

Analysis of vegetation modelling uncertainties due to soil moisture stress



Savanna

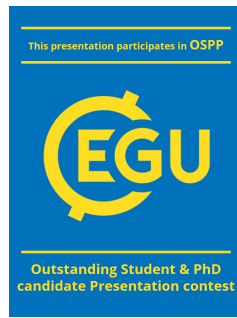


Monsoon forest



Mediterranean vegetation

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Methods

Model setup

- The P-model (Prentice et al. 2014, Wang et al. 2017; Stocker et al. 2020)

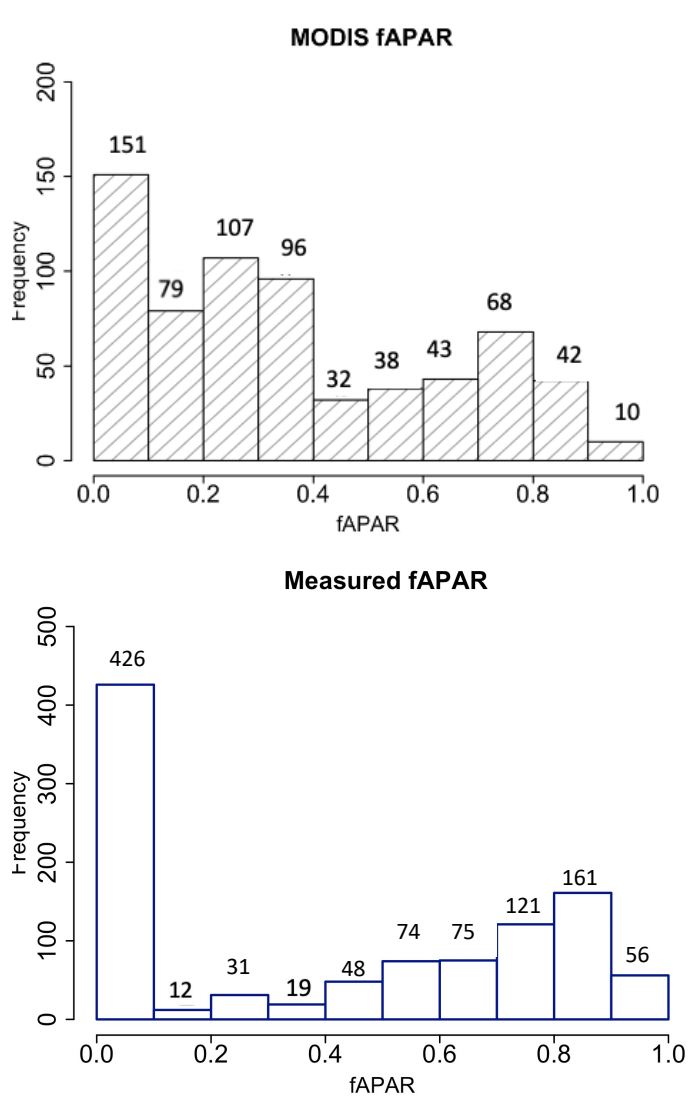
$$\text{GPP} = \text{PPFD} \cdot \text{fAPAR} \cdot \text{LUE} \cdot \beta(\theta)$$

- 73 FLUXNET sites for the uncertainty analysis
 - Satellite fAPAR from MODIS
 - fAPAR converted from measured LAI (using Beer–Lambert law)

