Evaluation of JULES in Simulating Energy, Water, and Carbon Exchanges

Across Multiple African Landscapes

This project is part of the Oppenheimer Programme in African Landscape Systems (OPALS): https://opals-exeter.org/ Enimhien Akhabue¹, Andrew Cunliffe¹, Tom Powell¹, Karina Williams^{1,2}, Anna Harper¹, and Petra Holden³







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1. Background

- ❖ Land surface models (LSMs) simulate energy, water, and carbon exchange.
- **These simulations underpin climate predictions, ecosystem assessments, and sustainable land management policies**.
- ❖ African ecosystems are **underrepresented** in LSM development and evaluation.
- ❖ This limits the accuracy of predictions for climate adaptation and land management.

Our Study

- *We evaluated the Joint UK Land Environment Simulator (JULES) using observations from 16 African eddy covariance flux tower sites.
- Sites span savannas, croplands, wetlands, & forests, covering diverse climatic zones.
- ❖ Fluxes assessed: **GPP**, **RECO**, **ET**, **LE**, **H**.
- ❖ Focus: How model performance varies across ecosystem types and climatic gradients (MAT, Aridity index and precipitation anomaly).

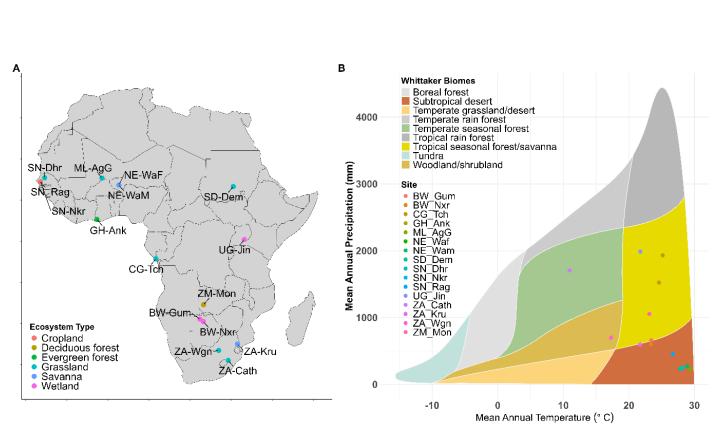
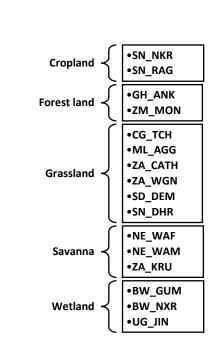


Figure 1. Flux tower sites across Africa spanning major climatic and ecosystem gradients (16 sites, 5 ecosystem types).

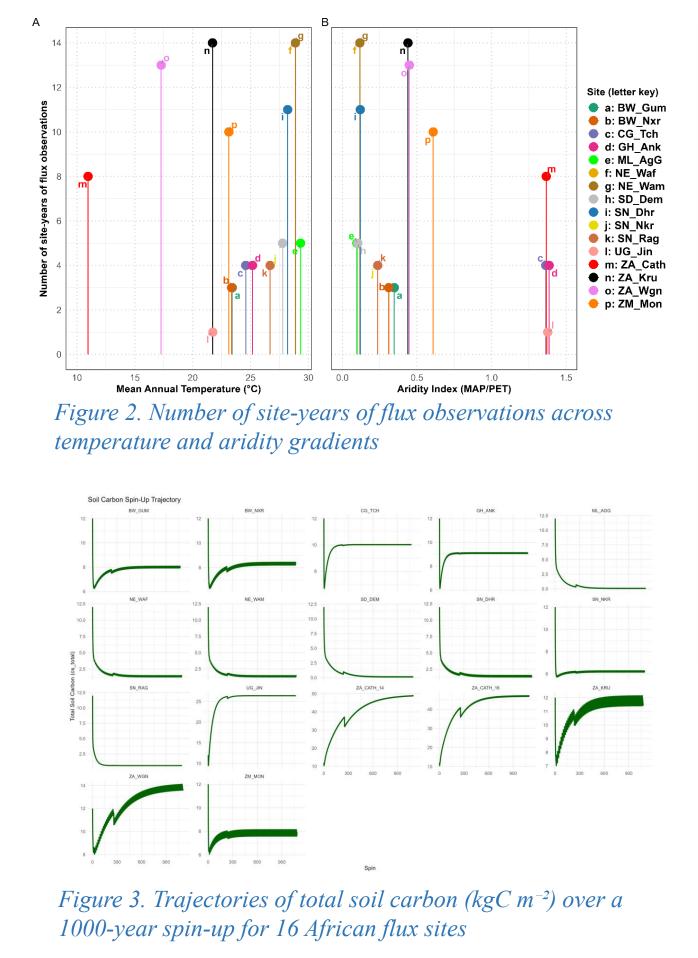


Improving African ecosystem representation in LSMs strengthens model predictions for climate and land management.

