Response: We thank the two reviewers and Dr. Harry ten Brink for thoughtful suggestions and constructive criticism that have helped us improve our manuscript. Below we provide responses to reviewer concerns and suggestions in blue font. All changes to the manuscript can be identified in the version submitted using Track Changes.

Anonymous Referee #1:

In this very nice paper the authors attack constraints on aerosol-cloud interactions using aircraft data off the California coast over many years of campaigns. Many studies use satellite observations to do this and this study provides an important ground truth evaluation of this that is needed by the field and gives additional information (for instance turbulence) that is not available from space. This study shows the utility of sulfate in predicting variability in Nd, which agrees with other studies. The data set in the study allows the authors to drill down into looking at other species (sea salt, dust, organics) that have more elusive effects on Nd. My corrections are mostly technical in nature.

L53 Adjustments may also include enhanced entrainment at cloud top (Ackerman et al., 2004).

Response: We added this effect and reference:

"For warm marine boundary layer (MBL) clouds at fixed liquid water, higher N_d values result in (i) higher cloud albedo (thus cooling the Earth and counteracting the greenhouse effect) (Twomey, 1977), (ii) delayed and/or reduced precipitation (Albrecht, 1989), and (iii) enhanced entrainment at cloud top (Ackerman et al., 2004)."

L56 This is still the case in more recent reviews (Bellouin et al., 2020).

Response: Reference was added in that line:

"The complex interactions and feedback mechanisms between aerosols, meteorology, and clouds leads to aerosol-cloud interactions as the largest source of uncertainty in climate models (IPCC, 2013; Bellouin et al., 2020)."

L181 In McCoy et al. 2018 the SS and DU was restricted to the submicron size bins from MERRA2 and only hydrophilic BC/OC were used. All mass concentrations were taken at 910 hPa. Not critical to your study, but good to keep in mind to comparing to the better resolved data from aircraft.

Response: A sentence was added at the end of the paragraph, which now reads:

"… A caveat to consider when comparing the findings of McCoy et al. (2018) to other aircraft studies is that McCoy et al. (2018) used mass concentrations retrieved exclusively at the 910 hPa model level (~ 915 m), and only considered mass concentrations pertaining to submicron SS/DU and hydrophilic BC/OC."

L351 While not essential to the analysis being performed here, one interesting possibility is for the authors to train on the NiCE or FASE campaign and test the regression on the other wildfire-affected campaign (reducing the risk of overfitting). One intriguing possibility is that not all fires produce similar aerosol in terms of CCN activitiy and influence on CCN. Were the fires during these campaigns in very different environments?

Response: We thank the reviewer for this insightful suggestion. Even though this study does not make use of training, we do address the reviewer's suggestion by analyzing on the NiCE and FASE campaigns separately. We find that FASE yields similar results to both campaigns combined, but NiCE presents better correlations between all four species analyzed and N_d. Table 8 and a figure in the supplement were modified to include the new results.

Text was added to the end of Section 3.3.2 which reads:

"The NiCE (2015) and FASE (2016) campaigns were influenced by smoke originating from different sources. NiCE was influenced by the Big Windy, Whiskey Complex, and Douglas Complex forest fires near the California-Oregon border, with a transport time of approximately two days to reach the base of aircraft operations in Marina and adjacent areas where most samples were collected (Maudlin et al., 2015). In contrast, FASE was influenced by the Soberanes fire approximately 30 km southwest of aircraft hangar (Braun et al., 2017). Hence, analyzing each campaign separately may provide some insights into the sensitivity of N_d to smoke from both different fuel types and with varying transport trajectories. NiCE fire data were linked to timber, grass and shrub models whereas those from FASE were associated with chaparral, tall grass, and timber (Braun et al., 2017; Mardi et al., 2018). The results are shown in Table 8 and Figure S4. When comparing FASE to both campaigns combined, the prediction of N_d using NSS-SO_4^{2-}, Na, Ox, and Fe is not improved, resulting in a ΔR^2_{adj} of -0.04, -0.04, 0.01, and -0.03, respectively. However, when comparing NiCE to both campaigns combined, the prediction of N_d using NSS-SO_4^{2-}, Na, Ox, and Fe is significantly improved, resulting in a ΔR^2_{adj} of 0.14, 0.29, 0.18, and 0.13, respectively. The difference between NiCE and FASE could be because different forest fires produce aerosols with varying aerosol chemical signatures and size distributions, as studies in the region have shown (Ma et al., 2019; Mardi et al., 2019). Alternatively, the difference could be due to the small sample size of NiCE (31 samples) as compared to FASE (136 samples) (Table 1). Certainly more research, including larger datasets, is warranted to investigate how different fuel types and plume aging times impact aerosol-cloud interactions."

L431 The R2 should always increase with more predictors, but R2_adj won't necessarily?

Response: R^2_{adj} is useful when comparing two regressions that have a different number of predictors. R^2 is corrected to produce R^2_{adj} using the number of predicting variables (P) and the number of data points used in the regression (N) via the equation:

$R^2_{adj} = 1 - (1- R^2) (N-1) / (N-P-1)$.

For large values of N, R^2_{adj} is about equal to R^2. For our data set, R^2 and R^2_{adj} differ by only about 2%. Therefore, the asymptotic behavior in R^2_{adj} is also observed in R^2, i.e., more predictors do not necessarily increase R^2 (or R^2_{adj}). Despite the small difference between R^2 and R^2_{adj}, we decided to use R^2_{adj} throughout the paper for the sake of rigor and consistency.

This issue is addressed by adding some text in Section 2.5, and in Section 3.2. The updated texts now read:

"However, when comparing the performance of correlations between regressions using a different number of predictor variables, it is necessary to use the adjusted coefficient of determination (R^2_{adj}), which is subscripted to distinguish it from the ordinary R^2, and is adjusted by using the number of predictors (P) and the number of data points (N) via the formula $R^2_{adj} = 1 - (1 - R^2)(N - 1)/(N - P - 1)$ (Kahane, 2008). For a large number of data points, $R^2_{adj} \sim R^2$; however, for the sake of rigor and consistency, R^2_{adj} is used instead of the ordinary R^2, except when reporting values from the literature."

"It is also interesting to note how R^2_{adj} increases asymptotically to ~ 0.6; this further makes the point that additional species do not necessarily improve predictability of N_d. The same asymptotic behavior is also exhibited with R^2, as R^2 and R^2_{adj} for these regressions differ by only ~ 2%."

L413 The authors might find it helpful to make a predictor correlation matrix figure for this section: https://seaborn.pydata.org/examples/many_pairwise_correlations.html

Response: We appreciate the suggestion and have added to the supplement a correlation matrix which includes both the 9 predictor variables and the response variable (N_d). This matrix is used to explain the possible multicollinearity causing some coefficients to have negative values. Text was added to Section 3.2, and now reads:

"The physical reason as to why these species have negative coefficients when mixed with NH_4^+ is not clear; perhaps the reason is due to the mathematics of the regression and not physically rooted, as the collinearity among three or more variables (called multicollinearity) can lead to unexpected signs for predictor coefficients (Kahane, 2008). Furthermore, a correlation matrix among the nine predicting species (Figure S2) shows a strong correlation for some pairs of species (NH_4^+-NO_3^-: R^2_{adj} = 0.48; NO_3^--V: R^2_{adj} = 0.49) and moderate correlation for other pairs (NH_4^+-V: R^2_{adj} = 0.27; NO_3^--Fe: R^2_{adj} = 0.22)."

L472 See note above regarding use of submicron SS from MERRA2 in the McCoy 2017/18 studies. One potential reason for this discrepancy is that the SS in MERRA2 is partially indicative of dynamical mixing and turbulence, which the present study has information about. Is it possible that the analysis approach in this study has disentangled this? L501 notes the strong dependence of ocean-derived species on turbulence. Would it be possible to make a bivariate plot of Nd as a function of SS and turbulence? This is done in Fig. 5, but going beyond binning into high and low turbulence might be interesting to see.

Response: The reviewer makes an excellent point in suggesting that the discrepancy between the value of the sea salt coefficient between McCoy et al. (2017, 2018) and the present study could be due to the combined effects of turbulence and sea salt, and that the present study offers an opportunity to separate these two effects. The reviewer's suggestions improved the quality of our paper and we are grateful. A new figure was made and added to Section 3.3.1.

Text was added to the end of Section 3.3.1 which reads:

"For Na, there is a better correlation at high turbulent conditions than at smooth conditions (R^2_{adj} = 0.26 and R^2_{adj} = 0.09 for high and low σ_w, respectively). This further strengthens the argument that turbulence plays an important role in the vertical transport of sea salt (and other ocean emissions) from the ocean surface to the cloud base. The present data set allows for deeper analysis into the entangled effects of sea salt and turbulence on N_d. More specifically, aerosol reanalysis products like those from MERRA-2 calculate the mass concentration of sea salt via parameterizations that link wind speed to sea salt emissions (Gong et al., 2003; Randles et al., 2017). Since wind speed affects turbulence, it follows that sea salt concentrations are not independent from turbulence, as turbulence is used to calculate sea salt concentrations. Subsequently, these sea salt concentrations are used to predict N_d (e.g., McCoy et al., 2017, 2018). The present study measured both sea salt (quantified by Na) and turbulence (quantified by σ_w) and thus offers an opportunity to try to isolate the effects of both factors on N_d (Figure 6). Two results emerge. First, more turbulence is correlated to more sea salt, which is consistent with what the models predict (Randles et al., 2017). Second, at a fixed concentration of Na, N_d does not vary significantly with σ_w, as evidenced by a weak change in color. However, at a fixed value of σ_w, N_d does vary significantly with Na, as evidenced by the noticeable change in color. Therefore, the independent measurement of both variables reveals that N_d is more sensitive to changes in Na than to changes in σ_w. We caution that σ_w is not obtained from below the cloud, but from within the cloud during sampling time (Figure S1)."

References:

Ackerman, A. S., Kirkpatrick, M. P., Stevens, D. E., and Toon, O. B.: The impact of humidity above stratiform clouds on indirect aerosol climate forcing, Nature, 432, 1014-1017, 10.1038/nature03174, 2004.

Bellouin, N., Quaas, J., Gryspeerdt, E., Kinne, S., Stier, P., Watsonâ˘AR˘ Parris, D., Boucher, O., Carslaw, K. S., Christensen, M., Daniau, A. L., Dufresne, J. L., Feingold, G., Fiedler, S., Forster, P., Gettelman, A., Haywood, J. M., Lohmann, U., Malavelle, F., Mauritsen, T., McCoy, D. T., Myhre, G., Mülmenstädt, J., Neubauer, D., Possner, A., Rugenstein, M., Sato, Y., Schulz, M., Schwartz, S. E., Sourdeval, O., Storelvmo, T., Toll, V., Winker, D., and Stevens, B.: Bounding Global Aerosol Radiative Forcing of Climate Change, Rev Geophys, 58, 10.1029/2019rg000660, 2020.

Anonymous Referee #2:

This paper describes the relationship between cloud droplet number concentration (Nd) and cloud water composition using field measurements by aircraft flights off the California coast over 4 multi-years campaigns. After the chemical analyses of the cloudwater samples, the data were statistically analyzed to find the best correlations between chemical species and Nd. The results highlight the importance of sulfate (both Total and non-sea-salt) in predicting Nd and its variability, confirming findings already reported in previous studies. But the authors investigate also the role of other chemical species (sea-salt, dust, organic matter) as well as of some other factors (i.e., turbulence, cloud height, etc.). This is a very well-written paper that clearly describes measurements, statistical approach and results which are also nicely compared to previous findings. Even the possible drawbacks of the methodology and of the dataset are well discussed by the Authors leaving no space for substantial criticism by my side. The results are of interest for a large community investigating aerosol-cloud interaction from experimental and modelling point of view and so the publication of this work is strongly recommended as it is.

I have only a question/comment (not influencing the final decision on this paper but maybe interesting for future works): have the Authors any measurements/estimations of the acidity of cloud water? pH has an important role in sulfate aerosol formation mechanism (Turnock et al., GRL, 2019), in the gas-particle partitioning of NH4 and NO3 and in solubility of metals (Pye et al., ACP, 2020). Can the Authors comment about the possibility of testing pH as a complementary predictor (maybe partially explaining the negative coefficients of some regressions)?

Pye, H. O. T., Nenes, A., Alexander, B., Ault, A. P., Barth, M. C., Clegg, S. L., Collett Jr., J. L., Fahey, K. M., Hennigan, C. J., Herrmann, H., Kanakidou, M., Kelly, J. T., Ku, I.-T., McNeill, V. F., Riemer, N., Schaefer, T., Shi, G., Tilgner, A., Walker, J. T., Wang, T., Weber, R., Xing, J., Zaveri, R. A., and Zuend, A.: The acidity of atmospheric particles and clouds, Atmos. Chem. Phys., 20, 4809–4888, https://doi.org/10.5194/acp-20-4809-2020, 2020.

Turnock, S. T., Mann, G. W., Woodhouse, M. T., Dalvi, M., O'Connor, F. M., Carslaw, K. S., and Spracklen, D. V.: The Impact of Changes in Cloud-Water pH on Aerosol Radiative Forcing, Geophys. Res. Lett., 46, 4039–4048, https://doi.org/10.1029/2019GL082067, 2019.

Response: We appreciate this thoughtful comment from the reviewer. To address the role of pH on the ability to predict cloud droplet number concentration (N_d), H^+ (as quantified by pH) is now included as a predicting species. Thus, the total number of species is now 80. However, pH is poorly correlated to N_d, thus making it a bad predictor of N_d, and is dropped from the analysis in Step 4 of the filtering algorithm (Figure 2). Therefore, the results of this study were not altered by adding pH as a predicting species. The following parts of the manuscript have been modified to reflect the inclusion of pH:

- Section 2.3 now includes a description of the pH analysis that reads:
  "Cloud water sample acidity was quantified by measuring pH (the aqueous concentration of hydrogen ions, H^+) using a Thermo Scientific Orion 9110DJWP Combination Semi-Micro pH Electrode for E-PEACE, NiCE, and BOAS, and a Thermo Scientific Orion 8103BNUWP

Ross Ultra Semi-Micro pH probe for FASE. […] This study uses air-equivalent concentrations for all species with the exception of H^+ (pH) that uses aqueous concentration."

- Table 2 and Figure 2 now include pH.
- Section 2.4 now includes a sentence highlighting that pH was removed from the analysis that reads:
  "Even though pH plays an important role in the partitioning of gases into particles and droplets, in addition to influencing aqueous reactions in droplets (e.g., Pye et al., 2020), pH was filtered out in Step 4 for being a poor predictor of N_d."

Comment from Dr. Harry ten Brink:

I welcome a study in which the data on aerosol-cloud interaction is generalised. As a surprise I notice that the parameterisation(s) as initiated 25 years ago like B&L still are central in modelling.

Following are comments and questions

-I would have projected that a negative relation of Nd with Na would be seen because the few large seasalt particles favourably compete with the smaller much more numerous sub-submicron CCN composed of nSS (Steve Ghan). While in the remote ocean seasalt could increase CDNC it seems highly unlikely this could occur off the coast in an area with sufficient small CCN as in your case.

Response: We appreciate this insightful comment. Indeed, the effect of giant cloud condensation nuclei (GCCN) like sea salt on cloud droplets and rain drops is of much interest to the aerosol-cloud research community and deserved a better discussion. However, no conclusive results were found in this study. A paragraph was added towards the end of Section 3.2 which reads:

"When considering a multi-species model to predict N_d, it is worthwhile to examine the coefficient of sea salt. Even though it is well established that more CCN leads to more droplets, the effect of giant CCN (GCCN), such as sea salt, is not as clear. Cloud microphysics studies suggest two mechanisms by which more sea salt leads to less N_d: (1) The large size and highly hygroscopic nature of sea salt causes these particles to activate into droplets before other smaller particles. This reduces the amount of available water vapor and creates unfavorable conditions for smaller particles to nucleate into droplets (e.g., Andreae & Rosenfeld, 2008). (2) GCCN nucleate into larger droplets as compared to CCN, which in turn are more likely to collide and coalesce with surrounding droplets. This combination of droplets creates larger but fewer droplets and ultimately leads to the formation of rain drops and precipitation (e.g., Feingold et al., 1999, Jung et al., 2015). Therefore, it is expected that the negative correlation between GCCN and N_d should translate into a negative coefficient for Na (the sea salt tracer) in a multi-predictor regression equation. However, this behavior was not observed in this study. A plausible explanation for this discrepancy is that the effect of GCCN on N_d is highly dependent on conditions like LWC and N_d itself (e.g., Feingold et al., 1999), and that this study did not capture the appropriate conditions to observe this effect. However, McCoy et al. (2017) did observe a negative coefficient for sea salt and ascribed it to a simulation artefact caused by the intimate link between sea salt generation and wind speed (i.e., turbulence). An attempt to isolate the effects of sea salt and turbulence on N_d is provided in Section 3.1.1."

-line 459 e.f. the negative correlation with NO3 in case it is combined with ammonium seems to me of quite some importance given the rather high values of the two as compared with sulphate. What about a combination of sulphate and nitrate or rather nSS and nitrate, both deriving from rather similar sources and possibly similar geographical location.

