Indications of a Decrease in the Depth of Deep Convective Cores with Increasing Aerosol Concentration during the CACTI Campaign

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(Manuscript received 2 May 2021, in final form 29 November 2021)

ABSTRACT: An aerosol indirect effect on deep convective cores (DCCs), by which increasing aerosol concentration increases cloud-top height via enhanced latent heating and updraft velocity, has been proposed in many studies. However, the magnitude of this effect remains uncertain due to aerosol measurement limitations, modulation of the effect by meteorological conditions, and difficulties untangling meteorological and aerosol effects on DCCs. The Cloud, Aerosol, and Complex Terrain Interactions (CACTI) campaign in 2018–19 produced concentrated aerosol and cloud observations in a location with frequent DCCs, providing an opportunity to examine the proposed aerosol indirect effect on DCC depth in a rigorous and robust manner. For periods throughout the campaign with well-mixed boundary layers, we analyze relationships that exist between aerosol variables (condensation nuclei concentration, 0.4% cloud condensation nuclei concentration, 55–1000-nm aerosol concentration, and aerosol optical depth) and meteorological variables [level of neutral buoyancy (LNB), convective available potential energy, midlevel relative humidity, and deep-layer vertical wind shear] with the maximum radar-echo-top height and cloud-top temperature (CTT) of DCCs. Meteorological variables such as LNB and deep-layer shear are strongly correlated with DCC depth. LNB is also highly correlated with three of the aerosol variables. After accounting for meteorological correlations, increasing values of the aerosol variables [with the exception of one formulation of aerosol optical depth (AOD)] are generally correlated at a statistically significant level with a warmer CTT of DCCs. Therefore, for the study region and period considered, increasing aerosol concentration is mostly associated with a decrease in DCC depth.

KEYWORDS: Aerosols; Buoyancy; Cloud microphysics; Convective storms; Convective-scale processes; Mesoscale systems; Thermodynamics; In situ atmospheric observations; Remote sensing

1. Introduction

The impact of atmospheric aerosols on clouds represents a key source of uncertainty in future climate projections (IPCC 2013). One particularly important problem is determining the effects of aerosols on deep convective cores (DCCs). Changes in the frequency, intensity, coverage, and vertical extent of DCCs can alter the global hydrologic cycle and radiation budget (Houze 1982; Ackermann et al. 1988; Randall et al. 1989). Despite nearly two decades of study, however, the effects of aerosols on DCCs remain inconclusive (e.g., Altaraz et al. 2014; Fan et al. 2016).

The primary pathway for aerosols to affect liquid phase clouds is through a decrease in cloud droplet size as the droplet concentration increases with increasing cloud condensation nuclei (CCN) concentration (e.g., Gunn and Phillips 1957; Borisy et al. 1998; Cecchini et al. 2017). This has been shown to decrease the efficiency of collision–coalescence in warm clouds, suppressing rainfall (e.g., Rosenfeld 1999; Braga et al. 2017; Toll et al. 2019).

In the case of mixed-phase DCCs, it is hypothesized that this suppression of rainfall in relatively higher CCN (i.e., “polluted”) conditions allows more liquid to rise above the freezing level in updrafts, where the addition of the latent heat of fusion increases the latent heat release. This extra heating is hypothesized to result in an “invigoration” of mixed-phase convection [hereafter aerosol-induced invigoration of convection (AIIC)] that can manifest as higher cloud tops, a higher center of mass of cloud water or ice, greater updraft mass flux, and/or greater updraft speeds (e.g., Andreae et al. 2004; Khain et al. 2005; Rosenfeld et al. 2008).

A large body of prior studies has been dedicated to this topic using numerical modeling or observational data, with

Guo et al. 2016; Peng et al. 2016; Chen et al. 2017; Fan et al. 2018),
2) others failing to find invigoration (e.g., Morrison and Grabowski 2011; Morrison 2012; Boucher and Quaas 2013; Wall et al. 2014; Grabowski 2015; Grabowski and Morrison 2016; White et al. 2017; Varble 2018; Miltenberger et al. 2018; Grabowski 2018; Heikenfeld et al. 2019; Grabowski and Morrison 2020),
3) and others finding a complex or multimodal response (e.g., Fan et al. 2007, 2009; van den Heever and Cotton 2007; Khain et al. 2008; Khain 2009; Lebo and Morrison 2014; Gryspeerdt et al. 2014b; Jiang et al. 2018; Marinescu et al. 2021).

There are a number of factors that produce these widely inconsistent results. In modeling studies, bin and multimoment bulk schemes often produce vastly different results (e.g., Lebo and Seinfeld 2011; Grabowski 2015; Grabowski and Morrison 2016; Fan et al. 2016) with all producing convective microphysical biases relative to observations (e.g., Fan et al. 2017; Stanford et al. 2019). The degree to which the two-way interaction between aerosols and environment is represented (e.g., how aerosols are generated and whether they can be eliminated by in-cloud scavenging) can also affect the cloud response (Miltenberger et al. 2018). Some schemes have a saturation adjustment stipulation that converts all supersaturation at each time step to condensate, while others allow supersaturation to persist, and this difference can profoundly change the way in which CCN are able to affect convective updrafts and the heating within them (Lebo et al. 2012; Grabowski and Morrison 2017). Some studies use three-dimensional domains while others use two dimensions, a choice characterized by several tradeoffs (e.g., Storer and van den Heever 2013; Lebo 2014; Altaraz et al. 2014), and model grid spacing also varies, with significant impacts on convective updraft properties (e.g., Bryan and Morrison 2003, 2012; Varble et al. 2014, 2020; Lebo and Morrison 2015; Wang et al. 2020). Finally, the uncertainty from the choice of microphysics scheme can exceed the effects caused by aerosol perturbations (e.g., White et al. 2017), as can the effects of small changes in initial conditions (Grabowski 2018) or the choice of atmospheric model (Marinescu et al. 2021). Grabowski (2019) argues that modeling approaches to date have not been sufficient to differentiate the effects of aerosol perturbations from the effects of initial condition uncertainty in a chaotic system like the atmosphere during moist convection.

