

Interactive comment on "The magnitude and causes of uncertainty in global model simulations of cloud condensation nuclei" *by* L. A. Lee et al.

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Received and published: 14 June 2013

Many thanks for your review and providing the annotated manuscript with detailed comments. As a result changes have been made to the paper as detailed below. Please find your comments in bold with a response in normal text. The additions to the paper are in italics.

How general are the results obtained for the presented 28 parameters to a more general class of models? What can be learned more generally?

This is an important and natural question that arises every time we present these or similar results. One could ask a similar same question of model intercomparisons, which dominate community efforts to understand the uncertainty in model predictions:

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what do multi-model ensembles tell us about uncertainties due to individual processes? Here, we have comprehensively explored parametric uncertainty in one model. An important follow-up will be to combine multi-model and multi-parameter ensembles in a single study. Of course, we cannot answer the question properly until we have tested several models. There are three points that can be made here: First, the perturbed parameters are embedded within a particular process representation, and most models tend to have broadly similar process representations (i.e., as close to reality as possible). A different process representation might lead to different parameter sensitivities, but since all models aim to represent real world processes, we would not expect vastly different results. Second, we have been able to provide a physically reasonable explanation for the sensitivity of each parameter, including its spatial and temporal variation. This provides some confidence that the sensitivities are physically based and not just model artefacts. Third, from a philosophical point of view, if different models, each with realistic representations of processes, all differ in their sensitivities, then any agreement between them in multi-model ensembles will be spurious. If that is the case, then we will be deluding ourselves about the usefulness of models to tell us anything about the real world.

'Expert elicitation' is a rather subjective process. There is no proof of its scientific benefit for the type of study presented. The authors are encouraged to make somewhat clearer what the shortcomings of this type of query are.

We have added the following text to the section on expert elicitation.

Added as paragraph following from Page 6302, Line 29: One aim of expert elicitation is to remove an element of the subjectivity in such studies. As a rule, a sensitivity study follows the path of an expert choosing a process to study and a few values of the associated parameter with which to run the model. In this study, we look at many more processes, so the subjectivity in choosing the processes is removed. We also ask experts to choose ranges that are beyond the normal values that are used to run the model, and in fact choose ranges outside of which the parameter value is highly unlikely to fall. This approach results in a range that is wider than would normally be considered in model sensitivity studies. Furthermore, the parameter ranges are elicited independently, so the uncertainty space is much larger than would normally be considered because we don't let the knowledge of a particular parameter influence the others; i.e., the experts are not asked to make any judgement on the joint space of all parameters. Comparison of the results with observations will enable experts to review their beliefs about model processes and parameters, which is an important follow-up study.

Would half the data yield similar results? How much is the emulator actually influenced by only a few parameters? Are the error bars essentially the results of only a few crucial parameters?

The choice to do 168 runs followed a pilot study in which 37 parameters were perturbed in 370 runs (following the usual recommended 10 runs per parameter). The number of runs required really depends on the smoothness of the model output and the number of 'active' parameters in the study. The smoothness of the model relates to how many points you need in a neighbourhood to provide enough information to estimate the whole neighbourhood adequately. Following the pilot study the number of runs required to produce a validated emulator and stable sensitivity results was tested, and with 37 parameters there was little degradation in the results with 6 runs per parameter. This is due to the fact that in the 37 parameter study there were lots of parameters that didn't contribute to the CCN uncertainty (which is why the full study included only 28 parameters). Some parameters do not contribute much to the CCN uncertainty, especially since we consider each grid box separately. In the most complex grid box (in terms of the number of contributing parameters) there are about 15 parameters contributing to the uncertainty in CCN, so we actually have at least 10 runs per active parameter. In every grid box the error bars are a result of only a few parameters, though these parameters change between grid boxes.

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The authors do not address the question of interactions between parameters and their interdependence. This could moderate the overall finding depending on the exact correlations of parameters. Investigate these issues further.

