Response to the Referee 1 for the Manuscript gmd-2021-333
"**Optimization of Snow-Related Parameters in Noah Land Surface Model (v3.4.1) Using Micro-Genetic Algorithm (v1.7a)**"
by Sujeong Lim, Hyeon-Ju Gim, Ebony Lee, Seungyeon Lee, Won Young Lee, Yong Hee Lee, Claudio Cassardo, and Seon Ki Park

The manuscript "Optimization of Snow-Related Parameters in Noah Land Surface Model (v3.4.1) Using Micro-Genetic Algorithm (v1.7a)" by Lim et al. addresses an important problem of model tuning/optimization. However, the results are not very encouraging, it shows very small improvements. Moreover, the manuscript seriously lacks in its analysis/validation part. Authors should come up with more results/analysis to claim substantial improvements in their method. The following are the comments, which may improve the manuscript.

⇒ We appreciate the valuable and constructive comments, which helped us improve the quality of the manuscript. We have included more analysis/validation to enhance the results. Unfortunately, we found that there was a mistake when we simulated some stations (urban and built-up lands (UB) in OPT_5 and cropland (CL) in OPT_6), thus we corrected the statistical values in the manuscripts. An item-by-item response to the comments is provided below.

1. *The improvements looks very small compare to the existing mean bias (table 4). The improvement ratio (equation 7), a metric used here gives an impression of big improvement, but in reality it is not so. For an example, improvement of RMSE from 6 to 5 will show about 16.5% improvements, but RMSE of 5 is still big. Statistically how significant are these improvements? Pls put significance level.*

   ⇒ We agree the improvement ratio may emphasize itself, even for the small changes. Nevertheless, the improvement ratio helps to objectively determine how much change has occurred in the value. To recognize the original magnitude of them, we included the RMSE value of CNTL in the caption of Table R1 below (it will replace Table 4 in the revised manuscript). In addition, the CNTL and OPTM (e.g., OPT_5 and OPT_6) experiments exhibit statistically significant linear relationships in the 95 % significance level. We have added this description in the revised manuscript.

2. *I would be interested to see some more graphical representations of analysis, rather than many statistical number presented here. There are so many numbers/numerical values mentioned in the manuscript (particularly the results). It is very hard to recognise changes in the box plot (Figure 4), as the improvements are really minute.*

   ⇒ We agree that the additional graphical representations are necessary to easily understand the changes between CNTL and OPTM experiments.

Thus, we have included the scatter plots for the observation and simulation results with the RMSE and R^2 to help to understand Figure 4 and this will be Figure 5 in the revised manuscript (Figure R1 below). Since the observation patterns are different for different stations, we selected the representative station as for each land cover type: Ulleungdo (UL) for deciduous broadleaf forest (DBF), Gumi (GM) for mixed forest (MF), Bukgangneong (NG) for woody savanna (WS), Boryeong (BR) for cropland (CL), and Seoul (SL) for urban and built-up lands (UB). Firstly, the overall fractional snow cover (FSC) relatively are hard to recognize the explicit bias patterns in the scatter plots; however, GM in MF shows increasing FSC to solve the underestimated problems. Most statistics indicate the improved RMSE and R^2 from the CNTL to OPT_5 and additionally improved in OPT_6. Secondly, snow albedo (SA) is overestimated in CNTL and it is reduced in OPT_5 and OPT_6. For instance, UL in DBF shows decreasing SA in OPT_5 and following OPT_6. Lastly, snow depth (SD) is optimized using the hourly in-situ observations (i.e., more data), and hence shows remarkable improvement compared to FSC and SA, both using the daily satellite observations. Most stations have recovered the under-estimated SD with decreasing RMSE and increasing R^2.

3. *Pls write what is shown in the y-axis in Figure 4*

   ⇒ We added the y-axis information (Fig. R2) as follows: (a) FSC bias, (b) SA bias, and (c) SD bias (cm). The wrong maximum and mean value of each bias in OPT_5 and OPT_6 have been corrected in the caption.

