

Ice-nucleating particles from open-lot livestock facilities in Texas Feedlot is a unique and constant source of atmospheric ice-nucleating particles

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Abstract.

This study presents a comprehensive investigation of ice-nucleating particles (INPs) from open-lot livestock facilities (OLLFs) in Texas, USA. A three-year field survey (2017 – 2019) was conducted to understand immersion-mode INP abundance from four commercial OLLFs in the Texas Panhandle in different seasons, including summer, spring, and winter. A high concentration of INPs in air, n_{INP} , of $1,171.6 \pm 691.6 \text{ L}^{-1}$ (average \pm standard error) was measured at $-25 \text{ }^\circ\text{C}$ for aerosol particles collected at the downwind edges of these OLLFs. An obvious seasonal variation in n_{INP} , peaking in summer, was observed at OLLFs with the maximum n_{INP} at the same temperature exceeding $10,000 \text{ L}^{-1}$ on July 23, 2018. The observed high n_{INP} is an order of magnitude higher than what has been found in previous studies on fertile and agricultural soil dust INPs, and we were able to detect INPs at temperatures as high as $-5 \text{ }^\circ\text{C}$. Interestingly, the n_{INP} values from our field survey exhibited a strong correlation with measured particulate matter mass concentration ($r = 0.94$; $> 3 \times 10^{-7} \text{ g L}^{-1}$ in summer), suggesting the importance of large particles in immersion freezing for INPs from OLLF. Motivated by these extremely high INP concentrations, we have conducted a systematic laboratory study at the Aerosol Interaction and Dynamics in the Atmosphere (AIDA) cloud chamber facility to gain further insights into INP propensity and properties of surface materials from two OLLF facilities, one in the Texas Panhandle and another from McGregor, Texas, as OLLF dust proxies. In the surface materials and aerosol particles from U.S. cattle feeding facilities. Using a modern suite of online and offline aerosol particle characterization instruments, we conducted a three-year field survey (2016–2019), Aerosol Interaction and Dynamics in the Atmosphere (AIDA) cloud chamber experiments, and ice crystal residual (ICR) analyses for the feedlot sample. Based on a modern suite of online and offline aerosol particle characterization instruments, we examined the ice nucleation (IN) efficiency of these materials in the temperature range between $-7.5 \text{ }^\circ\text{C}$ and $-29 \text{ }^\circ\text{C}$. Our laboratory results showed on average $\approx 50\%$ unique-supermicron size dominance in the feedlot INPs of both OLLF dust proxies with a high efficiency of immersion/condensation freezing, as represented by an ice nucleation active surface site density/concentration of INPs $n_{\text{s,geo}}$ (n_{INP} scaled to the total geometric particle surface area) of $\geq 10^{10} \text{ m}^{-2}$ at $-25 \text{ }^\circ\text{C}$. This $n_{\text{s,geo}}$ (several hundred and thousand INPs L^{-1} at $-20 \text{ }^\circ\text{C}$ and $-25 \text{ }^\circ\text{C}$, respectively) value agrees reasonably well with estimates from our field survey. Therefore, the usage of OLLF surface materials as dust surrogates was verified in our AIDA-controlled laboratory study. Thus, agricultural fields, especially OLLF animal feeding facilities, might represent important INP sources if these particles rise to sufficient height (i.e., cloud altitude) in the atmosphere. New data on the ice nucleation (IN) properties of agricultural-OLLF dust at heterogeneous freezing temperatures above ($T_s > -29 \text{ }^\circ\text{C}$) were generated, providing statistical context. Moreover, Overall, we successfully characterized physical, chemical, and biological properties of aerosol particles found at a cattle feedlot OLLF dust samples, thereby finding that their IN properties remain unchanged after their unique heat tolerant dry-heating at $100 \text{ }^\circ\text{C}$ but a subset of analyzed samples are influenced by boiling nature. Ice crystal residuals, or INPs that remain after the evaporation of water content, were rich in organics and low in salts. These findings imply the importance of heat-insensitive organics in OLLF dust INPs. Surprisingly, no known ice-nucleating microorganisms were found in our OLLF proxy samples. This negative result suggests that proteinaceous and biological ice-nucleating components are not the primary source of INPs from OLLFs. However, more systematic and careful studies are necessary to gain further insight into aerosol and INP properties (e.g., through analyses on ambient samples and ice crystal residuals from multiple seasons). The relationship between these measured properties and atmospheric IN parameterization relevant to mixed-phase clouds is discussed. In summary, we developed an INP parameterization for OLLF dust, which contributes to our INP parameterization and ICR characterization are meaningful for an improved understanding of INP emission and cloud microphysical processes in the supermicron-particle laden region. These unique-OLLF INPs may directly influence the lifetime of supercooled clouds in a unique manner for this region. An application of our IN

parameterization is crucial to explore the relationship between INP and supercooled cloud properties ~~explore INP relations to supercooled cloud properties~~ over such a predominant agricultural area.

1. Introduction

Atmospheric ice-nucleating particles (INPs) are a small subset of aerosol particles that initiate ice crystal formation in supercooled clouds (Vali, 1968; Chapter 9 of Pruppacher and Klett, 2010). While their importance, relevance, and perturbations to cloud and precipitation properties have been revealed by numerous past studies (e.g., Kanji et al., 2017 and references therein), the potential climatic impact of INPs and their representation in numerical models remain under debate (Storelvmo, 2017). One of the greatest challenges in the INP research field is the fact that INP sources are fast-changing worldwide in part due to the ongoing global climate change (Murray et al., 2021). Thus, it is crucial to identify and characterize any perturbation sources that alter INP abundance and cloud-phase feedback.

Recently, a resurgence of “fertile-and-agricultural soil dust” (soil dust hereafter) INP research has been underway in part because of recent concerns regarding hydrological cycle alternation contributed by modern agricultural practices (Overpeck and Udall, 2020; Alter et al., 2015). Moreover, since agricultural practices represent a substantial dust emission source, accounting for up to 25% of total global dust emission (Ginoux et al., 2012), a large amount of INPs are globally anticipated from agricultural activities. Motivated by these reasons as well as earlier studies on ice nucleation (IN) of surface soil organic and biological samples (Schnell and Vali, 1972; 1973), more recent studies utilized various online and offline instruments. In turn, scientists now have a better understanding of ambient INP concentrations (n_{INP} , per unit volume of air), especially through immersion freezing (i.e., the freezing propensity of INP immersed in supercooled water), from different agricultural sources (Conen et al., 2011; Hill et al., 2016; Steinke et al., 2016; Suski et al., 2018). These efforts allowed for the first-order estimates of immersion mode n_{INP} from soil dust that is relevant to mixed-phase clouds (O’Sullivan et al., 2014; Tobo et al., 2014; Steinke et al., 2020). For instance, by compiling the data from the Colorado State University continuous flow diffusion chamber and an ice spectrometer, the range of measured soil dust n_{INP} at $-20\text{ }^{\circ}\text{C}$ from Suski et al. (2018) spanned from ~ 0.3 to 10 L^{-1} . Based on global mean aerosol particle concentrations and immersion mode IN parameterization, O’Sullivan et al. (2014) estimated the simulated n_{INP} at $-20\text{ }^{\circ}\text{C}$ and 600 mb to range from ~ 0.01 to 8 L^{-1} . Similarly, Steinke et al. (2020) estimated that soil dust n_{INP} can be as high as $\approx 40\text{ L}^{-1}$ at $-20\text{ }^{\circ}\text{C}$ based on their laboratory-derived IN parameterization for soil dusts from Northwestern Germany and Wyoming, USA. Overall, these measurements and approximations represent the upper bound of general field-studied n_{INP} from different geographical areas summarized in Kanji et al. (2017; Fig. 1-10) in the same T range, i.e. ~ 0.002 to 60 L^{-1} (see Sect. 3.6 for more detailed comparison discussion).

Agricultural land use is in excess of 50% of total U.S. land use according to the U.S. Department of Agriculture, and there are $> 26,000$ “open-lot livestock facilities” (OLLFs) in the U.S. (Drouillard, 2018). The term OLLF is adapted to denote a particular type of animal-feeding operation, in which cattle livestock is raised in outdoor confinement, as distinct from partially or totally enclosed housing, and also as distinct from pasture or free-range production systems (Auvermann et al., 2004). OLLFs are common in semi-arid and arid climates. Contrasted with the alternative production systems typical of wetter and more temperate climates, they (1) are an intensified form of livestock production, generating more marketable product per unit land area with less built infrastructure, (2) make use of the elevated evaporative demand to reduce or eliminate precipitation-generated wastewater that must be controlled under water-quality regulations, and (3) capitalize on the nocturnal cooling characteristic of semi-arid and desert climates to avoid major investments in (and operating costs associated with) ventilation systems while still reducing the incidence and duration of livestock heat stress under most conditions, feedlots in the U.S. (Drouillard, 2018).

Globally, agricultural practices represent a substantial dust emission source, accounting for up to 25% of total (Ginoux et al., 2012), and may in part contribute to recent climate change and hydrological cycle alternation in the U.S. (Overpeck and Udall, 2020). In particular, the Texas Panhandle (northern most counties of Texas; also known as West Texas) is a major contributor to the U.S. cattle production, accounting for 42% of fed beef cattle in the U.S. and 30% of the total cattle population in Texas (> 11 million head). Annually, these cattle produce > 5 million tons of manure, which represents a complex microbial habitat containing bacteria and other microorganisms, on an as-collected basis (Von Essen and Auvermann, 2005) according to Texas A&M AgriLife Research. Agricultural dust particles observed at animal-feeding operations OLLFs have long been known to affect regional air quality in the Texas Panhandle because the dust emission flux and 24-hour averaged ground-level dust concentration can be as high as $23.5\text{ }\mu\text{g m}^{-2}\text{ s}^{-1}$ and $1,200\text{ }\mu\text{g m}^{-3}$ (Bush et al., 2014; Hiranuma et al., 2011; Von Essen and Auvermann, 2005). Furthermore, our previous study revealed a presence of OLLF-derived particles at 3.5 km downwind of the facility, suggesting their ability to be transported regionally (Hiranuma et al., 2011). Moreover, some recent studies suggest that aerosol particles emitted from agricultural activities might reach cloud heights due to wind erosion, scouring, and other relevant mechanisms (Steinke et al., 2020 and references therein; Duniway et al., 2019; Katra, 2020).

Specifically, open air feedlots (OAFs) in proximity to West Texas A&M University represent a significant emission source of dust particles, dominated by supermicron sizes in volume equivalent diameter (D_{ve}), resulting in a 24-hour averaged OAF dust concentration as high as $1200\text{ }\mu\text{g m}^{-3}$ (Hiranuma et al., 2011). The emission flux of PM_{10} (i.e., particulate matter smaller than $10\text{ }\mu\text{m}$ in diameter) from OAFs in this region exceeds $4.5\text{ }\mu\text{g m}^{-2}\text{ s}^{-1}$ up to $23.5\text{ }\mu\text{g m}^{-2}\text{ s}^{-1}$ depending on stocking density (Bush et al., 2014). Interestingly, our previous study revealed an inclusion of OAF derived particles at 3.5 kilometers downwind of the feedlot, suggesting their regional scale impact (Hiranuma et al., 2011). Moreover, some recent studies suggest that aerosol particles emitted from agricultural activities might reach out to cloud heights due to wind erosion and other relevant mechanisms (Steinke

et al., 2020 and references therein; Kutra, 2020; Duniway et al., 2019). However, their impact in cloud microphysics, especially IN, is overlooked and poorly constrained, although this region in the U.S. Southern High Plains is dominated by deep convective clouds, where aerosol cloud interactions, including cloud microphysics of INPs, play a crucial role in precipitation and thunderstorm processes (Li et al., 2017). To fill this gap, we comprehensively researched immersion mode freezing abilities (i.e., the freezing propensity of INP immersed in supercooled water; see Vali et al., 2015) and other important properties, including physical, chemical, and biological properties, of feedlot surface materials sampled at commercial and research OAFs in Texas. Recent modeling simulation and remote sensing studies suggest that immersion freezing, focused in this study, is the most relevant heterogeneous IN mechanism (out of several) through which ice crystals are formed in mixed phase clouds (Hande and Hoose, 2017; Westbrook and Illingworth, 2011).

1.2. Objective Due to the potential to act as a prevalent point source of microbiome-enriched dust particles in the Southern High Plains region, where a convective cloud and updraft system persists (Li et al., 2017), we hypothesized that an OLLF can be a source of soil dust INPs. To verify this hypothesis, IN propensities of aerosol particles from OLLFs, IN efficiencies of OLLF proxies, and their physicochemical and biological properties were studied in both field and laboratory settings. Our specific objective was to answer the following research questions: *[1] How do ambient INP results compare to samples of feedlot surface materials? What are the INP fractions of segregated supermicrometer OAF particles? Specifically, In this study, we examined and compared the immersion mode IN ability of ambient OAF-OLLF dust (sampled in the field and analyzed in an offline lab setting) and to surface-derived material samples aerosolized in the cloud simulation chamber, to shed light on long-standing discussion regarding the representativeness of dried, pulverized surface materials as surrogates for ambient dust particles in immersion freezing tests (Boose et al., 2016). We focused on the immersion mode freezing because recent modeling simulation and remote sensing studies suggest that immersion freezing is the most prominent heterogeneous IN mechanism, accounting for 85 to 99%, through which ice crystals are formed in mixed-phase clouds (Hande and Hoose, 2017; Westbrook and Illingworth, 2011). [2] What are the contributions of OAF particle composition to INP propensity? OAF-OLLF-emitted particles are known to include substantial amounts of organic materials. Our previous work using Raman micro-spectroscopy revealed that $\approx 96\%$ of ambient aerosol particles dust sampled at the downwind edge of OAFs an OLLF contains is composed of brown or black carbon, hydrophobic humic acid, water soluble organics, less soluble fatty acids and these carbonaceous materials mixed with salts and minerals (Hiranuma et al., 2011). Recently, organic acids (i.e., long-chain fatty acids) and heat stable organics were found to act as be acting as an efficient INPs (DeMott et al., 2018; Perkins et al., 2020). However, our knowledge regarding what particular features of OAF-OLLF dust trigger immersion freezing at in heterogeneous freezing temperatures (T_s ; i.e., size vs. composition) is still lacking. To improve our knowledge, we conducted single-particle composition analyses of different types of OAF-OLLF-derived ice crystal residual (ICR) samples. Finally, our study attempted to investigate the presence of any known biological INPs by taxonomic identification of the IN-active microbiome and by comparing the IN ability of heat-treated samples to non-heat-treated ones. [3] Can we identify any biological INPs? How does heating influence INP abundance in samples of feedlot surface materials? On average, a beef animal produces 82 lb. per day (wet or as is basis) of manure that is a complex microbial habitat, containing bacteria and other microorganisms, and is the predominant source of OAF dust when dried (Von Essen and Auvermann, 2005). For instance, the In general, cattle manure hosts a wide variety of bovine rumen bacteria (e.g., i.e., *Prevotellaceae*, *Clostridiales*), lipoprotein components of certain bacterial cell walls,) and as well as non-bacterial fauna of the rumen, such as fungal spores, lichens, fungi, *Plantae*, *Protista*, *Protozoa*, *Chromalveolata*, and *Archaea* (Nagaraja, 2016). In this study Hence, we examined if any IN-active cattle bovine microorganisms or associated fragments could be identified when aerosolized. Further, biogenic aerosol particles were found to promote nucleation of ice (Després et al., 2012; Suski et al., 2018), and they may be identified by comparing the IN ability of heat treated samples to non heat treated samples. The heat tolerance of supermicron dominant INPs in a test proxy dust (i.e., Arizona Test Dust, A2 fine test dust, Powder Technology Inc.) was previously found (Perkins et al., 2020). Our study complements this previous study by examining the heat tolerance of ‘natural’ organic rich surface material samples.*

2. Materials and Methods

2.1. Field description

Four commercial OLLFs, ranging from 0.5 to 2.6 km² (< 45,000 head capacity), located in the Texas Panhandle region were used as the ambient aerosol particle sampling sites. All four sites are located within a 53 km radius of West Texas A&M University in Canyon, Texas. Our experimental layouts at each site, denoted as OLLF-1 to OLLF-4, are shown in **Fig. 1** (no further specification is provided to protect location privacy). All sites have a capacity greater than 1,000 head, which are categorized as large concentrated animal feeding operation facilities for cattle under the U.S. Environmental Protection Agency’s definition. These OLLFs were selected primarily for the east-west orientation of their feeding and working alleys, which were nearly orthogonal to prevailing south to southwest winds, allowing for downwind and upwind sampling. Our sampling sites represent typical OLLFs, as more than 75% of cattle are produced in large concentrated animal feeding operation facilities in the U.S. (Drouillard, 2018).

2.1. Ambient samples. Aerosol particles were collected at OAFs to assess immersion freezing properties of “ambient” OAF-OLLF samples using offline immersion assays. These field samples were collected using 47 mm Nuclepore filters (Whatman, Track-Etched Membranes, 0.2 μm pore) through polycarbonate filter samplers. A filter holder was deployed at ~ 1.5 m above the ground. The filter sampling conditions measured locally (during individual sampling activities) are summarized in **Table 1**.

175 Our samples were collected in different meteorological seasons, including summers in 2017 – 2019, springs in 2018 and 2019, and
winter in 2019, in order to examine the seasonal variation in n_{INP} . In 2017, polycarbonate filter samplers were used at both upwind
and downwind edges (< 80 m away from OLLF pens) of OLLF-1, 2, and 3 to understand the spatial variation in n_{INP} within facilities
(Fig. 1). We sampled OAF particles in a wide variety of seasons and conditions, conducting ambient aerosol particle samplings at
180 the downwind edge of four different commercial feedyard (FY) facilities (> 45,000 head capacity, anonymously denoted as FY I-
IV) within a 33-mile radius of West Texas A&M University using an identical sampler in 2017–2019. Our sampling durations
varied, but were up to ~ 4.5 hours, and our final IN efficiency propensity results were scaled to the sampled volume of air afterwards
(Table 1). All filter samples were kept in sterilized tubes refrigerated at 4 °C until the immersion freezing measurements
commenced (typically within 24 hours after sampling).

To complement our downwind measurements, the polycarbonate filter samplers, simultaneous 1-min time-resolved mass
185 concentration measurements of PM_{10} (PM_x = particulate matter smaller than x μm) during individual sampling intervals were also
carried out using DustTrak particulate monitors (TSI Inc., Model 8520) equipped with a PM_{10} inlet. Additionally, tapered-element
oscillating microbalances (TEOMs; Thermo Scientific Inc., Model 1400ab; Patashnick and Rupprecht, 1991) were deployed at
OLLF-1 to continuously monitor PM_{10} mass concentration side-by-side with a polycarbonate filter sampler and DustTrak. In this
190 study, we used long term data from a tapered element oscillating microbalance (TEOM; Thermo Scientific Inc., Model 1400a;
Patashnick and Rupprecht, 1991) deployed at a feedlot as an *in situ* aerosol particle mass concentration monitor to estimate ambient
 n_{INP} . Our TEOM was equipped with a PM_{10} inlet. With an operating flow rate of 16.7 LPM, our TEOM measured < 1 g m^{-3}
of PM with a 5-minute time resolution. Two identical TEOMs were deployed at OLLF-1: one at the upwind edge and another at
downwind location of OLLF-1 (Fig. 1) FY I as illustrated in Upadhyay et al. (2008). Both TEOMs, and they were kept running
195 ran continuously during the entire 2016–2019 study period except for routine maintenance activities. The screened TEOM data
were used as ambient particle emission data to estimate n_{INP} from a feedlot. The inlets of DustTrak and TEOMs were maintained
at ~ 1.5 m above the ground to be consistent with our polycarbonate filter samplers. It is noteworthy that our TEOM and DustTrak
 PM_{10} measurements agreed within $\pm 40\%$ on average. we conducted the sampling at the upwind side at FY I in 2017 to check the
field-background INPs. Our sampling durations varied, but were up to ~ 4.5 hours, and our final IN efficiency results were scaled
200 to the sampled volume of air afterwards. All filter samples were kept in sterilized tubes refrigerated at 4°C until the immersion
freezing measurements, addressed in Sect. 2.5, began (typically within 24 hours after sampling).

2.2. Surface samples for laboratory-based experiments.

Besides field samples, we used two different types of OAF-OLLF surface-derived materials, namely Texas-Dust-01 (TXD01)
205 and Texas-Dust-05 (TXD05), were used as surrogates for dust particles observed at the downwind location of OAFs-OLLFs in
Texas. These proxy samples were used in our controlled laboratory lab study at the Aerosol Interaction and Dynamics in the
Atmosphere (AIDA) facility. TXD01 is a composite sample of surface soils from several commercial and experimental cattle
feedlots-OLLFs located in West Texas the Texas Panhandle. The other sample (TXD05) originates from a research feedlot in
McGregor, TX. Both samples represent a raw surface material composite from feedlot pens, where cattle are fed without antibiotics
or probiotics. All samples were ground, hammer-milled, and sieved for < 75 μm in grain size. Physically pulverizing the surface
210 samples simulates the primary emission mechanism and characteristic of OLLFs (Razote et al., 2006; Bush et al., 2014; von Holdt
et al., 2021).

Moreover, Dry-heated samples (i.e., ~ 100 °C oven-dried for approximately 12 hours) of each type were examined
215 analyzed in this study to assess the heat tolerance of TXD-INPs. Moreover, In addition, wet-boiled samples (i.e., filter samples
suspended in pure water and boiled for 20 minutes; Schiebel, 2017) were also examined examined for their INP abundance using
an offline freezing technique. Each sample was injected into the AIDA chamber using a rotating brush disperser (PALAS,
RGB1000) followed by passing through a series of inertial cyclone impactor stages to be sure to limit particle size of < 10 μm in
 D_{ve} . Subsequently, the OAF particle size distribution in the AIDA chamber was measured prior to each simulated adiabatic
expansion experiment.

A summary of our sample physical properties is provided in Table 2. Briefly, bulk density values of all samples were
220 measured using a gas displacement pycnometer (Quantachrome, 1200e Ultrapyc). As seen, all measured densities are almost
identical. There is at least no systematic difference between non-heated material densities and pre-heated ones, which may be
indicative of heat-resistant features, potentially due to pre-exposure to soil T on average higher than ambient T even at the depth
of 150 mm during summer (Cole et al., 2009). Next, geometric specific surface area (SSA) values were computed based on AIDA
aerosol particle size distribution measurements (i.e., fraction of total surface area concentration to total mass concentration
225 estimated from our the size distribution data; see next section and Table 3). Another measurement of Additionally, nitrogen
adsorption-based SSA, Brunauer-Emmett-Teller (BET) SSA, for each system all samples are also shown in Table 2. The
Autosorb iQ model 7 gas sorption system (Anton Paar, former Quantachrome Instruments) was used to measure BET SSAs in this
study. The measured BET SSA values of OAF-OLLF samples are slightly higher compared to those of previously measured
agricultural soil dust samples (0.74–2.31 $\text{m}^2 \text{g}^{-1}$) (O'Sullivan et al., 2014), but similar to that of microcline (K feldspar; 3.2 m^2
230 g^{-1}) (Atkinson et al., 2013) that is known to contain surfaces with a substantial amount of porous structures which suggests that
TXD01 and TXD05 are more porous than these previous soil samples, leading to higher BET SSA (Kiselev et al., 2017). On average,
our geometric SSA value (\pm standard error) is $4.59 \pm 0.81 \text{ m}^2 \text{g}^{-1}$, which is higher than the BET SSA values. As demonstrated in our
previous studies, a small SSA value generally indicates is often consistent with the presence of a large aerosol particle population

(Hiranuma et al., 2015). Hence, the predominance of larger particles in bulk powders assessed in BET is presumably responsible for the observed differences in these two SSA values (**Table 2**). Indeed, the particles observed in AIDA were all $\leq 6.5 \mu\text{m}$ volume equivalent diameter, D_{ve} (**Table 3**), whereas the particles evaluated by BET were up to $75 \mu\text{m}$. Therefore, in association with large grain size involved in the BET analysis, bulk samples might have exhibited smaller SSA than dry dispersed ones. Furthermore, our SSA measurements suggest heat-tolerance in our OAF-OLLF samples. We examined BET SSAs using two different degassing T s (55°C and 200°C) for each sample, and we did not observe any deviations exceeding within $\pm 10\%$ accuracy of the BET instrument. Geometric SSAs of non-heated and heated samples also agreed within given standard errors. Further discussions on representativeness of the surface samples used in this study compared to ambient OLLF soil dust are provided in Sect. 3.

As demonstrated in our previous study, the surface area distribution of ambient OLLF dust peaks in mode diameter at $\sim 10 \mu\text{m}$ (i.e., Fig. 5 of Hiranuma et al., 2011). This mode diameter is larger than surface-derived samples aerosolized and examined in the AIDA chamber (**Table 3**). However, it is cautiously noted that the ambient OLLF dust size distribution is not spatially uniform, and the emitting mechanism itself is not controllable as it highly depends on a unit of mobile livestock. Granting the primacy of hoof action as the decisive emissions mechanism of OLLF dust as described in Bush et al. (2014), a more controlled laboratory experiment has been desired to characterize IN ability of OLLF soil dust. The difference mentioned above and the demand for controllable investigation motivated analyzing IN properties of both bulk samples ($< 75 \mu\text{m}$ -sieved) and aerosolized samples ($\leq 6.5 \mu\text{m}$). Further results and discussions about representativeness of the surface samples used in this study compared to ambient OLLF soil dust are provided in Sect. 3.

2.3. Instrumentation overview. AIDA laboratory study

We used the AIDA ~~controlled~~ expansion cloud-simulation chamber (Möhler et al., 2003) and ~~an array a set~~ of analytical instruments at Karlsruhe Institute of Technology to conduct a laboratory campaign named TXDUST01 in 2018. This study aimed at investigating the immersion mode ice-nucleating properties, in particular immersion freezing (Vali et al., 2015), and to characterize and other properties characteristics of OAF-OLLF particles dust proxies. We chose the AIDA chamber as our study platform because using this chamber is appropriate for studying it simulates ice formation in mixed-phase clouds in a controlled setting with respect to both T ($\pm 0.3^\circ\text{C}$) and saturation humidity ($\pm 5\%$; (Fahey et al. 2014; Möhler et al., 2003). This chamber generates artificial clouds and activates particles in a simulated atmospheric cloud parcel via expansion cooling. The air volume adjacent to the chamber wall in the 84 m^3 vessel is much smaller in comparison to the actively mixed volume of the vessel. Hence, we neglect the so-called wall effect (e.g., particle wall deposition) in the AIDA experiment. The AIDA has been applied for the analysis of both ambient and lab-generated INPs and has facilitated characterization of many INP species with the IN efficiency uncertainty of $\pm 39\%$ (Steinke et al., 2020; Ullrich et al., 2017; Niemand et al., 2012; Hoose and Möhler, 2012). Note that the AIDA results provided a validation of the other INP spectrometers employed in this study.

