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Interactive comment on “The importance of radiation for semi-empirical water-use efficiency models” *by* Sven Boese et al.

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We thank Referee #3 for the positive and constructive appraisal of our article! Below, we respond to the general and specific points of the review.

AMBIGUITY OF THE MODELS. "Ambiguity in concepts such as WUE models, physiological WUE models? Are the authors talking about stomatal conductance models? Please clarify them and provide details." Thank you for pointing this out. The revised manuscript gives a more detailed introduction into the different types of WUE models and treats the terminology more carefully.

COLLINEARITY "The concerns include whether and how the authors test the collinearity between the variables such as Rg and GPP*VPD0.5 in the model ïňĄtting" This is a very good remark! The high degree of correlation is an important issue for these kind

of empirical analyses. This is particularly pertinent for isolating the fraction of evapotranspiration that we attribute to radiation. In the original paper, we analyzed the impact of collinearity on our results by accounting for the correlation of parameter uncertainties (Supplementary Materials S1). In the new manuscript the problem of collinearity and our treatment is given more prominence. We further moved the mentioned section from the supplement to the method section of the main document.

OVERPARAMETERIZATION "In addition to MEF, index such as AIC or AICc are needed to account for possible over-parameterization?" We fully agree with Referee #3 that overparameterization is an important issue in analyses focussed on model selection. We believe that we have adequately addressed this problem by exclusively using cross-validated Nash-Sutcliffe Efficiencies (MEF) in our model comparison. Adding further parameters to a model will generally allow the model to accommodate even observations that were the result of random errors or unattributed processes. The cross-validation penalizes such a over-parameterization by iteratively testing the model’s ability to predict observations that it wasn’t calibrated to. Using an information criterion, such as AIC, AICc or BIC, that directly accounts for the number of parameters used in the model is another possibility to represent model complexity. AICc can be expected to converge with cross-validation asymptotically (Stone, 1977). We are therefore confident that our results are not confounded by the number of model parameters. To illustrate this, we added a table to this comment (Fig. 1 of this response) that replicates Table 1 of the original paper (Fraction of sites with a higher or lower MEF). As is the appropriate usage for AICc, we counted the fraction of sites were the pairwise difference of AICc was smaller than -2 for the model of the row to be considered superior to that of the corresponding column. The table suggests that our conclusions are not sensitive to the choice of either AICc or cross-validated MEFs.

INTERACTION TERMS "How the authors deal with the interactive terms among those variables." This is an interesting question. In our analysis we aimed to obtain effective, parsimonious models with sufficient biological and physical plausibility. This is why we did not test all possible combinations of predictor variables. Attached to this comment is a plot (Fig. 2 of this response) that includes both the three models of the old manuscript (Zhou, +ETres, +Rg) and three new variants for questions raised by the other referees: +ETres_bnd has parameters constrained to positive values, +Rg_nl has a nonlinear response to radiation and Intrct has an interaction term of VPD with Rg. The model evaluation was performed in a comprehensive cross-validation scheme. The original +Rg variant was again confirmed to have the highest performance in this evaluation. In addition, this model is corroborated by the new results indicating higher importance of radiation for low vegetation, which makes equilibrium evaporation a plausible candidate explanation for the observed patterns (see below in our response, section PARAMETER DISTRIBUTIONS).

INTRODUCTORY DEFINITION OF MODELS - "p2, lines 5-15: this paragraph needs to clarify the difference between existing WUE models." - "P2, lines 22-29: there are several confusing/incorrect statements in this paragraph." - "P2, line16: what is physiological WUE models? Did the authors mean stomatal conductance models?" Thank you for pointing this out! We have revised the introduction of the paper accordingly, to better explain our approach and contrast it with existing models. We also discus how current models include the g0 conductance term. "the ratio GPP/ET is never constant and is considered to be proportional to vpd or squared rooted vpd depending on assumptions (Zhou et al., 2014)" Here, we referred to radiation, when stating that "The models implicitly assume that, at ecosystem-scale, GPP and ET respond equally to changes in radiation and that, therefore, the ratio of both is constant with regard to this factor." This has been clarified in the revised introduction.

