

Response to Reviewer Comments: **Revisiting large-scale interception patterns constrained by a synthesis of global experimental data**

Reviewer #2 (Yongqiang Zhang, Referee)

We appreciate the reviewer's constructive comments. Below we address one by one each of the points in blue fonts.

Major comments:

Comment 1.1: The advantage to use fPAR to estimate the cc has not been demonstrated. In Figure 3, please also show the comparison between the observed and the simulated using traditional LAI dataset. This is particularly important for displaying the novelty of this study.

Reply: Thank you for your suggestions. cc can be traditionally obtained from LAI based on Beer–Lambert's Law (Eq. (1)). In this equation, three parameters – i.e. extinction coefficient (κ), clumping index (C) and the cosine of the Sun zenith angle (μ) – need to be parameterized at a global scale. For most rainfall interception applications, C and μ are normally set to unity, and κ varies across different plant functional types (Van Dijk and Bruijnzeel, 2001; Zhang et al., 2019). However, C has recently been shown to be an important biophysical parameter in characterizing the effective LAI, and therefore affects transpiration and photosynthesis (Braghiere et al., 2019; 2020; 2021). In this regard, we think the influence of C on estimating cc should not be ignored in rainfall interception simulations. In our study, an important novelty is using an alternative approach to estimate cc to shortcut that complicated parameterization, that is annual average cc is approximated by the MODIS Vegetation Continuous Fields (VCF) products, and then linearly interpolated by the intra-annual dynamics of fPAR, as fPAR has been found to exhibit strong linear correlation to cc (Mu et al., 2018) (L185–197).

Action: To illustrate the performance of this new model, we will include a validation of the results of PML v2 (and GLEAM v3.5a) against *in situ* data, as the rainfall interception loss from PML v2 is actually estimated based on the same vD–B model forced by traditional LAI dataset (Zhang et al., 2016; 2019). A new figure (Fig. 8) will be included in the main paper, equivalent to the Fig. R1 shown below, which presents the field validation of I and I/P from the three different models. Compared to PML v2 and GLEAM v3.5a, the estimated I and I/P in this study have the highest correlation coefficients and lowest mean bias errors against field observations. This will be now included in the section “*Comparison to existing global datasets*”.

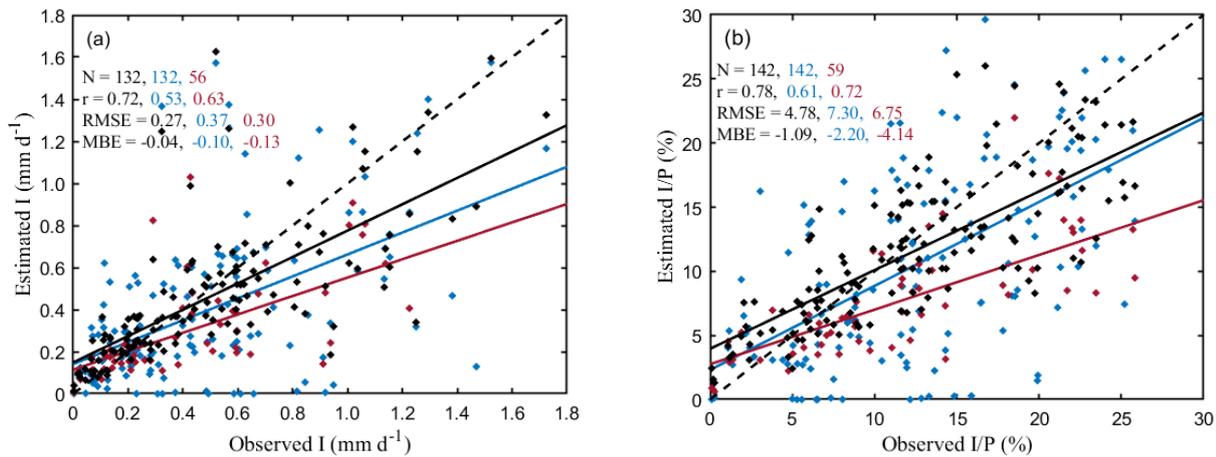


Figure R1. Field validation of rainfall interception loss from three different models. (a) I in mm d^{-1} , (b) I/P in %. Black, blue and red scatters represent the pixel-scale simulations from this study, GLEAM and PML model, respectively. Since the time series of PML v2 spans from 2003 to 2017, hence only 59 field observations can be used for validation. The solid lines in different colors are the regression lines, and the black dashed lines mark the 1-to-1 line.

