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1 **Dust–Cloud Vertical Configurations Influence the Effective Radius of Low-Level**
2 **Warm Clouds over Marine and Continental Environments**

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6 **Key Points:**

- 7 • Dust and cloud vertical configurations modulate dust effects on low-level warm
8 cloud droplet size
- 9 • Meteorological variability can obscure a dust-driven tendency toward smaller cloud
10 droplets
- 11 • Dust–cloud vertical configuration may reflect distinct microphysical and semi-
12 direct pathways
- 13

14 **Abstract**

15 Aerosol–cloud interactions remain a major source of uncertainty in climate forcing
16 estimates, partly because cloud responses depend on the location of aerosols relative to
17 clouds; yet for mineral dust, which accounting for about two-thirds of all aerosol mass, the
18 effects of dust–cloud vertical configuration on cloud droplet effective radius remain
19 unclear. Using multi-year observations from the Atmospheric Radiation Measurement sites
20 at the Eastern North Atlantic (ENA; marine) and Southern Great Plains (SGP; continental),
21 we quantify the sensitivity of low-level warm-cloud effective radius to dust-layer optical
22 depth—the dust aerosol–cloud interaction (dust-ACI) index—for dust located above (Top),
23 within (Middle), and below (Bottom) clouds. These configurations modulate the sign and
24 magnitude of the dust-ACI index. At ENA, the index is strongly positive for the Top
25 configuration (0.130 ± 0.065), weakly positive for the Middle (0.080 ± 0.029), and slightly
26 negative for the Bottom (-0.026 ± 0.021) configuration, whereas the Middle (-0.021 ± 0.057)
27 and Bottom (0.086 ± 0.041) responses reversing signs at SGP. After controlling for
28 meteorological covariability, dust-ACI indices become consistently positive across sites
29 and configurations, revealing that thermodynamic changes associated with vertical
30 configuration can mask an underlying dust microphysical brightening tendency. We propose
31 potential mechanisms whereby dust-induced semi-direct heating dominates in the Top
32 configuration, enhancing stability and suppressing entrainment to yield smaller droplets,
33 whereas the Middle and Bottom configurations reflect competing microphysical and
34 semi-direct pathways whose relative strengths differ between marine and continental
35 regimes. These results show that dust effects on clouds cannot be inferred from dust
36 loading alone, but require accurate representation of dust–cloud vertical configuration and
37 environmental regime.

38 **Plain Language Summary**

39 Dust particles in the atmosphere can modify cloud properties, but their effects
40 depend not only on dust amount, but also on the vertical position of dust relative to clouds.
41 In this study, we use multi-year ground-based observations from a marine site in the Eastern
42 North Atlantic and a continental site in the Southern Great Plains to examine the responses
43 of low-level warm clouds when dust is located above, within, or below the cloud layer. We
44 find that cloud responses vary substantially with dust–cloud vertical configuration. Dust
45 located above clouds, especially over the marine environment, is generally associated with
46 smaller cloud droplets, whereas dust located within or below clouds can produce different
47 responses over marine and continental environments. After accounting for local
48 meteorology, our results suggest that dust generally reduces cloud droplet size, but this
49 effect is masked or even reversed by direct meteorological effects on clouds. This matters
50 because assessments of dust-cloud interactions that consider only the total dust mass may
51 miss the influence of dust-cloud vertical distribution, leading to different estimates of how
52 dust affects cloud droplet size and reflectivity.

53 1 Introduction

54 Aerosol–cloud interactions remain one of the largest sources of uncertainty in
55 estimates of climate sensitivity and radiative forcing, exceeding even those associated with
56 greenhouse gas forcing (Bender, 2020; Im et al., 2026; Watson-Parris & Smith, 2022). This is
57 because aerosols influence the Earth’s radiation budget through multiple interacting
58 pathways that depend strongly on environmental conditions (Yu et al., 2024). Aerosols exert
59 direct radiative effects by scattering and absorbing solar and terrestrial radiation, thereby
60 modifying the atmospheric energy budget independently of clouds (Li et al., 2022). They also
61 induce semi-direct effects (SDE), in which heating by absorbing aerosols perturbs
62 atmospheric stability, cloud fraction, and cloud vertical structure (Adebisi et al., 2015; Koch
63 & Del Genio, 2010; Pandey & Adebisi, 2026b). In addition, aerosols can modify cloud
64 microphysics through indirect effects (IDE), altering cloud droplet number concentration,
65 cloud droplet effective radius (R_e), and cloud lifetime (Patnaude & Diao, 2020; Qiu et al.,
66 2024; Twomey, 1977). These processes are particularly consequential for low-level warm
67 clouds, which exert a strong cooling influence on the climate system due to their high albedo
68 and widespread coverage (Voigt et al., 2021). Because these clouds are tightly coupled to
69 boundary-layer thermodynamics and aerosol conditions, even modest aerosol
70 perturbations can produce substantial radiative impacts (Bellouin et al., 2020). As a result,
71 constraining aerosol–cloud interactions in low-level warm clouds is essential for narrowing
72 uncertainties in climate sensitivity and radiative forcing (Bellouin et al., 2020).

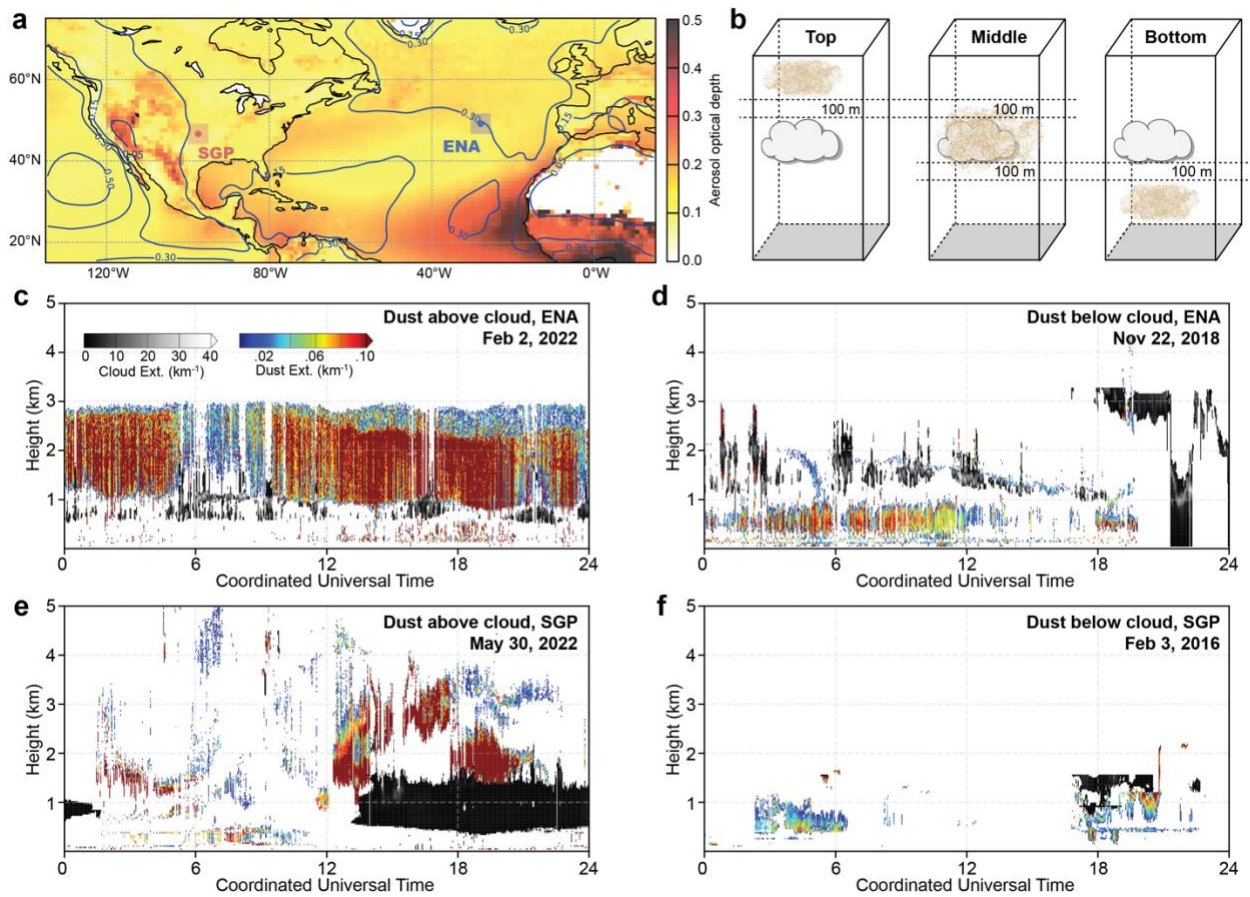
73 The magnitude and sign of aerosol effects on clouds depend strongly on the vertical
74 distribution of aerosols relative to cloud layers, as well as on the environmental setting in
75 which the interaction occurs (Adebisi et al., 2015; Lin et al., 2023). For absorbing aerosols,
76 the semi-direct effect is especially sensitive to aerosol–cloud geometry because the
77 location of radiative heating determines the thermodynamic response of the surrounding
78 atmosphere (Pandey & Adebisi, 2026a, 2026b). Specifically, when an absorbing aerosol
79 layer is located above clouds, solar absorption within the elevated layer warms the free
80 troposphere and increases lower-tropospheric stability, which can suppress cloud-top
81 entrainment and enhance cloud persistence or cloud fraction (Pandey & Adebisi, 2026a;
82 Wilcox, 2010). In contrast, when absorbing aerosols are embedded within the cloud layer,
83 localized radiative heating can promote evaporation of cloud droplets and destabilize the
84 cloud structure, potentially leading to partial cloud dissipation (Koch & Del Genio, 2010; Kok
85 et al., 2023). When aerosols are located below the cloud, radiative heating in the sub-cloud
86 layer may enhance turbulence and vertical moisture transport, thereby indirectly
87 influencing cloud development by modifying boundary-layer thermodynamics (McFarquhar
88 & Wang, 2006). In addition to these semi-direct pathways, indirect effects can occur when
89 aerosols are present within or below low-level clouds, where they act as cloud condensation

90 nuclei and influence cloud droplet sizes. The relative importance of these mechanisms
91 differs between marine and continental environments. For example, indirect effects tend to
92 be stronger over land, where background CCN concentrations are higher, and cloud
93 microphysics are more responsive to aerosol perturbations than over the ocean (Lohmann
94 & Lesins, 2003; Yang et al., 2022). These contrasts suggest that identical aerosol–cloud
95 vertical configurations may produce different cloud responses over ocean and land.

