Response to the Referee 2 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

This study worked on determining the optimal parameter values in the snow-related processes – snow cover fraction, snow albedo, and snow depth – of the Noah LSM, using the micro-genetic algorithm and the in-situ surface observations and remotely-sensed satellite data. The study area was South Korea. This manuscript does not have sufficient elements on the model development, it is rather a study of applying a certain optimization algorithm to calibrate the model parameters. I have doubts about the novelty of this manuscript and its suitability for consideration for publication in Geoscientific Model Development. Below are some comments which I hope could help improve the manuscript.

⇒ We really appreciate the valuable and constructive comments, which helped us improve the quality of the manuscript. Our study is a parameter estimation problem, which is based on the assumption that all the physical parameterization schemes are not perfect and have uncertainties, especially in their parameter values; thus, it is strongly and directly linked to 'assessment of model performance' through parameterization schemes, which corresponds to the scope of Geoscientific Model Development (GMD). Parameter estimation is a companion of parameterizations as it reduces the uncertainties in the parameter values of newly-developed parameterization schemes and enhances the model performance through the schemes; furthermore, a new method of comparing model results with observational data is developed in our study through various fitness functions in the course of optimization. In this sense, we believe that our study also indirectly satisfies the scopes of GMD, described as 'developments such as new parameterizations' as well as 'developing novel ways of comparing model results with observational data'. We have faithfully followed the reviewer's suggestions and included more analysis/validation to enhance the results. An item-by-item response to the comments is provided below.

1. *Short Introduction and unclear novelty of this study. The introduction is rather short and the novelty of this study is not explicitly stated.*

   ⇒ We appreciate the reviewer pointing this out. We have revised a paragraph (L35-48) in *Introduction* by adding more statements as follows (see blue parts):

   Uncertainties in parameterized physical processes have been observed and quantified in various numerical models (e.g., Mallet and Sportisse, 2006; Gubler et al., 2012; Shutts and Pallarès, 2014; Folberth et al., 2019; Li et al., 2020; Olafsson and Bao, 2020; Pathak et al., 2020; Souza et al., 2020). Such uncertainties can be also reduced by estimating optimal parameter values in the subgrid-scale parameterization schemes (e.g., Annan and Hargreaves, 2004; Lee et al., 2006; Neelin et al., 2010; Yu et al., 2013; Zhang et al., 2015; Kotsuki et al., 2018; Liet al., 2018; Chinta and Balaji, 2020). Because empirical parameters are commonly derived from the observations or theoretical calculations, their estimated values are strongly dependent on the local characteristics of the region and period where the observations are made. Thus, parameter estimation that fits the model outputs to the observations is essentially required to obtain an adequate parameter [1]. It may be done using a *trial and error* approach by manual, but the *optimization algorithm* helps to replace enormous experiments by automatically minimizing the difference between model and observations [2]. For example, a global optimization tool, called the micro-genetic algorithm (micro-GA), has been effectively used for estimating the optimal parameter values (e.g., Lee et al., 2006; Yu et al., 2013) and for finding the optimal set of parameterization schemes (e.g., Hong et al., 2014, 2015; Park and Park, 2021).

Most snow processes in the LSMs are parameterized based on the observations in specific local regions, and hence they may not represent adequately the situation in SK and be the source of uncertainties for numerical snow prediction over SK. This study aims at obtaining the optimal parameter values of the snow-related processes — snow cover, snow albedo, and snow depth — in a LSM using the micro-GA, which causes better LSM performance over SK. This study represents the first attempt to develop a coupled system of micro-GA and Noah LSM for parameter estimation of the snow processes. Section 2 describes the methodology, including the snow processes of the LSM and the micro-GA optimization tool. Section 3 explains experiment design. Results, discussion and conclusions are provided in sections 4, 5 and 6, respectively.