Comment 1.2: The variation in cc . The authors state that the time various parameter cc can be larger than unity. I would like to see the time variations of cc estimated from $fPAR$ and estimated from LAI, respectively. There will be never an issue based on the exponential function of LAI using Beer–Lambert's Law. This should be shown for at least the representative sites, such as EBF and DBF.

Reply: As mentioned above, in this study cc is derived from MOD44B product, which provides the percentage of each gridcell covered by tall vegetation (i.e. tree canopies) and short vegetation (i.e. non-tree vegetation). In theory, taking into account such subgrid heterogeneity enables the model to get more exact outcome. On the other hand, intra-annual dynamic cc estimated from the temporal changes in $fPAR$ could shortcut complicated parameterization using Beer–Lambert's Law equation. For these reasons, we did not use this traditional method to calculate cc .

Action: To compare our cc with that estimated from LAI, cc is calculated at representative sites using Beer–Lambert's Law with C and μ being set to unity. Taking the extinction coefficient of PAR as reference, the values of κ come from PML v2 model (Zhang et al., 2019). Figure R2 shows the time series of cc starting from 1 January 2003. The time variations of cc estimated from $fPAR$ overall agree well with that estimated from LAI at EBF, ENF, DNF and MF sites where are dominated by tall vegetation, while values of the former are significantly larger than the later at DBF and SHL sites dominated by short vegetation. Besides, it should be noted that cc derived from LAI can be even smaller than the annual fraction of short vegetation from MOD44B at low vegetation dominated sites. This comparison will be presented in the supplementary.

