Water Resources Resarch

Supporting Information for

Uncertain Benefits of Using Remotely Sensed Evapotranspiration for Streamflow Estimation–Insights from a Randomized, Large-Sample Experiment

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Table 1. List of different studies using ETRS for streamflow estimation and their findings.

References	ET_{RS} products	Stuy area/Model/Calibration technique	Key findings
Kunnath-Poovakka et al. (2016)	• CMRSET (ET) • AMSR-E (Soil moisture)	• Study area: 11 catchments in eastern Australia • Model: Simplified Australian Water Resource Assessment – Landscape model (AWRA-L) • Calibration technique: Shuffled Complex Evolution Uncertainty Algorithm with 15 different objective functions by combining the Root Mean Square Error and the correlation coefficient for ET and soil moisture	• Streamflow prediction in catchments with low average runoff can be improved using reliable ET products.
Demirel et al. (2018)	• Actual evapotranspiration (AET) based on MODIS data under cloud-free conditions	• Study area: The Skjern river basin in Denmark. • Model: mesoscale Hydrologic Model • Calibration technique: 7 behavioral simulations from the Shuffled complex evolution approach with the model performance criteria is the KGE for streamflow and SPAEF for AET. Three calibration scenarios: streamflow only, AET only, and both streamflow and AET	• Comparable model performance for streamflow in the case of streamflow calibration only and in the case of using both streamflow and AET for model calibration. • Much poorer model performance for streamflow for the case of AET-calibration only compare to the case of streamflow-calibration only.
Parajuli et al. (2018)	• SEBAL	• Study area: Big Sunflower River Watershed in Northwestern, Mississippi. • Model: SWAT • Calibration technique: Best parameter from SUFI-2 approach, three calibration scenarios: streamflow only, ET only, and both streamflow and ET	The streamflow-only and ET-only modeling scenarios showed equally good model performances for streamflow, followed by the flow-ET calibration scenario.
Rajib et al. (2018)	• MOD16A2	• Study area: Pipestem Creek watershed in North Dakota, United States • Model: modified SWAT • Calibration technique: SUFI-2 approach, 4 calibration scenarios: (M1) streamflow only, (M2) streamflow with biophysical parameters, (M3) streamflow and ET (lumped approach), (M4) streamflow and ET (distributed approach). KGE was used as the performance index for both streamflow and ET	• Including biophysical parameters (calibration scenario M2) slightly improve the model performance for ET and streamflow compared to that of M1 • Model performance for ET and streamflow in case of calibration scenario M3 increases compared to that of M1 and M2 for the validation increases • Model performance for ET and streamflow during the calibration period in the case of calibration scenario M3 is comparable with

References	ET_{RS} products	Stuy area/Model/Calibration technique	Key findings
			that of calibration scenarios M1 and M2. Model performance (M3) is the best for the validation period (among 4 calibrations scenarios)
Gui et al. (2019)	• NDVI-based ET algorithm	• Study area: 208 watersheds in the U.S. • Model: Xinanjiang model • Calibration technique: Three calibration scenarios: (1) streamflow only, (2) both streamflow and using both streamflow and ETRS for the entire period of record, (3) same as (2) but using ET_{RS} only during rainless periods. The optimal parameter set was determined by combining different optimization approaches.	• Lower model performance (mean NSE across 208 watershed) for streamflow was observed in calibration scenarios 2 and 3 compared to that of scenario 1.
Dembele et al. (2020)	• Twelve different ET_{RS} products	• Study area: Volta River basin, West Africa • Model: mesoscale Hydrologic Model (mHM) • Calibration technique: (1) Streamflow only and (2) 48 calibration scenarios as a combination of four distinct multivariate calibration strategies (the basin-average, pixel-wise, spatial bias accounting, and spatial bias-insensitive) using streamflow and ET.	• Adding ET_{RS} into the calibration scheme slightly tradeoff model performance for streamflow to improve the performance of the terrestrial water storage, temporal dynamics of soil moisture and spatila patterns of soil moisture.
Jiang et al. (2020)	• MOD16 ET	• Study area: 28 basins in the U.S. • Model: VIC • Calibration technique: Shuffled Complex Evolution, two calibration scenarios: (1) streamflow only, (2) spatial distributed ET calibration	• ET calibration yields better or similar streamflow performance in 29% of the basins compared to that from streamflow-based calibration,
Zhang et al. (2020)	• PLM-ET	• Study area: 222 basins in Australia • Model: Xinanjang and SIMHYD • Calibration technique: Genetic algorithm, four calibration scenarios: (1) streamflow-only, (2) ET only, (3) and (4) both ET and streamflow but with different objective functions.	• Model performance for streamflow in case of including ET_{RS} in the calibration (scenarios 2-4) calibration only is not as good as calibration against Q, especially in drier regions
Sirisena et al. (2020)	GLEAM ET	• Study area: four basins in the Chindwin River basin, Myanmar • Model: SWAT model • Calibration technique: three calibration scenarios: streamflow only, (2) ET only, and (3) both streamflow and ET	• In the single variable calibration scenarios (1 and 2), model performance for the targeted variable increases but for the other variable decreases. • Calibration that targets both ET and streamflow, acceptable model