Response: This is a sensible comment because it is based on the desire to deduce physical meaning from a mathematical result. However, we argue that the methodology used in this study

is limited and does not allow us to address such desire satisfactorily. The limitation is not in the method of ordinary least squares (OLS), but rather in the data set fed into the OLS method. More specifically, there are two limitations to the data set: (1) perhaps we did not define a strict enough definition of collinearity when filtering species, and (2) we did not test for multicollinearity in this study. Each limitation is described below.

(1) Say you have one independent (or response) variable, y, that you want to describe in terms of two dependent (or predicting) variables, x_1 and x_2, with a linear model of the form:

$$y = a\,x_1 + b\,x_2 + c$$

The ordinary least squares (OLS) method allows to find the coefficients (a, b, and c) which best describe the data. However, the OLS method rests on the assumption that the predicting variables x_1 and x_2 are not redundant. This redundancy is called "collinearity" and can be assessed by applying the OLS method to x_1 and x_2 with an equation of the form:

$$x_1 = a\,x_2 + b$$

The predicting variables are said to be collinear if the regression yields a large correlation coefficient (R). There is no universal definition of how large R needs to be for two predicting variables to be considered collinear. When collinear predictors are fed into a model, there is no guarantee that the sign or magnitude of the parameters will have any meaning. We decided that two predictors were collinear if $R > 0.6$, but this could very well have been a lenient criterion and could be a possible source of the unexpected sign and magnitude of the NO_3^-, V, and Fe predictors.

(2) Now, say you have one response variable, y, that you want to describe in terms of **three** predicting variables, x_1, x_2, and x_3, with a linear model of the form:

$$y = a\,x_1 + b\,x_2 + c\,x_3 + d$$

The OLS method again allows to find the coefficients (a, b, c, and d), which best describe the data. And again, the OLS method relies on the assumption that the predicting variables x_1, x_2, and x_3 are not redundant. To address this, the concept of "multicollinearity" is introduced, which can be assessed by applying the OLS method to x_1, x_2, and x_3 with an equation of the form:

$$x_1 = a\,x_2 + b\,x_3 + c$$

There is not a single metric to quantify multicollinearity, but for purposes of this rebuttal, we shall use the adjusted correlation coefficient (R_{adj}). Similar to using two collinear predictors, when multicollinear predictors are fed into a model, there is no guarantee that the sign or magnitude of the parameters will have any meaning. **Furthermore, it is critical to point out that just because the pairs x_1-x_2, x_1-x_3, and x_2-x_3 are not collinear does not guarantee that the x_1-x_2-x_3 set is not multicollinear.** Consider the fictitious data set below. If collinearity and multicollinearity were defined as $R_{adj} > 0.5$, the pairs x_1-x_2, x_1-x_3 and x_2-x_3 are

all not collinear, but the x_1-x_2-x_3 set is multicollinear. Thus, it is likely that the coefficients for predictors x_1, x_2, and x_3 might lack meaning.

x_1	x_2	x_3
0.43	0.21	0.51
0.04	-0.18	0.55
0.89	0.49	1.16
0.74	0.52	0.69
0.64	-0.56	2.48
0.65	-0.24	1.87
-0.01	-0.53	1.03
0.24	-0.81	2.16
0.21	0.97	-1.14
0.4	-0.62	2.14
0.75	-0.2	2.12
0.78	0.63	0.53
0.74	-0.6	2.97
0.23	0.28	-0.08
-0.54	-0.88	0.28
0.86	0.99	0.27
-0.44	-0.74	0.14
0.7	0.2	1.28
-0.51	0.29	-1.85
-0.97	-0.66	-1.16

Test for	Linear Equation	R_{adj}	
Collinearity between two variables	$x_1 = a\,x_2 + b$ or $x_2 = a\,x_1 + b$	0.4040	All pairs are not collinear
	$x_1 = a\,x_3 + b$ or $x_3 = a\,x_1 + b$	0.5953	
	$x_2 = a\,x_3 + b$ or $x_3 = a\,x_2 + b$	– 0.3481	
Multi-collinearity between three variables	$x_1 = a\,x_2 + b\,x_3 + c$ or $x_1 = a\,x_3 + b\,x_2 + c$	0.9966	The x_1-x_2-x_3 set is multicollinear
	$x_2 = a\,x_1 + b\,x_3 + c$ or $x_2 = a\,x_3 + b\,x_1 + c$	0.9956	
	$x_3 = a\,x_1 + b\,x_2 + c$ or $x_3 = a\,x_2 + b\,x_1 + c$	0.9968	

The chemical composition of cloud water is a complex system, e.g., not all species can be attributed to their own individual source, and complex chemical reactions take place within droplets. When considering a complex system like the chemical composition of cloud water, it is reasonable to state that the more species are used to predict N_d, the higher the probability that the set of species being considered is multicollinear. We did not test for multicollinearity in this study. Therefore, it is not surprising that unexpected negative coefficients only appear when considering many (five) predictors; recall that at six predictors, all regressions become statistically insignificant. In other words, the unexpected sign and magnitude of the coefficients for NO_3^-, V, and Fe in a regression with five predictors is likely caused by multicollinearity among the predictors. This makes it difficult to gain insight into the physical-chemical processes involved.

It is helpful to keep in mind the intention we had when implementing the multivariable regression method in Section 3.2: qualitatively identify the "ingredient species" that comprise a decent set of N_d predictors, which we found to be a form of sulfate, an ocean emission tracer, and an organic tracer. Not testing for collinearity does not invalidate our finding. However, we appreciate Dr. Harry ten Brink's comment and we added a paragraph at the end of Section 2.5 that reads:

"The correct functioning of the method of ordinary least squares requires that the set of n predicting variables in Equation 3 not be collinear. Multicollinearity is defined by a set of three or more predicting variables being collinear. Using a set of multicollinear predictors can produce unreliable estimates in both magnitude and sign of the coefficients (a_i) (Kahane, 2008). There is no universal marker for multicollinearity. Furthermore, multicollinearity can only be addressed when analyzing

all predictors together. For example, for a given set of three predictors (P_1, P_2, and P_3), even though the pairs P_1-P_2, P_1-P_3, and P_2-P_3 are not collinear, there is no guarantee that the P_1-P_2-P_3 set is not multicollinear. When considering a complex system such as the chemical composition of cloud water, it is reasonable to assume that as more species are used to predict N_d, the higher the probability that the set of species is multicollinear. We did not test for multicollinearity in this study; the consequences of not doing so are explored in Section 3.2."

And more discussion is provided in Section 3.2 that now reads:

"In addition, multicollinearity will become more likely as more predictors as considered. Therefore, it is not surprising that unexpected negative coefficients only appear when considering many (five) predictors. Lastly, a correlation matrix among the nine predicting species (Figure S2) shows a strong correlation for some pairs of species (NH_4^+-NO_3^-: R^2_{adj} = 0.48; NO_3^--V: R^2_{adj} = 0.49) and moderate correlation for other pairs (NH_4^+-V: R^2_{adj} = 0.27; NO_3^--Fe: R^2_{adj} = 0.22), thus strengthening the argument that the negative coefficients are due to mathematical multicollinearity and not a physical or chemical reason."

-line 132 sampling was inland in continental clouds

Response: This is a good observation but does not affect the final conclusions of this study. To avoid confusion, the word "continental" was added where appropriate in Section 1, which now reads:

"Leaitch et al. (1986) sampled continental stratiform and cumuliform clouds over Ontario, Canada […]. Leaitch et al. (1992) suggested that […] for both continental stratiform and cumuliform clouds […]."

Furthermore, the word "continental" is also added to the Leaitch et al. (1992) entry in Table 4.

-line 491. "…and it is worth noting that only five of our 385 samples are considered low turbulence according to the criterion of Leaitch et al.". This contradicts the later conclusion that the data can be translated to the NE-coast situation. There should at least some discussion on the absence of stratus-like clouds in your region.

Response: This comment contains several interesting points, please consider the following arguments:

(1) Leaitch et al. (1996) (abbreviated as L96 in this answer) encountered a certain range of turbulence conditions and we encountered a different range of turbulence conditions, as seen in the table below.

	Leaitch et al. (1996)	This study
Number of samples	24	385
Range of turbulence	0.07—0.81 m s^{-1}	0.10—0.51 m s^{-1}
33rd percentile, i.e., "smooth" conditions	0.17 m s^{-1}	0.27 m s^{-1}

66th percentile, i.e., "turbulent" conditions	0.23 m s^{-1}	0.32 m s^{-1}
Number (percentage) of smooth samples	4 (17%)	5 (1%)

We believe that the small overlap between our percentage of "smooth" (i.e., low turbulence) samples (1%) versus L96's (17%) does not invalidate our statement that the northeast Atlantic region resembles the northwest Pacific region. Rather, we believe that the small overlap can be explained from a statistical point of view, namely: (a) we have 16 times more data points than L96, and (b) we consider four campaigns/summers whereas L96 considers only one.

We found inspiration in L96's approach to use a distribution of turbulence measurements to statistically define turbulent and smooth conditions in terms of the 33rd and 66th percentile, respectively. Naturally, considering more data points will change the shape of the distribution and consequently also change the statistical definition of "smooth" and "turbulent". We consider that no edits on the manuscript are required to address this concern.

(2) Even though we think that the critique to our claim that the northeast Atlantic region resembles the northwest Pacific region is not justified based on the overlap of turbulence conditions (argument 1), we do think there is value to this critique because in Section 3.1, we compare our results to Leaitch et al. (1992). As pointed out by Dr. Harry ten Brink in the previous comment, Leaitch et al. (1992) studied continental clouds, whereas, L96 studied marine clouds. To address this valid concern, we adjusted our wording in Section 3.1 from "... suggestive of commonality between two **ocean** regions ..." to "... suggestive of commonality between two **coastal** regions ...".

(3) We respectfully disagree that stratus-like clouds are absent in our study region, since stratocumulus clouds are a type of stratus clouds. To leave no doubt in the mind of the reader on the abundance of stratocumulus/stratus-like clouds in the study region, Section 2.1 (which was renamed "Aircraft campaigns and study region") now includes a line of text which reads:

"The persistent summertime stratocumulus cloud deck located off the California coast offers the ideal natural laboratory to study aerosol-cloud-precipitation-meteorology interactions (Russell et al., 2013; Sorooshian et al., 2018)."

1006. first entry in the table: a common error made in citing this reference, though not expected in this paper on cloud-water sulphate: the unit in the Leaitsch et al. paper of 1992 is cw-sulphate in nequivalents/m3.

Response: This is a good point. A footnote on Table 4 mentions the different units of the Leaitch et al. (1992) paper. What is wished to be emphasized when comparing our study to the Leaitch et al. (1992) study is mainly the slope (a_1) for cloud water sulfate air-equivalent concentration. Fortunately, the value of the slope is not affected by the units of sulfate concentration, as shown in the box below. We consider that no edits on the manuscript are required to address this concern.

Sulfate concentration (x) has units of μg m^{-3}. The slope m is given by:	Sulfate concentration (x^*) has units of nEq m^{-3}, where x^* is proportional to x, i.e., $x^* = c\,x$. The slope (m^*) is given by:
$m = \frac{\log(y_2) - \log(y_1)}{\log(x_2) - \log(x_1)}$	$m^* = \frac{\log(y_2) - \log(y_1)}{\log(x_2^*) - \log(x_1^*)} = \frac{log\left(\frac{y_2}{y_1}\right)}{\log\left(\frac{x_2^*}{x_1^*}\right)} = \frac{log\left(\frac{y_2}{y_1}\right)}{\log\left(\frac{c\,x_2}{c\,x_1}\right)}$
$m = \frac{log\left(\frac{y_2}{y_1}\right)}{\log\left(\frac{x_2}{x_1}\right)}$	$m^* = \frac{log\left(\frac{y_2}{y_1}\right)}{\log\left(\frac{x_2}{x_1}\right)}$
$m = m^*$	

However, it is worth mentioning that Leaitch et al. (1992) used a log-log format, whereas Leaitch et al. (1996) used a log-linear format. In Table 4, we show the Leaitch et al. (1992) study, which has the same format (with exception of the units) as the other studies in Table 4; thus, no modifications to the table are required.

Finally I really dearly miss a back-trajectory analysis of at least some typical flights or those with high nSS / NO3 and Na.

Response: We appreciate the observation that including a back-trajectory analysis enriches a paper. However, several previous papers that have analyzed the study region all converge on the same conclusion: the air in the study region is influenced by air mass transport from the north and northwest. To address this concern other readers could also have, a short paragraph was added at the end of Section 2.1 (which was renamed to "Aircraft campaigns and study region"), and reads:

"Previous studies have used back-trajectory analysis to show that air in the MBL in the study region is predominantly influenced by air mass transport from the north and northwest (Schlosser et al., 2020; Wang et al., 2016; Wonaschütz et al., 2013). Thus, the cloud water in this study was influenced by a variety of local and long-range sources such as ship exhaust (Chen et al., 2012; Coggon et al., 2012), biomass burning (Prabhakar et al., 2014; Mardi et al., 2018), ocean emissions (Dadashazar et al., 2017; MacDonald et al., 2018), continental pollution (Ma et al., 2019; Wang et al., 2016), and dust (Mardi et al., 2019; Wang et al., 2014)."

On the Relationship Between Cloud Water Composition and Cloud Droplet Number Concentration

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Abstract

Aerosol-cloud interactions are the largest source of uncertainty in quantifying anthropogenic radiative forcing. The large uncertainty is, in part, due to the difficulty of predicting cloud microphysical parameters, such as the cloud droplet number concentration (N_d). Even though rigorous first-principle approaches exist to calculate N_d, the cloud and aerosol research community also relies on empirical approaches such as relating N_d to aerosol mass concentration. Here we analyze relationships between N_d and cloud water chemical composition, in addition to the effect of environmental factors on the degree of the relationships. Warm, marine, stratocumulus clouds off the California coast were sampled throughout four summer campaigns between 2011 and 2016. A total of 385 cloud water samples were collected and analyzed for ~~79~~80 chemical species. Single- and multi-species log-log linear regressions were performed to predict N_d using chemical composition. Single-species regressions reveal that the species that best predicts N_d is total sulfate (R^2_{adj} = 0.40). Multi-species regressions reveal that adding more species does not necessarily produce a better model, as six or more species yield regressions that are statistically insignificant. A commonality among the multi-species regressions that produce the highest correlation with N_d was that most included sulfate (either total or non-sea salt), an ocean emissions tracer (such as sodium), and an organic tracer (such as oxalate). Binning the data according to turbulence, smoke influence, and in-cloud height allowed examination of the effect of these environmental factors on the composition-N_d correlation. Accounting for turbulence, quantified as the standard deviation of vertical wind speed, showed that the correlation between N_d with both total sulfate and sodium increased at higher turbulence conditions, consistent with turbulence promoting the mixing between ocean surface and cloud base. Considering the influence of smoke significantly improved the correlation with N_d for two biomass burning tracer species in the study region, specifically oxalate and iron. When binning by in-cloud height, non-sea salt sulfate and sodium correlated best with N_d at cloud top, whereas iron and oxalate correlate best with N_d at cloud base.

1. Introduction

To assess the degree to which humans have altered Earth's climate, it is necessary to quantify the effect that particles in the air (i.e., aerosols) have on clouds. Some fraction of aerosols (called cloud condensation nuclei, CCN) activate into cloud droplets, thus impacting the cloud droplet number concentration (N_d). For warm marine boundary layer (MBL) clouds at fixed liquid water, higher N_d values result in (i) higher cloud albedo (thus cooling the Earth and counteracting the greenhouse effect) (Twomey, 1977), ~~and~~ (ii) delayed and/or reduced precipitation (Albrecht, 1989), and (iii) enhanced entrainment at cloud top (Ackerman et al., 2004). The complex interactions and feedback mechanisms between aerosols, meteorology, and clouds leads to aerosol-cloud interactions as the largest source of uncertainty in climate models (IPCC, 2013; Bellouin et al., 2020).

It is indispensable to know the value of N_d, but this is a difficult parameter to accurately simulate and retrieve (Fountoukis & Nenes, 2005). There is a need to improve N_d retrievals from satellite remote sensors, which provide broad spatial and temporal coverage in contrast to surface sites and airborne research flights. Currently, N_d retrievals are limited to inferred values based on values of cloud optical depth, cloud droplet effective radius, and temperature, along with assumptions such as vertical homogeneity of N_d and monotonic increases in liquid water content at a constant fraction of its adiabatic value (Grosvenor et al., 2018). Ultimately, measurements are needed to better inform climate models about the cloud droplet activation process and better constraining N_d values. Current general circulation models (GCMs) calculate N_d using the properties of aerosol particles in one of two ways (Ghan et al., 1997; Menon et al., 2002). First, there is a rigorous approach that is based on physical principles that predicts N_d based on aerosol properties and meteorological conditions (Abdul-Razzak & Ghan, 2000). Second, there is an empirical approach that parameterizes N_d using either the number concentration of aerosols, N_a [# cm^{-3}], the number concentration of CCN, N_{CCN} [# cm^{-3}], or the mass concentration of chemical species that comprise the aerosols (Ghan et al., 1997).