The method here takes into account interactions and interdependence of the parameters – surprisingly it showed very few interactions. The parameters are independent in the sense that the range of one does not determine the range of any others. The design was created with all parameters adjusted simultaneously and the emulator builds a function across the entire 28 dimension uncertainty space of the parameters. If there are any interdependencies in the way the CCN responds to the parameters it will be picked up in the emulator. The sensitivity analysis method used is a global sensitivity analysis which measures how each parameter's uncertainty affects the CCN via the main effect but also how the interactions of the parameter uncertainties affect the CCN via the total effect. In many cases the sum of the main effects is close to 100% meaning that the CCN uncertainty depends on each parameter independently. In some cases the main effects add up to about 80% meaning that 20% of the CCN uncertainty is due to the interdependence of the parameters. A priori there were thought to be more interactions between the parameters and so the emulation method was chosen over the one-at-a-time studies, but for CCN there are fewer than expected. There might be more interactions between the parameters when a different model output is considered or when larger spatial or temporal regions are considered, but this is not part of the current study.

In the paper, section 2.3 repeatedly discusses interactions as an inherent part of our methodology. We also mention interaction where it is important, such as for P21 and P22 (p6330), where we say "Both parameters (mass flux and size) have significant interactions with other parameters, with up to 20% of the total variance being due to interactions." Also, the Figure 9 caption defines the amount of interaction at the different ground sites.

We agree that it would be helpful to reiterate the small role of parameter interactions. We therefore add a new bullet point to the conclusions:

Interactions between parameters controlling CCN generally account for less than 20% of the uncertainty. This is smaller than we found in a previous study of 8 parameters (Lee et al, 2012). Although the same interactions must still be occurring in the present much larger study, their relative contribution to the overall uncertainty is less.

The authors should describe the key features of previous literature. What ways does the current study build on previous work?

We have added text to illustrate how our work builds in previous literature.

Added to P6299, Line 20. In order to make a realistic assessment of the spread in model simulations a more efficient statistical approach is required. We present a more efficient statistical approach here.

Reconsideration of the paper title.

We don't think the title needs to reflect every aspect of the paper. The abstract makes very clear that this is a parametric uncertainty analysis and the conclusions highlight the need for an assessment of structural uncertainty.

Remove some technical details from the abstract.

We have shortened the abstract.

Aerosol-cloud interaction effects are a major source of uncertainty in climate models so it is important to quantify the sources of uncertainty and thereby direct research efforts. However, the computational expense of global aerosol models has prevented a full statistical analysis of their outputs. Here we perform a variance-based analysis of a global 3-D aerosol microphysics model to quantify the magnitude and leading causes of parametric uncertainty in model-estimated present-day concentrations of cloud condensation nuclei (CCN). Twenty-eight model parameters covering essentially all important aerosol processes, emissions and representation of aerosol size distributions were defined based on expert elicitation. An uncertainty analysis was then performed based on a Monte Carlo-type sampling of an emulator built for each model grid cell. The stan-

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dard deviation around the mean CCN varies globally between about ± 30 % over some marine regions to $\pm 40-100$ % over most land areas and high latitudes, implying that aerosol processes and emissions are likely to be a significant source of uncertainty in model simulations of aerosol-cloud effects on climate. Among the most important contributors to CCN uncertainty are the sizes of emitted primary particles, including carbonaceous combustion particles from wildfires, biomass burning and fossil fuel use, as well as sulphate particles formed on sub-grid scales. Emissions of carbonaceous combustion particles affect CCN uncertainty more than sulphur emissions. Aerosol emission-related parameters dominate the uncertainty close to sources, while uncertainty in aerosol microphysical processes becomes increasingly important in remote regions, being dominated by deposition and aerosol sulphate formation during cloudprocessing. The results lead to several recommendations for research that would result in improved modelling of cloud-active aerosol on a global scale.

Are all the parameters sampled linearly?

We have added to the sampling text to clarify how the scaled and absolute parameters were sampled. When a parameter was used to scale a variable it was sampled uniformly over the log scale in order to provide a balance of points around the value 1. Added to Page 6304, Line 2: Parameters that are used to scale existing emissions are sampled uniformly over the log scale rather than the absolute scale to ensure a balance of points across the parameter uncertainty range. The scaled parameters are shown in Table 1.

Define FT.

Page 6313, Line 2: "FT" is now defined correctly when the parameter is introduced as follows: "free troposphere (FT)".

The Gaussian process allows the standard deviation to be computed given the error bars of the validation.

We have added the word 'validated' to show that we can only compute such numbers given the small error bars of the validation.

Added to Page 6339, Line 7: A validated Gaussian Process emulator of the model behaviour across the 28-dimensional parameter space in each grid box enables a full probability density distribution of CCN to be generated by Monte Carlo-type sampling for each grid box based on only 168 model runs.

Interactive comment on Atmos. Chem. Phys. Discuss., 13, 6295, 2013.

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