

Supplementary information to “Global long-term hourly 9 km terrestrial water-energy-carbon fluxes (FluxHourly), by Qianqian Han, Yijian Zeng, Yunfei Wang, Fakhreh (Sarah) Alidoost, Francesco Nattino, Yang Liu, Bob Su

Section 1 Protocol for data processing of fluxes samples (training & testing data)

We have developed the following protocol for data processing of eddy-covariance fluxes.

(1) We first plot a figure with LE/R_n and Pre/R_n to detect outlier stations (Abramowitz et al. 2024). We aggregated half-hourly original values into annual values to calculate LE/R_n and Pre/R_n . From Figure S1, 5 stations shows abnormal values, then we checked one by one the variables. The precipitation at station AU-Rob has problems, so this station was removed. AU-Ctr and AU-Cow just have high precipitation. FR-Lq1 and FR-Lq2 has abnormal R_n .

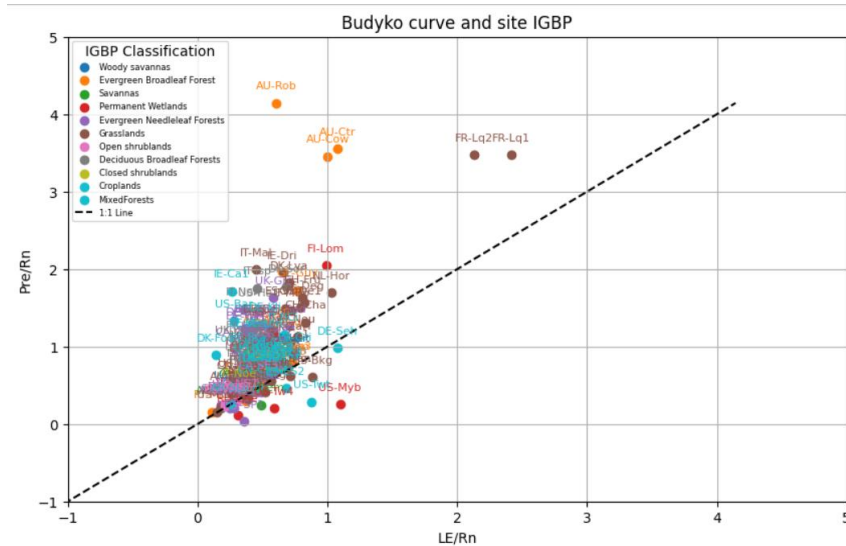


Figure S1. Distribution of site IGBP vegetation types on a Budyko style plot, using in-situ fluxes for all 170 sites.

(2) Use quality control of LE and H to keep only measurements, removing interpolated values.

(3) When $Precipitation > 0$ & $LE > (R_n - H)$, then we reject in-situ LE , H , implying that the measured LE has been contaminated by precipitation event.

(4) For R_n , only IT-LMa, FR-Lq1, FR-Lq2, IT-CA1, US-SP2 has strange values. These outliers were removed manually.

(5) Limit STEMMUS-SCOPE output LE and H based on the rule devised by (Wang et al. 2025).

If $G > 300$, then $G = 300$; if $G < -200$, then $G = -200$.

If $H < -250$, then $H = -250$; if $R_{in} > 10$ & $H > R_n$, then $H = R_n - G$, $LE = 0$; if $R_{in} \leq 10$ & $H > 100$, then $H = R_n - G$, $LE = 0$.

If $R_{in} > 10$ & $LE > 1.26 R_n$, then $LE = R_n - G - H$; if $R_{in} \leq 10$ & $LE > 100$, then $LE = R_n$, $H = -G$.

(6) Perform optimal interpolation for R_n , LE , H , and keep STEMMUS-SCOPE output for G , SIF685, SIF740 and GPP.

(7) Apply the Savitzky–Golay (S-G) filter on the seven (optimally interpolated) variables, then use the optimal interpolated values to subtract the S-G filtered result to get residuals.

(8) Calculate the standard deviation (std) based on the residuals data in two ways: a) daily std; b) use residuals in all stations in the same IGBP type and in the same hemisphere to calculate std for the same timestep in all years (Fig S1).

(9) Split data into 4 parts: training, testing_random, testing_time, testing_space. Station JP-SMF in training, testing_random and testing_time does not have in-situ Rn, station US-PFa in testing_space does not have in-situ Rn. These two stations were filtered out.

(10) Convert local time to UTC time.

(11) Resample from half-hourly to hourly.

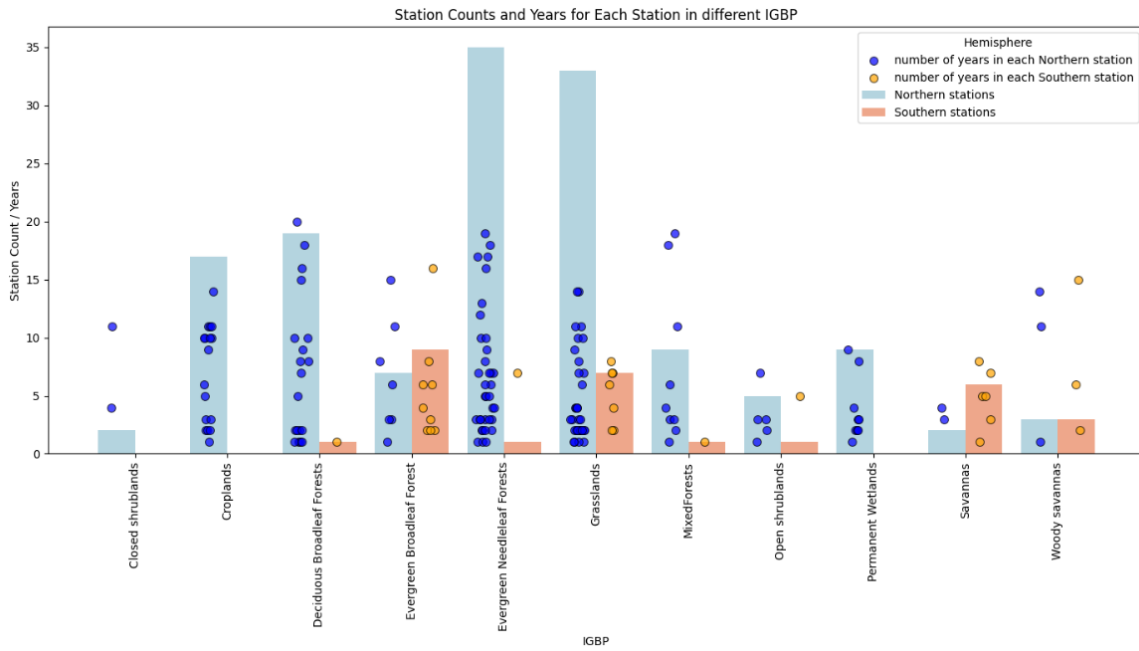
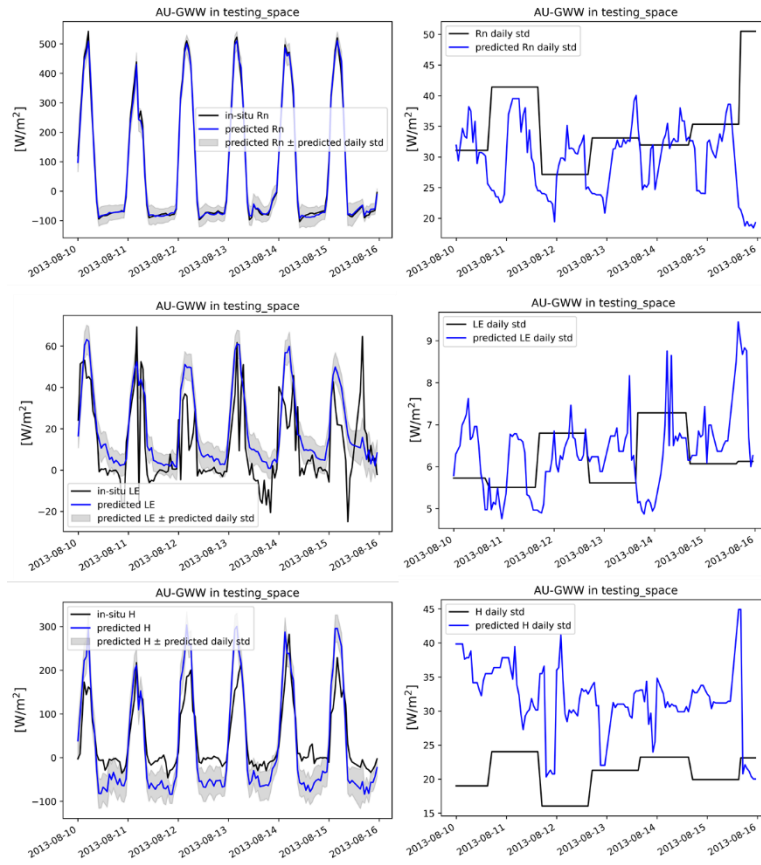


Figure S2. Stations statistics over each IGBP land cover class and each hemisphere

Because there is both diurnal and seasonal changes in fluxes, we first applied the Savitzky–Golay (S-G) filter on the optimal interpolation result to remove such patterns. Then we used the difference between the optimal interpolation result and the S-G filtered result to get residuals, from which we calculated std in two ways. This std can be understood as data fluctuation. We first used this std to train a Random Forest algorithm, then we used this trained Random Forest to upscale std to gridded scale for each grid and timestep. We call this std uncertainty and calculated it in two ways as follows.

- Daily std from the residuals (using 48 values with half-hourly data).
- Std from the same time step of residuals from different stations within one IGBP vegetation type.



