In this response to reviewer comments, the reviewer comments are italicized, and our responses are not.

*Anonymous Referee #3*
*Received and published: 13 May 2013*

*This is a very good paper on a topic of importance for Large Scale Models (LSMs), namely the treatment of cloud subgrid variability and associated processes involving cloud variables. The emergence of subgrid column generators in recent years has changed our thinking on cloud parameterizations, and having more options to generate distributions of cloud-related variates within the gridcells of LSMs can only have positive outcomes in the future, even if currently practical roadblocks remain for a full operational implementation. The paper is quite clearly written and well-structured, and I have no hesitation whatsoever to recommend its publication.*

Thank you for your review.

*Comments:*

*– A subcolumn generator algorithm curiously not mentioned is that of Norris et al (QJRMS, 2009) based on copulas. I think that for the sake of completeness this paper should be mentioned in the literature overview part of the paper.*

This paper has now been referenced.

*– Speaking of missing references, on the topic of geographically varying cloud overlap decorrelation lengths, Oreopoulos et al. (ACP, 2012) should be added when Shonk et al. is mentioned. This paper also parameterized cloud condensate vertical (rank) correlations which may be relevant to the discussion here.*

This reference has now been added.

*– I'm actually somewhat puzzled by the overlap discussion. All terminology and literature review quoted come from cloud fraction overlap, yet what is being vertically correlated here are cloud properties. It's not the same. All previous work on vertical correlations other than cloud fraction was about cloud water and the quantity of relevance was rank correlation rather than linear correlation of the condensate values themselves. Please comment.*

The revised manuscript adds the sentence "Unlike previous Monte-Carlo generators, which focused mostly on calculating cloud overlap and generating profiles of liquid cloud water, SILHS is used here to generate profiles of rain water and vertical velocity, along with profiles of liquid cloud water.”

*– Is there any reason why thin lines as in Fig. 5-8 cannot also be used for Figs. 1-4 instead of thick lines/symbols? The orange symbols (reference) can hardly be seen in some of the plots.*

We now use thinner lines in Figs. 1--4.

*– How does the computational cost of SILHS (cf. Table 1) scale with the number of sample points?*

The computational cost scales approximately linearly with the number of sample points.

*– Please clarify, does the implementation of SILHS resulting in Figs. 5-8 forego one of the its essential characteristics, i.e., importance sampling? That’s what the reference to "equal weighting" means to me.*

Yes, importance sampling is not used for the purpose of illustration in Figs. 5-8. The revised caption for Fig. 5 states: “(Importance sampling is foregone for the purpose of illustration in Figs.~\ref{fig:rico_rain_Nr_overlap_samples} through \ref{fig:dycoms2_rf02_w_overlap_samples}.) “

*– Perhaps I’d have known if I was up to date with all previous paper by the first author referenced herein, but can you please explain what the importance of liquid clouds is? Why can’t all this be generalized to comprise ice clouds as well?*

In principle, the method could be generalized to include ice clouds. In practice, the model that produces the subgrid PDFs from which the samples are drawn, CLUBB, sees only liquid at present.

*– What’s the nature of SILHS noise? Is it random?*

A batch of SILHS’ sample points drawn at one time is independent and uncorrelated with a batch of SILHS’ sample points drawn at a later time. In this sense, SILHS’ noise is random.

*-- What’s going to happen if averaging is performed over many realizations of the experiments shown? Convergence to the analytic solution?*

As more sample points are chosen per time step and grid box, the SILHS solution will converge to the analytic solution. An ensemble of simulations, each of which uses a different random seed in SILHS, might be expected to converge to a similarly configured simulation that uses analytic integration. But we have not tested this expectation.

*In a GCM implementation, will spatial averaging help the performance of the scheme?*

It would be interesting to try spatial averaging in a GCM, but we cannot do so at this point because SILHS has not yet been implemented in a GCM.