

## Response to referee comment RC2:

*We thank the referee for reviewing our work. We place the referee's comments as "C" and provide our response in italic as "R".*

C1: Stiegler et al. study the response of surface-atmosphere fluxes from an oil palm plantation to variability in climate including fire-induced haze. The analysis is important but there are many aspects of the manuscript which should be improved before it is ready for publication. On p 2 L 25 note that this is for the same total amount of PAR. Haze also decreases PAR at the surface and can decrease net photosynthesis for this reason.

*R1: We agree with the referee. We will update the paragraph and add information on the impact of increasing aerosol particles from biomass burning on the total amount of PAR.*

C2: p3 L20: this notion wasn't fully developed in the introduction. A good place to start might be: Steiner, A. L., Mermelstein, D., Cheng, S. J., Twine, T. E., & Oliphant, A. J.(2013). Observed impact of atmospheric aerosols on the surface energy budget. *Earth Interactions*, 17(14), 1–22. <https://doi.org/10.1175/2013EI000523.1>

*R2: We will update the manuscript and further develop the possible impact of aerosol particles on energy flux partitioning and CO<sub>2</sub> uptake during our study period. We did not measure aerosol concentration at the study site and defined the haze period based on fraction of diffuse radiation and the persistence of high values of fraction of diffuse radiation. Steiner et al. (2013) report that increased aerosol concentration and related increase in diffuse light increase plant photosynthesis and therefore decrease the ratio of sensible to latent heat. In our study we observe an increase in the ratio of sensible to latent heat which is likely due to water stress and related partial stomata closure due to high VPD. Wang et al. (2018) observe that increased aerosol concentration increase overall canopy photosynthesis but due to different processes in sun and shaded leaves. Sun-exposed leaves benefit from lower VPD while shaded leaves benefit from increased diffuse light conditions. In our study, during the haze drought period atmospheric VPD reached its overall peak and Bowen ratio concurrently increased. In our model we also observe an overall negative impact (decrease in CO<sub>2</sub> uptake) due to the high VPD.*

*At our study site, increased fraction of diffuse radiation due to biomass burning has an overall positive impact (increase in CO<sub>2</sub> uptake) and decreased PAR a negative impact on CO<sub>2</sub> uptake, which is in line with the findings of Malavelle et al (2019). However, while Malavelle et al (2019) conclude that the positive impact of increased diffuse light conditions offsets the negative impact of decreased PAR we observe that the increase in diffuse light conditions is not able to offset the negative impact in decreased PAR. We suggest that the strong intensity and relatively long duration of the haze, with persistently high values of fraction of diffuse radiation for approx. two months, inhibits a positive impact on CO<sub>2</sub> uptake.*

- *Steiner, A.L. et al. (2013): Observed impact of atmospheric aerosols on the surface energy budget, *Earth Interactions* 17 (14), 1-22.*
- *Wang, X. et al. (2018): Field evidences for the positive effects of aerosols on tree growth, *Global Change Biology* 24, 4983-4992.*
- *Malavelle, F.F. et al. (2019): Studying the impact of biomass burning aerosol radiative and climate effects on the Amazon rainforest productivity with an Earth system model, *Atmos. Chem. Phys.* 19, 1301-1326.*

C3: More detail about how transformation and adding an intercept reduced goodness-of-fit would be forthcoming. Especially adding the intercept; it is unclear to me how adding more parameters (in this case an intercept) would make goodness of fit worse.

*R3: In the case of transformation, we transformed each data by subtracting the mean and dividing it by the standard deviation. The transformed data had a mean zero with a standard deviation of 1. e.g.  $NEE\_transform = (NEE - mean(NEE))/sd(NEE) = scale(NEE)$ . In the case of the transformed data as well as when an intercept was added in the 24-hour original NEE model, Temperature and VPD became insignificant ( $p$ -value ~ [0.5 to 0.8]), and thus the goodness of fit decreased by 53%. In what follows, we show different cases where we examined different MLRMs in relation to setting up the model:*

Case 1:  $lm(formula = scale(NEE) \sim scale(VPD) + scale(CO2) + scale(fdifRad) + scale(wind) + scale(Tair))$

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-0.112342	0.051000	-2.203	0.028650 *
scale(VPD)	0.020793	0.086572	0.240	0.810408
scale(CO2)	0.177867	0.052516	3.387	0.000837 ***
scale(fdifRad)	0.121650	0.052972	2.296	0.022589 *
scale(wind)	-0.177130	0.053028	-3.340	0.000983 ***
scale(Tair)	0.009968	0.088540	0.113	0.910466