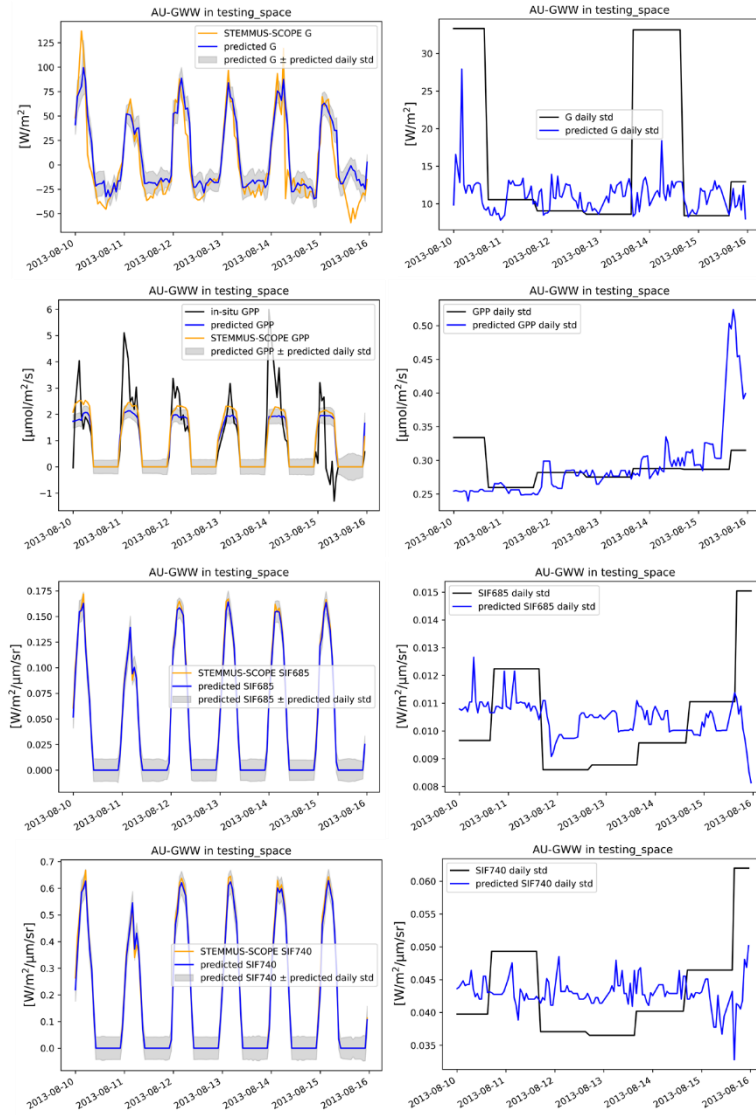
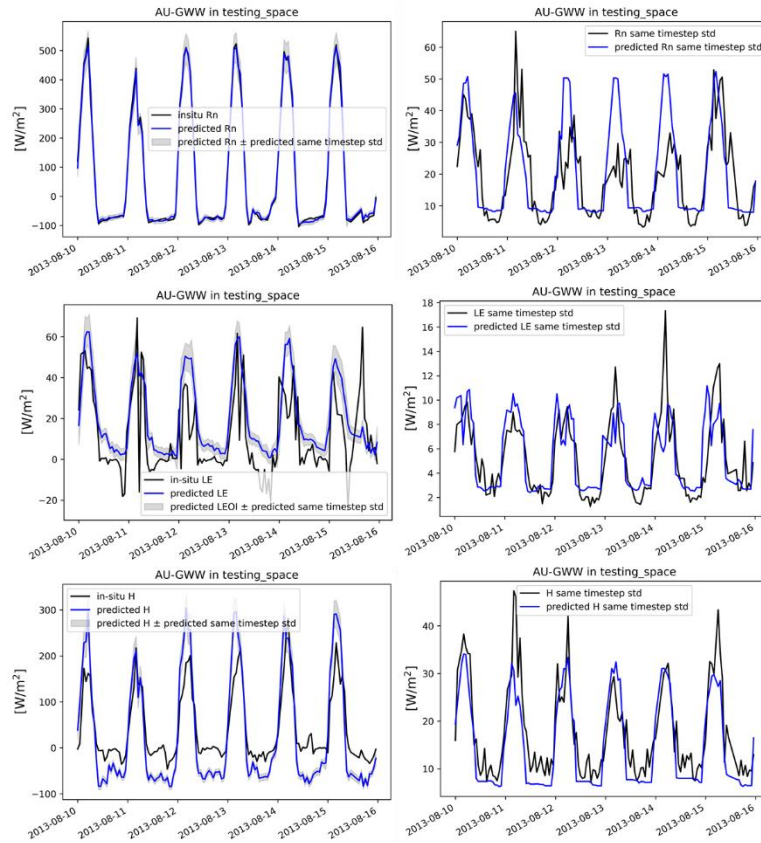


Figure S3. In-situ fluxes, predicted fluxes, and predicted daily std on 7 variables in AU-GWW station (right figures are calculated std and predicted std)



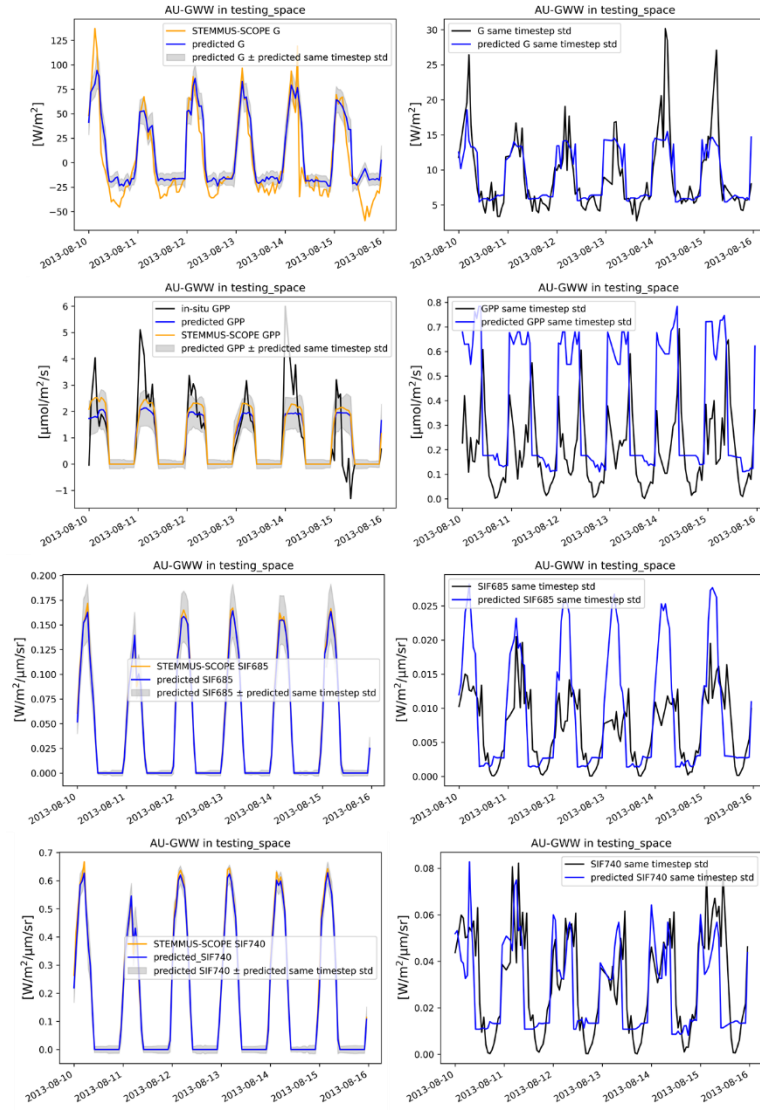


Figure S4. In-situ fluxes, predicted fluxes, and predicted same timestep std on 7 variables in AU-GWW station (right figures are calculated std and predicted std)