96 Mineral dust, a major contributor to global aerosol mass (Kim et al., 2014), accounts
97 for approximately one-third of global aerosol shortwave absorption (Sand et al., 2021).
98 Unlike other absorbing aerosols, dust particles span more than three orders of magnitude
99 in size, from submicron to coarse, a range that enables dust to interact with both shortwave
100 and longwave radiation (Adebisi & Kok, 2020; Adebisi et al., 2023; Kok et al., 2023). In
101 addition, large quantities of dust are transported westward from the North African deserts
102 across the North Atlantic Ocean and onward toward the Caribbean and North America (Fig.
103 1a). Additional dust sources over the North American continent contribute to the local
104 aerosol burden over the continent's interior (Kok et al., 2021). Over specific regions of the
105 North Atlantic Ocean and North America, previous studies have examined dust impacts on
106 cloud microphysics or radiative effects (Amiri-Farahani et al., 2017; Huang et al., 2019; Song
107 et al., 2018; Zheng et al., 2020), but few have systematically compared cloud responses
108 across distinct vertical arrangements such as dust above, within, or below clouds (Lin et al.,
109 2023; Pandey & Adebisi, 2026a). Moreover, most of these studies rely on satellite
110 observations, which provide broad spatial coverage but limited temporal continuity and
111 often insufficient vertical resolution to fully resolve dust–cloud overlap (Jia et al., 2021;
112 Painemal et al., 2020). Even fewer studies have contrasted cloud response between marine
113 and continental environments, where differences in thermodynamic state, background
114 aerosol composition, and boundary-layer dynamics may cause identical dust–cloud vertical
115 geometries to produce qualitatively different cloud responses (Jia et al., 2019; X. Ma et al.,
116 2018; Su et al., 2024).

117 To address these gaps, we use the multi-year, continuous, ground-based
118 observations from the U.S. Department of Energy's Atmospheric Radiation Measurement
119 (ARM) program at two contrasting sites: the Eastern North Atlantic (ENA, marine) and the
120 Southern Great Plains (SGP, continental). These two sites represent typical marine and
121 continental settings, and the large-scale aerosol and cloud environments over the two
122 regions are shown in Fig. 1a. The transport pathways to these two locations differ
123 substantially. Dust reaching the ENA typically undergoes long-distance transport across the
124 Atlantic Ocean or directly from northern Sahara dust sources, with a substantial fraction
125 arriving at elevated layers (Wang et al., 2020). By contrast, dust reaching the SGP is more
126 commonly associated with regional emission events and is frequently confined to the lower

127 troposphere (Evans, 2025; Lambert et al., 2020). Because these two locations are not
 128 directly along the major dust transport pathways, overall dust concentrations and frequency
 129 of occurrence are generally low, partially limiting analysis of dust–cloud interactions.
 130 Despite the limited occurrence and abundance, the two sites together provide an
 131 opportunity to examine how dust–cloud vertical configuration modulates cloud
 132 microphysical responses across contrasting environments. Leveraging these multi-year
 133 ARM datasets, we show that dust aerosol–cloud interactions and the associated response
 134 of cloud droplet effective radius to dust vary depending on whether dust resides above,
 135 within, or below the cloud layers, and that these responses diverge substantially between
 136 marine and continental regimes.



137

138 **Figure 1.** Overview of the observational context, dust–cloud configuration framework, and
 139 representative cases used in this study. (a) Climatological aerosol optical depth and single-
 140 layer low-level warm cloud fraction (contours) derived from MODIS for 2000–2012. The
 141 locations of the ARM ENA (blue) and SGP (red) sites are marked, and the shaded boxes
 142 denote the 5° × 5° regions centered on each site used for satellite data collocation (see Text
 143 S1 and Fig. S1). (b) Concept illustration of the three dust–cloud configurations (Top, Middle,
 144 and Bottom) used in this study, defined based on the relative vertical positions of dust layers

145 and cloud layers. Dashed lines indicate the vertical separation thresholds (± 100 m) used to
146 classify the configurations. Example cases of (c) the Top configuration (February 2, 2022)
147 and (d) the Bottom configuration (November 22, 2018) at ENA. Example cases of (e) the Top
148 configuration (May 30, 2022) and (f) the Bottom configuration (February 3, 2016) at SGP.

149 **2 Data and Methods**

150 2.1 Identifying dust and cloud layers

151 Aerosol information was obtained from the Raman Lidar Profiles-Feature detection
152 and Extinction (RLPROF-FEX) Value-Added Product at ENA and SGP sites between January
153 1, 2016, and December 31, 2025, corresponding to the maximum continuous overlapping
154 period for both sites. RLPROF-FEX provides aerosol optical properties, including aerosol
155 extinction, depolarization ratio, scattering ratio, and a feature mask for identifying aerosol
156 layers. The product has a temporal resolution of 2-min and a vertical resolution of 30-m, with
157 667 vertical levels, making it suitable for characterizing the vertical structure of dust
158 aerosols (Chand et al., 2023). To obtain reliable dust aerosol information, we followed the
159 product documentation and applied several quality-control criteria (Chand et al., 2023).
160 Specifically, we retained only profiles identified as aerosol by the feature mask, used
161 observations with total detection confidence greater than 0.3, and excluded retrievals with
162 poor quality (*quality flag* $\neq 0$). To avoid potential contamination of dust retrievals by
163 precipitation, profiles were removed if any height level within a given profile was flagged as
164 rain by the feature mask. Because incomplete near-surface lidar overlap can degrade
165 Raman lidar signal quality and lead to unstable retrievals, particularly within the lowest 0–
166 0.03 km, data below 0.03 km were excluded (Thorsen et al., 2015). The upper altitude limit
167 was set to 8 km to reduce the influence of low signal-to-noise ratios at higher altitudes on
168 aerosol extinction and depolarization retrievals (Newsom et al., 2022). The 0.03–8 km range
169 captures most tropospheric dust layers relevant to interactions with low-level warm clouds
170 and is consistent with commonly used altitude ranges in Raman lidar aerosol studies
171 (Chand et al., 2023). After applying these filters, 1,032,345 and 1,920,230 valid aerosol
172 profiles were retained at ENA and SGP, respectively.

173 To isolate the dust component from total aerosol extinction, we first calculated the
174 particle depolarization ratio (PDR) using the scattering ratio and observed depolarization
175 ratio provided by RLPROF-FEX. Dust particles are typically highly nonspherical and therefore
176 exhibit higher depolarization ratios than most non-dust aerosols, making depolarization
177 information an effective indicator for dust identification (Noh et al., 2017). However, the
178 observed depolarization ratio includes contributions from both particle and molecular
179 scattering, particularly under conditions of low aerosol loading or at higher altitudes. Direct
180 use of the observed depolarization ratio may therefore underestimate the contribution of

181 nonspherical dust particles. To reduce this effect, the observed depolarization ratio was
 182 corrected using the scattering ratio to derive PDR (Burton et al., 2015):

$$\begin{aligned}
 183 \quad & t = S + S\delta_m - \delta_m \\
 184 \quad & x_{num} = t\delta_{aerosol} - \delta_m \\
 185 \quad & x_{den} = S - 1 + S\delta_m - \delta_{aerosol} \\
 186 \quad & PDR = \frac{x_{num}}{x_{den}}
 \end{aligned}$$

187 where S is the scattering ratio, $\delta_{aerosol}$ is the observed depolarization ratio, and $\delta_m =$
 188 0.0049 is the molecular depolarization (Behrendt & Nakamura, 2002). The corrected PDR
 189 more directly reflects particle shape characteristics and is therefore more suitable for
 190 distinguishing dust from non-dust aerosols.

191 Under the external mixing assumption (Mamouri & Ansmann, 2014), aerosols were
 192 treated as a mixture of dust and non-dust components. The dust fraction, f_{dust} , was then
 193 estimated using a depolarization mixing relationship based on reference depolarization
 194 values for non-dust and pure dust particles (Freudenthaler et al., 2009; Noh et al., 2017).

$$195 \quad f_{dust} = \begin{cases} 1, & PDR \geq \delta_d \\ 0, & PDR \leq \delta_{nd} \\ \frac{(PDR - \delta_{nd})(1 + \delta_d)}{(\delta_d - \delta_{nd})(1 + PDR)}, & \delta_{nd} < PDR < \delta_d \end{cases}$$

196 where $\delta_{nd} = 0.15$ and $\delta_d = 0.31$ represent the reference values for non-dust and
 197 pure dust, respectively (Proestakis et al., 2024; Soupiona et al., 2020). This approach allows
 198 a continuous representation of mixed dust and non-dust conditions, thereby avoiding the
 199 potential bias introduced by simple threshold-based classification under aerosol mixing
 200 states. Dust extinction was then calculated as:

$$201 \quad ext_{dust}(z) = f_{dust}(z) \times ext_{aerosol}(z)$$

202 where $ext_{aerosol}(z)$ is the total aerosol extinction from RLPROF-FEX. To reduce the
 203 influence of cloud contamination and nonphysical retrievals, only extinction values less
 204 than 1.25 km^{-1} were retained (Kacenelenbogen et al., 2014), a threshold commonly used to
 205 distinguish aerosol from cloud signals. After the PDR-based dust-fraction retrieval and
 206 extinction filtering, 279,784 and 532,920 valid dust-aerosol profiles were retained at ENA
 207 and SGP, respectively. For each valid dust-aerosol profile, the dust layer was identified as
 208 the vertically continuous range with valid dust extinction. Dust-layer optical depth was
 209 calculated by vertically integrating dust extinction within the identified dust layer:

$$210 \quad DLOD = \int_{z_{DBH}}^{z_{DTH}} ext_{dust}(z) dz$$

211 where z_{DBH} and z_{DTH} denote the dust-layer base height (DBH) and dust-layer top
212 height (DTH), respectively. If multiple dust layers were present within a single profile, the
213 layer with the largest DLOD was selected as the dominant dust layer for subsequent analysis
214 (Haarig et al., 2022). Dust-layer thickness was defined as $z_{DTH} - z_{DBH}$, and dust-layer mean
215 height was defined as $(z_{DTH} + z_{DBH})/2$.

