons, which show positive biases in the fine fraction, while the underestimation in PM_{10} mirrors the illite behavior, where the model systematically underrepresents this mineral across all sizes (Fig. 6). While ~~these improvements in the coarse fraction align the~~ PM_{10} improvement is consistent with the JATAC 2022 elemental comparison, the $PM_{2.5}$ overestimation in both schemes is not observed for that dataset (Fig. 9), ~~the $PM_{2.5}$ overestimation persists in the DUSTRISK~~ possibly reflecting methodological differences between the two campaigns, either in the collection stage, where JATAC 2022 samples but not in JATAC 2022. This discrepancy might be due to methodological differences in fine particle measurement between campaigns. Notably, DUST-CM-02 shows improved spatial correlations for the ~~size-resolved sampling may better~~ capture the fine fraction, but not for the coarser fraction (Fig. 11), mirroring the JATAC 2022 comparison results (Fig. 9). This ~~divergence or in the measurement technique itself, as SEM-EDX analysis has known limitations in the fine size range ($>1\mu m$; (Laskin and Cowin, 2001; Kandler et al., 2018)).~~ The persistent near-zero slopes in PM_{10} and the consistent underestimation of ~~aluminum-Al~~ Al in coarser sizes ~~suggests across both datasets suggest~~ that the model may be missing a specific Al-rich coarse mineral phase, such as muscovite (Scheuven et al., 2013).

~~Both emission schemes substantially underestimate iron content, with DUST-CM-02 offering negligible improvement. This systematic underestimation, consistent with Iron (Fe) shows a striking contrast with the JATAC 2022 elemental comparison (results: rather than the consistent underestimation observed in that dataset (Table 6 and Fig. 9 & Table 6), stands in contrast with the mineral-level evaluation, where simulated hematite concentrations align comparatively better with observations (Figs. 5 & 8). While Fe is present in some forms of smectite, our current framework uses montmorillonite as the proxy for the smectite group due to its dominance in Saharan dust pathways toward Cape Verde (Moreno et al., 2006). Substituting montmorillonite with an Fe-rich smectite like nontronite would contribute approximately 22% of the smectite mass to the iron budget; however, this adjustment remains insufficient to bridge the substantial gap between the model and measurements (Tables 6 & 7). Regarding the spatial correlation coefficients, r_p for $PM_{2.5}$ is the highest among all comparisons and further improves with DUST-CM-02. Conversely, correlations for the PM_{10} are only moderate, though they also show improvement with DUST-CM-02. Interestingly,~~

~~), both schemes produce near-neutral biases for DUSTRISK 2022, with MB values of 0.6% and -0.7% for $PM_{2.5}$ and PM_{10} in DUST-CM-01, and 0.2% and 0.6% in DUST-CM-02 (Table 7), , though the model exhibits an inverse relationship between size fraction and correlation strength, with the finest particles yielding the most robust spatial agreement, and simultaneously exhibit a worse mean bias mean bias, with $PM_{2.5}$ showing slight overestimation and PM_{10} a slight underestimation. The slopes remain modest across both schemes and size fractions, though DUST-CM-02 shows a slight improvement in PM_{10} ($0.06x + 1.8$ to~~

1150 $0.13x + 2.9$; Table 7). This marked improvement relative to JATAC 2022 may partly reflect the surface-level sampling during NH winter, where dust composition and Fe-bearing mineral contributions differ from the Saharan Air Layer conditions sampled during JATAC 2022, and where the coexistence of mineral dust with Fe-rich particles from anthropogenic or biomass burning sources at surface level may complicate the attribution of measured Fe to dust alone. The spatial correlations for Fe are the highest of all elements in the dataset, with r_p values improving to 0.48 in $PM_{2.5}$ and 0.5 in PM_{10} under DUST-CM-02 (Fig. 11&
1155), suggesting that the model captures the geographical distribution of Fe-bearing minerals reasonably well (Fig. 11 and Table 7).

Calcium (Ca) shows a consistent systematic underestimation across both schemes (and size fractions as well as near-zero slopes for the corresponding linear fit equations which confirm the absence of any spatial skill (Fig. 11 and Table 7), directly mirroring the underrepresentation of calcite and gypsum discussed in earlier results (Figs. 5 & 7). While The spatial correlations improve only marginally under DUST-CM-02 provides a marginal improvement in r_p , the correlation coefficients for both
1160 size categories remain notably similar with the slightly larger gain in PM_{10} , though both remain very low (Fig. 11). This consistency The similarity in correlation strength between size fractions stands stand in contrast to the predominantly negative correlations found for Ca in JATAC 2022 results (Fig. 9), where positive, albeit weak, correlations were restricted exclusively to the coarsest size category suggesting that the source regions and transport pathways sampled during DUSTRISK 2022 are more consistent with the spatial distribution of Ca-bearing minerals prescribed in the model, even if their absolute abundance
1165 remains underestimated.