Research Aim

- Evaluate JULES across African ecosystems
- *Assess influence of MAT, AI, and precipitation anomaly with LMMs

2. Methods



JULES configuration and evaluation:

Model: JULES v7.1 (Met Office Rose suite baseline u-al752 baseline

Setup: Site-level, single-point runs at 30-min time steps.

Inputs: Site-specific PFT fractions, soil properties, and meteorological drivers.

Spin-up: 1000-year spin-up to equilibrate soil C pools before simulations.

Simulation period: Multi-year runs aligned with available flux tower records; outputs aggregated to daily resolution.

Model performance was evaluated with daily to annual metrics

Bias (systematic error)

RMSE (magnitude of error)

Correlation(r) (temporal correspondence)

Statistical models (GLMMs) (per-flux)

Bias ~ MAT + AI + PrecipAnomly + (1 | SiteID)

Rmse ~ MAT + AI + PrecipAnomly + (1 | SiteID)

Corr ~ MAT + AI + PrecipAnomly + (1 | SiteID)

4. conclusion

- > RECO is the weakest flux overall, with poor model—data agreement across most sites.
- > Wetlands are the poorest-performing ecosystems, with large errors across all fluxes.
- ➤ Water-related gradients dominate model performance: precipitation anomalies and aridity consistently increase bias and error across fluxes.
- ➤ GPP emerges as the most climate-sensitive flux, shifting with MAT, AI, and precipitation anomalies.
- ➤ **RECO** carries a clear MAT signal, and **ET** shows mixed responses under wetter and more humid conditions.

