Responses to reviews on:

Enhanced Watershed Modeling by Incorporating Remotely Sensed Evapotranspiration and Leaf Area Index

Sangchul Lee, Dongho Kim, Gregory W. McCarty, Martha Anderson, Feng Gao, Fangni Lei, Glenn E. Moglen, Xuesong Zhang, Haw Yen, Junyu Qi, Wade Crow, In-Young Yeo, Liang Sun

We thank the referee for the valuable comments on our manuscript. All comments are numbered and corresponding responses are followed by an arrow symbol (➔) with blue words. The line numbers (Line) referenced may have changed in the final version of the revised manuscript.

Reviewer #1: The authors apply remotely sensed evapotranspiration and leaf area index in addition to in-situ streamflow to calibrate a SWAT model in Tuckahoe Creek Watershed. The paper is well written, albeit the usage of numerous abbreviations. But, I am kind of skeptical to accept this version of the article.

Major comment:

1.1. Novelty: Even though the article is presented well, under the hood, it is a calibration paper constrained with two additional RS products which has been investigated previously by other researchers listed below.

- Parr, D., Wang, G., & Bjerklie, D. (2015). Integrating remote sensing data on evapotranspiration and leaf area index with hydrological modeling: Impacts on model performance and future predictions. Journal of Hydrometeorology, 16(5), 2086-2100.
- Andersen, J., Dybkjaer, G., Jensen, K. H., Refsgaard, J. C. and Rasmussen, K.: Use of remotely sensed precipitation and leaf area index in a distributed hydrological model, J. Hydrol., 264(1–4), 569 34–50, doi:10.1016/S0022-1694(02)00046-X, 2002.
- Jiang, D. and Wang, K.: The role of satellite-based remote sensing in improving simulated streamflow: A review, Water (Switzerland), 1615, doi:10.3390/w11081615, 2019.

➔ We have added several statements to emphasize the novelty of our study relative to previous studies in **Lines 477 – 484**.

Lines 477 – 484: Especially, our results provided several insights on the use of two additional RS products although previous studies already reported the advantages of them (Andersen et al., 2002; Jiang and Wang, 2019; Parr et al., 2015). First, our studies showed limitations on the single use of additional RS-ET product with the emphasis on the equifinality issue. In addition, a substantial reduction of model uncertainty was highlighted by the model evaluation at two spatial scales using two RS products. Lastly, this study chose the two RS products frequently used to monitor croplands, and thus our results could inform an improved modeling approach for agricultural watersheds.

Suggestion:

Methodology: 20,000 LHS samples have a wealth of information.

1.2. One way to provide insight would be to see among all the parameters that are being calibrated find the one which has the largest influence on the KGE values in par1 and par2. Investigating why these parameters are influential would a very good insight.

➔ We have conducted sensitivity analysis of calibrated parameters and calculated coefficient of variation (CV) to see which parameters have significant impacts on ET and LAI simulations. The Table 3 was updated to include sensitivity ranking, and the section 3.2 was made to show results. The analysis method and results have been illustrated in **Lines 325 – 335 and 411 – 426**, respectively.

Lines 325 – 335: Regarding the number of parameters and iterations, identifying the parameter with significant impacts on ET and LAI simulations could inform useful insight on the use of two additional remotely sensed constraints. First, we computed the parameter sensitivity for RS-ET and RS-LAI, separately. A global sensitivity that makes a linearly fitted line between the objective function with the parameter values was adopted (Khalid et al., 2016). The KGE values for a watershed-level ET and LAI during the calibration period were used as the objective function of the global sensitivity analysis to identify sensitive parameters for RS-ET and RS-LAI, respectively. Then, a coefficient of variation (CV) was computed for the top ten sensitive parameters for RS-ET and RS-LAI, respectively. CV is defined as the standard deviation divided by mean values (Lee et al., 2022). The static has been frequently used to quantify which parameters have greater impacts on simulation results (Her and Chaubey, 2015; Lee et al., 2022).