Case2:  $lm(formula = scale(NEE) \sim scale(CO2) + scale(fdifRad) + scale(wind))$

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-0.10971	0.04848	-2.263	0.024591 *
scale(CO2)	0.17776	0.05231	3.399	0.000803 ***
scale(fdifRad)	0.11620	0.04873	2.385	0.017930 *
scale(wind)	-0.17344	0.04763	-3.641	0.000338 ***

Case 3:  $lm(formula = NEE \sim VPD + CO2 + fdifRad + wind + Tair - 1)$

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
VPD	0.126540	0.057204	2.212	0.02798 *
CO2	0.014808	0.008446	1.753	0.08095 .
fdifRad	2.144689	1.297013	1.654	0.09964 .
wind	-1.635912	0.288365	-5.673	4.37e-08 ***
Tair	-0.313711	0.114494	-2.740	0.00665 **

Case 4:  $lm(\text{formula} = NEE \sim VPD + CO2 + \text{fdifRad} + \text{wind} + Tair)$

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-19.78924	6.57646	-3.009	0.002926 **
VPD	0.01612	0.06711	0.240	0.810408
CO2	0.03960	0.01169	3.387	0.000837 ***
fdifRad	2.99722	1.30513	2.296	0.022589 *
wind	-1.11112	0.33264	-3.340	0.000983 ***
Tair	0.01772	0.15742	0.113	0.910466

Case 5:  $lm(\text{formula} = NEE \sim CO2 + \text{fdifRad} + \text{wind})$

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-19.11845	4.67333	-4.091	6.01e-05 ***
CO2	0.03958	0.01165	3.399	0.000803 ***
fdifRad	2.86305	1.20054	2.385	0.017930 *
wind	-1.08794	0.29880	-3.641	0.000338 ***

Case Number	Goodness of fit	Insignificant p-values	AIC score
1	0.20	Temperature, VPD [0.8 to 0.9]	494
2	0.21	None	490
3	0.74	None	808
4	0.20	Temperature, VPD [0.8 to 0.9]	801
5	0.21	None	798

*In the above table, the AIC score differs substantially between models that used original and scaled data, where the model that used the scaled data had low values of AIC score. The model (case 3) that used the original data but excluded the intercept had a relatively high value of goodness of fit when compared with all other cases. Because the AIC score didn't change much between cases 3 and 4 and that case 3 had a relatively high goodness of fit value, we chose to use the model in case 3 for this study.*

C4: Also, are all of the terms necessary? Information criteria-type analyses (e.g. AIC, BIC) can help discriminate against unnecessary terms to come to a simpler and more robust synthesis. e.g. on L 30 p 5, all of these terms may be 'significant', but some may be relatively unimportant for explaining the variance of observations and can perhaps be safely excluded from the model.

*R4: Yes, we agree with the referee that information criteria-type analyses are important metrics that can help simplify statistical models and aid in deciding which variables to keep and which ones to discard. We did not include these metrics in our previous version of the manuscript. Now, we have included AIC scores along with the goodness of fit values for 5 different cases to show how we selected the model.*

*We would like to point out here that we initially included many more variables than specified in equations 1 to 3 in the manuscript for the model selection since we did not put a limit on the number of covariates to explain the observed NEE. In cases 1 to 5, we have showed that we did consider removing the unnecessary covariates on the basis of high p-values. Yes, we did not identify the “relatively unimportant” variables in explaining the variation in observations. If we had standardised the regression coefficients by using a “transformation approach” as we showed in some of the cases above, then we could have compared the regression coefficients to identify their relative importance; however, that was not the focus of the current study.*

C5: What was the cost function for determining parameters? Least squares?

*R5: We used three different models of NEE (as in equations 1 to 3) in the manuscript, which were the different “cost functions”. We used the built in linear regression function in R (“lm”) to fit the models (see cases above). Yes, the parameter estimates of the MLRMs were estimated using the ordinary least squares method.*

C6: I don't really understand section 2.3.1. Is this a type of sensitivity analysis? How does this add to an already unique analysis?

*R6: Yes, in a very general way it can be considered as a type of a sensitivity analysis. However, it is important to note that typically in a sensitivity analysis, model inputs (that are more uncertain) are varied to understand how the model outcomes change. In this case, the parameters of the model (the coefficients) would be considered more uncertain. However, we did not change the coefficients but changed the input variables (the predictors) to examine the effects on the response variable (NEE). Therefore, we would consider the analysis carried out in this section more as a prediction or a scenario type analysis rather than a sensitivity analysis – although both of them are quite closely linked.*

*This analysis helps us understand the likely impacts of changes in drought and haze on NEE.*

C7: 3.2 and elsewhere: expressing fluxes as means of half hourly values plus or minus standard error can be misleading: do these values integrate the same proportion of daytime and nighttime data? If one of the time periods has more nighttime data due to seasonal differences in prevailing winds, the values could be different for this reason. (The paragraph beginning line 22 is better.)