The potassium (K) content illustrated in FigureFig. 11 reveals an intriguing, a size-specific improvement under the DUST-CM-02 scheme. For the $PM_{2.5}$ fraction, the modified approach yields better agreement with observations, reducing the mean bias from 2.3% to 1 and mixed response to the scheme change. In $PM_{2.5}$, DUST-CM-02 reduces the overestimation from 1.6% to 0.8%, while PM_{10} remains largely unchanged (in PM_{10} , the MB remains near-neutral in DUST-CM-01 (0.2%) and increases
1170 slightly to 0.8% in DUST-CM-02 (Table 7). This bias reduction stems primarily from the reallocation of feldspar fractions into the finer size category. Such an improvement is particularly noteworthy because the preceding mineral evaluation of feldspar (Figs. 5 & 7) showed inconsistent performance. These results partially mirror the JATAC 2022 elemental comparison (The linear fit equation and spatial correlation coefficient for PM_{10} under DUST-CM-02 slightly deteriorates, indicating that the mass redistribution disrupts the spatial signal previously captured at this size (Table 7 and Fig. 10), where potassium showed the most significant improvements. However, 11). The bias reduction in $PM_{2.5}$, stems from the net effect of the scheme change on K-bearing minerals, while feldspar decreases under the modified scheme, the discrepancies between campaigns, such as the $PM_{2.5}$ overestimation which contrasts with JATAC 2022 results (Table 6), likely reflect seasonal shift in active dust source regions between the NH winter and summer (Schepanski et al., 2009).

For the fine potassium fraction specifically, the consistently low r_p values in both schemes suggest that the simulated
1180 spatial distribution does not align with observations. This decoupling points toward an additional, non-simulated K source; given that the observations coincide with the NH winter, this discrepancy could be attributable to Sahelian biomass burning (Teseche et al., 2011), a well-documented regional contributor of fine-mode potassium (Dang et al., 2022; Jahn et al., 2021). Although the current model overestimation in both DUST-CM-01 and DUST-CM-02 (Table 7) would superficially argue against the need for additional K mass, the poor spatial correlation suggests that the total observed K is governed by a combination

1185 ~~of dust and possible biomass burning patterns that the dust-only schemes cannot reconcile~~ show an improvement in MB due
to an increase on K fraction in BIN03, indicating that the feldspar reduction is offset by the concurrent increase in illite.
Here, the feldspar reduction is not compensated by illite, suggesting that the overall mineralogical signature changes between
NH winter and the NH summer Saharan conditions sampled during JATAC 2022 (Schepanski et al., 2009). This outcome is
particularly noteworthy given the inconsistent performance of both feldspar and illite in the preceding mineral-level evaluation
1190 (Figs. 5 & 7 & 6), and illustrates how elemental comparisons can provide diagnostic insight that mineral-level evaluations alone
may obscure, as the aggregated K signal integrates contributions from multiple minerals whose individual behaviors partially
cancel out.

Magnesium (Mg) displays a size-dependent performance pattern analogous to that of aluminum (Fig. 11). ~~Although the earlier
illite comparison showed a clear underestimation under the modified scheme~~ Despite the clear illite underestimation identified
1195 ~~in the mineral comparison~~ (Fig. 6), ~~this the~~ Mg elemental analysis reveals ~~a clear enhancement in model representation. In
the PM_{2.5} fraction, an overall improvement under DUST-CM-02. In PM_{2.5}, the near-neutral bias in DUST-CM-01 (0.1%),
shifts to a negligible underestimation in DUST-CM-02 shifts the model from a slight overestimation to a slight underestimation
, while for PM₁₀, (-0.1%), while in PM₁₀ the underestimation is significantly reduced, with mean biases effectively halved
halved, with a modest slope improvement~~ (Table 7). ~~In comparison, the~~ Compared to JATAC 2022 dataset exhibits a more severe
1200 ~~Mg underestimation~~, ~~were~~ Mg underestimation was more severe, the DUSTRISK 2022 biases are near-neutral, highlighting
the variability across campaigns. Despite these differences in magnitude, both datasets ~~demonstrate~~ show consistent size-
dependent improvements and strengthened ~~correlation coefficients under the modified scheme, particularly within the PM₁₀
spatial correlations under DUST-CM-02, particularly for PM₁₀ and BIN09 size categories~~ (Figs. 11 & 10). ~~This cross-campaign
consistency reinforces the conclusion that the redistribution of minerals into coarser fractions, specifically Mg -bearing illite,
yields a more robust representation of the dust plume's mineralogy~~