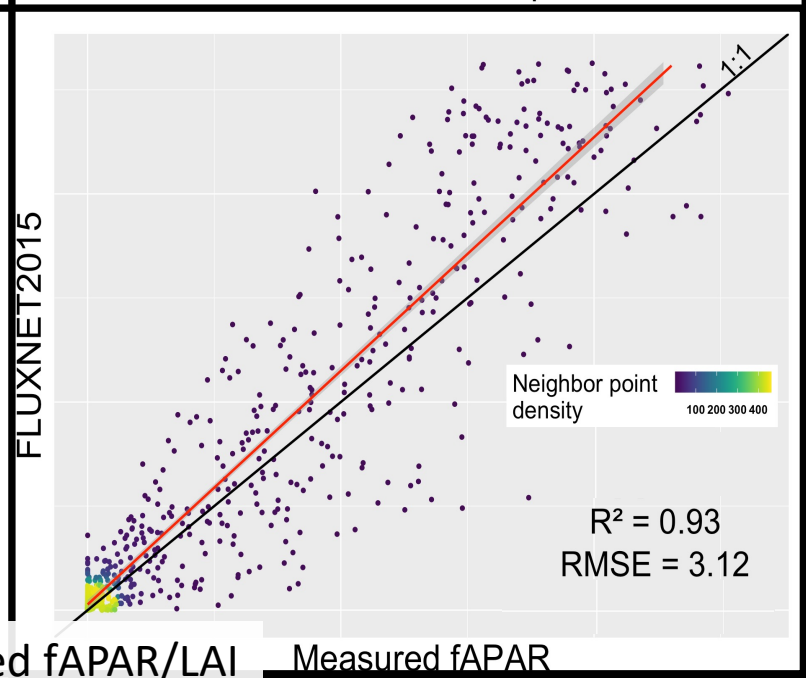
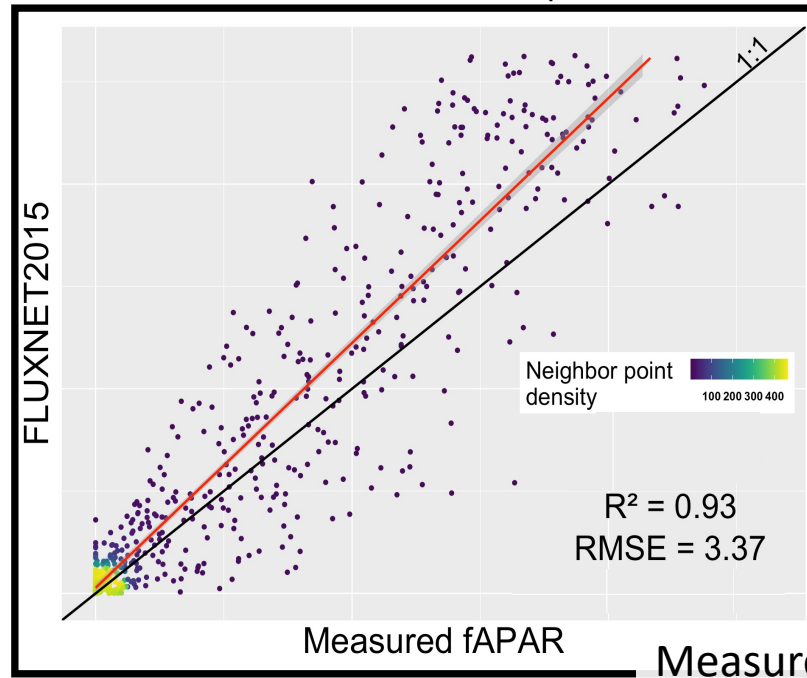