EFFECT OF WATER-LIMITATION ON COLLINEARITY "Not sure how water limitation can affect collinearity of parameters?" Referee #3 is right that we did not provide a sufficient explanation for our reasoning here. As we mention below, the degree of correlation between the predictor variables is a property of the additive models we identified. The dependency of GPP on radiation is an obvious case for that. We expected

this correlation (and the following collinearity) to decrease under water-limitation, as GPP is then no longer as easily determined by radiation. For example, during periods of extended droughts, we would expect day-to-day variability of GPP to be no longer a function of radiation and related covariates but rather variables reflecting soil-water availability. If this dependency of the covariates decreases, it would follow that the collinearity of the parameters decreases, too. However, the results were very inconclusive when adopting the aridity index (AI) that is used by the United Nations Environmental Program (defined as: AI = Precipitation / PET). We decided that the results were furthermore not pertinent to the main topic, which is why we decided to exclude this part from the new manuscript.

PARAMETER DISTRIBUTIONS "In results, in addition to the MEF, I would like to see the distribution of two other parameters (uwue and r) of all the sites." The updated manuscript now includes plots showing the distribution of the two parameters uWUE and r. Upon a comment by Referee #2, we stratified the data-set along the vegetation structure (low for grasslands and crops, high for all other plant functional types). Quoting from our reply to Referee #1: "When stratifying the data set like this, we found that uWUE was not significantly different for either vegetation type (Kolmogorov–Smirnov test) [Fig. 3 of this response]. However, we noted that grasslands and crops had a significantly higher mean value of r [Fig. 4 of this response]. This is a relevant finding, as it supports our proposed explanation that the radiation effect could be a sign of equilibrium transpiration (Jarvis and McNaughton, 1986). In a preceding study, McNaughton and Jarvis (1983) report that grasslands had a higher decoupling parameter Ω, quantifiying the contribution of equilibrium evaporation. As Jarvis and McNaughton (1986) discuss, a stronger atmospheric decoupling (high Ω) implies a higher relative share of equilibrium transpiration. Therefore, we repeated the analysis of the fraction of radiation-associated transpiration and found that this metric, ET_frac, was significantly higher for the low vegetation PFTs grassland and crops (0.53, 95% CI: 0.48-0.58) compared to high vegetation (0.39, 95% CI: 0.34-0.44) [Fig. 5 of this response]. We revised and adapted the manuscript accordingly!" The relevant plots have been attached to and renumbered for this comment (Fig. 3-5 of this response).

MONTHLY PATTERNS BY SITE "This is interesting ïňĄnding. Could it be possible for the authors to provide this similar ïňĄgure for each of the sites in the supplementary materials for the readers to eyeball the site difference or similarity?" The updated supplement now contains this figure as a matrix of monthly patterns for each site individually! The plot is also attached to this comment (Fig. 6).

COVARIANCE ASSUMPTIONS "More details are needed on the variance and covariance for each of the variables including GPP and ET, because this variance and covariance directly affect your L-M algorithm and likely results." The optimization approach of our analyses follows eq. 5–6 in Omlin and Reichert (1999) with a σ_meas of 1, hence being insensitive to the uncertainties in the forcing and target variables. In agreement with Lasslop et al. (2008), this approach does not consider correlations between the errors of the original latent heat and net ecosystem exchange fluxes.

LIMITATION OF THE MODELS "All the proposed models have their own assumptions and their possible violations. Please discuss them as well on how these violations could affect the results." This is a critical aspect for a model-selection exercise such as ours and is treated more diligently in the revised version of the manuscript.

DATA AVAILABILITY The data sets can be downloaded at http://fluxnet.fluxdata.org//data/download-data/

In addition, all specific points referring to spelling, coherence and citations were considered and integrated in the revised manuscript.

Thank you again for your assistance in improving this paper!

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model	Zhou	+ETres	+VPD	+Rg	+VPD+Rg
Zhou	NA	0.04	0.03	0.02	0
+ETres	0.83	NA	0.34	0.05	0
+VPD	0.78	0.58	NA	0.08	0
+Rg	0.96	0.93	0.89	NA	0.05
+VPD+Rg	0.98	0.99	0.94	0.58	NA

Fig. 1. Fraction of sites that had an delta-AICc smaller than -2 when comparing a model of a given row with a given column