The consistently low r_p for K and Mg in $PM_{2.5}$ suggest that the simulated spatial distributions of these elements do not align
with observations, pointing toward additional non-simulated sources. Given that the DUSTRISK 2022 observations coincide
with NH winter, this decoupling could partly reflect contributions from Sahelian biomass burning (Teschke et al., 2011), a
well-documented regional source of fine-mode K and Mg (Dang et al., 2022; Jahn et al., 2021). Although the near-neutral to
1210 positive mean biases would superficially argue against the need for additional mass, the poor spatial correlations suggest that
the total observed K and Mg are governed by a combination of dust and non-simulated sources that the dust-only framework
cannot reconcile.

~~In contrast, sulfur remains systematically and substantially~~ Sulfur (S) remains systematically underestimated across both
~~emission schemes. This persistent bias is~~ schemes and size fractions. The near-zero slopes throughout confirm the absence of
1215 ~~spatial skill in both schemes~~, accompanied by a deterioration in r_p values under DUST-CM-02 (Fig. 11 & Table 7) ~~mirroring
the poor~~. These results mirror the poor S performance observed in the JATAC 2022 dataset (Fig. 10) and are consistent with
the well-documented underrepresentation of gypsum in soil mineralogical databases, as discussed above.

The elemental comparisons reveal that while the modified emission scheme successfully addresses several key biases on the
mineralogical representation, particularly for Si , Al , and Mg , systematic underestimations persist for certain elements, notably

1220 Fe, Ca, and S. Interpretation of these discrepancies must consider potential contributions from non-mineral sources, given that the sampling campaign employed long integration periods during the NH winter, a season characterized by intense Sahelian biomass burning activity (Teseke et al., 2011). While biomass burning emissions typically contribute K, Mg, Fe, and Al to the fine aerosol fraction (Dang et al., 2022; Jahn et al., 2021; Paris et al., 2010), the model continues to overestimate Al and K content despite the improvements in Averaged over the DUSTRISK 2022 simulation period, DUST-CM-02. Furthermore, 1225 the high accuracy of the Mg simulation suggests that biomass burning may not be the primary driver of the observed mass concentrations in these samples. However, while a minor fraction of the missing Fe could be attributed to biomass burning, the persistence of this underestimation across multiple campaigns (Tables 7 & 6) points more definitively toward a fundamental modeling oversight by omitting Fe-rich minerals and by the simplified assumption of external mineral mixing (discrete particles).

1230 Together, these results highlight both the progress achieved with the produces substantial increases in phyllosilicate mass relative to DUST-CM-01, with illite, kaolinite, smectite, collectively showing 130% more mass, consistent with the redistribution observed in the JATAC 2022 period. Unlike JATAC 2022, however, hematite and calcite also show modest mass increases, 17% and 12%, respectively, reflecting differences in the size bin elemental composition impact of the ‘modified’ scheme and the persistent challenges facing mineral dust modeling frameworks. The improved representation of quartz and feldspar 1235 demonstrates that refined emission PSDs and mineral abundances can effectively propagate through the model to enhance both mineralogical and elemental fidelity. However, persistent discrepancies in elemental composition, compounded with campaign-specific variability, underscore fundamental structural limitations. Specifically, current frameworks struggle to represent the heterogeneous internal mixing of iron oxides and the complex speciation of magnesium within silicate aggregates. Furthermore, omissions within the soil mineralogy database remain a significant bottleneck. Addressing these limitations will require not 1240 only continued refinement of soil mineral assemblage databases and emission parameterizations, but also expanded observational constraints spanning multiple seasons, source regions, and atmospheric conditions to capture the full complexity of mineral dust composition. scheme between the two campaigns. Conversely, quartz (–53%), feldspar (–50%), and gypsum (–7%) decline significantly, though the reductions are somewhat less pronounced than in JATAC 2022 period. These differences likely reflect the distinct source regions characteristic of NH winter dust transported compared to the NH summer conditions sampled during 1245 JATAC 2022.