216 Cloud macrophysical properties, including cloud base height (CBH), cloud top height
217 (CTH), and number of cloud layers, were obtained from the Active Remote Sensing of Clouds
218 (ARSCL) Value-Added Product. ARSCL integrates active remote sensing measurements
219 from millimeter-wavelength cloud radar, lidar, and ceilometer observations to objectively
220 characterize the vertical distribution of hydrometeors, making it suitable for identifying
221 cloud boundaries (Clothiaux et al., 2001). The product has a temporal resolution of 4-s and
222 10 cloud layers, including the CBH and CTH of each layer. To match the temporal resolution
223 of RLPROF-FEX, ARSCL was resampled to a 2-min resolution. To avoid ambiguity in
224 matching cloud layers with dust layers under multilayer cloud conditions, this study
225 retained only single-layer cloud cases. The CBH and CTH were used to define the vertical
226 extent of the single cloud layer, and the cloud-layer mean height was defined as the
227 midpoint between CBH and CTH. Single-layer warm clouds were identified by matching the
228 CTH of each cloud layer to the corresponding RLPROF-FEX temperature profile and retaining
229 only cases where the cloud-top temperature was above 0 °C.

230 Cloud optical and microphysical properties, including cloud droplet effective radius
231 (R_e), cloud fraction, and liquid water path (LWP), were obtained from the Multifilter Rotating
232 Shadowband Radiometer Cloud Optical Depth (MFRSRCLDOD) Value-Added Product. This
233 product retrieves cloud optical depth from MFRSR shortwave radiation measurements and
234 estimates LWP and R_e using radiative transfer calculations (Turner et al., 2014). It is
235 primarily applicable to single-layer, horizontally homogeneous warm-cloud conditions
236 (Turner et al., 2014). This product has a temporal resolution of 20-s and was averaged to 2-
237 min intervals to match RLPROF-FEX and ARSCL. Following the product documentation,
238 samples with $LWP < 20 \text{ g m}^{-2}$ were excluded because of large retrieval uncertainty (Zheng et
239 al., 2020), whereas samples with $LWP > 300 \text{ g m}^{-2}$ were removed to reduce potential
240 precipitation influence (Zheng et al., 2020). Only cases with cloud fraction > 0.9 were
241 retained to ensure horizontally homogeneous cloud conditions (Turner et al., 2014). After
242 applying these filters, 49,719 and 19,631 valid single-layer warm-cloud samples were
243 retained at ENA and SGP, respectively.

244 The single-layer warm-cloud samples were then temporally matched with valid dust
245 profiles to construct the dust–cloud collocation dataset. A collocated period was defined
246 as a continuous sequence of 2-min timestamps during which both valid dust profiles and

247 valid single-layer warm-cloud observations were available. A sample was retained only
248 when valid dust and cloud information were present at the same 2-min timestamp. To focus
249 on low-level warm clouds, collocated samples were further retained only when CTH was
250 below 3 km (McHardy et al., 2018; Xi et al., 2022). After applying these collocations and low-
251 cloud filters, the final dust–cloud collocation dataset included 3,994 samples at ENA and
252 934 samples at SGP.

253 To provide an independent comparison with the ground-based ARM observations, we
254 also constructed a satellite-based dust–cloud collocation dataset. The detailed procedure
255 for identifying dust and cloud layers from satellite observations, including the satellite–site
256 sampling domain, satellite collocation procedure, and low-level warm-cloud screening, is
257 described in Text S1. This procedure yielded 720 and 316 satellite-based dust–cloud
258 collocation samples at ENA and SGP, respectively. Because the satellite and ARM
259 observations view the dust–cloud system from opposite directions, they provide
260 complementary constraints but are also subject to different attenuation-related
261 uncertainties. For ground-based lidar, uncertainties are generally larger when retrieving dust
262 layers above clouds because the lidar signal must pass through the cloud before reaching
263 the overlying aerosol layer. In contrast, for satellite-based lidar, uncertainties are generally
264 larger when retrieving dust layers below clouds because the lidar signal is attenuated by the
265 cloud before reaching the underlying aerosol layer (Kim et al., 2008). Despite these platform-
266 dependent limitations, the satellite observations provide an independent dataset for
267 evaluating whether the cloud responses inferred from the ground-based ARM observations
268 are consistent across observing systems.

269 2.2 Obtaining dust–cloud configuration

270 A unified framework was used to classify the relative vertical position of dust and
271 cloud based on dust- and cloud-layer heights (Fig. 1b). For each collocated sample, the
272 corresponding CBH, CTH, DBH, and DTH were used to determine the dust–cloud vertical
273 configuration. Thus, each 2-min sample was classified into the Top, Middle, or Bottom
274 configuration according to the relative positions of the dust and cloud layer boundaries. This
275 sample-level classification preserves the observed dust–cloud geometry at each timestamp
276 and avoids imposing a single representative category on samples that may experience
277 short-term changes in cloud or dust-layer height. Such an approach is consistent with
278 previous profile-based aerosol–cloud studies (Hong & Di Girolamo, 2022; Mann et al., 2014).
279 When the dust base is at least 100 m above the cloud top, the case is classified as “Top”,
280 indicating dust above the cloud. When the dust layer overlaps the cloud layer, allowing the
281 dust-layer top to extend up to 100 m above the cloud top and the dust-layer base to extend
282 up to 100 m below the cloud base, it is classified as “Middle”. When the dust layer is entirely

283 below the cloud, with its top at least 100 m below the cloud base, it is classified as “Bottom”.
284 This classification captures three typical dust–cloud configurations. A ± 100 m threshold is
285 used to reduce the impact of retrieval uncertainty and avoid misclassification due to small
286 height variations. The same criteria are applied to both ARM and satellite data to ensure
287 consistency and comparability across platforms. Representative ARM cases are shown in
288 Figure 1c–f to illustrate how different dust–cloud vertical configurations appear in
289 observations. Figure 1c and 1d show Top and Bottom cases at ENA, respectively, whereas
290 Figure 1e and f show Top and Bottom cases at SGP, respectively. The red boxes indicate the
291 height and time ranges of the dominant dust layer.

292 This classification framework was then applied to the dust–cloud collocation
293 samples. For the ground-based ARM observations, 236, 1,216, and 2,206 of the 3,994 ENA
294 collocated samples were classified as Top, Middle, and Bottom, respectively. At SGP, 8,
295 305, and 607 of the 934 collocated samples were classified as Top, Middle, and Bottom,
296 respectively. For the satellite observations, 339, 41, and 112 of the 720 ENA collocated
297 samples were classified as Top, Middle, and Bottom, respectively, whereas 85, 24, and 57
298 of the 316 SGP collocated samples were classified into the same three categories. Samples
299 that represented transitional geometries or did not satisfy the geometric criteria for the three
300 typical configurations were excluded from subsequent analyses.

301 2.3 Estimating cloud response to dust

302 To quantify the impact of dust on cloud responses, we estimate the dust aerosol–
303 cloud interaction (dust-ACI) index as the sensitivity of cloud droplet effective radius (R_e) to
304 dust-layer optical depth (DLOD), evaluated using a log–log regression applied separately to
305 each dust–cloud configuration, defined as:

$$306 \quad \beta_{R_e-DLOD} = -\frac{\partial \ln(R_e)}{\partial \ln(DLOD)}$$

307 where $\ln(R_e)$ and $\ln(DLOD)$ denote the natural-log-transformed cloud droplet
308 effective radius and dust-layer optical depth, respectively. Both variables were standardized
309 before regression to allow direct comparison of regression coefficients. β_{R_e-DLOD} is the
310 dust-ACI index. The negative sign ensures that a decrease in R_e with increasing DLOD yields
311 a positive value, consistent with the Twomey effect. To isolate microphysical responses
312 under comparable cloud water conditions, the analysis was repeated within three LWP
313 ranges (20–60, 60–100, and >100 g m⁻²). The regression was performed separately within
314 each LWP bin. These LWP ranges were selected to control for the direct influence of LWP on
315 R_e and to distinguish dust-ACI sensitivities under thin, moderately thick, and thicker liquid-
316 cloud conditions. The first two bins are consistent with LWP ranges commonly used in

317 aerosol–cloud interaction studies (Jia et al., 2019; X. Ma et al., 2018), whereas higher-LWP
318 conditions were combined into a single bin of $>100 \text{ g m}^{-2}$ to retain sufficient samples after
319 further stratification by dust–cloud vertical configuration. For all regressions, 95%
320 confidence intervals derived from the standard errors were used to quantify statistical
321 uncertainty.

322 2.4 Effects of meteorology on cloud response to DLOD

323 To separate the effects of dust and meteorology on cloud microphysics, we
324 incorporated meteorological variables from ARM radiosonde and Doppler lidar products.
325 Thermodynamic and horizontal-wind variables were obtained from the Gridded Sonde
326 (SONDEGRID) Value-Added Product, which is based on standard ARM radiosonde
327 observations and provides time–height fields at 1-min temporal resolution and 20-m vertical
328 resolution (Fairless et al., 2021). This structure makes SONDEGRID suitable for collocation
329 with other ARM products. Specifically, we extracted relative humidity (RH), temperature (T),
330 potential temperature, and wind speed from SONDEGRID. Vertical-motion information was
331 obtained from the Doppler Lidar Vertical Velocity Statistics Value-Added Product, which
332 provides Doppler-lidar-retrieved vertical velocity at 10-min temporal resolution and 30-m
333 vertical resolution. These variables were used to characterize the thermodynamic and
334 dynamic background near low-level warm clouds. All meteorological variables were linearly
335 interpolated to 2-min intervals to match the RLPROF-FEX observations.