Section 2. Comparison on testing_space set on monthly & hourly scale

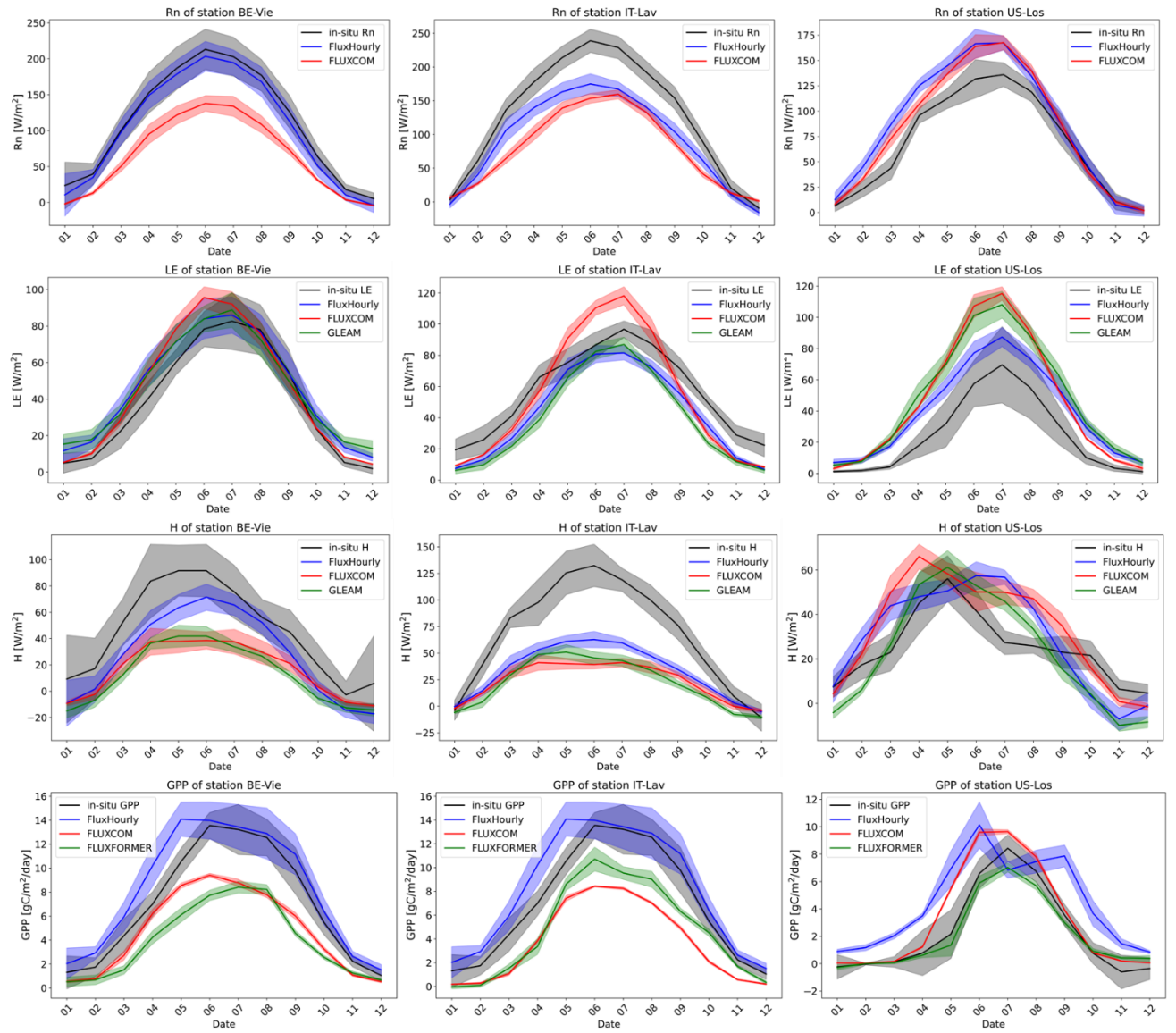
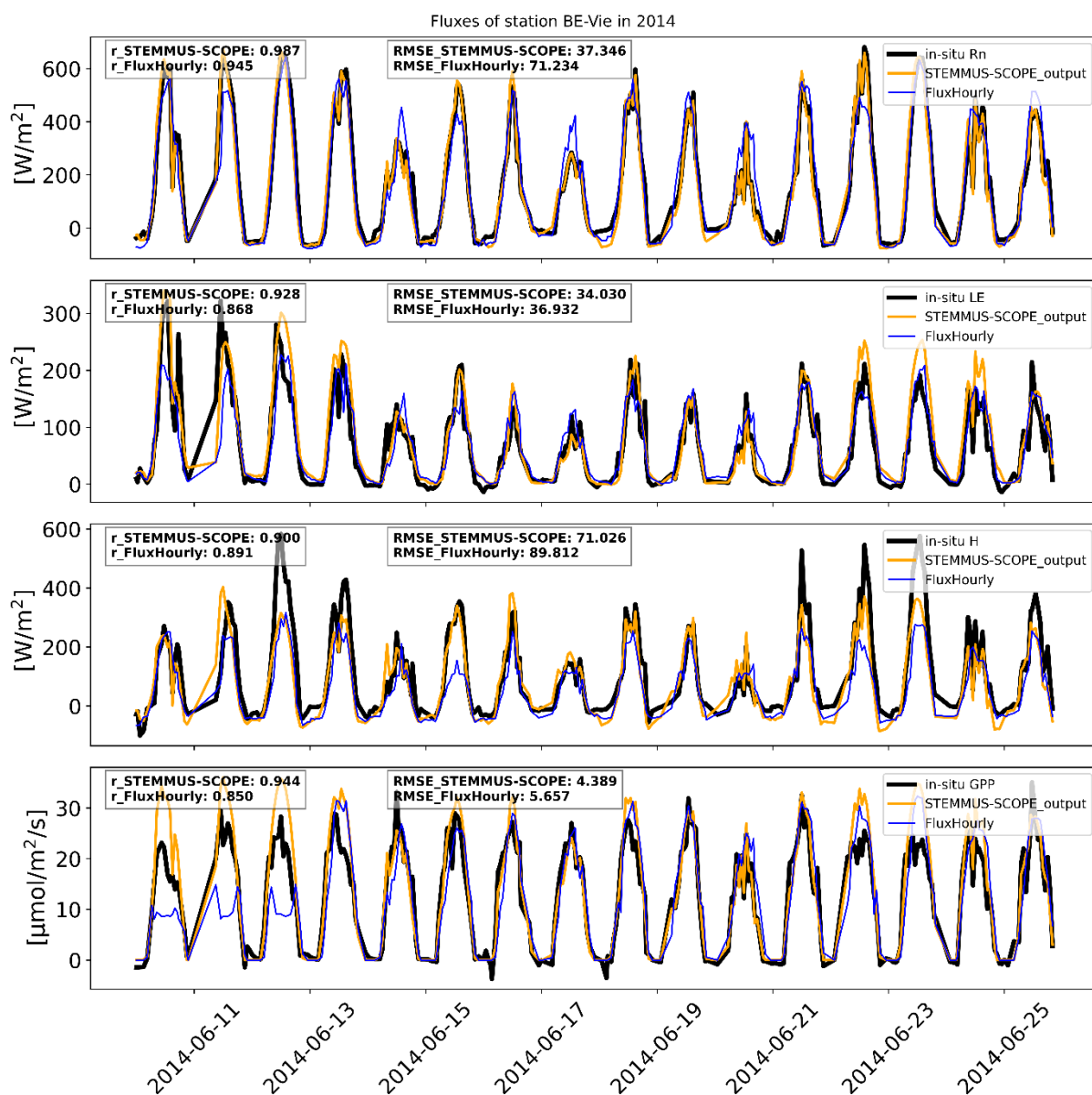
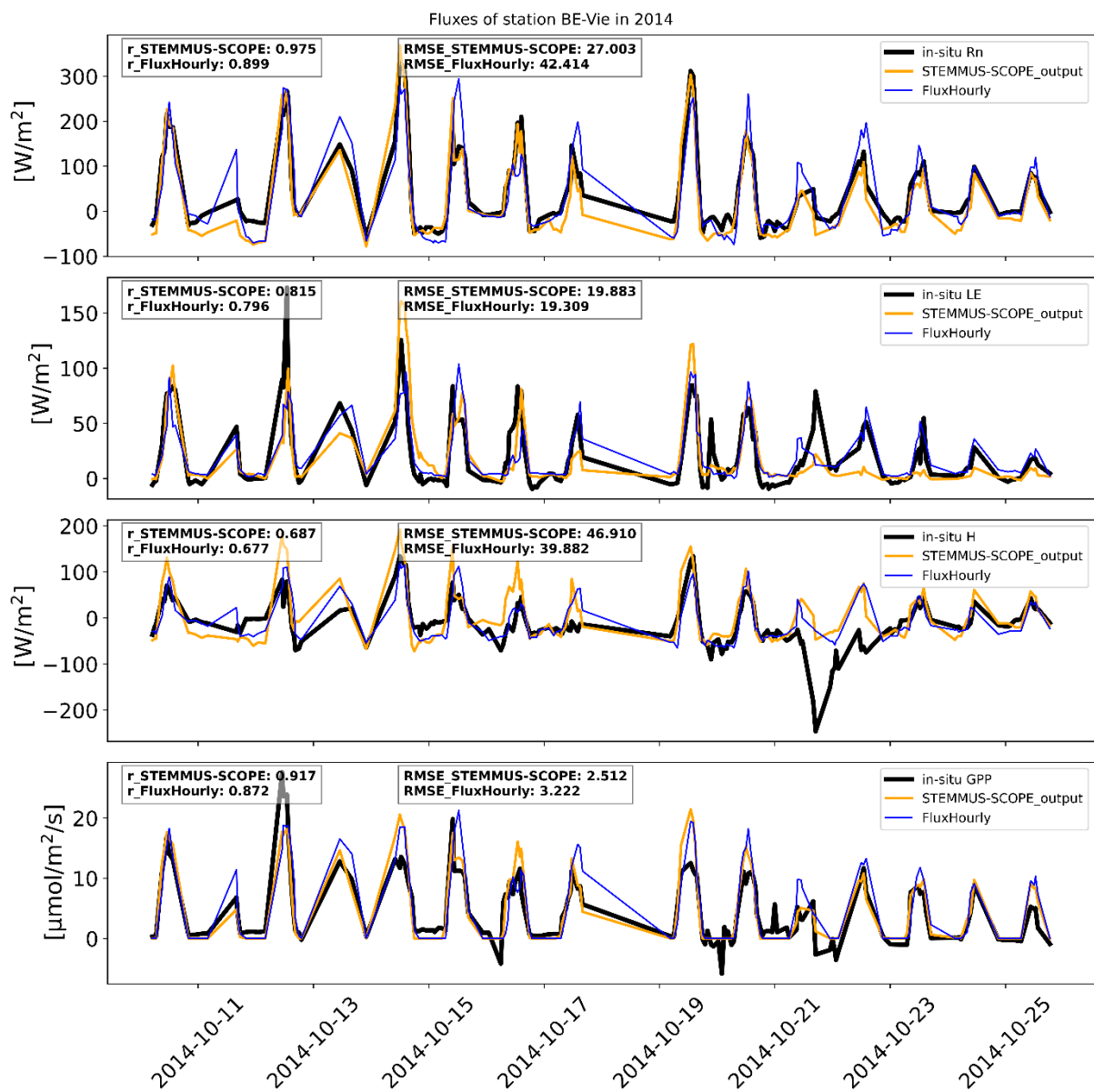
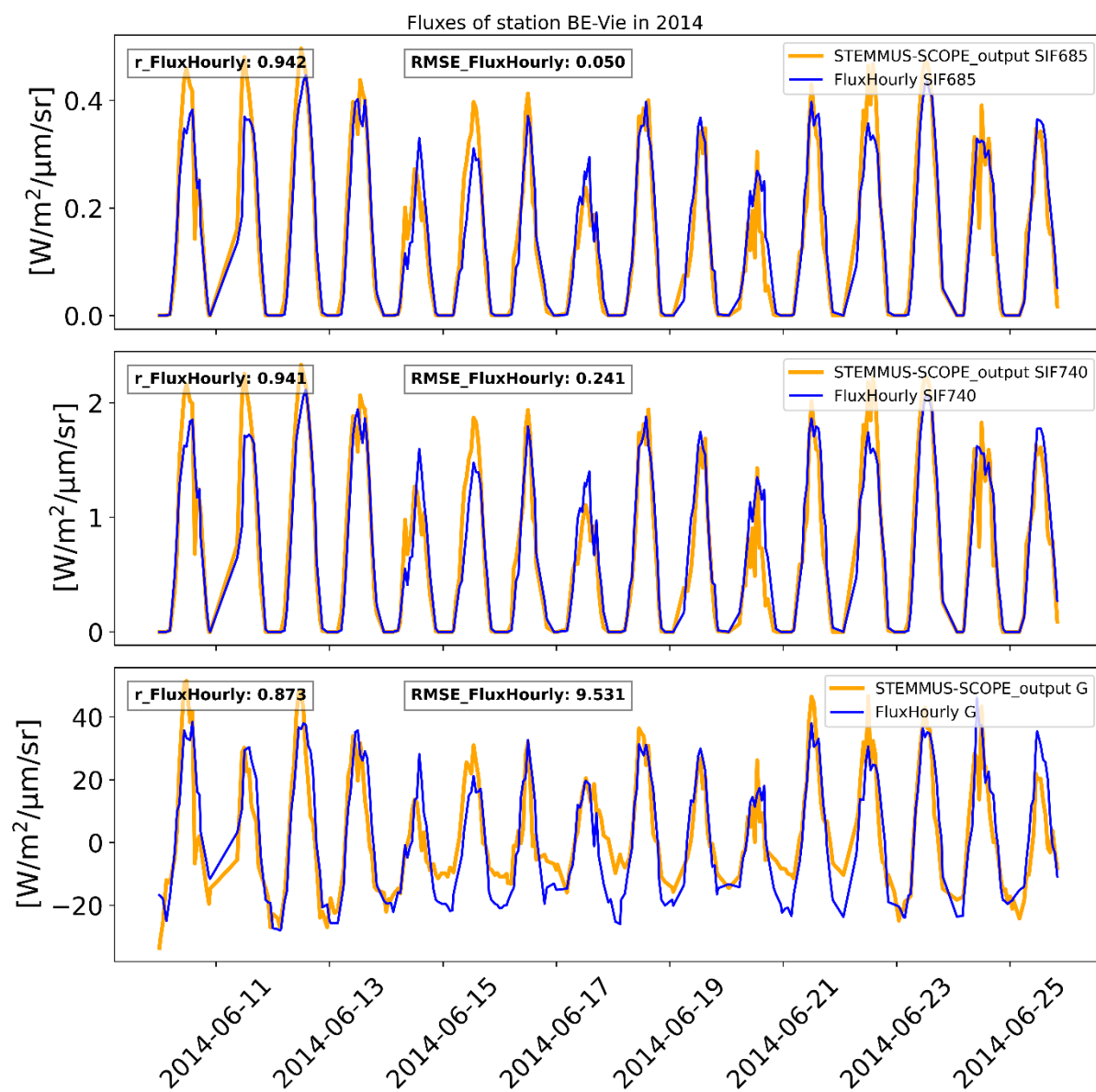


Figure S5. Monthly Rn, LE, H, GPP from in-situ, FluxHourly, FLUXCOM, GLEAM, FLUXFORMER in station BE-Vie, IT-Lav, US-Los