The rigorous approach predicts N_d by considering aerosol properties (e.g., size distribution and chemical composition), microphysical processes (e.g., the seeding of cloud droplets by particles, droplet growth, and droplet evaporation), and meteorological parameters (e.g., relative humidity and the vertical updraft velocity transporting aerosols to cloud base) (e.g., Chuang et al., 1992; Chuang & Penner, 1995; Nenes & Seinfeld, 2003; Partridge et al., 2012). This method is based on the physical principle that an aerosol particle needs to be a CCN in order to seed a cloud droplet; consequently, the input for this approach is N_a, from which to calculate N_{CCN}, and subsequently N_d. The requisite information for these calculations may not be readily available for GCMs. A limitation is that the spatial resolution of a GCM may be too coarse to capture the small-scale spatial variation of updraft velocity (Ghan et al., 2011; West et al., 2014).

The empirical parameterization approach of interest in the present study uses the mass concentration of one or several chemical species and correlates it/them directly to N_{CCN} or N_d. Aerosols containing the sulfate ion (SO_4^{2-}) have long been known to serve as effective CCN (Andreae & Rosenfeld, 2008; Charlson et al., 1992; Lance et al., 2009; Medina et al., 2007). Sulfate is both contained in sea salt and is a product of the oxidation of gaseous sulfur dioxide (SO_2) (Hegg et al., 1981; Quinn et al., 2017), so it is customary to isolate the anthropogenic contribution to total SO_4^{2-} by considering its non-sea salt fraction (NSS-SO_4^{2-}). Therefore, most studies choose either total SO_4^{2-} (denoted hereafter as Tot-SO_4^{2-}) or NSS-SO_4^{2-} to predict N_{CCN} and N_d (e.g., Leaitch et al., 1992; Novakov et al., 1994; Saxena & Menon, 1999). Using the mass concentration of SO_4^{2-} or any other chemical species to predict N_d: (i) circumvents the complex intermediate

microphysical steps to go from an aerosol particle to a cloud droplet and implicitly accounts for such meteorological variables like updraft velocity, (ii) is based on actual measurements, and (iii) can be compared directly to the mass concentration of different species produced by aerosol transport models (e.g., Boucher & Lohmann, 1995; Chen & Penner, 2005). The limitations of using an empirical parameterization are: (i) assuming a mass size distribution of the aerosols, (ii) assuming that one or a few chemical species are responsible for all CCN, and (iii) uncertainty in generalizing field data from one region (or a few regions) under specific conditions to the entire globe for all conditions (Pringle et al., 2009). Despite these drawbacks, empirical correlations of N_d and the mass concentration of different species are valuable. For example, of the 20 studies addressing the cloud albedo effect considered in the IPCC Fourth Assessment Report (IPCC, 2007), half relied on empirical relationships to calculate N_d (Pringle et al., 2009).

Several studies have developed empirical correlations between N_{CCN} and the mass concentration of SO_4^{2-} (e.g., Adams & Seinfeld, 2003; Hegg et al., 1993; Matsumoto et al., 1997). However, the present objective is to focus on improving the prediction of N_d, not N_{CCN}, using the mass concentration of SO_4^{2-} in addition to other species. A log-log relation is often used to correlate the mass concentration of SO_4^{2-} to N_d with an equation of the form (e.g., Lowenthal et al., 2004):

$$log(N_d) = a_0 + a_1\, log([SO_4^{2-}]) \quad (1)$$

where $[SO_4^{2-}]$ is the mass concentration in air [µg m^{-3}], and a_0 and a_1 are fitting parameters. A log-log relation is chosen to accommodate large ranges in N_d and SO_4^{2-} and to reduce sensitivity of results to the measurement accuracy of each individual parameter (Boucher & Lohmann, 1995). The mass concentration of SO_4^{2-} can be obtained by analyzing either aerosol particles or cloud water. When analyzing cloud water, the mass concentration of SO_4^{2-} dissolved in droplets [mg lit^{-1}] is converted to the air-equivalent mass concentration [µg m^{-3}] by multiplying by the liquid water content, LWC [g m^{-3}], in a cloud. The data used to create N_d-SO_4^{2-} empirical parameterizations are typically derived from field campaigns, which differ in the region of analysis, sampling platforms (aircraft or ground-based), measurement approach (e.g., in particle form or dissolved in cloud water), and number of species analyzed. While the literature evaluating relationships between cloud water composition and N_d is limited and largely from aircraft studies from more than a decade ago, there is a growing number of datasets characterizing N_d and cloud water composition that are of interest to continue this line of research. Examples include the recently completed Cloud, Aerosol, and Monsoon Processes Philippines Experiment (~~CAMP^{2}Ex~~CAMP^{2}Ex) and the North Atlantic Aerosols and Marine Ecosystems Study (NAAMES) (Behrenfeld et al., 2019), and the current multi-year Aerosol Cloud meTeorology Interactions oVer the western ATlantic Experiment (ACTIVATE) (Sorooshian et al., 2020). A summary of relevant past field work follows.

Leaitch et al. (1986) sampled continental stratiform and cumuliform clouds over Ontario, Canada and showed a roughly linear relationship between N_d and SO_4^{2-} at low SO_4^{2-} concentrations (below ~ 5 µg m^{-3}), and that the relationship leveled out at higher concentration (Novakov et al., 1994). Leaitch et al. (1992) suggested that the low R^2 values for the linear regression between N_d and SO_4^{2-} for both continental stratiform and cumuliform clouds (0.30 and 0.49, respectively) stemmed from factors such as (i) other chemical species besides SO_4^{2-}, and variability in both (ii) updraft wind speed and (iii) temperature. Pueschel et al. (1986) sampled clouds originating from marine and continental air masses at a ground-based observatory at Whiteface Mountain, New York. They found that emissions contributed strongly to SO_4^{2-}, and that a significant portion of SO_4^{2-}-containing particles acted as CCN, and thus likely impacted N_d. Novakov et al. (1994)

sampled marine cumulus and stratocumulus clouds by El Yunque peak in Puerto Rico. Although they showed that N_{CCN} and SO_4^{2-} were highly correlated in both cumulus and stratocumulus clouds, they also found that N_d and SO_4^{2-} were weakly correlated for stratocumulus clouds, and not correlated for cumulus clouds. They attributed this difference to the effect of entrainment and mixing on cloud microphysics. Leaitch et al. (1996) sampled marine stratus clouds over the Gulf of Maine and the Bay of Fundy during the North Atlantic Regional Experiment (NARE) and showed that SO_4^{2-} was better correlated with N_d than nitrate (NO_3^-) (with an R^2 of 0.30 and 0.12, respectively). The R^2 between N_d and SO_4^{2-} increased when the data were stratified into bins of low and high turbulence, which was quantified as the standard deviation of vertical wind speed. They found that in situations with lower supersaturations, N_d was more influenced by turbulence than by either SO_4^{2-} or N_a. Menon & Saxena (1998) and Saxena & Menon (1999) sampled orographic clouds at a ground-based station at Mt. Mitchell, North Carolina. They found that SO_4^{2-} was the main contributor to cloud water acidity and a reliable tracer for anthropogenic pollution. Log-log regressions of SO_4^{2-}-N_d were binned according to the level of SO_4^{2-}, with not much difference observed between the different levels of pollution. Borys et al. (1998) and Lowenthal & Borys (2000) sampled warm marine stratiform clouds on the Island of Tenerife in the Canary Islands. They found that N_d was influenced by NSS-SO_4^{2-}, NO_3^-, pollution-derived trace elements, and elemental carbon (EC), signifying that species other than SO_4^{2-} influenced N_d. Despite the sampling site's proximity to African deserts, the mass concentration of crustal elements contained in dust was found to have little correlation with N_d. Also, the sea salt tracer sodium (Na^+) was found to have little correlation with N_d. Several studies (e.g., Boucher & Lohmann, 1995; Lowenthal et al., 2004; Menon et al., 2002; Van Dingenen et al., 1995) have combined field data, such as those mentioned above, in addition to other data sets, with the intention of producing a robust empirical prediction of N_d. Menon et al. (2002) provided a log-log multi-species prediction of N_d using SO_4^{2-}, organic matter, and sea salt. Organic carbon has been shown to increase N_d, as it affects the surface tension of cloud droplets (e.g., Facchini et al., 1999; Nenes et al., 2002). Additionally, nitric acid (HNO_3) has been linked with increased CCN activity and N_d based on modeling studies (Hegg, 2000; Kulmala et al., 1993; Xue & Feingold, 2004).

McCoy et al. (2017) used N_d data from the Moderate-Resolution Imaging Spectroradiometer (MODIS) satellite instead of in situ measurements. Second, aerosol mass concentration data were obtained from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2; Gelaro et al., 2017) reanalysis product and various aerosol transport models instead of in situ measurements. Third, the study region was more global in nature (albeit focusing on marine stratocumulus clouds) instead of a specific region. Fourth, since reanalysis data were used, a multi-species, multi-variable linear regression was performed:

$$log(N_d) = a_0 + a_1\, log(SO_4^{2-}) + a_2\, log(SS) + a_3\, log(BC) + a_4\, log(OC) + a_5\, log(DU) \quad (2)$$

where SS is sea salt, BC is black carbon, OC is organic carbon, and DU is dust. McCoy et al. (2017) found that SO_4^{2-} was predominantly correlated with N_d, with sea salt, black carbon, organic carbon, and dust accounting for smaller contributions. A caveat to consider when comparing the findings of McCoy et al. (2018) to other aircraft studies is that McCoy et al. (2018) used mass concentrations retrieved exclusively at the 910 hPa model level (~ 915 m), and only considered mass concentrations pertaining to submicron SS/DU and hydrophilic BC/OC.

The field studies cited above still leave a series of unanswered questions that the current study aims to address: (i) How is the SO_4^{2-}-N_d relationship affected by vertical wind speed (Leaitch

et al., 1992), turbulence (Leaitch et al., 1996), and entrainment (Novakov et al., 1994)?; (ii) Why do species such as sea salt and dust play such a minor role in influencing N_d, even when located over the ocean and near a desert (Borys et al., 1998; McCoy et al., 2017, 2018)?; (iii) What is the relationship between organic matter and N_d (McCoy et al., 2018; Nenes et al., 2002)?; and (iv) Can the SO_4^{2-}-N_d correlation be improved by considering other chemical species (e.g., Hegg et al., 1993; Leaitch et al., 1992; Novakov & Penner, 1993)?. The present study will examine these questions using a data set comprised of in situ aircraft measurements collected off the California coast during four field campaigns. In addition to meteorological and aerosol and cloud microphysical measurements, a total of 385 cloud water samples were collected and analyzed for ~~79~~80 chemical species (ions and elements). Even though measurements were collected in only one localized region, it is expected that the variety of conditions encountered over four summers, together with the large number of chemical species analyzed, will help address the questions noted above. The results of this work have implications for simulations and retrievals of N_d, in addition to studies examining relationships between atmospheric chemistry and cloud microphysics.

2. Methodology

2.1. Aircraft campaigns and study region

This work reports results relevant to warm marine stratocumulus clouds off the California coast based on field measurements from four field campaigns between 2011 and 2016, each during the months of July and August. The persistent summertime stratocumulus cloud deck located off the California coast offers the ideal natural laboratory to study aerosol-cloud-precipitation-meteorology interactions (Russell et al., 2013; Sorooshian et al., 2018). For all field campaigns, the Center for Interdisciplinary Remotely-Piloted Aircraft Studies (CIRPAS) Twin Otter was deployed out of Marina, California with an almost identical instrumentation payload. The four campaigns addressed in this study are: the Eastern Pacific Emitted Aerosol Cloud Experiment (E-PEACE) (Russell et al., 2013; Wonaschütz et al., 2013), the Nucleation in California Experiment (NiCE) (Crosbie et al., 2016; Maudlin et al., 2015), the Biological and Oceanic Atmospheric Study (BOAS) (Wang et al., 2016), and the Fog and Stratocumulus Evolution (FASE) Experiment (Dadashazar et al., 2017; MacDonald et al., 2018). Research flight information and tracks are shown in Table 1 and Figure 1, respectively.

Previous studies have used back-trajectory analysis to show that air in the MBL in the study region is predominantly influenced by air mass transport from the north and northwest (Schlosser et al., 2020; Wang et al., 2016; Wonaschütz et al., 2013). Thus, the cloud water in this study was influenced by a variety of local and long-range sources such as ship exhaust (Chen et al., 2012; Coggon et al., 2012), biomass burning (Prabhakar et al., 2014; Mardi et al., 2018), ocean emissions (Dadashazar et al., 2017; MacDonald et al., 2018), continental pollution (Ma et al., 2019; Wang et al., 2016), and dust (Mardi et al., 2019; Wang et al., 2014).

2.2. Aircraft instrumentation

Aircraft instrumentation used in each campaign is described in detail in Sorooshian et al. (2018). The relevant instrumentation used in the present study is as follows: aerosol size distribution was measured using a Passive Cavity Aerosol Spectrometer Probe (PCASP; particle diameter (D_p) ~ 0.1–2.6 µm; Strapp et al., 1992); cloud droplet size distribution was measured using a Forward Scattering Spectrometer Probe (FSSP; D_p ~ 2–45 µm; Gerber et al., 1999) and a Cloud and Aerosol Spectrometer-Forward Scattering (CASF; D_p ~ 1–61 µm; Baumgardner et al., 2001); rain drop size distribution was measured using a Cloud Imaging Probe (CIP; D_p ~ 25–1600

μm; Baumgardner et al., 2001); cloud liquid water content (LWC) was measured using a Particulate Volume Monitor (PVM-100A; D_p ~ 3–50 μm; Gerber, 1994); three-dimensional wind speeds were calculated by combining the pressure measurements from a five-hole radome gust probe plumbed into the aircraft nose together with the aircraft velocity and altitude measurements provided by the aircraft's Global Positioning System/Inertial Navigation System (GPS/INS).

Since LWC played a critical role in converting aqueous concentration to air-equivalent concentration, the size range used to calculate N_d was bracketed to resemble the size range of the PVM-100A. Therefore, N_d was defined in this study to be equivalent to the integration of the cloud droplet size distribution between D_p ~ 3–50 μm, and was calculated using CASF (for E-PEACE) and FSSP (NiCE, BOAS, and FASE). For the NiCE campaingn, LWC measurements from the PVM-100A instrument were unreliable; therefore, the LWC for NiCE was calculated instead using FSSP data between D_p ~ 3–50 μm.

2.3. Cloud water collection and chemical analysis

A total of 385 cloud water samples were collected throughout the four campaigns using a modified Mohnen slotted-rod collector, reported to collect droplets with D_p ~ 5–35 μm (Hegg and Hobbs, 1986). The cloud water was collected in polyethylene bottles and stored at ~ 5°C for subsequent offline chemical analysis. The spatially-averaged location of each cloud water sample is shown in Figure 1. Cloud water samples were chemically analyzed post-flight for ions using ion chromatography (IC; Dionex ICS-2100) and for elements using inductively coupled plasma mass spectrometry (ICP-MS; Agilent 7700 Series) for E-PEACE, BOAS, and NiCE or triple quadrupole inductively coupled plasma mass spectrometry (ICP-QQQ; Agilent 8800 Series) for FASE. The limit of detection (LOD) for each ion and element measured is shown in Table S1. The concentration of non-sea salt (NSS) species was calculated using the relative abundance of a NSS species to Na^+ in natural sea salt (Seinfeld & Pandis, 2016). Cloud water sample acidity was quantified by measuring pH (the aqueous concentration of hydrogen ions, H^+) using a Thermo Scientific Orion 9110DJWP Combination Semi-Micro pH Electrode for E-PEACE, NiCE, and BOAS, and a Thermo Scientific Orion 8103BNUWP Ross Ultra Semi-Micro pH probe for FASE. Aqueous concentrations (i.e., mass concentrations in the droplets [mg L^{-1}]) were converted to air-equivalent concentrations (i.e., mass concentrations in the air [μg m_{air}^{-3}]) by multiplying aqueous concentrations by the LWC and dividing by the mass density of water. This study uses air-equivalent concentrations for all species with the exception of H^+ (pH) that uses aqueous concentration.

A total of ~~79~~80 species (29 measured ionic species, 46 measured elemental species, measured pH, and 4 NSS calculated species; Table 2) were considered in this study as an initial pool of candidate species that could potentially be used to predict N_d. To facilitate the statistical analysis in this study, the amount of chemical species were filtered from ~~79~~80 to only nine. The steps used in this filtering process are summarized in the next section.

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2.4. Filtering of chemical species

A focus in this study is to identify appropriate chemical species to use as predictors in a linear regression model (addressed in Section 2.5). Good statistical practice (e.g., Freund et al., 2010) recommends that two conditions must be met to produce a meaningful multivariable regression: (1) the independent/predictor variables must not be redundant, i.e., they must not be highly correlated among themselves (the property of high correlation is called collinearity), and (2) each independent/predictor variable must have some correlation with the dependent/response

variable. There is no universal rule to define what is "highly" correlated, rather, it depends on the nature of the data and the user's judgement.

