Review of ’Drizzle susceptibility from VOCALS’

submitted to ACP by C. R. Terai, R. Wood, D. C. Leon, and P. Zuidema

1. General comments

I have very much enjoyed reading this paper. It is well written, concise, interesting and at first it seems like all the relevant discussion is given. There are a lot of good and interesting ideas in this paper, e.g., the decomposition of S in column fraction and intensity. If the findings of this paper prove to be robust, they are very relevant for our understanding of aerosol indirect effects and can provide valuable input to the modeling community.

The authors claim to have extended the concept of precipitation susceptibility to include non-precipitating clouds, something which they describe as a major advantage of their study over previous ones. But they also admit that the results are in fact very sensitive to whether or not they include non-precipitating clouds (e.g. line 25, page 33399). This sensitivity of their findings, and the fact that including non-precipitating clouds into the precipitation susceptibility does not sound straightforward because

$$S = -\frac{d\ln R}{d\ln N} \tag{1}$$

becomes ill-defined for $R = 0$, made me look a bit deeper into their approach. Hence, the following major comments which point out some issues that need discussion and clarification.

2. Specific comments

There are two major questions I have about this paper and both are related the the susceptibility and how it is calculated.

1. Is the susceptibility and the procedure to calculate it described in the paper an unbiased estimator of the exponent β?
2. Can the concept of susceptibility be applied to non-precipitating clouds?

To explain the issues related to both questions a little bit better I introduce in the following some idealized models and datasets.

a. $R \sim N^{-\beta}$ *for precipitating clouds*

First we assume that all clouds are precipitating, i.e., we have a model for precipitation of the form

$$R = a\, N^{-\beta} \tag{2}$$

similar to Eq. (2) of the paper. Now we generate a data set which follows this model, i.e., we draw random samples for N in the range [50,500] (in the following I omit any units, variables are assumed to be properly normalized). Given $\beta = 1.25$, we calculate a so that $R = 1$ for $N = 50$. Susceptibility is defined as

$$S = -\frac{d\ln R}{d\ln N} \tag{3}$$

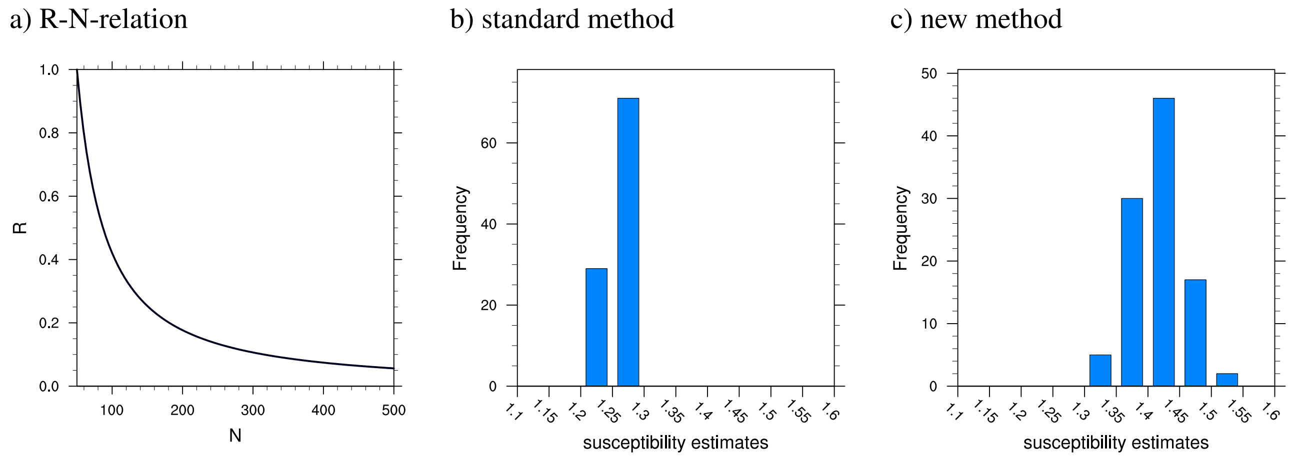

Figure 1: R-N-relation, Eq. (2), and histograms of susceptibility estimates for precipitating clouds using the standard approach and the new method suggested in the paper. The correct value would be $\beta = 1.25$.