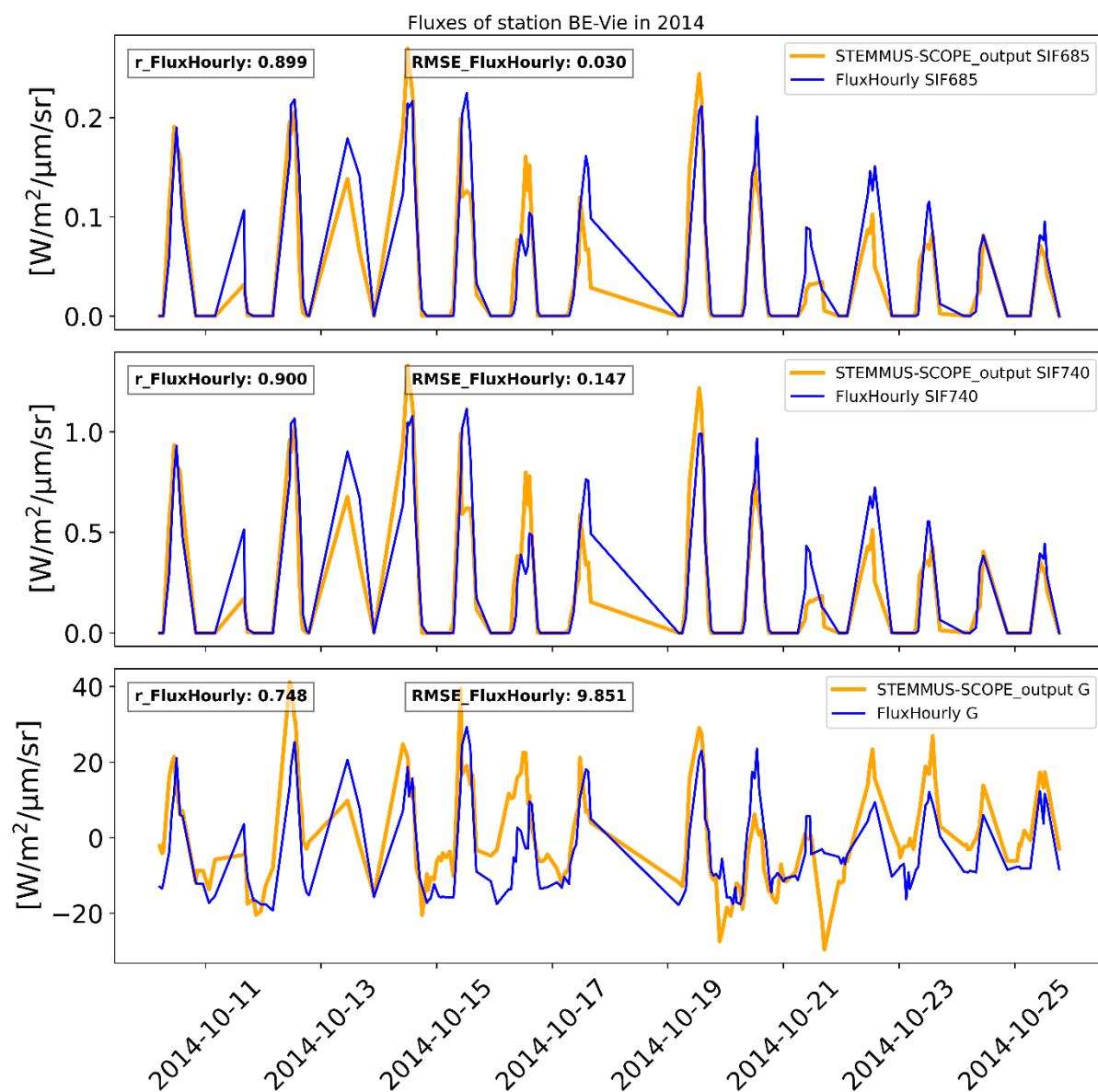
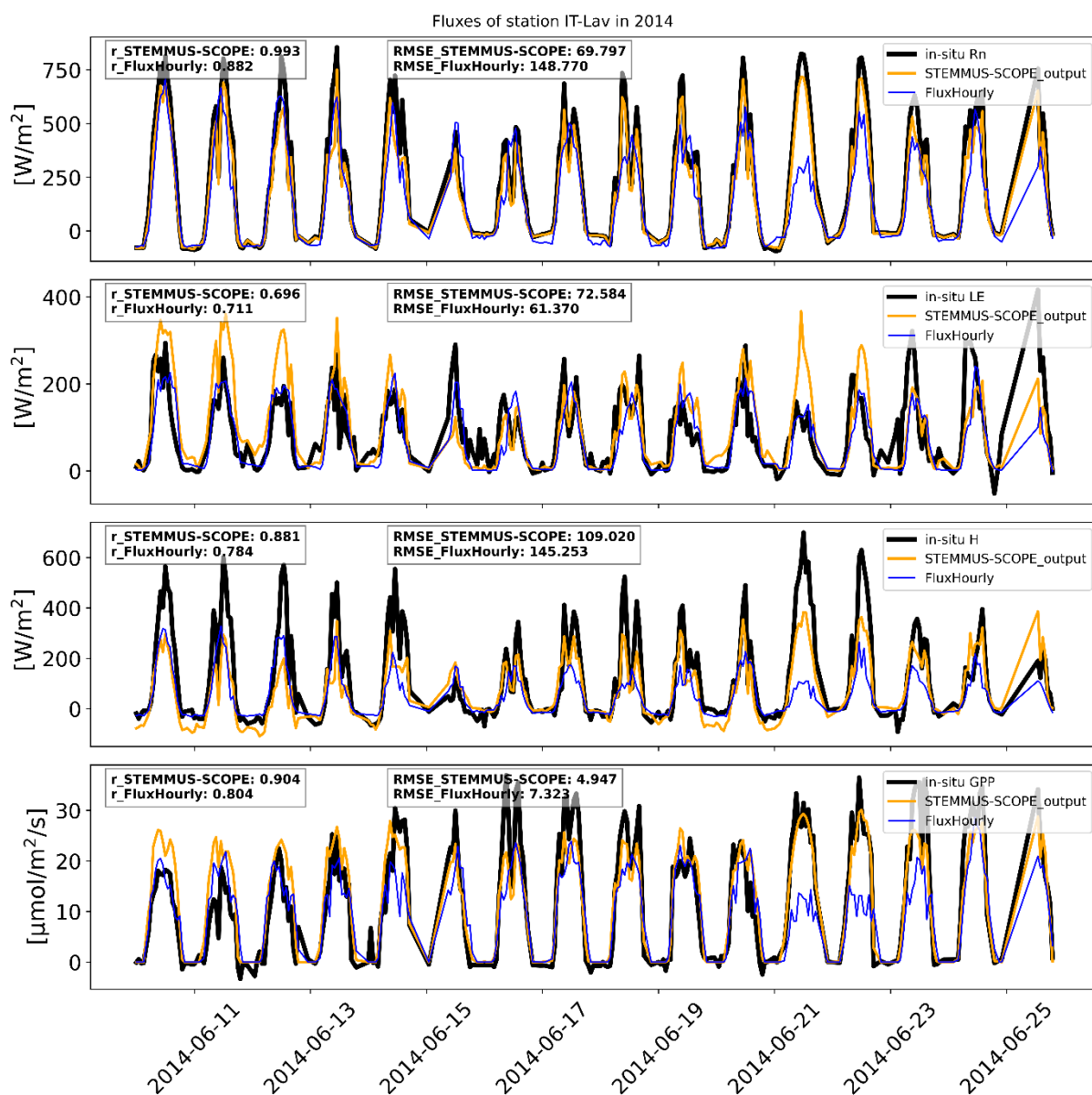
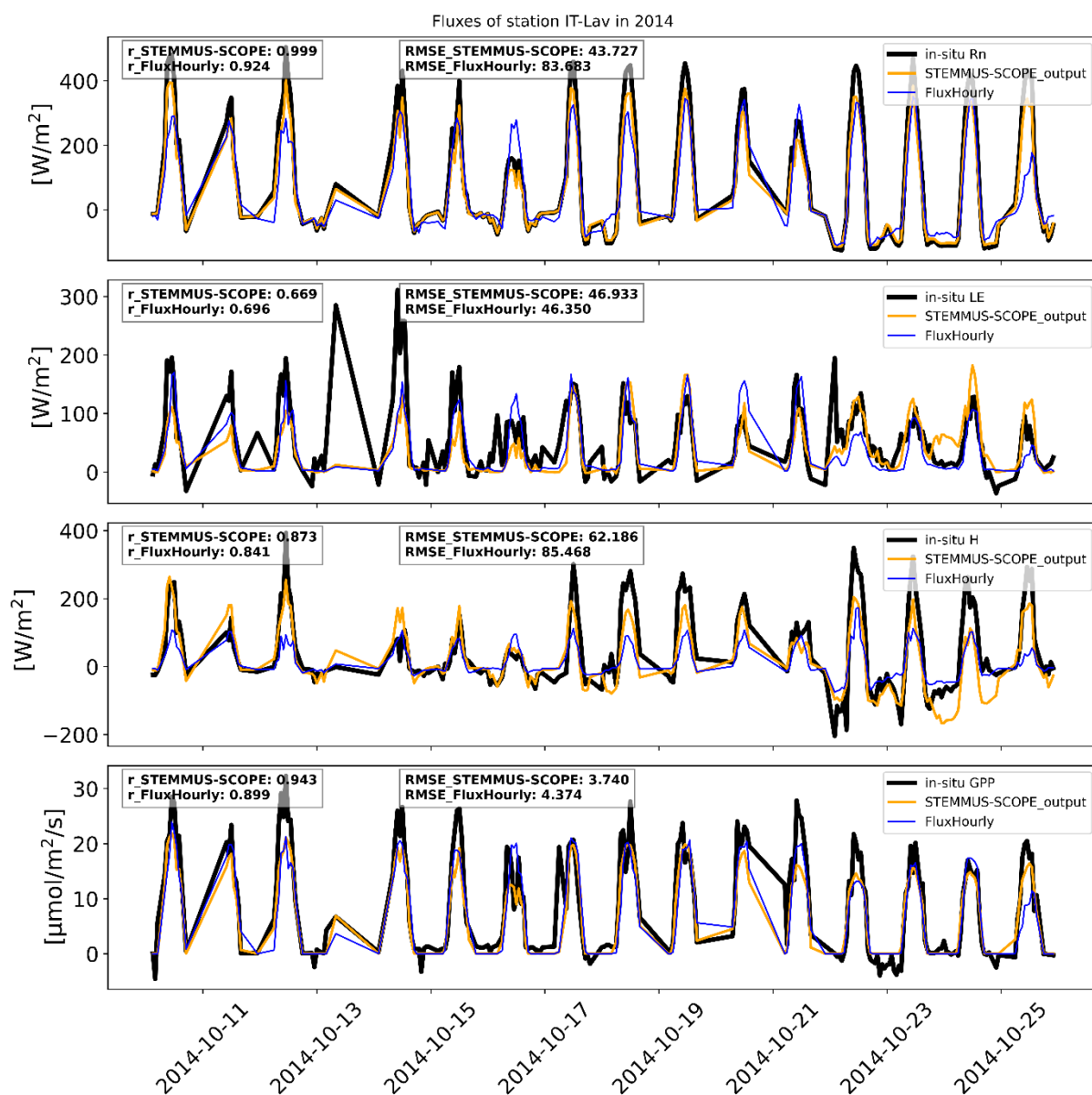
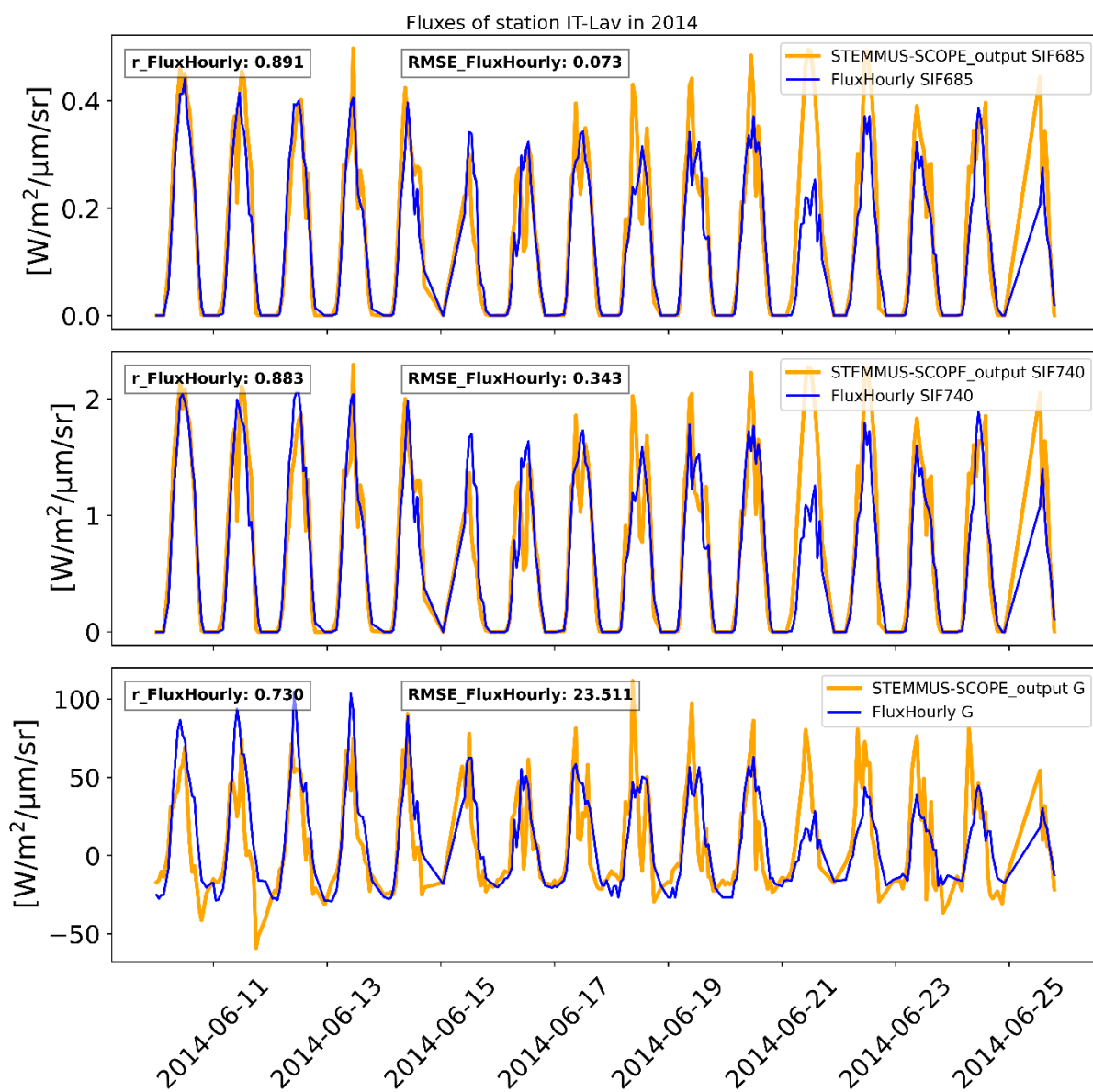


