Advancing Evapotranspiration Estimation in Arizona: Evaluating the Performance of Priestley-Taylor Jet Propulsion Laboratory and Penman-Monteith Models Using Flux Tower Observations

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1. Introduction

- Precise Evapotranspiration (ET) estimation supports effective water resource management.
- The PT–JPL model estimates ET by incorporating biophysical constraints into the Priestley–Taylor equation.
- In contrast, the Penman–Monteith (PM) model integrates aerodynamic and surface resistance parameters.
- These fundamental differences in formulation and parameterization can lead to varying model performance across different environmental conditions.

Objective:

- This study evaluates the performance of the PT–JPL and PM models over five flux tower sites in Arizona by comparing model outputs with observed data using statistical metrics and distribution analyses.

2. Materials and Methods

Study Area:

- Arizona's climate is characterized by arid to semi-arid conditions, with high temperatures, limited annual precipitation, and strong seasonal variability

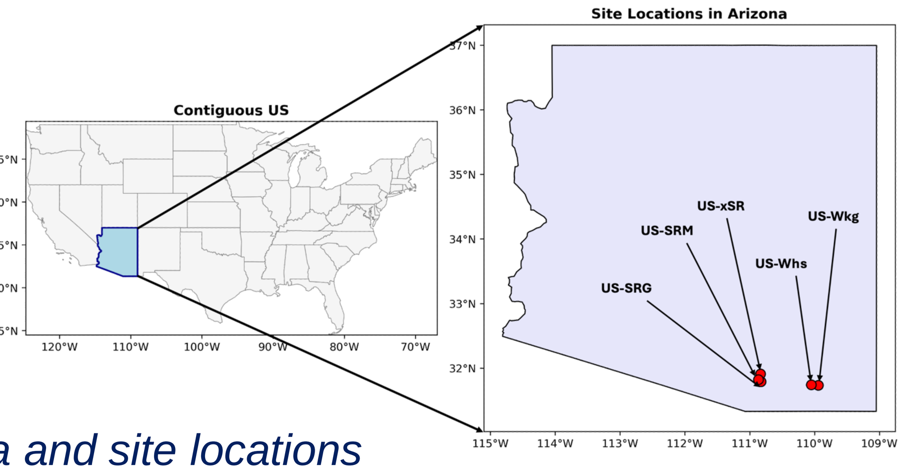


Fig. 1. Study area and site locations

Datasets:

Dataset Type	Model	Source	Product Name	Spatial Resolution	Temporal Resolution
Air Temperature	PM and PT-JPL	AORC	AORC Version 1.1	800 m	01-hourly
Air Pressure	PM and PT-JPL				
Wind Speed	PM				
Specific Humidity	PM and PT-JPL				
Downward Shortwave/Longwave	PM and PT-JPL				
Precipitation	PM				
LAI	PM	MODIS	MOD15A2H level 4	500 m	08-daily
Emissivity	PM and PT-JPL		MOD21A2 Version 6.1	1 km	
Land Cover	PM		MCD12Q1 Version 6.1 (LC_Type1)	500 m	yearly
Albedo	PM and PT-JPL	ERA5 Land	ERA5 Land	9 km	01-hourly
NDVI	PT-JPL	MODIS	MOD13Q1	Point based	16-daily
Observed ET	PM and PT-JPL	AmeriFlux	AmeriFlux	Point based	0.5-hourly

Table 1. Dataset used in this study to develop and validate both models

ET Modeling:

- ET was estimated using two approaches: the PT–JPL model and PM model.
- Both model outputs were compared to observed ET using metrics including Kling–Gupta Efficiency Skill Error (KGEss), coefficient of determination (R^2), and Root Mean Square Error (RMSE).

Kolmogorov–Smirnov (K–S) Test:

- This non-parametric test quantifies the maximum absolute difference (D) between the empirical cumulative distribution functions (CDFs) of the observed ET and the ET estimates from each model.