In observational studies, the foremost difficulty is that AIIC is likely a second-order effect on convective updraft intensity and depth, as compared to first-order effects from convection-relevant meteorological variables including convective available potential energy (CAPE), level of neutral buoyancy (LNB; also known as equilibrium level or maximum parcel level), vertical wind shear, and free-tropospheric relative humidity. Separating the effects of AIIC from meteorology can be difficult in observational studies and is often not done appropriately (as discussed in Varble 2018). Another challenge is that the scarcity of direct observations of aerosol or CCN concentrations has resulted in reliance on remotely sensed proxies like aerosol optical depth (AOD), but retrieved AOD increases with relative humidity as aerosols grow in size rather than number concentration, often in increasing proximity to clouds correlated with humidity. AOD is also not collocated with clouds because it needs to be retrieved in clear air conditions and is not necessarily a good proxy for CCN concentration in the limited depth convective inflow layer (e.g., Zhang et al. 2005; Mauger and Norris 2007; Chew et al. 2011; Chand et al. 2012; Omar et al. 2013; Altaraz et al. 2013; Gryspeerdt et al. 2014a; Ma et al. 2018). Some studies use aircraft measurements of aerosol and droplet size distributions (e.g., Andreae et al. 2004; Braga et al. 2017). These are the most definitive measurements for addressing the issue, but such sampling is limited to select field campaign cases that are insufficient to fully remove meteorological and cloud life cycle effects on aerosol–cloud correlations. Finally, in situ measured aerosol concentration often used in studies does not equate directly to CCN concentrations that depend on supersaturation. These many observational sampling limitations make isolation and quantification of an aerosol effect difficult.

Further observational study of AIIC is needed across new geographic regions and meteorological regimes using methods that carefully and appropriately quantify the complex relationships between convective vigor, relevant meteorological variables, and the concentration of CCN. This study will accomplish these goals using data gathered during the U.S. Department of Energy’s Atmospheric Radiation Measurement (ARM) Cloud, Aerosol, and Complex Terrain Interactions (CACTI) field campaign (Varble et al. 2021) that took place from 1 October 2018 to 30 April 2019 in central Argentina (Fig. 1).

2. Data and methods
   a. Aerosol data

Aerosol data were gathered at the ARM Mobile Facility 1 (AMF1), which was located at a site along the eastern slope of the Sierras de Córdoba mountain range (Fig. 1) for the duration of the CACTI campaign. Aerosol concentration (hereafter referred to as AC) is observed by the Ultra High Sensitivity Aerosol Spectrometer instrument (UHSAS; Koonz and Flynn 2018), which measures the sum of particle counts in the size range from 55 to 1000 nm. Condensation nuclei (CN) is observed by the fine mode Condensation Particle Counter (Kuang et al. 2018), which measures the number of particles > 10 nm that grow when subjected to supersaturation. CCN data come from the dual-column CCN counter (Uin et al. 2018). The CCN counter varies supersaturation at several setpoints between 0% and 1% at 1.5-hourly frequency in column A, and fixes it at 0.4% in column B. The instrument then measures, for each column, the number of aerosol particles that are activated (increase in size upon exposure to a supersaturation). Because of the short time that the supersaturation is at each setpoint in column A and its less stationary value near these setpoints, we use column B data in our analyses, and hereafter these data are referred to as simply “CCN.”
AOD at 500 nm was obtained from the Cimel sun photometer at the site (Gregory and Sivaraman 2018). AOD is not retrievable when optically thick clouds obscure the solar disc, and the instrument can output spurious high AOD values when the solar disc is behind a thin cirrus cloud or when the cloud fraction is high. The dataset, as obtained, is quality controlled to remove such spurious values. We manually examined footage from a camera attached to the instrument for ∼10% of cases to confirm that there were indeed no incidences of cloud-induced (or any other) spurious values detected. The AOD values also exhibit a diurnal cycle, with higher values occurring during lower solar zenith angles. To mitigate this issue as much as possible, we exclude any AOD values occurring with a solar zenith angle greater than 50°.

Detailed descriptions of all instruments can be found at https://www.arm.gov/capabilities. A time series of the above data is shown in Fig. 2, along with 2-m temperature and relative humidity, and gauge-measured precipitation, for context. The three surface-based variables (AC, CN, and CCN) are collected at a native frequency of 1 min⁻¹ or less, and as mentioned in the next section, sounding data are collected 4–5 times per day. Therefore the AC, CN, and CCN values used in the analyses presented later in this study are an average from 2 h before to 2 h after a sounding launch. For AOD, we define AOD2 as the mean of all values within ±2 h of a sounding, with a minimum of 2 AOD retrievals required in that period. AOD1 is defined as the mean of all values within a daylight period with at least 2 AOD retrievals. We experimented with a number of different methods of attributing the values to DCCs, and all methods yielded effects either similar to (but less conclusive than) those shown in later sections, or inconclusive results.

b. Atmospheric profiles

Radiosondes were launched at approximately 1200 (0900 local), 1500, 1800, 2100, and 0000 UTC on days forecasted to produce deep convection initiation throughout the campaign at AMF1. On other days, the radiosonde launches were changed to 1200, 1600, 2000, and 0000 UTC. Four meteorological variables with likely significant effects on deep convection were calculated from these soundings using the MetPy Python package (May et al. 2020). These are LNB, CAPE, bulk wind shear between 2 and 6 km MSL (hereafter SHR), and the mean midlevel relative humidity (between 700 and 500 hPa; hereafter MLRH). The specific vertical thresholds for SHR and MLRH were selected because they had the strongest effect on the depth of DCCs in analyses presented later in this study.