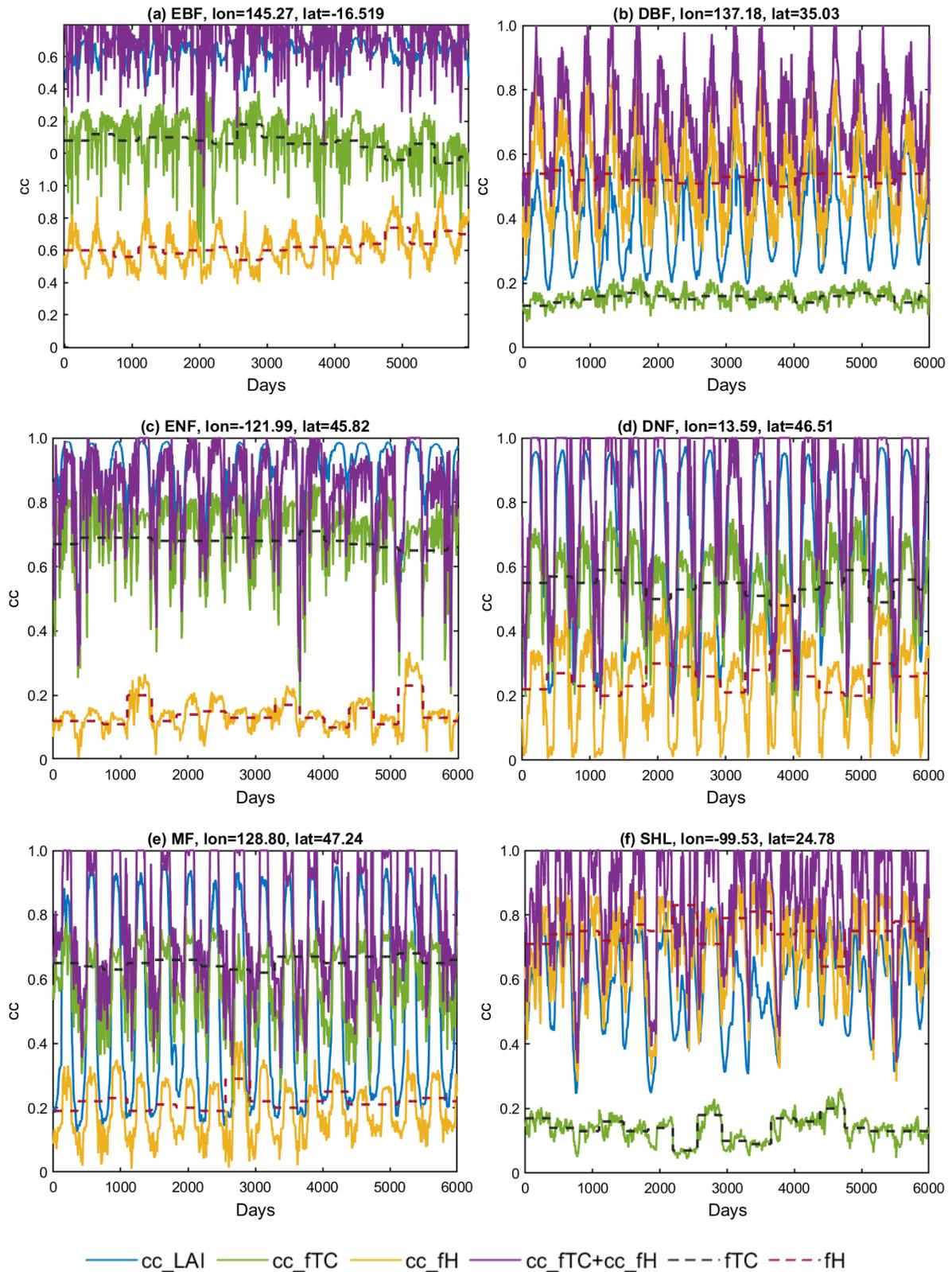


Figure R2. The time series of cc at representative sites. cc_{LAI} represents cc derived from LAI based on Beer–Lambert's Law. cc_{fTC} and cc_{fH} represent cc for tall and short vegetation, respectively, in this study estimated from $fPAR$. fTC and fH are the annual tree canopies and non-tree vegetation canopies from MOD44B product.

Comment 1.3: EBF results. The intercepted evaporation from EBF using the modified approach is very high. It is noticeably larger than the PML-V2 estimate. So, it is necessary to extract EBF sites for validation analysis. I am keen to know how much the modified approach improves the estimate at EBF sites, compared to the original one using the exponential equation.

Reply: Thanks for your advice. Although our estimates at EBF sites are generally larger than that from PML v2 (Fig. 8), they are overall comparable to field observations (Fig. S3) with a slight overestimation for small events and underestimation for large events (L309–313).

Action: In order to make a comparison, we validate the estimations from PML v2 and GLEAM v3.5a against *in situ* data at EBF sites, and results are shown in Fig. R3. Take note that the time series of PML v2 spans from 2003 to 2017, hence only 13 field observations can be used here. Although PML v2 shows the highest correlation coefficient for I/P , it significantly underestimates both I and I/P , especially for large events. GLEAM v3.5a shows a systematic underestimation as only forest interception is estimated. Compared to PML v2 and GLEAM v3.5a, our estimations overall present the best agreement with field observations, and have the lowest mean bias errors.