6 Conclusions

The implementation of the modified mineral simulation approach in COSMO5.05-MUSCAT significantly enhances the representation of dust aerosol composition, as demonstrated by the DUST-CM-02 and JAT-CM-02 simulation periods. By results demonstrate that adjusting the soil mineralogical database PSD prior to emission flux calculations, the model provides a substantially 1250 more accurate depiction of phyllosilicates and quartz when compared against North African aerosol measurements (Fig. 5). It effectively resolves the produces a more physically representative partitioning of mineral mass across size fractions. The most consequential improvement is the resolution of the systematic quartz overestimation (Table 4), which validates the redistribution

logic. The persistent underestimation of calcite and weak hematite correlations suggest that aerodynamic repartitioning alone cannot compensate for fundamental uncertainties in source soil mineralogy.

1255 Validation with in-situ elemental concentration-based, mineral phases measurements from JATAC 2022 further confirmed these improvements (Figs. 6 & 7). Validation across discrete size bins confirms that the modified scheme successfully extends the model's predictive skill into a broader size spectrum, particularly for silicon- and potassium-bearing minerals. However, the occasional decoupling of improved mean bias from stable or weakened spatial correlations indicates that while which propagates positively into the elemental Si budget and validates the core redistribution logic of the modified scheme. The concurrent increase in phyllosilicates mass across coarser size bins, consistent across both campaigns, further supports the hypothesis that aggregated phyllosilicates transport is better captured when the emitted PSD reflects a re-aggregated rather than fully dispersed soil. The elemental validation reinforces these findings: the consistent improvement in Al and Si contributions across size fractions and both campaigns confirms the cross-element coherence of the scheme, where improvements in mineral mass partitioning propagate predictably into elemental budgets.

1265 However, improvements in elemental mass bias do not systematically translate into improved spatial correlations, revealing a disconnect between reproducing the total mass balance is now more realistic, the model's sensitivity to specific source-region variability remains a challenge that purely structural scheme changes cannot yet overcome, and the spatial distribution. This decoupling points to limitations in the underlying source maps and the omission of specific mineral phases, such as muscovite, rather than deficiencies in the emission scheme itself, which has been evaluated against AERONET aerosol optical thickness in previous work and shown to reproduce dust loading reasonably well (Gómez Maqueo Anaya et al., 2025, 2024). Nevertheless, it should be noted that even with a well-constrained emission scheme, errors in source attribution for specific events would produce spatial mismatches indistinguishable from mineralogical errors when evaluated against point measurements, underscoring the importance of constraining dust transport independently before attributing residual biases to the mineralogical composition.

1275 The persistent underestimation of calcite and gypsum, reflected in the Ca and S elemental budgets, points to a structural limitation upstream of the emission scheme: both minerals are susceptible to dissolution during wet-sieving, causing their abundances to be systematically underrepresented in the GMINER SMA (Nickovic et al., 2012). This is consistent with findings from previous modeling studies, which show that Ca tends to be underestimated over North Africa regardless of the SMA employed, whether based on the Journet et al. (2014) compilation used in Menut et al. (2020) or the EMIT dataset (Green et al., 2020) applied in Mahowald et al. (2026), suggesting that the under-representation of calcite in existing soil mineralogy datasets is a systematic and widespread limitation. Given the high sensitivity of the model to initial assumptions on soil mineral distributions, achieving a good representation of the contribution of soluble minerals will ultimately require non-dispersive soil characterization techniques rather than refinements to the emission scheme.

1285 The complementary elemental validation for DUSTRISK and JATAC Iron deserves particular attention given its pivotal role in dust-atmosphere interactions, from direct radiative effects to biogeochemical impacts on ocean productivity (Li et al., 2024, 2021; Song et al., 2024). The JATAC 2022 campaigns highlights both the strengths and the inherent limitations of current modeling frameworks. Across both campaigns, elemental concentrations largely mirrored their mineralogical counterparts. Specifically the correction of

silicon and potassium biases demonstrates the consistency and improvement of the modified scheme. The successful refinement of aluminum concentrations across all size fractions further confirms that a more representative size-dependent distribution of phyllosilicates is key to bridging the gap between simulated mineralogy and in-situ observations (Figs. 10 & 11 and Tables 6 & 7).

While the model achieved a more representative size-dependent distribution of phyllosilicates, important discrepancies remain regarding spatial correlation. The differentiated spatial correlations suggest that model benefits are primarily concentrated in the finer size ranges; the persistent mismatch in coarser fractions likely stems from the omission of specific Al-rich coarse minerals, such as muscovite (Scheuven et al., 2013).