As using all ~~79~~80 species is impractical in terms of providing results that could be tested and/or used by others, a filtering method was used to reduce the number of species. The filtering method consisted of seven steps (Figure 2), the objective of which was to trim the total number of species by an order of magnitude, leaving just a few that exhibited the following characteristics: (1) the most data quality and quantity, (2) the least redundancy among themselves, (3) the highest correlation with N_d, and (4) the most physical meaning. The decision to remove a species becomes less objective and quantifiable towards the last steps in Figure 2. Each step is described below.

Step 1 removed species with less than 70% of data points. A species could have a low amount of points because it was not analyzed in a field campaign or because the data quality from the IC or ICP (ICP-MS or ICP-QQQ) was inadequate. Step 2 removed duplicate species that were measured by both IC and ICP. Step 3 addressed Condition (2) by removing species that were collinear (i.e., correlated among themselves). The criterion for a "high" correlation was to have a correlation coefficient (R) > 0.6 and a p-value < 0.05. For example, if a fixed number of five species were all highly correlated between each other, then only one of the five species was kept, and the rest were removed. This procedure is to consolidate "families" of three or more highly correlated species to a single species and does not apply to pairs of highly consolidated species. Step 4 addressed Condition (3) by removing species that were not correlated to N_d. The criterion for a "low" correlation was to have a coefficient of determination (R^2) < 0.1. Notice that Step 3 uses R whereas Step 4 uses R^2; this is because collinearity is determined not only by the value of R but also the sign of R. Step 5 removes all but one organic species, oxalate (Ox), since this species generally had the highest mass concentration of all the organic species and was considered to be representative of all other organic species. Step 6 removed species that could not easily be attributed to a physical process or chemical source. Step 7 added back into the analysis four species that had been removed. This was done for the sake of having species that are known to have relevant sources in the study region. Even though pH plays an important role in the partitioning of gases into particles and droplets, in addition to influencing aqueous reactions in droplets (e.g., Pye et al., 2020), pH was filtered out in Step 4 for being a poor predictor of N_d.

The nine species that survived the filtering scheme in Figure 2 are methanesulfonic acid (MSA), ammonium (NH_4^+), NO_3^-, Ox, Tot-SO_4^{2-}, NSS-SO_4^{2-}, Fe, Na, and vanadium (V). These species have known sources as follows. MSA: ocean biogenic (Sorooshian et al., 2009); NH_4^+: agriculture (Bauer et al., 2016), marine emissions (Bouwman et al., 1997), and wildfires (Reid et al., 1998); NO_3^- ~~,~~ and Ox: fire (Prabhakar et al., 2014; Maudlin et al., 2015); Tot-SO_4^{2-}: sea salt (Seinfeld & Pandis, 2016), ocean biogenic (Charlson et al., 1987), and shipping (Coggon et al., 2012), with NSS-SO_4^{2-} missing the sea salt contribution; Fe: dust (Jickells et al., 2005) and fire (Maudlin et al., 2015); Na: sea salt (Seinfeld & Pandis, 2016); V: shipping (Wang et al., 2014). Note that we retained both Tot-SO_4^{2-} and NSS-SO_4^{2-}; this is to evaluate which correlates more with N_d, as some studies have used Tot-SO_4^{2-} (e.g., Leaitch et al., 1992; Saxena & Menon, 1999), whereas other have used NSS-SO_4^{2-} (Novakov et al., 1994; Boucher & Lohmann, 1995). Sections 3.1 and 3.2 will discuss these nine species, and the rest of Section 3 will focus on only four species to be explained later. These species were analyzed by a multivariable regression model, which is described in the next section.

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2.5. Mathematical model

This study examines the relationship between cloud water mass concentration and N_d with a multivariable linear model similar to that of McCoy et al. (2017, 2018):

$$log(N_d) = a_0 + a_1\, log(M_1) + a_2\, log(M_2) + \cdots + a_n\, log(M_n) \quad (3)$$

where M_i is the air-equivalent mass concentration of species i [μg m^{-3}], a_i are fitting parameters, and n is the number of species being considered. N_d is the dependent (or response) variable, and M_1, M_2, …, M_n are the independent (or predictor) variables. The logarithmic forms of N_d and M_i were correlated to account for a numerically large range of several orders of magnitude, and because a log-log model is commonly used to correlate chemical composition to N_d (e.g., Boucher & Lohmann, 1995; Menon et al., 2002; McCoy et al., 2017).

The Matlab software package was used to obtain multivariable linear regressions of the form of Equation 3 using the method of ordinary least squares. The performance of a regression was quantified using the coefficient of determination (R^2). However, when comparing the performance of correlations between regressions using a different number of predictor variables, it is necessary to use the adjusted coefficient of determination (~~R_{adj}^2~~ R^2_{adj}), which is subscripted to distinguish it from the ordinary R^2, and is adjusted by using the number of predictors (P) and the number of data points (N) via the formula $R^2_{adj} = 1 - (1 - R^2)(N - 1)/(N - P - 1)$ (Kahane, 2008). For a large number of data points, $R^2_{adj} \sim R^2$; however, for the sake of rigor and consistency, R^2_{adj} is used instead of the ordinary R^2, except when reporting values from the literature. The statistical significance of correlations was quantified using the p-value obtained by doing a two-tailed Student's t-test. Both R_{adj}^2 and p-values were given by the Matlab software after regression. P-values were obtained for both the overall regression and each individual coefficient in the regression, e.g., if a regression has three predictors, there are a total of five p-values: one for the overall regression, three for the slope of each individual predicting variable, and one for the intercept. In this study, a regression was considered to be statistically significant if all the p-values were < 0.05.

The correct functioning of the method of ordinary least squares requires that the set of n predicting variables in Equation 3 not be collinear. Multicollinearity is defined by a set of three or more predicting variables being collinear. Using a set of multicollinear predictors can produce unreliable estimates in both magnitude and sign of the coefficients (a_i) (Kahane, 2008). There is no universal marker for multicollinearity. Furthermore, multicollinearity can only be addressed when analyzing all predictors together. For example, for a given set of three predictors (P_1, P_2, and P_3), even though the pairs P_1-P_2, P_1-P_3, and P_2-P_3 are not collinear, there is no guarantee that the P_1-P_2-P_3 set is not multicollinear. When considering a complex system such as the chemical composition of cloud water, it is reasonable to assume that as more species are used to predict N_d, the higher the probability that the set of species is multicollinear. We did not test for multicollinearity in this study; the consequences of not doing so are explored in Section 3.2.

2.6. Calculation of turbulence

Similar to Leaitch et al. (1992) and Feingold et al. (1999), this study analyzes the effect of turbulence on the ability to predict N_d. Turbulence was considered to be represented by the standard deviation of the vertical wind speed (w) and is represented as σ_w. Also similar to Leaitch et al. (1992), this study classified conditions into turbulent and smooth regimes by considering the upper and lower ~~33~~33rd percentile of σ_w, respectively. Although the rigorous approach to calculate σ_w uses the w from below the cloud (Twomey, 1959), this study used vertical wind speed data

collected throughout the sampling time (i.e., mostly inside the cloud, but also outside the cloud). This was mainly because not all cloud water samples had an accompanying measurement of w below the cloud. To justify using σ_w from the sampling time instead of below cloud σ_w, consider Figure S1, which shows a representative time series of altitude, w, and σ_w for a cloud water sample that was collected minutes before a below-cloud leg, which collected measurements of w. It can be seen that the plots of w and σ_w are similar, and that an average σ_w calculated either way is still in the bottom 33rd percentile. Therefore, for purposes of this study, we consider in-cloud turbulence to reasonably approximate below-cloud turbulence.

2.7. Determination of smoke influence

One of the objectives of this study is to analyze the extent to which the presence of smoke from wildfires affects the correlation between N_d and cloud water chemical composition. Thus, it was important to identify cloud water samples that were influenced by smoke. Only the NiCE and FASE campaigns were affected by wildfires. Mardi et al. (2018) identified vertical soundings in the NiCE and FASE campaigns that were influenced by smoke by establishing smoke influence to have a total aerosol number concentration (N_a) $\geq$ 1000 cm^{-3}, as measured by the PCASP, in addition to visual and olfactory detection of smoke by flight scientists. In this study, a cloud water sample was considered to be influenced by smoke if it was collected during a research flight (RF) that contains a vertical sounding identified by Mardi et al. (2018) to be influenced by smoke, even if the cloud water sample was not necessarily collected near the sounding labelled as smoke-influenced; this is a valid assumption based on the work of Mardi et al. (2019). The RFs considered to be smoke-influenced in this study were NiCE RFs 16—23 and FASE RFs 3—11 and 13—15.

3. Results and Discussion

With the refined list of nine physically-meaningful species from Section 2.4, we now proceed to address the following questions: (1) What single species best predicts N_d?; (2) How many species are sufficient to predict N_d?; (3) What is an effective combination of species to predict N_d?; and (4) How do several factors (i.e., turbulence, smoke-influence, and location along cloud depth) affect the ability to reliably predict N_d? These questions are addressed in order in Sections 3.1—3.4.

3.1. Single-variable prediction of N_d

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In this section, we analyze which of the nine species filtered out in Section 2.4 best predicts N_d by itself without binning by external factors. These single-predictor regressions with no binning are important, as they provide a baseline for subsequent sections in which multi-predictor regressions and binning are used. Table 3 and Figure 3 display the ability of each of the nine species to predict N_d. To have consistency with subsequent sections, R^2_{adj} is used instead of the ordinary R^2. The regression and the individual coefficients all were statistically significant.

Some previous studies predicted N_d using Tot-SO_4^{2-} (e.g., Leaitch et al., 1992; Saxena & Menon, 1999), whereas other studies used NSS-SO_4^{2-} (e.g., Novakov et al. 1994; Lowenthal et al., 2004). We find that Tot-SO_4^{2-} is the best predictor, and that is better correlated to N_d (R^2_{adj} = 0.40) than NSS-SO_4^{2-} (R^2_{adj} = 0.29). This is likely because Tot-SO_4^{2-} encompasses both sea salt particles and non-sea salt particles, and thus gives a better approximation to the total number concentration of CCN. In addition, Tot-SO_4^{2-} also had the largest slope (a_1 = 0.32), suggesting that N_d is more sensitive to changes in Tot-SO_4^{2-} than other chemical species. Although HNO_3 has been observed

to increase N_d (e.g., Xue & Feingold, 2004), NO_3^- was found to be only moderately correlated with N_d ($R^2_{adj} = 0.24$). The species with the lowest correlation was Fe ($R^2_{adj} = 0.05$). This low correlation with N_d was also presented by other crustal metals ~~that~~ like Al ($R^2_{adj} = 0.01$) and Ti ($R^2_{adj} \sim 0$) (not shown in Table 3). The low influence of crustal metals on N_d is consistent with the findings of Lowenthal & Borys (2000). Some physical meaning can be extracted from the intercept of the regression (a_0). If N_d is insensitive to the mass concentration of a species, then the slope (a_1) should be zero; and N_d would be constant with a value of $N_d = ~~10^{a_0}~~ 10^{a_0}$. These intercepts yield a range of N_d of 108–412 cm^{-3}. These values are not unrealistic in clouds in this study region (e.g., Chen et al., 2012; Lu et al., 2009; Wang et al., 2016).

To contrast with results of this work, Table 4 shows the regression parameters from other studies when correlating N_d and SO_4^{2-}. For the sake of completeness, Table 4 shows regressions that analyzed non-marine stratocumulus clouds, but in this comparison, we focus only on those regressions that analyzed stratocumulus clouds. Our results (i.e., a_i coefficients and R^2) for Tot-SO_4^{2-} reasonably match the results of Leaitch et al. (1992), suggestive of commonality between two ~~ocean~~coastal regions with differing meteorological conditions (i.e., northeast Pacific vs northwest Atlantic) (Sorooshian et al., 2019). Our results for NSS-SO_4^{2-} also reasonably match those of McCoy et al. (2017), which is noteworthy as McCoy et al. (2017) used satellite retrievals and model aerosol concentrations for several stratocumulus decks around the world, whereas our analysis used in situ data from a relatively small region. However, our NSS-SO_4^{2-} results differ significantly from those of Novakov et al. (1994), which is understandable since the regression presented by Novakov et al. (1994) has a p-value > 0.05. Our data set does not achieve the degree of correlation achieved by Lowenthal et al. (2004), who report the highest correlation for marine clouds ($R^2 = 0.82$). The studies that analyzed stratocumulus clouds all report intercept values (a_0) ~ 2.0, which is consistent with our data.

3.2. Multi-variable prediction of N_d

When previous studies correlated N_d (or N_{CCN}) and the air-equivalent concentration of chemical species and obtained a poor correlation, it was suggested that taking more chemical species into consideration would improve the correlation (e.g., Leaitch et al., 1992; Novakov et al., 1994). In this this section we address the issue: "How many chemical species are necessary to adequately predict N_d?". To answer this question, we use the nine filtered species from Section 2.4. Regressions of the form of Equation 3 are performed for every combination of species. The number of predictors in the regressions are varied from one up to eight. The number of combinations (C) that can be made with P predictors selected from S species is $C = S!/(S-P)!$. Combinations that include Tot-SO_4^{2-} and NSS-SO_4^{2-} together are not considered, thus leaving a total of 383 regressions.

Of the total 383 regression, only 67 were considered as statistically significant. Figure 4 shows the R^2_{adj} as a function of the number of predictors for both statistically significant and insignificant regressions; the percentage of regressions that were statistically significant is shown in Table S2. These results show that adding more predictors does not necessarily improve the correlation, as all correlations that use six or more predictors are statistically insignificant. This behavior is perhaps because the new species being added are redundant with respect to the species that are already in the model (i.e., the new species is mathematically collinear with the old species). It is also interesting to note how R^2_{adj} increases asymptotically to ~ 0.6; this further makes the point that additional species do not necessarily improve predictability of N_d. The same asymptotic behavior is also exhibited with R^2, as R^2 and R^2_{adj} for these regressions differ by only ~ 2%.

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We examined the best regressions produced by a given number of predictors to explore the factors that contribute to a respectable multivariable regression. Table 5 shows the three statistically significant regressions that had the highest R^2_{adj} for a given number of predictors (one to five). The predictors are ordered horizontally according to the value of their coefficient in order to show qualitatively which species is more dominant in a regression. Eight of the nine chemical species considered appear at least once in a regression, with the most common species being NH_4^+, a form of SO_4^{2-} (total or non-sea salt), Na, Ox, and MSA. Sulfate (total or non-sea salt) appears in 12 of the 15 regressions, and in eight regressions it has the largest coefficient; this speaks to the importance of SO_4^{2-} in predicting N_d. However, the appearance of Na and Ox and their non-negligible slope also highlights the importance of considering them as well in a correlation; this is clearly observed in the increase of R^2_{adj} when Na and Ox are added to a regression that contains only NSS-SO_4^{2-} (Table 6). We believe that the ingredients that yield the higher R^2_{adj} in Table ~~6~~5 are: (1) a form of SO_4^{2-} (such Tot-SO_4^{2-} or NSS-SO_4^{2-}), (2) a sea emissions tracer (such as Na), and (3) an organic tracer (such as Ox). NH_4^+ was present in all the regressions; however, given that it comes from diverse sources such as agriculture (ApSimon et al., 1987; Bauer et al., 2016), marine emissions (Bouwman et al., 1997; Paulot et al., 2015), and wildfires (Maudlin et al., 2015; Reid et al., 1998), it is difficult to assess if it contributes to the CCN budget or simply accompanies all types of CCN. In other words, we suspect that NH_4^+ appears in all correlations because it generally accompanies the three ingredients we propose make a good correlation: a form of SO_4^{2-}, a marine emissions tracer, and an organic tracer.

It is of interest to note that combining a sea salt tracer (such as Na) with NSS-SO_4^{2-} in a two-predictor model has about the same performance (R^2_{adj} = 0.41; Table 6) as a one-predictor model using Tot-SO_4^{2-} (R^2_{adj} = 0.40; Table 3). We believe this is because Tot-SO_4^{2-} encompasses the sea salt and the non-sea salt contribution to CCN about the same as the artificial mathematical separation of the two. Also of interest is that when only looking at the statistically significant regressions, only 17 regressions have species with negative coefficients (i.e., negative slopes). The species with negative coefficients are NO_3^-, Fe, and V (not shown); more specifically, NO_3^-, Fe, and V have negative coefficients when they are accompanied by NH_4^+ in the same regression. The physical reason as to why these species have negative coefficients when mixed with NH_4^+ is not clear; perhaps the reason is due to the mathematics of the regression and not physically rooted, as multicollinearity can lead to unexpected ~~signs for predictor coefficients (Kahane, 2008).~~magnitudes and signs for predictor coefficients (Kahane, 2008). In addition, multicollinearity will become more likely as more predictors as considered. Therefore, it is not surprising that unexpected negative coefficients only appear when considering many (five) predictors. Lastly, a correlation matrix among the nine predicting species (Figure S2) shows a strong correlation for some pairs of species (NH_4^+-NO_3^-: R^2_{adj} = 0.48; NO_3^--V: R^2_{adj} = 0.49) and moderate correlation for other pairs (NH_4^+-V: R^2_{adj} = 0.27; NO_3^--Fe: R^2_{adj} = 0.22), thus strengthening the argument that the negative coefficients are due to mathematical multicollinearity and not a physical or chemical reason.

