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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Temporal interpolation of land surface fluxes derived from remote sensing – results with an Unmanned Aerial System" *by* Sheng Wang et al.

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Response to the review of Referee 1. We have copied the comments of the referee hereunder with our comments appearing after the referee's comments.

This study "Temporal interpolation of land surface fluxes derived from remote sensing results with an Unmanned Aerial System" developed a simple but operational land surface modeling framework, simulating energy balance, water and CO2 fluxes between the land surface and the. Unmanned aerial system (UAS) can be applied flexibly, and can have high spatial-temporal resolution data, which is used widely in recent decades. This study used UAS to provide optical and thermal data as model inputs for land

surface-atmosphere fluxes monitoring. A dynamic soil vegetation atmosphere transfer model was developed here, together with the PT-JPL ET model and light use efficiency GPP model for simulating energy, water and CO2 cycles. The results showed that with using the data from UAS optical and thermal observations, the models were capable to simulate the energy, water and CO2 fluxes in a deciduous tree plantation area, indicating that the UAS observations could be served as "ground truth" to calibrate soil and vegetation parameters, highlighting the usage of multiple remote sensing data for land-atmosphere flux monitoring. I think this manuscript is well written and the logic is pretty clear. The results are supported by the data shown here, while the authors explained the results adequately and clearly, though I have several minor questions on the current manuscript.

Reply: Thank you for the insightful comments and suggestions, which are very helpful to improve the manuscript. We totally agree that the great potential of utilizing UAS for monitoring land surface energy, water and CO2 processes. The proposed model in our study is capable of temporal interpolating the remote sensing based snapshot estimates into the continuous records. Here, we have addressed your comments point-by-point.

(1) Introduction, why not introduce more about UAS? This is kind of a highlight of this study to use UAS data. Maybe include some introductions about recent studies using UAS data on GPP/ET simulations?

Reply: Thank you for the comments and suggestions. We have revised the introduction to add more review contents about UAS, particularly on applying UAS data for GPP / ET estimation. Please see Line 13-20 on P2 in the revised clean version.

(2) Why there is no UAS observation in July, and between May 25th and June 24th? In Fig. 2(c), the fIPAR seems to change a lot during 25/May to 24/June, thus, no observation during this time period may induce simulation errors in the model.

Reply: Thank you for the comments and suggestions. We totally agree with the reviewer's opinion on the importance of collecting observations during the period from May 25th to June 24th. However, due to technical issues, we did not manage to fly UAS over that period. On the other side, this low frequency of collecting UAS observations provides an opportunity to demonstrate that the "ground truth" collected from sparse remote sensing observations can be utilized to be temporally interpolated to obtain the continuous estimates.

(3) Why ignore the observation on 24/June when interpolate the UAS data.

Reply: Thank you for the comments and suggestions. We do incorporate the observation on June 24th into the temporal interpolation, but the observation on June 24th is not from UAS. The observations on that day are from the ground PAR sensors (Table 1). Due to technical issues, we did not manage to fly UAS over that period. However, to demonstrate the potential to use the proposed SVEN model to temporally interpolate the snapshot estimates, we have incorporated the ground IPAR observations on June 24th to simulate the process of vegetation growth in this period. To make the context clearer, we have revised the sentence on L10-15 on P6.

(4) Page 16, Ln. 2-3, not fully understand "This demonstrates that SVEN is capable to : : :.", syntax error?

Reply: Thank you for the comments and suggestions. We have revised this sentence. It should be that "Such simulation accuracy demonstrates that SVEN is capable of temporal interpolating the snapshot estimates or observations between remote sensing acquisitions to form continuous daily records." Please see L11-13 on P17.

(5) Fig. 5(a), Ts, kind of systematic overestimation of Ts sim compared to Ts obs? So can the model parameters be calibrated to reduce the overestimation?

Reply: Thank you for the comments and suggestions. Yes, we can try to reduce the systematic overestimation of Ts through calibration. However, this study used multi-objective calibration procedures to consider both Ts and soil moisture. As results

shown in the Pareto Front of Figure 5, if we want to obtain better performance of simulating Ts, the performance of simulated soil moisture could be degraded. Thus, based on the Pareto front in Figure 4, we choose the parameter sets to achieve relatively good simulations for both Ts and soil moisture. To make this context clearer, we have revised the manuscript. Please find the revised sentences of L20-25 on P16.

(6) Fig 5(c), the scatterplot of SM sim and SM obs is kind of wired, which is more obvious in Fig. 7, I am wondering why? And also why not show daily results together with the half-hourly and monthly results in Fig. 7.

Reply: Thank you for the comments and suggestions. They are very helpful. There are several reasons for the moderate performance of simulating soil moisture in this study. Such model performance may be due to the uncertainty in the model parameters related to θ. As shown in supplemental Table S5, the effective parameter values of the infiltration rate for the saturated soil (Ks) and fitting parameter of the Mualem model (n) were taken as the mean values from the look-up table without considering ranges of variability (standard deviations in the table). In fact, only one parameter, SWSmax, among the three parameters related to θ dynamics was calibrated with UAS estimates of θ in the root zone. To keep the model simple and operational, the SVEN model only used one soil layer to simulate the dynamics of soil water storage (Figure 3). Such simplification could also contribute to the relatively moderate performance of simulating θ. Additionally, UAS derived θ estimates used for calibration have errors of around 13% (Wang et al., 2018a), which can induce uncertainties in the simulated time series through error propagates in the parameter calibration. Furthermore, only seven snapshot estimates from UAS were used to calibrate the model with an average frequency of 25 days during the period of fast growth. It can be expected that improving the UAS based estimates of θ and increasing the number of observations for model calibration can improve the simulation performance. To elaborate details on the simulation performance of soil moisture, we have added discussion in L3-13 on P19. Thank you for the suggestion on the figure. We agree that combining daily results together with the half-hourly and monthly results could be better. We have revised Figure 7 and combined it with Figure 5 according to the reviewer's suggestions.

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