This mineralogical gap is further reflected by the magnesium results. Across both the JATAC and elemental comparison reveals a consistent Fe underestimation despite reasonable agreement in the hematite content in mineral compositions. Since hematite is the dominant Fe-bearing mineral in the model, this discrepancy points to insufficient Fe contributions from secondary mineral hosts. Illite, which is severely underestimated, would reduce the Fe budget, while the overestimation of smectite would partly compensate; however, the unclear diagnostics of both minerals, given that the elemental signals associated with them do not reflect the same degree of bias as the minerals themselves (Al, K and Mg), make it difficult to attribute the Fe underestimation unambiguously to either. This suggests that omitted Fe-rich phases may play an equally important role. Taken together, these results indicate that accurate Fe simulation requires both a better constrained mineral inventory and a model representation that accounts for the heterogeneous distribution of Fe across mineral hosts, silicate aggregates, and nanoscale oxide coatings (Lafon et al., 2004; Zhang et al., 2015). The DUSTRISK 2022 datasets, period offers a contrasting picture, with low Fe mean biases and moderate spatial correlations that could reflect genuine seasonal differences in source region composition. The potential influence of Sahelian biomass burning during NH winter (Teschke et al., 2011) complicates this interpretation, though the good agreement of simulated Mg concentrations with observations alongside the overestimation of Al and K argues against a dominant biomass burning signal, suggesting that the improved Fe agreement is not the result of compensating errors.

The Mg results provide a further diagnostic insight: despite illite being the underestimation of Mg is notably less severe than the pronounced underrepresentation of illite. Given that illite is the sole Mg-bearing mineral in the current model configuration, this discrepancy suggests that the elemental Mg budget is influenced by factors beyond the simulated illite mass the simulated Mg underestimation is considerably less severe than would be expected from the illite underestimation alone. This relative "success" in Mg representation compared to the illite mass bias could be due to natural Saharan illite posing a higher degree of Mg substitution than is currently discrepancy likely reflects the natural compositional variability of illite in Saharan dust, which occurs as a mixed-layer silicate with heterogeneous Mg content rather than the fixed stoichiometry assumed in the model's static stoichiometry. The persistence of these biases indicates that current soil mineral assemblages fail to accurately capture Mg speciation within mixed silicate aggregates (Kandler et al., 2018). Collectively, these findings underscore that future improvements in model fidelity will require a more comprehensive and complex mineralogical inventory that spans the full particle size spectrum. (Kandler et al., 2018).

Furthermore, significant inter-campaign discrepancies reveal Inter-campaign discrepancies further highlight that model validation is inherently sensitive to external factors beyond emission parameterization. For instance, the shift from aluminum factors beyond the emission scheme. The shift from Al underestimation in JATAC 2022 to overestimation in the finest fraction of DUSTRISK 2022 suggests underlying likely reflects methodological differences in campaign sampling. Furthermore, the more severe Mg deficit noted in JATAC 2022 could reflect reduced biomass burning interference during the NH summer SAL sampling rather than a shift in model performance (Figs. 10 & 11).

The persistent underestimation of elemental iron (Figs. 9 & 11), despite adequate hematite mass fractions (Figs. 5 & 8), highlights a fundamental limitation in treating minerals as internally homogeneous. This mineral-element discrepancy exposes a critical modeling limitation: iron exists predominantly as nanoscale oxide coatings or inclusions within other mineral phases (Lafon et al., 2004; Kandler et al., 2007) rather than as discrete particles. This structural complexity is intrinsically difficult to capture for frameworks that treat minerals as internally homogeneous particles. However, the high correlation coefficients observed for the DUSTRISK 2022 finest fractions indicate that while the total mass is shifted, the model effectively simulates the transport dynamics of iron-bearing clays. Beyond structural complexities, the observed underestimation may also stem from the selection of a non-iron-bearing smectite for this analysis, as well as the exclusion of other iron-contributing minerals from the model fine particle sampling between campaigns, including measurement uncertainties associated with SEM-EDX characterization of small particles, rather than a change in model behavior.

The persistent underestimation of calcite and gypsum further underscores the limitations of traditional, dispersive soil analysis methods, such as wet-sieving, for constraining dust emission schemes. These methodologies likely dissolve or redistribute soluble minerals as these two, failing to represent the natural state of soil aggregates. Given that shifting initial soil assumptions can alter mineral mass fractions by over 130%, the high sensitivity of the model demonstrates that achieving mineralogical fidelity requires a transition toward non-dispersive soil sampling techniques that preserve the physical and chemical integrity of the parent soil.