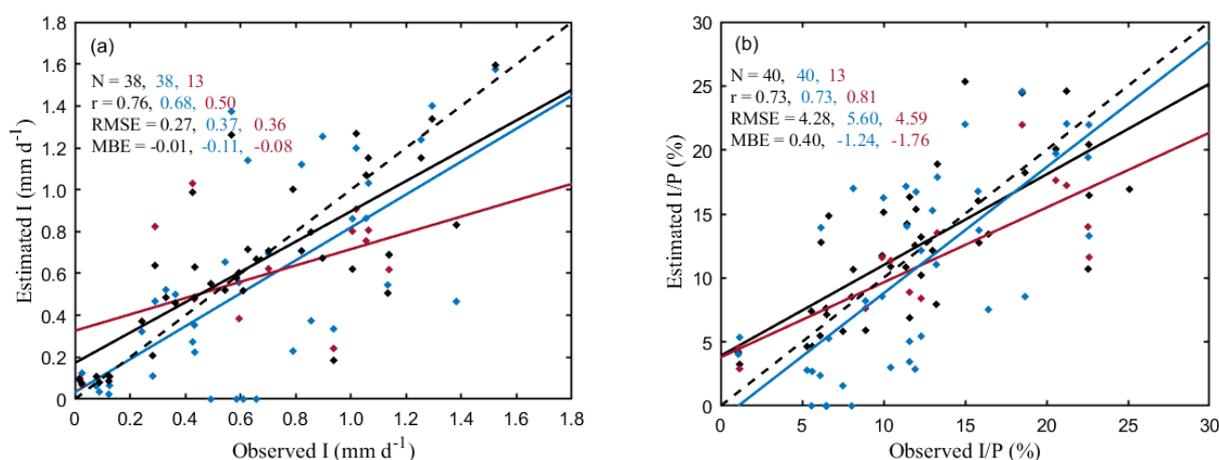


Fig R3. Field validation of rainfall interception loss for EBF sites. (a) I in mm d⁻¹, (b) I/P in %. Black, blue and red scatters represent the pixel-scale simulations from this study, GLEAM and PML model, respectively. Since the time series of PML v2 spans from 2003 to 2017, hence only 13 field observations can be used for validation. The solid lines in different colors are the regression lines, and the black dashed lines mark the 1-to-1 line.

Minor comments:

Comment 1.4: For the estimation of E_c . Line 286-292, the authors found that the E_c for short vegetation from 8 publications exhibits larger variability and is on average higher than that for tall vegetation, which is not consistent with previous expectations of lower E_c for short vegetation than that for tall vegetation. The aerodynamic resistance is one reason, as

wind speed on the top of canopy for tall vegetation should be higher than for short vegetation. But, in my opinion, surface temperature and available energy for short vegetation could be higher, leading to a higher E_c than that for tall vegetation. Finally, the authors used potential evaporation (E_p) as a proxy of E_c for short vegetation in the vD-B model. My question is which equation is used to calculate the potential evaporation (E_p)? Is it FAO P-M method? as the FAO P-M was setup for short vegetation. How about the comparisons between E_p and E_c (from the 8 publications) for short vegetation?

Reply: Thanks for your comments. In our study, the Priestley and Taylor-based potential evaporation (E_p) from GLEAM v3.5a is selected as a proxy of E_c for short vegetation (L151–153). As Table R1 shown, E_p is substantially lower than that observed E_c from 8 publications (L328–329). We agree that E_c derived from E_p might be lower than the actual evaporation rates from short vegetation. However, we do not agree that the available energy for short vegetation should be higher than that for forests, as the albedo is normally lower in forests. Besides, these short vegetation species from the 8 publications could not be representative for global short vegetation ecosystems, especially grasslands, as most of them are tall enough to fit funnels or gutters under them (L329–331). Notice that some values of these observed E_c (1.18–2.96 mm/h) are even larger than that for tall vegetation (Fig. 2(d)).

Action: E_p would be maintained in this study until a better method could be used to parameterize E_c for short vegetation.

Table R1. A detailed summary of short vegetation E_c , R and E_c/R from 8 publications, and their corresponding estimations in this study. “Lon.” and “Lat.” denote the longitude and latitude of experiment sites. The methods to obtain E_c include Regression (Reg) method and Optimization (Opt) method.