Lines 411 – 426: Among 34 parameters, the CV values of the top ten sensitivity parameters for RS-ET and RS-LAI were computed using PARs-1 and PARs-2, respectively (Fig. 3). The sensitivity ranking is listed in Table 3. Considering acceptable 14 parameter sets for streamflow and RS-ET (i.e., PARs-1), the parameters representing maximum canopy storage (CANMX) indicated the greatest CV value for RS-ET (Fig. 3a). In case of acceptable 6 parameter sets for streamflow, RS-ET, and RS-LAI (i.e., PARs-2), the parameter that controls the leaf area development of forest (FRGRW1) represented the greatest CV value (Fig. 3b). In other words, the CANMX and FRGRW1 values were more widely spread relative to parameters of PARs-1 and PARs-2, respectively.

The calibration results constrained by streamflow and RS-ET were most sensitive to maximum canopy storage. In the SWAT model, canopy evaporation is first considered to calculate actual ET (Neitsch et al., 2011) and thus CANMX likely showed the greatest CV. When SWAT was constrained by streamflow, RS-ET and RS-LAI, the parameter with respect to the leaf area development was most influential among parameters of PARs-2. As a single plant type, forest is a dominant plant accounting for 32.8% of the study site while corn and soybean cover approximately 27%. Therefore, the greatest CV value was found in the forest-related parameter.

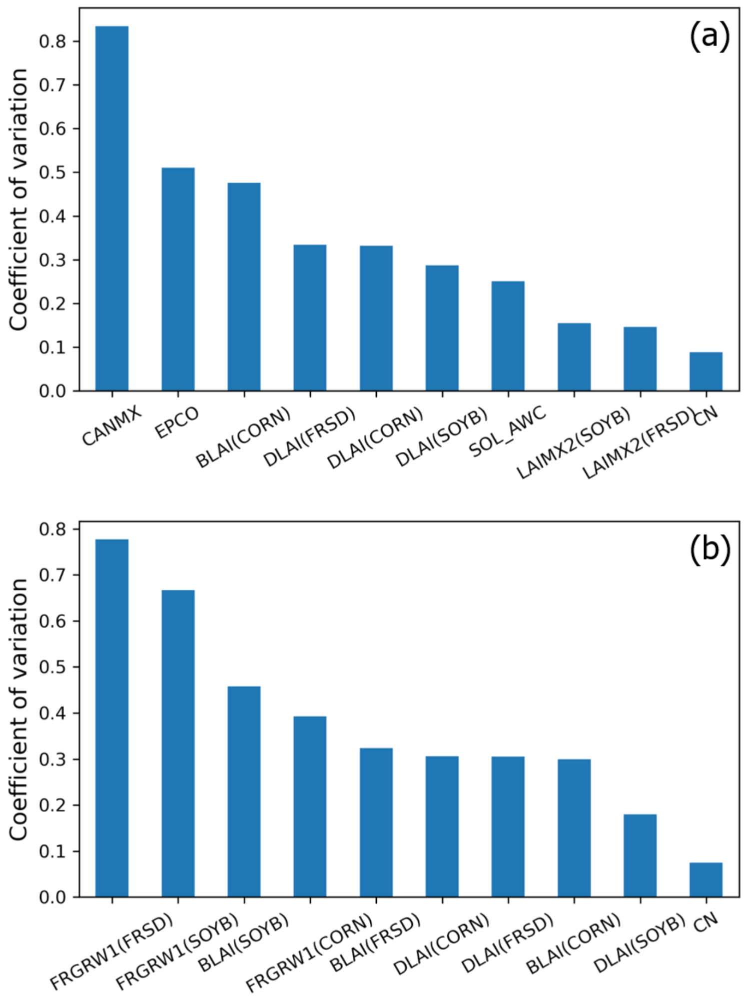


Fig. 1. Coefficient of variation (CV) values of the top ten sensitive parameters for RS-ET (a) and RS-LAI (b). (a) indicates the CV for PARs-1 (14 acceptable parameter sets for streamflow and RS-ET), and (b) indicates the CV for PARs-2 (6 acceptable parameter sets for streamflow, RS-ET, and RS-LAI)