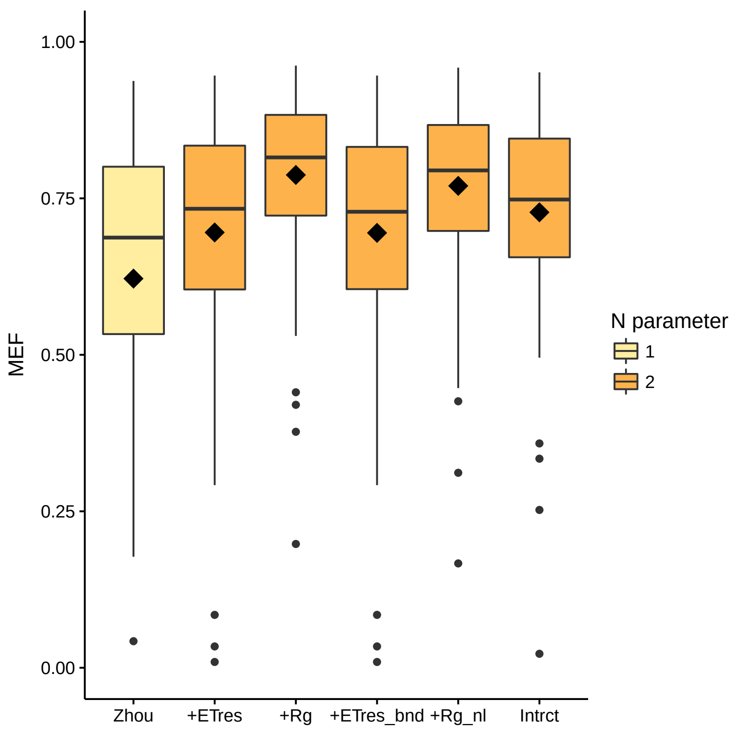

Fig. 2. Distribution of cross-validated model-efficiencies with three additional models (positive bounded parameters, nonlinear Rg response and a VPD-Rg interaction effect).

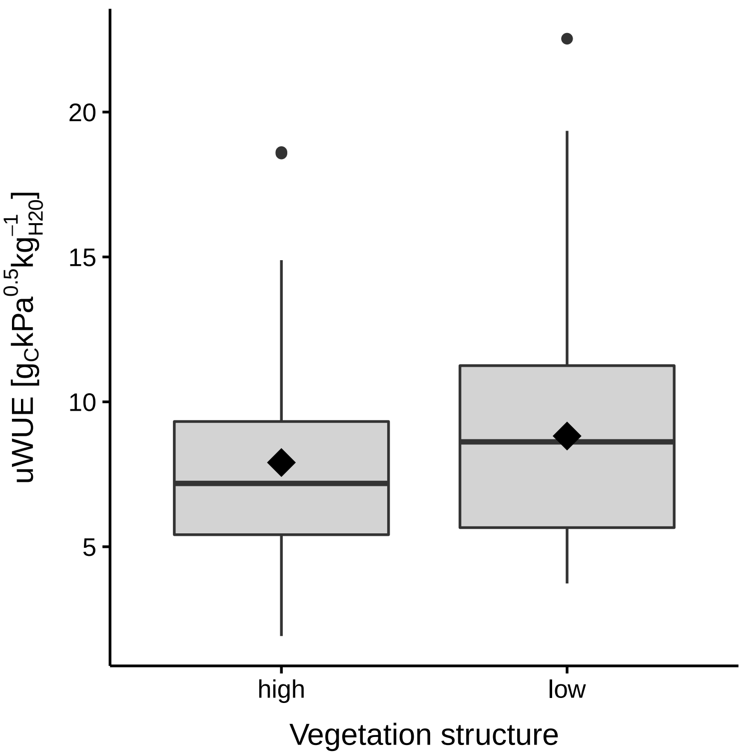

Fig. 3. Distribution of the parameter uWUE for all sites separated by vegetation structure.

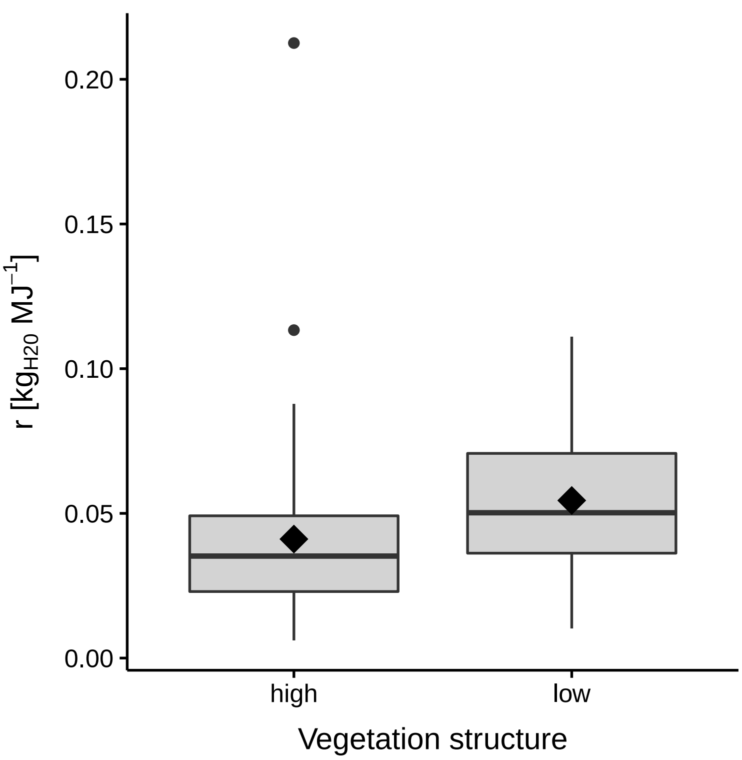

Fig. 4. Distribution of the parameter r for all sites separated by vegetation structure.