3. Results

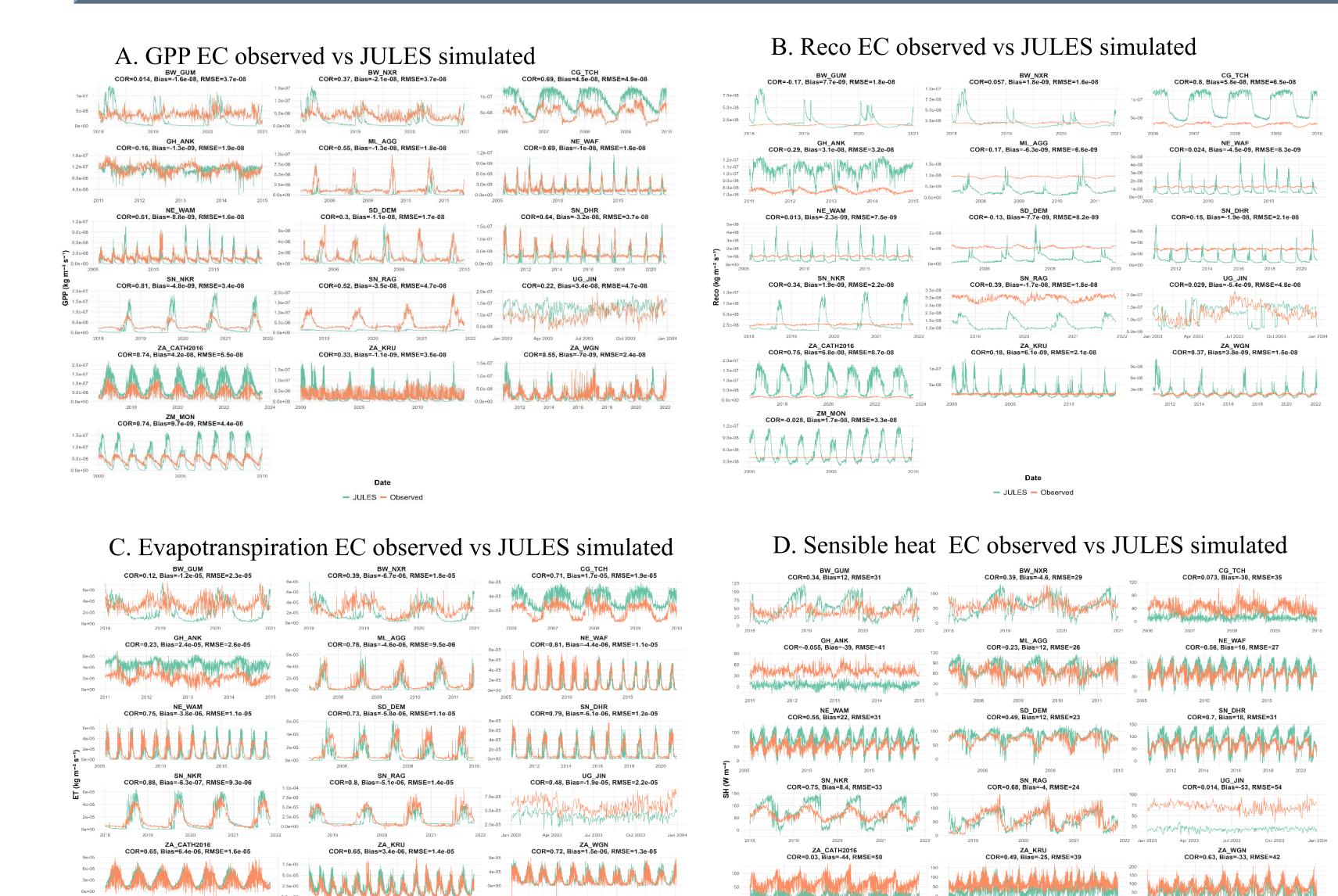


Figure 4. JULES simulated vs observed fluxes from EC flux towers across 16 sites in Africa

JULES performance varied systematically across ecosystems. Croplands were consistently well simulated, forests and grasslands showed mixed outcomes, savannas captured water and energy fluxes but struggled with carbon, and wetlands were consistently the weakest across all fluxes.

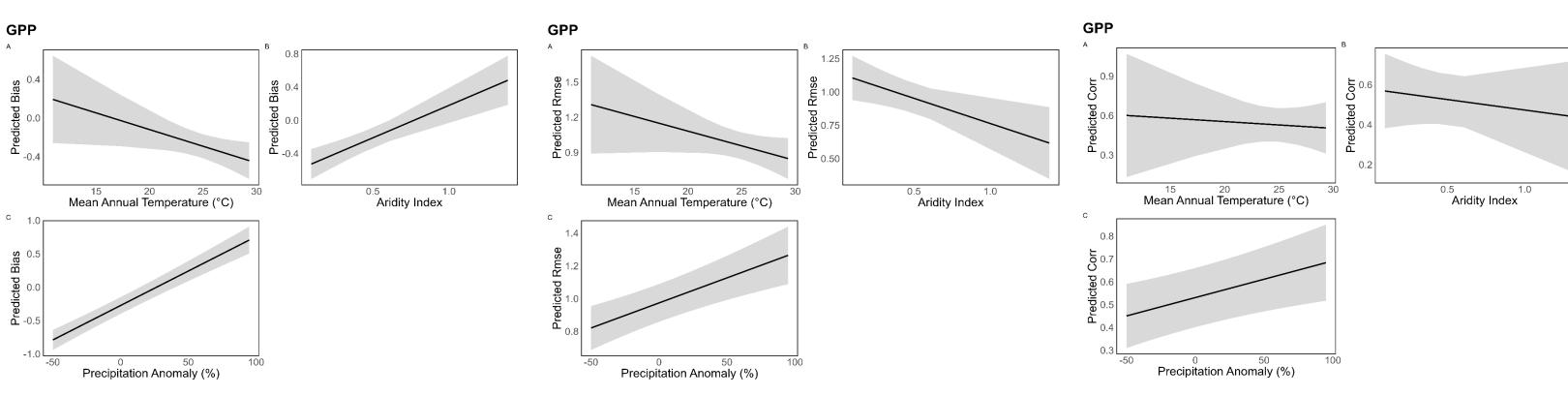


Figure 5. GPP predicted performance from linear mixed effects model

GPP bias decreased with warmer MAT but increased in drier sites and wetter-than-average years. RMSE showed similar climate dependencies, with errors lowest at warm sites but highest in dry and anomalously wet conditions. Correlation improved only during wetter-than-average periods, while MAT and AI effects were weak.