When considering a multi-species model to predict N_d, it is worthwhile to examine the coefficient of sea salt. Even though it is well established that more CCN leads to more droplets, the effect of giant CCN (GCCN), such as sea salt, is not as clear. Cloud microphysics studies suggest two mechanisms by which more sea salt leads to less N_d: (1) The large size and highly hygroscopic nature of sea salt causes these particles to activate into droplets before other smaller particles. This reduces the amount of available water vapor and creates unfavorable conditions for smaller particles to nucleate into droplets (e.g., Andreae & Rosenfeld, 2008). (2) GCCN nucleate

into larger droplets as compared to CCN, which in turn are more likely to collide and coalesce with surrounding droplets. This combination of droplets creates larger but fewer droplets and ultimately leads to the formation of rain drops and precipitation (e.g., Feingold et al., 1999, Jung et al., 2015). Therefore, it is expected that the negative correlation between GCCN and N_d should translate into a negative coefficient for Na (the sea salt tracer) in a multi-predictor regression equation. However, this behavior was not observed in this study. A plausible explanation for this discrepancy is that the effect of GCCN on N_d is highly dependent on conditions like LWC and N_d itself (e.g., Feingold et al., 1999), and that this study did not capture the appropriate conditions to observe this effect. However, McCoy et al. (2017) did observe a negative coefficient for sea salt and ascribed it to a simulation artefact caused by the intimate link between sea salt generation and wind speed (i.e., turbulence). An attempt to isolate the effects of sea salt and turbulence on N_d is provided in Section 3.1.1.

Menon et al. (2002) and McCoy et al. (2017, 2018) are among the few studies that have used multiple species to predict N_d (Table 7). Menon et al. (2002) used three species (sulfate, organic matter, and sea salt). McCoy et al. (2017, 2018) used five species (sulfate, sea salt, black carbon, organic carbon, and dust), but the 2017 study found the contribution of organic matter to be negligible. ~~McCoy et al. (2017) observed a negative coefficient for sea salt (i.e., more sea salt leads to fewer cloud droplets); however, we do not observe the same trend in our results, as the sea salt tracer (Na) always has a positive coefficient.~~ In order to intercompare results with previous studies, we selected species homologous to those of McCoy et al. (2017, 2018). We select NSS-SO_4^{2-} for sulfate, Na for sea salt, oxalate for organic carbon, and Fe for dust. We did not measure a species analogous to black carbon. The subsequent analysis examines only these four species using single-predictor regressions.

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3.3. Analysis of meteorological factors through binning

Historically, the effect that meteorological factors have on the composition-N_d (or -N_{CCN}) empirical relationship has been examined by analyzing regressions after binning by turbulence (Leaitch et al., 1996), cloud type (Leaitch et al., 1992; Novakov & Penner, 1993), and region (McCoy et al., 2018). The following sections address the effects of turbulence, smoke influence, and location along cloud depth.

3.3.1. Effect of turbulence

Building upon the work of Leaitch et al. (1996), who studied how turbulence affects the correlation between Tot-SO_4^{2-} and N_d, this study extends that analysis to examine four additional species. Similar to Leaitch et al. (1996), this study quantified turbulence by the standard deviation of vertical wind speed (σ_w). Our range of σ_w was 0.10—0.51 m s^{-1}. Low turbulence was considered to be in the bottom 33rd percentile ($\leq$ 0.27 m s^{-1}), whereas high turbulence was taken to be values in the top 33rd percentile ($\geq$ 0.33 m s^{-1}). Leaitch el al. (1996) considered low and high turbulence to be $\sigma_w < 0.17$ m s^{-1} and $\sigma_w > 0.23$ m s^{-1}, respectively, and it is worth noting that only five of our 385 samples are considered low turbulence according to the criterion of Leaitch et al. (1996). Figure 5 and Table 8 show how R^2_{adj} depends on the predicting species and the turbulence regime; the scatterplots from which the R^2_{adj} are taken are shown in Figure ~~S2~~S3.

For NSS-SO_4^{2-}, there is no significant difference in R^2_{adj} when comparing all the points or by binning by σ_w. However, this is not the case for Tot-SO_4^{2-}, in which there is a large difference in the degree of correlation (R^2_{adj} = 0.27 and R^2_{adj} = 0.55 for low σ_w and high σ_w, respectively). This is in agreement with Leaitch et al. (1996), in which the correlation (albeit, not log-log)

between Tot-SO_4^{2-} and N_d yielded an R^2 = 0.53 and R^2 = 0.91 for low and high σ_w, respectively. The difference in the behavior between Tot-SO_4^{2-} and NSS-SO_4^{2-} hints that the sea salt contributions to SO_4^{2-} (i.e., ocean-derived species) are the ones affected by turbulence, and hence explains the insensitivity NSS-SO_4^{2-} has to turbulence.

~~For Na, there is a better correlation at high turbulent conditions than at smooth conditions (R^2_{adj} = 0.26 and R^2_{adj} = 0.09 for high and low σ_w, respectively). This further strengthens the argument that turbulence plays an important role in the vertical transport of sea salt (and other ocean emissions) from the ocean surface to the cloud base.~~

For Ox, the correlation improves at low turbulence (R^2_{adj} = 0.30), but not at high turbulence (R^2_{adj} = 0.09). We believe Ox behaves differently than Na because it does not necessarily just enter the cloud from below via updrafts, but rather it enters the cloud from above via entrainment of air from the free troposphere that can at times be enriched with organic species in the study region (Coggon et al., 2014; Crosbie et al., 2016; Hersey et al., 2009; Sorooshian et al., 2007).

For Fe, all turbulence scenarios yield a low correlation between Fe and N_d, indicating that, overall, Fe is not a good predictor for N_d.

For Na, there is a better correlation at high turbulent conditions than at smooth conditions (R^2_{adj} = 0.26 and R^2_{adj} = 0.09 for high and low σ_w, respectively). This further strengthens the argument that turbulence plays an important role in the vertical transport of sea salt (and other ocean emissions) from the ocean surface to the cloud base. The present data set allows for deeper analysis into the entangled effects of sea salt and turbulence on N_d. More specifically, aerosol reanalysis products like those from MERRA-2 calculate the mass concentration of sea salt via parameterizations that link wind speed to sea salt emissions (Gong et al., 2003; Randles et al., 2017). Since wind speed affects turbulence, it follows that sea salt concentrations are not independent from turbulence, as turbulence is used to calculate sea salt concentrations. Subsequently, these sea salt concentrations are used to predict N_d (e.g., McCoy et al., 2017, 2018). The present study measured both sea salt (quantified by Na) and turbulence (quantified by σ_w) and thus offers an opportunity to try to isolate the effects of both factors on N_d (Figure 6). Two results emerge. First, more turbulence is correlated to more sea salt, which is consistent with what the models predict (Randles et al., 2017). Second, at a fixed concentration of Na, N_d does not vary significantly with σ_w, as evidenced by a weak change in color. However, at a fixed value of σ_w, N_d does vary significantly with Na, as evidenced by the noticeable change in color. Therefore, the independent measurement of both variables reveals that N_d is more sensitive to changes in Na than to changes in σ_w. We caution that σ_w is not obtained from below the cloud, but from within the cloud during sampling time (Figure S1).

3.3.2. Effect of smoke influence

The clouds in the study region are affected by the smoke from wildfires (e.g., Dadashazar et al., 2019; Maudlin et al., 2015; Schlosser et al., 2017). As mentioned in Section 2.7, Mardi et al. (2018) used the same data set as this study and identified research flights (RFs) that contained smoke-influenced cloud soundings, namely NiCE RFs 16–23 and FASE RFs 3–11 and 13–15. In this study, we considered that all cloud water samples collected during the aforementioned RFs were influenced by smoke. Furthermore, we did not distinguish if the smoke was above or below in the cloud; this is an important caveat, as cloud microphysical properties seem to depend on the surrounding smoke vertical profile (e.g., Diamond et al, 2018; Koch & Del Genio, 2010). The correlation between N_d and composition as a function of smoke influence is shown in Figure ~~6~~7 and Table 8, and the scatterplots from which the R^2_{adj} are taken are shown in Figure ~~S3~~S4.

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Species that are produced during wildfires exhibited an improvement in R^2_{adj} when considering only the smoke-influenced cases. The opposite is true for species not produced during wildfires. More specifically, Ox and Fe showed an increase in correlation for smoke-influenced conditions (R^2_{adj} = 0.42 and R^2_{adj} = 0.15 for Ox and Fe, respectively) and a small decrease in for smoke-free conditions (R^2_{adj} = 0.07 and R^2_{adj} = 0.04 for Ox and Fe, respectively). This is most likely because Ox and Fe concentrations increase during wildfires (e.g., Maudlin et al., 2015) and thus contribute appreciably to the regional CCN during the summertime when wildfires are prevalent.

NSS-SO_4^{2-} and Na showed a decrease in correlation for smoke-influenced conditions (R^2_{adj} = 0.22 and R^2_{adj} = 0.17 for NSS-SO_4^{2-} and Na, respectively), and an increase for smoke-free conditions (R^2_{adj} = 0.36 and R^2_{adj} = 0.24 for NSS-SO_4^{2-} and Na, respectively). We suspect this is because even though wildfires can produce NSS-SO_4^{2-} (e.g., Reid et al., 1998) and Na (e.g., Hudson et al., 2004; Silva et al., 1999), these species are not produced as effectively as Ox or Fe. For example, Maudlin et al. (2015) measured aerosol mass concentration in the study region during both smoke-influenced and non-smoke-influenced conditions. They reported an increase in mass concentration for NSS-SO_4^{2-}, Na, Ox, and Fe to be 30%, 120%, 220%, and 408%, respectively, for submicron particles, and -2%, -28%, 164%, and 97%, respectively, for supermicrometer particles. Consequently, Ox and Fe are produced more in wildfires in the study region than NSS-SO_4^{2-} and Na.

The NiCE (2015) and FASE (2016) campaigns were influenced by smoke originating from different sources. NiCE was influenced by the Big Windy, Whiskey Complex, and Douglas Complex forest fires near the California-Oregon border, with a transport time of approximately two days to reach the base of aircraft operations in Marina and adjacent areas where most samples were collected (Maudlin et al., 2015). In contrast, FASE was influenced by the Soberanes fire approximately 30 km southwest of aircraft hangar (Braun et al., 2017). Hence, analyzing each campaign separately may provide some insights into the sensitivity of N_d to smoke from both different fuel types and with varying transport trajectories. NiCE fire data were linked to timber, grass and shrub models whereas those from FASE were associated with chaparral, tall grass, and timber (Braun et al., 2017; Mardi et al., 2018). The results are shown in Table 8 and Figure S4. When comparing FASE to both campaigns combined, the prediction of N_d using NSS-SO_4^{2-}, Na, Ox, and Fe is not improved, resulting in a ΔR^2_{adj} of -0.04, -0.04, 0.01, and -0.03, respectively. However, when comparing NiCE to both campaigns combined, the prediction of N_d using NSS-SO_4^{2-}, Na, Ox, and Fe is significantly improved, resulting in a ΔR^2_{adj} of 0.14, 0.29, 0.18, and 0.13, respectively. The difference between NiCE and FASE could be because different forest fires produce aerosols with varying aerosol chemical signatures and size distributions, as studies in the region have shown (Ma et al., 2019; Mardi et al., 2019). Alternatively, the difference could be due to the small sample size of NiCE (31 samples) as compared to FASE (136 samples) (Table 1). Certainly more research, including larger datasets, is warranted to investigate how different fuel types and plume aging times impact aerosol-cloud interactions.

3.3.3. Effect of in-cloud height

MacDonald et al. (2018) used the same data set as this study to show that the chemical composition of cloud water varies with height within a cloud. It is therefore reasonable that the N_d-chemical composition relationship also varies with in-cloud height. The correlation between N_d and composition as a dependence of in-cloud height is shown in Figure ~~7~~8 and Table 8, and the scatterplots from which the R^2_{adj} are taken are shown in Figure ~~S4~~S5.

Ox and Fe exhibit a better correlation when focusing on the bottom third of the cloud (R^2_{adj} = 0.29 and R^2_{adj} = 0.20 for Ox and Fe, respectively). When focusing on the top third of the cloud, the correlation decreased for Ox (R^2_{adj} = 0.08) and remained unchanged for Fe (R^2_{adj} = 0.03). One possible hypothesis to explain why Ox and Fe are better predictors of N_d at cloud base is that smokes affects cloud microphysics (N_d and effective radius) more at cloud base that at cloud top, regardless of whether the smoke was above or below the cloud (Diamond et al., 2018; Mardi et al., 2019).

NSS-SO_4^{2-} and Na exhibit a better correlation with N_d when focusing on the top third of the cloud (R^2_{adj} = 0.33 and R^2_{adj} = 0.33 for NSS-SO_4^{2-} and Na, respectively). The correlation decreases when focusing on the bottom third of the cloud (R^2_{adj} = 0.17 and R^2_{adj} = 0.10 for NSS-SO_4^{2-} and Na, respectively). Tot-SO_4^{2-} also follows this pattern (R^2_{adj} = 0.56 and R^2_{adj} = 0.22 for top and bottom, respectively).

It is not entirely clear why NSS-SO_4^{2-} and Na would be better correlated with N_d in the top third of clouds. MacDonald et al. (2018) noted that the concentration of chemical species varies as a function of in-cloud height and is not the same for all species; the concentration of Na is greatest at cloud base whereas that of NSS-SO_4^{2-} and Ox are greatest mid-cloud. It would be expected that the vertical profile of concentration is related to the ability to predict N_d (i.e., that a larger concentration of a species leads to a better correlation with N_d), but that expectation is not observed in these results. It is also interesting to point out that there is not much difference in R^2_{adj} when considering all cloud thirds versus only the middle third; this makes sense, as almost half of the cloud water samples (46%) were collected in the middle third of the cloud.

The dependence of the correlation between chemical composition and N_d on in-cloud height is of relevance to remote sensing, which relies on satellite measurement of cloud top properties such as cloud top temperature to then calculate a constant N_d throughout the cloud depth (e.g., Grosvenor et al., 2018).

4. Conclusions

This study used a four-year data set of airborne measurements collected in warm marine stratocumulus clouds off the California coast and analyzed the extent to which the chemical composition of cloud water can be used to predict N_d. A total of ~~79~~80 species were filtered to nine to examine the prediction of N_d using a single-species model, and then using a multi-species model. The ~~79~~nine species were subsequently filtered to four to examine how the four single-species models were affected by environmental factors, namely, turbulence, smoke influence, and vertical location within a cloud. The most important findings of this paper are:

1. The species that best predicted N_d is Tot-SO_4^{2-} with R^2_{adj} = 0.40, followed by NH_4^+ (R^2_{adj} = 0.34), NSS-SO_4^{2-} (R^2_{adj} = 0.29), MSA (R^2_{adj} = 0.26), and NO_3^- (R^2_{adj} = 0.24).
2. The prediction of N_d can be improved by using a multi-species model. However, increasing the number of species caused the R^2_{adj} to asymptotically approach ~ 0.6. Furthermore, the regressions with six or more species became statistically insignificant.
3. Analyzing the three best correlations for each of the n-species models (where n = 1—5) shows that the factors that constitute a good regression are: a form of SO_4^{2-} (total or non-sea salt), an ocean emissions tracer, and an organic tracer.
4. Greater turbulence (approximated as the standard deviation of vertical wind speed) improves the ability of ocean-derived species to predict N_d, as observed when comparing regressions

using turbulent data points versus all data points for Tot-SO_4^{2-} (ΔR^2_{adj} = 0.15) and Na (ΔR^2_{adj} = 0.07), but not for NSS-SO_4^{2-} (ΔR^2_{adj} = -0.01) or Ox (ΔR^2_{adj} = -0.06).

5. The influence of smoke significantly affects those species that best predict N_d. Ox (a species known to be produced during biomass burning) was best correlated with N_d (R^2_{adj} = 0.42) under smoke-influenced conditions.
6. Vertical location within the cloud affects the ability to predict N_d. The species that are best correlated with N_d at cloud top are Tot-SO_4^{2-} (R^2_{adj} = 0.56) and NSS-SO_4^{2-} (R^2_{adj} = 0.33); those best correlated with N_d at cloud base are fire tracers such as Ox (R^2_{adj} = 0.29) and Fe (R^2_{adj} = 0.20), as it has been reported that the base of a cloud is more sensitive to the influence of smoke.

Data Availability

All data used in this work can be found on the Figshare database (Sorooshian et al., ~~2018;~~ ~~hhttps~~2017; https://figshare.com/articles/A_Multi-Year_Data_Set_on_Aerosol-Cloud-Precipitation-Meteorology_Interactions_for_Marine_Stratocumulus_Clouds/5099983).

Author Contributions

All coauthors contributed to some aspect of the data collection. ABM and AS conducted the data analysis and interpretation. ABM and AS prepared the manuscript with contributions from all coauthors.

Competing Interests

The authors declare that they have no conflict of interest.

Acknowledgements

Alexander B. MacDonald acknowledges support from the Mexican National Council for Science and Technology (CONACYT). We acknowledge Agilent Technologies for their support and Shane Snyder's laboratories for ICP-QQQ data.