References	Lon.	Lat.	Duration	Vegetation	Observations				Estimates		
					E_c	Method	R	E_c/R	E_c	R	E_c/R
Návar et al. (1999)	-99.53	24.78	1995.09–1997.04	Thornscrub	2.96	Reg	18.08	0.164	0.10	3.15	0.065
Návar and Bryan (1994)	-99.53	24.78	1987.05–08	Shrubs	2.95	Reg	13.52	0.218	0.16	6.54	0.028
Zhang et al., (2018)	100.01	37.59	2012.06.01–2012.09.11	Potentilla fruticosa	0.09		0.60	0.150	0.11	1.99	0.058
Herbst et al. (2006)	-1.70	51.60	2004.06.21–2005.02.09	Hedgerow							
				Full leaf	0.37		1.84	0.201			
				Leafless	0.10		1.40	0.071	0.03	2.02	0.017
Fernandes et al. (2017)	-47.67	-2.61	2012.07–2013.05	Sugarcane							
				Tillering	0.10	Opt	3.10	0.032			
				Stems elongation	0.58	Opt	3.10	0.187	0.14	6.81	0.027
				Ripening	0.69	Opt	3.10	0.223			
Finch and Riche (2010)	-0.35	51.81	1997.06.26–1998.01.19	Miscanthus	0.15	Opt	1.20	0.125	0.03	1.91	0.021
Nazari et al. (2020)	51.63	35.28	2015&2016.05–09	Maize							
				Seedling				1.500			
				Jointing				0.298			
				Tasseling				0.208			
				Maturity				0.256			
				Average	1.59	Reg	3.65	0.436	0.09	0.51	0.176
Van Dijk and Bruijnzeel (2001)	108.07	-7.05	1995.01.08–1995.05.11	Mixed crops	1.18	Opt	4.70	0.251	0.13	7.48	0.018
			1999.01.02–1999.07.17	Mixed crops	0.55	Opt	4.30	0.127	0.13	5.87	0.029

Comment 1.5: For short vegetation interception. Line 325-329, result shows both the modeled I and I/P for short vegetation are smaller than observations, and authors think lower estimates of E_c from E_p for short vegetation caused this underestimation. Therefore, I may not agree that E_c for short vegetation should be lower than that for tall vegetation. On the other hand, Zhang et al (2016a, 2017) (in lines 340-342) reports about two times I/P values than this study's modeled values. I guess that differences in vegetation index, eg, LAI between grassland, crop, and shrub can also largely affect the lower modeled I/P values. Can you compare how modeled or observed I/P change over LAI for short vegetation?

Reply: As mentioned above, we think the most likely reason for this lower performance is that these short vegetation species from the 8 publications could not be representative for global short vegetation ecosystems, especially grasslands, as most of them are tall enough to fit funnels or gutters under them (L329–331). The lower estimates of E_c might be the secondary cause. In theory, LAI should have a significant impact on I/P , as a larger LAI indicates a larger canopy cover and storage capacity. However, we only have 16 observed I/P (see Fig. 3) for short vegetation, half of which are obtained after 2003. That means a few data can support such comparison due to lack of LAI data.

Action: No corresponding analysis due to lack of data.

Comment 1.6: Figure 5, “a”, “b”, “c”, “d” are not shown in each plot.

Reply: We thank the reviewer for pointing this out.

Action: We will add labels of panels in Fig. 5 (see Fig. R4).