We then omitted soundings from periods where surface-based air properties including aerosol concentrations would not be expected to be representative of those feeding the updraft of a DCC based on thermodynamic stability. After examining soundings throughout the campaign and data from the 17 flights of the G-1 aircraft during intensive observing periods, we determined that a sounding with the following criteria should be deemed “valid”:

1) CAPE of the most unstable parcel and the surface-based parcel must exceed 100 J kg⁻¹. This ensures that synoptically forced stratiform cases are excluded, and that the surface-based parcel is conditionally unstable such that it can produce moist convection.
2) The most unstable parcel cannot originate more than 200 m above the surface-based lifting condensation level (LCL). This ensures that surface-based parcels are likely to be ingested into cloud base.
3) The potential temperature of the most unstable parcel cannot exceed that of the surface-based parcel by more than 2 K. In soundings with a “classic” dry adiabatic profile up to cloud base, 2 K represented the scale of variability within the convective boundary layer.

Of the 935 AMF1 soundings launched during CACTI, 282 were deemed valid (shown in the time series in Figs. 2f,g). We also experimented with a number of other criteria for defining
valid soundings, and the results of the analyses presented later in this study did not vary substantially.

c. Identifying DCCs

We identify DCCs in two independent datasets: full volume scans from the C-band Scanning ARM Precipitation Radar (CSAPR2) located at AMF1 (Hardin et al. 2020), and 11.2-μm infrared brightness temperature from the GOES-16 satellite. CSAPR2 conducted full volume scans every 15 min from 1 October to 2 March, at which point its ability to scan azimuthally was disabled. Within the 1 October to 2 March period, data are unavailable for 42 days. A full volume scan consisted of a series of plan position indicator (PPI) scans at successively higher elevation angles, followed by a series of hemispheric range–height indicator (RHI) scans. Volume scans were interpolated to a 3D Cartesian grid at 0.018 horizontal and 200-m vertical resolution using the Radx software (Dixon 2010; now part of the LROSE software package) with the "INTERP_MODE_CART" method and a minimum of three points for interpolation. Within the 3D data, DCCs were identified using the following procedure:

1) The reflectivity data at each vertical level are smoothed in the horizontal using a three-point uniform filter.
2) Local maxima in the reflectivity field at 5 km MSL are identified using the Python library scikit-image (van der Walt et al. 2014). The algorithm requires the user to specify a minimum reflectivity value and a minimum distance between local maxima. We added an additional constraint that the maxima must

FIG. 2. Time series for the full CACTI campaign of (a) CCN and AC, (b) CN, (c) AOD at 500 nm, (d) 2-m relative humidity, (e) surface precipitation, (f) LNB, and (g) SHR from the 282 valid soundings. All instruments were located at AMF1.
exceed a relative threshold above the surrounding field within a 5-pixel radius. After experimentation to match an intuitive partitioning of convective cells, we chose minimum reflectivity, minimum distance, and minimum relative thresholds of $20 \text{ dB}_Z$, 7 pixels, and $5 \text{ dB}_Z$, respectively. The 5-km level was selected because it represents a reasonable minimum depth for deep precipitating convection while also retaining much of the cellular structure present at lower levels.

3) The DCC is then defined in the vertical by following the local horizontal maxima (within a three-gridpoint radius) at each level upward until reflectivity falls below $15 \text{ dB}_Z$. Because the DCC follows the local horizontal maxima, it can be tilted in the vertical and join or diverge from another DCC at various levels, which is consistent with the structure of deep convective systems.

4) Any DCCs that fall within 10 km of the outer edge of the radar domain or within 2 km of the edge of the “cone of silence” at any level are then excluded from the analysis, and is not numbered.

5) Only DCCs that extend above 6.5 km MSL are included in the subsequent analysis. Ongoing work indicates a distinct bimodal distribution of convective cloud tops, with a “shallow” mode below 6 km and a “deep” mode above 6 km. Thus, a 6.5-km height threshold ensures a distribution firmly within the deep mode.

An example of the process is shown in Fig. 3, where the DCCs identified in a CSAPR2 scan are shown at multiple levels.

**GOES-16** scans at 15-min frequency were obtained from the ARM catalog (**ARM 2018**). To identify DCCs, we begin with the 11.2-$\mu$m infrared brightness temperature field, smoothed with a three-point uniform filter, and the cloud optical depth (COD) product, smoothed with a five-point uniform filter (Fig. 4). The COD field requires the coarser filter because it is noisier. The coldest point in the temperature field within a 108-km radius of AMF1 (approximately equivalent to the CSAPR2 domain) is then identified, and if it is cooler than $-24.8^\circ\text{C}$, it is considered a candidate DCC. The $-4^\circ\text{C}$ temperature threshold excludes low clouds and high terrain, and it is used as an initial filter by a number of past studies (e.g., **Li et al. 2011**; **Varble 2018**). Then the COD field is considered at the grid point of the candidate DCC, and if COD $\geq 30$ during the night or COD $\geq 50$ during the day, it becomes a valid DCC and is used in subsequent analyses. The threshold changes between night and day because the COD algorithm is calculated differently when there is no visible light, and experimentation determined that the chosen COD threshold best identifies the tops of DCCs and excludes cirrus and altocumulus clouds, as verified during periods when CSAPR2 reflectivity is available. The 11.2-$\mu$m infrared brightness temperature...
of this valid DCC is saved as the cloud-top temperature (CTT) for that GOES-16 scan. An example is shown in Fig. 4.