Figure S6. Rn, LE, H, G, GPP, SIF685, SIF740 in BE-Vie, June and Oct (time is in local time)







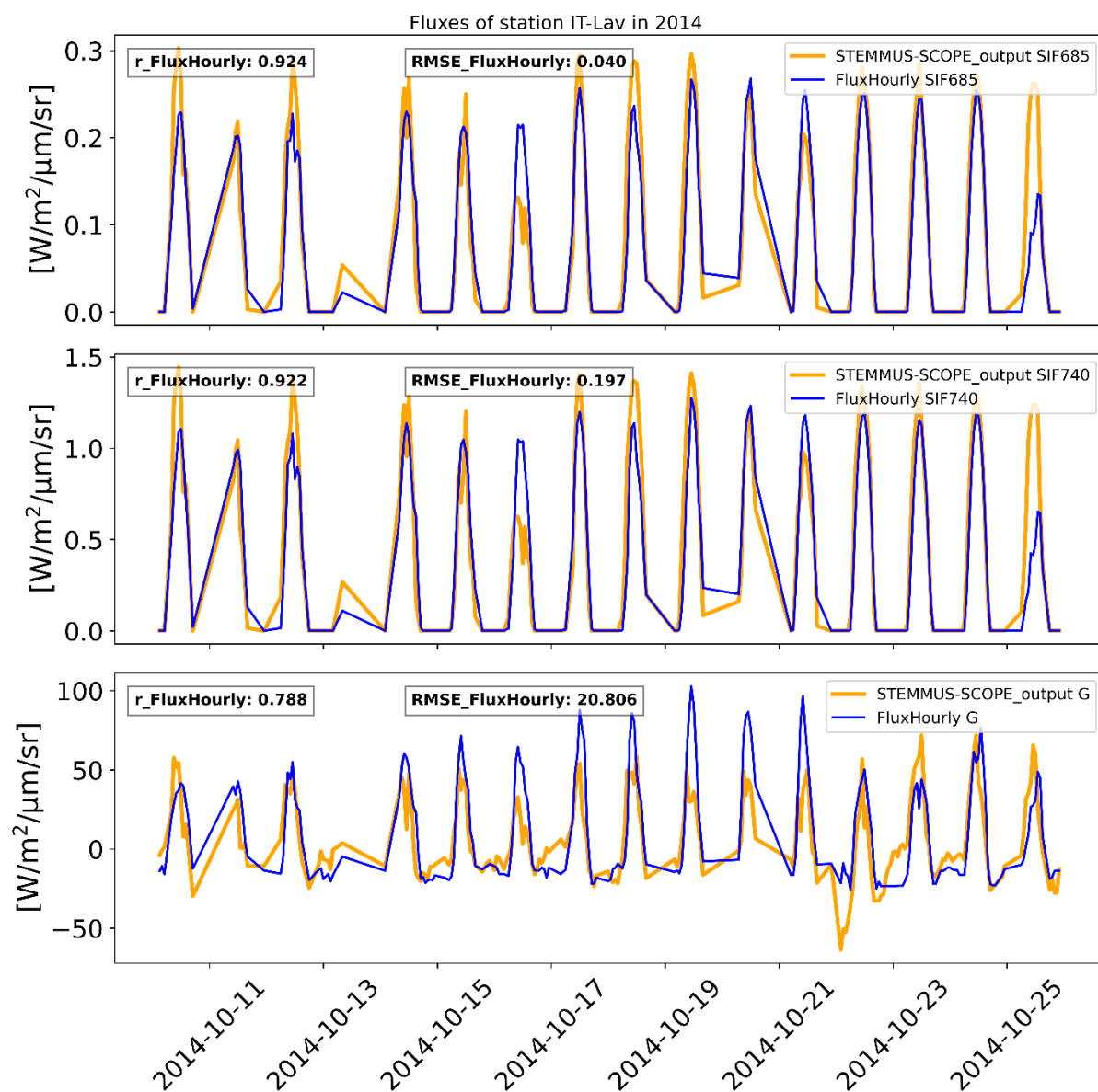
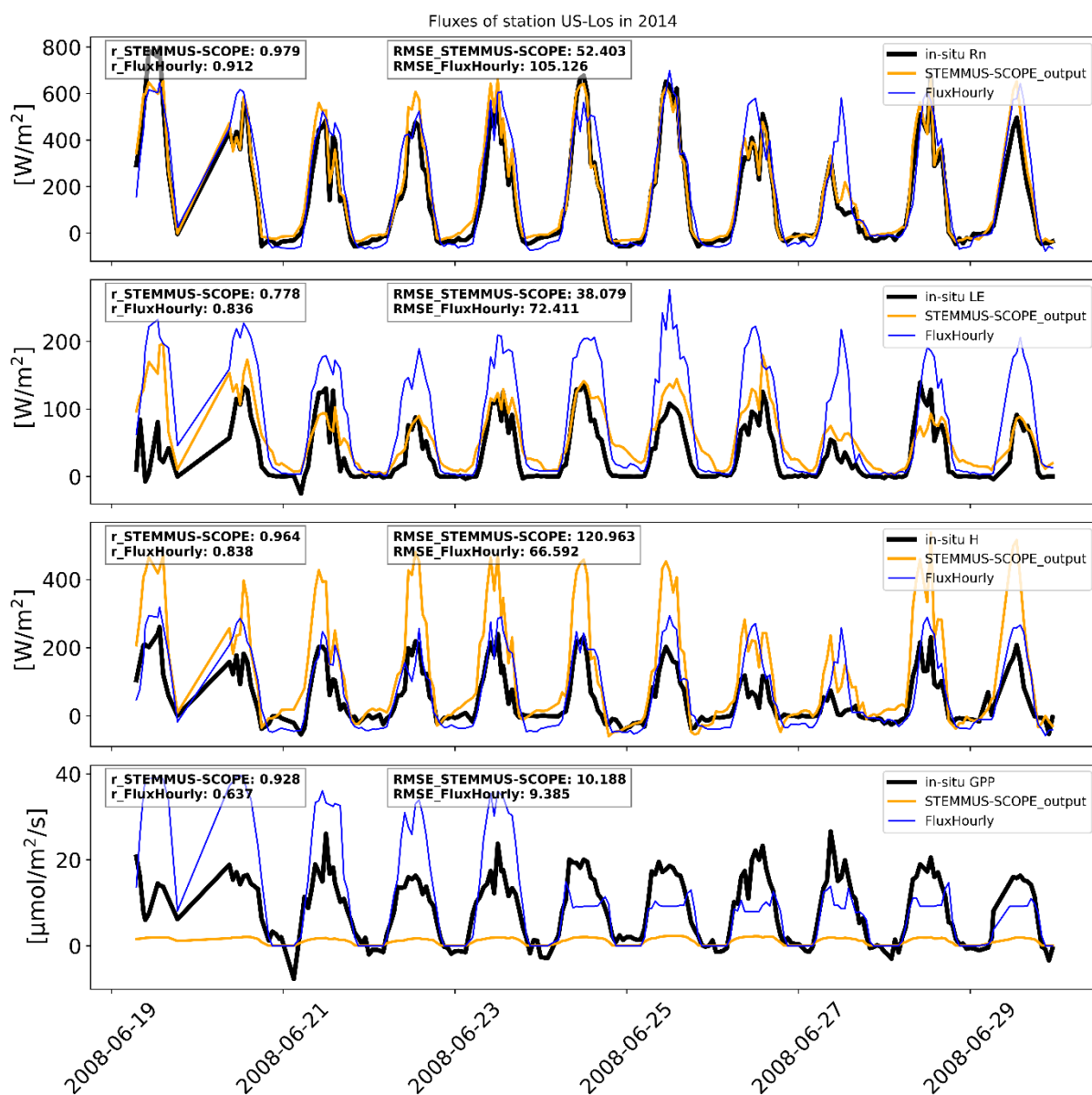
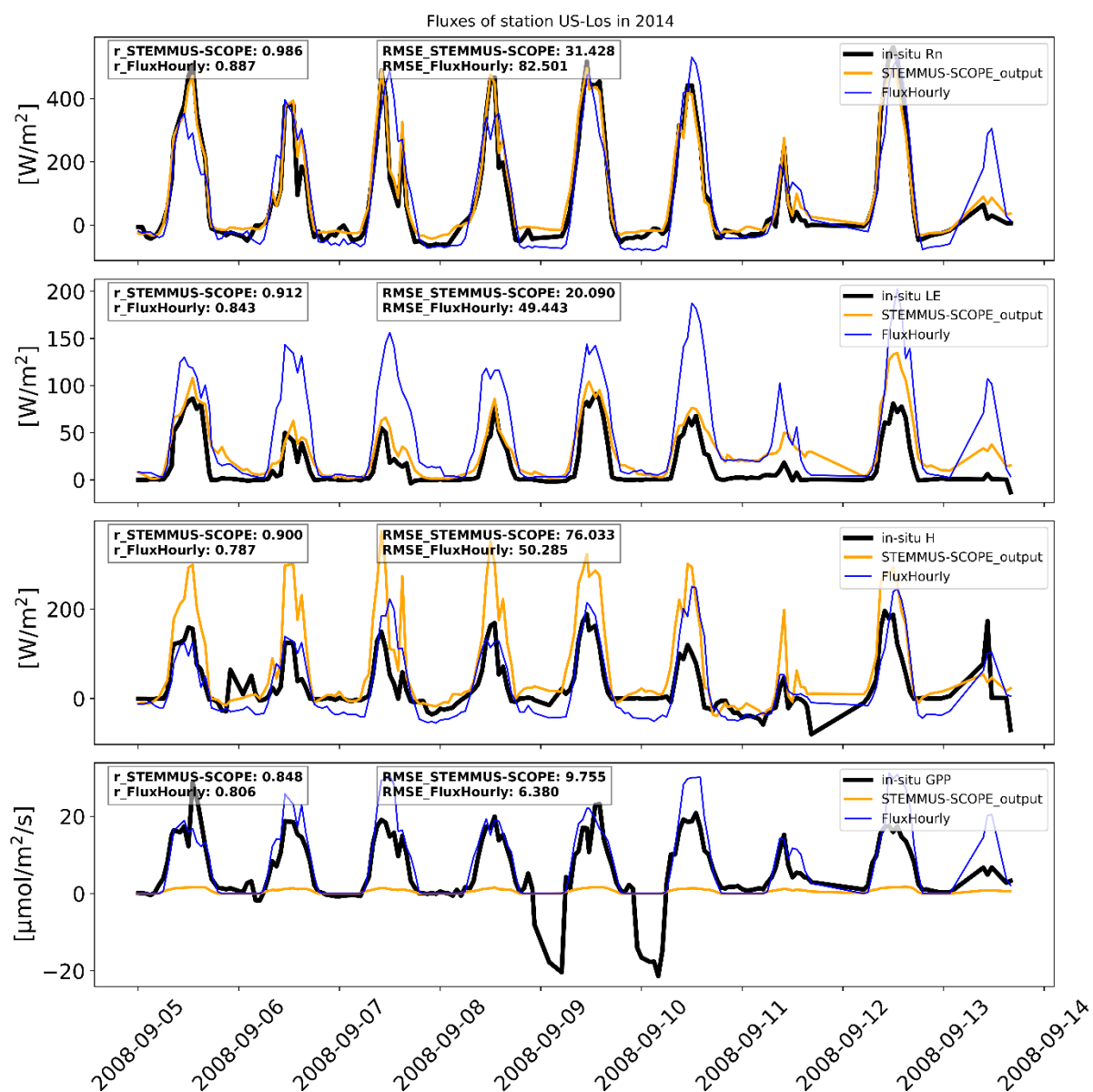
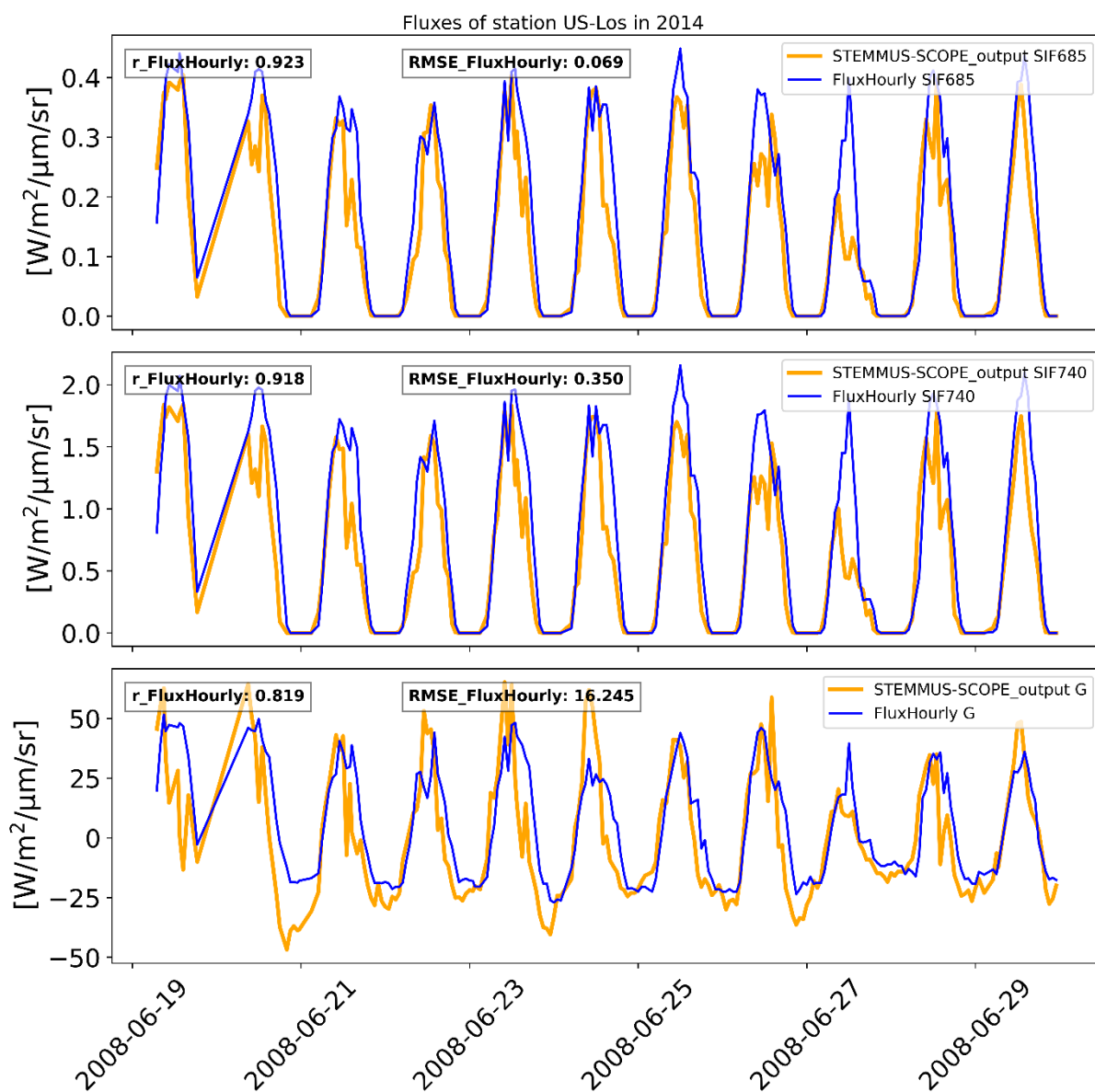