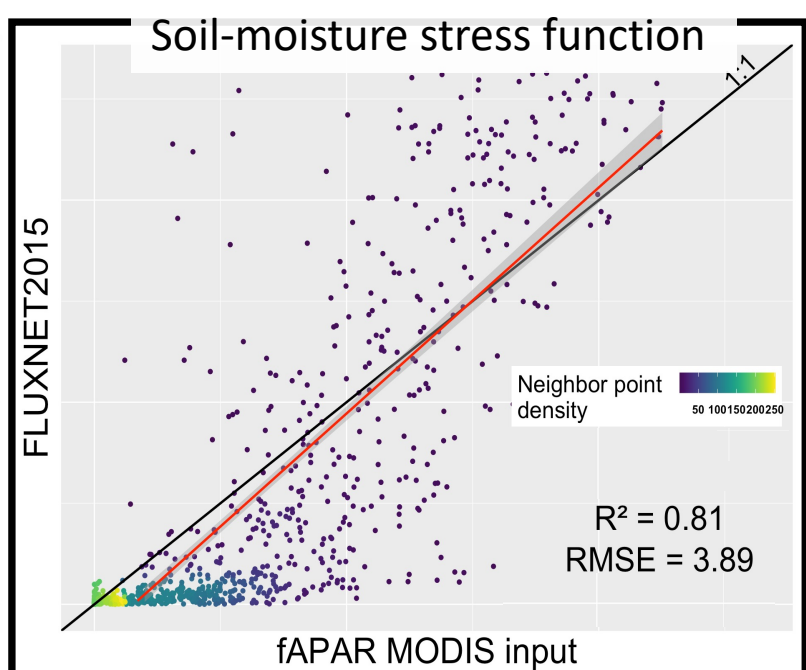
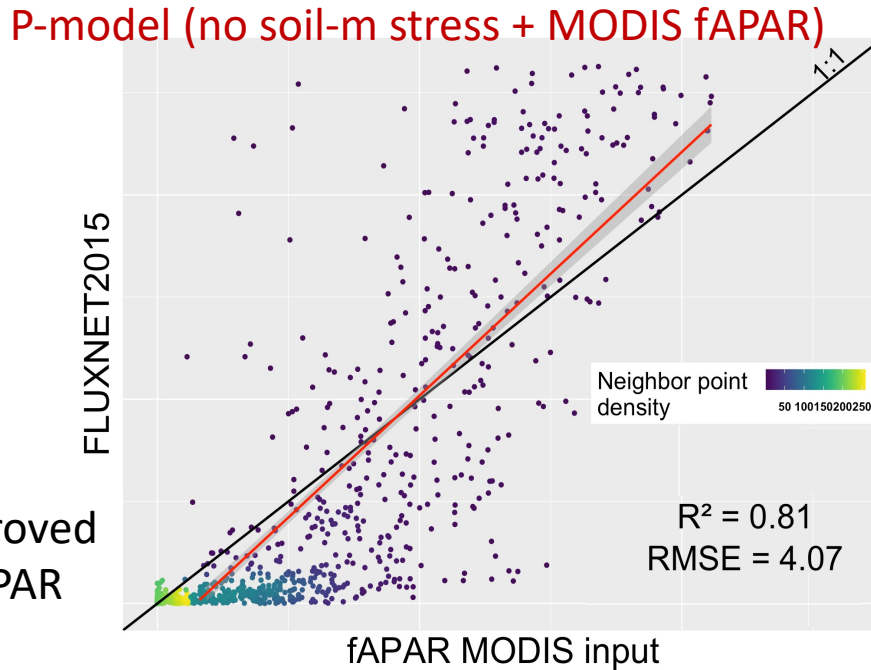
Analysis