3. Univariate statistics

a. Correlation among environmental variables

We first examine correlations between the meteorological and aerosol variables in univariate space for all representative periods in order to understand potential impacts on aerosol–DCC relationship interpretation. The very strong positive correlation between LNB and CAPE is immediately apparent in both the 282 valid soundings (Fig. 5a), and the subset of 148 soundings that is associated with at least one DCC in the GOES-16 CTT data (Fig. 5b), with $R^2$ values of 0.65 and 0.75, respectively. This very strong correlation makes sense given the use of LNB in computing CAPE. There is a weak negative correlation between MLRH and LNB in both the full dataset (Fig. 5a) and the GOES-16 subset (Fig. 5b), potentially reflecting moistening and stabilization of the troposphere via ongoing precipitating convection and/or steeper lapse rates being associated with both higher LNB and drier conditions. Similarly, there is a weak negative correlation between MLRH and CAPE in the GOES-16 subset (Fig. 5b), though no correlation exists in the full dataset (Fig. 5a). SHR has no significant correlations with any of the other meteorological variables, or aerosol variables for that matter.

Among the aerosol variables, the strongest correlation is between AC and CCN, with $R^2$ values of 0.87 and 0.92 in the respective datasets. The two AOD variables, AOD1 and AOD2, also have a very strong correlation with one another. The next strongest correlation for aerosol variables is between CN and AC, with $R^2$ values of 0.26 and 0.32 in the respective datasets (Fig. 5). There is only a moderate correlation between CCN and CN ($R^2$ values of 0.14 and 0.21). Of the three surface-based aerosol measurements, CCN has the strongest relationship with AOD1 and AOD2. In the GOES-16 subset (Fig. 5b), CCN is moderately correlated with AOD1 ($R^2 = 0.15$), but strongly correlated with AOD2 ($R^2 = 0.26$). AC has a weaker relationship with the AOD variables. In the GOES-16 subset (Fig. 5b), AC is weakly correlated with AOD1, but moderately correlated with AOD2. There is no useful correlation between CN and AOD1 or AOD2 in either of the datasets.

In the pairs of meteorological variables with aerosol variables, the strongest relationship is between LNB and the AOD variables. It is strong in the full dataset, and even stronger in the GOES-16 subset. The relationship is similar between CAPE and the AOD variables. Two of the surface aerosol variables, CCN and AC, are also positively correlated with LNB and CAPE, though the correlation is much weaker (Fig. 5). Interestingly, the third surface aerosol variable, CN, has almost no relationship with the thermodynamic variables, with only a weak correlation with CAPE in the GOES-16 subset (Fig. 5b).

The comparison among aerosol variables warrants some further discussion of what the variables are measuring and how this affects their relationship to one another. AC is a count of all aerosols in the 55–1000-nm range (though counts in the lower end of that range are biased low; Cai et al. 2008). CCN is a measure of only the number of aerosols that are activated when subjected to 0.4% supersaturation, a condition which often excludes particles in the lower end of the AC size distribution (they are less likely to be activated). The CN variable includes even smaller aerosols than AC (as small as 10 nm), subjected to a very high supersaturation, which yields much greater aerosol counts than either AC or CCN. Their differences are evident in Fig. 2a and Fig. 2b, with CCN having the lowest concentrations, AC being slightly higher, and CN having concentrations often >3 times higher than the other two. Depending on the supersaturations experienced...
within a particular DCC, any of the three variables may be representative of the activated nuclei.

The formulation of AOD impacts its relationship with the surface-based aerosol variables. The correlation of CCN and AC with AOD2 is much stronger than the correlation of CCN and AC with AOD1. This likely reflects the fact that AOD1 is mean of all AOD retrievals in a daylight period, while AOD2 is a mean calculated over the same (4-h) period as the surface-based variables. Even for AOD2, however, its relationship with the surface-based variables would not be expected to be extremely strong, as AOD retrievals respond to aerosol concentrations throughout the atmospheric column, and thus can be impacted by aerosols aloft that are divorced from those in the boundary layer. AOD also responds more to larger, optically active aerosols, and is thus often more closely related to total aerosol mass than number concentration. This is supported by the fact that the surface-based variable most strongly correlated with AOD1 and AOD2 is CCN, which is the most sensitive of the three to the larger side of the aerosol size spectrum. Similarly, AOD1 and AOD2 are least correlated (no correlation) with CN, which responds most strongly of the three to the smaller side of the aerosol size spectrum. Additionally, AOD1 and AOD2 are more strongly correlated with LNB and CAPE than they are with any of the surface-based aerosol variables, which implies that it may also be more strongly responding to the cloud fraction and/or relative humidity than changes in boundary layer aerosol concentrations, as described in Chand et al. (2012).

We next examine the relationship between these variables and the intensity of DCCs. As described in section 2, we define the intensity of DCCs using two different methods: core echo tops analyzed in 3D Cartesian gridded PPI volumes from CSAPR2 and CTT from GOES-16 scans.