References	ET_{RS} products	Stuy area/Model/Calibration technique	Key findings
			performance was achieved with both variables
Willem Vervoort et al. (2014)	• MOD16A3	• Study area: four catchments in New South Wales, Australia • Model: IHACRES • Calibration technique: shuffled complex evolution, three calibration scenarios: (1) streamflow only, (2) ET only, and (3) both streamflow and ET, results were compared with the case of using parameter regionalization and using ET_{RS} as direct model input.	• Calibration with ET and streamflow does not improve streamflow skills. Calibration against only ET is the worst, even worse than the parameter regionalization approach.

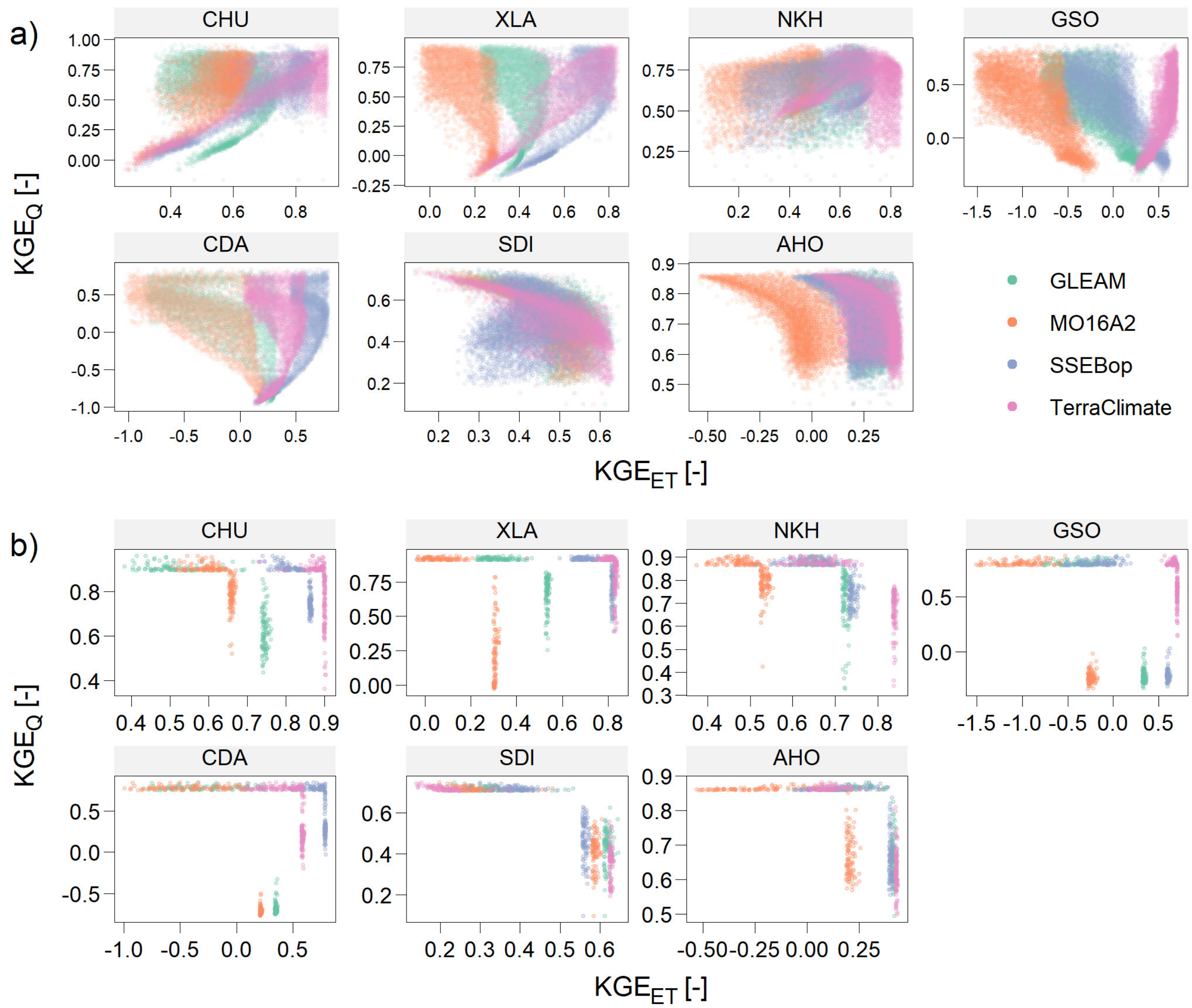

Figure S1. Distribution of KGE scores for ET (KGE_{ET}) versus KGE scores for streamflow (KGE_Q) for each catchment and ET_{RS} product. Panel a shows the scores of all 10,000 models and panel b shows the scores of models that are in either the top 100 for KGE_Q or the top 100 for KGE_{ET}. Note the large differences in x- and y-axis scales among the catchments.