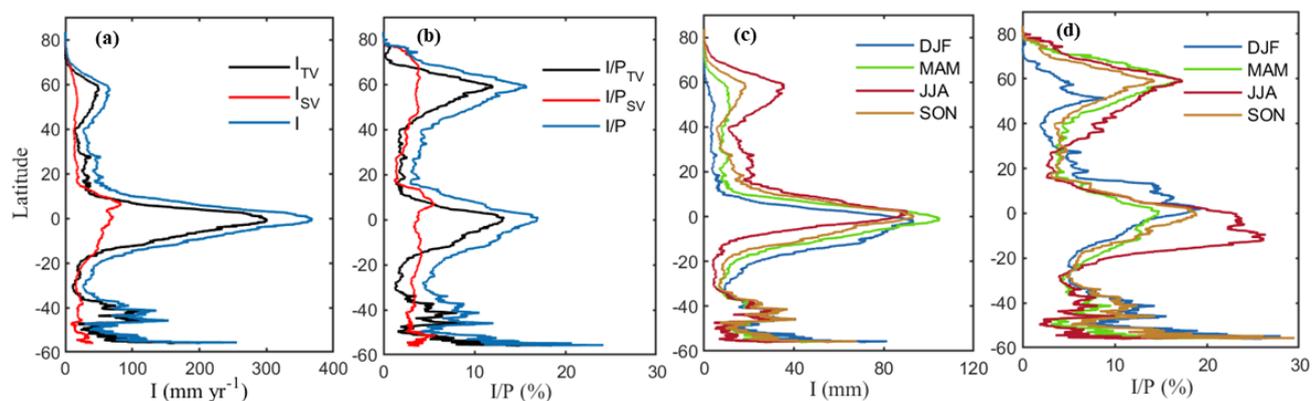


Figure R4. Variation of average I along different latitudinal bands. (a) I (mm yr^{-1}) for tall vegetation, short vegetation and their sum. (b) Same but for I/P (%). Seasonal patterns of I in mm yr^{-1} (c), and of I/P in % (d).

Comment 1.7: Lines 405-409, “that the measured I is overall higher than the global estimates, except in EBF.” I think this may also partly because that the precipitation input for the vD-B model is systematically lower than the observed precipitation from filed experiments.

Reply: We thank the reviewer for the comment. we certainly agree with the reviewer's points that to a certain degree, the underestimation of I in tall vegetation ecosystems could

be explained by the lower precipitation (L313–315). Figure R5, equivalent to Fig. S4, shows the linear regression between forcing and observed precipitation. Forcing precipitation is overall lower than the observed precipitation in forests, especially for larger events. Similar validation results are found for both I and I/P (see Fig. 3), and the discrepancy between estimations and observations is attenuated when expressing the results as I/P (higher correlation coefficient).

Action: We will state Fig. 7 more clearly in the main text.

“Notice that the measured I is overall higher than the global estimates, except in EBF. While in terms of I/P , the estimates agree well with the field data in forests. This might be caused by the lower forcing precipitation in forests (Fig. S4).”