An overall AIDA experimental schematic is shown in Fig. 2. Our OLLF dust proxy sample was injected into the AIDA chamber in an aerosolized form through a rotating brush disperser (PALAS, RGB1000) followed by passing through a series of inertial cyclone impactor stages to limit particle size to $< 10 \mu\text{m}$ in D_{ve} . Subsequently, the OLLF particle size distribution in the AIDA chamber was measured prior to each simulated adiabatic expansion experiment. Specifically, More specifically, DNA sampling for metagenomics analysis was also conducted to study biological components of the OAF bulk/aerosolized samples. Prior to each expansion experiment, a combination of a scanning mobility particle sizer (SMPS, TSI Inc., Model 3080 differential mobility analyzer and Model 3010 condensation particle counter), an aerosol particle sizer (APS, TSI Inc., Model 3321), and a condensation particle counter (CPC; TSI Inc., Model 3076) collectively measured the total number and size distribution of aerosol particles at the a horizontally extended outlet of the AIDA chamber (Möhler et al., 2006). As seen in Fig. 2, a set of cComplementary filter sampling of the aerosol particles directly from the AIDA chamber was also collected was performed prior to expansion experiments for three purposes: (1) and these samples were used to examine the condensation/immersion freezing ability of aerosol particle collected on nitrocellulose membrane filters (Millipore HABG04700, nominal porosity $0.45 \mu\text{m}$) INPs in the dynamic filter processing chamber (DFPC; (Santachiara et al., 2010), (2) using them to perform measurements with the IN Spectrometer of the Karlsruhe Institute of Technology (INSEKT; Schiebel, 2017; Schneider et al., 2021), and (3) conducting metagenomics analyses to study biological components of the aerosolized samples. The DFPC technique was used to measure the number concentration, ice activation fractions, and the nucleation site density of the INPs under different T conditions and for different particle sizes (i.e., PM_{10} vs Total). Afterwards, each particle type (i.e., TXD01 and TXD05) was individually examined for its immersion freezing ability during expansion experiments. To complement the AIDA chamber immersion results, the IN Spectrometer of the Karlsruhe Institute of Technology (INSEKT) was used for filter samples aerosol particles collected on 47 mm Nuclepore filters (Whatman WHA10417012, pore size $0.2 \mu\text{m}$) as well as for $< 75 \mu\text{m}$ sieved-bulk samples collected (Schiebel, 2017). The DFPC technique was also used to measure the number concentration, ice-activated fraction, and nucleation efficiency of the INPs under different T conditions and for different particle sizes (i.e., PM_{10} vs. total) collected on nitrocellulose membrane filters (Millipore HABG04700, nominal porosity $0.45 \mu\text{m}$). More specifically, DNA sampling for metagenomics analysis to study biological components of the OLLF bulk samples was also conducted on aerosol particles collected on the Nuclepore filters through an independent inlet to study biological components of the OAF bulk/aerosolized samples.

Another motivation for using the AIDA facility is its ice-selecting pumped counterflow virtual impactor (IS-PCVI; Hiranuma et al., 2016). As detailed in Supplemental Information (SI) Sect. S1, The IS-PCVI instrument separates ICRs from

interstitial particles, including cloud droplets, at T s below $-20\text{ }^{\circ}\text{C}$ (Hiranuma et al., 2016). Preserving ICRs, which are leftover INPs after the evaporation of water content, by the IS-PCVI is key for elucidating physicochemical identities of INPs. ICRs were collected using TEM-grids (Ted Pella Inc., 01844N-F/01896N-F/162-100), and also compared to the total aerosol particles collected directly from the AIDA chamber on Nuclepore™ filters (Whatman, Track-Etched Membranes, $0.2\text{ }\mu\text{m}$ pore size). More detailed information of our IS-PCVI experiments in this study is provided below. Offline single particle analyses were conducted using an electron microscope (JEOL, JSM-6010LA) equipped with an energy dispersive X-ray spectroscopy function. Through this unique capability and subsequent analyses of ICR samples, we obtained detailed information on ICR composition of individual residual particles. In addition, we used a single particle mass spectrometer to characterize aerosol particle chemical compositions of our surface samples (presented in Supplemental Information (SI) Sect. S1S2). Individual details of all lab and field instruments and techniques are introduced in sections in Sects. 2.4–2.8 below.

2.4. AIDA platform and IN experiments. We chose the AIDA chamber as our study platform because using this chamber is appropriate for studying ice formation in mixed phase clouds in a controlled setting with respect to both T and saturation (Möhler et al., 2003). This chamber generates artificial clouds and activates particles in a simulated atmospheric cloud parcel via expansion cooling. The air volume adjacent to the chamber wall in the 84 m^3 vessel is much smaller in comparison to the actively mixed volume of the vessel. Hence, we neglect the wall effect (e.g., particle wall deposition) in the AIDA experiment. The AIDA has been applied for the analysis of both ambient and lab generated INPs and has facilitated characterization of many INP species (Steinke et al., 2020; Ullrich et al., 2017; Niemand et al., 2012; Hoose and Möhler, 2012). Note that the AIDA results provided a validation of the other INP spectrometers employed in this study.

Prior to each expansion experiment, a combination of a scanning mobility particle sizer (TSI Inc., Model 3080 differential mobility analyzer and Model 3010 condensation particle counter), an aerosol particle sizer (TSI Inc., Model 3321), and a counter (CPC; TSI Inc., Model 3076) collectively measured the total number and size distribution of aerosol particles at the horizontally extended outlet of the AIDA chamber (Möhler et al., 2006). Followed by the injection and size distribution measurement, each sample was examined for its immersion freezing ability by the expansion experiment individually.

As shown in Table 3, we conducted 10 AIDA experiments. All lab data associated with this study were archived according to the AIDA experiment number. As seen in Table 3, the mode diameters of TXD01 samples in AIDA were in general smaller than TXD05 samples, consistent with our SSA measurements (see Table 2). Shown in Fig. 1 are expansion experiment profiles of these 10 experiments with different samples, including TXD01 (i) (iii), TXD05 (iv) (vi), TXD01H (vii) (viii), and TXD05H (ix) (x). These profiles represent data points measured in the chamber over a series of time, such as T (a), pressure (b), relative humidity (RH , c), and aerosol particles and hydrometeor concentration (d) for each AIDA experiment. The pressure within the chamber was reduced ($\Delta P \sim 180\text{--}290\text{ hPa}$), causing the T to drop and a simulated adiabatic ‘expansion’ to occur. As can be seen, measurements were made by AIDA simulated immersion freezing at water saturation (RH with respect to water around 100%). A droplet ice threshold typically coincides with $\geq 20\text{ }\mu\text{m}$ $D_{w,c}$ (Hiranuma et al., 2016). Thus, the number concentration of $> 20\text{ }\mu\text{m}$ $D_{w,c}$ AIDA particles measured by a wet optical particle counter (Benz et al., 2005) primarily represents pristine ice crystals formed during the expansion (Figs. 1d).

2.5.4. Offline immersion freezing experiment techniques.

To assess the ambient n_{INP} through samples collected in the field, we used an offline droplet-freezing assay instrument, the West Texas Cryogenic Refrigerator Applied to Freezing Test system (WT-CRAFT; (Hiranuma et al., 2019; Cory, 2019; Vepuri et al., 2021)). Briefly, WT-CRAFT enables a simulation of atmospheric immersion freezing using aerosol particles containing supercooled droplets containing aerosol particles at $T > -25\text{ }^{\circ}\text{C}$. WT-CRAFT was a replica of NIPR-CRAFT (Tobo, 2016), but the two systems currently possess different sensitivities to artifact and detectable T ranges as described in Hiranuma et al. (2019); Vepuri et al. (2021). In this study, for each ambient sample, we evaluated 70 solution droplets ($3\text{ }\mu\text{L}$ each) placed on a hydrophobic Vaseline layer per experiment with a cooling rate of $1\text{ }^{\circ}\text{C min}^{-1}$. All droplets were prepared using filter rinse suspensions with high-performance liquid chromatography (HPLC)-grade water. The amount of HPLC water was determined based on the total amount of air sampled through the cross section of filter (Table 1), which limits with the detection capability to $0.001\text{--}0.05\text{ INP per L of air}$ (standard T and pressure, STP) of air. In other words, as described in Vepuri et al. (2021), by optimizing the suspension water volume, the first frozen droplet observed was considered to have $0.001\text{--}0.05\text{ INP L}^{-1}$ in this study. The each freezing event moment was determined optically based on the change in droplet brightness when the initially transparent liquid droplets became opaque upon freezing. If the freezing temperature (T) was not obvious for any droplets, the 8-bit grayscale images were assessed using ImageJ software to determine the T of phase change shift. After the measurement, we calculated the frozen fraction and estimated the n_{INP} per volume of air as a function of T , $n_{\text{INP}}(T)$, for every $0.5\text{ }^{\circ}\text{C}$ following the parameterization described in Eqns. 1–2 of DeMott et al. (2017). As shown in Hiranuma et al. (2019, i.e., Table S2), the T uncertainty in WT-CRAFT is $\pm 0.5\text{ }^{\circ}\text{C}$. The n_{INP} experimental uncertainty is typically represented by 95% binomial confidence intervals (CI95%). While the background freezing contribution of the field blank filter was negligible ($< 3\%$) at $-25\text{ }^{\circ}\text{C}$, we purposely limited our WT-CRAFT data analysis to the T range between $0\text{ }^{\circ}\text{C}$ and $-25\text{ }^{\circ}\text{C}$ to eliminate any possible artifacts in our WT-CRAFT data.

The INSEKT system is another offline immersion freezing technique used to assess the ability of surface OLLF samples collected on 47 mm polycarbonate filters ($0.2\text{ }\mu\text{m}$ pore size) at the AIDA facility. All filter samples were collected

350 from the AIDA chamber prior to individual expansion experiments with a sampling flow rate of 10 L min⁻¹, and a total of ≈ 600 L of air was sampled through a cross section of each 47 mm polycarbonate filter (see Table 3 for corresponding AIDA experiments). As described in Schiebel (2017), the design and concept of INSEKT is based on the CSU-IS instrument (Hill et al., 2014 and 2016). With 96 wells (50 μL suspension to fill for each), INSEKT estimated reasonable INP concentrations per unit volume of suspension as well as air along with binomial CI95% for each sample according to Eqns. 3.18–3.21 in Schiebel (2017). For INSEKT analysis, aerosol particles were washed off the filter and the resulting suspension is divided into volumes of 50 μL, which were placed in wells of a sterile PCR tray. It was then placed in an aluminum block thermostated with an ethanol cooling bath (LAUDA RP 890; Lauda), which was cooled down at a rate of 0.33°C min⁻¹. If a well froze upon the presence of an INP, a camera detected the brightness changes. The T uncertainty of INSEKT was ± 0.5 °C, and the INP concentrations error was estimated by means of the binomial CI95% for each sample. The derivation of n_{INP} based on Vali (1971) is described in SI Sect. S4. In this study, filter-collected aerosol particles were suspended in 8 ml filtered nanopure water, which has negligible contribution to background freezing, and used to characterize their IN efficiency (Schneider et al., 2020/2021). Similar to WT-CRAFT, the amount of pure water to generate a stock suspension was adjusted for the first frozen aliquot-well observed to contain be considered as ≈ 0.015 INP L⁻¹ in this study, based on the total amount of air sampled through the cross section of filter. A series of diluted suspensions (×15 and to ×225) was consistently analyzed for each sample to acquire an INP spectra covering a wide range of heterogeneous freezing temperatures T_s (-7.5 °C to -25.5 °C). For the overlapping temperatures T_s , we chose the data exhibiting the minimum CI95% as representative n_{INP} for given T . In addition, SI Sect. S2-S3 provides a comparison of our two immersion freezing techniques and results, which are reasonably comparable.

365 ~~Condensation/immersion~~ Immersion/condensation-mode n_{INP} INP concentrations were also measured at CNR-ISAC by means of the Dynamic Filter Processing Chamber (DFPC) (Santachiara et al., 2010; Hiranuma et al., 2019). The DFPC chamber is a replica of the Langer dynamic developing chamber (Langer and Rogers, 1975). A systematic uncertainty in terms of T in DFPC is within ± 0.1 °C (Table S1 in Hiranuma et al., 2019). With a water saturation error of ± 0.01, an ice detection error of ± 33%, and the experimental standard deviation, the overall $n_{\text{INP}}(T)$ IN efficiency uncertainties of DFPC are estimated to be less than ± 62% for this study. The application of DFPC for immersion freezing has been verified in previous inter-comparison studies (DeMott et al., 2018; Hiranuma et al., 2019). For the DFPC analyses, aerosol particles were collected on nitrocellulose black gridded membrane filters (0.45 μm porosity, Millipore) from the AIDA chamber prior to each expansion experiment (Table 3). Two parallel samplers employed in this study had an identical sampling flow rate of 2 L min⁻¹, and a total of 100 L of air was sampled for each system. One sampling system collected the total aerosol particles, while another one was equipped with a cyclone impactor (MesaLabs, SCC0732, S/N 13864) to collect only submicron-sized aerosol particles. This impactor was characterized with a cut-off size around 1 μm in aerodynamic diameter (50% cut-off diameter at 0.9 μm) at 2 L min⁻¹ flow rate (Kenny, et al., 2000). Therefore, the latter line selectively collected particles smaller than 1 μm in aerodynamic diameter. The cut-size efficiency of this cyclone impactor was tested in the lab against NaCl particles. Particle transmission efficiency along the total sampling line was taken into account by estimating gravitational losses in the horizontal tract of the sampling tube and inertial losses in the bend. At a particle size of 10 μm (larger than what was measured in the AIDA chamber), the overall particle transmission efficiency was higher than 86%. For a particle size of 2 μm, the particle loss is estimated to be ≈ 2.5%. Due to the small loss, we neglected any corrections for aerosol particle counts. After collection, the filters were safely kept in Petri dishes at room T until the freezing experiments were initiated.

375 ~~The DFPC instrument assessed IN abilities of TXD01 and TXD05 aerosol particles that have different size ranges. Prior to the DFPC measurement, the sampled filter was inserted onto a metal plate and covered with a smooth surface of paraffin in order to assure good thermal contact between of the filter and with the supporting substrate. Subsequently, the paraffin was slightly heated and rapidly cooled in order to fill the filter pores. DFPC controlled the T_s of the filter and the air, saturated with respect to finely-minced ice, with the flow continuously grazing the filter. IN measurements of total aerosol particles, $n_{\text{INP, total}}$, as well as, measurements of PM_{10} , $n_{\text{INP, PM}_{10}}$, were performed at water supersaturation, SS_{w} , of 2%, and T_{filter} of -18 °C and -22 °C. The supersaturation was calculated theoretically from vapor pressures of over ice and water. The exposure time of the filter was 20 min to grow visible ice crystals on INPs at the considered RH and T_s condition. Use of the dynamic chamber circumvents some of the problems arising with the static chamber, e.g., that the moisture supply under static conditions may be rather inadequate at a filter surface both in overcoming the effect of hygroscopic particles and in activating all potential INPs. The use of the dynamic chamber is advantageous compared to other techniques as the supersaturation is maintained and less impacted by the effect of hygroscopic particles or ice crystal growth, which might lead to an incomplete activation of the INPs on the filter substrate.~~

400 2.65. Extraction of total DNA from bulk and aerosolized dust samples.

405 Total DNA was extracted from Texas dust samples TXD01 and TXD05 prior to and after aerosolization in the AIDA cloud chamber. From bulk samples of dust, total DNA was extracted from 157.1 mg (TXD01) and 128.8 mg (TXD05). To sample aerosolized dust from the AIDA cloud chambers, stainless steel filter holders containing nucleopore filters (47mm diameter and 0.2 μm pore size) were used. These filters were previously sterilized in a standard vapor autoclave and fitted onto the AIDA cloud chamber for aerosol particle sampling prior to the expansion IN experiment. After the conclusion of the experiments, the holders were removed from the chamber to extract total DNA directly from the nucleopore filters. DNA extractions were performed using the FastDNA® Spin Kit for Soil (MP Biomedicals) as described in the manufacturer's protocol. Filters were aseptically removed from holders and placed in the Lysing Matrix E tube for mechanical cell disruption, which was carried out with the FastPrep®

Instrument (MP Biomedicals). The concentration and purity of the extracted DNA was measured by using the Qubit™ 3.0 (Thermo Fisher Scientific). The volume of each sample was 50–100 µL.

Next, our metagenomics analysis method of total DNA is described. The amplification of phylogenetic marker genes and the metagenomics analysis of amplicons from each dust sample were performed by Eurofins Genomics Germany GmbH using the INVIEW Microbiome Profiling 3.0 protocol in order to identify and classify the microbial population (*Fungi*, *Bacteria*, and *Archaea*) of each sample. To achieve this, the hypervariable regions V1–V3 and V3–V5 of the bacterial 16S rRNA gene, the fungal internal transcribed spacer (ITS2) gene and part of the archaeal 16S rRNA gene were amplified by polymerase chain reaction from each sample using in-house primers. Amplicons were sequenced with the MiSeq next generation sequencing system with the 2 × 300 bp paired-end read module.

As the first step of the microbiome analysis, all reads with ambiguous bases ("N") were removed. Chimeric reads were identified and removed based on the de-novo algorithm of UCHIME (Edgar et al., 2011) as implemented in the VSEARCH package (Rognes et al., 2016). The remaining set of high-quality reads was processed using minimum entropy decomposition (MED) (Eren et al., 2013 and 2015). MED provides a computationally efficient means to partition marker gene datasets into operational taxonomic units (OTUs). Each OTU represents a distinct cluster with significant sequence divergent from any other cluster. By employing Shannon entropy, MED uses only the information-rich nucleotide positions across reads and iteratively partitions large datasets while omitting stochastic variation. The MED procedure outperforms classical identity-based clustering algorithms. Sequences can be partitioned based on relevant single nucleotide differences without being susceptible to random sequencing errors. This allows a decomposition of sequence datasets with a single nucleotide resolution. Furthermore, the MED procedure identifies and filters random "noise" in the dataset, i.e., sequences with very low abundance (less than 0.02% of the average sample size).

To assign taxonomic information to each OTU, DC-MEGABLAST alignments of cluster-representative sequences to the sequence database were performed. The most specific taxonomic assignment for each OTU was then transferred from the set of best-matching reference sequences (lowest common taxonomic unit of all the best matches). A sequence identity of 70% across at least 80% of the representative sequence was the minimal requirement for considering reference sequences. Further processing of OTUs and taxonomic assignments was performed using the QIIME software package (version 1.9.1, <http://qiime.org/>). Abundances of bacterial taxonomic units were normalized using lineage-specific copy numbers of the relevant marker genes to improve estimates (Angly, 2014). Taxonomic assignments were performed using the NCBI_nt reference database (Release 2019-01-05).

~~2.7. Ice selecting pumped counterflow virtual impactor (IS-PCVI) sampling. The IS-PCVI is a custom built instrument that can accommodate a substantially larger counterflow in comparison to commercially available PCVIs (e.g., Boulter et al., 2006). Such a large counterflow allows the IS-PCVI to have critical cut-off sizes of larger than 10 µm (more than twice as large as regular PCVIs) and, therefore, to inertially separate ice crystals from droplets found in mixed-phase clouds. As described in Hiranuma et al. (2016), the development of the IS-PCVI was guided by computation fluid dynamics simulations, and performance was verified in the lab using the AIDA chamber. Verifications include its transmission efficiencies and cut sizes up to ~30 µm, ice phase separation based on the cut size, validation of the evaporation section as part of the IS-PCVI outlet, performance of the interstitial particle sampling and minimum artifact detection (up to 5%).~~

~~IS-PCVI properties were determined to realize the critical cut size of ice crystals >24 micron diameter estimated based on Fig. 9 of Hiranuma et al. (2016). During TXDUST01, the output flow was fixed at 2.5 lpm. Contrarily, the input and counter flows were slightly varied as listed in the table. Nonetheless, we used a moderate virtual concentration factor (i.e., Output/Input > 25) to ensure extracting ICRs (Hiranuma et al., 2016). Fig. 2 shows temporal profiles of IS-PCVI experimental parameters during the AIDA cloud simulation experiments. The number concentration of > 20 µm D_{ve} -AIDA particles (i.e., above droplet ice threshold size) was measured by the welas optical particle counter (Benz et al., 2005) virtually overlapped with our residual count (Figs. 2d). This comparability validated our choice of flow setting as well as resulting critical cut size of IS-PCVI (> 24 µm).~~

~~2.8. Field mass concentration measurement. In this study, we used long term data from a tapered element oscillating microbalance (TEOM; Thermo Scientific Inc., Model 1400a; Patashniek and Rupprecht, 1991) deployed at a feedlot as an *in situ* aerosol particle mass concentration monitor to estimate ambient n_{IND} . Our TEOM was equipped with a PM₁₀ inlet. With an operation flow of 16.7 lpm, our TEOM measured < 1 g m⁻³ of PM with a 5 minute time resolution. Two identical TEOMs were deployed at the upwind and downwind location of FY I as illustrated in Upadhyay et al. (2008), and they were kept running continuously during the entire 2016–2019 study period. The screened TEOM data were used as ambient particle emission data to estimate n_{IND} from a feedlot.~~

~~To complement the TEOM measurements and our aerosol particle sampling activities at each field, simultaneous mass concentration measurements of PM₁₀ were also carried out at both downwind and upwind edges using DustTrak continuous particulate monitors (TSI Inc., Model 8520). The time series of upwind and downwind particle mass concentrations were measured by DustTrak instruments equipped with a PM₁₀ inlet (not shown). Our TEOM measurement time resolution is 5 min, and some data are patchy due to maintenance periods. Nevertheless, it is noteworthy that our TEOM and DustTrak PM₁₀ measurements, conducted in a side-by-side position, agree within ± 40% on average. The often-observed downwind particle concentration of ≥ 1000 µg m⁻³ (> 10⁻⁶ g L⁻¹) is consistent with previous studies (Bush et al., 2014; Hiranuma et al., 2011). On the other hand, the~~

observed mass concentration at the upwind sites was typically substantially lower, $< 100 \mu\text{g m}^{-3}$ (or $< 10^{-7} \text{g L}^{-1}$), except for known/recorded interruptions (e.g., a car passing by), resulting in transient increase in mass concentration. We note that, as part of our TEOM data screening and evaluation protocol, all systematic errors (i.e., mass concentration outside of measurable limits, noise $> 100\%$, $3.5 \text{ lpm} < \text{main flow} < 2.5 \text{ lpm}$, and $14 \text{ lpm} < \text{sheath flow} < 13 \text{ lpm}$) were excluded from our data analysis.

In 2017, an optical particle sizer (OPS; TSI Inc., 3330) was used to measure particle size distributions at FY I-III. The time series of upwind and downwind particle size distributions measured by OPS (not shown) are very similar to our previous observation in 2008 (Fig. 5 of Hiranuma et al., 2011). We carried out the OPS measurements at the upwind site at the beginning and the end of dust sampling periods using an identical instrument. As can be seen in Fig. 5 of Hiranuma et al. (2011), while supermicron particles prevailed at the downwind site, the submicron population dominated at the upwind site, indicating that the observed supermicron ambient dust originated from a feedlot.

2.96. n_{INP} IN estimation and IN parameterization method

All IN data based on from AIDA, WT-CRAFT, INSEKT, and DFPC experiments were converted to and stored in $n_{\text{INP}}(T)$ INP concentration per unit standard air volume, INP concentration per unit aerosol particle mass $[n_m(T)]$, and INP concentration per unit aerosol particle surface as a function of T $[n_{s,\text{geo}}(T)]$; $n_{\text{INP}}(T)$, $n_m(T)$, and $n_{s,\text{geo}}(T)$, respectively (DeMott et al., 2017; Ullrich et al., 2017; Hiranuma et al., 2015). The derivation process of these quantities are summarized in SI Sect. 4. These conversions required only scaling measured or estimated $n_{\text{INP}}(T)$ from each method to aerosol particle mass or surface area parameters provided in Tables 1–3. Niemand et al. (2012) infers that the application of n_s is valid for small percentages of IN active fraction ($\leq 1\%$). From the numbers of $N_{\text{total},0}$ given in Table 3 (total number concentration of particles at the initial stage prior to expansion), we examined on average $\sim 200,000 \text{ L}^{-1}$ aerosol particles in the immersion freezing mode in AIDA. Even assuming we evaluate INP up to $2,000 \text{ L}^{-1}$, our INP fraction is 1%. Thus, our n_s parameterization is reasonable.

A consistent data interpolation method is important to systematically compare immersion freezing data from different IN measurement methodologies. In this study, we present T -binned-average IN data (i.e., $0.5 \text{ }^\circ\text{C}$ bins) as for the lab and field IN data. By following the inter-comparison method described in our previous studies (Hiranuma et al., 2015), all lab data were binned/interpolated in a consistent manner using a $0.5 \text{ }^\circ\text{C}$ resolution data.

3. Results and Discussion and Discussion

3.1. Ambient INP spectra

To evaluate the immersion freezing efficiency of ambient aerosol particles collected at OLLFs samples, we converted our WT-CRAFT-based INP measurements to ice-nucleating efficiency metrics, such as n_{INP} , n_m , and $n_{s,\text{geo}}$ (SI Sect. 4 DeMott et al., 2017; Hiranuma et al., 2015). Individual values of cumulative mass (derived from DustTrak measurements), n_{INP} , and n_m for each sampling date are provided in Table 1. On average, an extremely high cumulative n_{INP} at $-25 \text{ }^\circ\text{C}$ of $1,171.6 \pm 691.6 \text{ L}^{-1}$ (standard error) L^{-1} was found at the downwind site. Shown in Fig. 3 is a compilation of $n_{s,\text{geo}}(T)$ and $n_{\text{INP}}(T)$ spectra for all of our WT-CRAFT measurements in 2017–2019 in part presented in Whiteside et al. (2018). Figure 3a shows the n_{INP} comparison between downwind samples and upwind samples collected simultaneously at OLLF-1, 2, and 3 in 2017. Additionally, Fig. 3b summarizes the n_{INP} diversity between downwind and upwind in $\log(n_{\text{INP,downwind}}/n_{\text{INP,upwind}})$, which represents the log-scaled ratio of individual measurements at each OLLF site at given T s. These n_{INP} ratios are shown only for the T range covered by both downwind and upwind data. As can be seen in these two panels, none of upwind spectra show n_{INP} above $-14 \text{ }^\circ\text{C}$ whereas we detected $n_{\text{INP,downwind}}$ at T s above $-10.5 \text{ }^\circ\text{C}$, suggesting that the INPs that are active at T s above $-14 \text{ }^\circ\text{C}$ originate in OLLFs. In fact, across the examined freezing T s, the downwind spectra from all OLLFs exhibit higher n_{INP} than the upwind spectra; therefore, the $\log(n_{\text{INP,downwind}}/n_{\text{INP,upwind}})$ values are above zero at T s below $-14 \text{ }^\circ\text{C}$. The source of upwind INPs is unknown. However, because the measured n_{INP} is low at high T , the CI95% error of $n_{\text{INP,upwind}}$ at around $-15 \text{ }^\circ\text{C}$ is relatively large as compared to that at a lower T (Fig. 3a). Hence, the difference between $n_{\text{INP,downwind}}$ and $n_{\text{INP,upwind}}$ is not conclusive beyond the uncertainty at this T . Furthermore, since our polycarbonate filter samplers were deployed in the close proximity of livestock pens ($< 80 \text{ m}$ away as discussed in Sect. 2.1), the influence of soil dust even at an upwind site could not be ruled out depending on local meteorological conditions and livestock activities. Thus, it may be possible that a short episode of soil dust results in high n_{INP} at a specific T range for the upwind sample. Nonetheless, the downwind n_{INP} values are indeed higher than $n_{\text{INP,upwind}}$ (beyond uncertainties) at T s below $-20 \text{ }^\circ\text{C}$. At $-25 \text{ }^\circ\text{C}$, all $n_{\text{INP,downwind}}$ values appear to be an order magnitude higher than the upwind ones without any exceptions, indicating that OLLF is a source of a notable amount of INPs across the examined T range.