336 Candidate meteorological variables were selected based on both physical relevance
337 and statistical redundancy. RH, T, vertical wind shear (VWS), vertical velocity (VV), and
338 lower-tropospheric stability (LTS) represent moisture conditions, thermal state, dynamical
339 shear, vertical motion, and lower-tropospheric stability, respectively, thereby covering the
340 main meteorological pathways that can modulate cloud droplet effective radius (Su et al.,
341 2024; Wall et al., 2022). Because variables at different levels may contain redundant
342 information, we examined collinearity among candidate variables using correlation
343 matrices and retained representative variables that were most consistent with the height
344 range of low-level warm clouds and had the most direct physical interpretation (see Text S2
345 and Fig. S2 for details). Specifically, RH and T were averaged over 750–850 hPa ($\text{RH}_{750-850}$ and
346 $\text{T}_{750-850}$) to represent humidity and temperature near the cloud layer. Higher RH can help
347 maintain liquid cloud water, whereas temperature variations can influence condensation,
348 evaporation, and both the retrieval and physical variability of R_e (Chen et al., 2008; Martins
349 et al., 2011). VWS was defined as the zonal wind-speed difference between 725 and 925 hPa
350 ($\text{VWS}_{725-925}$) to characterize dynamical mixing across the cloud layer; stronger wind shear
351 may modify cloud-top entrainment and aerosol–cloud contact efficiency (Fan et al., 2009;
352 Yamaguchi et al., 2019). VV was averaged over 750–850 hPa ($\text{VV}_{750-850}$) to represent upward

353 or downward motion near the cloud layer. Upward motion generally favors water vapor
 354 condensation and droplet growth, whereas subsidence can enhance evaporation or
 355 suppress cloud development (Peng et al., 2005). LTS_{700} was defined as the difference
 356 between the potential temperature at 700 hPa and the near-surface potential temperature
 357 and was used to describe lower-tropospheric stability. Stronger stability generally limits
 358 vertical mixing and may alter cloud-top entrainment and boundary-layer moisture structure
 359 (Wang et al., 2023; Wood & Bretherton, 2006). This variable selection is also consistent with
 360 previous aerosol–cloud interaction studies that controlled for near-cloud humidity, stability,
 361 wind shear, and vertical motion (Su et al., 2024; Wall et al., 2022).

362 For each dust–cloud vertical configuration, a multiple linear regression model was
 363 applied to quantify the joint effects of dust and meteorological conditions on R_e :

$$364 \quad \ln(R_e) = \alpha_0 + b_{R_e-DLOD}^* \ln(DLOD) + \sum_i \alpha_{R_e-x_i} X_i + \epsilon$$

365 where α_0 is the intercept, ϵ is the residual term, and X_i represents the
 366 meteorological variables (i.e., $RH_{750-850}$, $T_{750-850}$, LTS_{700} , $VWS_{725-925}$, $VV_{750-850}$). To facilitate
 367 comparison of the relative effects of different predictors, $\ln(R_e)$, $\ln(DLOD)$, and all
 368 meteorological variables were standardized prior to regression. The resulting coefficients,
 369 therefore, represent standardized regression coefficients. Specifically, $b_{R_e-DLOD}^*$ denotes
 370 the standardized regression coefficient of $\ln(DLOD)$ on $\ln(R_e)$ after controlling for
 371 meteorological factors, whereas $\alpha_{R_e-x_i}$ represents the standardized regression coefficient
 372 of each meteorological variable (X_i) on $\ln(R_e)$. To remain consistent with the dust-ACI
 373 definition introduced above, the dust-ACI index with minimized meteorological modulation
 374 was defined as:

$$375 \quad \beta_{R_e-DLOD}^* = -b_{R_e-DLOD}^*$$

376 Thus, the original β_{R_e-DLOD} represents the dust-ACI index derived from the bivariate
 377 regression (see Section 2.3). Because this regression does not explicitly account for
 378 meteorological covariability, β_{R_e-DLOD} likely reflects both dust-related effects and
 379 variations in the meteorological background. In contrast, $\beta_{R_e-DLOD}^*$ represents the
 380 independent contribution of DLOD to R_e after controlling for meteorological variables and is
 381 used to characterize the dust-ACI index after minimizing the influence of meteorology.
 382 Therefore, comparing their difference ($\beta_{R_e-DLOD} - \beta_{R_e-DLOD}^*$) allows us to estimate the extent
 383 to which meteorological conditions modulate, enhance, or suppress the apparent dust–
 384 cloud interaction inferred from the bivariate regression. Similarly, to show the sensitivity of
 385 R_e to meteorological conditions compared to the dust-ACI index, we present the result as
 386 negative $\alpha_{R_e-x_i}$.

387 **3 Results**

388 3.1 Characteristics of dust–cloud configurations

389 Over the ENA and SGP, we find that dust aerosols are more likely to occur below
390 (Bottom) and within (Middle) low-level clouds than above them (Top). Specifically, at ENA,
391 3,994 valid dust–cloud matched samples were identified, of which 3,658 were assigned to
392 one of the three configurations. The remaining matched samples were valid collocations but
393 did not meet the criteria for the three configuration categories (see Section 2.2). Among the
394 classified samples, 60.3% are Bottom configuration, 33.2% are Middle configuration, and
395 6.5% are Top configuration (Fig. 2a). Because of the stringent criteria required for the dust–
396 cloud configurations (see Sections 2.1 and 2.2 above), the number of Top configuration
397 cases is limited (see Fig. S3a). Similarly, at SGP, 934 valid dust–cloud matched samples
398 were identified, of which 920 met the classification criteria (see Section 2.2) and were
399 assigned to one of the three configurations: 66.0%, 33.2%, and 0.9% were Bottom, Middle,
400 and Top configurations, respectively (Fig. 2a). Because the Top configuration has a small
401 percentage (only eight samples) at SGP, we exclude this category from subsequent analysis.
402 Between the Bottom and Middle configurations that dominate the overall dust–cloud
403 vertical distributions, winter is the only season in which the Middle configuration occurs
404 more frequently than the Bottom configuration (Fig. S3a). Overall, the median DLOD for the
405 Top configuration is higher than those of the Middle and Bottom configurations by factors of
406 2 and 3, respectively, despite its limited occurrence at the ENA site (Fig. 2b). Similarly, the
407 median DLOD over SGP for the Middle configuration is a factor 1.7 higher than the Bottom
408 configuration (Fig. 2f).

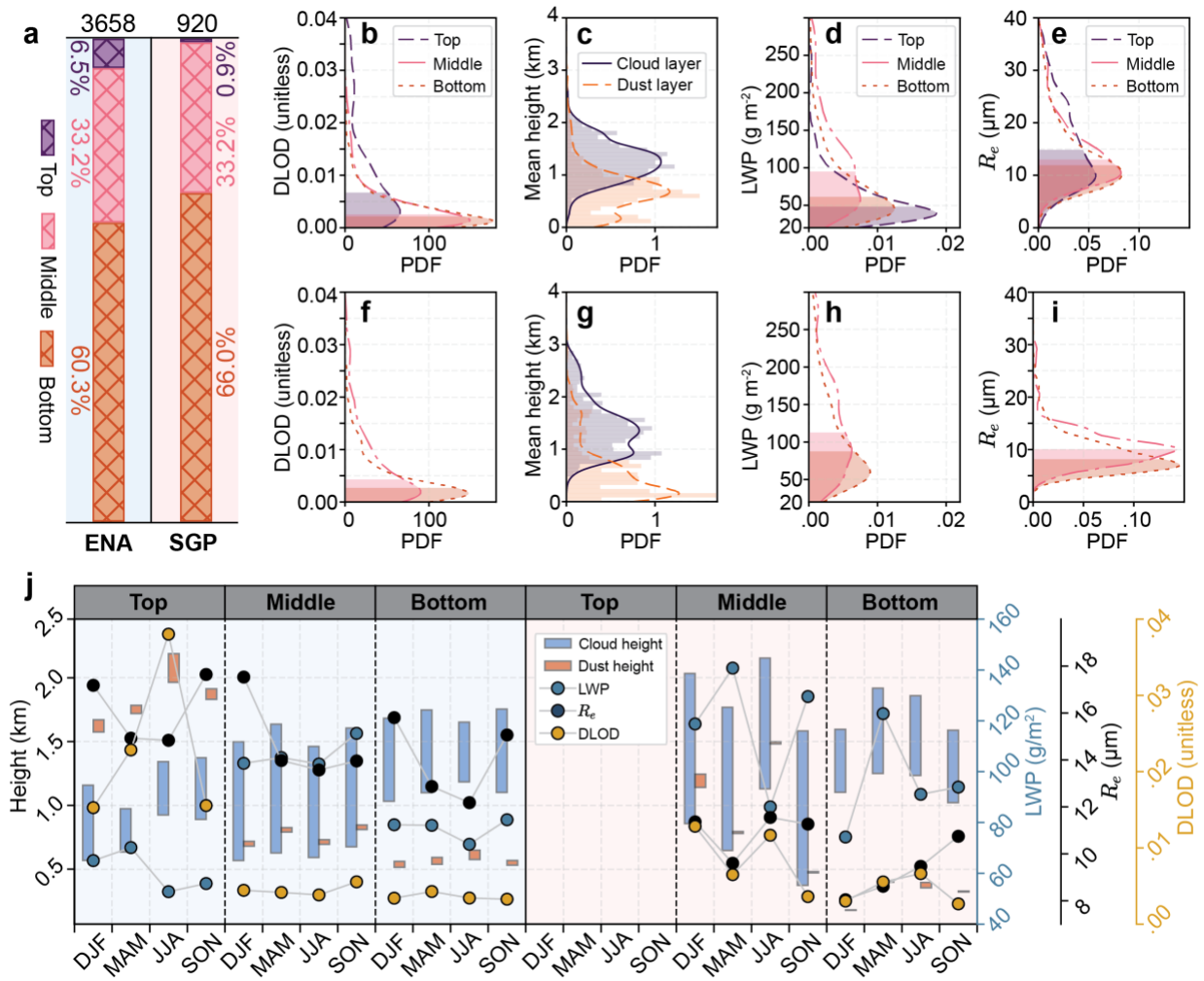
409 Relative to the ground-based lidar observations at ENA and SGP, the infrequent
410 overpass of satellite-based lidar observations has a higher frequency of occurrence for the
411 Top configurations over ENA (68.9%) and SGP (51.2%) than Middle and Bottom (Fig. S4a).
412 This is expected given the satellite sensor’s scanning direction, which often results in higher
413 uncertainties where signal attenuation is greater – that is, dust below and within the cloud
414 for CALIPSO (Liu et al., 2009). The dominant configurations, Top and Bottom, show opposite
415 seasonal patterns between ENA and SGP: Top is more frequent at ENA in spring and
416 summer, whereas Bottom is more frequent at ENA in fall and winter (Fig. S3b). In contrast to
417 ENA, the occurrence frequency at SGP is higher for the Bottom configuration in spring and
418 summer and for the Top configuration in fall and winter (Fig. S3b). This satellite-based
419 frequency of occurrence for Bottom configuration is consistent with ground-based lidar
420 observation at SGP (Fig. S3a and 3b). Furthermore, DLOD magnitude also varies by dust–
421 cloud vertical configuration. Although Top configurations occur most frequently, higher
422 DLOD values are generally found when dust is within or below clouds (Fig. S4b). This pattern