Financial Support

These field campaigns were funded by Office of Naval Research grants N00014-10-1-0811, N00014-11-1-0783, N00014-10-1-0200, N00014-04-1-0118, and N00014-16-1-2567. This work was also partially supported by NASA grant 80NSSC19K0442 in support of the ACTIVATE Earth Venture Suborbital-3 (EVS-3) investigation, which is funded by NASA's Earth Science Division and managed through the Earth System Science Pathfinder Program Office.

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Table 1. Summary of field campaign data sets used in this study and statistics related to cloud water sample collection. Smoke-influenced RFs were NiCE RFs 16—23 and FASE RFs 3—11 and 13—15.

Field campaign	Dates (mm/dd/yyyy)	# of RFs	# of samples	# of fire-impacted samples
Eastern Pacific Emitted Aerosol Cloud Experiment (E-PEACE)	07/08/2011 – 08/18/2011	30	82	0
Nucleation in California Experiment (NiCE)	07/08/2013 – 08/07/2013	23	119	31
Biological and Oceanic Atmospheric Study (BOAS)	07/02/2015 – 07/24/2015	15	29	0
Fog and Stratocumulus Evolution Experiment (FASE)	07/18/2016 – 08/12/2016	16	155	136

Field campaign	Dates (mm/dd/yyyy)	# of RFs	# of samples	# of fire-impacted samples
Eastern Pacific Emitted Aerosol Cloud Experiment (E-PEACE)	07/08/2011 – 08/18/2011	30	82	0
Nucleation in California Experiment (NiCE)	07/08/2013 – 08/07/2013	23	119	31
Biological and Oceanic Atmospheric Study (BOAS)	07/02/2015 – 07/24/2015	15	29	0
Fog and Stratocumulus Evolution Experiment (FASE)	07/18/2016 – 08/12/2016	16	155	136

Table 2. Summary of chemical species analyzed in this study. IC = ion chromatography; ICP = ICP-MS or ICP-QQQ. Note: NSS species, with the exception of NSS-SO_4^{2-}, were calculated using elements, not ions, hence they have no superscript charge.

Elements (ICP)				Inorganic ions (IC)	Organic ions (IC)
1	Ag	24	Na	47 Ammonium (NH_4^+)	66 Acetate
2	Al	25	Nb	48 Bromide (Br^-)	67 Adipate
3	As	26	Ni	49 Calcium (Ca^{2+})	68 Butyrate
4	B	27	P	50 Chloride (Cl^-)	69 Formate
5	Ba	28	Pb	51 Fluoride (F^-)	70 Glutarate
6	Br	29	Pd	52 Lithium (Li^+)	71 Glycolate
7	C	30	Rb	53 Magnesium (Mg^{2+})	72 Glyoxylate
8	Ca	31	Rh	54 Methanesulfonic acid (MSA)	73 Lactate
9	Cd	32	Ru	55 Nitrate (NO_3^-)	74 Maleate
10	Cl	33	S	56 Nitrite (NO_2^-)	75 Malonate
11	Co	34	Sb	57 Potassium (K^+)	76 Oxalate
12	Cr	35	Se	58 Sodium (Na^+)	77 Propionate
13	Cs	36	Si	59 Sulfate (SO_4^{2-})	78 Pyruvate
14	Cu	37	Sn		79 Succinate
15	Fe	38	Sr	Amines (IC)	
16	Ga	39	Ta	60 Diethyl ammonium (DEA)	
17	Hf	40	Te	61 Dimethyl ammonium (DMA)	
18	I	41	Ti		
19	K	42	V	NSS species (calculated)	
20	Li	43	W	62 NSS Calcium (NSS-Ca)	
21	Mg	44	Y	63 NSS Potassium (NSS-K)	
22	Mn	45	Zn	64 NSS Magnesium (NSS-Mg)	
23	Mo	46	Zr	65 NSS Sulfate (NSS-SO_4^{2-})	

Elements (ICP)				Inorganic ions (IC)	Organic ions (IC)
1	Ag	24	Na	47 Ammonium (NH_4^+)	66 Acetate
2	Al	25	Nb	48 Bromide (Br^-)	67 Adipate
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4	B	27	P	50 Chloride (Cl^-)	69 Formate
5	Ba	28	Pb	51 Fluoride (F^-)	70 Glutarate
6	Br	29	Pd	52 Lithium (Li^+)	71 Glycolate
7	C	30	Rb	53 Magnesium (Mg^{2+})	72 Glyoxylate
8	Ca	31	Rh	54 Methanesulfonic acid (MSA)	73 Lactate

9	Cd	32	Ru	55	Nitrate (NO_3^-)	74	Maleate
10	Cl	33	S	56	Nitrite (NO_2^-)	75	Malonate
11	Co	34	Sb	57	Potassium (K^+)	76	Oxalate
12	Cr	35	Se	58	Sodium (Na^+)	77	Propionate
13	Cs	36	Si	59	Sulfate (SO_4^{2-})	78	Pyruvate
14	Cu	37	Sn			79	Succinate
15	Fe	38	Sr		Amines (IC)		
16	Ga	39	Ta	60	Diethylamine (DEA)		Acidity (pH)
17	Hf	40	Te	61	Dimethylamine (DMA)	80	Hydrogen ion (H^+)
18	I	41	Ti				
19	K	42	V		NSS species (calculated)		
20	Li	43	W	62	NSS Calcium (NSS-Ca)		
21	Mg	44	Y	63	NSS Potassium (NSS-K)		
22	Mn	45	Zn	64	NSS Magnesium (NSS-Mg)		
23	Mo	46	Zr	65	NSS Sulfate (NSS-SO_4^{2-})		

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Table 3. Summary of one-predictor models for N_d based on using any of nine of the final chemical species that were identified after applying the filtering scheme shown in Figure 2. The coefficients correspond to a linear model of the form $\log(N_d) = a_0 + a_1 \log(M_i)$, where M_i is the mass concentration of species i.

Species	R^2_{adj}	Coefficients	
		a_0	a_1
Tot-SO_4^{2-}	0.40	2.05	0.32
NH_4^+	0.34	2.33	0.25
NSS-SO_4^{2-}	0.29	2.13	0.28
MSA	0.26	2.37	0.31
NO_3^-	0.24	2.12	0.25
Na	0.19	2.03	0.13
Ox	0.15	2.26	0.18
V	0.14	2.61	0.15
Fe	0.05	2.26	0.09

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Na	0.19	2.03	0.13
Ox	0.15	2.26	0.18
V	0.14	2.61	0.15
Fe	0.05	2.26	0.09

Table 4. Comparison of coefficient values for studies that correlate N_d to SO_4^{2-} (total or non-sea salt). The coefficients correspond to a linear model of the form $\log(N_d) = a_0 + a_1 \log(SO_4^{2-})$.

Reference	a_0	a_1	SO_4^{2-}	R^2	Cloud type
Leaitch et al. (1992)[a]	1.95	0.257	Tot	0.3	Stratocumulus
	2.33	0.186	Tot	0.49	Cumulus
Novakov et al. (1994)	2.323	0.091	NSS	0.50[b]	Marine stratocumulus
	2.43	-0.056	NSS	0.03	Marine cumulus
Van Dingenen et al. (1995)[c]	2.33	0.4	NSS	0.42	All cloud types combined
Boucher & Lohmann (1995)[c]	2.24	0.257	NSS	[d]	Continental stratus
	2.54	0.186	NSS	[d]	Continental cumulus
	2.06	0.48	NSS	[d]	Marine
	2.21	0.41	NSS	[d]	All cloud types combined
Saxena & Menon (1999)	0.67	0.66	Tot	[d]	Continental orographic clouds
Lowenthal et al. (2004)	2.32	0.74	NSS	0.82	Marine
	2.38	0.49	NSS	0.66	Continental
	2.39	0.5	NSS	0.81	Combined
McCoy et al. (2017)	2.11	0.41	NSS	0.36	Marine stratocumulus

[a] The units of SO_4^{2-} for this regression are nEq m^{-3}. All other studies report SO_4^{2-} in units of μg m^{-3}. However, the value of a_1 is not affected by the units of concentration.

[b] The R^2 has a $p > 0.05$ due to having few data points.

[c] These regressions were made using data compiled from several studies and assume that $N_{CCN} \sim N_d$.

[d] Study does not report R^2.

Reference	a_0	a_1	SO_4^{2-}	R^2	Cloud type
Leaitch et al. (1992)[a]	1.95	0.257	Tot	0.3	Continental stratocumulus
	2.33	0.186	Tot	0.49	Continental cumulus
Novakov et al. (1994)	2.323	0.091	NSS	0.50[b]	Marine stratocumulus
	2.43	-0.056	NSS	0.03	Marine cumulus
Van Dingenen et al. (1995)[c]	2.33	0.4	NSS	0.42	All cloud types combined
Boucher & Lohmann (1995)[c]	2.24	0.257	NSS	[d]	Continental stratus
	2.54	0.186	NSS	[d]	Continental cumulus
	2.06	0.48	NSS	[d]	Marine
	2.21	0.41	NSS	[d]	All cloud types combined
Saxena & Menon (1999)	0.67	0.66	Tot	[d]	Continental orographic clouds
Lowenthal et al. (2004)	2.32	0.74	NSS	0.82	Marine
	2.38	0.49	NSS	0.66	Continental
	2.39	0.5	NSS	0.81	Combined

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McCoy et al. (2017)	2.11	0.41	NSS	0.36	Marine stratocumulus

[a] The units of SO_4^{2-} for this regression are nEq m^{-3}. All other studies report SO_4^{2-} in units of μg m^{-3}. However, the value of the slope (a_1) is not affected by the units of concentration.

[b] The R^2 has a p > 0.05 due to having few data points.

[c] These regressions were made using data compiled from several studies and assume that $N_{CCN} \sim N_d$.

[d] Study does not report R^2.

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Table 5. The top three statistically significant regressions with the highest R^2_{adj} for a given number of predictors. The coefficients correspond to a linear model of the form $\log(N_d) = a_0 + \Sigma\, a_i \log(P_i)$.

# of Predictors	Predictors (P_i) and their respective coefficients (a_i)											
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	a_4	P_4	a_5	P_5	R^2_{adj}
1	2.05	0.32	Tot-SO_4^{2-}									0.40
	2.33	0.25	NH_4^+									0.34
	2.13	0.28	NSS-SO_4^{2-}									0.29
2	2.18	0.22	Tot-SO_4^{2-}	0.12	NH_4^+							0.48
	2.43	0.21	MSA	0.15	NH_4^+							0.44
	2.25	0.19	NH_4^+	0.09	Na							0.42
3	2.25	0.13	NSS-SO_4^{2-}	0.13	NH_4^+	0.10	Na					0.50
	2.24	0.19	Tot-SO_4^{2-}	0.10	Ox	0.07	NH_4^+					0.49
	2.25	0.17	Tot-SO_4^{2-}	0.11	NH_4^+	0.08	MSA					0.49
4	2.32	0.21	Tot-SO_4^{2-}	0.20	Ox	0.09	NH_4^+	-0.15	NO_3^-			0.52
	2.29	0.11	NSS-SO_4^{2-}	0.10	Ox	0.09	Na	0.08	NH_4^+			0.51
	2.31	0.11	NH_4^+	0.10	NSS	0.10	MSA	0.08	Na			0.51
5	2.10	0.13	Na	0.12	Ox	0.11	NSS-SO_4^{2-}	0.08	NH_4^+	-0.05	V	0.56
	2.40	0.23	Ox	0.13	NSS-SO_4^{2-}	0.10	NH_4^+	0.09	Na	-0.17	NO_3^-	0.55
	2.36	0.14	NH_4^+	0.14	MSA	0.12	NSS-SO_4^{2-}	0.07	Na	-0.08	NO_3^-	0.52

# of Predictors	Predictors (P_i) and their respective coefficients (a_i)											
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	a_4	P_4	a_5	P_5	R^2_{adj}
1	2.05	0.32	Tot-SO_4^{2-}									0.40
	2.33	0.25	NH_4^+									0.34
	2.13	0.28	NSS-SO_4^{2-}									0.29
2	2.18	0.22	Tot-SO_4^{2-}	0.12	NH_4^+							0.48
	2.43	0.21	MSA	0.15	NH_4^+							0.44
	2.25	0.19	NH_4^+	0.09	Na							0.42
3	2.25	0.13	NSS-SO_4^{2-}	0.13	NH_4^+	0.10	Na					0.50
	2.24	0.19	Tot-SO_4^{2-}	0.10	Ox	0.07	NH_4^+					0.49
	2.25	0.17	Tot-SO_4^{2-}	0.11	NH_4^+	0.08	MSA					0.49
4	2.32	0.21	Tot-SO_4^{2-}	0.20	Ox	0.09	NH_4^+	-0.15	NO_3^-			0.52
	2.29	0.11	NSS-SO_4^{2-}	0.10	Ox	0.09	Na	0.08	NH_4^+			0.51
	2.31	0.11	NH_4^+	0.10	NSS	0.10	MSA	0.08	Na			0.51
5	2.10	0.13	Na	0.12	Ox	0.11	NSS-SO_4^{2-}	0.08	NH_4^+	-0.05	V	0.56
	2.40	0.23	Ox	0.13	NSS-SO_4^{2-}	0.10	NH_4^+	0.09	Na	-0.17	NO_3^-	0.55
	2.36	0.14	NH_4^+	0.14	MSA	0.12	NSS-SO_4^{2-}	0.07	Na	-0.08	NO_3^-	0.52

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Table 6. Comparison of regressions containing NSS-SO_4^{2-}, Na, and Ox.

# of Predictors	Predictors (P_i) and their respective coefficients (a_i)							
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	R^2_{adj}
1	2.13	0.28	NSS-SO_4^{2-}					0.29
2	2.12	0.23	NSS-SO_4^{2-}	0.12	Na			0.40
	2.26	0.24	NSS-SO_4^{2-}	0.12	Ox			0.34
3	2.22	0.22	NSS-SO_4^{2-}	0.10	Na	0.08	Ox	0.42

# of Predictors	Predictors (P_i) and their respective coefficients (a_i)							
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	R^2_{adj}
1	2.13	0.28	NSS-SO_4^{2-}					0.29
2	2.12	0.23	NSS-SO_4^{2-}	0.12	Na			0.40
	2.26	0.24	NSS-SO_4^{2-}	0.12	Ox			0.34
3	2.22	0.22	NSS-SO_4^{2-}	0.10	Na	0.08	Ox	0.42

Table 7. Results of multivariable regressions from previous studies that have correlated N_d to mass concentrations. The regression corresponds to a model like Equation 3. OM = Organic Matter, SS = Sea Salt, BC = Black Carbon, DU = Dust.

Reference	Predictors (P_i) and their respective coefficients (a_i)									R^2	Cloud type
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	a_4	P_4		
Menon et al. (2002)[a]	2.41	0.50	$NSS\text{-}SO_4^{2-}$	0.13	OM[b]						Continental
	2.41	0.50	$NSS\text{-}SO_4^{2-}$	0.13	OM	0.05	SS				Marine
McCoy et al. (2017)	1.78	0.31	$NSS\text{-}SO_4^{2-}$	-0.19	SS	0.057	BC	0.031	DU	0.44	Marine stratocumulus (global average)
McCoy et al. (2018)	2.03	0.2	$NSS\text{-}SO_4^{2-}$	-0.04	SS	-0.03	BC	0	DU	0.08	Marine stratocumulus (just Californian coast)

[a] This study obtains data from other studies and calculates organic matter.

[b] OM = Organic Matter, SS = Sea Salt, BC = Black Carbon, DU = Dust.

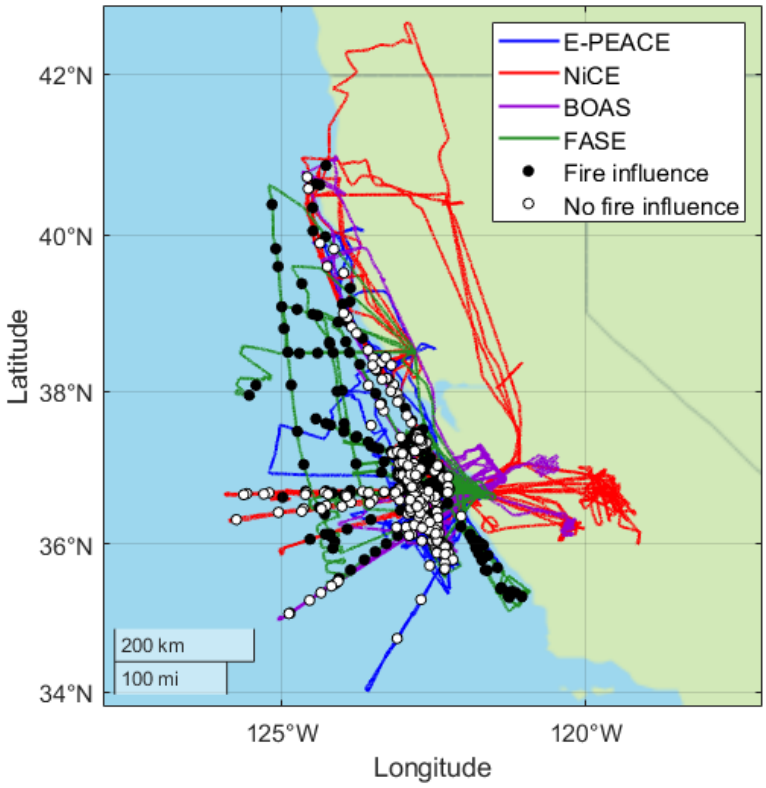
Reference	Predictors (P_i) and their respective coefficients (a_i)									R^2	Cloud type
	a_0	a_1	P_1	a_2	P_2	a_3	P_3	a_4	P_4		
Menon et al. (2002)[a]	2.41	0.50	$NSS\text{-}SO_4^{2-}$	0.13	OM						Continental
	2.41	0.50	$NSS\text{-}SO_4^{2-}$	0.13	OM	0.05	SS				Marine
McCoy et al. (2017)	1.78	0.31	$NSS\text{-}SO_4^{2-}$	-0.19	SS	0.057	BC	0.031	DU	0.44	Marine stratocumulus (global average)
McCoy et al. (2018)	2.03	0.2	$NSS\text{-}SO_4^{2-}$	-0.04	SS	-0.03	BC	0	DU	0.08	Marine stratocumulus (just Californian coast)

[a] This study obtains data from other studies and calculates organic matter.