Shown in Fig. 4 is a compilation of $n_{\text{INP,downwind}}$ based on the sampling season (i.e., summer, spring, and winter). Overall, we detected INPs at T s lower than $-5 \text{ }^\circ\text{C}$, and the range of $n_{\text{INP,downwind}}$ at $-20 \text{ }^\circ\text{C}$ varied in different seasons in 2017–2019: summer ($5.0 - 421.7 \text{ L}^{-1}$), spring ($4.2 - 31.2 \text{ L}^{-1}$), and winter ($0.9 - 20.4 \text{ L}^{-1}$). As inferred from Fig. 4, this seasonality holds true for all investigated T s. The observed seasonal variation in n_{INP} corresponds to that in cumulative PM mass (Table 1). More interestingly, we observed a prominent linear relationship between aerosol particle mass and INP number concentration (at $-25 \text{ }^\circ\text{C}$; Fig. 45a). Further convincingly, the n_{INP} values scaled to the mass (n_m ; Fig. 45b) shows a nearly constant value ($\approx 3 \times 10^9 \text{ g}^{-1}$) hovering at $-25 \text{ }^\circ\text{C}$ (independent of particle mass concentration). These results imply the following: (1) ambient meteorological conditions, as summarized in Table 1, might not be determining factors for n_{INP} for our study sites; and (2) there is a predominance

of supermicron INPs from the feedlot, which dominates particle mass. Individual values of cumulative mass (derived from DustTrak measurements), n_{INP} , and n_{m} for each sampling date are provided in [Table 1](#).

We note that the background freezing contribution of the field blank filter was negligible ($< 3\%$) at T_s above -25°C . Regardless, to eliminate any possible artifacts in our WT-CRAFT data, we purposely limited our WT-CRAFT data analysis in the T range between 0°C and -25°C and excluded any uncertain systematically erroneous data. Shown in [Fig. 3](#) is a compilation of $n_{\text{s,geo}}(T)$ and $n_{\text{INP}}(T)$ spectra for all of our WT-CRAFT measurements in 2017–2019 in part presented in [Whiteside et al. \(2018\)](#). [Figure 6](#) depicts the $n_{\text{s,geo}}$ spectra of aerosol particles from OLLF downwind ambient samples, color-coded with different sampling seasons. As seen in the figure, the seasonal diversity of $n_{\text{s,geo,downwind}}$ is less apparent as compared to that of $n_{\text{INP,downwind}}$ ([Fig. 4](#)). There is no systematic difference in the range of $n_{\text{INP,downwind}}$ in different seasons in 2017–2019 at -20°C : summer ($6.7 \times 10^7 - 2.7 \times 10^9 \text{ m}^{-2}$), spring ($2.4 \times 10^8 - 2.3 \times 10^9 \text{ m}^{-2}$), and winter ($1.2 \times 10^8 - 2.9 \times 10^8 \text{ m}^{-2}$). This observation is consistent with the prescribed dominance and importance of large particles as soil dust INPs.

our field $n_{\text{s,geo}}(T)$ spectra are comparable with the lab-derived immersion spectra of surface materials ([Sect. 3.2](#)) within the range of Min–Max for $T > -25^\circ\text{C}$ (at 0.5°C intervals), validating the atmospheric relevance of our controlled-chamber experimental results. Without scaling to the surface area, $n_{\text{INP}}(T)$ spectra exhibited a wide range of INPs over three orders of magnitude; e.g., -25°C (10.07 to $> 10,000 \text{ L}^{-1}$).

More interestingly, we observed a prominent linear relationship between aerosol particle mass and INP number concentration (at -25°C , [Fig. 4a](#)). Convincingly, the INP scaled to the mass (n_{m} , [Fig. 4b](#)) shows a nearly constant value ($\sim 3 \times 10^9 \text{ g}^{-1}$) hovering at -25°C (independent of particle mass concentration). These results imply the following: (1) ambient meteorological conditions, as summarized in [Table 1](#), might not be determining factors for n_{INP} for our study sites; and (2) there is a predominance of supermicron INPs from the feedlot, which dominates particle mass. Individual values of cumulative mass (derived from DustTrak measurements), n_{INP} , and n_{m} for each sampling date are provided in [Table 1](#).

Overall, our offline measurements of ambient n_{INP} concentration using field filter samples collected in the field OLLFs show more than several hundred INPs L^{-1} at below -20°C . More interestingly, there is a notable correlation between INP and ambient aerosol particle mass concentrations based on our 2017–2019 field study, which indicates the importance of large supermicron aerosol particles as INPs. This motivates the need for further characterization of our OAF-OLLF samples in a controlled-lab setting in order to identify what particulate size population (i.e., supermicron vs. submicron) and other properties triggers their IN in a controlled lab setting.

3.2. IN efficiencies of surface materials

As shown in [Table 3](#), we conducted 10 AIDA experiments to measure IN efficiency of two surface materials; TXD01 and TXD05. Dry-heated samples of each type were also examined: TXD01H and TXD05H. All lab data associated with this study were archived according to the AIDA experiment number (i.e., TXDUST01 number), and we share these IDs with other associated measurements (e.g., INSEKT). As seen in [Table 3](#), the mode diameters of TXD01 samples in AIDA were in general smaller than that of TXD05 samples, which is consistent with our SSA measurements (see [Table 2](#)). Shown in [Fig. 47](#) are expansion experiment profiles of these 10 experiments with different samples, including TXD01 (i)–(iii), TXD05 (iv)–(vi), TXD01H (vii)–(viii), and TXD05H (ix)–(x). These profiles represent data points measured in the chamber over a series of time, such as T (a), pressure (b), relative humidity (RH , c), and aerosol particles and hydrometeor concentration (d) for each AIDA experiment. For a cloud formation experiment, the pressure within the chamber was reduced ($\Delta P \sim -180 - 290 \text{ hPa}$), causing the T to drop and a simulated adiabatic ‘expansion’ to occur. As can be seen, measurements were made by AIDA-simulated immersion freezing at water saturation (RH with respect to water around 100%). A droplet-ice threshold typically coincides with $\geq 20 \mu\text{m } D_{\text{ve}}$ (Hiranuma et al., 2016). Thus, the number concentration of $> 20 \mu\text{m } D_{\text{ve}}$ AIDA particles measured by a wet optical particle counter (Benz et al., 2005) primarily represents pristine ice crystals formed during the expansion ([Figs. 47d](#)). The RH dropped during some expansions at low T_s ([Figs. 7c.iii and 7c.vi](#)). At these T_s , ice crystal grow rather fast at the expense of available water vapor in the AIDA chamber, which causes the observed RH drop. Nevertheless, droplets were fully activated within ≈ 100 seconds of each expansion while reaching the peak RH , where we see the steep slope of $\Delta RH/\Delta t$ in [Fig. 7](#). Further, as seen in [Fig. 7d](#), particles of $> 20 \mu\text{m } D_{\text{ve}}$ are not increasing and the total aerosol concentration measured by CPC also does not change after the RH peak. Thus, all predominant ice formation occurs at or before the RH peak through immersion freezing. Lastly, we made sure to only report our IN efficiency at T_s higher than $\sim -30^\circ\text{C}$, corresponding to saturated condition in the AIDA vessel.

[Figure 5–8](#) summarizes our $n_{\text{s,geo}}(T)$ spectra of our surface material samples TXD01 and TXD05 derived from the AIDA, and INSEKT, and DFPC (total aerosol) experiments in comparison to six reference soil dust $n_{\text{s,geo}}$ spectra, O14, S16, S20, T14 (Wyoming), T14 (China), and U17, available in previously published studies (O’Sullivan et al., 2014; Steinke et al., 2016; 2020; Tobo et al., 2014; Ullrich et al., 2017), as well as our previous field data ([Fig. 3](#)). Our $n_{\text{s,geo}}(T)$ spectra are composed of the results of two techniques, AIDA and INSEKT. Dry-heated untreated dry samples were assessed by both all three techniques. Further complementarily, INSEKT was also used to assess immersion freezing efficiency of wet-boiled (i.e., heated) filter samples (dry heated vs. wet-boiled) as well as bulk TXD01 and TXD05 materials (filter suspension vs. bulk). As explained in [Sect. 2.4](#), a series of diluted samples were examined in INSEKT. We made sure to assess at least a few degrees of common-overlapping T intervals in a series of measurements to see if $n_{\text{s,geo}}$ values from multiple measurements they agree within CL95% and, if so, to stitch-merge the results together. For each sample, the spectra nearly overlap each other at $T \sim -25^\circ\text{C}$, verifying their comparability and complementing features.

Further, $n_{s,geo}$ s seen in Fig. 58, our OAF-OLLF spectra are comparable to the previous agricultural soil dust-soil dust $n_{s,geo}$ parameterization at relatively low T (e.g., the $n_{s,geo}$ value of range in orders of magnitude from 10^9 to 10^{10} m^{-2} at around -2625 °C). At T above -20 °C, the INSEKT results suggest that the bulk TXD01 sample (bulk) appears to be more active than TXD05 filter-collected samples beyond the $n_{s,geo}(T)$ uncertainty (Figs. 8a and 8c). On the other hand, the INSEKT analyses of TXD05 (Figs. 8b and 8d) and all other filter samples did not find a notable difference amongst all samples. Furthermore, the lab-derived immersion spectra of both surface materials are reasonably comparable to the minimum – maximum boundaries of our field $n_{s,geo}$ spectra for $T > -25$ °C. While the variability of $n_{s,geo}$ at a single T could vary several orders of magnitude, similar variations are found for both lab and field results, implying the similarity of freezing efficiencies of our lab and field samples. Without scaling to the surface area, n_{INP} spectra exhibited a wide range of INPs over three orders of magnitude; e.g., -25 °C (10.07 to $> 10,000$ L^{-1}). These results suggest that (1) there is a difference in the INP abundance between bulk (< 75 μm -sieved) and aerosolized/filtered-samples for TXD01 (≈ 6.5 μm ; Table 3) presumably due to different properties in particles of these two size subsets ($6.5 - 75$ μm and ≈ 6.5 μm) and/or different amount of IN-active soil organic matter (Tobo et al, 2014), (2) different physicochemical properties found for our TXD05 samples may not impact their INP propensities, and (3) TXD05 might be more representative of atmospherically relevant dust (see Table 2 and SI Sect. S2). ($\pm 39\%$), presumably due to the different sample source (Fig. 5.ii).

Nonetheless, our AIDA INSEKT results virtually fall within the range of our field-derived $n_{s,geo}(T)$ values, validating the atmospheric relevance of our lab results (regardless of varied particle size distributions and sample types; see Table 3). Ice crystals formed on the membrane filter were visually assessed as a function of T (-18 °C and -22 °C) and SS_w . Our DFPC-derived $n_{s,geo}(T)$ values in Fig. 8 are shown in Fig. 6, superposed on our INSEKT data (adapted from Fig. 5). As seen, at the measured T_s , the DFPC data agreed reasonably well with the INSEKT results at the measured T_s -within our error ranges. This comparability suggests that freezing ability is similar for condensation and immersion for our surface samples. More importantly, Table 4 summarizes the comparison of the submicron vs. supermicron INPs for a set of eight samples measured at -18 °C and -22 °C by DFPC. Due to limited range of T_s and samples assessed by DFPC, we cannot provide any statistical variability of our individual data. But, on average, the supermicron INP fraction, given by $[(n_{INP,total} - n_{INP,PM1}) / n_{INP,total}] \times 100$, shows that this fraction contributed $49.749.7\% \pm 6.06.0\%$ (average \pm standard error) of total INP for TXD01 and TXD05 samples at the measured T_s . This highlights the importance of the coarse fraction in the INP population. Note that we also compared/examined the submicron vs. supermicron INPs for $n_{s,geo}(T)$ values. The $n_{s,geo}(T)$ represents the IN efficiency scaled to the surface area, and our PM_{10} $n_{s,geo}(T)$ and supermicron $n_{s,geo}(T)$ were virtually identical, implying non-size dependent IN ability across the sizes evaluated in this study. Since DeMott et al. (2010) successfully demonstrated the correlation between immersion-mode n_{INP} and the number concentration of aerosol particles larger than 0.5 μm diameter based on the compilation of field data for more than a decade, a number of studies have shown the evidence that supermicron aerosol particles dominate INPs across the world. For example, Mason et al. (2016) reported a substantial fraction of supermicron INPs through immersion freezing at relatively a high T ($> 78\%$ at -15 °C) measured at seven different sites over North America and Europe. Even at -20 °C, the author reported the fraction of supermicron INPs larger than 50% . Compared to these numbers, our laboratory data show lower fractions, but the INP sources are presumably different. Based on findings from recent study of size-resolved INPs vs. fluorescent biological particles, these INPs activated at -15 °C are typically thought to be biological (e.g., Huffman et al., 2013; Huang et al., 2021). While there has been more evidence that terrestrial and marine biological particles play an important role in immersion freezing of supermicron-sized particles (e.g., Ladino et al., 2019; Si et al., 2018; Creamean et al., 2018), the atmospheric implication of such rare aerosol species and the overall impact on aerosol-cloud interactions is still under debate. More recently, high IN efficiency by supermicron INPs derived from quartz-rich atmospheric mineral dusts have been reported from different locations, including East Asia (Chen et al., 2021) and eastern Mediterranean (Reicher et al., 2019). These mineral components usually contribute to IN at low T_s . However, there has not been much discussion of large soil dust particles, especially organics, and their contribution to atmospheric ice nucleation in previous studies. Hence, direct implications of which components contribute to IN at different T_s to the observed freezing properties of OLLF particles is still missing. Lastly, while we did not see a systematic increase of supermicron INP fraction as a function of T as shown in Mason et al. (2016; i.e., INP fraction at -15 °C larger than at -20 °C), our results in Table 4 support that $n_{INP,total}$ is always higher than $n_{INP,PM1}$ for any type of samples used in this study.

More interestingly, our comparison between non-heated vs. heated samples indicated no substantial suppression in IN ability by heating, especially for dry-heated samples. This heat-resistant feature of OAF-OLLF samples may be due to their pre-exposure to dry, high ambient and soil T conditions (Cole et al., 2009). Further, our mass spectrometry analysis on these two subsets revealed no significant deviation in chemical compositions (SI Sect. S4S2). Complementarily/Additionally, our metagenomics analysis also found no deviation in terms of bacteria and fungi speciation between dry-heated and non-heat-treated samples as discussed below. As other analyses showed, the difference between non heated and dry heated samples in terms of $n_{s,geo}(T)$ was not seen for TXD01 from DFPC beyond the error ranges. The reason is unknown. Nonetheless, our DFPC results suggest the heat resistivity of Texas agricultural dust simulants. A detailed comparison of the non-heat-treated sample to the heated-sample is discussed in Sect. 3.6 and SI Sect. S3.

3.3. Submicron vs. Supermicron INP. The DFPC instrument assessed IN abilities of TXD01 and TXD05 aerosol particles that have different size ranges. Prior to the DFPC measurement, the sampled filter was inserted onto a metal plate and covered with a smooth surface of paraffin in order to assure good thermal contact of the filter with the supporting substrate. Subsequently, the paraffin was slightly heated and rapidly cooled in order to fill the filter pores. DFPC controlled the T_s of the filter and the air, saturated with respect to finely minced ice, with the flow continuously grazing the filter. Measurements were performed at water

supersaturation, SS_w , of 2%, and T_{filter} of 18°C and 22°C. The supersaturation was calculated theoretically from vapor pressures of ice and water. The exposure time of the filter was 20 min to grow visible ice crystals on INPs at the considered RH and T . Use of the dynamic chamber circumvents some of the problems arising with the static chamber, e.g., that the moisture supply under static conditions may be rather inadequate at a filter surface both in overcoming the effect of hygroscopic particles and in activating all potential INPs.

Ice crystals formed on the membrane filter were visually assessed as a function of T (18°C and 22°C) and SS_w . Our DFPC derived $n_{s,geo}(T)$ values are shown in Fig. 6, superposed on our INSEKT data (adapted from Fig. 5). As seen, at the measured T_s , the DFPC data agreed reasonably well with the INSEKT results within our error ranges. As other analyses showed, the difference between non-heated and dry-heated samples in terms of $n_{s,geo}(T)$ was not seen for TXD01 from DFPC beyond the error ranges. The reason is unknown. Nonetheless, our DFPC results suggest the heat resistivity of Texas agricultural dust simulants.

IN ability of TXD samples was evaluated with both $n_{s,geo}(T)$ and n_{INP} . Note that we also examined the submicron vs. supermicron INPs for $n_{s,geo}(T)$. The $n_{s,geo}(T)$ represents the IN efficiency scaled to the surface area, and our PM_{10} $n_{s,geo}(T)$ and supermicron $n_{s,geo}(T)$ were virtually identical, implying non size dependent IN ability across the sizes evaluated in this study. Table 4 summarizes the comparison of the submicron vs. supermicron INPs. Supermicron INP fraction, $[(n_{\text{INP,total}} - n_{\text{INP,PM}_{10}}) / n_{\text{INP,total}}] \times 100$, shows that this fraction contributed $49.7\% \pm 6.0\%$ (average \pm standard error) of total INP for TXD samples at the measured T_s . This highlights the importance of the coarse fraction in the INP population.

3.4. IN parameterization. The exponential fits for T binned $n_{s,geo}(T)$ data of all lab and field measurements are summarized in Table 5. Fit parameters, computationally optimized for given the best correlation coefficient (r) for each category are given in this table. As can be inferred from the table, the overall $\Delta \log(n_{s,geo})/\Delta T$ value is similar for all non-heated categories (0.20–0.42). This range of deviations is roughly similar to what we previously observed for supermicron IN active cellulose particles (0.26–0.40) (Hiranuma et al., 2019). Slightly higher $\Delta \log(n_{s,geo})/\Delta T$ values were observed for wet-boiled particles (0.59–0.61) than others may be indicative of an alternation in freezing efficiency via hydrolysis and discharge of ice-nucleating materials in wet-boiled samples (Welti et al., 2014). Suppression of $n_{s,geo}$ for wet-boiled samples at T above 20°C can be found in Fig. 5.ii. Nonetheless, the observed consistency in the spectral slopes suggests that lab and field measurements exhibit similar IN above examined T_s . More importantly, this parameterization offers a simple representation of natural supermicron-dominant INPs (nearly half of OAF INPs is supermicron in diameter; see Sect. 3.3) in a very simple manner. Since our immersion parameterization is solely a function of a single parameter, T , this parameterization can be easily incorporated in many model platforms in a computationally friendly manner.

3.5.3. Metagenomics analysis

Table 6-5 summarizes our results of metagenomics analysis. The diversity of the microbiome in the dust samples identified microorganisms common in soil, bovine manure, and inhabitants of the bovine rumen, as expected (detailed in SI S3Sect. S5). Interestingly, no known IN-active species of microorganisms (active at T_s above -10°C) were detected, although genera of *Bacteria* (*Pseudomonas*) and *Fungi* (*Fusarium*, *Mortierella*) known to include species with IN activity were detected, albeit in negligible numbers. This insignificance of IN-active microbiome and relatively high importance of non-biological supermicron particles as OAFOLLF-INPs are deemed valid/robust. Unless otherwise, the observed strong mass dependency of OAFOLLF- n_{INP} INPs (Fig. 45a) cannot be explained as microorganisms typically contains small mass. We also found very little difference in the bacterial and eukaryotic metagenome in bulk and heat-treated dust samples (no data for *Archaea* were obtained from heat-treated dust samples). Heat treatment of dust samples at 100°C for 12 hours apparently did not destroy the DNA in our samples, even though most microbial cells were killed. Thus, no notable difference after dry-heating was observed for both TXD01 and TXD05, representing an important negative result (Table 65). This negative result is important because it agrees with our metagenomics analysis, where no known IN-active bacteria were detected. The diversity of the bacterial microbiome in both samples showed a considerable difference after aerosolization of dust in the AIDA cloud chamber and the subsequent IN experiments in simulated clouds. In aerosolized dust, a significant increase of desiccation-resistant *Actinobacteria* was observed in both samples. Further, we also identified a significant decrease of non-desiccation-non-resistant *Proteobacteria*, *Firmicutes*, and *Bacteroides* in aerosolized particles (Table 65). This result implies that aerosolization and microbial dispersion in the atmosphere may alter microbiome diversity and population, at least for our samples. This unique effect was not observed for *Fungi* and *Archaea* (see SI Sect. S3-S5 for more details).

3.6.4. Ice residual analysis

A total of 1,259 aerosol and residual particles in the diameter range of 0.2 to 3 μm were assessed through electron microscopy for their physicochemical properties. All of our single particle analyses were carried out with the following parameters: electron beam accelerating voltages of 15 keV, spot size of 50, and the working distance of 10 mm. Table 7-6 summarizes the size properties of analyzed particles. The number of measured particles was limited depending on the particle availability on each substrate. Nevertheless, we looked into/examined at least 100 particles for each sample type, as seen in the table. Out of these particles, the diameter of TXD01 (0.84625 μm) particles was on average smaller than TXD05 (1.050875 μm). This observation is consistent

with our offline particle characterizations (Table 2) and the AIDA size measurements (Table 3). For the samples used in this study, we could not identify any systematic differences between aerosol particles and residuals in terms of size. ~~An exception was TXD01, where the mode diameter of residuals appeared to be larger than aerosol particles. Regardless~~ Likewise, while we found substantial fractions of supermicron diameter particles in TXD01 (28.29.2%) and TXD05 (38.844%), ~~there is no obvious enrichment in supermicron population in our ice crystal residuals from this study (Table 6).~~

Higher aspect ratios in residuals compared to aerosol particles were found for both TXD01 and TXD05 samples. This difference indicates a relative increase in non-spherical particles, ~~that have a higher aspect ratio,~~ in residuals. In short, Hiranuma et al. (2008) found that quasi-spherical ~~OAF-OLLF~~ particles were predominantly salt-rich hygroscopic particles, whereas non-spherical amorphous particles were found to be organic-dominant with negligible hygroscopicity. Thus, our results ~~suggest~~ simply the inclusion of non-hygroscopic particles as ice residuals.

Next, the elemental composition ~~from~~through energy dispersive X-ray spectroscopy analysis revealed some notable differences between aerosol particle samples and residual samples. In this study, we followed the H13 classification scheme to define particle types in the electron microscopy analysis (Hiranuma et al., 2013). Briefly, we semi-quantitatively assessed atomic weight percentage of ~~o~~rganic (C, N, O), ~~s~~alt-rich (Na, Mg, K, P), ~~m~~ineral-rich (Al, Si, Ca), and ~~o~~ther. We detected carbon in all particles exclusively, but a background signal from polycarbonate substrate film could not be separated and ruled out. Table 8-7 shows the summary of particle types based on their elemental compositions for samples used in this study. It should be noted that the “rich” used in the names of particle classes only indicates intensive characteristic peaks in the energy dispersive X-ray spectra, and > 99.9% of particles (except a few aluminosilicate particles) examined in this study were predominantly composed of carbon elements as organics-mixed particles. As seen in the table, an increase in exclusively organic fractions as well as a substantial decrease in salt-rich particles in residuals persisted for both TXD01 and TXD05 samples. The organic type fraction in heated-aerosols is slightly smaller than that in non-heated aerosols. Nevertheless, the increase of organic type fraction for heated-ICRs implies an insignificant ~~heating~~ effect of ~~heating~~ as well as ~~the~~an importance of heat-resistant ~~and~~ing organics for immersion freezing of ~~OAF-OLLF~~ materials. This observation supports the result in Table 76. The reduction in salt-rich particles percentage might be relevant to an increase in aspect ratio (Hiranuma et al., 2008). The observed relative increase in organic-including particles, which might be substantially less hygroscopic compared to salt-rich particles, is also indicative of the predominance of immersion freezing ~~as an IN mechanism of OLLF particles~~ (rather than condensation freezing; ~~)(Belosi and Santachiara, 2019)~~ ~~as an IN mechanism of OAF particles~~. Indeed, immersion is a dominant mechanism of IN in mixed-phase clouds (Hande and Hoose, 2017). Regardless, liquid cloud formation might be a prerequisite for activating ~~OAF-OLLF~~ particles as ice crystals in the atmosphere.

Finally, our attempts to analyze the size-resolved abundance of each composition class was not conclusive (not shown), possibly due to limitations in the small population examined. Nonetheless, finding no clear size-dependence of elemental compositions in both total aerosol and residual samples was an important negative result, which is consistent with findings through aerosol single particle spectrometry (SI ~~S1~~Sect. S2).

3.75. Estimated INPs released from a ~~feedlot~~OLLF.

Upon ~~a~~ confirmation of ~~the~~ comparability between field and lab $n_{s,geo}(T)$ values, we proceeded with ambient n_{INP} estimation based on our field mass concentration data, ~~using the OLLF-1 TEOM PM₁₀ data.~~ We elected to use the OLLF-1 data due to their ~~reasonable spatiotemporal coverage (i.e., two identical model TEOMs deployed at the downwind and upwind sites for 2017 – 2019).~~ A summary of TEOM mass concentration data in different seasons over 2017 – 2019 are available in Table 8. Frequently, ~~the observed PM₁₀ concentration exceeded 10⁻⁷ g L⁻¹, which is consistent with previous studies (Bush et al., 2014; Hiranuma et al., 2011).~~ On the other hand, the observed mass concentration at the upwind sites was typically substantially lower except for ~~known/recorded interruptions (e.g., a tractor-trailer passing by), resulting in transient increase in mass concentration.~~ As the upwind n_{INP} can be considered non-negligible (see Sect. 3.1), we subtracted mass concentrations measured at a nominal upwind edge from the downwind TEOM mass concentration values to compute PM₁₀ from OLLF-1. The screened TEOM data were used as ambient particle concentration data to estimate n_{INP} from an OLLF.