The seasonal comparison between DUSTRISK (NH winter) and JATAC (NH summer) 2022 further underlines the influence of source region activity. While phyllosilicate increases were consistent across seasons, calcite decreased more strongly during summer (−14%), together with further declines in quartz, feldspar, and gypsum content. These differences reflect shifts in dominant dust-emitting regions and associated meteorology, underscoring the need to account for temporal variability when evaluating mineral fractions in transport models.

Taken together, these results demonstrate both progress and remaining challenges in modeling dust mineralogy. The ‘modified’ scheme clearly improves the size-resolved representation of phyllosilicates, quartz, and feldspar across both mineral and elemental scales. However, persistent biases in iron, calcium, and magnesium highlight the magnesium, and sulfur point to inherent limitations in representing the heterogeneous internal mixing and complex speciation of natural mineral dust. Critically, the These findings indicate that future progress will require a more complete mineral inventory, particularly for Fe-rich, Mg-bearing, and soluble mineral phases, alongside soil characterization approaches that better preserve the in-situ abundance of dissolution-prone minerals, and observational constraints spanning multiple seasons and source regions to capture the full compositional complexity of mineral dust.

The elemental validation approach employed here ~~provides-offers~~ a complementary and ~~previously~~-underutilized pathway for model evaluation. ~~By-converting~~ Converting simulated mineral compositions to elemental mass fractions ~~and-comparing them against measured elemental abundances, this methodology offers several distinct advantages. First, it enables-exposes~~ discrepancies between mineral- and elemental-level performance that mineral-only comparisons would miss, while also enabling validation against the extensive body of ~~published-elemental-composition-measurements from techniques such as X-ray fluorescence-XRF~~ and electron microscopy ~~. Second, it-exposes-discrepancies between mineral-level measurements in the literature. The Fe results exemplify the diagnostic value of this dual framework: the divergence between mineral- and element-level performance that would remain hidden in mineral-only comparisons. Third, it provides independent constraints on mineralogical simulations that can reveal limitations in both emission parameterizations and fundamental assumptions about particle internal structure. The mineral-element discrepancies identified for Fe exemplify how this dual-validation-framework diagnoses-elemental-level performance reveals~~ complexities in dust composition, such as heterogeneous Fe distribution across mineral hosts, that direct mineral measurements alone cannot ~~adequately~~-capture, underscoring its value-potential for advancing mineralogical representation in atmospheric models.

Future progress will ~~depend-on-improved-mineralogical-datasets, better integration of observations into models, and advances in-representing-the-internal-complexity-of-mineral-dust-particles~~require advances on multiple fronts. Improved soil mineralogical databases that preserve the in-situ abundance of soluble and the aggregates of fine-grained minerals, through non-dispersive characterization techniques are a prerequisite for correcting the structural biases in calcite, gypsum, and iron identified here. The emergence of hyperspectral measurements from NASA-retrievals from NASA's EMIT mission (Green et al., 2020), alongside combined with field campaigns providing ~~detailed-size-resolved composition-at-both~~ mineral and elemental levels-composition across multiple seasons and source regions, offers a ~~pathway-to-reduce-current-uncertainties. Incorporating such multi-scale observations, particularly for iron oxides and mixed silicate phases, will help resolve biases in key radiatively active minerals and improve constraints on dust-climate interactions. Additionally, developing modeling frameworks that can represent minerals promising pathway to better constrain emission parameterizations. At the modeling level, representing minerals as internally~~ mixed aggregates rather than discrete ~~particles-may-homogeneous spherical particles will likely~~ be necessary to ~~bridge-the persistent-reconcile the~~ mineral-element discrepancies identified ~~here~~and to capture the compositional complexity of natural dust. Recent studies (Li et al., 2021, 2024; Obiso et al., 2024) reinforce that refining soil mineral maps and dust size distributions is critical for advancing our understanding of dust's climatic and biogeochemical roles (Mahowald et al., 2026; Li et al., 2021, 2024; Obiso et al., 2024), and the dual mineral-elemental validation framework demonstrated here provides a transferable methodology for evaluating such improvements as they emerge.

Code availability. The version of code used for the modeled minerals is available at <https://doi.org/10.5281/zenodo.20290654>.

Data availability. The dataset for reproducing the graphs presented here are available at <https://doi.org/10.5281/zenodo.21132304>.

A JATAC in-situ aerosol measurements: mineral phase criteria

Table A1. Ideal ~~normalized~~elemental mass compositions ~~for the~~used to identify modeled mineral classes, normalized to the sum of selected elements. Elements not shown are zero. Value ranges are derived from data by Journet et al. (2008) and <https://webmineral.com/>.