*R7: Due to the proximity of our study site to the equator the difference in day length between summer solstice and winter solstice is only 12 minutes. Therefore, we consider the impact of differences in day length on the fluxes as negligible. Average friction velocity ( $u^*$ ) during both day and night time, is slightly higher during the pre-drought period ( $0.26 \pm 0.16 \text{ m s}^{-1}$ ) as compared to the other periods ( $0.21 \pm 0.14 \text{ m s}^{-1}$ ).*

C8: bottom of p 7: define 'dim light'. Light that is 'dim' to our eyes is probably below the CO<sub>2</sub> compensation point (because human eyes respond logarithmically to light levels).

*R8: We will update the manuscript and change the wording. In this specific case, dim light conditions refer to a reduction in the overall day time (6:00-18:30 h local time) levels of PAR and incoming solar radiation during the haze period and not, as the current wording might suggest, to dim light conditions during dusk or dawn.*

C9: The paragraph on L 10 p 8 is unconvincing: was energy flux partitioning impacted by haze in addition to surface drying or was the latter the most important? Energy flux analyses in the manuscript could be better-developed as a whole.

*R9: We will update the paragraph. Soil moisture continued to decrease over the non-haze drought and haze drought period (Table 1) but the overall decrease in deep layer (100 cm) soil moisture was less pronounced as in 30 cm and 60 cm depth. Oil palm is able to uptake water from deep soil and store the water in the trunk during night that supports water use during peak hours of photosynthesis (Niu et al., 2015; Meijide et al., 2017). Therefore, soil moisture might only be a minor factor of the observed changes in energy flux partitioning. We will add more information on energy flux partitioning into sensible and latent heat in the manuscript.*

- *Niu, F. et al. (2015): Oil palm water use: calibration of a sap flux method and a field measurement scheme, Tree Physiol. 35 (5), 563-573.*
- *Meijide, A. et al. (2017): Controls of water and energy fluxes in oil palm plantations: Environmental variables and oil palm age, Agricultural and Forest Meteorology 239, 71-85.*

C10: Section 3.4: I'm not sure how extending the analyses behind the range of variability observed in the (linear) models is a good way to estimate the impacts of additional haze. This could bring for example far more ozone, which was not considered and is probably critical for photosynthesis here. In brief, I recommend dropping the intensified drought/haze analysis with a non-mechanistic model and adding instead more detail about sensible and latent heat fluxes, the analysis of which at the moment seems like an afterthought.

*R10: We thank the referee for raising the concern whether extending the analyses behind the range of variability observed in the data is a good way to estimate the impacts of additional haze. This is an important point that the referee raised. Indeed, this is a limitation for not only statistical models but also for mechanistic models, where both of the models may not realistically estimate the impacts of additional haze unless they are developed using that range in the first place. However, numerous mechanistic land surface models have been run on domains where they looked at responses of these models to future climatic conditions and also at large time-steps such as on century time-scales. The predictions of such models can involve relatively large uncertainties. On the grounds that we did not consider relatively large changes in the variables (i.e. we only considered +/- 20%) and the time-step that we think it might occur is not more than 5 years. Daily average NEE during the haze drought period ranged between -3.61 and 4.80  $\mu\text{mol m}^{-2} \text{s}^{-1}$ .*

*We will make this statement clear in the manuscript and so we acknowledge that the outcomes of our model application has some limitations and is simple but we think it can still be useful, for e.g. it can serve as a hypothesis that can be looked into in the future as more data becomes available.*

C11: 4.1: 'relatively resistant against drying soil'...with respect to the range of drying observed here. It probably just wasn't quite dry enough rather than the plants being insensitive to soil moisture.

R11: We agree with the referee and we will update the manuscript and change the paragraph. Oil palm is able to uptake water from deep soil and store the water in the trunk during night that supports water use during peak hours of photosynthesis (Niu et al., 2015; Meijide et al., 2017). Soil moisture conditions in the deeper soil layer (100 cm depth) showed a relatively moderate decrease during both non-haze drought and haze drought period and remained higher as compared to soil moisture conditions in the upper layers (30 cm and 60 cm depth) (Table 1). Therefore, with respect to the range of drying soil observed in this study, the relatively moderate decrease in soil moisture in deeper soil layers was not reflected in a decrease in NEE.