423 may partly reflect lidar detection selectivity. For CALIPSO, which observes from above,
424 cloud attenuation can make dust below or within clouds more difficult to detect unless the
425 dust layer is optically thick. Conversely, for ground-based ARM lidar, dust above clouds can
426 be more difficult to detect consistently because cloud layers may attenuate the upward-
427 looking lidar signal. Thus, the configurations that are less favorable for each lidar viewing
428 geometry tend to show higher DLOD, suggesting that configuration-dependent DLOD
429 differences reflect both physical dust loading and retrieval sensitivity.

430 The site-to-site differences in dust–cloud configuration frequencies are consistent
431 with distinct background vertical structures of dust and clouds at ENA and SGP. At ENA,
432 dust-layer height shows two distinct peaks, with a stronger peak near 800 m (Fig. 2c),
433 whereas at SGP, dust is primarily concentrated near the surface, at approximately 200 m
434 (Fig. 2g). Clouds at ENA are mainly confined to a narrower height range, while those at SGP
435 span a broader vertical range (Fig. 2c and 2g). These contrasting dust and cloud height
436 distributions help explain why Bottom and Middle configurations dominate at both sites,
437 while Top cases are relatively rare, especially at SGP. Because these configurations
438 represent distinct dust–cloud vertical contexts, we next examine whether cloud properties
439 vary systematically among them. We find that these dust–cloud configurations exhibit
440 distinct cloud properties, including R_e and LWP. Specifically, the probability distributions
441 indicate that the median LWP for the Middle configurations (95.8 and 113.3 g m⁻²) is higher
442 over both ENA and SGP than those for the Top (48.4 g m⁻² for ENA) and Bottom (61.3 and 88.4
443 g m⁻²) configurations (Fig. 2d and 2h). As a function of season, both the Middle and Bottom
444 show relatively higher LWP values in spring and fall than in summer and winter at the ENA
445 and SGP sites (blue lines in Fig. 2j). There are also distinct changes in R_e across the different
446 dust-cloud configurations at both ENA and SGP. Specifically, the median values of R_e for the
447 Top configuration (14.9 μm for ENA) are higher than the Middle (13.1 and 10.1 μm), which
448 are higher than the Bottom configurations (11.9 and 8.2 μm), across both sites (Fig. 2e and
449 2i). In addition, seasonal variations in R_e show contrasting patterns between the two sites:
450 for both the Middle and Bottom configurations, R_e is highest in winter and lowest in summer
451 at ENA, whereas it is generally higher in summer–autumn than in winter–spring at SGP (black
452 lines in Fig. 2j).

453 Our result also shows differences in the mean height and geometric thickness of the
454 cloud layer over both ENA and SGP, with seasonal variability differing from that of LWP and
455 R_e (see Fig. 2j). Specifically, we find that the Middle configurations generally have low-level
456 clouds that are geometrically thicker (0.93 and 1.13 km) than Bottom (0.60 and 0.59 km) and
457 Top (0.46 km for ENA) configurations over both ENA and SGP. These differences in geometric
458 cloud thickness are consistent with differences in LWP and R_e , particularly between the
459 Middle and Bottom configurations. Specifically, thicker clouds with higher LWP and R_e

460 occur in the Middle configuration than in the Bottom configuration across seasons (Fig. 2j).
 461 In addition, the mean cloud heights (defined as the mean of cloud base and top heights) are
 462 higher for Bottom configurations than for Top and Middle configurations (Fig. 2j). This is
 463 because of the higher cloud-base height, leading to a larger difference in cloud-base heights
 464 among the configurations than in cloud-top heights, which is likely associated with radiative
 465 warming by shortwave-absorbing dust aerosols in the boundary layer or stronger vertical
 466 wind shear resulting in stronger boundary-layer turbulence (Bottom higher than Middle).
 467 Overall, the different dust-cloud configurations exhibit distinct mean cloud properties, with
 468 differences between land and ocean, suggesting differences in cloud responses to dust.



469

470 **Figure 2.** Dust–cloud vertical configurations and associated properties at ENA and SGP. (a)
 471 Fractional and total occurrence of Top, Middle, and Bottom configurations at ENA and SGP.
 472 (b) Probability density functions (PDF) of dust-layer optical depth (DLOD) at ENA. (c) PDF of
 473 cloud- and dust-layer heights during dust–cloud collocation at ENA. (d, e) PDF of liquid water
 474 path (LWP) and cloud droplet effective radius (R_e) at ENA. (f–i) Same as (b–e), but for SGP.
 475 Shaded areas indicate the lower 50% of each distribution. (j) Seasonal variations in cloud

476 height, dust height, LWP, R_e , and DLOD for each vertical configuration at ENA (blue
477 background) and SGP (red background), shaded bars denote cloud and dust vertical ranges,
478 and markers indicate seasonal mean cloud and dust properties.

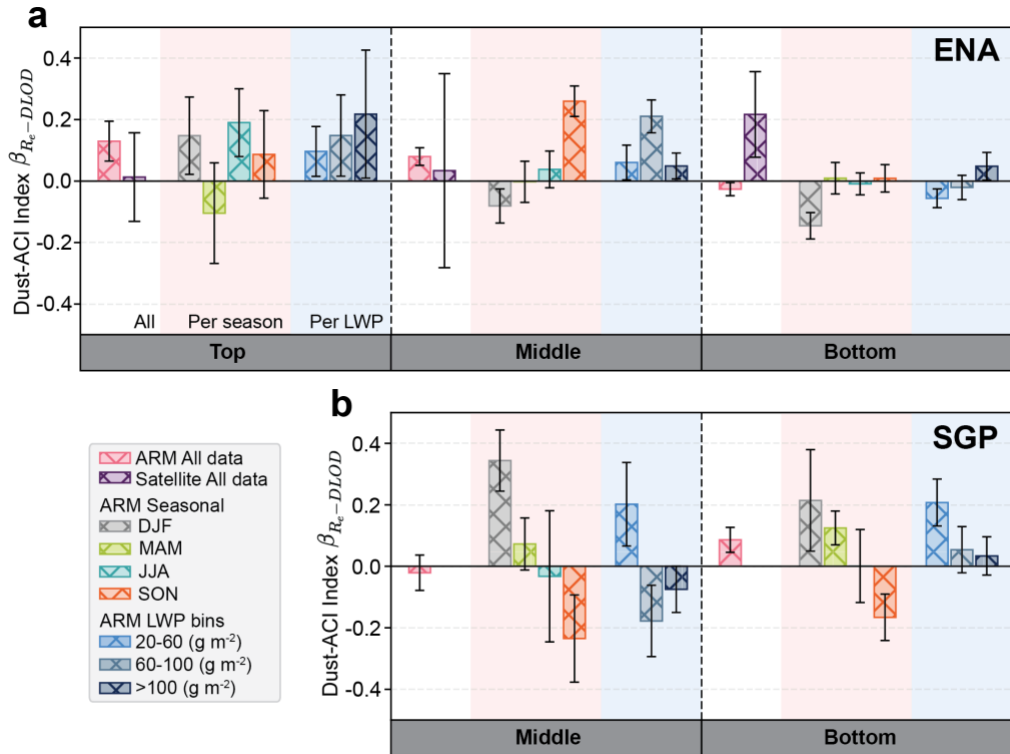
479 3.2 Cloud Response to Dust-Cloud Configurations

480 To better understand the cloud response to dust, we estimate dust aerosol–cloud
481 interaction (dust-ACI) index as the sensitivity of cloud droplet effective radius to dust-layer
482 optical depth (β_{R_e-DLOD} ; see Section 2.3 above), and find a marked difference in cloud
483 response across different dust–cloud vertical configurations and across marine and
484 continental environments (Fig. 3). At ENA (marine environment; Fig. 3a), our results show a
485 strong positive dust-ACI index for the Top configuration (0.130 ± 0.065) and a weakly positive
486 dust-ACI index for the Middle configuration (0.080 ± 0.029), indicating a cloud brightening
487 effect, where increases in DLOD are associated with decreases in R_e (see pink bars in Fig.
488 3a). In contrast, our results also show a slightly negative dust-ACI index for the Bottom
489 configuration (-0.026 ± 0.021), indicating increases in DLOD are associated with increases
490 in R_e (see pink bars in Fig. 3a). These relationships between dust and R_e vary with season for
491 each configuration (red background in Fig. 3a). For the Top configuration, a negative dust-
492 ACI index occurs only in spring (MAM), whereas the positive responses in the other three
493 seasons dominate the mean positive dust-ACI index. For the Middle configuration, the mean
494 positive dust-ACI index is mainly driven by the positive response in fall (SON), which
495 compensates for the negative responses in winter (DJF) (Fig. 3a). Similarly, the mean
496 negative dust-ACI index for the Bottom configuration is primarily dominated by the winter
497 response, while the dust-ACI index remains close to zero in the other seasons (Fig. 3a). In
498 addition to seasonal variations, the dust-ACI index across different dust–cloud
499 configurations also depends on LWP (blue background in Fig. 3a). Specifically, we find that
500 the dust-ACI index increases for higher LWP clouds for Top and Bottom configurations.
501 Indeed, for the Bottom configuration, the dust-ACI index increases from negative for low-
502 LWP clouds ($20\text{--}60 \text{ g m}^{-2}$) to positive for high-LWP clouds ($>100 \text{ g m}^{-2}$). For the Middle
503 configuration, the dust-ACI index is highest for LWP in the range of $60\text{--}100 \text{ g m}^{-2}$, dominated
504 by positive dust-ACI index in the summer and influenced by environmental factors (see
505 Section 3.3 below).