~~To estimate n_{INP} , we first used the $n_{s,geo}(T)$ parameterization given in SI Sect. S6. Due to the atmospheric relevance and T coverage extending to -5 °C, we used a fit of Field Median in Table S3 Table 5 (Eqn. Field Median) to compute representative $n_{s,geo}(T)$ relevant to OLLF. To convert $n_{s,geo}$ to n_{INP} , we have adapted Equations (1) – (3) in Hiranuma et al. (2015). Briefly, the measured mass concentration as well as field SSA were used to convert from $n_{s,geo}(T)$ to $n_{INP}(T)$:~~

$$n_{INP}(T)(L^{-1}) = n_{s,geo}(T)(m^{-2}) \times Geometric\ SSA \left(\frac{m^2}{g} \right) \times Mass\ Conc. \left(\frac{g}{L} \right). \quad (1)$$

~~where the geometric SSA value for field data, approximately ~ 0.4 m² g⁻¹, is derived from particle size distribution measurements presented in Fig. 3 of Hiranuma et al. (2011). As seen in Fig. 7b, average estimated INPs at three different T_s , 15°C, 20°C, and 25°C, are shown as a gray dashed line, black dashed line and black solid line, respectively. Our results show that the aerosol particles downwind of a feedlot contain several thousand INPs L⁻¹ (median = 1,656 L⁻¹; average = 5,251 L⁻¹) at standard T and pressure (STP) at 25°C, which is three orders of magnitude higher than typical ambient n_{INP} from continental sources as reported in DeMott et al. (2010).~~

Table 8 summarizes the TEOM mass concentrations and estimated annual and seasonal n_{INP} in different seasons over 2017–2019. In general, PM_{10} mass concentrations from OLLF-1 (average \pm standard errors) were high in meteorological summers ($3.9 \times 10^{-7} \pm 5.6 \times 10^{-8} \text{ g L}^{-1}$) and springs ($4.5 \times 10^{-7} \pm 2.4 \times 10^{-7} \text{ g L}^{-1}$) as compared to fall ($2.4 \times 10^{-7} \pm 4.4 \times 10^{-8} \text{ g L}^{-1}$) and winter ($1.5 \times 10^{-7} \pm 5.3 \times 10^{-8} \text{ g L}^{-1}$). A similar trend was found for the upwind PM_{10} mass concentration: summer ($3.4 \times 10^{-8} \pm 9.0 \times 10^{-9} \text{ g L}^{-1}$) > spring ($2.8 \times 10^{-8} \pm 9.3 \times 10^{-9} \text{ g L}^{-1}$) > fall ($1.8 \times 10^{-8} \pm 5.7 \times 10^{-9} \text{ g L}^{-1}$) > winter ($1.4 \times 10^{-8} \pm 7.1 \times 10^{-10} \text{ g L}^{-1}$). But, the measured values at the upwind location are consistently an order magnitude lower than that from the downwind location.

On average, the estimated mean n_{INP} values at -15, -20, and -25 °C in 2016–2019 were estimated as 46.8 (± 25.3 seasonal standard deviation; same hereafter), 288.1 (± 156.1), and 5,250.9 ($\pm 2,845.6$) L^{-1} , respectively. In addition, the median n_{INP} at -15, -20, and -25 °C in 2016–2019 were estimated as 14.7 (± 9.2), 90.9 (± 56.4), and 1,656.3 ($\pm 1,028.1$) L^{-1} , respectively. As our n_{INP} is linearly scaled to mass concentration (Eqn. 1), estimated n_{INP} showed a similar seasonal variability as seen in mass concentration. For instance, at -20 °C, the cumulative n_{INP} averages for each meteorological season over three 2016–2019 were estimated as follows: spring ($315.4 \pm 164.9 \text{ L}^{-1}$) > summer ($270.4 \pm 39.0 \text{ L}^{-1}$) > fall ($165.1 \pm 30.8 \text{ L}^{-1}$) > winter ($106.9 \pm 36.8 \text{ L}^{-1}$). The observed high n_{INP} values were expected for such a high PM_{10} mass concentrations emitted from the cattle feedyard, which represent an important point source of agricultural aerosol particle emission. However, we reemphasize that the IN efficiency of OLLF aerosol particles is somehow similar to other agricultural aerosol particles found in previous studies as discussed in Sect. 3.2 (Fig. 8).

Figure 79 displays summarizes the TEOM mass concentration measured at the downwind side of FY time series over 2017–2019 as well as cumulative n_{INP} concentrations estimated at T s of -15 °C, -20 °C and -25 °C. The background mass concentration measured at the upwind location (1.7×10^{-8} to $2.6 \times 10^{-8} \text{ g L}^{-1}$ avg. \pm std. error. = $2.24 \times 10^{-8} \pm 1.42 \times 10^{-10} \text{ g L}^{-1}$) is shown in with a red dashed line in Fig. 97a and subtracted from the downwind data. The resulting downwind-OLLF mass concentration was on average is $4.12 \times 10^{-7} \pm 2.96 \times 10^{-9} \text{ g L}^{-1}$ (or $411.57 \pm 2.96 \mu\text{g m}^{-3}$). Annual averages of OLLF mass concentrations are indicated with a blue dashed line in Fig. 97a. On average, the downwind concentration exhibited higher mass concentration by more than an order of magnitude. This result implies a constant high particle load from the FY OLLF, which was also seen by a previous study at FY the same OLLF (Hiranuma et al., 2011; Bush et al., 2014). Seasonal variation is also seen in Fig. 97a, as the annual peak of mass concentration ($> 10^{-5} \text{ g L}^{-1}$) coincided with summer in each case.

Figure 97b shows associated n_{INP} estimations. As seen in Fig. 9b, average estimated INPs at three different T s, -15 °C, -20 °C, and -25 °C, are shown as a gray dashed line, black dashed line and black solid line, respectively. Our results show that the aerosol particles downwind of a feedlot contain several thousand INPs L^{-1} (median = 1,656 L^{-1} ; average = 5,251 L^{-1}) at standard T and pressure (STP) at -25 °C, which is three orders of magnitude higher than typical ambient n_{INP} from continental sources as reported in DeMott et al. (2010). More discussion of OLLF n_{INP} in comparison with previous studies is provided in Sect. 3.6.

To estimate n_{INP} , we first used the $n_{s,\text{geo}}(T)$ parameterization given in Table 5 (Eqn. Field-Median) to compute $n_{s,\text{geo}}(T)$. To convert $n_{s,\text{geo}}$ to n_{INP} , we have adapted Equations (1)–(3) in Hiranuma et al. (2015). Briefly, the measured mass concentration as well as field SSA were used to convert from $n_{s,\text{geo}}(T)$ to $n_{\text{INP}}(T)$:

$$n_{\text{INP}}(T)(\text{L}^{-1}) = n_{s,\text{geo}}(T)(\text{m}^{-2}) \times \text{Geometric SSA} \left(\frac{\text{m}^2}{\text{g}} \right) \times \text{Mass Conc.} \left(\frac{\text{g}}{\text{L}} \right) \quad (1)$$

where the geometric SSA value for field data, approximately $0.4 \text{ m}^2 \text{ g}^{-1}$, is derived from particle size distribution measurements presented in Fig. 3 of Hiranuma et al. (2011). As seen in Fig. 7b, average estimated INPs at three different T s, -15 °C, -20 °C, and -25 °C, are shown as a gray dashed line, black dashed line and black solid line, respectively. Our results show that the aerosol particles downwind of a feedlot contain several thousand INPs L^{-1} (median = 1,656 L^{-1} ; average = 5,251 L^{-1}) at standard T and pressure (STP) at -25 °C, which is three orders of magnitude higher than typical ambient n_{INP} from continental sources as reported in DeMott et al. (2010).

While fine submicron mode might dominate number concentrations of aerosol particles at cloud heights, the presence of supermicron particles in clouds is evident over the arid Southwestern U.S. (Pinnick et al., 1993). The existence of supermicron particles at cloud altitudes is especially non-negligible when we consider atmospheric immersion freezing, which initiates on the surface of a few in a million particles. Our lab and field measurements-based parameterizations open up further study opportunities to incorporate supermicron INPs from agricultural source in the atmospheric modeling simulation and may provide a hint to reveal the identity of INPs at relatively high T s (> -15 °C). Note that the existence of supermicron particles at cloud altitudes is especially non-negligible when we consider atmospheric immersion freezing, which initiates on the surface of a few in a million particles.

3.6. Comparison to previous soil dust IN studies

Figure 10 summarizes our field measured n_{INP} (Fig. 4) as well as estimated atmospheric n_{INP} in the T range between -5 °C and -25 °C (Sect. 3.5) in comparison to previously reported ambient n_{INP} of soil dust and a compilation of other field-measured n_{INP} from across the world. We purposely selected to display our estimated n_{INP} with standard deviations and global reference field n_{INP} data from Kanji et al. (2017) at their T points (i.e., -15, -20, and -25 °C) to make all comparisons visible in this figure. It is clear that the estimated n_{INP} from OLLF are within OLLF field-measured n_{INP} , implying that our n_{INP} estimation is reasonable and atmospherically relevant. It is also apparent that the OLLF n_{INP} spectra are consistently located above or overlapping with the upper bound of soil dust n_{INP} spectra from previous studies across the T range we examined in our field study (i.e., T above -25 °C). Although our INP detection limit of 0.05 L^{-1} in this study is not as good as Suski et al (2018; $\approx 0.002 \text{ L}^{-1}$), our data exceed their

815 data from crop fields (soybean, sorghum, wheat, and corn) or are at least positioned towards the higher bound of the S18 data points. The observed consistent gap between our OLLF data and previous data holds true even when compared to the globally compiled n_{INP} from multiple field campaigns at -15, -20, and -25 °C (Kanji et al., 2017), indicating that absolute INPs per unit volume at OLLF are much higher than previously investigated field INP sources. However, it is important to revisit our IN efficiency discussion included in **Sect. 3.2**. In short, our $n_{\text{s,geo}}$ values derived from surface materials as well as field OFFL samples are comparable to other reference soil and desert dust $n_{\text{s,geo}}$ (**Fig. 8**). Altogether, we conclude that OLLF soil dust is an important point-source of atmospheric INPs, which have comparable or higher IN efficiency compared to formally assessed soil dusts.

820 One unique aspect of our OLLF samples is their heat tolerance. Previously, Suski et al. (2018) found that heat-treatment (95 °C for 20 min) can suppress the n_{INP} of wheat harvest soil dust sample from Kansas, USA by more than two orders of magnitude at -12 °C. The authors concluded that the decomposition of IN-active heat labile organics and bacteria is responsible for the observed n_{INP} suppression. This result is consistent with the impact of heat treatment on the IN efficiency of soil dust sample from different regions, such as the one from a lodgepole pine forest in Wyoming, USA (Hill et al., 2016; 105 °C for 20 min) and another from Central Yakutia (Conen et al., 2011; 100 °C for 10 min). Similarly, Tobo et al. (2014) found that the 300 °C combustion can reduce the IN fraction of Wyoming soil dust at -24 °C by the same orders of magnitude as Suski et al. (2018) observed. In contrast, Steinke et al (2016) found no notable effect of heat treatment (~ 110 °C) on the Argentinian soil dust IN efficiency at ~ -24 °C. This heat insensitive nature of Argentinian soil dust may have coincided with its lack of IN-active proteins and/or heat sensitive microbes, which aligns with the absence of known IN-active microbes in our OLLF samples (**Sect. 3.3**).
825 Suppression of $n_{\text{s,geo}}$ for wet-boiled samples of TXD01H at T above -20 °C can be found in **Table 5** and **Fig. 8c**. Nonetheless, the observed consistency in the spectral slopes suggests that lab and field measurements exhibit similar IN above examined T s. An example case of the negligible impact of the wet-boiling process on a field OLLF sample is discussed in **SI Sect. S3**. In total, our findings and the observation in Steinke et al. (2016) eliminate proteinaceous and biological ice-nucleating components as the primary source of IN abundance in air. The choice of 100-110 °C for heat treatment seems valid because proteinaceous structures will be destroyed below ~ 100 °C (Steinke et al., 2016). For example, Szyrmer and Zawadzki (1997) found some known cell-free IN-active microbes (e.g., Fusarial nuclei) are stable only up to 60 °C. Other than this study, ice nucleation activity by bacteria (Morris et al., 2004; Christner et al., 2008), fungi (Humphreys et al., 2001), and lichens (Henderson-Begg, et al., 2009) has been shown to be heat-sensitive irreversibly at 100 °C or below. Other soil organic components can be decomposed at T between 100 °C and 300 °C (Tobo et al., 2014).

830 **44. Summary-Conclusions**

835 This study was composed of two parts: (1) A multi-year field investigation of immersion-mode INPs from four commercial OLLFs in the Texas Panhandle in 2017 – 2019; (2) an AIDA laboratory campaign, which investigated the INP propensity and properties of two OLLF soil dust proxies. Our field and laboratory findings support that OLLFs are a substantial source of microbiome-enriched dust particles and soil dust INPs, which are estimated to exceed several hundred and several thousand INPs L⁻¹ at -20 °C and -25 °C, respectively.

840 From the first year of our field work, we found that OLLF is a source of INPs that can be active at T s below ~ -5 °C. Briefly, the analysis of log ratio of $n_{\text{INP,downwind}}$ to $n_{\text{INP,upwind}}$ from three different OLLFs consistently shows that the INP abundance at the downwind site of each OLLF is an order magnitude higher than at the nominal upwind edge across the examined T range (\geq -25 °C). This difference between downwind and upwind INPs clearly indicates that a vast majority of INPs found in our field sites (as high as 11,000 INP L⁻¹ cumulatively at -25 °C) are from OLLFs (**Table 1**). Over the three years of our field OLLF investigation, there was a clear seasonal variation in n_{INP} . Briefly, summer n_{INP} at -20 °C from the downwind edge of OLLFs (5.0 – 421.7 L⁻¹) was notably higher than that of spring (4.2 – 31.2 L⁻¹) and winter (0.9 – 20.4 L⁻¹). The observed seasonal trend persisted for all heterogeneous freezing T s investigated in this study ($T > -25$ °C). Interestingly, the observed n_{INP} seasonality strongly correlated to that of PM₁₀ mass ($r = 0.94$). This relationship implies the importance of large particles, which dominate aerosol surface area and mass, on IN of OLLF dust. By scaling our n_{INP} to the aerosol particle surface area, we are no longer able to see any clear seasonal variation in $n_{\text{s,geo}}$; thereby, we conclude that the abundance of INP from OLLFs depends on dust quantity at ground-level at given time, but its IN efficiency is consistent throughout the seasons at least for 2017 – 2019. These findings also suggest that future studies of soil dust INP might need to focus on statistically validating the link between large supermicron particles and INPs with longer observations from a multitude of regions, which might ultimately result in providing a simple IN parameterization for cloud and climate models.

850 The importance of large aerosol particles on immersion freezing, motivated by our field work, was verified in our controlled-AIDA laboratory study, using ground-collected samples from the OLLFs. The DFPC offline freezing instrument assessed IN abilities of OLLF dust surrogates with PM₁ and > PM₁ (total) size fractions, and revealed that on average ~ 50% of OLLF n_{INP} derived from supermicron aerosol particle population in the assessed T range between -18 and -22 °C. Besides, several unique characteristics of OLLF INPs were disclosed. For instance, a comparability of results from our condensation freezing instrument (DFPC) and immersion freezing assay (INSEKT) was found. A similar observation was previously made for another composition (mineral dust) in Wex et al. (2014); this similarity suggests that freezing ability is similar for condensation and immersion for our surface OLLF samples. Further, the comparability between immersion mode IN ability of ambient OLLF dust (sampled in the field and analyzed in the offline lab setting) and that of surface material samples aerosolized in the cloud simulation chamber sheds light on the representativeness of dried, pulverized surface materials as surrogates for ambient dust particles in

870 immersion freezing tests (Boose et al., 2016). In short, our AIDA-INSEKT results for OLLF proxies reasonably agree with the range of our field-derived $n_{s,geo}$ values, validating the atmospheric relevance of our lab results (especially TXD05 regardless of varied particle size distributions and sample types; see **Table 3**). Additionally, the observed consistency in the spectral slopes (i.e., **Table 5**) suggests that lab and field measurements exhibit similar IN ~~ability in~~ at examined T_s .

875 Insignificance of dry-heating (100 °C for 24 hours) was demonstrated for both types of OLLF proxies. Previously, Steinke et al (2016) found no notable effect of heat treatment (~ 110 °C) on the Argentinian soil dust IN efficiency at ~ -24 °C. This heat insensitive nature of Argentinian soil dust might have coincided with its lack of IN--active proteins, which align with our ~~findings~~ ~~lack of~~ ~~of~~ ~~no~~ known IN--active microbiomes in our OLLF samples (**Sect. 3.43**). While suppression of $n_{s,geo}$ for wet-boiled (100 °C for 20 min) samples at T above -20 °C was found for both proxies (**Fig. 8**), ~~it is not conclusive~~ how OLLF soil dust is susceptible ~~ive~~ to heat ~~is not conclusive~~. An example case of negligible impact of wet-boiling process on a field OLLF sample is discussed in **SI Sect. S3**. In total, our findings and the observation in Steinke et al. (2016) eliminate proteinaceous and biological ice-nucleating components to be considered as the primary source of superb IN abundance from OLLFs. The future sampling of more ambient filters from multiple seasons and systematic analysis of non-heated vs. wet-boiled treatment of ambient samples may provide more conclusive idea of heat resistivity of ambient OLLF-INPs. ~~Our AIDA and INSEKT controlled experiments (immersion freezing) with OAF samples were successful, and we verified strong comparability of our field and controlled lab results. Overall, we found that particle size is one of the most important particulate features of OAF dust, triggering immersion freezing in heterogeneous freezing T_s . In fact, supermicrometer OAF particles are responsible for nearly 50% of measured INPs. Due to the observed predominance of supermicron OAF particles, a substantially high number of INPs from feedlots (several thousands of INPs L^{-1} at -25 °C) is expected. Ambient meteorological conditions seemed to not be determining factors for INP concentrations and emissions. But, higher time and bin resolutions as well as vertical profiles are necessary to further verify size related statistics.~~

885 The predominance of organics with salt contents (e.g., potassium) in ~~OAF-OLLF~~ particle composition is consistent with our previous study of ~~OLLF soil dust-TXD~~ particle composition analyses (Hiranuma et al., 2011). ~~Based on findings from this study~~ ~~Further~~, ICR analysis revealed a ~~relative~~ increase in organic inclusion (and decrease in salt inclusion) in residuals, highlighting the importance of organic material ~~infor atmospheric immersion to be~~ ~~OAF-OLLF-derived INPs for atmospheric immersion~~. ~~The insignificance of dry heating was demonstrated with~~ ~~Even after dry heating treatment, the increase inof organics fraction was found infor the ICR of our OLLFdry heated samples. Therefore, the investigation of heat-insensitive organics is key to further understand the properties of soil dust INPs, (Table 8) as well as the nearly identical shape of INP spectra for non heated and heated samples (Fig. 5). Other properties were size independent and might not be relevant OAF IN. We found no notable biological INPs, and the OAF samples and particles used in this study were heat tolerant with respect to IN potential. Thus, we conclude that the observed variability of 3–4 orders of magnitude at a single T could be explained by differences in these inherent physicochemical properties (i.e., size and non-proteinaceous organic fraction), which may in part explain a previously observed gap between online and offline IN measuring systems (Hiranuma et al., 2015). Developing an atmospheric IN parameterization based on findings in this study offers an efficient representation of natural, supermicron dominant INPs. Due to its simplicity, our new parameterization can be used for atmospheric modeling applications at any scale. Our OAF INP parameterization should be included in atmospheric models and compared to nucleation theory and empirical IN parameterization (Phillips et al., 2013). Currently, ice formation processes are poorly represented in the climate models, and more studies will help to fill this gap, especially in the U.S. Southern High Plains region. and (Further research should focus on understanding how organic composition influences IN. Our previous work using Raman micro-spectroscopy revealed that ambient ~~aerosol particlesdust~~ sampled at ~~OAFs~~ ~~OLLFs are internally mixed withis composed of~~ brown or black carbon, hydrophobic humic acid, water soluble organics, less soluble fatty acids, and carbonaceous materials mixed with salts and minerals. But, our current knowledge regarding IN--active organics is still limited.~~

890 While we could not rule out the possibility of IN ~~of from~~ ~~TXD01 and TXD05 samples~~ triggered by biological INPs, our current results did not support it. In the future, we also need to carry out an identical metagenomics analysis for ICR samples collected at various T_s . Extracting enough DNA out of ICR samples would be challenging and is currently not feasible at the AIDA facility. Facilitating a dynamic cooling expansion chamber, and collecting ICRs for a prolonged expansion experiment period would be a potential resolution. Moreover, our metagenomics analysis indicated that most microorganisms were alive, but it did not provide any quantitative percentage. Therefore, we must do metatranscriptomics (analysis of RNA) in the future ~~to examine gene expression in the microbial population, as only live organisms produce RNA~~. More interdisciplinary, collaborative studies (e.g., how the diet of cattle, inclusion of antibiotics, probiotics etc. influences INP abundance in samples of feedlot surface materials) would also be useful.

895 *Data availability.* ~~Original data created for the study will be available in the Supplement upon publication~~ ~~Original data created for the study are or will be available in a persistent repository upon publication (<https://issues.pangaea.de/browse/PDI-25320> or West Texas A&M research web).~~

900 *Supplement.* The supplement related to this article is available online at: www.atmospheric-chemistry-and-physics.net

930 *Author contributions.* N.H., ~~B.W.A.~~ and N.S.U., ~~B.W.A.~~ and O.M. designed research; N.H., B.W.A., F.B., J.B., K.C., D.G., K.H., Y.H., H.S., X.S., I.S., N.S.U., F.V., ~~L.L.~~ and O.M. performed research; N.H., F.B., R.F., D.G., K.H., Y.H., G.S., X.S., I.S., N.S.U., H.S.K.V., F.V., ~~L.L.~~ and O.M. analyzed data; and N.H., F.B., D.G., and X.S. wrote the paper. N.H. led the revision effort with support of all authors.

Competing interests. The authors declare no conflict of interest.

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Figures and Tables

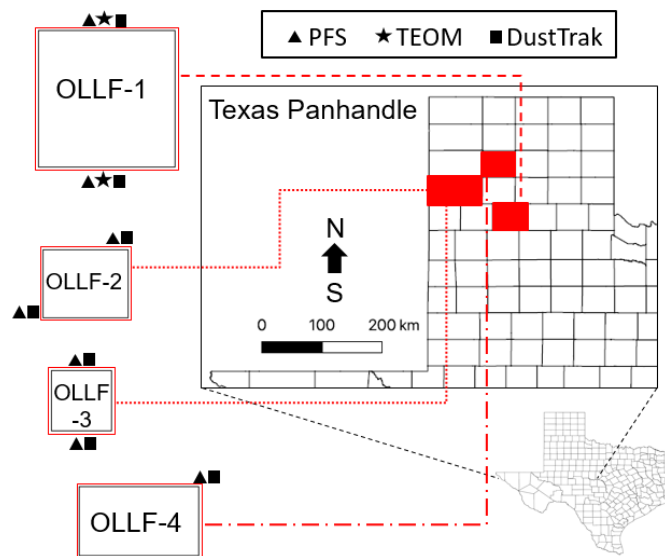


Figure 1. Schematic of the field sampling activity at individual sites (only the counties are shown). The dimension of each facility (east – west × north – south) is (1) 1.6×1.6 km, (2) 1.0×0.8 km, (3) 0.7×0.7 km, and (4) 0.8×1.4 km. A combination of polycarbonate filter samplers (PFSs) and DustTrak instruments was used at the nominally upwind and downwind edges of OLLF-1 to OLLF-3. Two tapered-element oscillating microbalances (TEOMs) were deployed at OLLF-1 alongside other instruments.

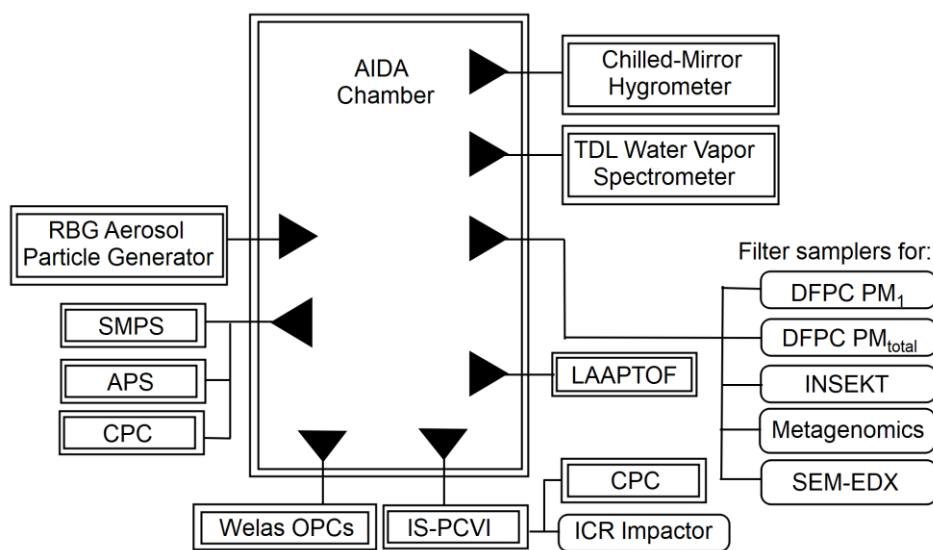


Figure 2. Lab experimental schematic of the AIDA facility. All samples were injected using a rotating brush generator (RBG) for aerosol particle generation. Multiple extramural instruments, welas optical particle counters (OPCs), an ice selective pumped counterflow virtual impactor (IS-PCVI), a hygrometer, a tunable diode laser (TDL) spectrometer, a laser ablation aerosol particle time-of-flight mass spectrometer (LAAPTOF; see SI), and aerosol particle counters/sizers (SMPS, APS, CPCs), are connected to

the AIDA chamber. Downstream filters and an impactor collected aerosol particles and ice crystal residuals for multiple offline analyses.