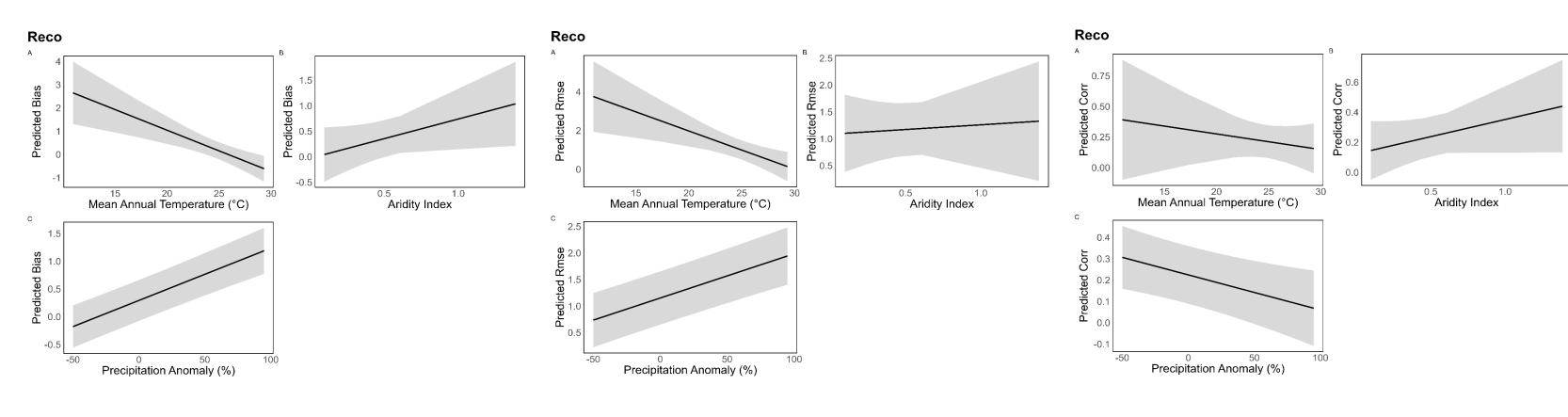


Figure 6. Reco predicted performance from linear mixed effects model

Reco bias declined with warmer MAT but increased during wetter-than-average years, while aridity showed only a weak effect. Errors (RMSE) were lowest at warm sites but rose under rainfall surpluses, consistent with the strongest anomaly signal. Correlation declined during wetter periods, while MAT and AI effects were weak

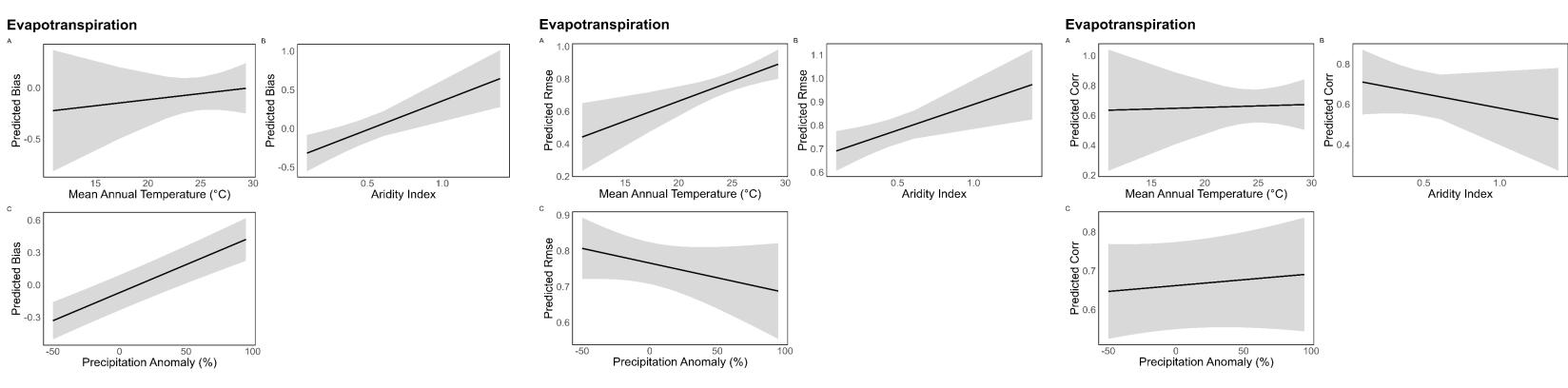


Figure 7. ET predicted performance from linear mixed effects model

ET bias increased under wetter conditions and more humid climates, while temperature had little effect. Errors (RMSE) rose with higher MAT and AI, though wetter years slightly reduced errors. Correlation showed only weak and uncertain responses to climate gradients.

5. Next steps

- •Assess inter-annual variability of GPP using hydrological years at sites with ≥4 years of data.
- •Analyse intra-annual (seasonal) variability in 3-month windows to test JULES' seasonal timing.
- •Identify how well JULES captures year-to-year anomalies and seasonal dynamics of GPP.