506 These dust-ACI indices from ground-based instruments at ENA are further used to
507 assess satellite-derived dust-ACI indices as a function of the dust–cloud configuration. We
508 find that satellite-derived mean dust-ACI indices for Top and Middle configurations are
509 largely consistent with those from ground-based instruments at ENA (except for Bottom),
510 although with different magnitudes (Fig. 3a). Specifically, we find that the satellite-based
511 mean dust-ACI indices are 0.013 ± 0.144 and 0.033 ± 0.316 for Top and Middle
512 configurations, compared to 0.130 ± 0.065 and 0.080 ± 0.029 from ground-based

513 instruments. For the Bottom configuration, the results are opposite, showing 0.217 ± 0.140
514 for satellite-based dust-ACI relative to -0.026 ± 0.021 from ground-based observation. This
515 difference in the sign of dust-ACI may reflect both sample size (see Fig. S4a) and differences
516 in retrieval sensitivity and the representation of below-cloud dust layers between satellite
517 and ground-based observations. Specifically, because satellite-retrieved R_e primarily
518 represents cloud-top conditions, below-cloud dust is more difficult to compare directly with
519 satellite-retrieved cloud microphysical properties (Platnick, 2000).

520 In contrast to the marine environment at ENA, we find different low-level cloud
521 responses to DLOD at SGP (Fig. 3b). Because the Top category contains too few samples for
522 a robust estimate, only the Middle and Bottom configurations are analyzed. We find that the
523 mean dust-ACI indices are negative for the Middle configuration at SGP (-0.021 ± 0.057 ,
524 positive for ENA) and positive for the Bottom configuration (0.086 ± 0.041 , negative for ENA).
525 These contrasting cloud responses to aerosols, such as dust, between marine and
526 continental environments have also been documented in previous studies for non-dust
527 aerosols (X. Ma et al., 2018) and attributed to differences in boundary layer coupling and
528 thermodynamics, including surface fluxes, updraft differences between ocean and land (Su
529 et al., 2024). In addition, the dust-ACI indices at SGP vary with season and LWP (Fig. 3b).
530 Specifically, we find that the mean negative dust-ACI index for the Middle configuration is
531 driven by negative responses in summer and fall, whereas the mean positive dust-ACI index
532 for the Bottom configuration is driven by the positive responses in winter and spring. Across
533 LWP regimes, the dust-ACI index changes from strongly positive for low-LWP clouds for both
534 Middle and Bottom configurations to weak positive (Bottom) or negative (Middle) dust-ACI
535 indices for high-LWP clouds, indicating an increase in R_e as LWP and associated available
536 water vapor increase. Overall, the contrast between ENA and SGP suggests that dust
537 impacts on cloud responses are jointly modulated by dust loading, vertical configuration,
538 and environmental background, with marine and continental regimes favoring distinct cloud
539 response patterns.



540

541 **Figure 3.** Cloud droplet radius sensitivity (β_{R_e-DLOD}) under different dust-cloud
 542 configurations (white background) and further stratified by season (red background) and
 543 LWP regimes (blue background) at (a) ENA and (b) SGP. Vertical lines denote the 95%
 544 confidence intervals.

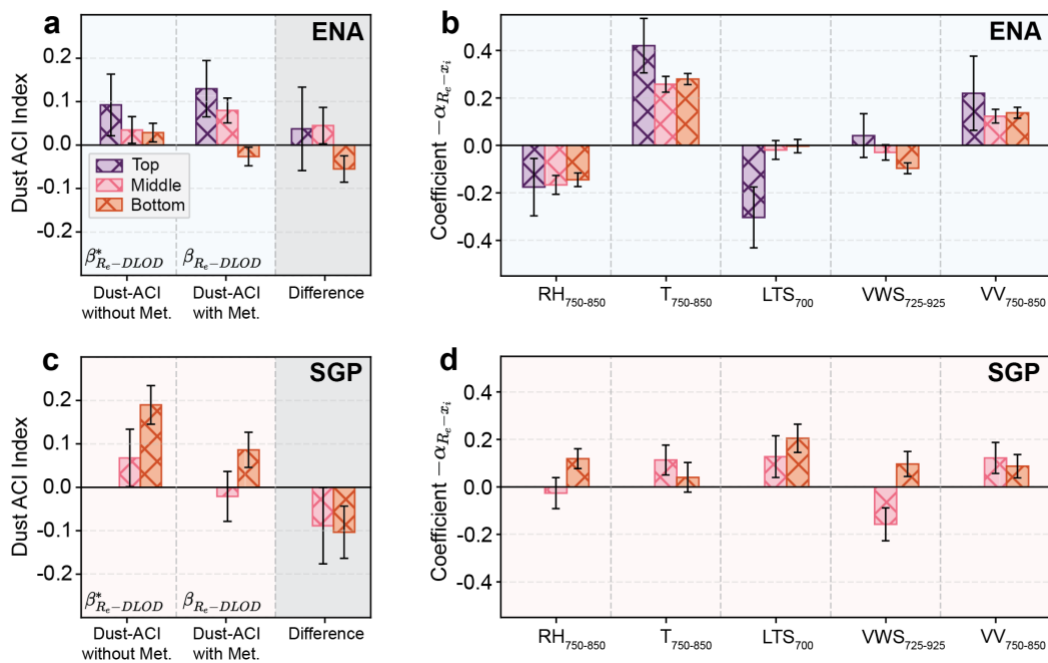
545 3.3 Influence of Meteorology on Cloud Response to Dust-Cloud Configurations

546 To better understand the role of local meteorology on the low-level cloud responses,
 547 we break down the dust-ACI index as a function of common meteorological variables that
 548 influence low-level cloud development (Adebiyi & Zuidema, 2018). Although several
 549 meteorological variables influence cloud development differently over land and ocean
 550 (Ghonima et al., 2016; Jian et al., 2021; Klein et al., 2018), we limit our focus to five common
 551 variables ($RH_{750-850}$, $T_{750-850}$, LTS_{700} , $VWS_{725-925}$, and $VV_{750-850}$) to minimize multicollinearity
 552 arising from potential cross-correlations among them (see Text S2 and Fig. S2). For these
 553 five meteorological variables, we conduct a multiple linear regression analysis in which R_e
 554 is regressed on the variables and DLOD to minimize the confounding influence of
 555 meteorology on dust-cloud interactions (see Section 2.4). The results show that local
 556 meteorology substantially confounds estimates of the dust-ACI index, masking the direct
 557 microphysical responses of clouds to dust, the extent of which depends on dust-cloud
 558 configurations (Fig. 4). Specifically, the results show that the dust-ACI indices are largely
 559 positive after minimizing meteorological influence, suggesting that direct dust interactions
 560 often lead to decreases in R_e both over ocean and land. The highest dust-ACI index for ENA

561 remains for the Top configuration (0.092 ± 0.071), and the dust-ACI indices for the Bottom
562 configuration are higher than those for the Middle configuration at both ENA and SGP (first
563 column in Fig. 4a and 4c). At ENA, the dust-ACI index is 0.035 ± 0.031 for the Middle
564 configuration and 0.029 ± 0.022 for the Bottom configuration; similarly, at SGP, it is $0.068 \pm$
565 0.067 for the Middle configuration and 0.190 ± 0.044 for the Bottom configuration. This
566 difference in dust-ACI indices for direct dust interaction is associated with the competing
567 microphysical and semi-direct influence of dust on R_e (see Fig. 5). When comparing the
568 dust-ACI indices with and without the confounding influence of meteorology at ENA (Fig. 4a),
569 we find that meteorological conditions tend to anomalously enhance dust–cloud
570 interactions (decrease R_e) for Top and Middle configurations and suppress (increase R_e)
571 dust–cloud interactions for Bottom configuration. At SGP, meteorological conditions
572 anomalously suppress dust–cloud interactions in both the Middle and Bottom
573 configurations, even changing the dust-ACI index from positive to negative for the Middle
574 configuration.