2. *Insufficient details on the methods/procedures. Section 2.2 and Table 2 miss necessary details on the selected parameters and settings for the different experiments.*

   ⇒ In Section 2.2, we have focused on the GA algorithm itself and the fitness function. Descriptions on the selected parameters and settings for different experiments are separately provided in Section 3. We have added more details on the parameter settings in Section 3 (after L233 in the original manuscript) as follows:

   It is known that the best performance in micro-GA is done with a population size of 5 and a uniform crossover (i.e., crossover operator = 1.0) with elitism [3, 4, 5]. The uniform crossover makes all populations perform a crossover at every generation to acquire the diversity [6]. The number of parameters to be optimized is 5 for OPT_5 and 1 for OPT_W. The number of chromosomes determines the number of cases expressed in a binary format. For example, the selected parameters — P_s, $\alpha_{max,CofE}$, C, P_1,

P_2, and W_{max} — use different chromosomes, i.e., 5, 5, 5, 6, 4, and 5, respectively; thus, the total number of chromosomes is 30 for OPT_5 and 5 for OPT_6. The maximum value of generations at the end of optimization is generally set to 100 [4, 5, 7], whereas we increased generations up to 200 in OPT_5 due to larger number of parameters to be optimized.

Table R1: The input parameters for micro-GA in experiments OPT_5 and OPT_W.

Input Parameter	OPT_5	OPT_W
Population size	5	5
Crossover operator	1.0	1.0
Elitism	on	on
Number of parameters	5	1
Number of chromosomes	30	5
Maximum value of generations	200	100

3. *I advise the authors to add more figures to show the comparison, via scatter plot, time series plot to show the modelling results in different perspectives. Besides the RMSE value, what about the performance of the model in terms of other commonly used metrics such as R or R^2 value?*

   ⇒ Following the reviewer's comments, we have conducted additional analyses and added more figures, including scatter plots and times series. Figure R1 (see below) represents the scatter plots of observations versus model results along with the values of RMSD and R^2. Consistent with the statistical results in the original manuscript, OPT_6 shows improved snow variables in the scatter plots for Ulleungdo (UL) in the deciduous broadleaf forest (DBF). In particular, compared to CNTL, optimization results in notable increase in the underestimated snow depth (SD; Fig R1c) and negligible changes in fractional snow cover (FSC; Fig R1a) and snow albedo (SA; Fig R1b). In statistical analyses, represented by RMSE and R^2, OPT_5 and OPT_6 are generally closer to observations than CNTL while OPT_6 shows the lowest RMSE and the highest R^2. We have added the scatter diagrams and statistical analyses for other stations and land cover types in the revised manuscript (see Fig. R1 therein). In Fig R2, we analyzed the time series of the differences of secondary variables (e.g., soil temperature, soil moisture, and sensible heat flux) between OPT_6 and CNTL (i.e., OPT_6 minus CNTL). Although these variables are not directly optimized, they respond to the optimized snow parameters through associated physical processes. For example, soil temperature in the first soil layer (7 cm) increases as SD increases after optimization, which consequently increases sensible heat flux. The residual of surface energy balance is close to zero (not shown), implying that the surface energy balance is well conserved even after optimization. Soil moisture depends on snow melt, following the trend of increased snowfall in the previous winter. Extreme fluctuations sometimes appear in the time series analyses due to nonlinear effects, but we can understand the overall tendency according to the increased SD in the land surface. We also added R^2 in Table 4 of the original manuscript (see Table R2 below). Both FSC and SD showed improvement in terms of RMSE and R^2. The SA worsened in OPT_5 but it showed less deterioration in OPT_6, getting closer to CNTL in terms of R^2.

Table R2: 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 %

4. *Results need more description and particularly figures. I advise adding more figures on the modelling results, and particularly representing the spatial patterns of modeling results. The author studied South Korea, readers are interested in the spatial distribution of model performance.*

   ⇒ We appreciate the reviewer's valuable comment. As the Noah LSM is a one-dimensional column model, we should run the off-line Noah LSM over all the grid point by point, which requires a large amount of computational time. Thus, we have sampled representative stations in this study for effective optimization. Based on the promising optimization results in the off-line Noah LSM, we plan to extend our study to optimize the online mode of Noah LSM, coupled to an atmospheric model (e.g., WRF). Then, we will be able to assess the model performance in terms of spatial distributions, and we will do more experiments following the reviewer's comment in our follow-up study.