Table 1. Description, ranges, and sensitivity ranking of calibrated parameters

Parameter	Description (units)	Range	Sensitivity ranki	
			RS-ET	RS-L
CN[!]	SCS runoff curve number	-20 – 20%	1	10
GW_DELAY[!]	Groundwater delay (days)	0 – 500	26	34
ALPHA_BF[!]	Baseflow alpha factor ($days^{-1}$)	0 – 1	32	30
GWQMN[!]	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	0 – 5000	33	31
GW_REVAP[!]	Groundwater "revap" coefficient	0.02 – 0.2	24	23
REVAPMN[!]	Threshold depth of water in the shallow aquifer for "revap" to occur (mm H_2O)	0 – 1000	29	27
SOL_AWC[!]	Available water capacity of the soil layer (mm H_2O ·mm $soil^{-1}$)	-50 – 50%	2	26
CH_K2*	Effective hydraulic conductivity in the main channel alluvium	0 – 500	31	22
CH_N2*	Manning's "n" value for the tributary channels	0.01 – 0.3	28	28
SURLAG[$]	Surface runoff lag coefficient	0.5 – 24	30	29
ESCO[!]	Soil evaporation compensation factor	0 – 1	13	25
EPCO[!]	Plant uptake compensation factor	0 – 1	3	20
CANMX[!]	Maximum canopy storage (mm H_2O)	0 – 100	4	18
BIO_E[!] (corn)	Radiation use efficiency in ambient CO_2 ((kg/ha)/(MJ/m^2))	10 – 90	27	19
BIO_E[!] (soybean)			21	33
BIO_E[!] (forest)			25	13
BLAI[!] (corn)	Maximum potential leaf area index (m^2m^{-2})	0.5 – 10	9	3
BLAI[!] (soybean)			12	4
BLAI[!] (forest)			20	1
FRGRW1[!] (corn)	Fraction of the plant growing season of total potential heat units corresponding to the first point on the leaf area development curve	0 – 0.5	22	8
FRGRW1[!] (soybean)			23	9
FRGRW1[!] (forest)			34	7
FRGRW2[!] (corn)	Fraction of the plant growing season of total potential heat units corresponding to the second point on the leaf area development curve	0.5 – 1	15	17
FRGRW2[!] (soybean)			14	15
FRGRW2[!] (forest)			16	16
LAIMX1[!] (corn)	Fraction of the maximum leaf area index corresponding to the first point on the leaf area development curve	0 – 0.5	18	12
LAIMX1[!] (soybean)			17	14
LAIMX1[!] (forest)			19	11
LAIMX2[!] (corn)	Fraction of the maximum leaf area index corresponding to the second point	0.5 – 1	11	32
LAIMX2[!] (soybean)			8	21
LAIMX2[!] (forest)			7	24
DLAI[!] (corn)	Leaf to biomass fraction	0.15 – 1.00	5	6
DLAI[!] (soybean)			10	5
DLAI[!] (forest)			6	2

Note: !, *, and $ indicate the parameters whose values differ by the hru, sub-watershed, and watershed levels. The gray box indicates the top ten sensitive parameters. RS-ET and RS-LAI indicate remotely sensed evapotranspiration and leaf area index, respectively.