575 In addition, the results show the relationship between each meteorological variable
576 and cloud R_e , indicating their contributions to the anomalous enhancement or suppression
577 of dust–cloud interactions. First, we find that an in-cloud increase in RH is associated with
578 increases in R_e , except over land at SGP when dust is below the cloud (first column in Fig.
579 4b and 4d). Although increased R_e is expected for higher RH, it is likely that the advection of
580 boundary-layer fine aerosols (including dust) over land into the cloud layer overcomes the
581 increase in available moisture, resulting in a reduction in the cloud’s R_e when dust is below
582 cloud. Second, we find that an increase in in-cloud temperature is associated with a
583 reduction in R_e , regardless of the dust–cloud configuration over ENA and SGP (second
584 column in Fig. 4b and 4d). Such increases in in-cloud temperature can be caused by the
585 shortwave absorption by dust particles heating the cloud layer (Koch & Del Genio, 2010; Kok
586 et al., 2023), advection of warm free-tropospheric air entraining through the cloud top, or
587 warm convective thermals increasing sensible heat flux from the surface, effectively raising
588 the in-cloud temperature (Wood, 2012). Third, an increase in LTS is associated with
589 increased cloud R_e over the ocean at ENA but reduced cloud R_e over land at SGP (third
590 column in Fig. 4b and 4d). In both cases, the influence of LTS is stronger for the Top and
591 Middle configurations than for the Bottom configurations. The strong LTS for the Top
592 configuration is consistent with dust semi-direct effects when dust is above the cloud,
593 resulting in moisture buildup in the boundary and cloud layer and an increase in R_e (Kok et
594 al., 2023). In contrast, when dust is within or below clouds, other competing processes likely
595 confound the effect of LTS, reducing its influence on cloud R_e . Fourth, we find that VWS has
596 a contrasting influence on R_e at ENA and SGP (fourth column in Fig. 4b and 4d). Specifically,
597 stronger VWS is associated with increased R_e for Middle configurations, although stronger

598 over land at SGP than over ocean at ENA. In contrast, R_e responds differently to stronger
 599 VWS for Bottom configurations, resulting in increased R_e at ENA and decreased R_e at SGP.
 600 Finally, our results also show that increases in upward vertical velocity reduce the cloud R_e ,
 601 regardless of the dust–cloud configuration over ENA and SGP (last column in Fig. 4b and 4d).
 602 Overall, these results indicate that local meteorology modulates the dust-ACI index,
 603 indirectly influencing dust–cloud interaction, sometimes differently over ocean and land.



604
 605 **Figure 4.** Confounding influence of meteorology on dust-cloud interactions under different
 606 dust–cloud vertical configurations. (a) Comparison of dust-ACI index estimated without
 607 meteorology ($\beta_{R_e-DLOD}^*$; minimizing the influence of meteorology), with meteorology
 608 (β_{R_e-DLOD} that is, the influence of meteorology remains), and their differences ($\beta_{R_e-DLOD} -$
 609 $\beta_{R_e-DLOD}^*$) in the ENA site under different dust–cloud configurations. (b) Standardized
 610 coefficients for meteorological variables ($-\alpha_{R_e-x_i}$) at the ENA site under different dust–
 611 cloud configurations. Note that the standardized coefficients for the meteorological
 612 variables are multiplied by -1 for comparison with the dust-ACI index (see Section 2.4).
 613 Panel (c) and (d) show the corresponding results for the SGP site. The figures are such that
 614 positive values indicate a decrease in cloud droplet effective radius with increasing
 615 predictor values. Vertical lines denote the 95% confidence intervals.

3.4 Potential Pathways Explaining Cloud Response to Dust-Cloud Configuration

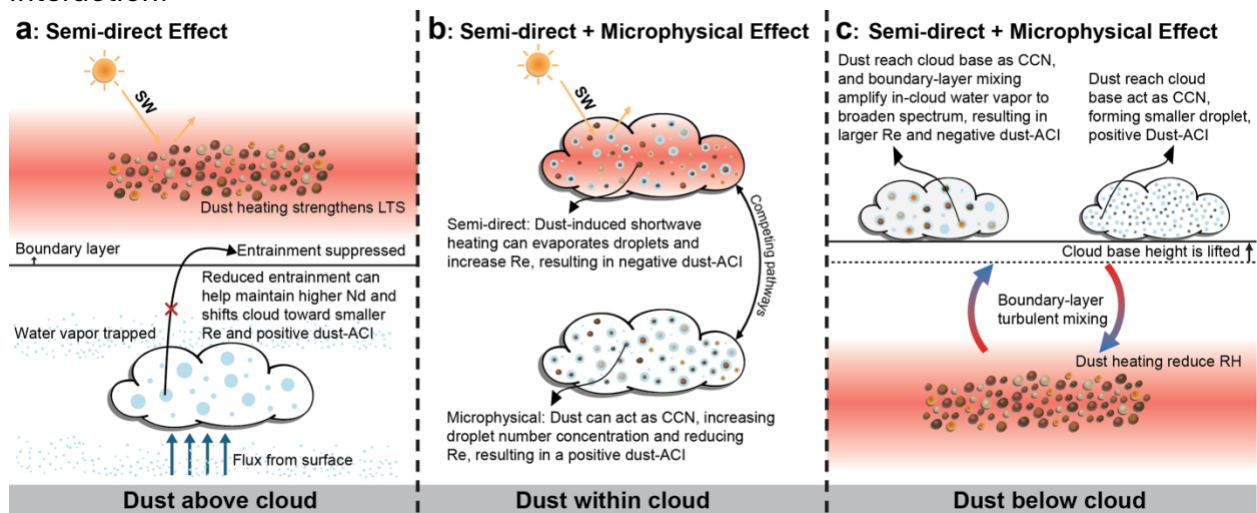
616
 617 Our findings above suggest that processes associated with dust–cloud interactions
 618 across different dust–cloud configurations are often more interconnected than can be
 619 explained by semi-direct (thermodynamic) or microphysical effects alone. Therefore, we
 620 propose the following pathways by which dust influences cloud droplet effective radius (R_e)
 621 across different dust–cloud configurations. First, when dust is above the cloud, the

622 dominant pathway influencing changes in R_e is likely the semi-direct effect, whereby dust-
623 induced shortwave absorption warms the free troposphere (Wilcox, 2010), strengthens the
624 lower-tropospheric stability (Johnson et al., 2004; Amiri-Farahani et al., 2017), suppresses
625 cloud-top entrainment of dry air (Brioude et al., 2009), and traps moisture within the
626 boundary layer (Fig. 5a; Kok et al., 2023). With less entrainment of dry air, the low-level cloud
627 can maintain higher droplet number concentrations, which likely shifts the cloud droplet
628 distribution toward smaller R_e for a comparable liquid water path (Twomey, 1977). In
629 addition, enhanced shortwave-induced stability may also prolong cloud persistence, and
630 thinner, shallower clouds with reduced turbulent mixing may more readily preserve high
631 droplet number concentrations, further reducing R_e . In contrast to the shortwave warming
632 above the cloud, the longwave-induced changes at cloud top, recently highlighted by
633 Pandey and Adebisi (2026a, 2026b), are likely small due to the observed low DLOD values
634 (Fig. 2b and 2f), thereby limiting their impacts on R_e . Furthermore, this pathway is supported
635 by the strong response of R_e to LTS, VWS, and VV over ENA (Fig. 4b and 4d) as well as thinner
636 clouds and lower cloud-top height (Fig. 2j). The net result is a reduction in R_e , consistent
637 with the strong positive dust-ACI index observed at ENA for the Top configuration.

638 Second, when dust co-exists within the cloud layer, R_e is simultaneously influenced
639 by competing microphysical and semi-direct pathways, making the net response strongly
640 dependent on the ambient environment (Fig. 5b). On the one hand, dust can act as a
641 conventional CCN (although with low hygroscopicity) (Karydis et al., 2011), increasing the
642 droplet number concentration and shifting the size distribution toward smaller droplets,
643 thereby reducing R_e (Karydis et al., 2017). On the other hand, dust absorption of shortwave
644 radiation within the cloud can warm the layer and promote partial evaporation, which may
645 either reduce or broaden the droplet spectrum depending on humidity and LWP. Over the
646 ocean at ENA, where background CCN is low, the additional fine-mode dust CCN are
647 comparatively more influential, yielding smaller R_e and a positive dust-ACI index. The
648 supporting meteorology reinforces this cloud brightening pathway (Fig. 4b), whereby
649 stronger upward vertical velocity enhances supersaturation that activates a larger number
650 of CCN and yields more numerous smaller droplets, an effect that is especially pronounced
651 in the updraft-sensitive (aerosol-limited) marine regime (Peng et al., 2005; Reutter et al.,
652 2009). Over land at SGP, the already high background CCN concentration diminishes the
653 marginal sensitivity of R_e to additional fine-mode dust, so the semi-direct warming-driven
654 evaporation can dominate, sometimes leading to larger R_e and a negative dust-ACI index.
655 This tendency is strengthened by meteorological conditions that promote droplet growth,
656 including increased vertical wind shear (Fig. 4d), which enhances turbulent mixing and can
657 deepen the cloud layer (Fig. 2j), both of which favor a larger cloud droplet effective radius.

658 Third, when dust is below the cloud layer, our result suggests that influence on R_e is
659 likely governed by competing thermodynamic and microphysical pathways that diverge
660 markedly between ocean and land (Fig. 5c). Sub-cloud radiative heating by dust warms the
661 boundary layer, reduces sub-cloud relative humidity, elevates cloud base height, and
662 modifies turbulent mixing (Koch & Del Genio, 2010; Kok et al., 2023), consistent with
663 observed properties for Bottom configurations (Fig. 2j). Over ENA, weaker marine boundary-
664 layer mixing and slower aerosol processing favor coarser dust acting as giant CCN at cloud

665 base, producing fewer but larger droplets that increase R_e , yielding a negative dust-ACI
 666 index, an effect amplified at low LWP (Fig. 3a). Additionally, shear-driven turbulent mixing
 667 within the boundary layer can help increase in-cloud water vapor, and consequently
 668 broaden the droplet spectrum, thereby increasing R_e resulting in a negative dust-ACI index
 669 (Fig. 4b). Over land at SGP, stronger convective boundary-layer mixing can exist, efficiently
 670 transporting finer, locally emitted dust particles upward to the cloud base, where they
 671 activate predominantly as conventional CCN, increasing droplet number concentration,
 672 reducing R_e , and producing a positive dust-ACI index, with high LWP weakening this
 673 sensitivity (Fig. 3b). Overall, these configuration-specific and environment-dependent
 674 mechanisms highlight that the sign and magnitude of dust effects on R_e emerge from a
 675 balance between semi-direct thermodynamic adjustments and microphysical pathways,
 676 which must be disentangled from meteorological confounding to isolate the true dust–cloud
 677 interaction.