4. *I found the validation part of the manuscript is very weak. Perhaps you need to do more simulations/analysis to establish that your optimization method works better that the default model.*

   ⇒ We prepared additional analyses with the scatter plots for snow variables (Fig. R1), as mentioned in #2 above, and the time series of secondary variables (e.g., soil temperature, soil moisture, and sensible heat flux) through the snow optimization (Fig. R3).
   As the off-line Noah LSM is one-dimensional, it requires lots of computing time for simulations and verifications at all the grid points. We plan to address more stations in our further study. Moreover, we also plan to optimize the Noah LSM in a coupled land-atmosphere prediction system to produce two-dimensional data in one model run. This statement will be added in the revised manuscript.

5. *In several previous studies it has been shown that improvement or incorporation of real physical processes, such as discrete treatment of snow layer, more realistic snow physics significantly improves simulation of snow (e.g., Niu et al., 2011; Saha et al., 2017). Does your optimization fares better than above?*

⇒ We agree with the reviewer that some previous studies have improved snow simulation through more realistic physical parameterization [1] or discrete treatment of snow layer [2]. We can develop more realistic parameterization schemes and make improvement in the model performance; however, those scheme are still under uncertainty, especially in parameter values. Moreover, the model performance by more realistic parameterization scheme may significantly improve in one region but it may less significantly improve or even deteriorate in other places, due to uncertainties in parameter values. *Parameter estimation* is not competing with the development of more realistic physical parameterization; it is rather an effort to further improve the model performance by reducing uncertainty in pre-existing parameterization schemes by optimizing the parameter values inside the schemes based on the observational data that reflect local characteristics. If the employed parameterization scheme has less uncertainty, improvement by parameter estimation on that scheme may not be significant; if the scheme has large uncertainty in parameter values, parameter estimation may bring about prominent improvement in the scheme's performance. Therefore, we believe that development of more realistic physical parameterization scheme, followed by appropriate parameter estimation, will create a strong synergy between them that results in higher model performance, as indicated in [3].

6. *Apart from RMSE, authors may also show any improvements in the correlation skill*

   ⇒ We included the coefficient of determination (R^2), which measures the proportion of variation for a dependent variable that can be explained by an independent variable, in Table R1. Like the RMSE, the R^2 of FSC and SD also improved in OPTM. The SA was weakly worsened in OPT_5, but it was almost recovered to the CNTL in OPT_6.

7. *How the seasonal cycle of snow parameters looks like (model vs observations)? Do you see improvements there also ?*

   ⇒ Snow parameters do not have the observations; thus, it is impossible to compare the snow-related parameters between model and observations. In addition, the snow is found over South Korea only in the wintertime, so it is hard to identify the seasonable cycle of snow parameters in our study.

8. *What are the effects of optimized model on skin and sub-surface temperature, soil moisture, surface energy balance etc?*

   ⇒ We investigate the responses of secondary variables due to optimization of snow parameter (Fig. R3). We bring the results of UL in DBF which shows enhancements on all of snow variables in Fig. R1. Increased SD warms the soil temperature in the first soil layer (7 cm) through the land surface insulative response, resulting in larger sensible heat flux. The residual of the surface energy balance equation gets close zero, thus the surface energy balance is conserved after optimization (Figure is not shown). Finally, the soil moisture depends on the snow melt, hence it follows the increased snowfall in the previous winter. Because this is an hourly data, extreme fluctuations sometimes appear in the time series analyses, but we can understand the overall tendency from the increased SD.

9. *As mentioned in the beginning, the ultimate goal is to improve forecast of snow over SK, I believe all-grid point simulation (gridded) would be a better strategy to really demonstrate the usefulness of this method.*

   $\Rightarrow$ We fully agree with the reviewer. As mentioned in #4 above, running the off-line Noah LSM over all grid points requires a large amount of computational time. Thus, we have sampled representative stations in this study for effective optimization. Following the reviewer's suggestion, we will do simulations over all the grid points in our further study. Based on the promising results using the off-line Noah LSM, we have a plan to optimize the Noah LSM in a coupled land-atmosphere prediction system (e.g., Weather Research and Forecasting (WRF)-Noah LSM). While the off-line Noah LSM is a one-dimensional column model, the Noah LSM coupled to WRF is able to simulate the two-dimensional features with prescribed spatial resolution. Moreover, it can interact with not only the multiple soil layers but also the atmospheric layers. As a further study, we anticipate the optimized snow parameters can lead to forecast improvement in the atmospheric variables through the changes of heat fluxes as well as snow variables in the LSM.