5. *Discussion is completely missing. The current manuscript has no discussion. I strongly advise the authors to compare their findings with existing literature. In addition, what are the limitation of the study? And any potential solutions for future studies? What are effects of some settings or input on the modelling results? Lots of aspects need to be discussed.*

   ⇒ We have included the *Discussion* section before the *Conclusion* as follows:

Generally, the Noah LSM tends to simulate less snow amount during the peak winter and earlier snow melting, and consequently overestimates SA [8]. Our experiment with no optimization (CNTL) reveals underestimation of SD and FSC and overestimation of SA, compared to the in-situ or satellite observations. We developed a coupled system of micro-GA and Noah LSM to reduce the uncertainties in parameterized snow processes through optimization of parameter values. Our results showed improvement in all snow variables in terms of RMSE by 6.5 %, 8.5 %, and 17.7 % for FSC, SA, and SD, respectively. Furthermore, SD increased after optimization, which lead to increases in both soil temperature and sensible heat flux due to insulating response; soil moisture also increased due to increased SD in previous years. This implies that the optimized snow parameters not only let the model solutions close to the observations but also act in physically consistent manner.

The coupling system of micro-GA and Noah LSM automatically estimates the optimal snow-related parameters by objectively comparing observations and model solutions through the fitness function. Instead of trial-and-error procedures, it has an advantage to reduce a substantial amount of computational time. The original micro-GA reduces the computational time using the elitism and re-initialization methods in the small number of individuals. We have developed a parallel system on the coupled system to further improve the computational efficiency in this study; it enables us to simultaneously execute multiple individuals in a one generation and multiple Noah LSM runs in one individual.

Based on the encouraging optimization results in the off-line Noah LSM, we plan to optimize the Noah LSM in a coupled land-atmosphere prediction system. The online Noah LSM can produce spatial distribution of model variables over the land surface, which allows two-dimensional assessment of model performance. We anticipate the optimized snow parameters can lead to positive effects on the atmospheric variables through the changes of heat fluxes as well as snow variables in Noah LSM. As a result, we can identify how optimal parameters are appreciated in SK in terms of both horizontal and vertical distributions. In addition, our coupled system of micro-GA and Noah LSM can be utilized to optimize other parameters in Nosh LSM.

References

[1] 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.

[2] Duan Q., Schaake J., Andréassian V., Franks S., Goteti G., Gupta H. V., Gusev Y. M., Habets F., Hall A., Hay L., Hogue T., Huang M., Leavesley G., Liang X., Nasonova O. N., Noilhan J., Oudin L. , Sorooshian S., Wagener T., and Wood E. F.: Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops, J. Hydrol., 320, 3-17, 2006.

[3] Carroll, D. L.: Genetic algorithms and optimizing chemical oxygen-iodine lasers, Developments in theoretical and applied mechanics, 18, 411–424, 1996.

[4] Yu, X., Park, S.K., Lee, Y.H., and Choi, Y.-S.: Quantitative precipitation forecast of a tropical cyclone through optimal parameter estimation in a convective parameterization. SOLA, 9, 36–39, 2013.

[5] Yoon J. W., Lim S., and Park S. K.: Combinational Optimization of the WRF Physical Parameterization Schemes to Improve Numerical Sea Breeze Prediction Using Micro-Genetic Algorithm. Appl. Sci., 11, 11221, https://doi.org/10.3390/app112311221, 2021.

[6] Lee, J., Kim, S. M., Park, H. S., and Woo, B. H.: Optimum design of cold-formed steel channel beams using micro Genetic Algorithm. Eng. Struct., 27, 17-24, 2005.

[7] Zhu, J., Shu, J., and Yu, X.: Improvement of typhoon rainfall prediction based on optimization of the Kain-Fritsch convection parameterization scheme using a micro-genetic algorithm. Front. Earth Sci, 13, 721–732, 2019.

[8] 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.