and one can easily show that for the given model S equals β. Now we calculate S from random samples of N and a corresponding R, i.e., by using Eq. (3) for randomly chosen pairwise data of our dataset.
The result is shown in Fig. 1 which supports the idea that S provides an unbiased estimator of β. Of course this is not yet a rigorous proof, and we have not yet modeled an measurement errors (something we could do easily by perturbing R).
Next we use the procedure described in section 2.5 of the paper. A dataset with 100 random samples is used to calculate N_+ and N_- and the corresponding rain rates. This procedure is repeated 100 times simulating 100 flight legs. The result is shown in Fig. 2 and suggests that this S as defined by Eq. (4) of the paper is not an unbiased estimator of β. The problem, in my opinion, is the averaging performed on the data, which does not preserve non-linear relationships, i.e., the procedure cannot provide an unbiased estimate of β and the result should maybe not be called precipitation susceptibility. If anything, the authors introduce a new metric which might or might not be a useful one.

b. $R \sim N^{-\beta}$ *including non-precipitating clouds*

A model that includes non-precipitating clouds is

$$R = \begin{cases} a \left[\left(\frac{N}{N_0} \right)^{-\beta} - 1 \right], & \text{for } N \geq N_0 \\ 0, & \text{else.} \end{cases} \tag{4}$$

and here we set $\beta = 1.25$, $N_0 = 300$, and again $R = 1$ for $N = 50$. We repeat the exercise of calculating S from random samples of this relationship as described in the previous sections. For the standard approach we, of course, have to ignore values of $N > N_0$ because of $R = 0$. For the new method suggested in the paper, we can include $N > N_0$ as long we are not very unlucky, i.e., as long as $R_+ > 0$.
Figure 2 shows the results. For this model with a precipitation threshold N_0 neither the standard approach for susceptibility nor the new method provide an unbiased estimate of $\beta = 1.25$. Both methods result in a susceptibility estimate which is much larger. Of course, if we know a, then a simple transformation, $\hat{R} = R/a + 1$, makes it possible to calculate β from the data using the standard method (Fig. 2d).
The goal of calculating the precipitation susceptibility is, of course, not necessarily to estimate the exponent β,

it would maybe be sufficient if S provides a good estimate of the dependency of R on N in a large part of the parameter space. Figure 2a shows also the power law relations for $R = (N/50)^{-1.5}$ and $R = (N/50)^{-3.0}$ and from this one could argue that $\beta = 1.5$ is a reasonable estimate of the sensitivity of this model in some part of the parameter space, but $\beta = 3$ or larger is probably not. So even when we do not expect that S is an unbiased estimator of β in Eq. (4), the sensitivity suggested by S using the method used in the paper is much to high and misleading.

c. *binned data with random noise*

As a further step to mimic the analysis method of the paper the data is binned into 4 bins n_1, n_2, n_3 and n_4 with N-thresholds of 450, 350, 250, 150 and 50. The model of the previous section is used but with $N_0 = 450$, i.e. R approaches zero but all data has $R > 0$. To make the data a bit more realistic, random noise is added to R. It is interesting to note that the standard calculation of S is quite sensitive to random noise, while the new method suggested in the paper is more robust. In the following only the result from the new method is shown.

Figure 3 shows the binned susceptibility estimates. Each bin contains 500 estimates, each estimate is based on 100 randomized data samples. In bin n_4 with the lowest $N \in (150, 50]$ the mean of S is 1.48. This is actually a quite reasonable value which can be interpreted a useful power-law model in this range of N. This shows that the binning improves the result of the suggested method and that the bad result of the previous section was, to some extent, due to a too large range of N, i.e. no binning. For the other bins the S-estimates are unfortunately higher and the interpretation of S becomes again more difficult. This Fig. 3 shows in fact a certain similarity to Fig. 3 of the paper, and I would ask the authors to provide further evidence that their results are not an artifact of the analysis method.

d. *Some questions and comments*

As I have shown, the susceptibility S might lead to spurious results with unrealistic large values when R is close to zero or when non-precipitating clouds are included. Therefore I wonder whether the results for the bin h_1 can be included in the statistics. If this data is excluded, then the dependency of S on cloud depth becomes much less convincing, as the susceptibility is close to 1 for the remaining bins.