- Niu, F. et al. (2015): Oil palm water use: calibration of a sap flux method and a field measurement scheme, *Tree Physiol.* 35 (5), 563-573.
- Meijide, A. et al. (2017): Controls of water and energy fluxes in oil palm plantations: Environmental variables and oil palm age, *Agricultural and Forest Meteorology* 239, 71-85.

C12: Good detail about oil palm physiology throughout. More biogeochemical/biogeophysical studies should include these important details about fruiting, etc.

R12: We will update the manuscript with more information on fruiting and other details about oil palm physiology.

C13: Interesting that oil palm is insensitive to VPD up to 17 hPa given the rather large sensitivity of other tropical plants to VPD, see: Fu, Z., et al., 2019. The surface-atmosphere exchange of carbon dioxide in tropical rainforests: Sensitivity to environmental drivers and flux measurement methodology. *Agric. For. Meteorol.* 263, 292-307. Kiew, F., et al., 2018. CO<sub>2</sub> balance of a secondary tropical peat swamp forest in Sarawak, Malaysia. *Agric. For. Meteorol.* 248, 494–501. Wu, J., et al., 2017. Partitioning controls on Amazon forest photosynthesis between environmental and biotic factors at hourly to inter- annual timescales. *Glob. ChangeBiol.* 23, 1240–1257.

R13: We will update the manuscript with a discussion on the effect of VPD on oil palm compared with other tropical plants as suggested by the referee.

C14: Section 4.2 is likewise weak...the model cannot consider the impacts of elevated temperatures beyond temperature optimums on reducing photosynthesis. Include instead perhaps an analysis of energy fluxes, which comprise hypothesis b and are never adequately described thereafter.

R14: We also agree with the referee here that the current model is built on the dataset that may not have included elevated temperatures which might be clearly important for downregulating oil-palm photosynthesis. Indeed, we do have data-sets covering a few more years which show that air temperature is within the range of the 2015-ENSO year. Our current data does therefore include elevated temperatures to an extent and so we are focusing on short-term responses.

Rising CO<sub>2</sub> and the deforestation of surrounding forests can likely enhance temperatures of oil-palm in the future. In either of these cases, our model application might not be suitable. Therefore, in the updated version of the manuscript we will change the term “future” into “short-term response of oil palm to changed climatic conditions”. These short-term responses of oil palm focus on the current life cycle of the oil palm plantation, which was planted in 2002 and is therefore closer to rotation now, which happens 25 years after the planting. Therefore, these short-term responses do not include elevated temperature

associated with rising CO<sub>2</sub> levels beyond the temperature optimum of oil palm photosynthesis.

C15: Conclusions and elsewhere: some discussion of ozone would be forthcoming. This isn't measured (and rarely is) but may (or may not) be important here.

R15: We will update the manuscript with a discussion on possible impact of ozone on oil palm photosynthesis. Ground-level ozone exerts strong toxicity on tropical and sub-tropical agricultural and natural vegetation (Moraes et al., 2004; Felzer et al., 2007; Zhang et al., 2014; Chen et al., 2018). Ozone concentration has not been measured in this study but biomass burning is considered to significantly affect near-surface ozone concentration due to emission of ozone precursor gases (Kita et al., 2000) and fire air pollution generally leads to a decrease in gross primary productivity (GPP) (Yue & Unger, 2010). To our knowledge, no study has focused on ozone concentration from biomass burning during the 2015 ENSO event but studies observe a strong increase in ozone concentration from biomass burning during the 1997-ENSO (Thompson et al., 2001) and during the 2006-ENSO event (Nassar et al., 2009). At our study site, we therefore expect an increase in ground-level ozone concentration during the haze drought period which might have negatively affected oil palm carbon sequestration.

- Moraes, R.M. et al. (2004): Photosynthetic responses of tropical trees to short-term exposure to ozone, *Photosynthetica* 42 (2), 291-293.
- Felzer, B.S. et al. (2007): Impacts of ozone on trees and crops, *C. R. Geoscience* 339, 784-798.
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- Chen, Z. et al. (2018): Effects of elevated ozone levels on photosynthesis, biomass and non-structural carbohydrates of *Phoebe bournei* and *Phoebe zhennan* in subtropical China, *Front. Plant Sci.* 9: 1764.
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- Thompson, A.M. et al. (2001): Tropical tropospheric ozone and biomass burning, *Science* 291, 2128-2132.
- Nassar, R. et al. (2009): Analysis of tropical tropospheric ozone, carbon monoxide, and water vapour during the 2006 El Niño using TES observations and the GEOS-Chem model, *J. Geophys. Res.* 114, D17304.