678

679 **Figure 5.** Schematic diagram of dust-ACI pathways under different vertical configurations.
 680 (a) Dust above cloud, where dust heating strengthens lower-tropospheric stability,
 681 suppresses entrainment, maintains cloud number concentration (N_d), and reduces cloud
 682 droplet effective radius (R_e); (b) Dust within cloud, where semi-direct evaporation and CCN
 683 activation compete to either increase or decrease R_e ; and (c) dust below cloud, where sub-
 684 cloud heating and boundary-layer mixing regulate whether the R_e response is dominated by
 685 water-vapor influence that broadens droplet-spectrum, or conventional CCN activation that
 686 narrows it.

687 4 Discussion and Summary

688 Understanding how low-level clouds respond to mineral dust under different vertical
 689 configurations and meteorological conditions is critical for constraining aerosol–cloud
 690 interactions, an important component of regional climate systems. Using ground-based
 691 observations at the U.S. Department of Energy Atmospheric Radiation Measurement sites
 692 at the Eastern North Atlantic (ENA, marine) and the Southern Great Plains (SGP,
 693 continental), our analysis demonstrates that the response of low-level clouds to dust
 694 depends strongly on the relative vertical configuration between dust and cloud layers –

695 classified as dust above (Top), within (Middle), or below (Bottom) the cloud – and these
696 responses differ substantially between marine and continental environments. Across both
697 the ENA and SGP, ground-based lidar shows that the Bottom and Middle dust–cloud
698 configurations occur substantially more frequently than the Top configuration. This low
699 occurrence frequency of the Top configuration contrasts with satellite-based observations,
700 which show higher occurrence rates than those of the Bottom configuration, highlighting the
701 difficulty of observing dust above clouds for surface lidars (Griesche et al., 2024; Thorsen et
702 al., 2011). Despite its relatively low occurrence frequency, the Top configuration at ENA
703 exhibits the strongest positive dust-ACI index (log–log sensitivity of the cloud droplet
704 effective radius to dust-layer optical depth), indicating cloud brightening through reductions
705 in R_e with increasing DLOD, aided by local meteorology. In contrast, the Bottom and Middle
706 configurations exhibit contrasting dust-ACI indices over ocean and land that are strongly
707 modulated by LWP and local meteorological conditions. Specifically, over the marine site at
708 ENA, local meteorology amplifies the positive dust-ACI index for the Middle configuration
709 and suppresses it for the Bottom configuration. In addition, increased LWP in both
710 configurations enhances the dust-ACI index, even resulting in positive values at the high-
711 LWP regime for the Bottom configuration. Over the continental site at SGP, LWP and local
712 meteorology suppress the dust-ACI indices for both the Middle and Bottom configurations,
713 resulting in a negative dust-ACI index for the Middle configuration and a reduced positive
714 dust-ACI index for the Bottom configuration.

715 These contrasting cloud responses can be understood through three pathways that
716 balance semi-direct and microphysical effects (Fig. 5). For the Top configuration, shortwave
717 absorption warms the overlying free troposphere and strengthens lower-tropospheric
718 stability, suppressing cloud-top entrainment of dry air and preserving higher droplet number
719 concentrations in the resulting thinner, shallower clouds, thereby reducing R_e and
720 producing the strong positive dust-ACI index at ENA. For the Middle configuration,
721 competing pathways dominate in different regimes, whereby over the marine ENA, where
722 background CCN are scarce, fine-mode dust activates additional droplets and reduces R_e ,
723 whereas over the continental SGP, abundant background CCN mute this effect while in-
724 cloud absorptive warming evaporates droplets and increases R_e . For the Bottom
725 configuration, sub-cloud heating elevates the cloud base, and the dominant nucleating
726 mode diverges between environments: coarse dust can act as giant CCN over the weakly
727 mixed marine boundary layer aided by increased in-cloud water vapor, forming fewer, larger
728 droplets, while strong continental mixing delivers finer dust that activates as conventional
729 CCN, reducing R_e . Across all three configurations, local meteorology modulates dust-cloud
730 sensitivities, masking an underlying microphysical brightening that emerges once
731 meteorological covariability is removed.

732 Our findings have important implications for the assessment of dust–cloud
733 interactions in climate models. Current climate and regional models typically represent
734 aerosol–cloud interactions using column-integrated aerosol optical depth or near-surface
735 aerosol concentration as proxies for the aerosol burden that influences clouds (P.-L. Ma et
736 al., 2018; Painemal et al., 2020). Our results demonstrate that such column-integrated
737 metrics are insufficient to capture the configuration-dependent cloud responses

738 documented here, because the sign and magnitude of the dust-ACI index depend not only
739 on dust loading but critically on where dust resides relative to the cloud layer (Fig. 3 and 4).
740 In addition, this problem is compounded by the well-documented difficulty that climate
741 models have in accurately simulating dust vertical distributions, particularly the elevated
742 transport of coarse dust that characterizes long-range pathways to sites such as ENA
743 (Adebisi et al., 2023; O’Sullivan et al., 2020). Furthermore, our results highlight that the
744 environmental regime (marine or continental) influences the microphysical and semi-direct
745 (thermodynamic) pathways through which dust affects R_e , because this determines
746 whether meteorology enhances or suppresses dust–cloud interactions (Fig. 4).

747 Our findings are subject to some caveats. First, an important limitation of our study
748 is the low occurrence frequency of the Top dust–cloud configuration at both ARM sites,
749 particularly at SGP, where it is too rare for robust statistical analysis. This limitation arises
750 partly from the physical rarity of elevated dust above low-level clouds at these locations, but
751 also from an inherent constraint of ground-based lidar. Specifically, signal attenuation by
752 the intervening cloud layer reduces sensitivity to aerosol layers residing above clouds,
753 increasing retrieval uncertainty for the Top configuration relative to the Bottom configuration
754 (Proestakis et al., 2018; Thorsen et al., 2017). This asymmetry is the inverse of the
755 attenuation challenge faced by spaceborne lidars such as CALIPSO, for which cloud
756 attenuation preferentially limits detection of below-cloud dust and therefore under-sample
757 the Bottom configuration (Fig. 2a and Fig. S4a). One approach for future studies to minimize
758 this limitation is to perform coordinated aircraft-based in situ measurements during dust
759 transport events, which could provide direct characterization of above-cloud dust
760 properties that are inaccessible to passive or attenuated lidar retrievals (Cochrane et al.,
761 2019; Wang et al., 2022). Second, another key limitation is that the median DLOD at both
762 ENA and SGP is very low (Fig. 2b and 2f), reflecting their position off the major dust-transport
763 corridors (Wang et al., 2020; Lambert et al., 2020). At such low loadings, the dust-induced
764 perturbation to cloud droplet effective radius is small and difficult to separate from
765 meteorological covariability, limiting statistical power and the generalizability of the inferred
766 sensitivities. As such, our observed sensitivities likely represent the lower bound of dust–
767 cloud interactions (Kok et al., 2023). Importantly, the balance between semi-direct and
768 microphysical pathways is likely nonlinear; under high-DLOD conditions, stronger
769 shortwave absorption could amplify semi-direct or thermodynamic adjustments relative to
770 microphysical effects (Pandey et al., 2026c), potentially altering the sign and magnitude of
771 the dust-ACI index reported here. Third, although our multiple linear regression controls for
772 five meteorological variables, it cannot fully isolate the dust signal, because dust-induced
773 semi-direct heating is itself embedded within the thermodynamic background (Johnson et
774 al., 2004). Consequently, the meteorology-adjusted dust-ACI index likely reflects statistical
775 covariability rather than a fully causal attribution of cloud responses to dust (Su et al., 2024).
776 Regardless of these observational and methodological limitations, our findings indicate that
777 future estimates of dust radiative forcing will depend critically on how well models and
778 observations represent dust–cloud vertical configuration, because this configuration
779 determines whether dust brightens or darkens low-level clouds through changes in cloud
780 droplet effective radius and associated cloud albedo.

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784 **Open Research**

785 The processed data and analysis code used to reproduce the results in this study are
786 available through Zenodo at <https://zenodo.org/records/20696213>. The original
787 observational data used in this study were obtained from publicly available data
788 repositories. CALIPSO fine- and coarse-mode dust products developed by Proestakis et al.
789 (2024) are available at <https://zenodo.org/records/10389741>. CloudSat observations are
790 available from the CloudSat Data Processing Center at
791 <https://www.cloudsat.cira.colostate.edu/>. MODIS data were obtained from the A-Train
792 Data Depot at NASA GES DISC at
793 <https://atrain.gesdisc.eosdis.nasa.gov/data/MAC/MAC06S0.002/>. ARM observations were
794 obtained from the U.S. Department of Energy Atmospheric Radiation Measurement Data
795 Center, including RLPROF-FEX for aerosol extinction, depolarization ratio, and scattering
796 ratio at <https://www.arm.gov/data/science-data-products/vaps/rlprof-fex>; ARSCL for cloud
797 base height, cloud top height, and cloud-layer information at
798 <https://www.arm.gov/data/science-data-products/vaps/arscl>; MFRSRCLDOD for cloud
799 droplet effective radius and liquid water path at [https://www.arm.gov/data/science-data-](https://www.arm.gov/data/science-data-products/vaps/mfrsrclod)
800 [products/vaps/mfrsrclod](https://www.arm.gov/data/science-data-products/vaps/mfrsrclod); SONDEGRID for relative humidity, temperature, potential
801 temperature, and wind speed at [https://www.arm.gov/data/science-data-](https://www.arm.gov/data/science-data-products/vaps/sondegrid)
802 [products/vaps/sondegrid](https://www.arm.gov/data/science-data-products/vaps/sondegrid); and DLPROF-WSTATS for Doppler-lidar vertical velocity statistics
803 at <https://www.arm.gov/data/science-data-products/vaps/dlprof-wstats>.

804 **Conflict of Interest**

805 The authors declare there are no conflicts of interest for this study.

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