I would like to emphasize again that S does not need to be an unbiased estimator of β in Eqs. (2) or (4) to be useful, but it would be important to show what we can actually learn from S and, maybe even more important, it should be emphasized that the actual functional dependency of R on N might be very different from any simple dependency suggested by S.

The authors have a very nice and valuable dataset, but I would recommend to use more robust statistical methods to analyze the data. Maybe even something as simple as a scatter plot of R vs N for each bin might be useful and could be shown in the paper to provide further evidence of the postulated sensitivities.

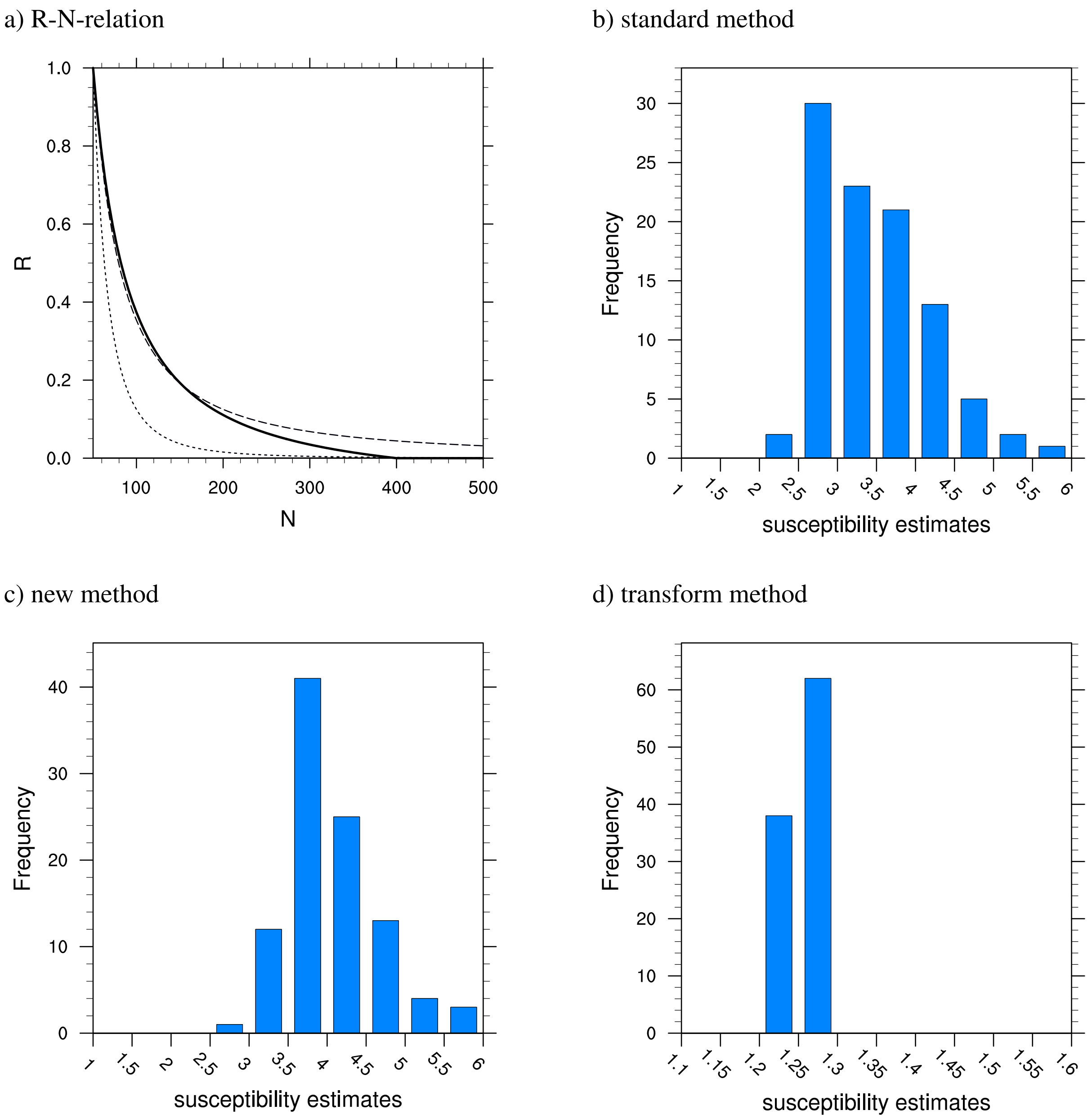