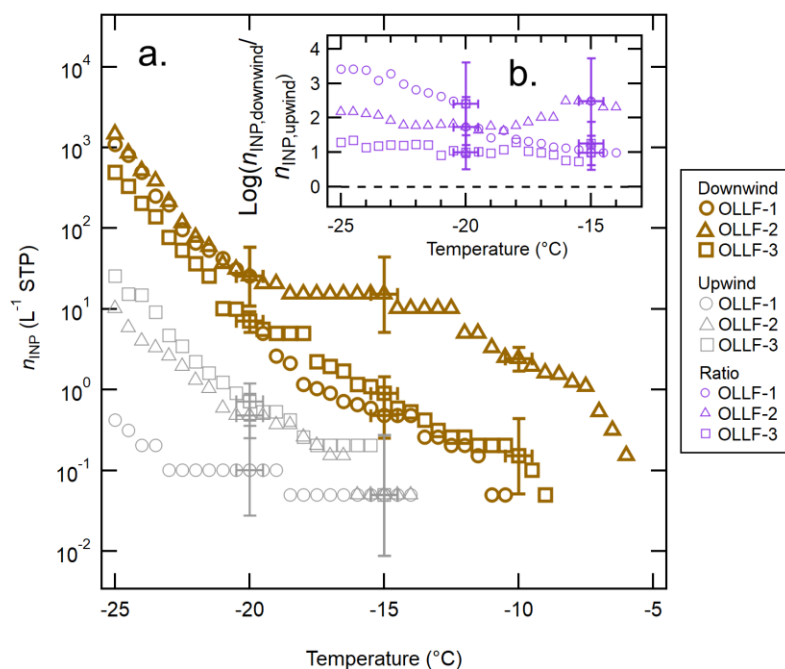


Figure 3. The n_{INP} spectra of OLLF aerosol particles from field ambient samples: a comparison of the downwind n_{INP} (brown) to the upwind n_{INP} (grey) from Summer 2017 is shown in (a). Different symbol shapes correspond to individual OLLF sites as indicated in the legend. The uncertainties in T and n_{sNP} are ± 0.5 °C and $\pm \text{CI95\%}$, respectively. Error bars are shown at selected T s to make all data points visible. The log-scaled downwind-to-upwind n_{INP} ratios, $\log(n_{\text{INP,downwind}}/n_{\text{INP,upwind}})$, for the overlapping T ranges are shown in (b). Note that the uncertainty in this ratio is $> 50\%$ due to large CI95% errors for measured n_{INP} . The black dashed line represents the ratio of zero (i.e., no difference between $n_{\text{INP,downwind}}$ and $n_{\text{INP,upwind}}$).

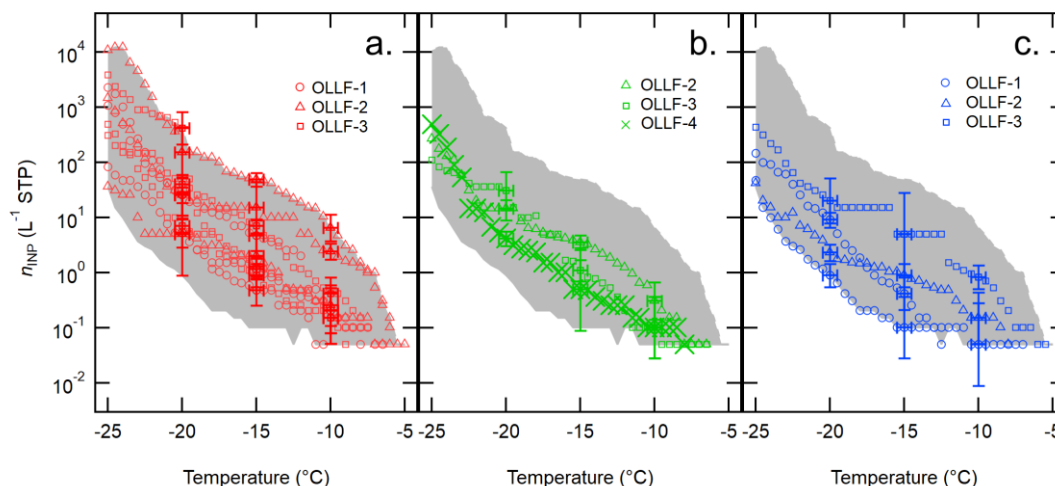


Figure 4. Downwind OLLF n_{INP} spectra from 2017 – 2019 sorted based on meteorological seasons are shown; summer (a), spring (b), and winter (c). The uncertainties in T and $n_{\text{s,geo}}$ are ± 0.5 °C and $\pm \text{CI95\%}$, respectively, and error bars are shown at -5, -10, and -15 °C. Shaded area represents minimum – maximum n_{INP} .

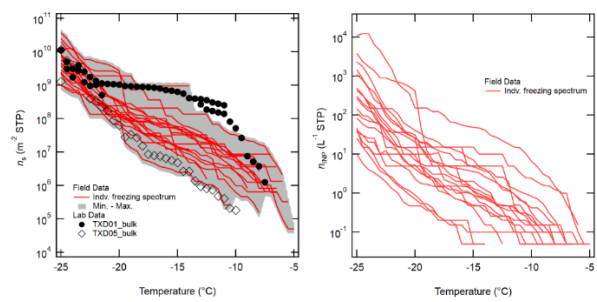


Figure 3. The $n_{s,geo}(T)$ spectra (a) and $n_{INP}(T)$ spectra (b) of FY samples. The gray shaded area represents the minimum and maximum $n_{s,geo}(T)$ values (CI95% values included) with the $0.5^{\circ}C$ T interval. A subset of lab $n_{s,geo}(T)$ spectral data discussed in Sect. 3.2 (i.e., TXD01_bulk and TXD05_bulk), composed of the AIDA and INSEKT data, are superposed to guide the reader’s eye.

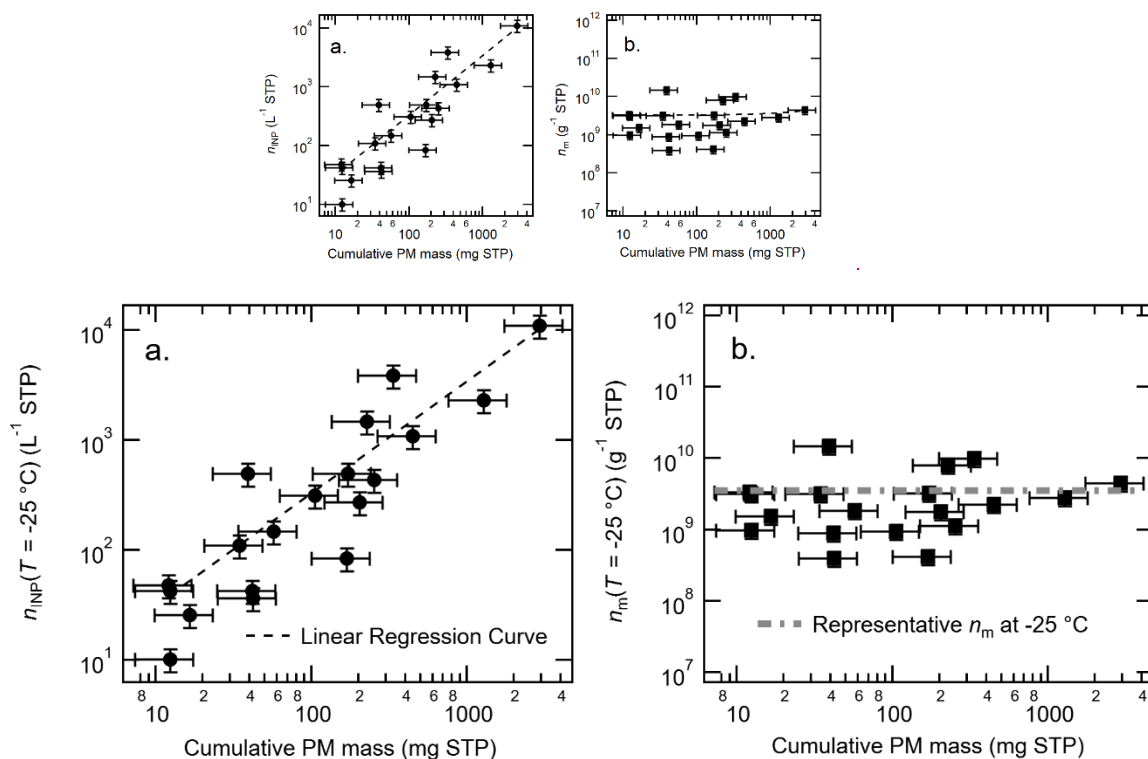


Figure 45. Correlation between cumulative PM mass vs. n_{INP} (a) and vs. n_m (b) at -25 °C ; a linear regression curve in log scale ($n_{\text{INP}} = 3.51 \times \text{Cumulative PM Mass} - 2.41$; $r = 0.94$) is shown in (a), and the constant value of representative n_m at the given T ($3.55 \times 10^9\text{ g}^{-1}$), which is a median n_m value of minimum – maximum, is shown in (b). Note the errors in cumulative PM mass are $\pm 40.4\%$ as discussed in Sect. 3.1, derived from calibration of two DustTrak instruments against TEOM in a side by side position. The uncertainty in n_{INP} and n_m is $\pm 23.5\%$ (Hiranuma et al., 2019).

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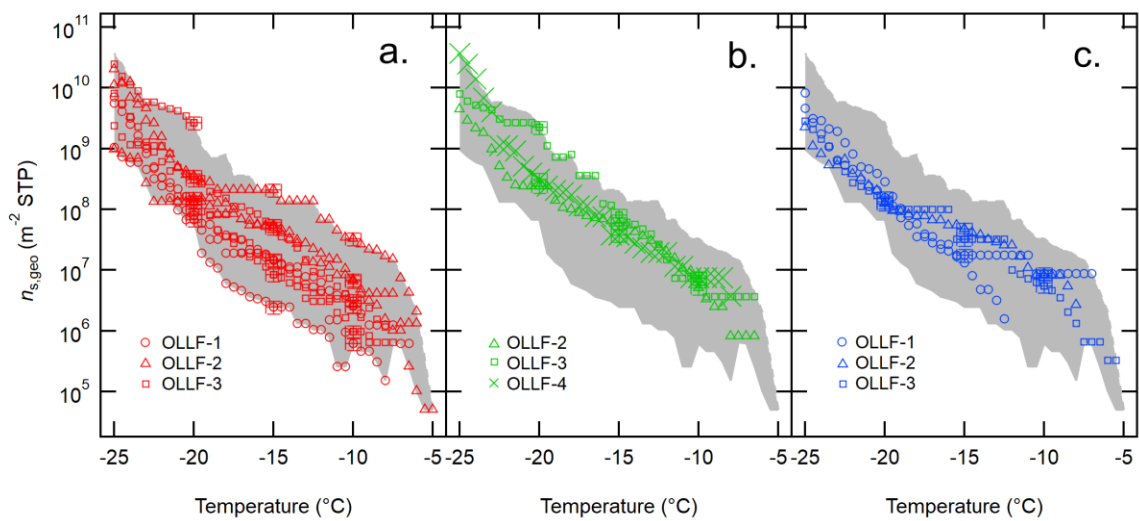


Figure 6. The $n_{s,geo}$ spectra of OLLF aerosol particles from field ambient samples collected in 2017 – 2019. All downwind $n_{s,geo}$ spectra from summer (a), spring (b), and winter (c) are shown. Different symbol shapes correspond to individual OLLF sites as indicated in the legend. The uncertainties in T and $n_{s,geo}$ are ± 0.5 °C and $\pm 23.5\%$, respectively, and representing error bars are shown at -5, -10, and -15 °C. Shaded area represents minimum – maximum $n_{s,geo}$.

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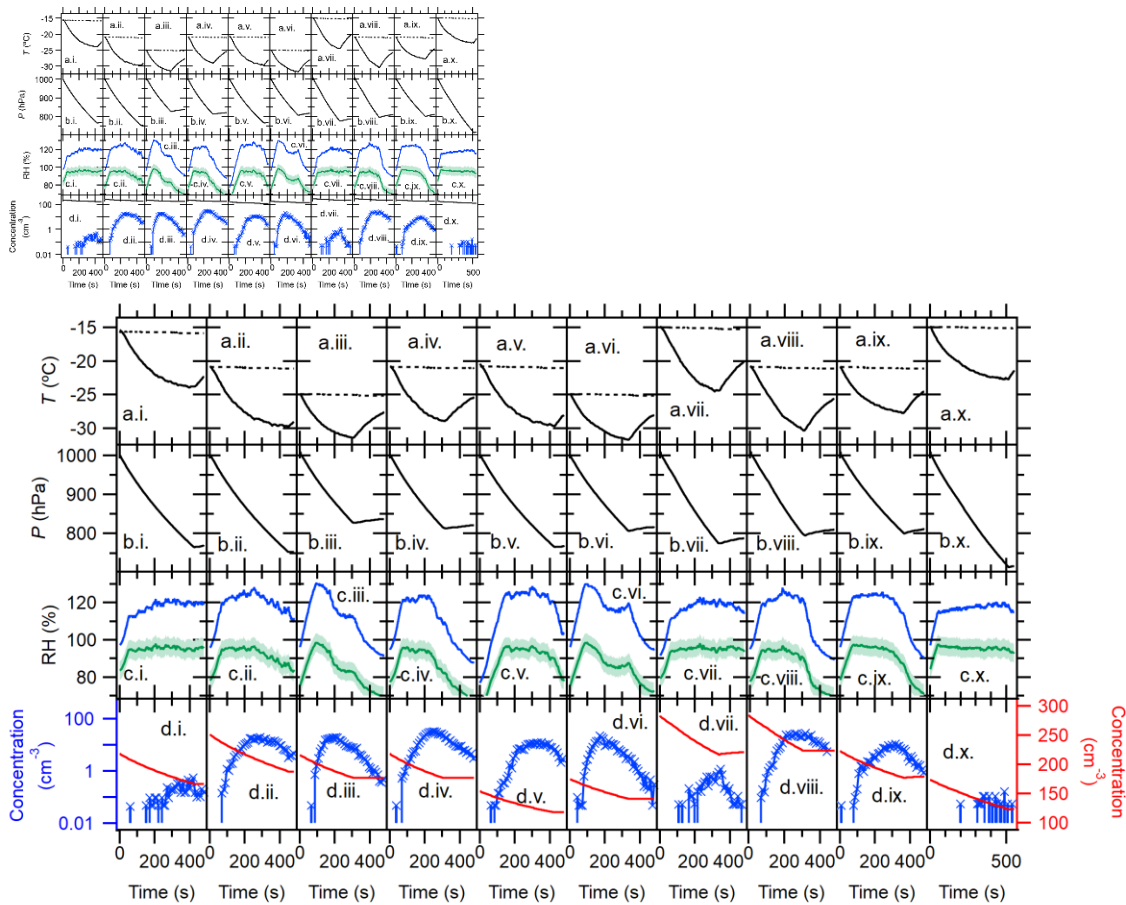
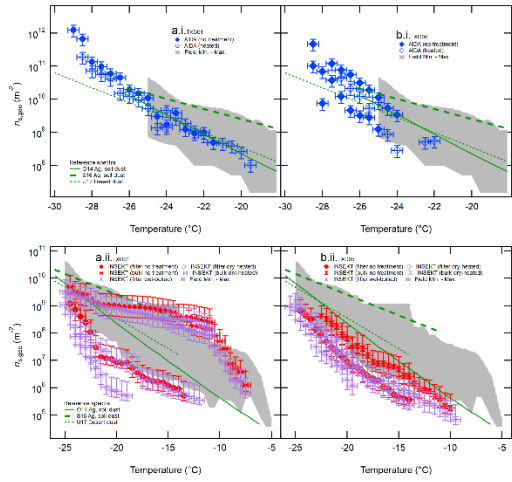


Figure 17. Temporal profiles of the AIDA immersion freezing experiment [TXDUST01_07 (i), _08 (ii), _30 (iii), _12 (iv), _13 (v), _32 (vi), _3 (vii), _4 (viii), _16 (ix), _17 (x)]. Arrays of alphabetical panels represent the chamber gas T (solid line) and the chamber wall T (dashed line) (a), P in the AIDA chamber vessel (b), RH with respect to water (green line) and ice (blue line) (c), and aerosol particle concentration initially measured by the CPC (black-red solid line) as well as number concentration of $> 20 \mu\text{m}$ D_{ve} AIDA particles measured by a welas optical particle counter (blue line) (d). Horizontal numerical panels represent different sample types and AIDA experiments, including TXD01 (i)–(iii), TXD05 (iv)–(vi), TXD01H (vii)–(viii), and TXD05H (ix)–(x). RH s were determined with an accuracy of $\pm 5\%$, represented as green shaded area in (c), using the mean gas T and the mean water vapor concentration.

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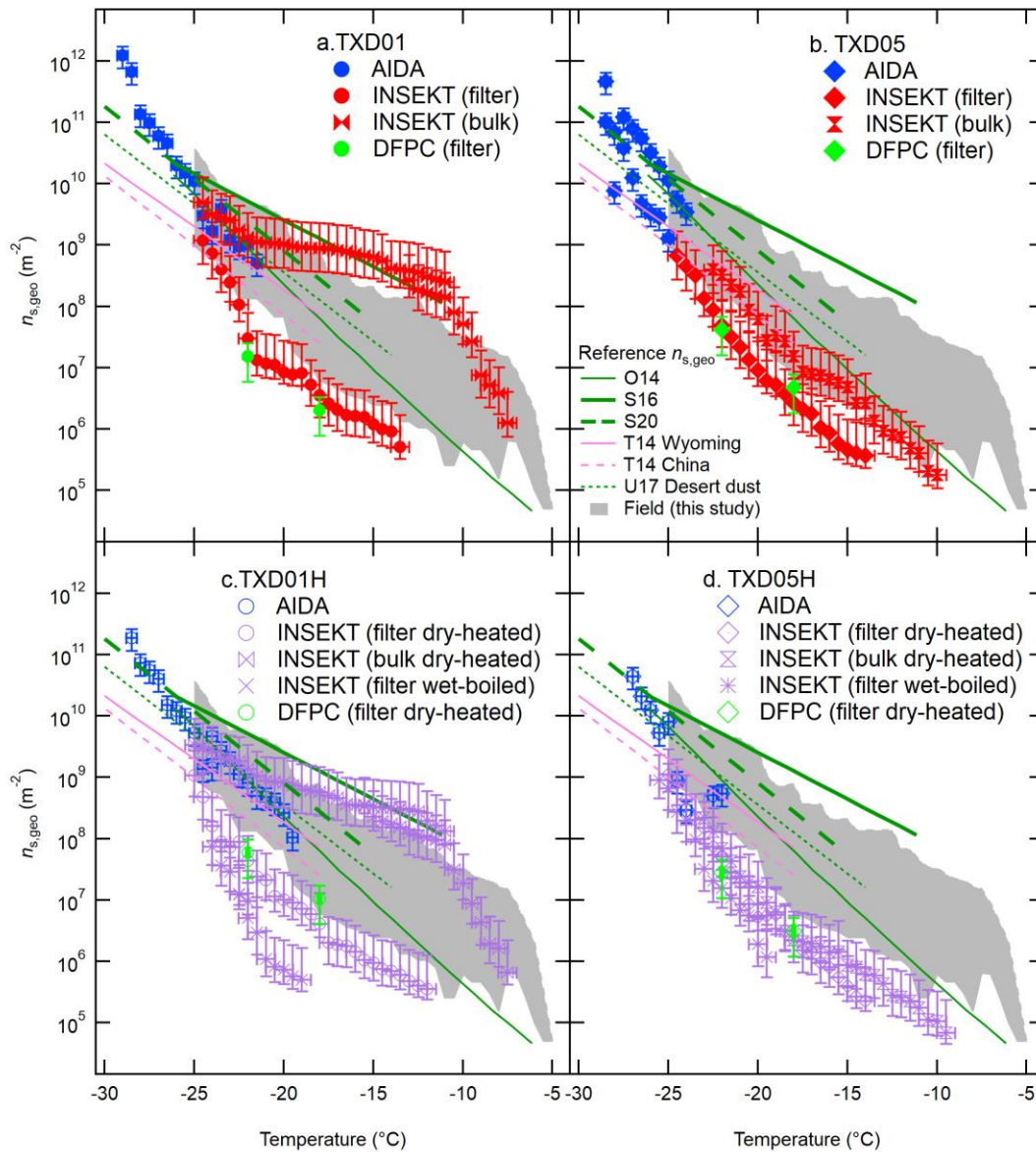


Figure 58. IN-spectra of OAF aerosol particles. IN-active surface-site density, $n_{s,geo}(T)$, of surface materials, TXD01 (panel a), and TXD05 (panel b), TXD01H (c), and TXD05H (d), was assessed by AIDA, (i) and INSEKT, and DFPC (total aerosol particles) (ii) as a function of T . A comparison of the non heat-treated sample to the heated sample is shown. Six reference $n_{s,geo}(T)$ curves for soil dust similar dust samples and desert dust are adapted from O'Sullivan et al. (2014; O14), Steinke et al. (2016; S16), Steinke et al. (2020; S20), and Ullrich et al. (2017; U17), and Tobo et al. (2014; T14). The grey-shaded area represents the range of our field $n_{s,geo}(T)$ values at $0.5\text{ }^{\circ}\text{C}$ interval for $-5\text{ }^{\circ}\text{C} > T > -25\text{ }^{\circ}\text{C}$ (Fig. 63).

1275

1280

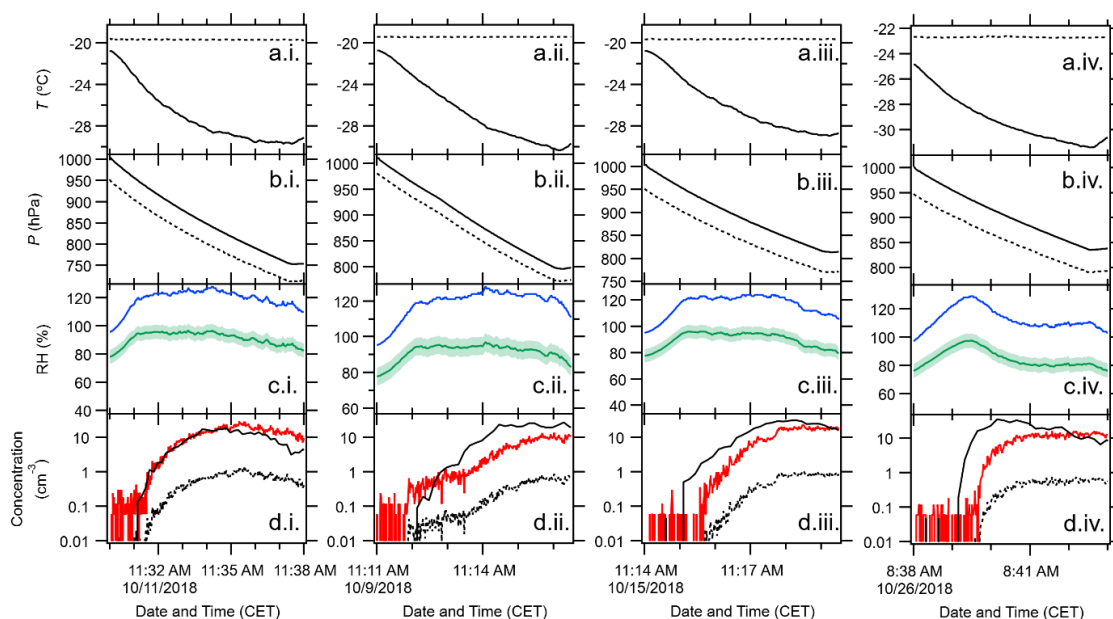


Figure 2. Temporal plots of the AIDA freezing experiment. Arrays of alphabetical panels represent the chamber gas T (solid line) and the IS PCVI nozzle T (dashed line) (a), P in the AIDA chamber (solid line) and the IS PCVI (dashed line) (b), RH with respect to water (green line) and ice (blue line) (c), and residuals measured by the CPC (red solid line) and corrected residual concentration according to Eqn. (6) of Hiranuma et al. (2016) (black dashed line) (d). In Panel (d), the number concentration of $> 20 \mu\text{m}$ D_{ve} AIDA particles measured by the welas optical particle counter (black solid line) is also shown. Horizontal numerical panels represent different sample types and AIDA experiments, including TXD01 (TXDUST01_08) (i), dry heated TXD01 (TXDUST01_04) (ii), TXD05 (TXDUST01_12) (iii), and dry heated TXD05 (TXDUST01_31) (iv). RH s were determined with an accuracy of $\pm 5\%$ using the mean gas T and the mean water vapor concentration. Note that the minimum detection of CPC is 0.1 cm^{-3} , and only negligible background particle concentration was observed prior to each expansion. The CF to IF ratios of 0.180 (ii) and 0.136 (i, iii and iv) correspond to critical ice particle cut sizes of $> 24 \mu\text{m}$ volume equivalent diameter, according to Fig. 9 of Hiranuma et al. (2016), transmitting pristine ice crystals downstream of the IS PCVI.

1285

1290

1295

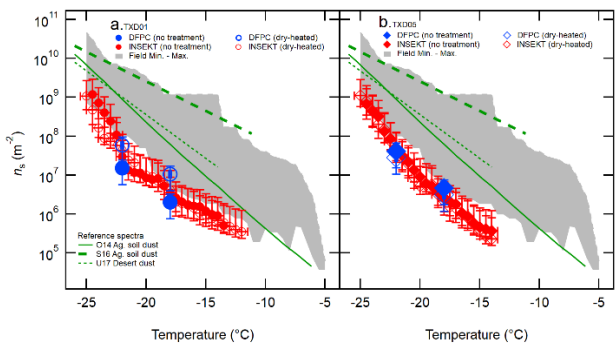
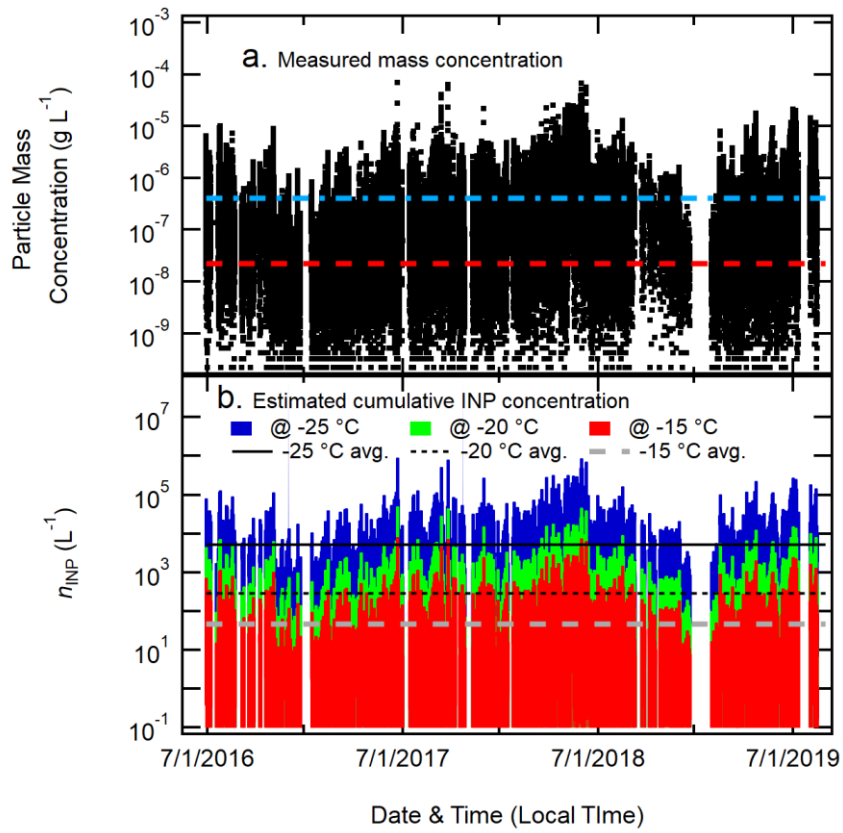


Figure 6. IN active surface site density, $n_{s,geo}(T)$, of TXD01 (panel a) and TXD05 (panel b) measured by DFPC (Total) and INSEKT (adapted from Fig. 5). A comparison of non heat treated sample to dry heated sample for both instruments is shown. Three reference $n_{s,geo}(T)$ lines for similar dust samples are adapted from O14, S16, and U17. The grey shaded area represents the range of our field $n_{s,geo}(T)$ values at 0.5 $^{\circ}C$ interval for $-5^{\circ}C > T > -25^{\circ}C$ (SIS1).

