Response to Reviewer Comments

We thank the anonymous reviewer for their reading and suggestions. We have made some changes in the manuscript to reflect the concerns, and address them below, with the comments in blue.

Comment:

> It is known that particle filter handles nonlinearity well in low-dimensional systems, but it has some limitation when dimensionality scales up. The work presented used a clever separation between the model parameters (reduced dimension space) and actual high-dimensional model states, so that particle filtering happens in the reduced space so you don't worry about filter degeneracy. To apply to the high-dimensional lake simulation problem, clearly some other components (the sampler, the nonlinear BiLSTM) are needed to go back and forth between the reduced-dimension space and the full physical space. However, in your introduction Line 45-48 the DA and particle filtering approach is motivated as a proof of concept for "other higher-dimensional problems", which sounds too ambitious to me. While you successfully demonstrated the used of particle filtering for model parameters and sampling of model states in this particular lake model case, the method is not general to all high-dimensional problems. Is it possible to always come up with a reduced dimensional space (some model parameters are not global) so that this approach can be applied? I hope the authors can consider rephrasing this motivation in the introduction, maybe making it more clear that the idea is to apply particle filtering in a low-dimensional space to ensure its performance, so that readers are not misled.

We agree that the statement in the final introduction paragraph is a bit too ambitious, at least in comparison with the results shown in this paper. The new version provides a more modest statement:

> *We investigate the viability of this approach and analyze the performance of individual components. The results demonstrate that while our methodology improves model performance, the framework requires further improvements to become usable for practical applications.*

At the same time, we make a note that the Bayesian inference package we used (SPUX) is capable of inferring model parameter distributions in relatively high-dimensional parameter spaces (10 or more parameters [Sukys, J. 2020, unpublished], or several time-dependent parameters [Bacci et al 2022]), but with significantly less computationally demanding state models. Typically hydrodynamic lake models do not stipulate many parameters to be calibrated, and a good fidelity model can be obtained with the calibration of around 5 appropriately chosen parameters. With a better and more sensitive error model together with a shorter dataset (~1 month of observation instead of the original 11 months), we believe that we would have been able to achieve good results in a higher-dimensional parameter space.