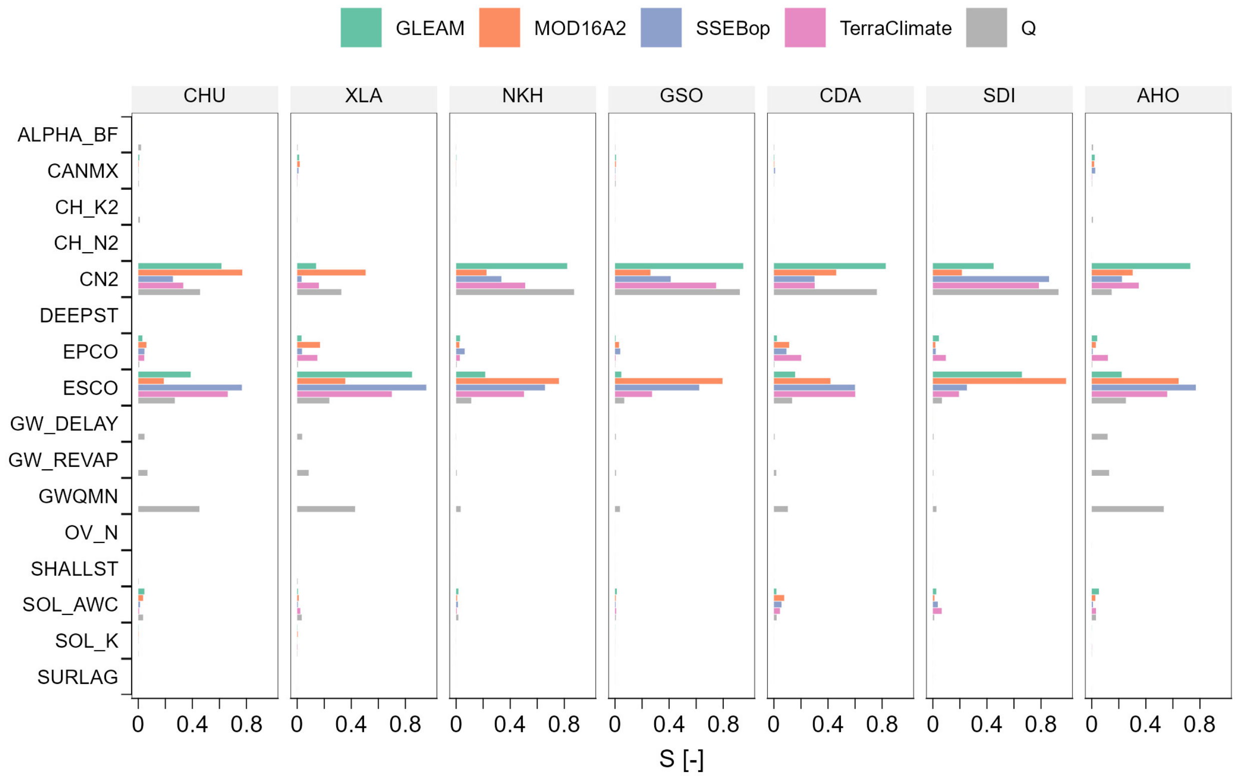

Figure S2. Total sensitivity (S) of streamflow and ET with respect to each model parameter in each catchment and variable (ET_{RS} product and observed streamflow Q). The objective function used in this analysis is the $KGE_{ET} + KGE_Q$.