Table 8. Summary of the R^2_{adj} obtained when correlating mass concentration of a species to N_d under different atmospheric conditions.

Binning criterion	Data points considered	R^2_{adj} NSS-SO_4^{2-}	Na	Ox	Fe
None	All	0.29	0.19	0.15	0.05
Turbulence	High σ_w	0.27	0.26	0.09	0.02[a]
	Low σ_w	0.27	0.09	0.30	0.07
Smoke influence	Smoke	0.22	0.17	0.42	0.15
	No smoke	0.36	0.24	0.07	0.04
Normalized cloud height	Top third	0.33	0.33	0.08	0.03
	Middle third	0.29	0.16	0.16	0.03
	Bottom third	0.17	0.10	0.29	0.20

[a] This R^2_{adj} has a p-value > 0.05.



1643
1644

Binning criterion	Data points considered	R^2_{adj} NSS-SO_4^{2-}	Na	Ox	Fe
None	All	0.29	0.19	0.15	0.05
Turbulence	High σ_w	0.27	0.26	0.09	0.02[a]
	Low σ_w	0.27	0.09	0.30	0.07
Smoke influence	No smoke	0.36	0.24	0.07	0.04
	Smoke	0.22	0.17	0.42	0.15
	NiCE[b]	0.36	0.46	0.60	0.28
	FASE[b]	0.18	0.13	0.41	0.12
Normalized cloud height	Top third	0.33	0.33	0.08	0.03
	Middle third	0.29	0.16	0.16	0.03
	Bottom third	0.17	0.10	0.29	0.20

[a] This R^2_{adj} has a p-value > 0.05.

[b] Only smoke-influenced samples in this campaign were considered.

1645

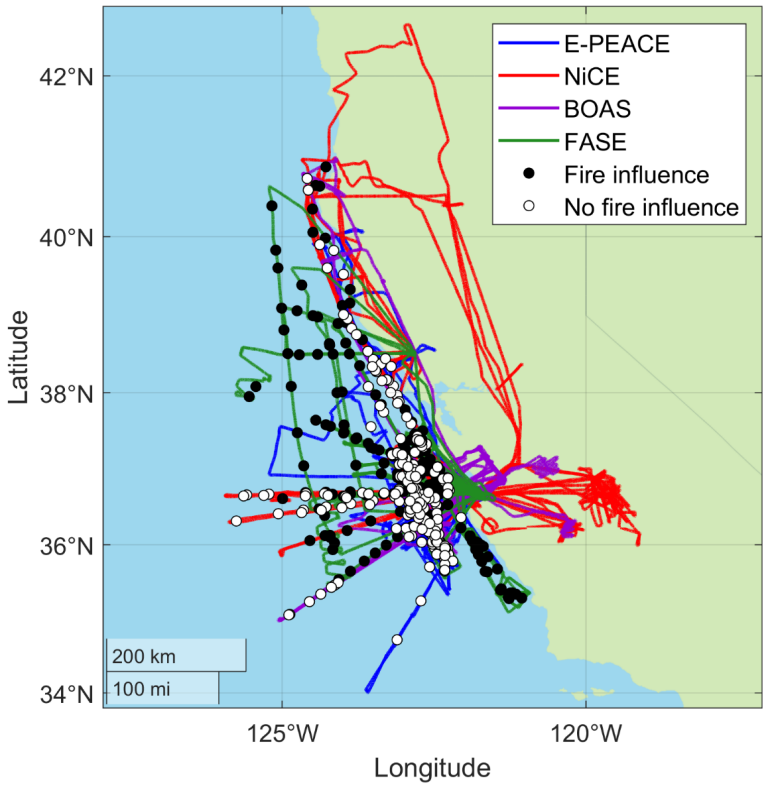
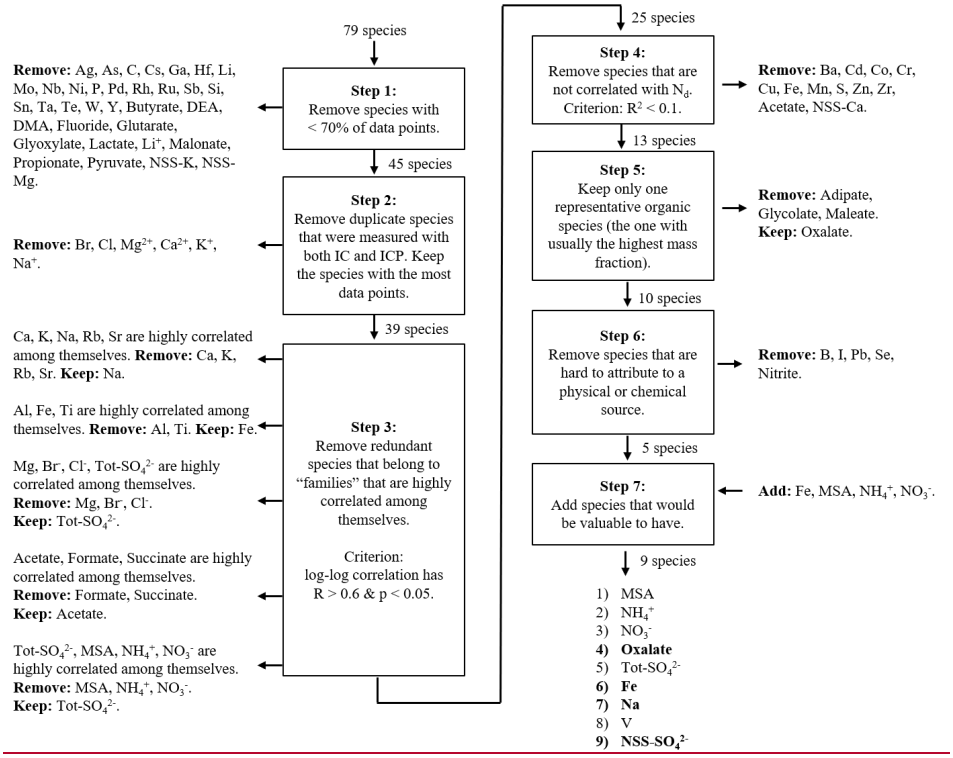


Figure 1. Flight paths for each of the four campaigns used in this study. Markers indicate the average location at which the cloud water samples were collected. Smoke- and non-smoke-influenced samples are indicated with filled and open markers, respectively.


79 species
Step 1: Remove species with < 70% of data points.
Remove: Ag, As, C, Cs, Ga, Hf, Li, Mo, Nb, Ni, P, Pd, Rh, Ru, Sb, Si, Sn, Ta, Te, W, Y, Butyrate, DEA, DMA, Fluoride, Glutarate, Glyoxylate, Lactate, Li+, Malonate, Propionate, Pyruvate, NSS-K, NSS-Mg.
45 species
Step 2: Remove duplicate species that were measured with both IC and ICP. Keep the species with the most data points.
Remove: Br, Cl, Mg2+, Ca2+, K+, Na+.
39 species
Step 3: Remove redundant species that belong to "families" that are highly correlated among themselves.
Criterion: log-log correlation has R > 0.6 & p < 0.05.
Ca, K, Na, Rb, Sr are highly correlated among themselves. Remove: Ca, K, Rb, Sr. Keep: Na.
Al, Fe, Ti are highly correlated among themselves. Remove: Al, Ti. Keep: Fe.
Mg, Br-, Cl-, Tot-SO4 2- are highly correlated among themselves. Remove: Mg, Br-, Cl-. Keep: Tot-SO4 2-.
Acetate, Formate, Succinate are highly correlated among themselves. Remove: Formate, Succinate. Keep: Acetate.
Tot-SO4 2-, MSA, NH4+, NO3- are highly correlated among themselves. Remove: MSA, NH4+, NO3-. Keep: Tot-SO4 2-.
25 species
Step 4: Remove species that are not correlated with Nd. Criterion: R2 < 0.1.
Remove: Ba, Cd, Co, Cr, Cu, Fe, Mn, S, Zn, Zr, Acetate, NSS-Ca.
13 species
Step 5: Keep only one representative organic species (the one with usually the highest mass fraction).
Remove: Adipate, Glycolate, Maleate. Keep: Oxalate.
10 species
Step 6: Remove species that are hard to attribute to a physical or chemical source.
Remove: B, I, Pb, Se, Nitrite.
5 species
Step 7: Add species that would be valuable to have.
Add: Fe, MSA, NH4+, NO3-.
9 species
1) MSA
2) NH4+
3) NO3-
4) Oxalate
5) Tot-SO4 2-
6) Fe
7) Na
8) V
9) NSS-SO4 2-

1653
1654

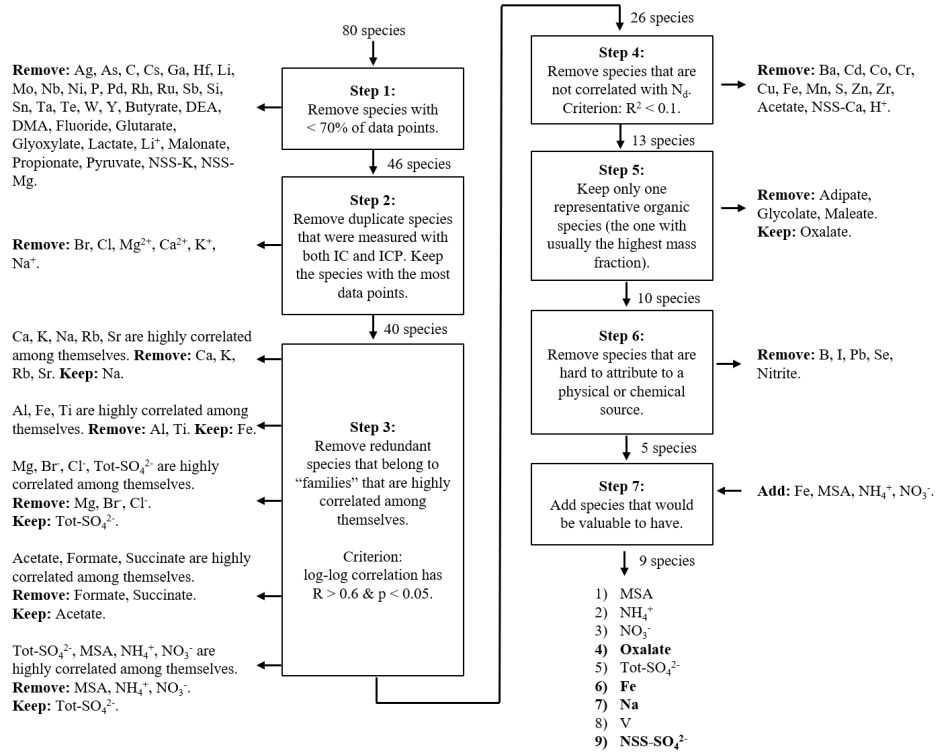
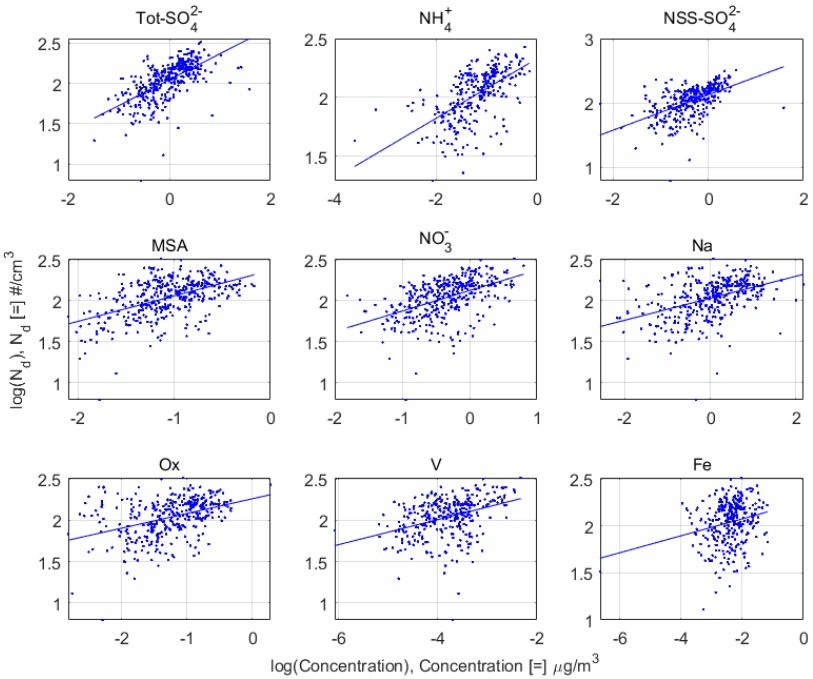


Figure 2. Algorithm used to filter the number of species from ~~79~~80 to 9. The four bolded species are the ones used in Section 3.3). ICP = ICP-MS + ICP-QQQ.


Tot-SO4 2-
NH4 +
NSS-SO4 2-
MSA
NO3 -
Na
Ox
V
Fe
log(Nd), Nd [=] #/cm3
log(Concentration), Concentration [=] μg/m3

1661
1662

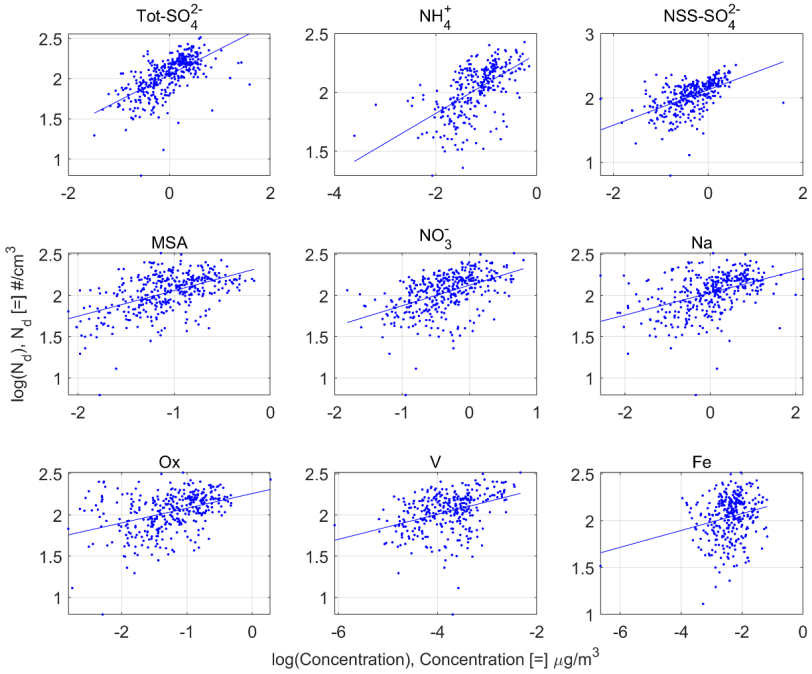


Figure 3. Scatter plot for the nine filtered species from Figure 2. The lines are linear regression models of the form $\log(N_d) = a_0 + a_1 \log(M_i)$, where M_i is the mass concentration of species i.