1300

1305



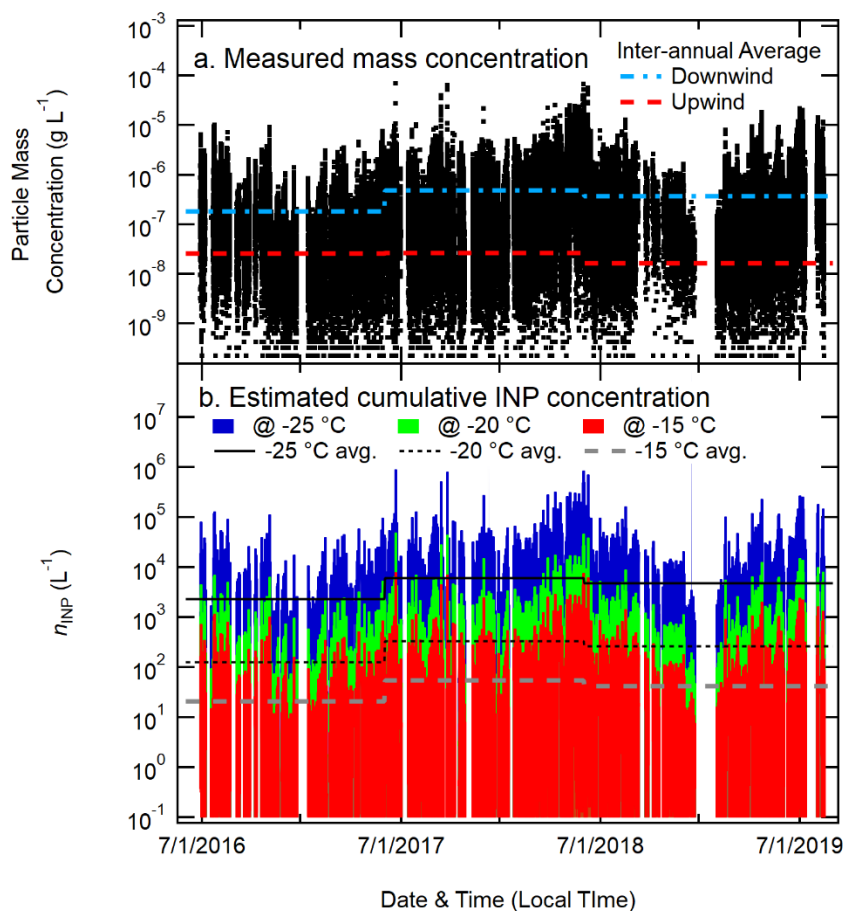


Figure 79. OLLF-OLLF INP concentrations. Time-series plot of TEOM mass concentration measured at the downwind side of OLLF-OLLF (a) and cumulative n_{INP} INP concentrations estimated at T_s of -15 °C, -20 °C, and -25 °C (b). In Panel a, inter-annual average mass concentrations of aerosol particles from OLLF (blue dashed line) and upwind (red dashed line) are shown (numbers adapted from Table 8). In Panel b, likewise, inter-annual average n_{INP} estimated at -15, -20, and -25 °C (reported in Table 8) are also shown. Meteorological summer in Texas is used for the beginning and ending time stamps of each year.

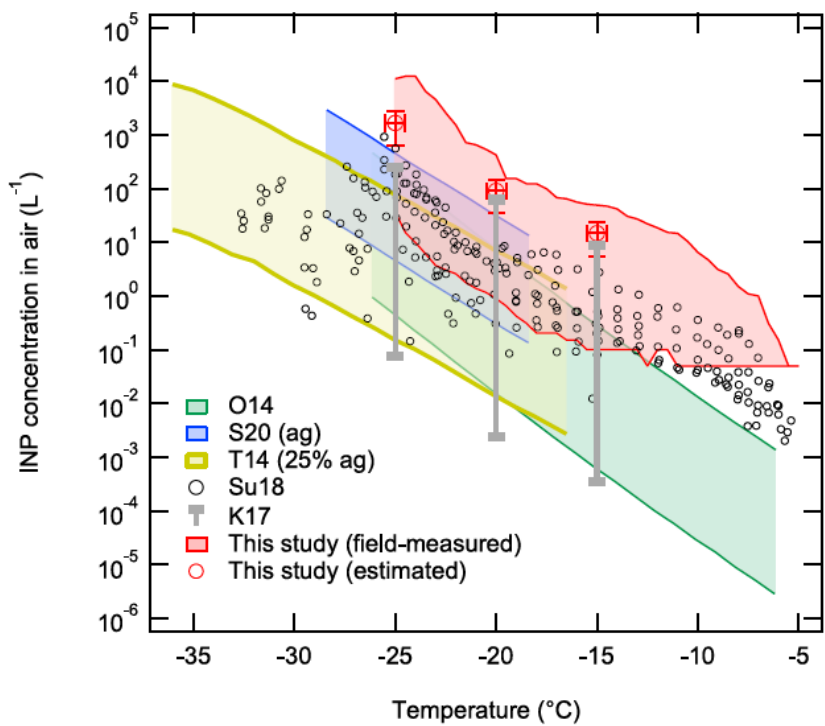


Figure 10. Ambient INP concentrations of soil dusts and aerosol particles as a function of T . The red-shaded area represents the range of our field n_{INP} values at $0.5\text{ }^{\circ}\text{C}$ interval for $-5\text{ }^{\circ}\text{C} > T > -25\text{ }^{\circ}\text{C}$ from this study (Fig. 4). The red open symbols are our estimated median (\pm standard deviation) at -15 , -20 , and $-25\text{ }^{\circ}\text{C}$ discussed in Sect. 3.5. Five reference data are adapted from O’Sullivan et al. (2014 Fig. 9; O14), Steinke et al. (2020 Fig. 3; S20), Tobo et al. (2014 Fig. 6b; T14), Suski et al. (2018 Fig. 1a-d; Su18), and Kanji et al. (2017 Fig. 1-10; K17). Note that we display the maximum and minimum at -15 , -20 , and $-25\text{ }^{\circ}\text{C}$ of K17 in comparison to our estimation.

Table 1. Summary of the ambient aerosol particle filter sampling conditions: UW denotes upwind.

Year	Date	Location	Start Time (Local)	End Time (Local)	Sample Flow (μmLPM)*	Total volume of sampled air (L STP)	T (°C)	P (mb)	Relative Humidity (%)
2019	20190715	<u>OLLF-1FY-I</u>	18:45:00	22:05:00	4.19	838.0	30.1 ± 3.2	1015.6 ± 0.2	42.0 ± 10.8
	20190716	<u>OLLF-2FY-II</u>	18:45:00	20:29:00	4.30	447.2	34.0 ± 0.7	1016.0 ± 0.2	27.8 ± 1.7
	20190724	<u>OLLF-3FY-III</u>	19:24:00	20:34:00	9.08	317.8	28.9 ± 0.8	1020.6 ± 0.1	31.6 ± 1.4
	20190226	<u>OLLF-1FY-I</u>	16:08:00	19:09:00	3.95	715.0	20.5 ± 2.7	1014.8 ± 0.2	14.3 ± 2.9
	20190328	<u>OLLF-2FY-II</u>	16:26:00	20:52:00	5.00	1330.0	19.4 ± 1.5	1012.8 ± 0.2	26.5 ± 6.8
	20190420	<u>OLLF-3FY-III</u>	17:05:00	21:05:00	4.15	996.0	27.0 ± 2.9	1009.0 ± 0.4	16.6 ± 5.0
	20190116	<u>OLLF-1FY-I</u>	16:03:00	19:33:00	3.97	832.7	16.5 ± 1.9	1014.7 ± 0.4	30.3 ± 3.1
	20190117	<u>OLLF-2FY-II</u>	15:48:00	19:30:00	3.97	880.2	11.0 ± 0.2	1016.9 ± 3.5	30.2 ± 5.6
20190118	<u>OLLF-3FY-III</u>	15:40:00	18:40:00	3.62	651.6	11.5 ± 3.9	1005.3 ± 2.2	41.1 ± 21.8	
2018	20180722	<u>OLLF-1FY-I</u>	18:42:00	22:39:00	6.58	1560.0	33.4 ± 4.3	1015.7 ± 0.3	17.8 ± 5.8
	20180723	<u>OLLF-2FY-II</u>	18:42:00	22:17:00	5.46	1173.8	28.4 ± 2.2	1022.5 ± 0.7	39 ± 5.1
	20180724	<u>OLLF-3FY-III</u>	18:20:00	22:13:00	3.65	850.3	28.9 ± 1.4	1023.3 ± 0.6	38.1 ± 2.6
	20180416	<u>OLLF-4FY-IV</u>	16:53:30	20:06:40	5.99	1158.0	27.2 ± 1.3	1009.8 ± 8.0	5.6 ± 0.8
2017	20170709	<u>OLLF-1FY-I</u>	19:32:45	22:26:00	5.28	915.6	27.9 ± 2.9	1017.0 ± 0.4	52.8 ± 13.1
	20170710	<u>OLLF-2FY-II</u>	18:06:00	22:06:30	5.10	1227.2	30.5 ± 2.5	1015.5 ± 0.3	30.8 ± 5.1
	20170711	<u>OLLF-3FY-III</u>	18:28:00	22:08:00	5.13	1128.0	29.9 ± 2.5	1015.2 ± 0.4	26.6 ± 6.0
	20170709	<u>OLLF-1-UW</u> <u>FY-I-UW</u>	19:50:00	22:47:00	5.28	935.2	27.9 ± 2.9	1017.0 ± 0.4	52.8 ± 13.1
	20170710	<u>OLLF-2-UW</u> <u>FY-II-UW</u>	18:28:00	22:24:00	5.10	1204.2	30.5 ± 2.5	1015.5 ± 0.3	30.8 ± 5.1
	20170711	<u>OLLF-3-UW</u> <u>FY-III-UW</u>	18:41:45	21:54:00	5.12	983.5	29.9 ± 2.5	1015.2 ± 0.4	26.6 ± 6.0

Year	Date	Location	Start Time (Local)	End Time (Local)	Cumulative PM mass (μg STP)†	n_{NP} @ -25°C (L ⁻¹ STP)	n_{m} @ -25°C (g ⁻¹ STP)
2019	20190715	<u>OLLF-1FY-I</u>	18:45:00	22:05:00	168.2	8.38E+01	4.18E+08
	20190716	<u>OLLF-2FY-II</u>	18:45:00	20:29:00	41.9	3.66E+01	3.91E+08
	20190724	<u>OLLF-3FY-III</u>	19:24:00	20:34:00	105.0	3.11E+02	9.42E+08
	20190226	<u>OLLF-1FY-I</u>	16:08:00	19:09:00	57.2	1.48E+02	1.84E+09
	20190328	<u>OLLF-2FY-II</u>	16:26:00	20:52:00	204.5	2.72E+02	1.77E+09
	20190420	<u>OLLF-3FY-III</u>	17:05:00	21:05:00	34.5	1.10E+02	3.18E+09
	20190116	<u>OLLF-1FY-I</u>	16:03:00	19:33:00	12.0	4.78E+01	3.31E+09
	20190117	<u>OLLF-2FY-II</u>	15:48:00	19:30:00	41.5	4.22E+01	8.94E+08
20190118	<u>OLLF-3FY-III</u>	15:40:00	18:40:00	251.8	4.35E+02	1.13E+09	
2018	20180722	<u>OLLF-1FY-I</u>	18:42:00	22:39:00	1281.0	2.31E+03	2.81E+09
	20180723	<u>OLLF-2FY-II</u>	18:42:00	22:17:00	2917.9	1.10E+04	4.43E+09
	20180724	<u>OLLF-3FY-III</u>	18:20:00	22:13:00	334.1	3.87E+03	9.84E+09
	20180416	<u>OLLF-4FY-IV</u>	4:53:30	8:06:40	38.9	4.93E+02	1.47E+10
2017	20170709	<u>OLLF-1FY-I</u>	19:32:45	22:26:00	445.3	1.09E+03	2.25E+09
	20170710	<u>OLLF-2FY-II</u>	18:06:00	22:06:30	226.5	1.48E+03	8.00E+09
	20170711	<u>OLLF-3FY-III</u>	18:28:00	22:08:00	171.5	4.92E+02	3.23E+09
	20170709	<u>OLLF-1-UW</u> <u>FY-I-UW</u>	19:50:00	22:47:00	12.4	4.22E+01	3.18E+09
	20170710	<u>OLLF-2-UW</u> <u>FY-II-UW</u>	18:28:00	22:24:00	12.4	1.01E+01	9.78E+08
	20170711	<u>OLLF-3-UW</u> <u>FY-III-UW</u>	18:41:45	21:54:00	16.5	2.57E+01	1.53E+09

*A mass flow controller or a critical orifice was used to ensure a constant flow throughout each sampling activity. An air flow rate was measured with a flowmeter (TSI Inc., Model 4140). †Cumulative values of mass collected on a filter were estimated by integrating DustTrak mass data, sampling time, and flow rate.

Table 2. Properties of OLLF samples: non-heated (TXD01 & TXD05) and dry-heated (TXD01H & TXD05H).

System	TXD01	TXD05	TXD01H	TXD05H
¹ Density, g cm ⁻³	1.89 ± 0.06	2.05 ± 0.06	1.94 ± 0.06	2.00 ± 0.06
Geometric SSA, m ² g ⁻¹	4.95 ± 0.82	3.97 ± 0.02	5.62 ± 0.16	4.04 ± 0.11
² BET-based SSA, m ² g ⁻¹	3.23 ± 0.20	2.41 ± 0.20	3.23 ± 0.32	2.41 ± 0.24

¹With a measurement relative standard deviation of ± 0.06-3%, our system is capable of measuring densities of other powder samples, such as illite NX (2.91 g cm⁻³) and fibrous cellulose (1.62 g cm⁻³). Note that these values are similar to the density values reported by manufacturers for illite NX (2.65 g cm⁻³) and fibrous cellulose (1.5 g cm⁻³). ²Brunauer et al., 1938.

Table 3. Characterization of particle properties: assessed prior to AIDA expansion experiments (H denotes dry-heated).

Experiment ID	Aerosol Particle Type	Mode (Min–Max) Diameter, μm^{**}	Aerosol Particle Measurements			
			$N_{total,0}$, $\times 10^3 \text{ L}^{-1}$	$S_{total,0}$, $\times 10^{-9} \text{ m}^2 \text{ L}^{-1}$	$M_{total,0}$, $\times 10^{-9} \text{ g L}^{-1}$	Geometric SSA, $\text{m}^2 \text{ g}^{-1}$
TXDUST01_7	TXD01	0.55 (0.10–3.16)	213.7	98.8	18.4	5.38
TXDUST01_8*	TXD01	0.54 (0.11–2.69)	266.3	115.5	21.1	5.46
TXDUST01_30	TXD01	0.72 (0.08–6.44)	210.6	119.0	29.7	4.01
TXDUST01_12*	TXD05	0.67 (0.09–5.14)	199.2	163.5	41.1	3.98
TXDUST01_13	TXD05	0.71 (0.10–4.71)	155.0	117.2	29.6	3.95
TXDUST01_32	TXD05	0.84 (0.15–4.37)	163.3	124.9	33.2	3.77
TXDUST01_3*	TXD01H	0.53 (0.10–2.69)	301.1	130.5	23.7	5.51
TXDUST01_4	TXD01H	0.52 (0.08–3.05)	282.1	137.1	23.9	5.73
TXDUST01_16*	TXD05H	0.78 (0.12–4.95)	227.4	195.1	49.3	3.96
TXDUST01_17	TXD05H	0.74 (0.12–4.59)	185.7	119.7	29.1	4.12

*INSEKT and DFPC samples were collected. **Based on the $dS/d\log D_{ve}$ fit; Min–Max values are estimated at $0.1 \times 10^{-9} \text{ m}^2 \text{ L}^{-1}$; $N_{total,0}$ = total number concentration of particles at the initial stage ($t = 0$) prior to expansion; $S_{total,0}$ = total surface concentration of particles at the initial stage ($t = 0$) prior to expansion; $M_{total,0}$ = total mass concentration of particles at the initial stage ($t = 0$) prior to expansion; D_{ve} = volume equivalent diameter.

Table 4. DFPC-estimated n_{INP} INP concentration for TXD01 and TXD05 samples: H denotes the dry-heated sample. The subscripts of Tot and PM_{10} represent INP obtained from total aerosol particles and that from PM_{10} size-segregated aerosol particles, respectively. Standard deviations were derived based on multiple measurements for each sample. Only PM_{10} of TXD01 sample was examined due to the data limitation. This size limit is valid since we observed only $< 10\text{--}6.44 \mu\text{m}$ aerosol particles in AIDA (Table 3). Supermicron INP fraction (%) is calculated by $[(n_{INP,tot} - n_{INP,PM10}) / n_{INP,tot}] \times 100$. Note the change of supermicron INP fraction at two temperatures before and after the dry-heated treatment is due to different total aerosol particles available in AIDA (Table 3). A comparison of $n_{s,geo}$ shows a reasonable agreement within the uncertainties reported in Sect. 2.4.

Dust	$n_{INP} \times 10^3 (\text{L}^{-1}) \pm$ standard dev.		Supermicron INP fraction (%)	
	-18 °C	-22 °C	-18 °C	-22 °C
TXD01 _{Tot}	340.0 ± 211.0	2580.0 ± 698.0	26.5	46.5
TSD01 _{PM10}	250.0 ± 90.0	1380.0 ± 219.0		
TXD01H _{Tot}	1266.7 ± 192.5	7141.7 ± 885.0	72.4	60.2
TSD01H _{PM10}	350.0 ± 120.0	2841.7 ± 375.8		
TXD05 _{Tot}	770.0 ± 110.0	6780.0 ± 426.0	58.4	48.4
TSD05 _{PM10}	320.0 ± 116.0	3500.0 ± 1066.0		
TXD05H _{Tot}	508.3 ± 100.0	4575.0 ± 1080.8	60.7	24.6
TSD05H _{PM10}	200.0 ± 45.8	3450.0 ± 715.8		

Table 5. OAF INP parameterization: List of exponential fit parameters to the $n_{s,geo}(T)$ for T binned ensemble datasets of lab study as well as field study. The datasets are fitted in the log space. The correlation coefficient, r , for each fit is also shown. All $n_{s,geo}(T)$ values are in m^{-2} . T is in $^{\circ}C$. Note the fifth order polynomial fit function is sensitive for all decimals shown here. To reproduce the fitted curves, we needed to include all decimals.

Fitted dataset: Sample-ID (INSEKT sample type)	Fitted T range	Fit Parameters						r	$\Delta \log (n_{s,geo})/\Delta T$
		$n_{s,geo}(T) = \exp(a + bT + cT^2 + dT^3 + eT^4 + fT^5)$							
		a (m^{-2})	b ($m^{-2}^{\circ}C^{-1}$)	c ($m^{-2}^{\circ}C^{-2}$)	d ($m^{-2}^{\circ}C^{-3}$)	e ($m^{-2}^{\circ}C^{-4}$)	f ($m^{-2}^{\circ}C^{-5}$)		
TXD01 (bulk)	$-29^{\circ}C < T < -7.5^{\circ}C$	-10.419739 559253788	-4.7365147 08000364	-0.19248508 975777787	0.00251437671 56404874	0.00028172574 60974357	3.664760242 99544e-06	0.99	0.28
TXD01H (bulk)	$-28.5^{\circ}C < T < -7.5^{\circ}C$	-22.024766 92454698	-8.0272347 73393355	-0.56209071 67927012	-0.01665207 3879196847	-0.000169949 36493112665	-1.220059988 9511637e-07	0.99	0.26
TXD01 (filter)	$-29^{\circ}C < T < -13.5^{\circ}C$	-649.60926 61424044	-166.17848 015453706	-16.3314245 41701384	-0.78540314 3752226	-0.018456365 06788169	-0.000170230 48008878034	0.99	0.41
TXD01H (filter, dry-heated)	$-28.5^{\circ}C < T < -12^{\circ}C$	17.88551115 2572057	-1.8325915 290723702	-0.56508783 20173172	-0.04817379 804678202	-0.001623522 4213422987	-1.973016312 032128e-05	0.97	0.35
TXD01H (filter, wet-boiled)	$-28.5^{\circ}C < T < -19^{\circ}C$	-28.412.092 220119186	-6043.6351 1549024	-511.447808 94398167	-21.5309744 85881597	-0.450854168 6398098	-0.0027571323 824947974	0.99	0.59
TXD05 (bulk)	$-28.5^{\circ}C < T < -10^{\circ}C$	-50.0223271 755289954	-16.045730 78900857	-1.61735618 28000045	-0.08074357 074021918	-0.001935789 3701810924	-1.807679158 9170566e-05	0.64	0.35
TXD05H (bulk)	$-27^{\circ}C < T < -9.5^{\circ}C$	-28.411321 02063094	-9.8209130 42395558	-0.90949367 95258034	-0.03972654 718668897	-0.000763624 4274088211	-5.200001963 207848e-06	0.99	0.33
TXD05 (filter)	$-28.5^{\circ}C < T < -14^{\circ}C$	-313.30582 52180446	-75.912698 717769	-6.90433259 32941135	-0.30470826 275283364	-0.006460682 825298372	-5.275536449 8764944e-05	0.62	0.42
TXD05H (filter, dry-heated)	$-27^{\circ}C < T < -14^{\circ}C$	-452.01181 238097746	-117.32306 672273883	-11.7623689 34161058	-0.58361828 71815894	-0.014288215 373972207	-0.000138670 0575218297	0.97	0.41
TXD05H (filter, wet-boiled)	$-27^{\circ}C < T < -19.5^{\circ}C$	41020.32207 07645	9026.32749022 4949	791.389548393 1685	34.5511122099 4813	0.75123943012 70052	0.006507672 03399298	0.97	0.61
Field_Median	$-25^{\circ}C < T < -5^{\circ}C$	-29.6470105 67958052	-16.317058286 439328	-2.3094959896 54582	-0.1625704680 7120043	-0.0055239335 23123538	-7.23939690 197926e-05	0.94	0.52
Field_Max	$-25^{\circ}C < T < -5^{\circ}C$	-33.2233240 5003339	-17.918940688 15357	-2.5378700781 94984	-0.1780842253 8269214	-0.0060285094 90726683	-7.87080475 404568e-05	0.93	0.53
Field_Min	$-25^{\circ}C < T < -5^{\circ}C$	-3.69823327 95064234	-5.3479986075 34987	-0.6782792077 804785	-0.0412234682 7949928	-0.0011424218 790211352	-1.19396607 8225184e-05	0.99	0.44

Table 65. Abundance of major bacterial phyla in dust samples TXD01 and TXD05. Numbers indicate percentage of the OTUs for each phylum in the total bacterial microbiome. The percentage of *Actinobacteria* in the microbiome is increased in aerosolized samples.

Taxonomy	Bulk TXD01	Bulk TXD01 (Dry-Heated)	Aerosolized TXD01	Bulk TXD05	Bulk TXD05 (Dry-Heated)	Aerosolized TXD05
<i>Actinobacteria</i>	40.1%	42.2%	60.1%	51.7%	67.1%	92.9%
<i>Chloroflexi</i>	4.4%	4.9%	4.0%	9.3%	4.0%	1.1%
Unclassified	3.8%	4.0%	4.0%	8.1%	9.9%	2.6%
<i>Proteobacteria</i>	19.9%	16.8%	11.4%	13.0%	10.3%	0.6%
<i>Firmicutes</i>	17.2%	17.5%	13.6%	15.4%	7.3%	2.8%
<i>Bacteroidetes</i>	12.6%	13.1%	6.5%	2.3%	1.4%	0.0%
<i>Gemmatimonadetes</i>	1.6%	1.3%	0.4%	0.1%	0.0%	0.0%
<i>Cyanobacteria</i>	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%
<i>Fibrobacteres</i>	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
<i>Nitrospinae</i>	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
<i>Planctomycetes</i>	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
<i>Rhodothermaeota</i>	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
<i>Spirochaetes</i>	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%

Table 76. Summary of particle size properties through electron microscopy.

Sample Type	Measured Particles	*Diameter (μm)		**Aspect Ratio		Spermicron Size Fraction (%)
		Average	Std. Error	Average	Std. Error	
TXD01 aerosol	159	0.80	0.03	1.46	0.04	<u>27.7%</u>
TXD01 residual	185	0.87	0.03	1.56 \uparrow	0.04	<u>29.2%</u>
TXD01H dry-heated aerosol	162	0.82	0.03	1.42	0.03	<u>26.5%</u>
TXD01H dry-heated residual	126	0.90	0.04	1.48 \uparrow	0.05	<u>33.3%</u>
TXD01 cumulative	632	0.84	0.02	1.48	0.02	<u>29.2%</u>
TXD05 aerosol	194	0.99	0.03	1.37	0.03	<u>44.3%</u>
TXD05 residual	164	1.17	0.03	1.49 \uparrow	0.03	<u>56.7%</u>
TXD05H dry-heated aerosol	100	1.23	0.04	1.41	0.05	<u>64.0%</u>
TXD05H dry-heated residual	169	0.90	0.03	1.49 \uparrow	0.04	<u>27.8%</u>
TXD05 cumulative	627	1.05	0.02	1.44	0.02	<u>38.8%</u>

*Average of 2-D cross sections. **Ratio of cross sections (i.e., longer cross section/shorter cross section).

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Table 87. Summary of particle composition types through energy dispersive X-ray spectroscopy.

Particle Type	TXD01 Abundance (%)				TXD05 Abundance (%)			
	Aerosol	Residual	Dry-heated Aerosol	Dry-heated Residual	Aerosol	Residual	Dry-heated Aerosol	Dry-heated Residual
Organic	5.0	7.6 \uparrow	3.1	9.5 \uparrow	8.2	9.1 \uparrow	3.0	11.2 \uparrow
Salt-rich	34.6	10.3 \downarrow	35.8	4.0 \downarrow	22.2	4.9 \downarrow	15.0	10.1 \downarrow
Mineral-rich	57.2	77.8	56.2	70.6	68.0	82.9	79.0	74.6
Other	3.1	4.3	4.9	15.9	1.5	3.0	3.0	4.1

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Table 8. Inter-annual and seasonal PM_{10} mass concentrations from OLLF-1 as well as estimated n_{INP} .