Class name	Atomic range <u>Element</u>	Value range	Class name	Atomic range <u>Element</u>	Value range
Kaolinite	Si	0.486	Quartz	Si	1.0
	Al	0.483	Calcite	Ca	1.0
	Fe	0.01	Gypsum	Ca	0.554
	Ti	0.02		S	0.445
Illite	Mg	0.027	Feldspar	Na	0.02
	K	0.09		Al	0.238
	Al	0.218		Si	0.538
	Si	0.538		K	0.1
	Ca	0.03		Ca	0.08
	Fe	0.07		Fe	0.01
	Ti	0.01	Hematite	Fe	0.9
Smectite	Mg	0.029		Si	0.04
	Al	0.211		Al	0.06
	Si	0.673			
	Ca	0.022			
	Fe	0.06			

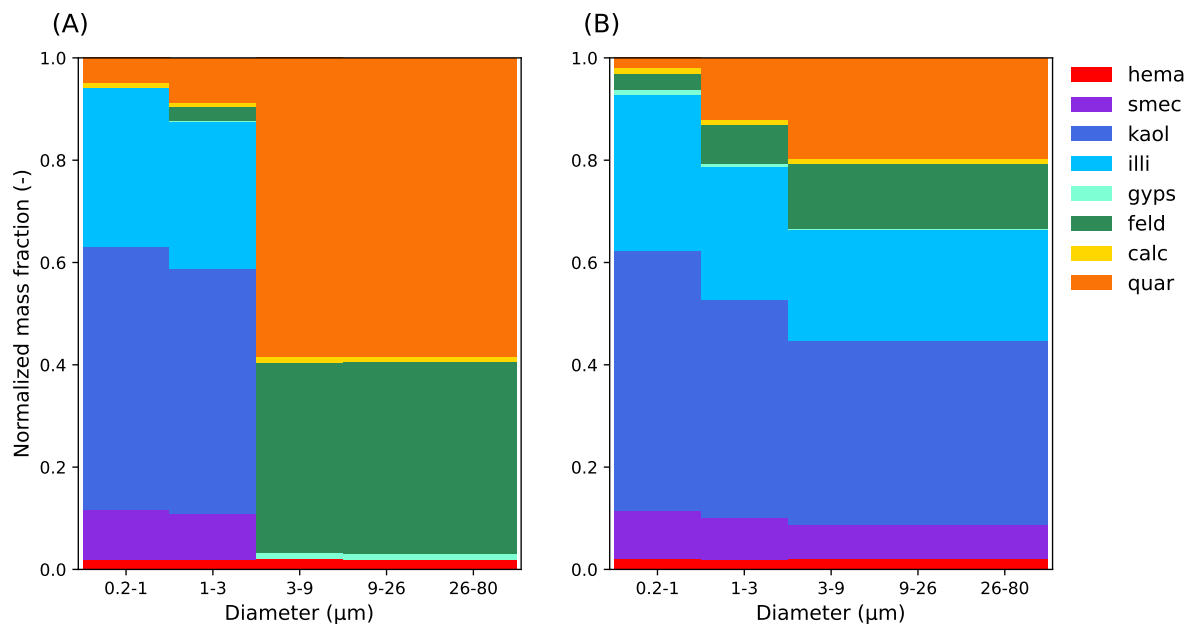


Figure B1. Comparison of normalized mineral mass size distributions for the Haplic Xerosol soil type located in the northwestern Sahara (22.75°N, 6.5°W). Panel (A) illustrates the soil mineral physical size distributions (PSDs) according to the GMINER database. Panel (B) depicts the resulting emitted aerosol mineral PSDs, representing the initial state of the dust plume immediately following emission. The aerosol PSD is derived by applying the BFT-based modification approach (Perlwitz et al., 2015a; Gonçalves Ageitos et al., 2023) to the underlying soil data. Quar: quartz; calc: calcite; feld: feldspars; gyps: gypsum; illi: illite; kaol: kaolinite; smec: smectite; hema: hematite.