References

[1] Niu, G.-Y., et al.: The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements, J. Geophys. Res., 116, D12109, doi:10.1029/2010JD015139, 2011.

[2] Saha, S. K., Sujith K., Pokhrel S., Chaudhari H. S., and Hazra A.: Effects of multilayer snow scheme on the simulation of snow: Offline Noah and coupled with NCEP CFSv2, J. Adv. Model. Earth Sy., 9, 271-290, doi:10.1002/2016MS000845, 2017.

[3] Duan, Q., Di, Z., Quan, J., Wang, C., Gong, W., Gan, Y., Ye, A., Miao, C., Miao, S., Liang, X., and Fan, S.: Automatic Model Calibration: A New Way to Improve Numerical Weather Forecasting, Bull. Am. Meteorol. Soc., 98, 959-970, 2017.

Table R1: Improvement ratio (%) in RMSE, coefficient of determination (R^2), and mean bias (MB) of snow variables from CNTL to OPT_5, and OPT_6 over the ten representative stations. The statistic values in CNTL are following: RMSE is 0.270 for FSC, 0.155 for SA, and 10.599 for SD; R^2 is 0.219 for FSC, 0.183 for SA, and 0.806 for SD; MB is -0.107 for FSC, 0.0513 for SA and -5.38 cm for SD. The CNTL and OPTM (e.g., OPT_5 and OPT_6) experiments exhibit statistically significant linear relationships at the 95 % significance level.

EXP	OPT_5			OPT_6		
Snow Variable	FSC	SA	SD	FSC	SA	SD
RMSE	1.3 %	6.7 %	13.8 %	6.5 %	8.5 %	17.7 %
R^2	3.1 %	-2.4 %	1.6 %	16.4 %	-0.2 %	3.0 %
MB	-31.8 %	28.5 %	40.9 %	-19.6 %	32.6 %	45.1 %