- Model Performance: comparing modelled GPP against observed GPP
- Uncertainty Analysis: comparing MODIS fAPAR and back calculated fAPAR from two methods:
 - P-model $\beta(\theta)$
 - P-model Water Deficit (does not compensate fAPAR uncertainties)
- Two ways of fAPAR estimates:
 1. Inversion of Eddy covariance-based GPP
 2. Nonlinear Least Squares + Bootstrapping method

Model Evaluation: comparison of modelled GPP and observed GPP



Improved
fAPAR



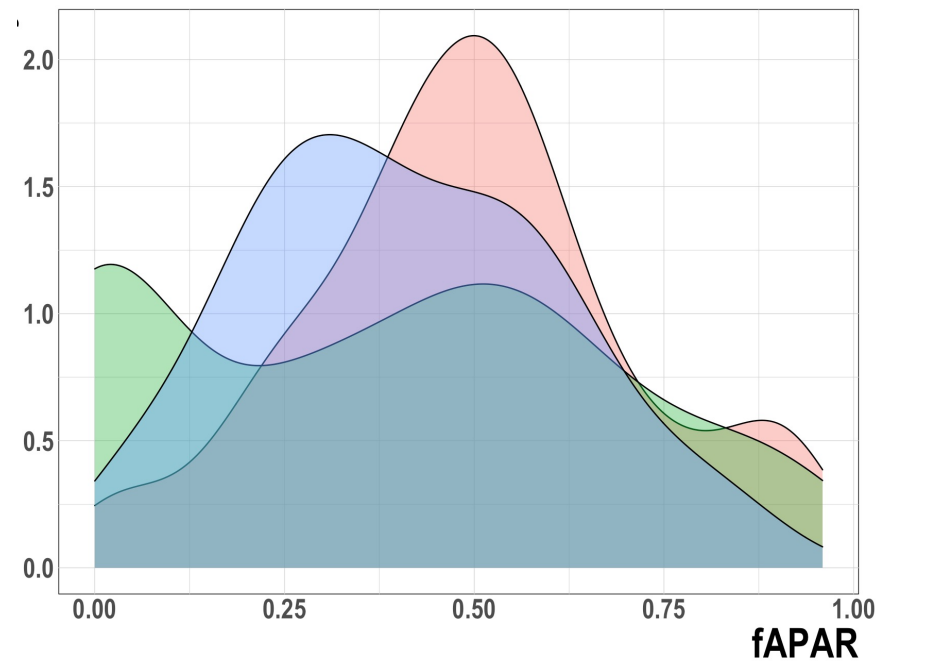
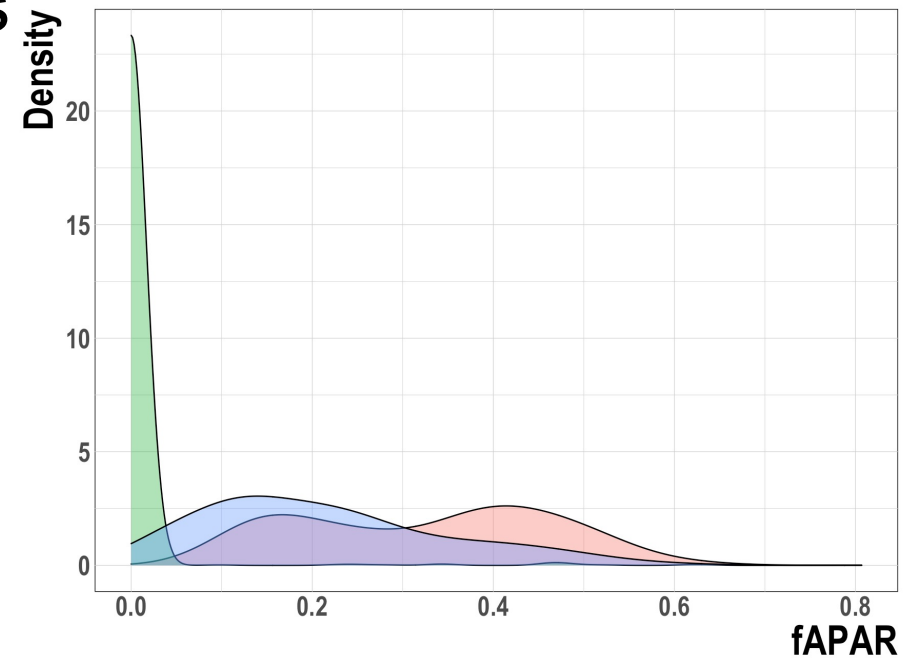
Uncertainty analysis

