General comments:

It is a good idea to directly estimate daily land surface-air temperature difference (Tsa) and sensible heat flux (H) using machine learning method. The manuscript explores the linkage between Tsa and its predictors and demonstrates the feasibility of establishing this linkage using machine learning. The performance of the developed product is comprehensively evaluated and superior to that of corresponding reanalysis products and satellite product. I expected to see the complete product soon.

Re: Thanks for your positive comments. The data are now publicly available for download at www.glass.hku.hk.

Point1:

How to remove the effects of spatial resolution mismatch between multi-source predictors on the estimated Tsa and H?

Response1: Thank you for your thoughtful comment. To address the issue of spatial resolution mismatch and ensure spatial consistency across datasets, we resampled all input variables to a common spatial resolution of 1 km prior to model training. Specifically, the DSR, DLW, and Rn products (originally at 0.05° resolution) and the NDVI and LAI products (originally at 250 m resolution) were resampled using the bilinear interpolation method. This approach helps to reduce potential artifacts caused by resolution differences and ensures that the predictors are spatially aligned. A detailed description of this preprocessing step has been included in lines 237-239 of Section 2.2.2 as “To maintain spatial consistency, the DSR, DLW, and Rn products, originally at a 0.05° spatial resolution, and the NDVI and LAI products, at 250 m resolution, were resampled to 1 km using the bilinear interpolation method”.

Moreover, as shown in Fig. 14, the estimated H exhibits finer spatial detail compared to FLUXCOM and ERA5-Land products, suggesting that the current resolution mismatch has a limited impact on the estimation results. In future work, we plan to further improve the model performance as higher-resolution datasets become available.

Point2:

If the estimated Tsa is used to derive the physically based model, what is the accuracy of H.

Response2: Thank you for your comment. To address this problem, we already conducted an independent validation using 3,391 samples, as presented in Table 8 of the manuscript. The results show that the use of estimated Tsa led to an RMSE of 54.08 $W \cdot m^{-2}$ (uncertainty of 5.3%), which is comparable to the result obtained from in-situ Tsa (RMSE = 51.35 W·m^{-2}). This suggests that the estimated Tsa provides reliable input for deriving H through the physical model.

Furthermore, we analyzed the performance across different land cover types. The uncertainty varied depending on land cover, with some types (e.g., CRO, GRA and SHR) even showing lower RMSEs when using estimated Tsa compared to in-situ observations. We have clarified these findings in the manuscript (see lines 810-817 and Table 8) as:

to Tsa from in-situ measurements (RMSE = 51.35 Wm^{-2}). Additionally, the uncertainty varied across different land cover types, as shown in Table 8. Utilizing Tsa from GLASS and estimated Tsa, uncertainty ranged from 6.01% to 23.1%, with the highest and lowest uncertainties observed in GLASS for FOR and SAV, yielding RMSEs of 65.72 Wm^{-2} and 59.45 Wm^{-2}, respectively. However, for certain land cover types such as CRO and GRA, lower RMSEs were noted when employing Tsa from GLASS and estimated Tsa compared to in-situ measurements, specifically. Specially, the RMSEs were 35.62 Wm^{-2} and 46.2 Wm^{-2} for CRO, and 46.14 Wm^{-2} and 45.76 Wm^{-2} for GRA. Moreover, across all five land cover types, RMSE values consistently exceeded 35 Wm^{-2} when utilizing different Tsa data sources. This could be due to the fact that the uncertainty of parameterized method in getting r_{ah} was not accounted for. Therefore, accurately estimating r_{ah} is curial in physical model and the machine learning method used in this study effectively mitigates this issue after our experiments.

Table 8. The RMSE values of daily H calculated from physical model across five land cover types using the Tsa obtained from GLASS, Estimated Tsa and in-situ measurements.

Land cover	Data source of Tsa			No. of samples
	GLASS	Estimated Tsa	sites	
CRO	35.62	46.2	46.25	385
FOR	65.72	57.46	53.4	1894
GRA	46.14	45.76	47.16	648
SAV	59.45	62.04	56.08	369
SHR	41.44	26.35	34.95	95

It is worth noting, however, that the uncertainties associated with other parameters in the physical model (e.g., aerodynamic resistance) were not considered in this study, which may contribute to the remaining errors. We have acknowledged this limitation in lines 817-818 as "This could be due to the fact that the uncertainty of parameterized method in getting r_{ah} was not accounted for.". In addition, our results show that the machine learning-based approach adopted in this study helps mitigate the impact of such uncertainties and provides more accurate H estimates overall.