### b. CSAPR2 DCCs

There were 2388 DCCs identified in the CSAPR2 data within 2 h of a valid sounding, with each DCC attributed once to the closest sounding. For each variable, DCCs are

![Figure 5](image-url)
partitioned into five approximately equal samples corresponding to the 0th–20th, 20th–40th, 40th–60th, 60th–80th, and 80th–100th percentiles of the variable. Each of these five groups is referred to as the first through fifth quintiles, respectively. The depth of the DCCs as represented by the 15-dBZ echo-top height increases with increasing LNB (Fig. 6a), with statistically significant differences at the 95% confidence level if the notched areas around the medians do not overlap, using the method of McGill et al. (1978). LNB (km) and SHR (m s\(^{-1}\)) of the samples in each quintile annotated, where the center line denotes the mean.

FIG. 6. Echo-top height of DCCs identified in the CSAPR2 data, as a function of quintiles of (a) LNB, (b) CAPE, (c) SHR, (d) MLRH, (e) CCN, (f) CN, (g) AC, and (h) AOD1. The total number of samples included in each subplot are, respectively, 2388, 2388, 2388, 2388, 2345, 2120, 2388, and 1510. The total number of unique soundings corresponding to those samples are, respectively, 77, 77, 77, 77, 76, 69, 77, and 46. The difference between medians is statistically significant at the 95% confidence level if the notched areas around the medians do not overlap, using the method of McGill et al. (1978). LNB (km) and SHR (m s\(^{-1}\)) of the samples in each quintile annotated, where the center line denotes the mean.

The depth of DCCs also increases as a function of CAPE (Fig. 6b), though the effect is not quite as consistent across the five quintiles as that of LNB, with a slight decrease in echo-top height from the second to third quintile. The effect of SHR on DCC depth, at least in this univariate treatment, is more subtle (Fig. 6c). The depth increases gradually from the first to the fifth quintile, but the only statistically significant comparison is that DCC depth is greater when SHR values are in the fifth quintile than it is when SHR values are in the first quintile. The effect of MLRH is obscured in the univariate space due to changes in LNB between quintiles, with DCC depth appearing to be responding primarily to LNB (Fig. 6d). Similarly, the effects of LNB on DCC depth are such that they obscure any potential signal for the aerosols variables: CCN, CN, AC, and AOD1 (Figs. 6e–h). This is most pronounced for AOD1, for which greater values generally correlate with deeper DCCs but also higher LNB values. Thus, no effect from aerosols can be discerned from the data in Fig. 6, and it is clear that LNB (which largely encapsulates effects of CAPE) needs to be controlled for to isolate DCC depth.
relationships with other variables. All of the results described for AOD1 in Fig. 6h also apply to AOD2, which is omitted for brevity.

c. GOES-16 cloud-top temperature

Because the CSAPR2 radar was down for parts of the campaign, it has fewer independent samples (soundings) than the full CACTI period allows. It also relies on a 3D Cartesian gridding of reflectivity data and a reflectivity threshold which may not well capture the true cloud top. Therefore, we next examine GOES-16 CTT as a function of the environmental variables, for times only within 2 h of a valid sounding, and each instance attributed once to the closest sounding.

Increasing values of LNB are correlated with colder CTT values, with statistically significant differences between all quintiles except for the first and second (Fig. 7a). There is a similar effect from CAPE, though the second, third, and fourth quintiles are not significantly colder than one another (Fig. 7b). Increasing values of SHR are generally associated with colder CTTs, though the fourth and fifth quintiles are not significantly colder than the third (Fig. 7c). The relationship between MLRH and CTT is mostly obscured by the effects of the LNB of each quintile, though CTT in the fifth quintile is significantly colder than all the others, despite having the smallest value of LNB, perhaps suggesting colder CTT with increasing MLRH (Fig. 7d). Looking from the first through fifth quintiles of CCN, there is a general increase in LNB (similar correlation also evident in Fig. 5b), but no significant trend in CTT (Fig. 7e). The lack of a trend in CTT, despite gradually increasing LNB values, potentially suggests subtle warming of CTT as a function of increasing CCN values. For CN, increasing values do not have any correlation with LNB, but the CTT in the fourth and fifth quintiles is significantly warmer than CTT in the first and second quintiles, suggesting subtle warming as a function of CN (Fig. 7f). Looking from the first through fifth quintiles of AC, there is a general increase in LNB, with perhaps a slightly warming CTT,
suggesting subtle warming of CTT as a function of increasing AC values (Fig. 7g). AOD1 is very strongly correlated with LNB, and correspondingly, the CTT becomes significantly colder from the third to fifth quintiles (Fig. 7h). This precludes isolation of any relationship between AOD1 and CTT. All of the results described for AOD1 in Fig. 7h also apply to AOD2, which is omitted for brevity.

We next apply a filter to the CTT data that helps isolate the effects of AIIC. We include only those with temperatures below the $\sim 20^\circ$C level to increase the probability that precipitation processes are mixed-phase and an LCL warmer than the $12^\circ$C level to ensure a deep region of liquid cloud susceptible to warm rain suppression. The $\sim 20^\circ$C CTT threshold also represents a good delineator between a shallow and a deep mode in the distribution of convective clouds during CACTI (not shown).