3. Results

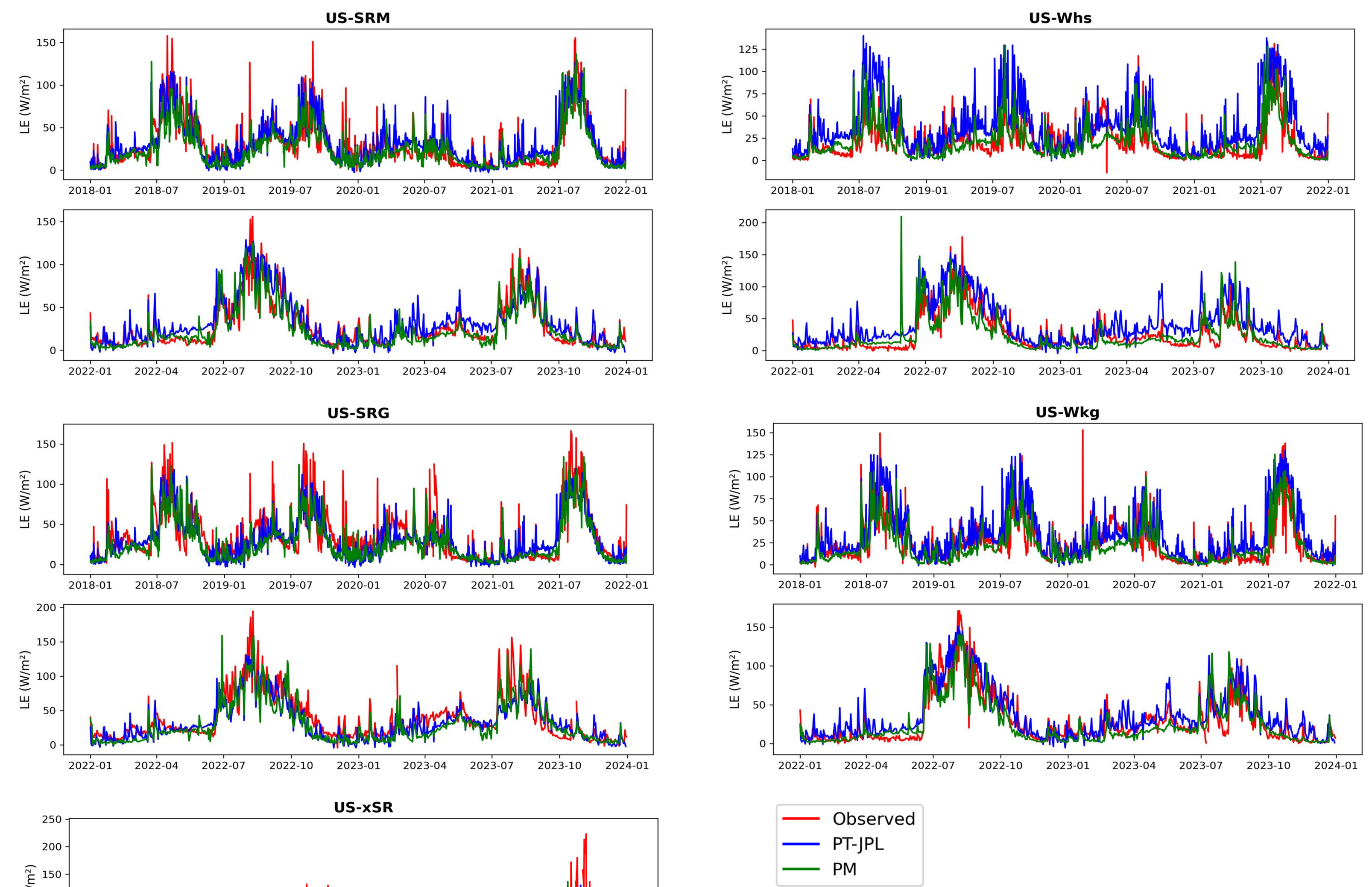
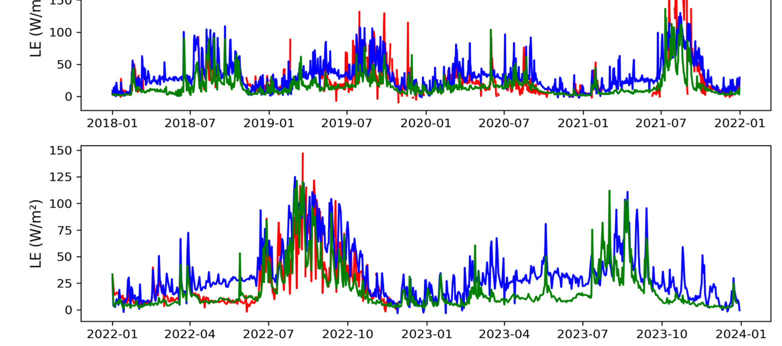



Fig 2. Time-series plot of ET estimation using both methods over 5 flux tower sites. For PM: 2018-2022 (calibration), 2022-2024 (validation). For PT-JPL: (2018-2024) since it does not need calibration.