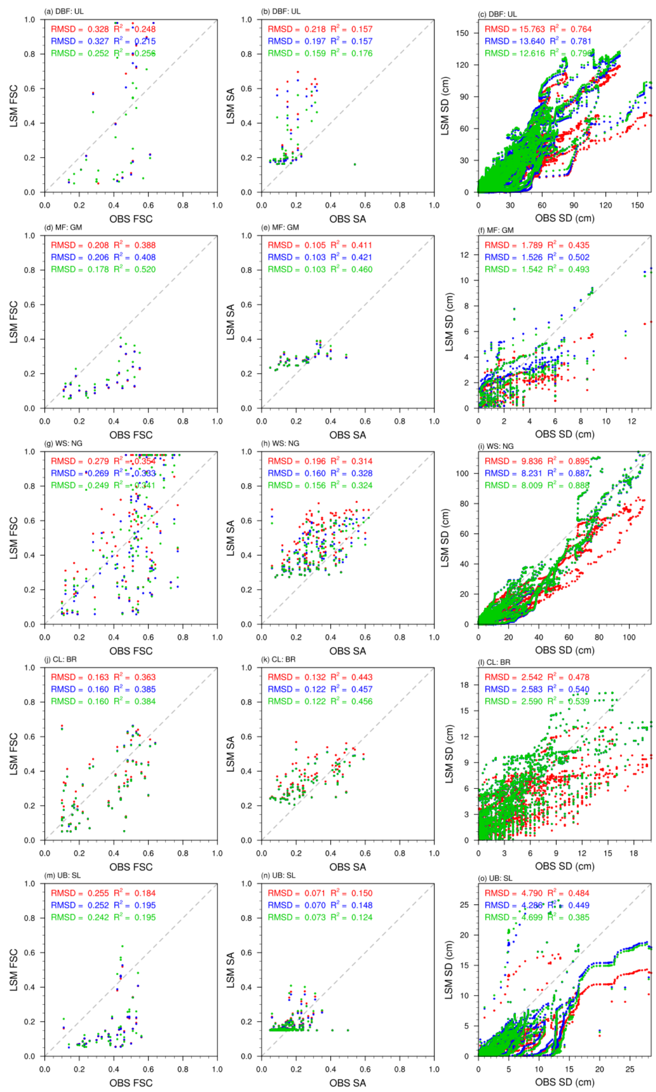

Figure R1: Scatter plots for the observation (OBS) and land surface model (LSM) results: CNTL (red), OPT_5 (blue) and OPT_6 (green). The representative station in each land cover type are analyzed such as (a)-(c) DBF: UL, (d)-(f) MF: GM, (g)-(i) WS: NG, (j)-(l) CL: BR, (m)-(o) UB: SL. From the left to right panels, they are the FSC, SA, and SD (cm). Compared to observations, the statistics (e.g., RMSE and R^2) in each experiment are indicated in each panel.

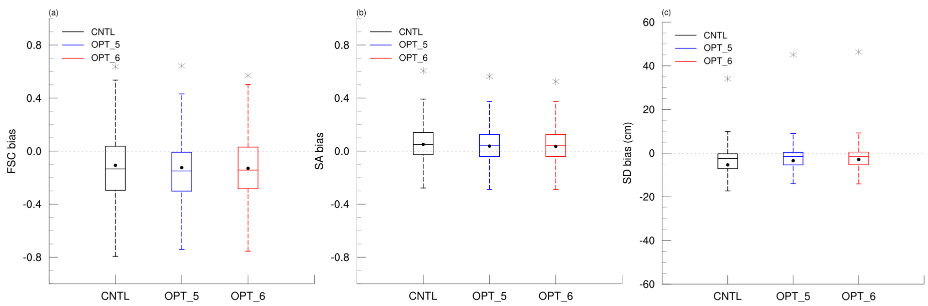

Figure R2: Box plots of (a) FSC, (b) SA, and (c) SD (cm) for CNTL, OPT_5 and OPT_6. The maximum differences are indicated with the black star symbol (e.g., 0.637 (CNTL), 0.643 (OPT_5), 0.570 (OPT_6) for FSC, 0.605 (CNTL), 0.563 (OPT_5), and 0.525 (OPT_6) for SA, and 34.1 cm (CNTL), 45.1 cm (OPT_5), and 46.3 cm (OPT_6) for SD). Each mean of snow variables is indicated as a black circle (e.g., -0.107 (CNTL), -0.125 (OPT_5), and -0.130 (OPT_6) for FSC, 0.0513 (CNTL), 0.0381 (OPT_5), and 0.0359 (OPT_6) for SA, and -5.38 cm (CNTL), -3.46 cm (OPT_5), and -2.93 cm (OPT_6) for SD).

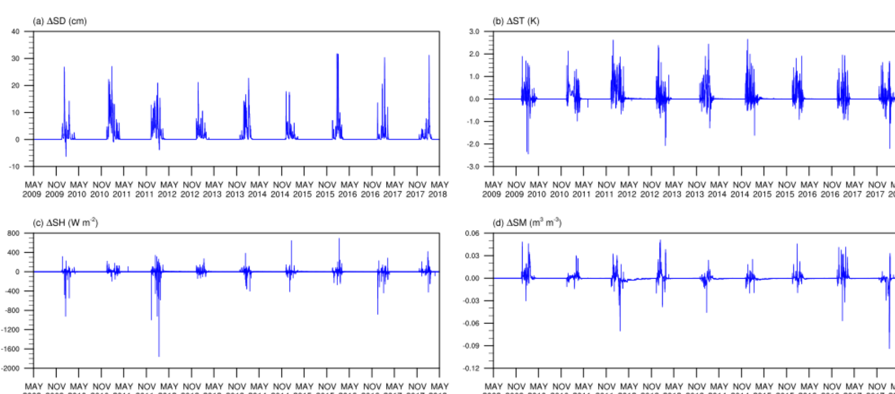

Figure R3: Time series of difference between CNTL to OPT_6 for the UL in DBF during the May 2009 to April 2018.: (a) SD (cm), (b) soil temperature at the top soil layer (ST; 7 cm) (K), (c) sensible heat flux (SH; W m^{-2}), (d) soil moisture at the top soil layer (7 cm) (SM; m^3 m^{-3})