$$fAPAR = \frac{GPP}{LUE \times soi_water_stress}$$

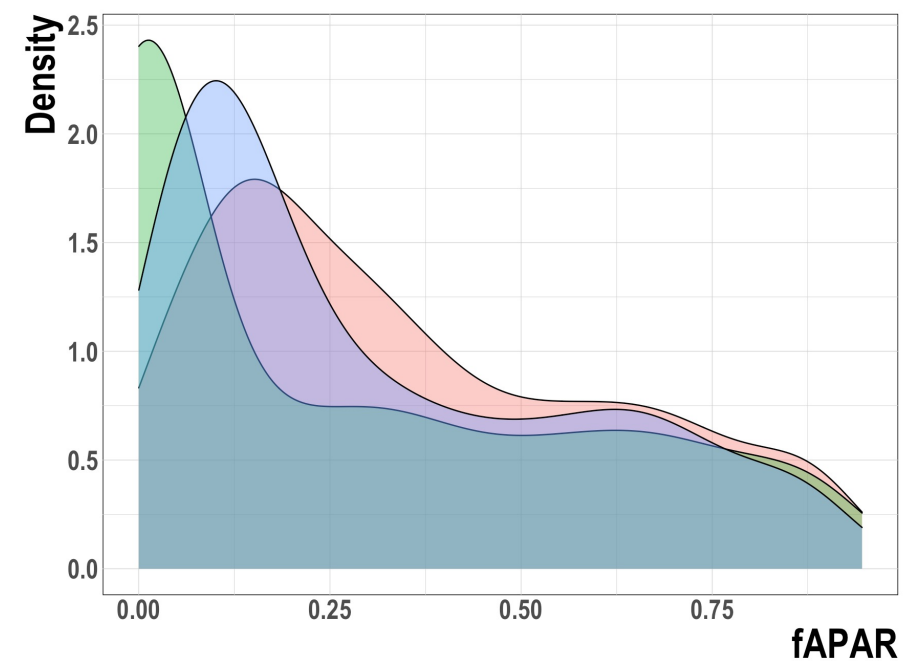
fAPAR from methods:

- MODIS
- SoilMoistureFunction
- WaterDeficit

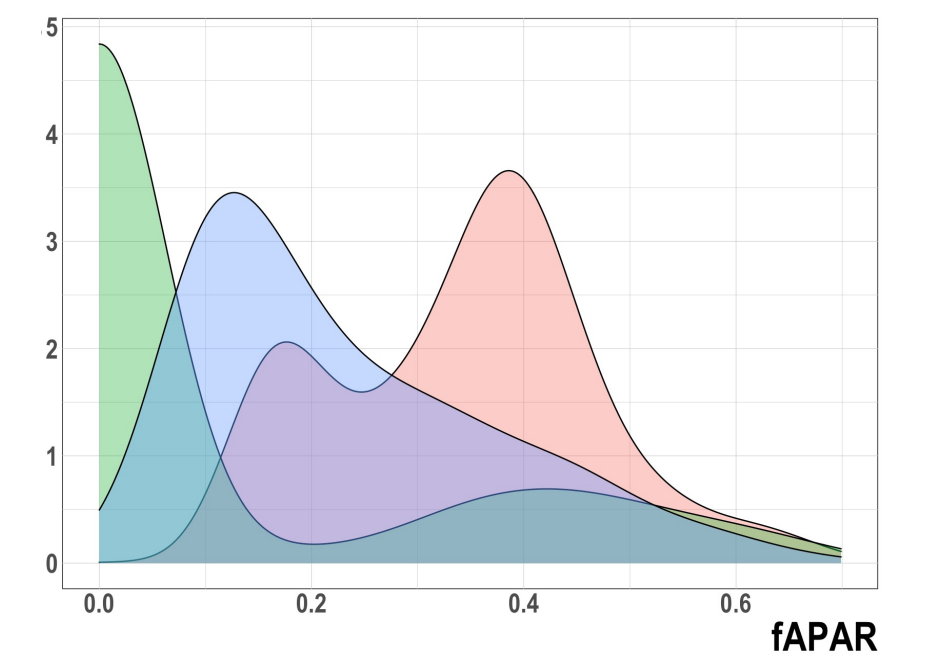
Savanna (n = 1202, number of sites = 6) Deciduous broadleaf forest (n = 1202, number of sites = 4)



Grassland (n = 4239, number of sites = 18)