Both models capture seasonal ET trends, but PM outperforms PT–JPL in accuracy; however, both underestimate high ET values

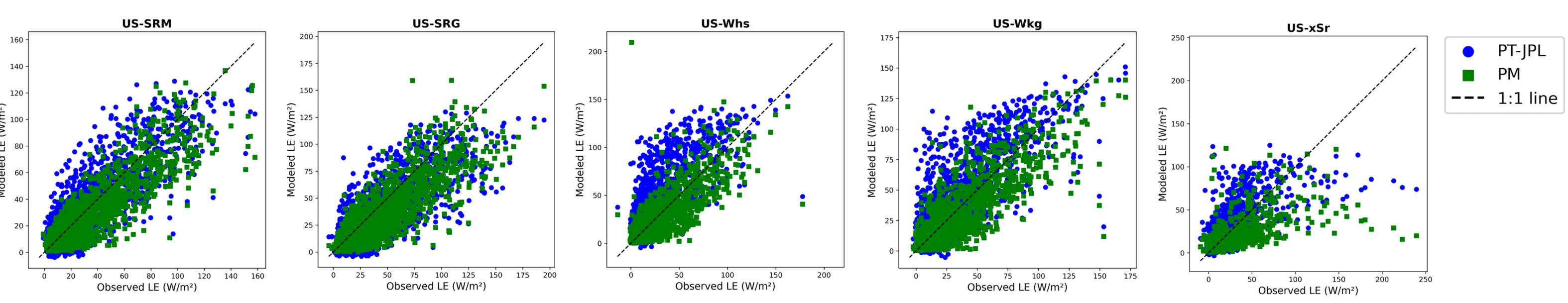
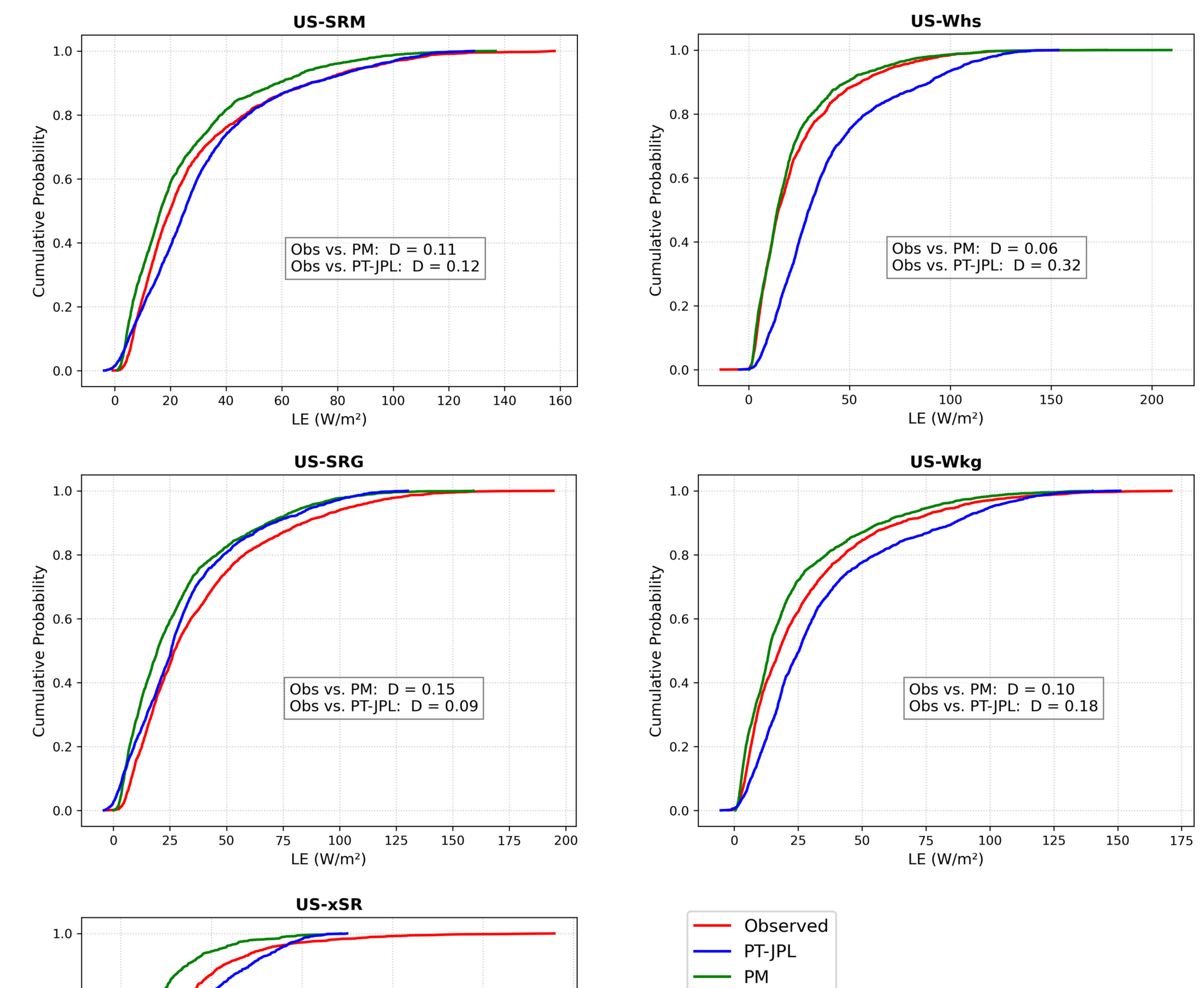