	PM_{10} Mass Concentration (g L^{-1})		Estimated $n_{\text{INP}}(T)$ (L^{-1})		
	*OLLF	Upwind	$T = -15\text{ }^\circ\text{C}$	$T = -20\text{ }^\circ\text{C}$	$T = -25\text{ }^\circ\text{C}$
2016 – 2017	<u>1.8E-07</u>	<u>2.6E-08</u>	<u>20.7</u>	<u>127.5</u>	<u>2323.4</u>
Summer	<u>3.7E-07</u>	<u>5.2E-08</u>	<u>42.3</u>	<u>260.5</u>	<u>4747.7</u>
Fall	<u>1.6E-07</u>	<u>2.8E-08</u>	<u>18.1</u>	<u>111.7</u>	<u>2036.3</u>
Winter	<u>6.3E-08</u>	<u>1.5E-08</u>	<u>7.2</u>	<u>44.2</u>	<u>806.2</u>
Spring	<u>1.6E-07</u>	<u>2.1E-08</u>	<u>17.7</u>	<u>108.9</u>	<u>1985.5</u>
2017 – 2018	<u>4.8E-07</u>	<u>2.6E-08</u>	<u>54.6</u>	<u>336.4</u>	<u>6133.0</u>
Summer	<u>3.0E-07</u>	<u>2.3E-08</u>	<u>33.8</u>	<u>208.5</u>	<u>3801.1</u>
Fall	<u>3.1E-07</u>	<u>1.9E-08</u>	<u>35.4</u>	<u>218.2</u>	<u>3978.3</u>
Winter	<u>2.5E-07</u>	<u>1.3E-08</u>	<u>27.9</u>	<u>171.7</u>	<u>3129.6</u>
Spring	<u>9.2E-07</u>	<u>4.6E-08</u>	<u>104.1</u>	<u>641.3</u>	<u>11690.9</u>
2018 – 2019	<u>3.7E-07</u>	<u>1.7E-08</u>	<u>42.3</u>	<u>260.7</u>	<u>4752.5</u>
Summer	<u>4.9E-07</u>	<u>2.6E-08</u>	<u>55.6</u>	<u>342.3</u>	<u>6240.6</u>
Fall	<u>2.4E-07</u>	<u>7.9E-09</u>	<u>26.8</u>	<u>165.3</u>	<u>3013.0</u>
Winter	<u>1.5E-07</u>	<u>1.3E-08</u>	<u>17.0</u>	<u>104.8</u>	<u>1910.2</u>
Spring	<u>2.8E-07</u>	<u>1.6E-08</u>	<u>31.8</u>	<u>195.8</u>	<u>3570.0</u>

*Upwind concentration is subtracted.

Supplementary Information for

Ice-nucleating particles from open-lot livestock facilities in Texas ~~Feedlot is a unique and constant source of atmospheric ice-nucleating particles~~

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25 Supplementary text S1 to ~~S3~~S6
Figures S1 to ~~S3~~S5
Tables S1 ~~to S3~~
SI References

S1. Ice-selecting pumped counterflow virtual impactor (IS-PCVI) sampling

30 The IS-PCVI is a custom-built instrument that can accommodate a substantially larger counterflow in comparison to commercially available PCVIs (e.g., Boulter et al., 2006). Such a large counterflow allows the IS-PCVI to have critical cut-off sizes of larger than 10 μm (more than twice as large as regular PCVIs) and, therefore, to inertially separate ice crystals from droplets found in mixed-phase clouds. As described in Hiranuma et al. (2016), the development of the IS-PCVI was guided by computation fluid dynamics simulations, and performance was verified in the lab using the AIDA chamber. Verifications include its transmission efficiencies ($\approx 93\%$; See Fig. 7) and cut-sizes up to
35 $\sim 30 \mu\text{m}$, ice phase separation based on the cut-size, validation of the evaporation section as part of the IS-PCVI outlet, performance of the interstitial particle sampling and minimum artifact detection (up to 5%).

40 Table S1 summarizes the IS-PCVI properties used in four AIDA experiments during the TXDUST AIDA laboratory campaign. We selected these four experiments to focus on analyzing ice crystal residuals of each sample (i.e., TXD01, TXD01H, TXD05, and TXD05H) due to their similar critical cut-size and/or experimental conditions. The flow conditions in the IS-PCVI were chosen to ascertain the critical cut-size of ice crystals $>24 \mu\text{m}$ diameter, which can be estimated based on Fig. 9 of Hiranuma et al. (2016). During the TXDUST01 campaign, the output flow of IS-PCVI was constant at 2.5 LPM, while the input and counter flows were slightly varied as listed in Table S1. Nonetheless, we used a moderate virtual concentration factor (i.e., Output/Input > 25) to ensure we collected a reasonable amount of ice crystal residuals on the substrates deployed downstream of IS-PCVI. Fig. S1 shows temporal profiles of IS-PCVI experimental parameters during four AIDA cloud simulation experiments, in which ice crystal residuals were characterized and sampled. The number concentration of particles above a droplet-ice threshold size in the AIDA chamber was measured by the wlas optical particle counter (Benz et al., 2005). These numbers virtually agreed with our residual count measured by a condensation particle counter (CPC, TSI Inc., Model 3076) after IS-PCVI (Figs. 2 and S1d). This comparability validated our choice of flow setting as well as the resulting critical cut-size of IS-PCVI ($> 24 \mu\text{m}$).

Table S1. Characterization of IS-PCVI properties during the AIDA expansion experiments. The critical cut-size of ice crystals was determined by the conditions of the input flow, output flow, effective counterflow (ECF), counterflow (CF), counterflow-to-input ratio, and pump flow.

Exp. ID	Reference time (CET)	Aerosol particle type	Cloud type	IS-PCVI properties						critical cut-size (μm)
				Input (LPM)	Output (LPM)	ECF (LPM)	CF (LPM)	CF/Input ratio	Pump (LPM)	
TXDUS T01_08	10/11/2018 11:30:00	TXD01	Mixed-Phase	70.0	2.5	7.0	9.5	0.136	77.0	24.0
TXDUS T01_04	10/9/2018 11:11:00	TXD01 Dry-Heated	Mixed-Phase	50.0	2.5	6.5	9.0	0.180	56.5	29.4
TXDUS T01_12	10/15/2018 11:14:00	TXD05	Mixed-Phase	70.0	2.5	7.0	9.5	0.136	77.0	24.0
TXDUS T01_31	10/26/2018 8:38:00	TXD05 Dry-Heated	Mixed-Phase	70.0	2.5	7.0	9.5	0.136	77.0	24.0

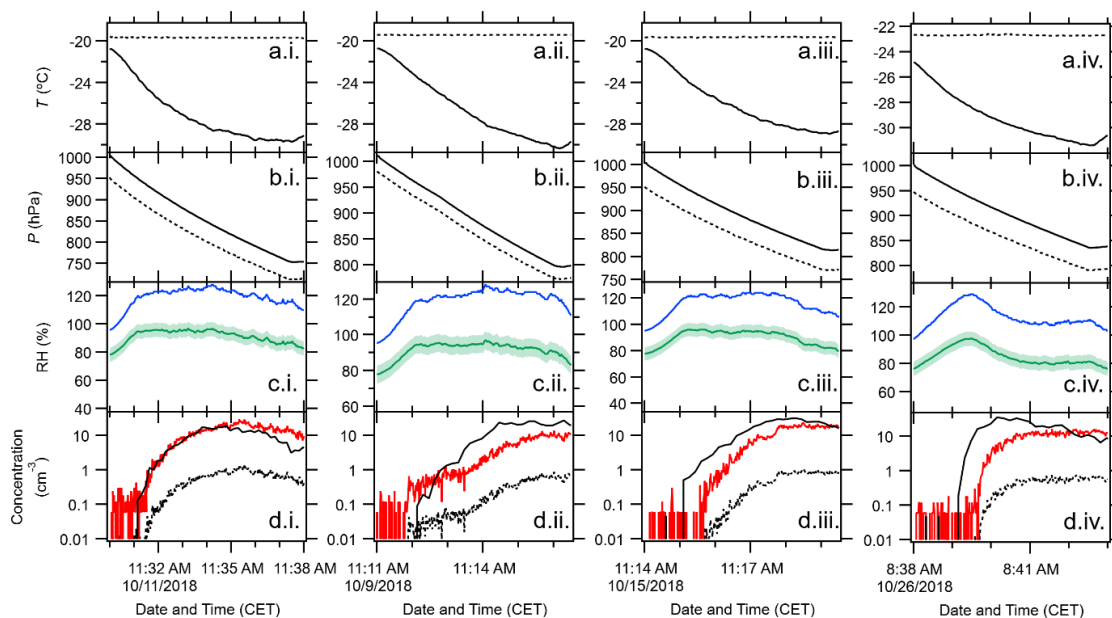


Figure S1. Temporal plots of the AIDA freezing experiments. Arrays of alphabetical panels represent the chamber gas T (solid line) and the IS-PCVI nozzle T (dashed line) (a), P in the AIDA chamber (solid line) and the IS-PCVI (dashed line) (b), RH with respect to water (green line) and ice (blue line) (c), and residuals measured by the CPC (red solid line) and corrected residual concentration according to Eqn. (6) of Hiranuma et al. (2016) (black dashed line) (d). In Panel (d), the number concentration of AIDA particles that have sizes above a droplet-ice threshold size (black solid line) is also shown. Horizontal numerical panels represent different sample types and AIDA experiments, including TXD01 (TXDUST01_08) (i), dry-heated TXD01 (TXDUST01_04) (ii), TXD05 (TXDUST01_12) (iii), and dry-heated TXD05 (TXDUST01_31) (iv). RH s were determined with an accuracy of $\pm 5\%$ using the mean gas T and the mean water vapor concentration. Note that the minimum detection of CPC is 0.1 cm^{-3} , and only negligible background particle concentration was observed prior to each expansion. The counterflow to input flow ratios of 0.180 (ii) and 0.136 (i, iii and iv) correspond to critical ice particle cut-sizes of $\geq 24 \mu\text{m}$ volume-equivalent diameter, according to Fig. 9 of Hiranuma et al. (2016), transmitting pristine ice crystals downstream of the IS-PCVI.

S4S2. Chemical Composition Analysis

Single particle mass spectra of dry dispersed TXD particles in the size range between 200 and 2500 nm (vacuum aerodynamic diameter) were measured in the lab using a laser ablation aerosol particle time-of-flight mass spectrometer (LAAPTOF; AeroMegt GmbH) (Shen et al., 2018; 2019). Both untreated and heat-treated samples were examined. The powder particles were generated by powder dispersion using a rotating brush generator (PALAS GmbH, RBG1000), where small volumes of dry TXD sample were dispersed by dry synthetic air.

The averaged mass spectra of TXD01 and TXD05 are shown in Fig. S4S2. We found no significant alternations in chemical composition and size distribution after dry-heating treatment; thereby, only spectra measured for the non-treated samples are shown. Nonetheless, this negative result supports the heat tolerance of TXD particles. In general, the mass spectra of the dry dispersed particles showed high signals of organic markers at mass-to-charge ratio, m/z , of +44 ($\text{COO}/\text{C}_2\text{H}_6\text{N}^+$), -26 ($\text{CN}/\text{C}_2\text{H}_2$), -42 ($\text{CNO}/\text{C}_2\text{H}_2\text{O}^-$), -45 (COOH^-), -59 (CH_2COOH^-), -71 ($\text{CCH}_2\text{COOH}^-$), +30 ($\text{NO}/\text{CH}_3\text{NH}/\text{CH}_2\text{O}^+$), +58 ($\text{C}_2\text{H}_5\text{-NH-CH}_2^+$), and +59 ($(\text{CH}_3)_3\text{N}^+$). These are typical markers for organic acids and amine-containing particles. For example, peaks at m/z of +44 can be attributed to $\text{COO}/\text{CH}_2\text{NO}^+$ derived from organic compounds/nitrogen containing organic compounds (Schneider et al., 2011). It should be noted that m/z 44 can also be contributed by SiO^+ , which is silicon marker (Silva and Prather, 2000). Further, -45 (COOH^-), -59 (CH_2COOH^-), and -71 ($\text{CCH}_2\text{COOH}^-$) are the markers for carboxylic acids. Peak at m/z of +30 can be attributed to NO^+ arising from nitrate, ammonium (Murphy et al., 2006; Shen et al., 2018), and CH_3NH^+ from amines (Silva and Prather, 2000; Schmidt et al., 2017). The other amine markers at +58 ($\text{C}_2\text{H}_5\text{NHCH}_2^+$) and +59 ($(\text{CH}_3)_3\text{N}^+$) were identified by previous studies (e.g., Angelino et al., 2001; Pratt et al., 2009; Schmidt et al., 2017).

For the inorganic markers, the characteristic ions were found on the peaks at m/z +23 (Na^+), +24 (Mg^+), +27 (Al^+), +28 (Si^+), +39 (K^+), +40 (Ca^+), +44 (SiO^+), +56 (CaO/Fe^+), +64/66 (Zn^+), -97 (HSO_4^-), +30 (NO^+), -63 (PO_2^-), -79 (PO_3^-), and -95 (PO_4^-). Calcium and sodium are used as additives in the diet fed to the cattle, and they also exist in the unpaved road dust (National Research Council, 2000; Ocsay et al., 2006). Manure is a source of ammonium and phosphate. Minor fractions of other salts and mineral dust constituents, found in this work, were also identified in the field samples (Hiranuma et al., 2011 and references therein). As mentioned above, +30 NO^+ can arise from ammonium (Murphy et al., 2006; Shen et al., 2018). In addition, -63 (PO_2^-), -79 (PO_3^-), and -95 (PO_4^-) are phosphate markers (Schmidt et al., 2017; Zawadowicz et al., 2017). However, our inorganic quantification is inconclusive, and the result may deviate from other quantitative composition analyses.

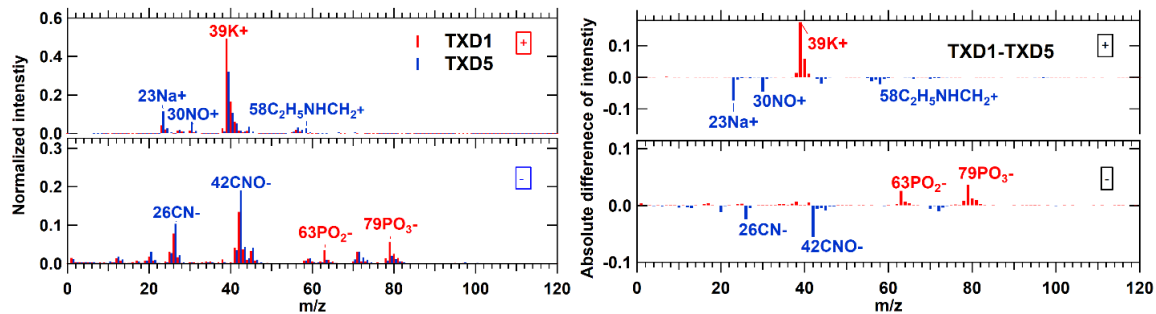
Comparing TXD01 to TXD05, we found that TXD01 had more intensive phosphate (-63, -79) and potassium (+39) compared to TXD05 (Fig. S4S2). In particular, phosphate intensity was a few times higher than TXD05. On the other hand, TXD05 had a higher signals of sodium- and nitrogen-containing compounds as well as stronger amine markers, i.e., m/z +30 ($\text{NO}/\text{CH}_3\text{NH}^+$) and +58 ($\text{C}_2\text{H}_5\text{-NH-CH}_2^+$), than TXD01.

A more detailed analysis of the individual mass spectra revealed several distinct particle types. Using a combination of the fuzzy c-means clustering (Shen et al., 2019) and the marker peak search method based on the above-mentioned and other characteristic ions, we found several distinct composition classes, such as "Potassium rich," "Potassium and phosphate rich," "Potassium, sodium, and ammonium rich," "Amine rich," and "Mineral and Metal rich." We note that the "rich" used here only indicates intensive characteristic peaks in the mass spectra rather than a large mass fraction. Figure S2-S3 shows the fuzzy classification results. As can be seen, there was no notable size dependent composition for any sample types. No obvious change in chemical compositions and size distribution was found after dry-heating treatment. A slight decrease in organic-potassium mixtures was found for dry-heated particle samples in comparison to non-heated ones, but the difference was insignificant. A significant amount of carboxylic acid groups (i.e., m/z -45 and -71) was found in each particle. These prevalent organic markers suggest that, regardless of the classification, TXD are organically predominant in nature. This organic predominance as well as the substantial inclusion of salts (e.g., potassium) are consistent with our previous study of TXD particles' composition (Hiranuma et al., 2011). We also note that our LAAPTOF aerosol particle chemical composition analysis was not intended to find inactive composition. Ice-nucleating particles (INPs) generally represent a small subset of aerosol particles

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(roughly one per million, even at low T_s). Thus, examining aerosol particle chemical composition cannot be directly linked to the role of chemistry in IN. In other words, aerosol particle composition does not necessarily represent ice-nucleating particle (INP) composition. A complementary elemental composition of ice crystal residuals is discussed in the main manuscript. But, aerosol particle composition data are important for understanding the general chemical compositions of our samples.

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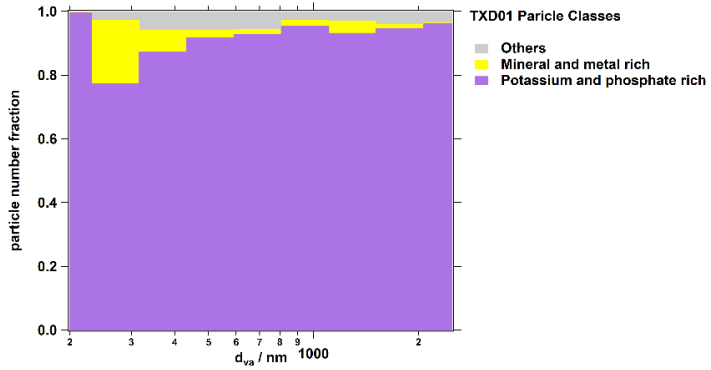
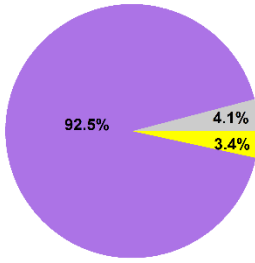


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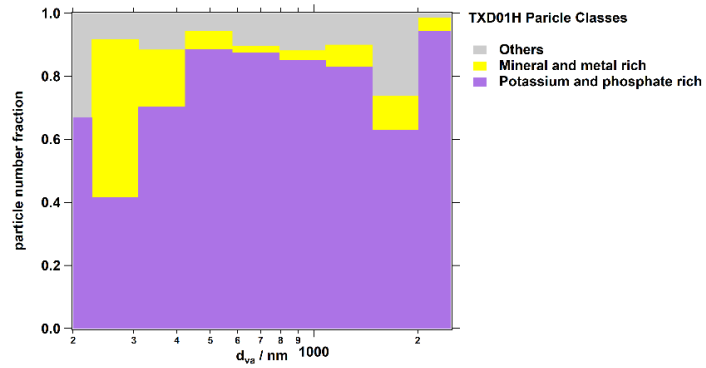
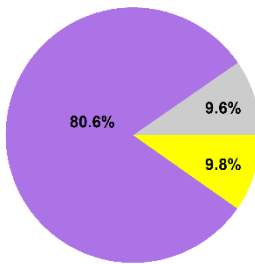
Figure S4S2. Laboratory reference mass spectra of dry dispersed TXD01 and TXD05 particles with LAAPTOF. The left panels show the stacked averaged spectra of cations (top) and anions (bottom) found in TXD01 and TXD05. The right panels represent the absolute signal difference. These mass spectra represent a compilation of > 450 of the particles for each type (TXD01: 972 and TXD05: 472). Note that each ion peak intensity is normalized to the sum of ion signals in each spectrum before further compilation.

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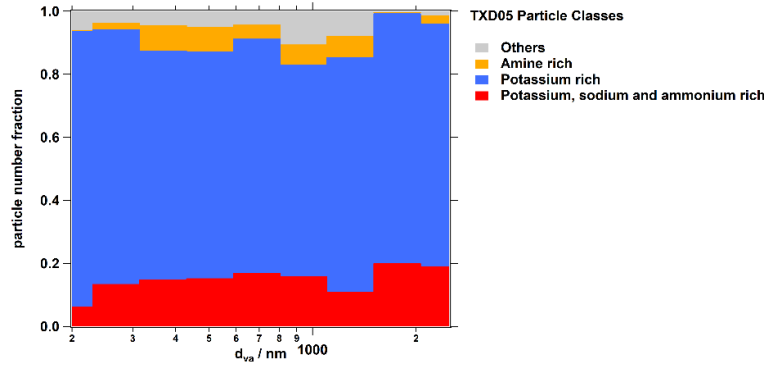
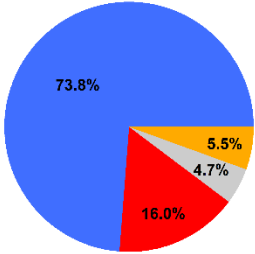
a. TXD01



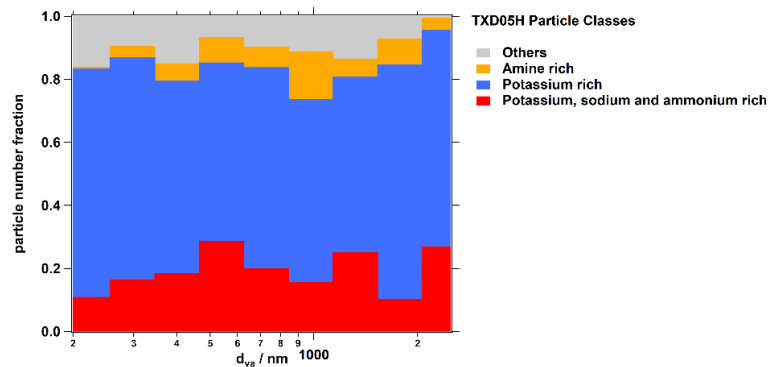
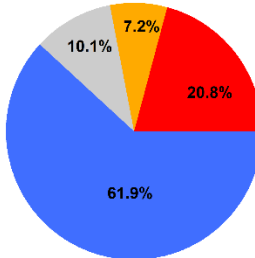
b. TXD01H



c. TXD05



d. TXD05H



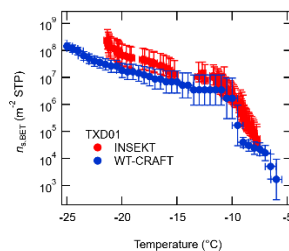
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Figure S2S3. Particle population fraction and size distribution based on clustered types, for TXD01 (a), TXD01H (b), TXD05 (c), and TXD05H (d). Note that the class named “others” (in grey color) is the small fraction of particles with unknown patterns. This class differs across TXD particle samples.

S2S3. Comparison of two immersion freezing techniques.

As shown in Fig. S3S4, the West Texas Cryogenic Refrigerator Applied to Freezing Test system (WT-CRAFT) system and the Ice Nucleation SpEctrometer of the Karlsruhe Institute of Technology (INSEKT) measured the immersion mode freezing efficiency of a bulk test open-lot livestock facility (OLLF) open-air feedlot material (TXD01). This complementary analysis was performed meaningful to indirectly validate WT-CRAFT against the Ice Nucleation SpEctrometer of the Karlsruhe Institute of Technology (INSEKT) measurements. The data from both techniques were analyzed with the method described in the main manuscript Sect. 2.4. The comparison to INSEKT showed that the ice nucleation (IN)-active surface site density values as function of temperature (T), $n_{s,geo}(T)$, over $-8^\circ\text{C} > \text{Temperature } (T) > -21^\circ\text{C}$ agreed within an order of magnitude CI95% and $\pm 0.5^\circ\text{C}$ T errors. Further, both methods successfully captured a local maximum in freezing spectra shown in Fig. S3 S4 at around -10°C , suggesting that they are comparable immersion freezing detection techniques. The uncertainty of INSEKT with respect to T is $\pm 0.5^\circ\text{C}$ (Schiebel, 2017). We note the following two caveats: (1) the geometric specific surface area (SSA) of $4.95 \text{ m}^2 \text{ g}^{-1}$ (Table 2) was used to convert from n_m to $n_{s,geo}$ according to Eqns. [1] – [3] in Sect. S4, and (2) while the BET and geometric SSA difference is small according to Table 2, the BET SSA and associated IN-active surface site density values scaled to BET SSA, $n_{s,BET}$, may be more representative for a bulk TXD01 sample. According to Eqn. 4 of Hiranuma et al. (2015), the $n_{s,BET}$ value can be easily obtained by scaling n_m to BET SSA. In the case of TXD01, the difference between $n_{s,BET}$ and $n_{s,geo}$ can be represented by the ratio of BET SSA to geometric SSA $n_{s,geo}$.

In addition to the bulk TXD01 sample, the comparability of the two immersion freezing techniques was assessed using the field aerosol particle samples collected using polycarbonate filter samplers (PFSs) at OLLF-3 in 2019. We chose this sample for the comparison since its INP concentration, n_{INP} , spectra fall between the measured maximum and minimum $n_{INP}(T)$ in 2017-2019 even when considering CI95% bounds. Thus, it is representative for the field OLLF $n_{INP}(T)$ data presented in this study. Furthermore, with this sample, we also conducted the INSEKT wet-boiling treatment analysis. Figure S5 shows the $n_{INP}(T)$ spectra of the same sample measured by WT-CRAFT and INSEKT in the T range between -8°C and -22.5°C . As can be seen, both techniques successfully generated $n_{INP}(T)$ data virtually overlapping and within error bars, only at $T < -22^\circ\text{C}$, WT-CRAFT measures lower values. The two methods correlate well with each other, with the Pearson correlation coefficient (r) of 0.90 ($n_{INP,INSEKT} = (2.1213 \times n_{INP,WT-CRAFT}) - 11.2310$). The comparison of non-heated vs. wet-boiled $n_{INP,INSEKT}$ data for the overlapping T ranges showed negligible difference between $n_{INP,non-heated}$ and $n_{INP,wet-boiled}$. The correlation plot of non-heated vs. wet-boiled (Fig. S5b) indicates no difference within CI95% uncertainties [$r = 0.97$; $n_{INP,wet-boiled} = (1.0849 \times n_{INP,non-heated}) + 7.1958$], suggesting heat resistivity of OLLF-INPs collected on this PFS sample.