In this cold CTT–warm LCL subset, the effects of LNB and CAPE on CTT are similar to those in the full dataset, although the relationship is less robust (cf. Figs. 7a,b with Figs. 8a,b). In fact, the CTT in the fourth CAPE quintile is significantly warmer than the third and second quintiles (Fig. 8b). This may be a product of the $>25\%$ decrease in sample size that the subset yields. The relationship between SHR and CTT, however, is more robust in this subset, with CTTs generally becoming colder with increasing quintile. This trend levels off with fourth and fifth quintiles, which are not significantly colder than the third, potentially due to the competing effect from their lower LNB (Fig. 8c). The effect of MLRH is somewhat obscured by the effects of the LNB of each quintile, though CTT in the fifth quintile is significantly colder than all the others, despite having the smallest value of LNB, suggesting colder CTT with increasing MLRH (Fig. 8d). For CCN and AC, there is an increase in LNB with increasing quintile, but this does not yield any significant decrease in CTT (Figs. 8e,g). This suggests a subtle trend of warmer CTT with increasing CCN and AC. For CN, increasing values generally correspond to increasing LNB, with a slight warming of CTT moving from the first to fifth quintile,
suggesting warming CTT as a function of CN (Fig. 8f). Increasing values of AOD1 are again strongly correlated with increasing LNB, though CTT does not become significantly cooler from the third through fifth quintiles (Fig. 8h). All of the results described for AOD1 in Fig. 8h also apply to AOD2, which is omitted for brevity.

4. Bivariate statistics

A more complex bivariate treatment of relationships allows for better control of LNB’s effect on other relationships. Variables are divided into “low” (<40th percentile) and “high” (>60th percentile) categories, and this yields four combinations (low–low, low–high, high–low, high–high) for a pair of variables.

In the full GOES-16 dataset, during periods of low LNB, the increase from low to high SHR yields much colder CTTs. During periods of high LNB, the increase from low to high SHR also yields colder CTTs (Fig. 9a). During periods of low SHR, the increase from low to high LNB yields much colder CTTs, and it does the same during periods of high SHR. Thus, increasing SHR is associated with cooling CTTs. For periods of low LNB, the increase in MLRH from low to high yields no significant change in CTTs, but LNB for low LNB–low MLRH is 0.7 km higher than that for low LNB–high MLRH, which makes the comparison inconclusive (Fig. 9b). For periods of high LNB, higher MLRH is associated with significantly colder CTTs at both high LNB and low LNB (Fig. 9d). Under high LNB conditions, increased AC corresponds to significantly warmer CTTs, despite LNB at high AC that is 0.5 km taller (Fig. 9e).

We conduct the same analysis using the cold CTT–warm LCL subset, as this represents the conditions under which AICL would be expected. The results are very similar to those for the full GOES-16 period. Increasing SHR is associated with significantly colder CTTs (Fig. 10a). Increasing MLRH is associated with significantly colder CTTs when LNB is high (Fig. 10b). For CCN, increased concentrations correspond to significantly warmer CTTs when LNB is high (Fig. 10c), even with slightly higher LNB for the high CCN bin. An increase in CN is correlated with significantly warmer CTTs at both high LNB and low LNB (Fig. 10d).

In summary, the bivariate analysis suggests that at least during periods in the 60th–100th percentiles of LNB, increases in all three surface-based aerosol variables are associated with significantly warmer CTTs. The analysis is not conducted for AOD1 or AOD2, as values of each are available for only ~55% and ~25%, respectively, of the times when DCCs are observed in the GOES-16 dataset, and the 4

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**Fig. 9.** CTT from the full GOES-16 dataset as a function of bivariate combinations of (a) LNB and SHR, (b) LNB and MLRH, (c) LNB and CCN, (d) LNB and CN, and (e) LNB and AC. The total number of samples included in each subplot are, respectively, 617, 626, 602, 543, and 617. The number of samples in each bivariate combination varies between 110 and 205. The number of corresponding unique soundings in each bivariate combination varies between 12 and 41. LNB (km) and SHR (m s$^{-1}$) of the samples in each quintile annotated; “L-” indicates the “low” (<40th percentile) category of a variable and “H-“ indicates the “high” (>60th percentile) category.
subdivisions of the multivariate treatment reduce the sample size in some bins below levels that are appropriate for analysis. This marks the limit of what can be gleaned from this bivariate treatment and motivates a more complex multivariate analysis to better isolate signals in the aerosol and meteorological variables.

5. Multivariate statistics

a. Multiple linear regression

To elucidate additional relationships using multivariate techniques, we first perform least squares multiple linear regression on the cold CTT–warm LCL subset of the GOES-16 CTT dataset (used in Figs. 8 and 10). The regression utilizes standardized anomalies of each variable, so the magnitudes of the coefficients correspond to their relative contribution to the relationship. We performed the regression with every permutation of the eight atmospheric and aerosol variables, and determined that including both LNB and CAPE, both very highly correlated, consistently relegated CAPE to a small coefficient with very little contribution to the fit, so it is omitted in the analyses presented. We similarly only include one aerosol variable in each regression, as including all of them at once does not improve the fit and makes it difficult to discern their individual effects.

The first regression includes all of the available CCN observations for the cold CTT–warm LCL subset (675 samples) and achieves a fit with $R^2 = 0.36$ (Fig. 11a), indicating that the included variables explain 36% of the observed variance in CTT. The most important variable is LNB with a standardized coefficient of $-0.56$, followed by SHR $(-0.32)$, MLRH $(-0.21)$, and finally CCN $(0.14)$. The negative signs on the coefficients of the first three variables indicate that they are associated with decreasing CTT (i.e., taller DCCs), and the positive coefficient for CCN indicates that it is associated with warming CTT. The 95% confidence intervals on each variable indicate that (1) LNB contributes significantly more than the other variables, 2) SHR contributes significantly more than MLRH or CCN, 3) MLRH and CCN do not contribute significantly more than one another, and 4) all variables contribute more than zero.