Fig 3. Scatterplot of ET: blue circles and orange squares represent ET data points from PT-JPL and PM models, respectively.

Method	Site	2018 - 2022				2022 – 2024			
		KGEss	R^2	RMSE	Bias Ratio	KGEss	R^2	RMSE	Bias Ratio
PT-JPL vs. Observed	US-SRG	0.76	0.57	21.36	0.6	0.80	0.68	19.25	0.5
	US-SRM	0.87	0.67	16.04	0.5	0.86	0.73	14.87	0.5
	US-Whs	0.40	0.49	25.97	1.2	0.53	0.69	23.97	1.0
	US-Wkg	0.69	0.58	20.71	0.8	0.81	0.75	18.11	0.6
	US-xSR	0.66	0.38	23.96	0.9	0.66	0.61	21.06	0.8
Average		0.68	0.54	21.61	0.8	0.73	0.69	19.45	0.69
PM vs. Observed	US-SRG	0.74	0.69	19.76	0.5	0.80	0.75	18.34	0.5
	US-SRM	0.79	0.75	15.02	0.5	0.88	0.83	11.66	0.4
	US-Whs	0.83	0.63	13.12	0.6	0.86	0.68	16.52	0.7
	US-Wkg	0.80	0.67	14.91	0.6	0.85	0.78	15.60	0.5
	US-xSR	0.44	0.31	26.24	1.0	0.80	0.65	16.30	0.6
Average		0.72	0.61	17.81	0.64	0.84	0.74	15.68	0.54

Table 2. Comparison of PT-JPL and PM model performance against observed latent heat flux across multiple flux tower sites.

3. Results



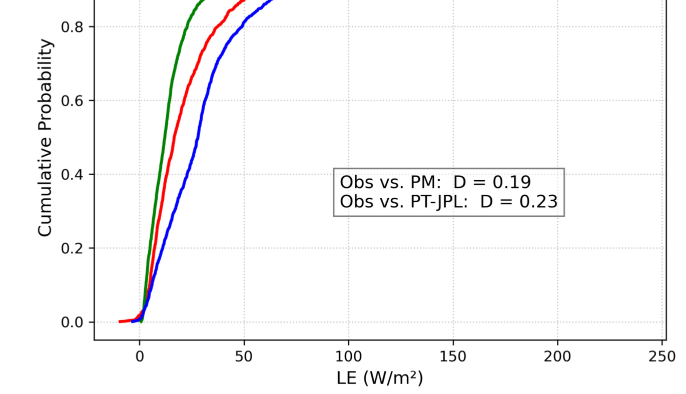


Fig 4. Cumulative distribution function and K-S test results for both models: PT-JPL and PM ET vs. observed ET.

4. Conclusion

- PM outperforms PT–JPL, with higher average KGEss (0.72–0.84), R^2 (0.61–0.74), and lower RMSE (15.68–17.81 W/m²) compared to PT–JPL (KGEss: 0.68–0.73, R^2: 0.54–0.69, RMSE: 19.45–21.61 W/m²) for both periods.
- The bias ratio analysis further supports this, showing lower average bias ratios for PM (0.64–0.54) than PT–JPL (0.80–0.69).
- The K–S test confirms significant differences ($p < 0.001$) between observed and modeled ET distributions, with D = 0.09–0.32 for PT–JPL vs. observed and D = 0.06–0.19 for PM vs. observed.
- PT–JPL overestimates ET, while PM underestimates it, particularly at higher fluxes.
- This discrepancy underscores the need for further refinement in model parameterization, improved input data resolution, and incorporation of additional environmental constraints to enhance predictive accuracy.
- Future research should integrate machine learning techniques, data assimilation methods, and enhanced meteorological datasets to optimize ET model performance in water-limited environments.

Acknowledgments

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