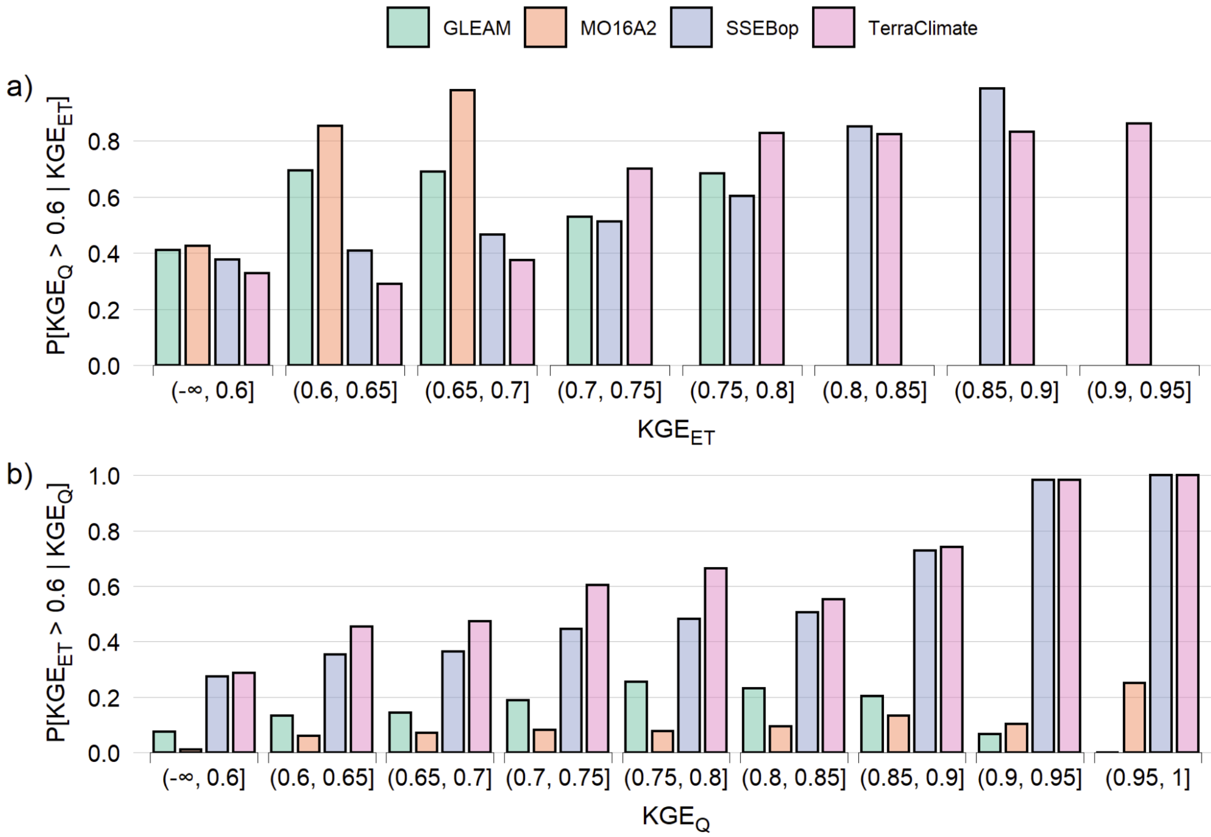

Figure S3. a) Conditional probability of having a good streamflow score ($KGE_Q > 0.6$) given a range of values of KGE_{ET}. b) Conditional probability of having a good ET score ($KGE_{ET} > 0.6$) given a range of values of KGE_Q.