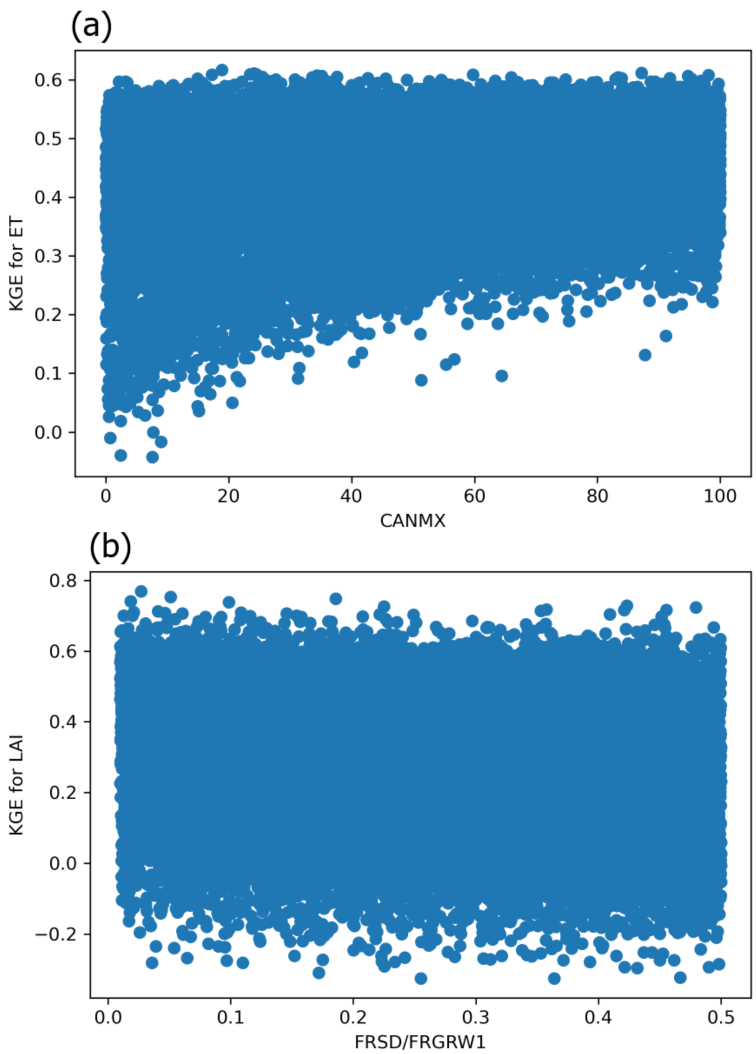
1.3. Also, how to choose between single parameter set which gets best performance compared to a cluster of parameters (close in values) which gives good performance?

➔ In general, the single parameter set with the best performance is often selected for a scenario-based modeling approach. However, this practice faces the equifinality issue because the best single parameter set may not be better than decent multiple parameter sets when a model calibration is made by one observation. To address this issue, this study emphasized the benefits of two remotely sensed constraints since the additional constraints gradually reduce the number of decent multiple parameter sets. We have discussed this issue in **Lines 485 – 494** in the section 4. and provided the conclusion that the use of multiple model constraints is needed for future studies as RS data are increasingly available. Since this study was conducted to reduce the parameter uncertainty, we have avoided illustrating the selection method of the single parameter set.

Lines 485 – 494: In hydrologic modeling studies, the single parameter set with the best model performance is commonly identified during model calibration and validation, and the single parameter set is used to anticipate the impacts of climate change, land use, and best management practices implementation on watershed processes (Tan et al., 2020). As aforementioned, this approach cannot be free from an uncertainty problem. Some studies often reported the range of prediction outputs from all parameter sets with decent performance measures rather than the single prediction output with the best performance (Her et al., 2019; Lee et al., 2020, 2021). The remotely sensed products are freely available, which provides opportunity to reduce the parameter uncertainty (Yeo et al., 2019). Our results would help future stuidies to use additional constratins, generating model predictions with reduced uncertainty.

1.4. Is there a relationship (linear/non-linear) between parameter values and KGE?

➔ We have representatively compared the KGE values and CANMX/FRGRW1(FRSD) as below. Non-linear relationships were observed. Those results were not supportive of the major findings of our manuscript, so these results were excluded in our manuscript.



These are some of the questions that the authors can address to bring more value to science aspects of the paper.