

1 Understanding the drivers of marine liquid-water
2 cloud occurrence and properties with global
3 observations using neural networks
4 — RESPONSE TO REFEREE 3 —

5

6

contact: hendrik.andersen@kit.edu

7 We would like to thank referee 3 for her/his review of the manuscript and
8 her/his constructive criticism. Comments by the referee are colored in blue, our
9 replies are colored in black.

10 This paper pursues a promising approach to study the sensitivity of
11 marine liquid-water cloud properties on a set of meteorological and aerosol
12 predictors, using an artificial neural network approach. It steers clear of
13 correlative approaches for studying aerosol-cloud interactions and instead
14 considers the meteorological context, segregated by region / meteorological
15 regime. In essence, this amounts to a multi-variate analysis based on an
16 optimal combination of satellite and re-analysis data. The paper is very well
17 written, clearly represents new ideas, and has the potential to lead to major
18 improvements in our assessment of ACI, regionally and globally. It is rare
19 to see such a high-quality paper. I only have minor comments, which don't
20 necessarily have to be addressed in this manuscript, but could be considered in
21 future work. The most important ones are probably #1 regarding scale, and
22 regarding the quality (reliability) of the data. Also, follow-up papers might
23 consider using the co-sensitivity of some predictors (details below).

24 In a separate comment to the editor, I recommended that the paper be
25 highlighted because it seems highly innovative in its approach and deviates
26 from the traditional correlative aerosol-cloud interaction studies. I believe that
27 it has potential to change the direction of this field of research.

28

29 Thank you very much for this kind assessment. We respond to each point
30 individually below.

31

32 **General comments:**

33 p5,L18: In the spirit of the McComiskey and Feingold ACI papers, it would
34 have been interesting to also consider the impact of scale on ACI relationships.
35 Here, one specific scale has been used (dictated by the analysis grid) - but it
36 may not be straightforward to generalize these relationships.

37 This is a good point and we agree that the scale of the data sets used to study
38 aerosol-cloud interactions influences the derived sensitivities (McComiskey
39 et al., 2009; McComiskey and Feingold, 2012). Here, we use temporally and
40 spatially highly aggregated data sets (monthly means in the defined equal-area
41 regions), as with this study, we are specifically interested in the very large
42 scale mechanisms and patterns of the aerosol-cloud-climate system. This
43 is certainly not the scale at which the processes occur, so that our derived
44 sensitivities may not match the magnitude of the sensitivities at the process
45 scale. An analysis of the impact of the extent of spatial aggregation of the $1^\circ \times 1^\circ$
46 data on the derived sensitivities would be interesting; however, the spatial
47 aggregation we chose was needed for sampling reasons (sufficient number of
48 observations for the statistical model). In the revised version of the manuscript,
49 we discuss this on P6L1-3. (*"As the temporal and spatial scales considered*
50 *in this study are not on the same scale as the actual processes, so that the*
51 *calculated sensitivities may not match the magnitude of the sensitivities at*
52 *the process scale (McComiskey et al., 2009; McComiskey and Feingold, 2012)."*)

53
54 p6,L4: "skill of simple correlation between AOD & cloud properties": It
55 is a bit unclear, which "simple correlations" specifically have been used for
56 this study. This statement calls for elaboration. The statement on p6,L6/7
57 shows the intent - the "simple correlations" are used as a baseline to show
58 the improved predictive skill of ANN. The quantitative results would be more

59 useful by including more information about that baseline.

60 Here, with "simple correlation" we referred to a "simple" Pearson correlation
61 between AOD and either CLF/CDR/LWP/COT in each equal area region. In
62 the revised version of the manuscript, we describe this at P6L8, however, in the
63 current version of the manuscript, the results of Pearson correlations between
64 $\log(\text{AI})$ and the respective cloud properties is illustrated in figure 2.

65

66 p6,L11 (fig 4): How/where are the equal-area regions defined? Are those
67 just pixel aggregated that meet the selection criteria for the sensitivity analysis?

68 This is explained in the manuscript on P4L33-P5L3. The equal-area regions are
69 defined by dividing the space between 60°N and 60°S (and all longitudes) into
70 20x40 equally sized areas. The original 1°x1° data is aggregated in these regions
71 at their original spatial resolution. The selection criteria for the sensitivity
72 analysis is checked for each equal-area region (but only for the sensitivity
73 analysis - in figure 4, all equal-area regions are shown). In the revised version of
74 the manuscript, we added some information to the caption of figure 4 for clarity.

75

76 p9, Fig 5. How is the CF and LWP sensitivity to AOD compatible? Is it
77 a fair statement to say that we get more clouds with lower LWP for higher
78 aerosol loading, while COD stays the same (perhaps because the "classical"
79 indirect effect kicks in) - or can we not make such a blanket statement?