Figure 2: (a) R-N-relation including non-precipitating clouds, Eq. (4), with $\beta = -1.25$ and $N_0 = 300$ and histograms of susceptibility estimates. The standard approach (b), the new method suggested in the paper (c) and a 'transform' method using the transformation $\hat{R} = R/a + 1$ before applying the standard approach. The correct value would be $\beta = 1.25$. The dashed and dotted lines in (a) are the power laws $R = (N/50)^{-1.5}$ and $R = (N/50)^{-3.0}$.

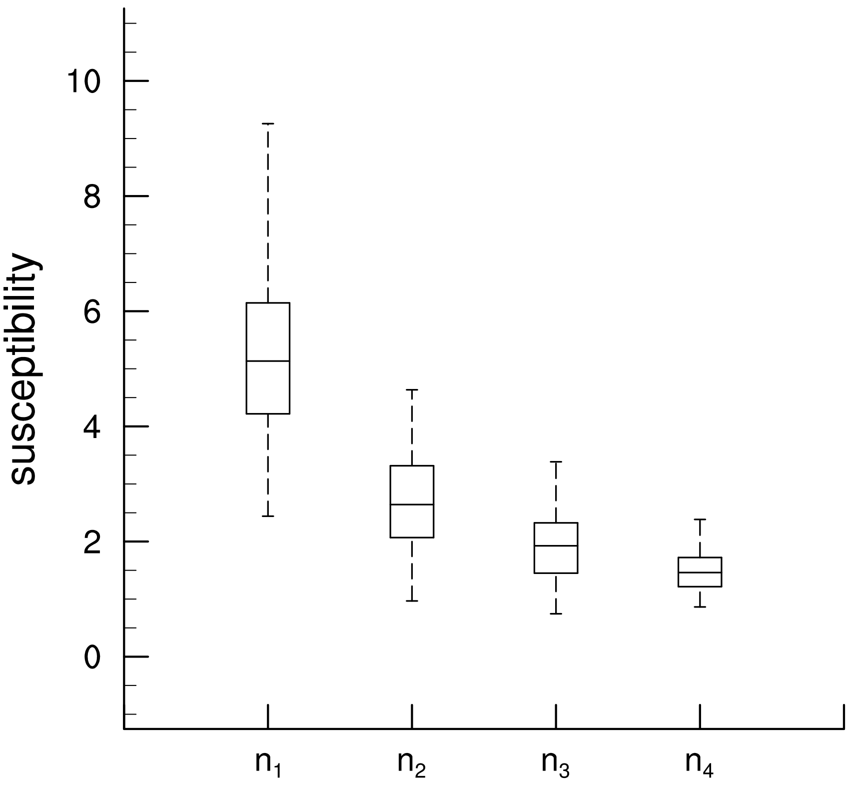

Figure 3: Box-whisker plot of the susceptibility estimates for N-bins with n_1: $N \in$ (450,350], n_2: $N \in$ (350,250], n_3: $N \in$ (250,150], n_4: $N \in$ (150,50]. Whiskers are 2nd and 98th percentile.