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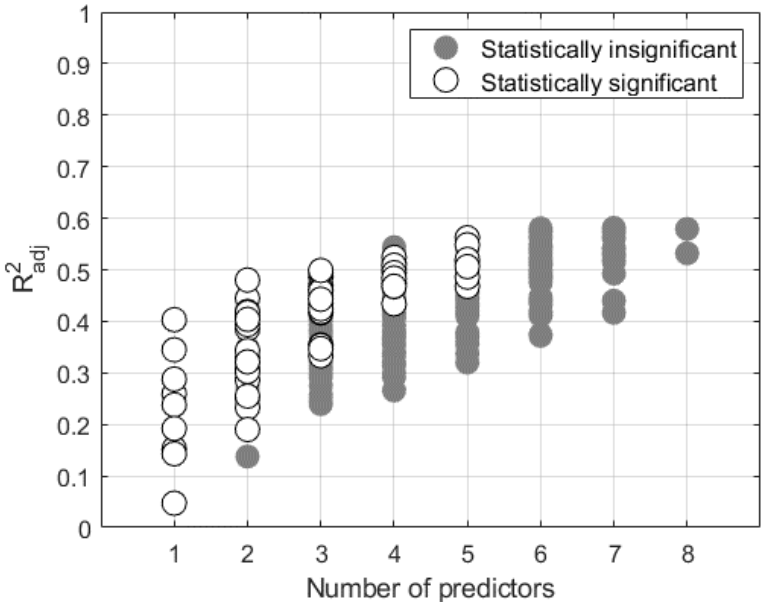

Statistically insignificant
Statistically significant
R^2_{adj}
Number of predictors
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
1
2
3
4
5
6
7
8

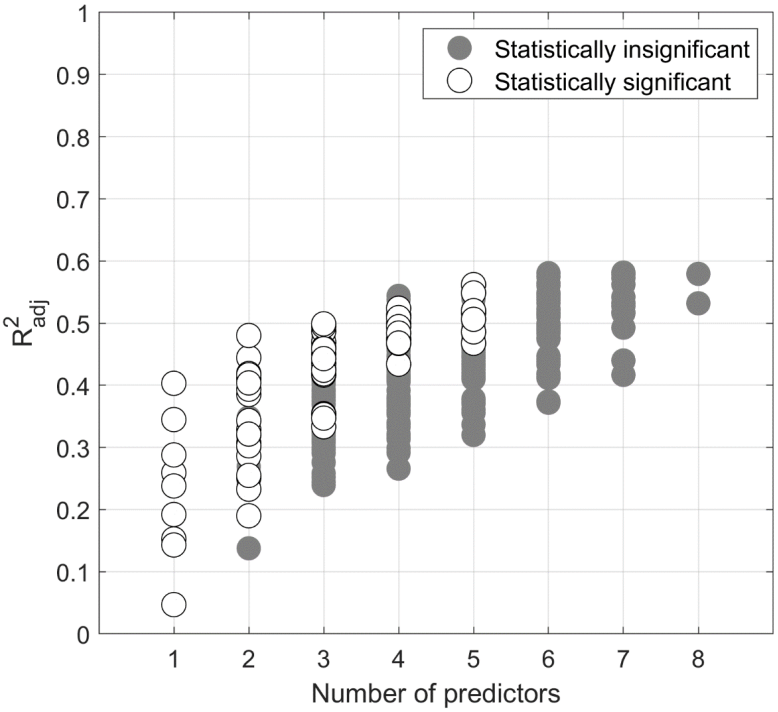
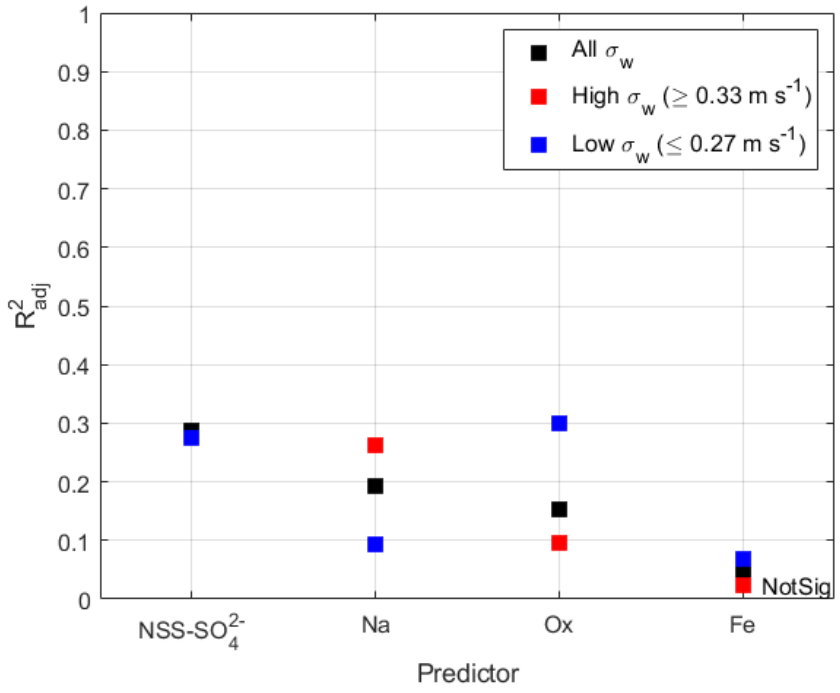


Figure 4. Plot showing which of the 383 regressions are statistically significant. This plot ignores the regressions that use both NSS-SO_4^{2-} and Tot-SO_4^{2-} simultaneously.


All σ_w
High σ_w ($\geq$ 0.33 m s^{-1})
Low σ_w ($\leq$ 0.27 m s^{-1})
R^2_{adj}
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
NotSig
NSS-SO_4^{2-}
Na
Ox
Fe
Predictor

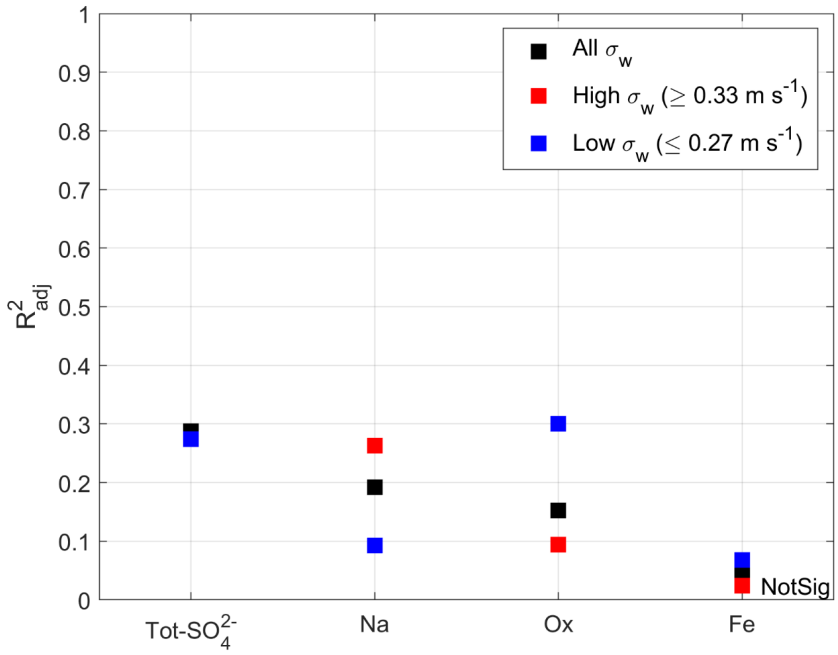
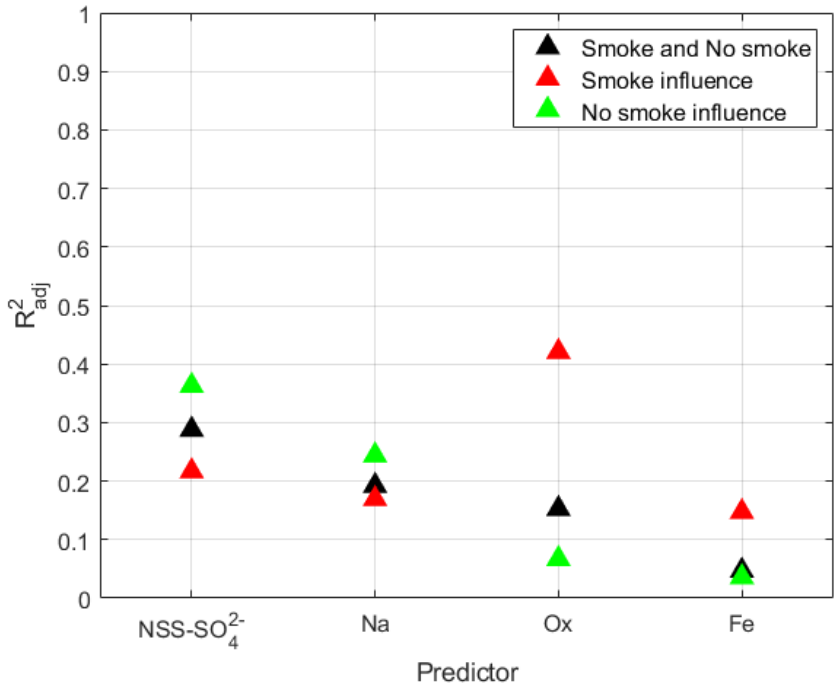


Figure 5. Effect of turbulence (quantified using σ_w) on the ability of a single species to predict N_d. For NSS-SO_4^{2-}, the high (red) and low (blue) σ_w data points overlap. NotSig = Not statistically significant according to the definition in Section 2.5.


Smoke and No smoke
Smoke influence
No smoke influence
R^2_{adj}
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
NSS-SO_4^{2-}
Na
Ox
Fe
Predictor

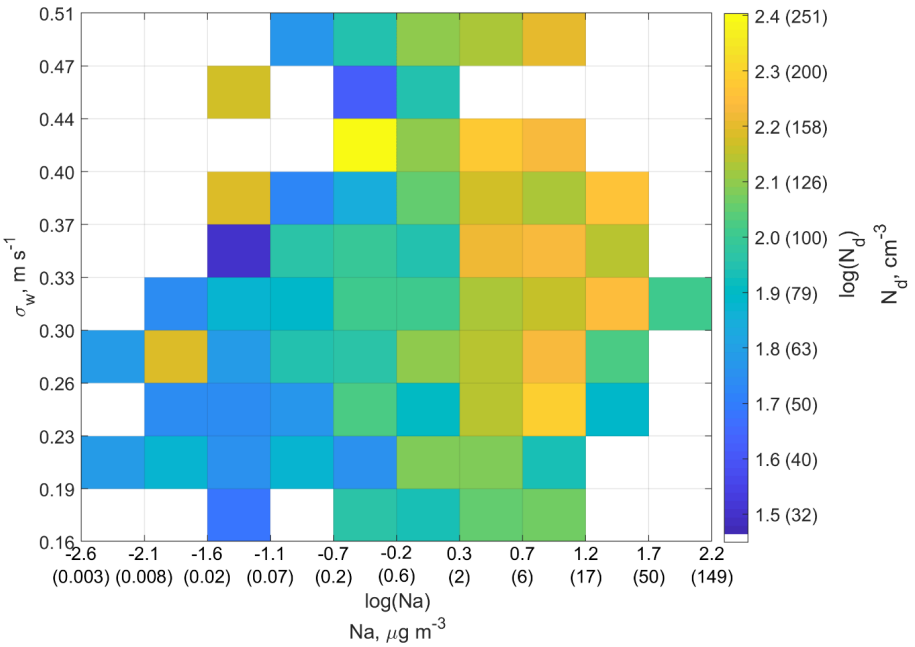


Figure 6. Heatmap showing the dependence of N_d on both σ_w and Na. The lower and upper bounds for the x-axis, y-axis, and color bar cover the entire range of σ_w, Na, and N_d, respectively. To assist in physical interpretation, the tick markings on the x-axis and color bar show two numbers: those without parenthesis correspond to log(Na) or log(N_d); those within parenthesis correspond to Na or N_d, in their respective units.

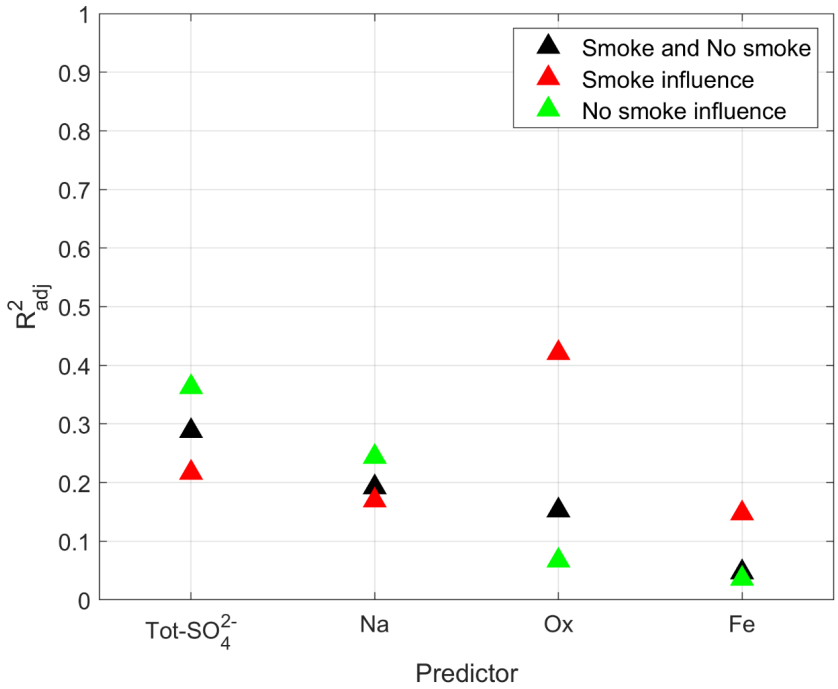
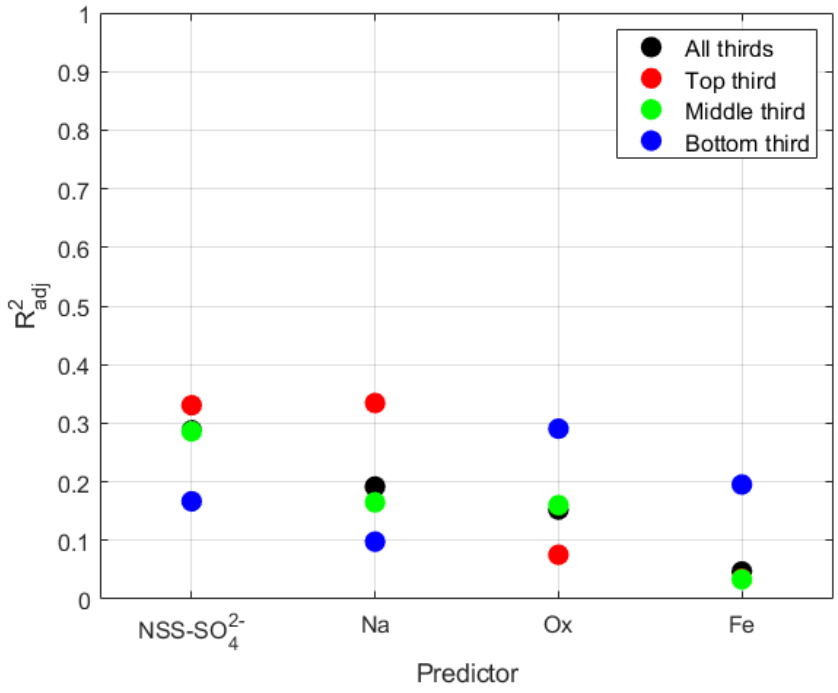


Figure 7. Effect of the influence of smoke on the ability of a single species to predict N_d.


All thirds
Top third
Middle third
Bottom third
R^2_{adj}
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
NSS-SO_4^{2-}
Na
Ox
Fe
Predictor

1699
1700

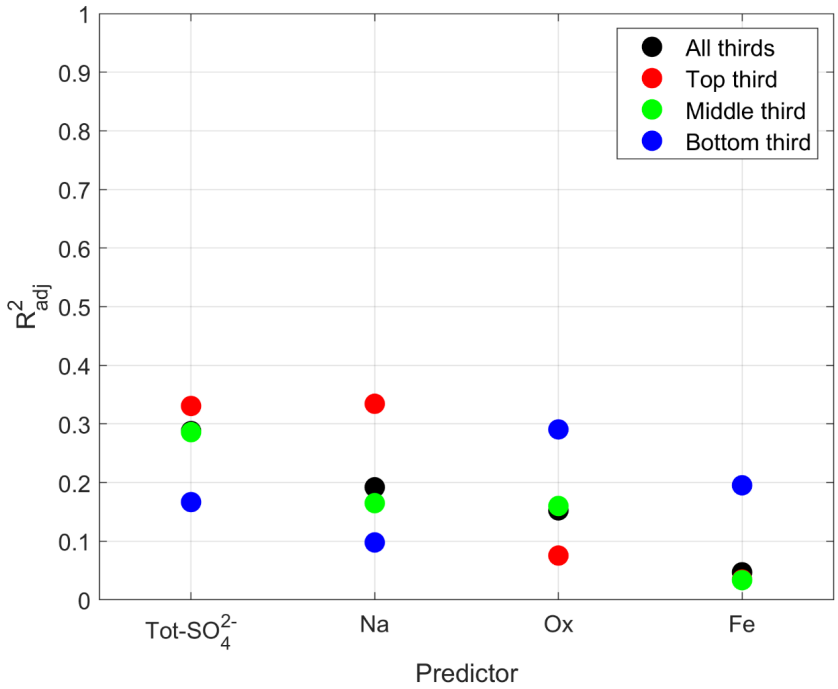


Figure ~~7~~8. Effect of the influence of normalized cloud height on the ability of a single species to predict N_d. For Fe, the top 3rd (red) data point overlaps with the middle and bottom 3rd (green and blue) data points.