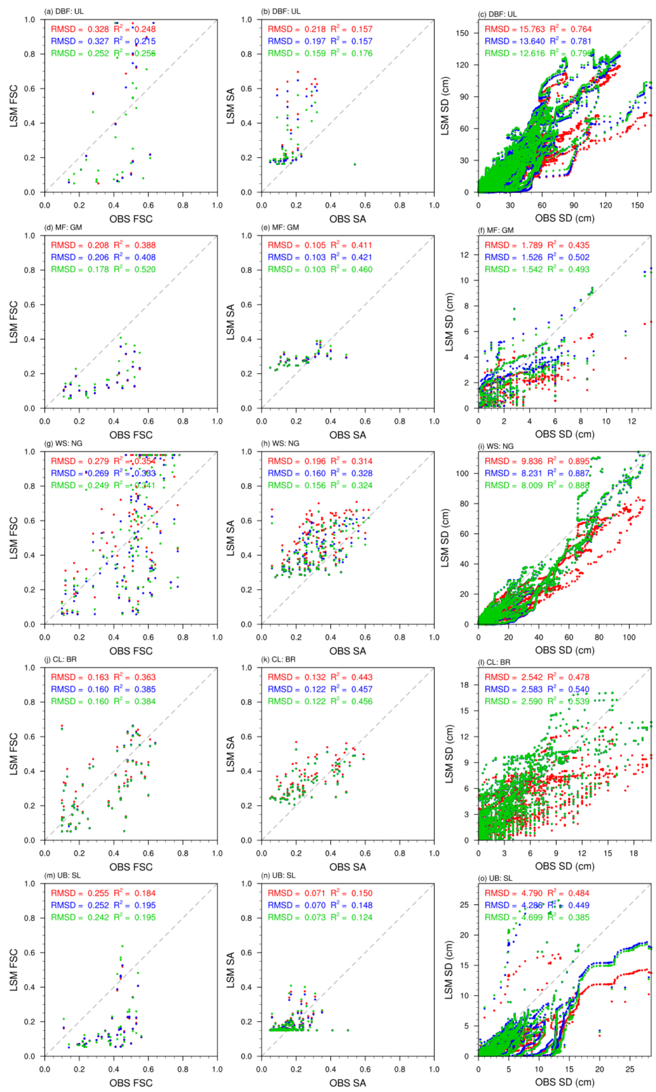

Figure R1: Scatter plots for the observation (OBS) and land surface model (LSM) results: CNTL (red), OPT_5 (blue) and OPT_6 (green). The representative station in each land cover type are analyzed such as (a)-(c) DBF: UL, (d)-(f) MF: GM, (g)-(i) WS: NG, (j)-(l) CL: BR, (m)-(o) UB: SL. From the left to 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.

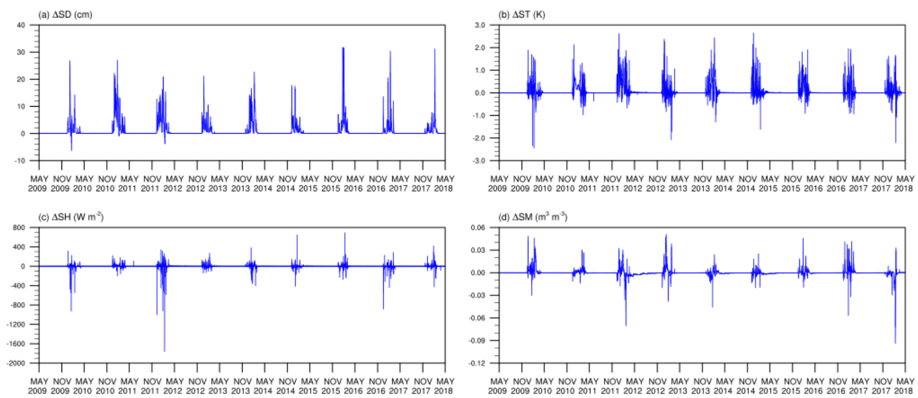

Figure R2: Time series of difference between CNTL to OPT_6 for the UL in DBF during the May 2009 to April 2018.: (a) SD (cm), (b) soil temperature at the top soil layer (7 cm) (ST; K), (c) Sensible heat flux (SH; W m^{-2}), (d) soil moisture at the top soil layer (7 cm) (SM; m^3 m^{-3})