Figure S7. Rn, LE, H, G, GPP, SIF685, SIF740 in IT-Lav, June and Oct (time is in local time).







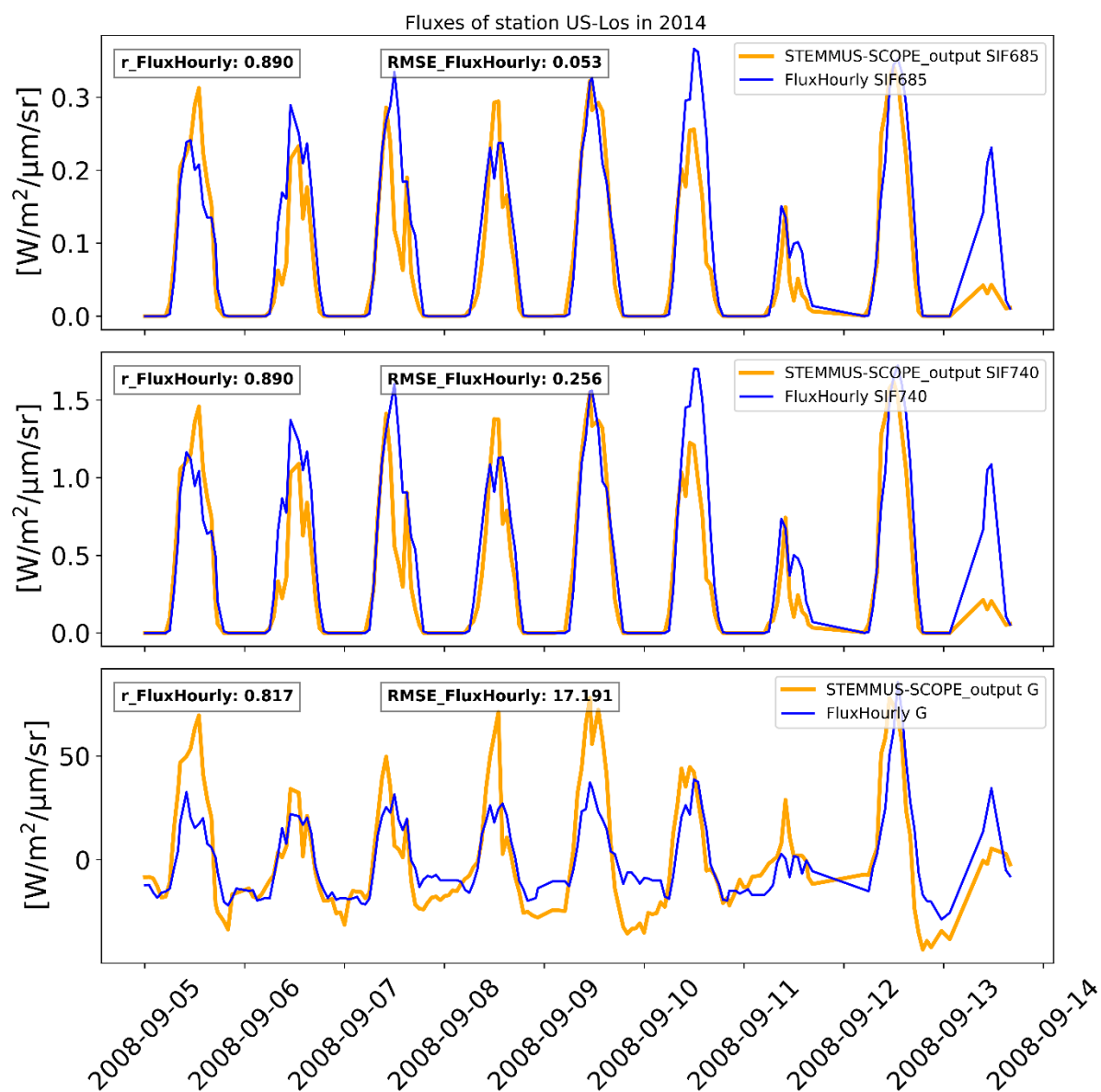
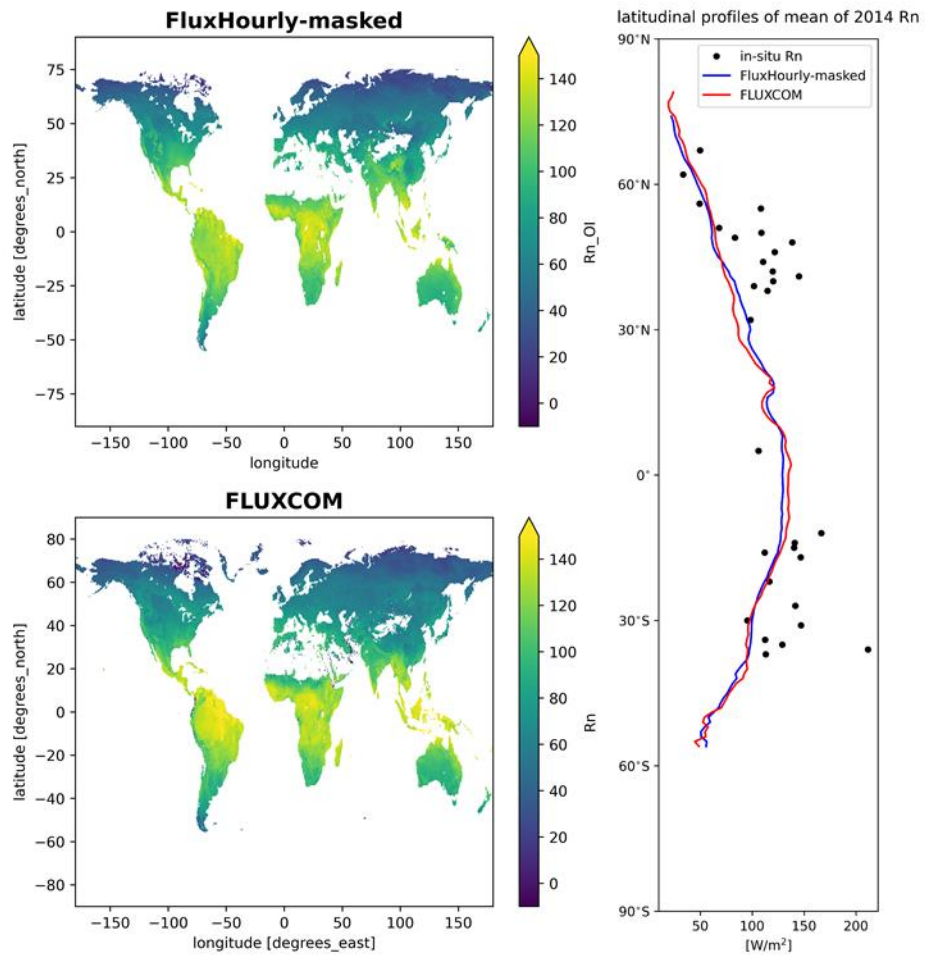
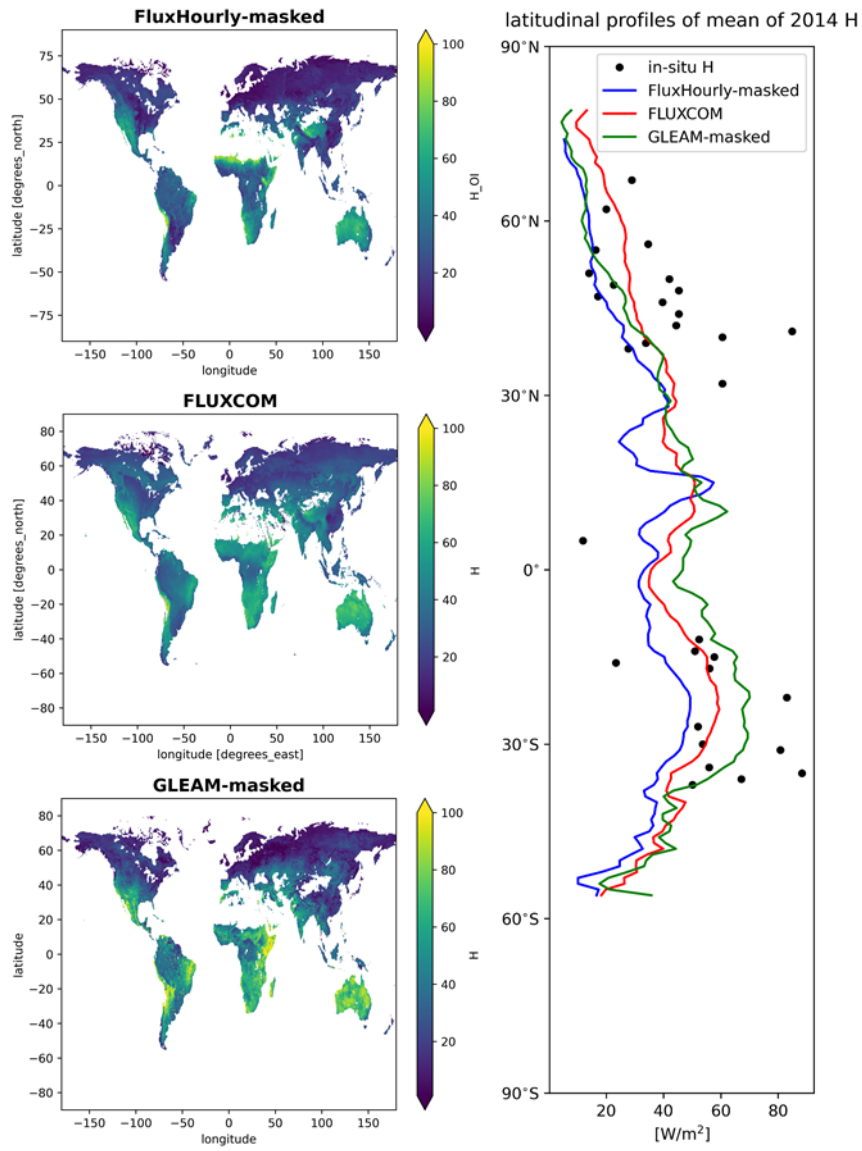
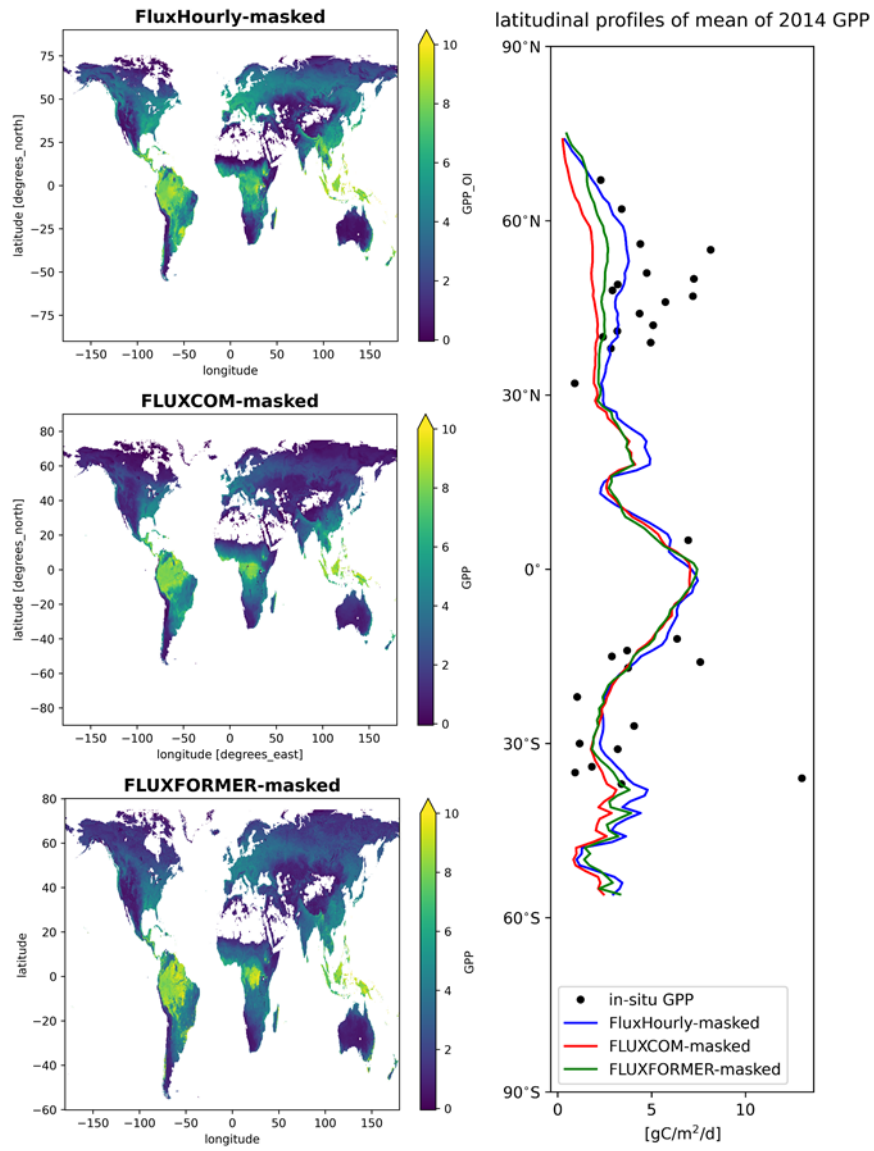


Figure S8. Rn, LE, H, G, GPP, SIF685, SIF740 in US-Los, June and Sep (time is in local time).