80 The CLF sensitivity to AOD/AI is probably the sensitivity that is the most
81 uncertain, due to cloud contamination of the satellite aerosol retrievals and
82 the influence of confounding variables on both CLF and the satellite retrieved
83 aerosol quantity. While we weaken the influence of confounding variables by
84 including them in the ANN, we are not able to reduce effects related to data
85 quality (this is discussed on P13L4-6 in the revised version of the manuscript:

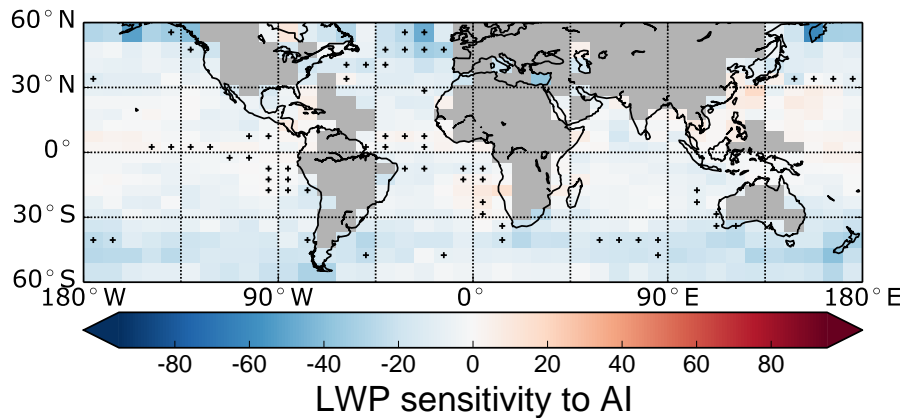


Figure 1: Global map of LWP sensitivity to AI: The globally averaged sensitivities are based on the regions marked with a '+'.

86 ” While the influence of confounding factors is limited by the multivariate
 87 approach, effects concerning data quality (e.g. cloud contamination) are not
 88 accounted for and need to be considered when interpreting the CLF sensitivity
 89 to AI.”). One should also note that the averaged LWP sensitivities rely on very
 90 few regions (due to the selection criteria) and should thus not be considered
 91 global. In most regions, the sensitivity of LWP to AI is relatively low.

92 While it makes sense to combine the sensitivities as proposed by you, one needs
 93 to remember that these are derived from separate ANNs. While LWP and
 94 CLF in the respective ANNs respond to AI/AOD in the way that you point
 95 out, changes in LWP might also affect CLF and vice versa, which would not
 96 be accounted for. Therefore, we are somewhat cautious in the interpretation of
 97 combined sensitivities.

98

99 p10, L5: Would it make sense to plot co-sensitivity maps, considering that
 100 many predictands co-vary with predictors. In the inverse theory equivalent,
 101 one would consider the off-diagonal elements of the covariance matrices. After
 102 all, one of the attractive features of this analysis is that it allows multi-variate

103 analysis of ACI, fully considering the meteorologic conditions - but then the
104 plots / analysis do not reap the full benefits of this approach. The authors do
105 explain some of the co-variabilities/co-sensitivities, but then again it would be
106 even better to have some graphical representation for some of these connections.
107 Yes, this is a good idea - and an idea which we discussed internally, as well.
108 Ultimately, this level of detail exceeds the scope of this study, as one would
109 have to create co-sensitivity plots for each grid-cell-specific ANN individually
110 and would thus not be able to produce summarized global co-sensitivities easily.
111 This is an idea we are currently pursuing in a more detailed regional study.

112

113 p10,L28: Does the CDR - AOD relationship for the SE Atlantic region
114 make sense? For the outflow from the Arabian peninsula and the Sahara, it
115 does, and the manuscript explains this with dust - but on the West coast of
116 Namibia and Angola the dust is confined to the coast. It is possible that the
117 identified relationships here points to limitations of the data set(s) that serve
118 as the basis. Perhaps dust is overrepresented in the data? Overall, it would be
119 good to see a discussion in which regions we would trust the correlations (given
120 the uncertainties in the data).

121 This is a good question - in a regional study some years ago, we found that in
122 certain conditions (stable/humid), AI and CDR are positively related in the
123 Southeast Atlantic (Andersen and Cermak, 2015). However, in most cases,
124 the AI-CDR relationship was found to be negative as in (e.g. Costantino and
125 Bréon, 2013). This specific regional sensitivity may be affected by retrieval or
126 sampling issues, as now discussed in the revised version of the manuscript on
127 P10L5-8 (*"Issues of sampling (few aerosol retrievals in high CLF-regions) or
128 scale (highly aggregated data) or their combination might affect the observed
129 CDR sensitivity to AI in this region."*).

130

131 p12, L15: So, cloud radiative effect sensitivities are actually not (yet) ad-
132 dressed in the manuscript. Instead, cloud properties are analyzed. Earlier in
133 the manuscript (p4,L24), it is stated that cloud radiative effects are analyzed.
134 This should be fixed (minor comment).

135 Yes, you are correct. We have deleted the mentioned text passage in the revised
136 manuscript.

137 References

138 Andersen, H. and Cermak, J. (2015). How thermodynamic environments control
139 stratocumulus microphysics and interactions with aerosols. *Environmental*
140 *Research Letters*, 10(2):24004.

141 Costantino, L. and Bréon, F.-M. (2013). Aerosol indirect effect on warm clouds
142 over South-East Atlantic, from co-located MODIS and CALIPSO observa-
143 tions. *Atmospheric Chemistry and Physics*, 13(1):69–88.

144 McComiskey, A. and Feingold, G. (2012). The scale problem in quantifying
145 aerosol indirect effects. *Atmospheric Chemistry and Physics*, 12(2):1031–1049.

146 McComiskey, A., Feingold, G., Frisch, a. S., Turner, D. D., Miller, M. a., Chiu,
147 J. C., Min, Q., and Ogren, J. a. (2009). An assessment of aerosol-cloud
148 interactions in marine stratus clouds based on surface remote sensing. *Journal*
149 *of Geophysical Research: Atmospheres*, 114(D9):D09203.