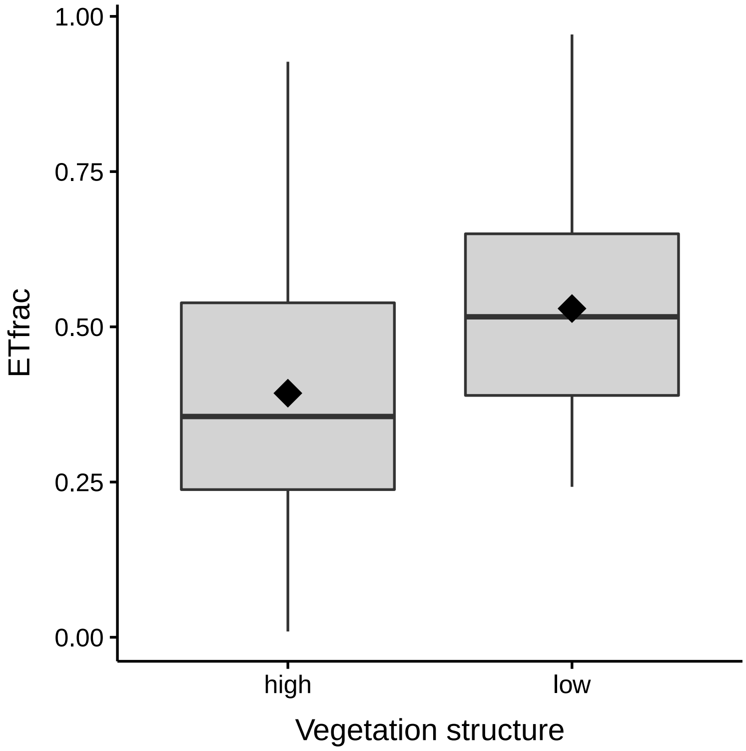

Fig. 5. Distribution of the fraction of radiation-associated ET for all sites separated by vegetation structure.

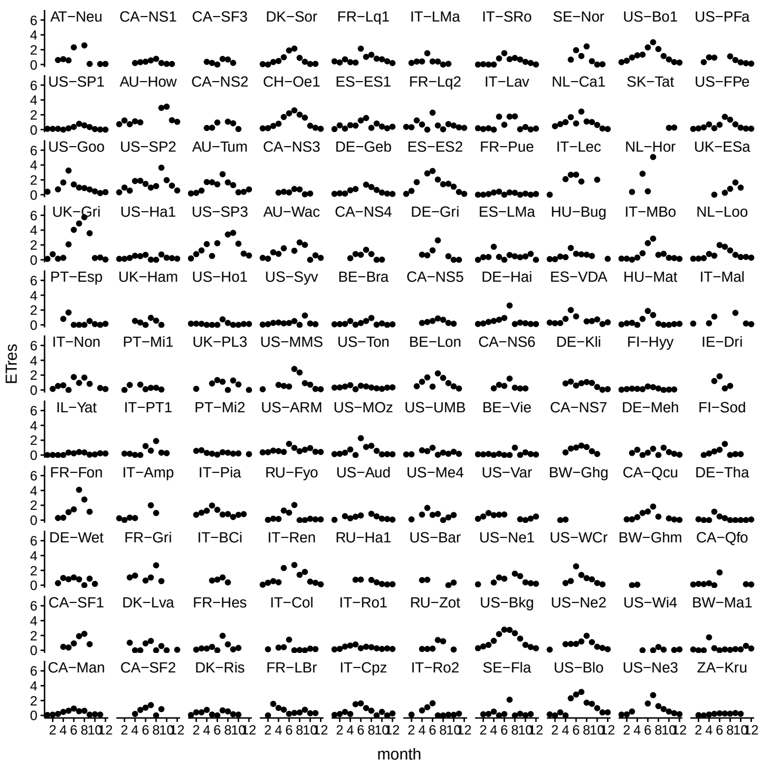

Fig. 6. Month-wise estimates of ETres for all sites included in the analysis.