Section 3. Inter comparison with existing flux datasets on spatial pattern







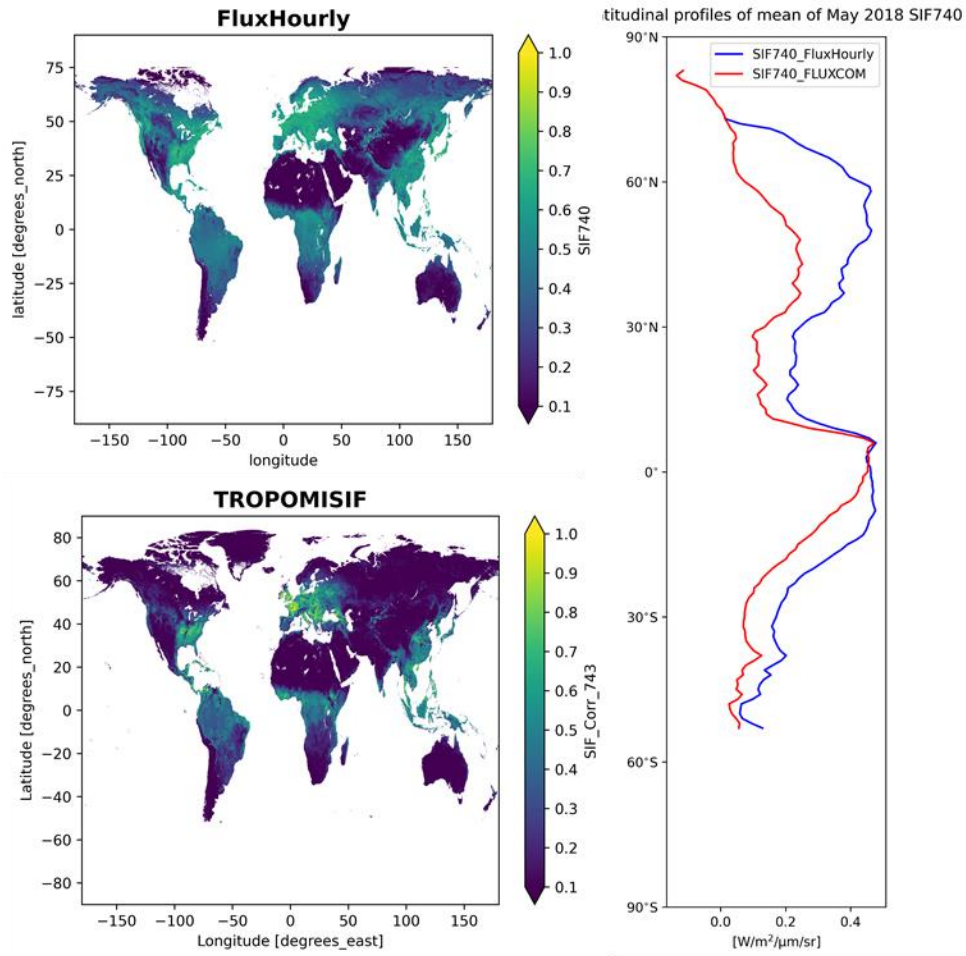


Figure S9. Annual mean of predicted hourly 9 km Rn, H, GPP, SIF740 by RF_OI, and FLUXCOM, GLEAM, FLUXFORMER (only for GPP) in 2014 and TROPOMISIF (only for SIF740 in May 2018). Note: GPP is masked by both FLUXCOM and FLUXFORMER as both datasets has missing values. Rn and H is masked by FLUXCOM.