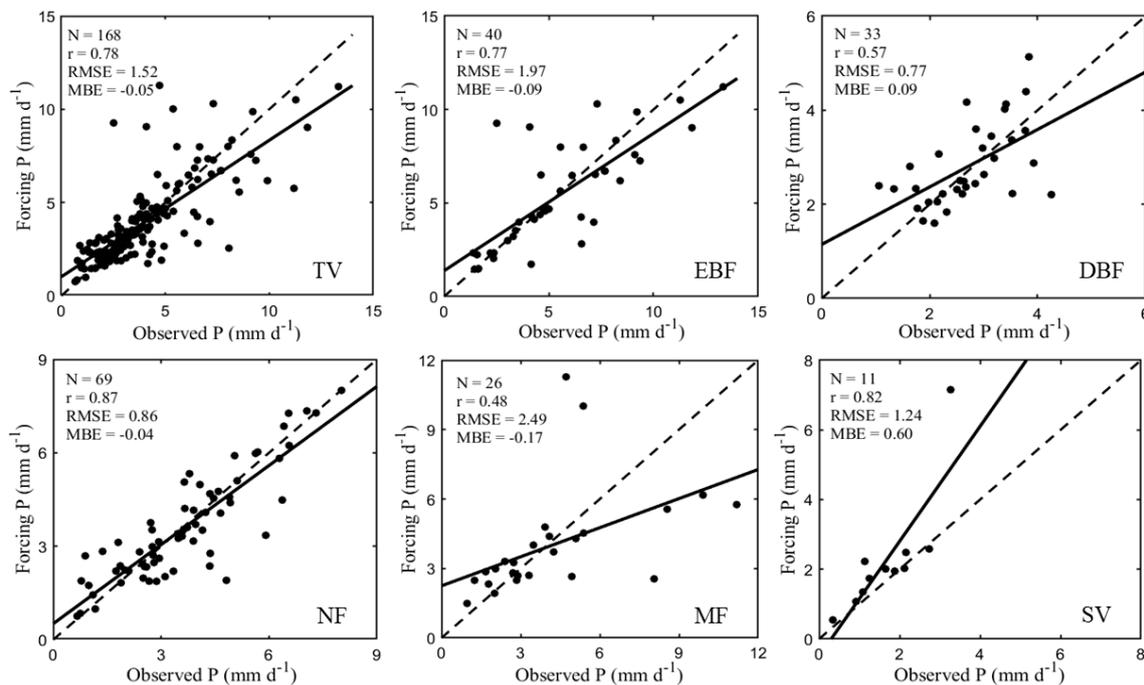


Figure R5. Linear regression between forcing and observed precipitation over field campaigns. TV, EBF, DBF, NF, MF and SV represent Tall Vegetation, Evergreen Broadleaf Forests, Deciduous Broadleaf Forests, Needleleaf Forests, Mixed Forests and Short Vegetation, separately.

Comment 1.8: PML-V2. A wrong reference is used for PML-V2. Please cite Zhang et al. (2019) as well (See line 425). Zhang, Y., Kong, D., Gan, R., Chiew, F.H.S., McVicar, T.R., Zhang, Q., and Yang, Y., 2019. Coupled estimation of 500m and 8-day resolution global evapotranspiration and gross primary production in 2002-2017. Remote Sens. Environ. 222, 165-182, doi:10.1016/j.rse.2018.12.031

Reply: Thank you for pointing this out.

Action: We will add this citation in text as following.

“PML is based on the same vD – B model, but with different parameterizations (Zhang et al., 2016; 2019).”

References

- Braghiere, R. K., Quaife, T., Black, E., He, L., and Chen, J.: Underestimation of global photosynthesis in Earth system 490 models due to representation of vegetation structure, *Global Biogeochem. Cycles*, 33, 1358-1369, <https://doi.org/10.1029/2018GB006135>, 2019.
- Braghiere, R. K., Quaife, T., Black, E., Ryu, Y., Chen, Q., De Kauwe, M. G., and Baldocchi, D.: Influence of sun zenith angle on canopy clumping and the resulting impacts on photosynthesis, *Agr Forest Meteorol*, 291, 108065, <https://doi.org/10.1016/j.agrformet.2020.108065>, 2020. 495
- Braghiere, R. K., Wang, Y., Doughty, R., Sousa, D., Magney, T., Widlowski, J.-L., Longo, M., Bloom, A. A., Worden, J., Gentine, P., and Frankenberg, C.: Accounting for canopy structure improves hyperspectral radiative transfer and sun-induced chlorophyll fluorescence representations in a new generation Earth System model, *Remote Sens. Environ.*, 261, <https://doi.org/10.1016/j.rse.2021.112497>, 2021.
- Mu, X., Song, W., Gao, Z., McVicar, T. R., Donohue, R. J., and Yan, G.: Fractional vegetation cover estimation by using multi-angle vegetation index, *Remote Sens. Environ.*, 216, 44-56, <https://doi.org/10.1016/j.rse.2018.06.022>, 2018.
- Van Dijk, A. and Bruijnzeel, L.: Modelling rainfall interception by vegetation of variable density using an adapted analytical model. Part 1. Model description, *J. Hydrol.*, 247, 230-238, [https://doi.org/10.1016/S0022-1694\(01\)00392-4](https://doi.org/10.1016/S0022-1694(01)00392-4), 2001.
- Zhang, Y., Kong, D., Gan, R., Chiew, F.H.S., McVicar, T.R., Zhang, Q., & Yang, Y.: Coupled estimation of 500m and 8-day resolution global evapotranspiration and gross primary production in 2002-2017. *Remote Sensing Environ.* 222, 165-182. <https://doi:10.1016/j.rse.2018.12.031>, 2019.
- Zhang, Y., Peña-Arancibia, J. L., McVicar, T. R., Chiew, F. H., Vaze, J., Liu, C., Lu, X., Zheng, H., Wang, Y., and Liu, Y. Y.: Multi-decadal trends in global terrestrial evapotranspiration and its components, *Sci Rep*, 6, 1-12, <https://doi.org/10.1038/srep19124>, 2016.