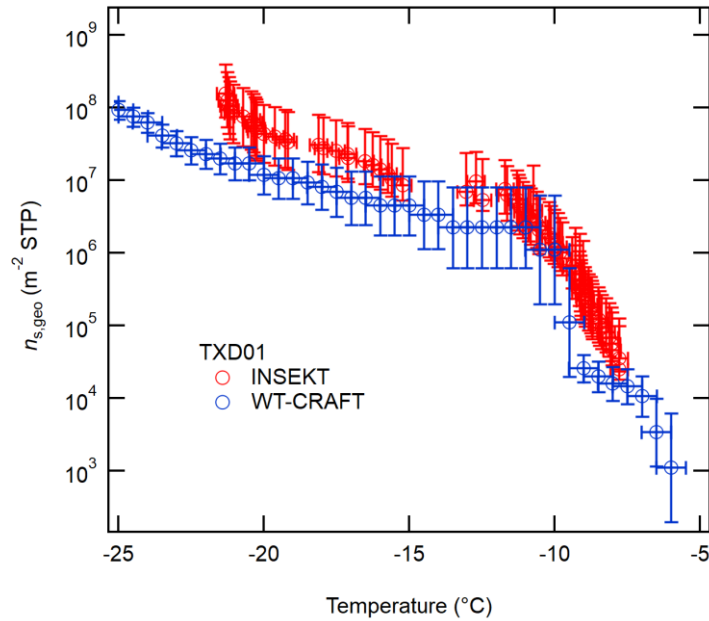


Figure S3S4. Immersion freezing $n_{s,geo}(T)$ spectra of the bulk TXD01b sample measured by KIT-INSEKT and WT-CRAFT for their compatibility test. This figure shows the BET surface-scaled $n_s(T)$ spectra (Hiranuma et al., 2015). For the ice-nucleating particle measurement uncertainty, 95% binomial sampling confidence intervals (CI95%), are computed using the procedure described in Schiebel (2017, Eqn. 3.21). The vertical error bars represent CI95%.

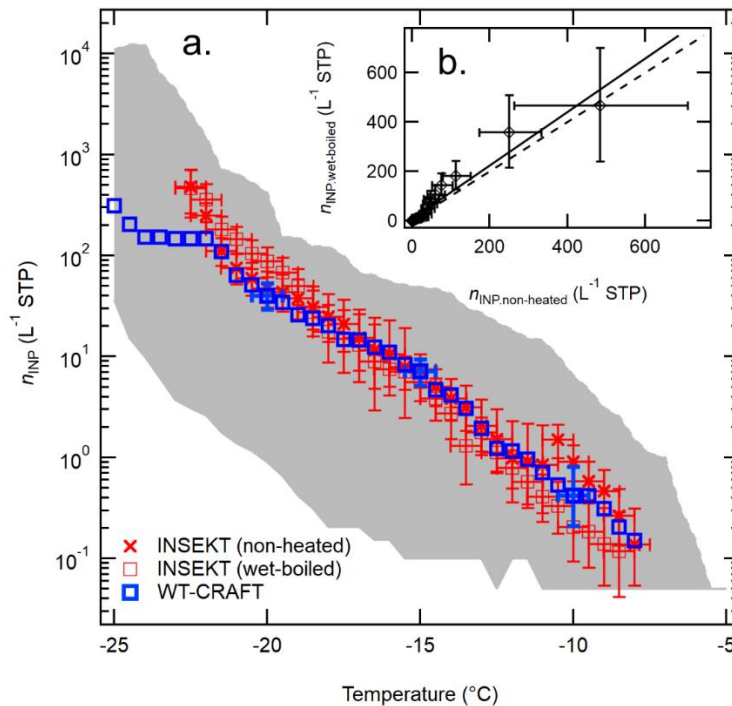


Figure S5. The $n_{NP}(T)$ spectra of aerosol particles collected at OLLF-3 in summer 2019, measured with WT-CRAFT (blue) and INSEKT (red): a comparison of the non-heated $n_{NP,non-heated}(T)$ (red cross) to the wet-boiled $n_{NP,wet-boiled}(T)$ (red square) INSEKT measurements and non-treated WT-CRAFT measurements is shown in (a). The uncertainties in T and n_{NP} are ± 0.5 °C and \pm CI95%, respectively. Error bars are shown at selected T s for the WT-CRAFT data to make all data points visible. The correlation of non-heated vs. wet-boiled plot for the overlapping T ranges from INSEKT is shown in (b). The black dashed line represents the 1:1 curve to

210 guide the reader's eye (i.e., no difference between $n_{INP,non-heated}$ and $n_{INP,wet-boiled}$). Shaded area represents max – min $n_{INP}(T)$ for all our OLLF samples collected in 2017 – 2019.

215 **S4. Derivation of n_{INP} , n_m , and $n_{s,geo}$**

Here we describe the conversion procedure used to derive ambient n_{INP} , n_m , and $n_{s,geo}$. Initially, we computed the $C_{INP}(T)$ value, which is the nucleus concentration in ultrapure water suspension (L^{-1} water) at a given T as described in Vali (1971). This $C_{INP}(T)$ value was calculated as a function of unfrozen fraction, $f_{unfrozen}(T)$ (i.e., the ratio of number of droplets unfrozen to the total number of droplets) as:

$$220 \quad C_{INP}(T) = - \frac{\ln(f_{unfrozen}(T))}{V_d} \quad [1]$$

in which, V_d is the volume of the droplet (3 μL) for WT-CRAFT and sample in a well (50 μL) for INSEKT.

225 Next, we converted $C_{INP}(T)$ to $n_{INP}(T)$: INP in the unit volume of atmospheric air at standard T and pressure (STP) conditions, which is 273.15 K and 1013 mbar. The cumulative n_{INP} per unit volume of sample air, described in the previous study DeMott et al. (2017), was then estimated as:

$$n_{INP}(T) = C_{INP}(T) \times (DF) \times \frac{V_l}{V_{air}} \quad [2]$$

230 where DF is a serial dilution factor (e.g., DF = 1 or 10 or 100 and so on). The sampled air volume (V_{air}) is given in **Table 1**. The suspension volume (V) is optimized to achieve the detection limit of 0.05 INP L^{-1} (corresponding to the first frozen droplet).

Finally, based on Eqn. 3 of Hiranuma et al. (2015), the $n_{s,geo}(T)$ and $n_m(T)$ values can be derived as:

$$235 \quad n_m(T) = \frac{n_{INP}(T)}{M_{ve}} \approx \left(\frac{S_{total}}{M_{total}} \right) n_{s,geo}(T) \quad [3]$$

240 where M_{ve} is the mass of a spherical particle of volume equivalent diameter (g), and S_{total}/M_{total} is a geometric specific surface area (Hiranuma et al., 2015). The value used for converting field $n_m(T)$ to $n_{s,geo}(T)$ data, $\sim 0.4 \text{ m}^2 \text{ g}^{-1}$, is derived from particle size distribution measurements presented in Fig. 3 of Hiranuma et al. (2011).

S35. Taxonomic diversity of two Texas dust samples. We examined the diversity of *Archaea*, *Bacteria*, and *Fungi* in TXD01 and TXD05. Bulk samples, dry-heated bulks (100°C for 12 hours), and aerosolized particles collected on nuclepore filters were analyzed. Useful data for *Bacteria* were generated from the amplification and sequencing of the V3-V5 region of the 16S rDNA phylogenetic marker down to the genus and species-level. The predominant phyla of *Archaea* consisted of methanogens, colonizers of the bovine rumen, as expected (Fouts et al., 2012) (Table S4aS2a). The bacterial fraction of the microbiome was dominated by *Actinobacteria* (the most abundant phylum, common soil inhabitants), *Proteobacteria*, *Firmicutes* (diverse bacterial phyla with species living in the soil as well as in the bovine rumen), and *Bacteroidetes* (common members of the bovine rumen microflora) (Fouts et al., 2012; Chaucheyras-Durand and Ossa, 2014). No known IN-active bacterial species were identified in either sample (Després et al., 2012), although the genus *Pseudomonas* (containing IN-active species) was detected in low numbers (Table S4bS2b). The predominant fungal taxa in our samples belong to *Pezizomycetes* (*Ascomycota*), common soil inhabitants. In this taxon, the coprophilic genus *Ascobolus* was detected in high numbers, as expected (Sarrocchio, 2016). The genera *Fusarium* (*Ascomycota-Hypocreales*) and *Mortierella* (*Mucoromycota-Mortierellales*) were also detected in low numbers. These genera contain species with IN activity; however, the phylogenetic analysis did not detect any known IN-active species of these genera (Table S4cS2c). Nonetheless, it is very interesting that we did not identify any known IN-active biological species in our samples.

Table S4S2. Abundance of major orders of *Archaea* in dust samples TXD01 and TXD05 (a). Numbers indicate percentage of the OTUs for each phylum in the total archaeal microbiome. The analysis of the aerosolized TXD01 sample and of dry heat-treated bulk samples did not generate any useful data. Abundance of major bacterial and eukaryotic (incl. fungal) orders in dust samples TXD01 and TXD05 are shown in (b) and (c). Numbers indicate percentage of the OTUs for each order in the total bacterial and eukaryotic microbiome.

a. Archaea Taxonomy	Bulk TXD01	Bulk TXD01 (Dry-heated)	Aerosolized TXD01	Bulk TXD05	Bulk TXD05 (Dry-heated)	Aerosolized TXD05
Unclassified	4.10%	-	-	0.00%	-	0.00%
<i>Euryarchaeota; Methanobacteria; Methanobacteriales</i>	58.40%	-	-	77.70%	-	93.80%
<i>Euryarchaeota; Methanomicrobia; Methanomicrobiales</i>	18.30%	-	-	1.50%	-	0.10%
<i>Euryarchaeota; Methanomicrobia; Methanosarcinales</i>	0.60%	-	-	5.00%	-	0.00%
<i>Euryarchaeota; Thermoplasmata; Methanomassiliicoccales</i>	12.30%	-	-	0.00%	-	0.00%
<i>Thaumarchaeota; Nitrososphaeria; Nitrososphaerales</i>	6.30%	-	-	15.80%	-	6.10%
b. Bacteria Taxonomy	Bulk TXD01	Bulk TXD01 (Dry-heated)	Aerosolized TXD01	Bulk TXD05	Bulk TXD05 (Dry-heated)	Aerosolized TXD05
Unclassified	3.80%	4.00%	4.00%	8.10%	8.60%	2.60%
<i>Actinobacteria; Acidimicrobiales</i>	1.50%	1.50%	0.80%	1.40%	1.20%	0.20%
<i>Actinobacteria; unclassified</i>	0.50%	1.20%	3.00%	4.70%	6.60%	2.10%
<i>Actinobacteria; Actinomycetales</i>	0.30%	0.30%	0.20%	0.10%	0.00%	0.00%
<i>Actinobacteria; Bifidobacteriales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Actinobacteria; Corynebacteriales</i>	11.10%	11.40%	16.40%	14.00%	12.90%	13.70%
<i>Actinobacteria; Frankiales</i>	0.50%	0.30%	0.20%	0.00%	0.00%	0.00%
<i>Actinobacteria; Geodermatophilales</i>	0.40%	0.60%	0.30%	0.00%	0.00%	0.00%
<i>Actinobacteria; Glycomycetales</i>	0.00%	0.00%	0.20%	0.00%	0.30%	0.40%
<i>Actinobacteria; Jiangellales</i>	0.10%	0.10%	0.00%	0.10%	0.20%	0.00%

<i>Actinobacteria; Kineosporiales</i>	0.00%	0.10%	0.00%	0.00%	0.00%	0.00%
<i>Actinobacteria; Micrococcales</i>	20.10%	20.10%	12.30%	13.00%	12.20%	2.10%
<i>Actinobacteria; Micromonosporales</i>	0.00%	0.00%	0.10%	0.00%	0.10%	0.00%
<i>Actinobacteria; Propionibacteriales</i>	5.60%	5.90%	5.00%	3.90%	2.70%	0.20%
<i>Actinobacteria; Pseudonocardiales</i>	0.00%	0.00%	7.70%	6.70%	14.30%	39.20%
<i>Actinobacteria; Streptomycetales</i>	0.20%	0.60%	11.30%	5.60%	11.90%	28.60%
<i>Actinobacteria; Streptosporangiales</i>	0.00%	0.00%	2.30%	1.70%	4.70%	6.50%
<i>Actinobacteria; Coriobacteriales</i>	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%
<i>Actinobacteria; Solirubrobacterales</i>	0.00%	0.00%	0.20%	0.40%	0.50%	0.00%
<i>Bacteroidetes; unclassified</i>	0.10%	0.10%	0.10%	0.80%	0.50%	0.00%
<i>Bacteroidetes; Chitinophagales</i>	0.70%	0.60%	0.30%	0.00%	0.00%	0.00%
<i>Bacteroidetes; Cytophagales</i>	1.60%	2.50%	0.70%	0.10%	0.20%	0.00%
<i>Bacteroidetes; Flavobacteriales</i>	8.60%	8.60%	4.20%	0.10%	0.00%	0.00%
<i>Bacteroidetes; Saprospirales</i>	0.20%	0.10%	0.10%	0.00%	0.00%	0.00%
<i>Bacteroidetes; Sphingobacteriales</i>	1.50%	1.30%	1.10%	1.30%	0.90%	0.00%
<i>Chloroflexi; Sphaerobacterales</i>	4.40%	4.90%	4.00%	9.30%	4.00%	1.10%
<i>Cyanobacteria; Chroococcales</i>	0.30%	0.10%	0.00%	0.00%	0.00%	0.00%
<i>Fibrobacteres; Fibrobacterales</i>	0.20%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Firmicutes; unclassified</i>	0.10%	0.10%	0.10%	0.00%	0.00%	0.00%
<i>Firmicutes; Bacilli; unclassified</i>	0.00%	0.00%	0.10%	0.10%	0.10%	0.00%
<i>Firmicutes; Bacillales</i>	11.90%	12.40%	6.10%	5.30%	3.90%	2.40%
<i>Firmicutes; Lactobacillales</i>	1.50%	1.20%	0.60%	1.50%	0.60%	0.00%
<i>Firmicutes; Clostridiales</i>	3.20%	3.40%	5.90%	6.90%	1.80%	0.30%
<i>Firmicutes; Erysipelotrichales</i>	0.40%	0.40%	1.00%	1.50%	0.40%	0.10%
<i>Firmicutes; Acidaminococcales</i>	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%
<i>Firmicutes; Tissierellia; unclassified</i>	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%
<i>Firmicutes; Tissierellales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Gemmatimonadetes; Gemmatimonadales</i>	0.80%	0.90%	0.40%	0.00%	0.00%	0.00%
<i>Gemmatimonadetes; Longimicrobiales</i>	0.80%	0.50%	0.00%	0.10%	0.00%	0.00%
<i>Nitrospinae; Nitrospinales</i>	0.10%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Planctomycetes; Candidatus Brocadiales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; unclassified</i>	0.40%	0.30%	0.10%	0.50%	0.20%	0.00%
<i>Proteobacteria; Alphaproteobacteria; unclassified</i>	0.30%	0.30%	0.30%	0.00%	0.10%	0.00%
<i>Proteobacteria; Alphaproteobacteria; Caulobacterales</i>	1.10%	1.20%	0.50%	0.00%	0.00%	0.00%
<i>Proteobacteria; Alphaproteobacteria; Rhizobiales</i>	4.40%	2.90%	2.90%	1.00%	1.40%	0.00%
<i>Proteobacteria; Alphaproteobacteria; Rhodobacterales</i>	1.30%	1.60%	0.50%	0.50%	0.30%	0.00%
<i>Proteobacteria; Alphaproteobacteria; Rhodospirillales</i>	0.00%	0.10%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; Alphaproteobacteria; Sphingomonadales</i>	2.60%	3.30%	1.60%	0.10%	0.20%	0.00%
<i>Proteobacteria; Betaproteobacteria; Burkholderiales</i>	0.80%	0.70%	1.30%	2.00%	3.60%	0.00%
<i>Proteobacteria; Deltaproteobacteria; Desulfuromonadales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; Deltaproteobacteria; Myxococcales</i>	0.00%	0.00%	0.00%	0.00%	0.10%	0.00%
<i>Proteobacteria; Gammaproteobacteria; unclassified</i>	0.10%	0.00%	0.00%	0.30%	0.00%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Aeromonadales</i>	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%

<i>Proteobacteria; Gammaproteobacteria; Cardiobacteriales</i>	0.10%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Cellvibrionales</i>	3.40%	2.40%	0.40%	0.00%	0.20%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Chromatiales</i>	0.10%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Enterobacterales</i>	0.00%	0.00%	1.60%	6.10%	4.00%	0.50%
<i>Proteobacteria; Gammaproteobacteria; Nevskiales</i>	0.20%	0.10%	0.00%	0.00%	0.00%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Oceanospirillales</i>	0.00%	0.00%	0.00%	0.10%	0.10%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Pseudomonadales</i>	0.70%	0.30%	0.60%	1.80%	1.00%	0.00%
<i>Proteobacteria; Gammaproteobacteria; Xanthomonadales</i>	2.80%	2.20%	1.00%	0.30%	0.20%	0.00%
<i>Proteobacteria; Bdellovibrionales</i>	1.20%	1.40%	0.50%	0.10%	0.00%	0.00%
<i>Rhodothermaeota; Rhodothermales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Spirochaetes; Spirochaetales</i>	0.00%	0.00%	0.00%	0.10%	0.00%	0.00%
c. Eukaryotic Taxonomy	Bulk TXD01	Bulk TXD01 (Dry-heated)	Aerosolized TXD01	Bulk TXD05	Bulk TXD05 (Dry-heated)	Aerosolized TXD05
Unclassified	18.10%	19.20%	0.30%	0.50%	0.00%	1.60%
<i>Trichiida</i>	0.70%	1.30%	0.00%	0.00%	0.30%	0.00%
<i>Oligohymenophorea; Philasterida</i>	5.10%	0.90%	0.00%	0.00%	0.00%	0.00%
<i>Oligohymenophorea; Sessilida</i>	0.30%	5.40%	0.00%	0.00%	0.00%	0.00%
<i>Phylopharyngea; Chlamyodontida</i>	0.10%	0.40%	0.00%	0.00%	0.00%	0.00%
<i>Spirotrichea; Sporadotrichida</i>	0.90%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Ascomycota; unclassified</i>	0.60%	0.80%	1.10%	1.40%	0.00%	0.90%
<i>Ascomycota; Capnodiales</i>	0.70%	0.50%	0.00%	0.00%	1.10%	0.00%
<i>Ascomycota; Pleosporales</i>	2.10%	0.70%	0.00%	0.00%	0.00%	0.00%
<i>Ascomycota; Eurotiales</i>	0.10%	1.40%	1.30%	2.40%	0.00%	2.80%
<i>Ascomycota; Onygenales</i>	0.00%	0.00%	1.70%	1.40%	1.20%	5.20%
<i>Ascomycota; Pertusariales</i>	0.30%	0.00%	0.00%	0.00%	1.80%	0.00%
<i>Ascomycota; Leotiomyces; unclassified</i>	6.10%	0.40%	0.10%	0.00%	0.00%	0.00%
<i>Ascomycota; Rhytismatales</i>	0.00%	6.90%	0.00%	0.00%	0.00%	0.00%
<i>Ascomycota; Thelebolales</i>	1.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Ascomycota; Pezizales</i>	46.90%	1.50%	68.00%	64.60%	0.00%	20.40%
<i>Ascomycota; Saccharomycetales</i>	0.50%	45.90%	0.10%	0.20%	65.90%	0.10%
<i>Ascomycota; Glomerellales</i>	0.20%	0.10%	0.00%	0.00%	0.10%	0.00%
<i>Ascomycota; Hypocreales</i>	0.30%	0.20%	16.90%	16.90%	0.00%	59.50%
<i>Ascomycota; Melanosporales</i>	0.00%	0.20%	0.10%	0.00%	18.80%	0.10%
<i>Ascomycota; Microascales</i>	2.40%	0.00%	0.60%	2.10%	0.10%	3.10%
<i>Ascomycota; Sordariales</i>	9.20%	2.30%	5.30%	3.70%	0.80%	2.80%
<i>Basidiomycota; unclassified</i>	0.00%	6.60%	0.00%	0.00%	5.80%	0.00%
<i>Basidiomycota; Sporidiobolales</i>	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Basidiomycota; Tremellomycetes; unclassified</i>	0.20%	0.00%	0.00%	0.00%	0.00%	0.00%

<i>Basidiomycota; Trichosporonales</i>	0.00%	0.20%	4.40%	6.40%	0.00%	3.30%
<i>Basidiomycota; Wallemiales</i>	0.00%	0.00%	0.00%	0.00%	4.10%	0.00%
<i>Chytridiomycota; Rhizophlyctidales</i>	1.00%	0.00%	0.00%	0.00%	0.00%	0.00%
<i>Chytridiomycota; Spizellomycetales</i>	1.60%	1.40%	0.00%	0.00%	0.00%	0.00%
<i>Chytridiomycota; Neocallimastigales</i>	1.00%	1.90%	0.00%	0.00%	0.00%	0.00%
<i>Mucoromycota; Mortierellales</i>	0.50%	1.30%	0.00%	0.00%	0.00%	0.00%
<i>Mucoromycota; Mucorales</i>	0.10%	0.50%	0.10%	0.40%	0.00%	0.20%

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S6. IN parameterization

The exponential fits for T -binned $n_{s,geo}$ data of all lab and field measurements are summarized in **Table S3**. Fit parameters, computationally optimized for given the best correlation coefficient (r) for each category are provided in this table. As can be inferred from the table, the overall $\Delta \log(n_{s,geo})/\Delta T$ value is similar for all non-heated categories (0.20 – 0.42). This range of deviations is roughly similar to what we previously observed for supermicron IN-active cellulose particles (0.26 – 0.40; Hiranuma et al., 2019). Slightly higher $\Delta \log(n_{s,geo})/\Delta T$ values were observed for wet-boiled particles (0.59 – 0.61) than others may be indicative of an alternation in freezing efficiency. This parameterization offers a simple representation of supermicron-dominant INPs from OLLF, which can act as an important point source of agricultural INPs (nearly half of OLLF-INPs is supermicron in diameter; see **Sect. 3.2**) in a very simple manner. Since our immersion parameterization is solely a function of a single parameter, T , this parameterization can be easily incorporated in many model platforms in a computationally-friendly manner. Offering a universal single parameterization for soil dust-derived INPs is not the scope of this work. As OLLF represents a point source of fresh livestock-generated dust, we expect that it would have different ice nucleation efficiency than aged/weathered dusts. Individual parameterizations are useful to analyze spectra by comparing $\Delta \log(n_{s,geo})/\Delta T$ values etc. Nonetheless, our **Fig. 8** shows a comparison of our $n_{s,geo}$ data with six relevant IN parameterizations of soil/desert dust.

Table S3. OLLF-INP parameterization: List of exponential fit parameters to the $n_{s,geo}$ for T -binned ensemble datasets of lab study as well as field study. The datasets are fitted in the log space. The correlation coefficient, r , for each fit is also shown. All $n_{s,geo}$ values are in m^{-2} . T is in $^{\circ}C$. Note the fifth-order polynomial fit function is sensitive for all decimals shown here. To reproduce the fitted curves, we needed to include all decimals.

Fitted dataset: Sample ID (INSEKT sample type)	Fitted T range	Fit Parameters						r	$\frac{\Delta \log(n_{s,geo})}{\Delta T}$
		$n_{s,geo}(T) = \exp(a + b \cdot T + c \cdot T^2 + d \cdot T^3 + e \cdot T^4 + f \cdot T^5)$							
		a (m^{-2})	b ($m^{-2} \cdot ^{\circ}C^{-1}$)	c ($m^{-2} \cdot ^{\circ}C^{-2}$)	d ($m^{-2} \cdot ^{\circ}C^{-3}$)	e ($m^{-2} \cdot ^{\circ}C^{-4}$)	f ($m^{-2} \cdot ^{\circ}C^{-5}$)		
TXD01 (bulk)	$-29^{\circ}C < T < -7.5^{\circ}C$	-10.419739 559253788	-4.7365147 08000364	-0.19248508 975777787	0.00251437671 56404874	0.00028172574 60974357	3.664760242 99544e-06	0.99	0.28
TXD01H (bulk)	$-28.5^{\circ}C < T < -7.5^{\circ}C$	-22.024766 92454698	-8.0272347 73393355	-0.56209071 67927012	-0.01665207 3879196847	-0.000169949 36493112665	-1.220059988 9511637e-07	0.99	0.26
TXD01 (filter)	$-29^{\circ}C < T < -13.5^{\circ}C$	-649.60926 61424044	-166.17848 015453706	-16.3314245 41701384	-0.78540314 3752226	-0.018456365 06788169	-0.000170230 48008878034	0.99	0.41
TXD01H (filter, dry-heated)	$-28.5^{\circ}C < T < -12^{\circ}C$	17.88551115 2572057	-1.8325915 290723702	-0.56508783 20173172	-0.04817379 804678202	-0.001623522 1213422987	-1.973016312 032128e-05	0.97	0.35
TXD01H (filter, wet-boiled)	$-28.5^{\circ}C < T < -19^{\circ}C$	-28412.092 220119186	-6043.6351 1549024	-511.447808 94398167	-21.5309744 85881597	-0.450854168 6398098	-0.003757133 824947974	0.99	0.59
TXD05 (bulk)	$-28.5^{\circ}C < T < -10^{\circ}C$	-50.023271 755289954	-16.045730 78900857	-1.61735618 28000045	-0.08074357 074021918	-0.001935789 3701810924	-1.807679158 9170566e-05	0.64	0.35
TXD05H (bulk)	$-27^{\circ}C < T < -9.5^{\circ}C$	-28.411321 02063094	-9.8209130 42395558	-0.90949367 95258034	-0.03972654 718668897	-0.000763624 4274088211	-5.200001963 207848e-06	0.99	0.33
TXD05 (filter)	$-28.5^{\circ}C < T < -14^{\circ}C$	-313.30582 52180446	-75.912698 717769	-6.90433259 32941135	-0.30470826 275283364	-0.006460682 825298372	-5.275536449 8764944e-05	0.62	0.42
TXD05H (filter, dry-heated)	$-27^{\circ}C < T < -14^{\circ}C$	-452.01181 238097746	-117.32306 672273883	-11.7623689 34161058	-0.58361828 71815891	-0.014288215 373972207	-0.000138670 0575218297	0.97	0.41
TXD05H (filter, wet-boiled)	$-27^{\circ}C < T < -19.5^{\circ}C$	41020.32207 07645	9026.32749022 4949	791.389548393168 5	34.5511122099 4813	0.75123943012 70052	0.006507672 03399298	0.97	0.61
Field Median	$-25^{\circ}C < T < -5^{\circ}C$	-29.6470105 67958052	-16.317058386 439328	-2.3094959896 54582	-0.1625704680 7120043	-0.0055239335 23123538	-7.23939690 197926e-05	0.94	0.52
Field_Max	$-25^{\circ}C < T < -5^{\circ}C$	-33.2233240 5003339	-17.918940688 15357	-2.5378700781 94984	-0.1780842253 8269214	-0.0060285094 90726683	-7.87080475 404568e-05	0.93	0.53
Field_Min	$-25^{\circ}C < T < -5^{\circ}C$	-3.69823327 95064234	-5.3479986075 34987	-0.6782792077 804785	-0.0412234682 7949928	-0.0011424218 790211352	-1.19396607 8225184e-05	0.99	0.44

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