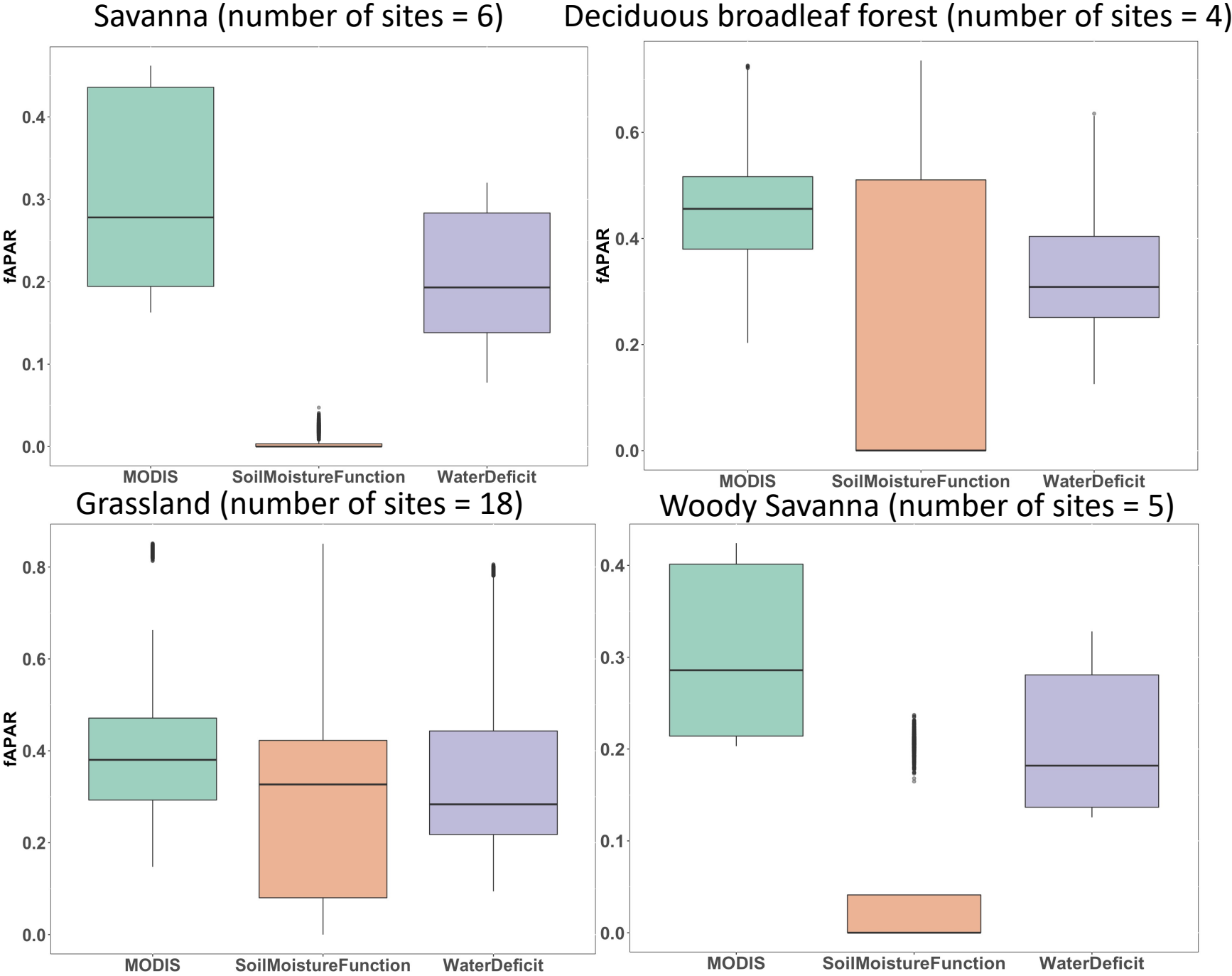


Woody Savanna (n = 1338, number of sites = 5)



Uncertainty analysis

Nonlinear Least Squares +
Bootstrapping method
(sample size = 999)



Final remarks

1. fAPAR quality highly impacts GPP estimates.
2. In general, soil-moisture stress improves model performance, but sometimes results can be biased.
3. The application of P-model soil-moisture function compensates uncertainties in fAPAR.
4. However, global calibration frameworks can unbalance model performance in sites where fAPAR estimates are reliable.