The second regression includes all of the available CN observations for the subset and achieves a fit with $R^2 = 0.35$ (Fig. 11b). The most important variable is LNB $(-0.54)$, followed by SHR $(-0.34)$, CN $(0.29)$, and finally MLRH $(-0.19)$. A third regression including all of the available AC observations for the subset achieves a fit with $R^2 = 0.37$ (Fig. 11c). The most important variable is LNB $(-0.58)$, followed by SHR $(-0.31)$, AC $(0.21)$, and finally MLRH $(-0.18)$. The fourth regression includes all of the available AOD1 observations for the subset, and achieves a fit with $R^2 = 0.46$ (Fig. 11d). The most important variable is LNB $(-0.68)$, followed by SHR $(-0.30)$, MLRH $(-0.22)$, and finally AOD1 $(0.13)$. The fifth regression includes all of the available AOD2 observations for the subset, and it does not produce a useful or significant result, with SHR as the most important variable $(-0.51)$, none of the other variables significantly different than one another, and no significant effect from MLRH or AOD2 (Fig. 11e).

In summary, the first four regressions indicate that LNB has the greatest contribution to the fit by a statistically significant margin, and SHR is the second most important variable, though in two of them it is not significantly greater than the third-place variable. In the first four regressions, the third-place or fourth-place variable is either MLRH or CN, MLRH and CN do not contribute significantly more than one another, and all variables contribute more than zero.
b. Random forest model

Due to limitations of multivariable linear regression, an additional approach of a random forest machine learning algorithm (Breiman 2001) from the scikit-learn Python package (Pedregosa et al. 2011) is implemented. Random forests are an ensemble method that work by forming a large number of individual decision trees with limited subsets of data and descriptive variables, which then averages the output of each of the individual tree elements (Breiman 2001). Originally designed to mitigate the overfitting tendencies of decision trees, they offer a powerful technique for regression and classification, as well as being amenable to model interrogation useful for understanding important features in datasets. The dataset is first put through a random split in which 70% of the samples are used for training the model, and 30% are used for testing. We then train a random forest regression model with 100 trees, with no constraint on maximum depth and split quality determined using mean squared error. Note that this corresponds to default values in scikit-learn. An additional exhaustive hyper parameter search showed no appreciable change in model performance. All results shown are evaluated over the test dataset.

The resulting regression yields a predicted CTT as a function of the input variables, and we present the corresponding \( R^2 \) value between predicted CTT and observed CTT, as is done in the multiple linear regression presented in section 5a. To calculate the relative importance of each feature (input variable) to the model, we use permutation feature importance, which is defined as the decrease in model performance when the values in a column are randomly reshuffled (Breiman 2001). This maintains the range and distribution of values but removes any correlation of the input with the output. In this case we test the permutation feature importance using the withheld test set to provide an independent verification of feature importance on data the model has not previously seen.

The first random forest regression includes all of the available CCN observations for the cold CTT–warm LCL subset (719 samples with 70% training–30% test split) and achieves a fit with \( R^2 = 0.75 \) (Fig. 12a). The most important variable is LNB, followed by SHR, then MLRH, and finally CCN. LNB is significantly more important than SHR, SHR is more significantly more important than MLRH, MLRH is significantly more important than CN, and all four variables contribute more than zero.

The second random forest regression includes all of the available CCN observations for the subset and achieves a fit with \( R^2 = 0.69 \) (Fig. 12b). The most important variable is LNB, followed by SHR, then CN, and finally MLRH. A third random forest regression including all of the available AC observations for the subset achieves a fit with \( R^2 = 0.75 \) (Fig. 12c). The most important variable is LNB, followed by SHR, then MLRH and AC. The fourth random forest regression includes all of the available AOD2 observations for the subset and achieves a fit with \( R^2 = 0.82 \) (Fig. 12d). The most important variable is LNB, followed by SHR, then MLRH, and finally AOD2. The fifth random forest regression includes all of the available AOD2 observations for the subset and achieves a fit with \( R^2 = 0.73 \) (Fig. 12e). The most important variable is SHR, followed by AOD2, then MLRH and LNB. This is an unusual result when compared to the other four regressions, and may be due to the fact that the sample size AOD2 is less than half that of AOD1, and less than 25% of that of the surface-based variables.

Because the random forest model can predict complex nonlinear relationships between input variables and the output

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**FIG. 11.** The MLR results for the subset of cold CTTs with warm LCLs, with \( R^2 \) values for the resulting fit, and coefficients from standardized anomalies, for a four-variable combination including (a) CCN, (b) CN, (c) AC, (d) AOD1, and (e) AOD2 as the fourth variables. A negative coefficient indicates that increasing values of the variable are associated with colder CTT. The difference between the coefficients is statistically significant at the 95% confidence level if the black whiskers do not overlap. The total number of samples included in each subplot are, respectively, 675, 651, 719, 390, and 159. The total number of unique soundings corresponding to those samples are, respectively, 102, 97, 106, 60, and 25.
variable, the sign of the contribution from each input variable cannot be output from the model in a straightforward way. It is possible, however, to gain some insight into the sign of each relationship by varying the values of each input variable one at a time (within the “test” subset) and then observing the effect on the output of predicted CTT. For each of the five random forest regression model in Fig. 12, we used the same LNB, SHR, and MLRH dataset, but then used five different versions of the respective aerosol dataset: the original dataset and the original dataset multiplied by 0.5, 0.75, 1.5, and 2.

For the first regression, the move from the 0.5× CCN dataset to the 2× CCN dataset yields a slight warming of CTT, though the increase is not statistically significant (Fig. 13a). For the second regression, increasing CN yields a strong increase in CTT, with 2× being significantly warmer than 0.5× and 0.75× (Fig. 13b). For the third regression, the move from the 0.5× AC dataset to the 2× AC dataset causes an increase in CTT, with the 1.5× and 2× datasets having significantly warmer CTT than the 0.5× and 0.75× datasets (Fig. 13c). For the fourth regression, increasing AOD1 yields no statistically significant change in CTT (Fig. 13d). In the fifth regression, there is no significant change in CTT as a function of increasing AOD2 (Fig. 13e). Thus, the relationships in the random forest regressions are a significantly warmer CTT...
with increasing aerosol concentrations for two variables (AC and CN), with no statistically significant effect for the other three variables (CCN, AOD1, and AOD2).