Section 4. Diurnal patterns and seasonal changes: Rn, H, G

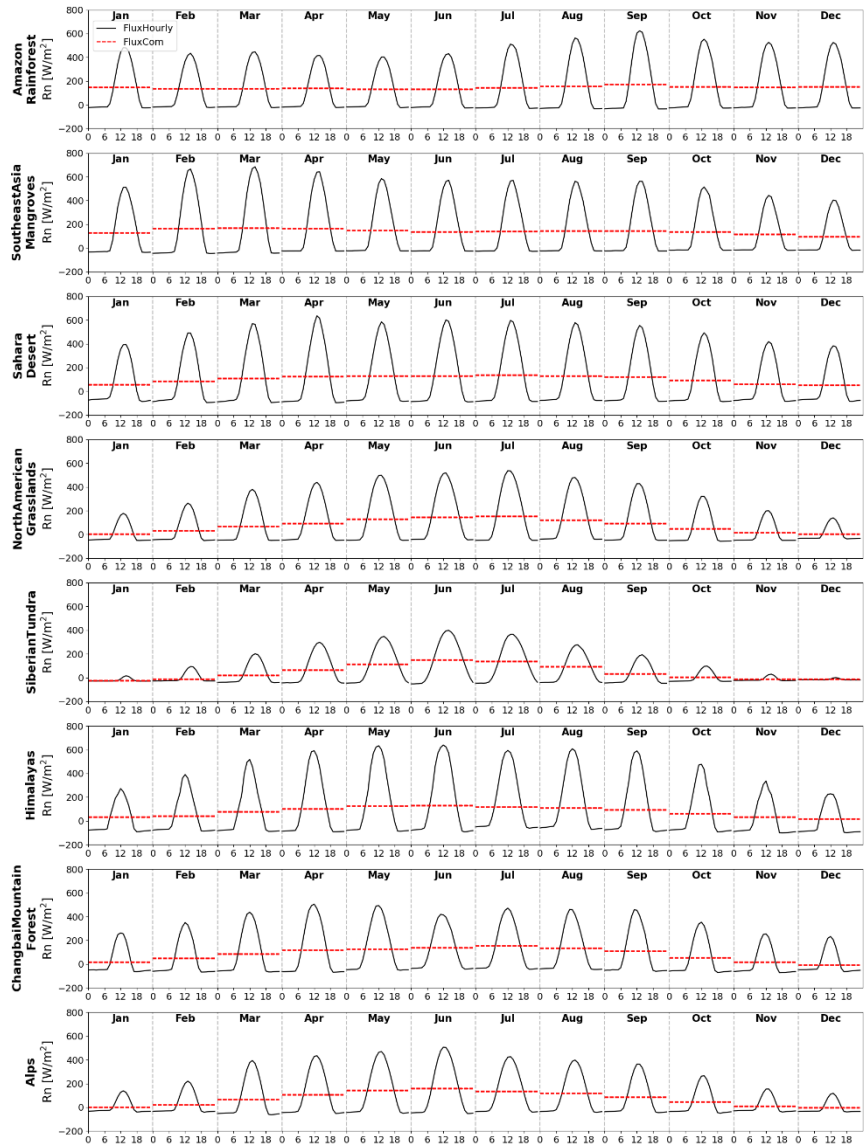


Figure S10. Diurnal cycles of Rn for 8 regions for each month of the year, where each panel refers to a region. The data is converted to local time zone.

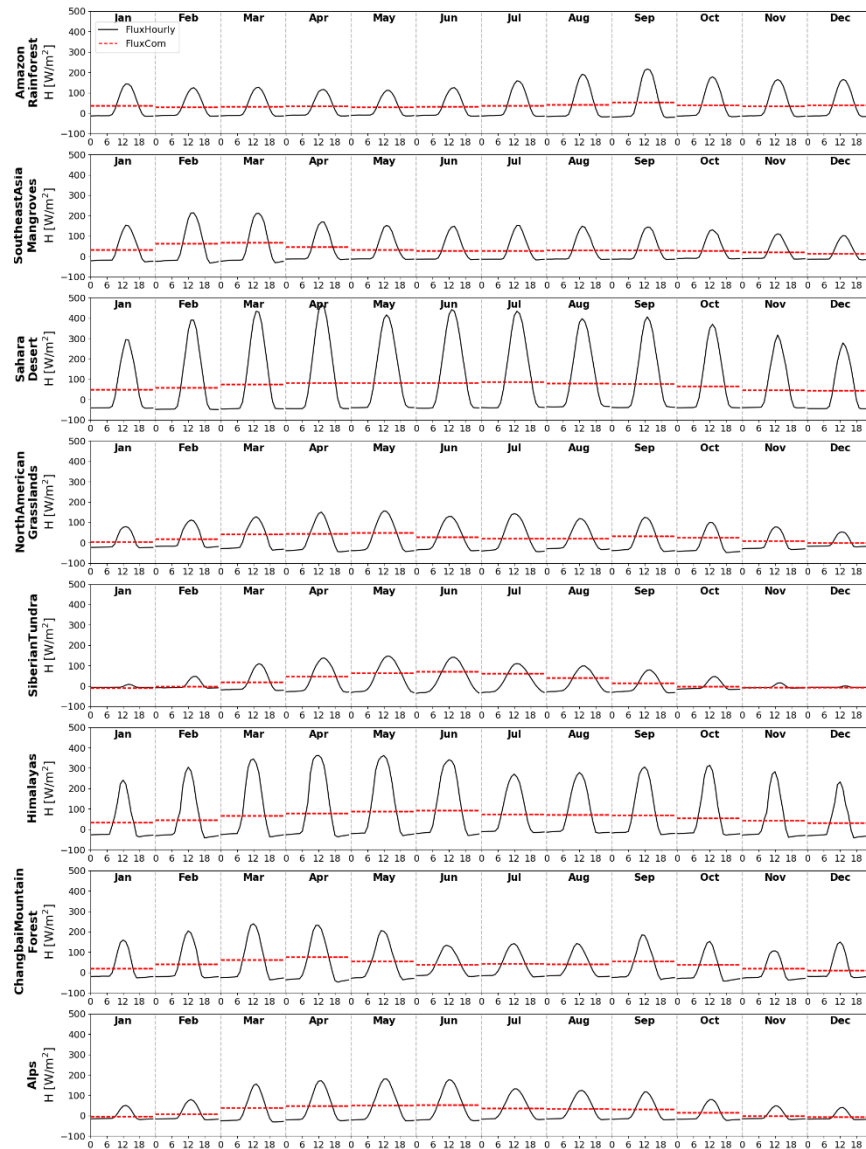


Figure S11. Diurnal cycles of H for 8 regions for each month of the year, where each panel refers to a region. The data is converted to local time zone.

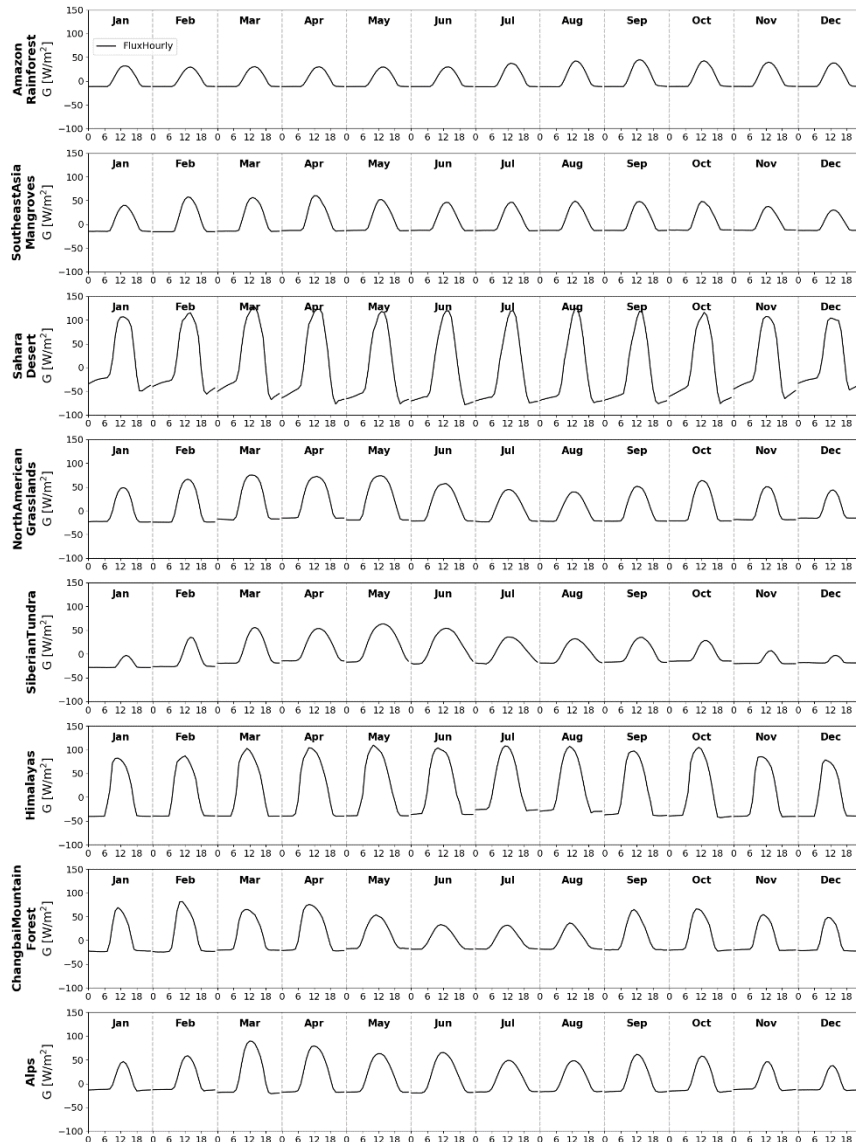


Figure S12. Diurnal cycles of G for 8 regions for each month of the year, where each panel refers to a region. The data is converted to local time zone.

Section 5. Köppen–Geiger (KG) climate classification full name

Af – tropical rainforest climate,
 Am – tropical monsoon climate,
 Aw – tropical wet and dry or savanna climate,
 BSh – hot semi-arid climate,
 BSk – cold semi-arid climate,
 BWh – hot desert climate,
 BWk – cold desert climate,
 Cfa – humid subtropical climate,
 Cfb – temperate oceanic climate,
 Cfc – subpolar oceanic climate,
 Csa – hot-summer Mediterranean climate,
 Csb – warm-summer Mediterranean climate,
 Csc – cold-summer Mediterranean climate,
 Cwa – monsoon-influenced humid subtropical climate,
 Cwb – subtropical highland climate,
 Cwc – cold subtropical highland climate,
 Dfa – hot-summer humid continental climate,

Dfb – warm-summer humid continental climate,
Dfc – subarctic climate,
Dfd - extremely cold subarctic climate,
Dsa - mediterranean-influenced hot-summer humid continental climate,
Dsb – mediterranean-influenced warm-summer humid continental climate,
Dsc – mediterranean-influenced subarctic climate,
Dwa – monsoon-influenced hot-summer humid continental climate,
Dwb – monsoon-influenced warm-summer humid continental climate,
Dwc – monsoon-influenced subarctic climate,
Dwd – monsoon-influenced extremely cold subarctic climate.
EF – ice cap climate.
ET – tundra climate.

References

Abramowitz, G., Ukkola, A., Hobeichi, S., Cranko Page, J., Lipson, M., De Kauwe, M.G., Green, S., Brenner, C., Frame, J., & Nearing, G. On the predictability of turbulent fluxes from land: PLUMBER2 MIP experimental description and preliminary results. *Biogeosciences*, 21, 5517-5538, 2024
Wang, Y., Zeng, Y., Alidoost, F., Schilperoort, B., Song, Z., Yu, D., Tang, E., Han, Q., Liu, Z., Peng, X., Zhang, C., Retsios, B., Girgin, S., Lü, X., Zuo, Q., Cai, H., Yu, Q., Van der Tol, C., & Su, Z. A physically consistent dataset of water-energy-carbon fluxes across the Soil-Plant-Atmosphere Continuum. *Sci. Data*2025