C High-resolution imagery of illite-like mineral dust

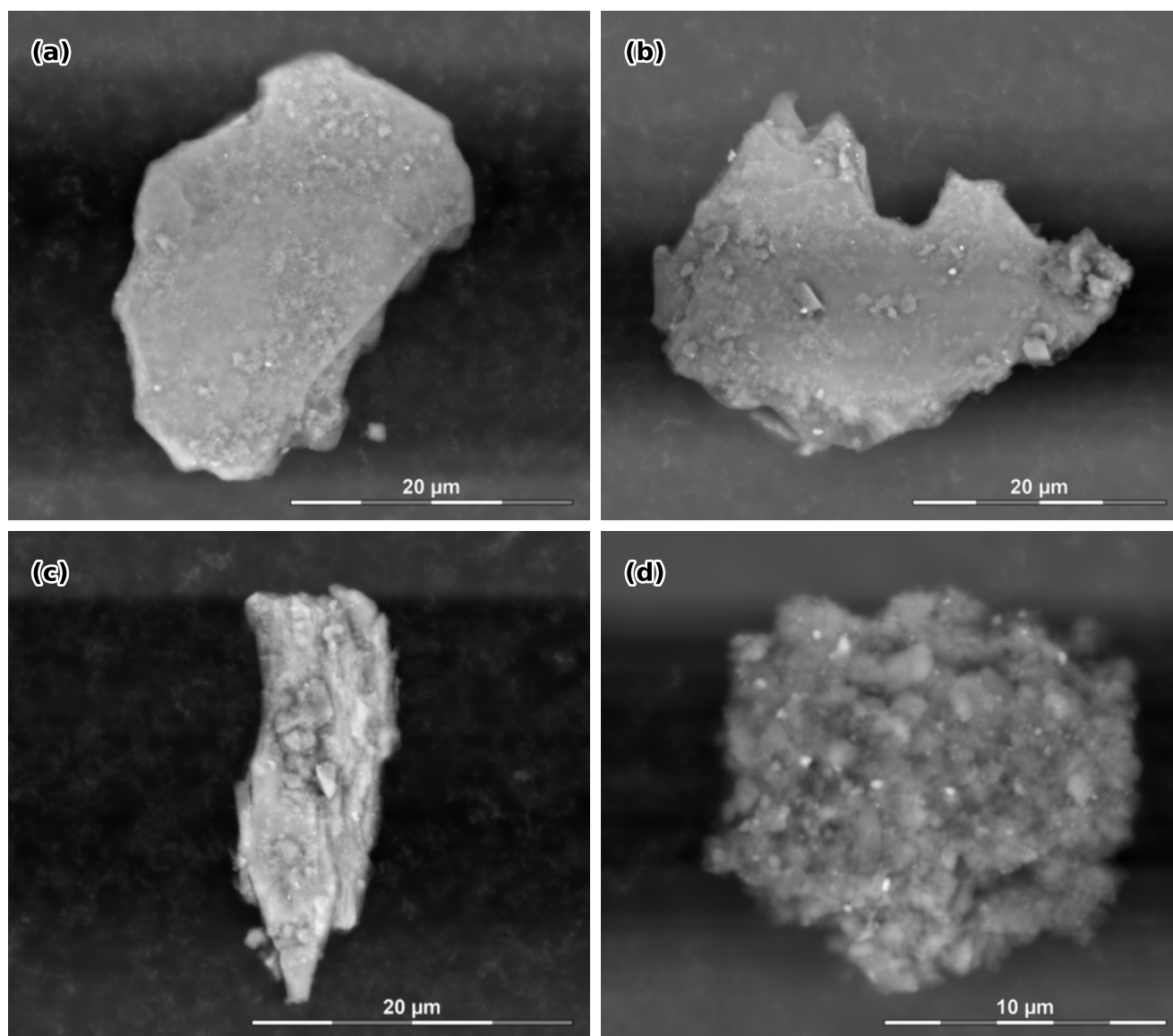


Figure C1. Backscatter-electron images of large mineral dust particles with an illite-like composition, but different structure; sampled over São Vicente, Cabo Verde, on 17 June 2022 at an altitude of 2499–3384 m above sea level. The length given at the scale bar refers to its total length.

Author contributions. SGMA drafted the manuscript. SA, KK, DA, MK, MH, IT, and KS reviewed and edited the manuscript. SGMA, HB, DA, BH, MH, and KS contributed to the conceptualization of the study. SGMA prepared the figures and organized the datasets. EJSS and KWF were responsible for the elemental analysis of samples collected during the DUSTRISK 2022 campaign. SA and KK conducted the elemental analysis and mineral characterization of the samples collected by MK during the JATAC 2022 campaign. MF led the software development by restructuring the code associated with the MUSCAT dust emission scheme. SGMA, MF, BH, KS, and IT contributed to code development related to the inclusion of mineralogy. SGMA, SA, KK, and KS performed the formal data analysis.

Competing interests. The authors declare that they have no conflict of interest

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Furthermore, ChatGPT and Gemini were utilized to rephrase and shorten sentences, as well to identify the appropriate prepositions.

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