6. Summary and Conclusions

The 7-month CACTI campaign featured frequent deep convection initiation, with frequent collocated atmospheric soundings and a suite of aerosol measurements, representing a favorable dataset for the difficult task of isolating possible effects of aerosols on the depth of DCCs from those of meteorology. DCCs were defined in two independent datasets: 3D volumes from a C-band scanning radar, and infrared brightness temperature from the GOES-16 satellite. Four meteorological variables with effects on deep convection were identified in the soundings: level of neutral buoyancy (LNB), convective available potential energy (CAPE), 2–6 km MSL bulk shear (SHR), and mean 700–500-hPa relative humidity (MLRH). Five aerosol variables were identified from instruments at the same study site: the concentration of aerosols activated at 0.4% supersaturation (CCN), the concentration of aerosols > 10 nm in diameter (CN), the concentration of aerosols in the 55–1000-nm range (AC), and Cimel sun photometer aerosol optical depth (AOD1 and AOD2).

Increasing values of the meteorological variables are all correlated with deeper DCCs at a statistically significant level, with the strongest effect coming from LNB. The correlation between meteorology and aerosols consisted primarily of the effects from LNB and CAPE. Increasing values of LNB and CAPE are strongly correlated with increasing AOD1 and AOD2, and moderately correlated with increasing CCN and AC. In a univariate treatment, it is difficult to discern any significant correlation between the aerosol variables and the depth of DCCs that is independent of the influence from LNB. Moving to a bivariate treatment, a significant correlation between higher concentrations of three aerosol variables (CCN, CN, and AC) and warmer infrared cloud-top temperatures (CTTs) emerges, suggesting convection becomes shallower with increasing aerosol concentration. Moving to a multivariate treatment from multiple linear regression, correlation between increasing values of four of the aerosol variables and warmer CTTs is confirmed, independent of the effects of the four meteorological variables. There is no significant effect on CTT from the fifth variable, AOD2. A final multivariate method, regression from a random forest machine learning model, confirms that CN and AC have a statistically significant warming effect on CTT, though it yields an inconclusive nonlinear relationship for the other three variables (CCN, AOD1, and AOD2). The findings of increasing CTT as a function of increasing aerosol concentrations exist regardless of whether samples are limited to the conditions conducive to the mixed-phase aerosol–convective invigoration hypothesis—relatively deep warm cloud depth and cold cloud top. Therefore we find a general signal of DCCs becoming shallower as a function of increasing aerosol concentration during the CACTI campaign, though there is some uncertainty in this signal.

There are additional findings that should be considered in interpreting past studies and designing future ones. Similar to a study at a site in the Southern Great Plains of the United States by Varble (2018), aerosol concentrations (with the exception of CN) in the CACTI region are moderately to strongly correlated with LNB and CAPE. Such correlations with meteorological variables that have first-order effects on the depth of DCCs must be accounted for. This is especially true with the ground-based AOD used in this study, which was very well correlated with LNB and CAPE and had the weakest (negative or insignificant) correlation with the depth of DCCs after a careful multivariate analysis. Without the multivariate analysis, which accounted for the effects of LNB and CAPE, AOD would have instead appeared positively correlated with DCC depth. Spaceborne AOD measurements introduce further sources of uncertainty.

There are some caveats that are important to consider when interpreting our findings. The 7-month period with over 900 soundings is long by some standards, but when the constraints are applied to narrow the analysis to convective events conducive to potential mixed-phase invigoration, the analysis relies on 106 soundings. This may be insufficient to capture mixed-phase invigoration. We also did not attempt to account for stages of the life cycle or modes of organization of deep convection, which may respond differently to aerosol perturbations. Aerosol effects also may be nonlinear and/or nonmonotonic as aerosol concentration increases. Our study also relies on measurements from a single point to represent the conditions for all DCCs within a 108-km radius, and therefore does not account for vertical and horizontal heterogeneities in aerosol concentration. Finally, this study may have indeed captured a legitimate signal that is only valid in the climate and geography of the study region.

A prime subject for further study is the effect of geography and regionally varying meteorological parameters on the sign of aerosol–convective effects. It would also be fruitful, as the era of high-resolution meteorological parameters on the sign of aerosol–convective effects. It would also be fruitful, as the era of high-resolution infrared brightness temperature data from GOES-16 grows to include many years, that observational studies be conducted at sites with longer multiyear, high-quality in situ aerosol datasets.

Acknowledgments. This research was supported by U.S. Department of Energy Grant DE-SC0020056. Additional support was provided by the U.S. Department of Energy Office of Science Biological and Environmental Research as part of the Atmospheric System Research program. Pacific Northwest National Laboratory is operated by Battelle for the U.S. Department of Energy under Contract DE-AC05-76RLO1830. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding organizations. Analyses were performed using Python software packages. We thank ARM, NOAA, Unidata, the University of Utah Center for High Performance Computing, the Compute and Data Environment for Science at Oak Ridge National Laboratory, and the National Energy Research Scientific Computing Center at Lawrence Berkeley National Laboratory.
National Laboratory for the provision of datasets, software, and computing resources.

Data availability statement. All code used in this study is available from the authors upon request. Data are all freely available online for download from https://adc.arm.gov/discovery/.

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