Response to referee comment RC1:

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: Overall, this is a well written manuscript with some interesting insights. Not only the in-situ observations, the authors also use a multi linear regression model in this study. The authors aim to investigate the impacts of ENSO events on an oil palm plantation from the aspects of CO2, water and energy exchange. The manuscript contains a clear and concise title. However, I do feel the information are overloaded in the manuscript in which the readers may find it difficult to explicitly articulate the key points.

> *R1: We adapted the manuscript with a clearer storyline in the results (3.3) and discussion section (4.1, 4.2) to ensure better readability and better articulation of the key points.*

C2: The authors also discussed the response of oil palm (NEE) to drought and haze conditions solely on the productivity aspect. It is however not clear about the relative contribution of GPP to the NEE. I find it is a bit misleading – was the ecosystem respiration also affected by drought and haze?

> *R2: We updated the methods section with the following paragraph:*
>
> *Initially, we applied CO_2 flux partitioning of NEE into gross primary production (GPP) and respiration using (a) a non-linear regression model based on Reichstein et al. (2005) and (b) CO_2 flux partitioning based on CLM-Palm (Fan et al., 2015) which is a sub-model within the framework of the Community Land Model (CLM4.5) (Oleson et al., 2013). The non-linear regression model underestimated NEE by 58%, on average, most likely because the model struggles to assess the temperature sensitivity of ecosystem respiration using the filtered night time data (Oikawa et al., 2017). CLM-Palm struggled to represent daily average NEE during the non-haze drought and haze drought periods, most likely due to the models' soil water stress function (Sellers et al., 2013) and missing plant hydraulic processes in the overarching CLM4.5 (Oleson et al., 2013). Therefore, we decided to solely focus on NEE to describe the overall CO_2 flux behaviour of the oil palm plantation during the extreme events of drought and haze. However, we used the night time NEE (=respiration) as a proxy for the overall behaviour of oil palm monoculture respiration and disentangled its driving climatic variables.*
>
> *Further, we updated the manuscript with a discussion on the behaviour of respiration:*
>
> *Temperature increase and related heat stress is another factor which might negatively affect the growth of oil palm (Oettli et al., 2018). Our analysis did not support this finding because during the non-haze drought the effect of increasing temperature on NEE was almost negligible. During the haze drought, higher air temperature had a positive impact on CO2 uptake although the haze period experienced the highest air temperature during the entire study period. Changes in temperature and moisture availability also impact oil palm ecosystem respiration. Matysek et al. (2018) observed high heterotrophic carbon loss from drained peat soils in a Malaysian oil palm plantation during the dry season and Sigau & Hamid (2018) found similar behaviour in Malaysian rubber and oil palm plantations on drying Haplic Nitisols soils but both studies report only minor impact of increased soil temperature on soil respiration. Autotrophic respiration, however, tends to decrease with increasing leaf temperature (Slot et al., 2014). In our study, the increase in air temperature tended to increase night time ecosystem respiration and therefore might also lead to higher day time respiration during the non-haze drought and haze drought period.*

C3: There are in fact several publications on the effect of ENSO events on the ecosystem productivity either in oil palm plantation, forest or other ecosystems. However, I did not see the authors discussed or compared their results with that of the published findings.

R3: We updated the manuscript with a discussion on the effect of ENSO events on the ecosystem productivity in other ecosystems such as forests and plantations (section 4.1).

C4: It is also interesting to note that oil palm plantation was a net sink of CO_2 during the ENSO year. Please find the specific comments below.

R4: ENSO in 2015 was characterized by a distinct drought period which lasted in our study region from May until October 2015. During the haze drought period, the oil palm plantation was carbon neutral due to the dense smoke and overall reduction in available PAR. After the end of the haze drought period towards the beginning of the wet season we observe a short transition period where carbon uptake is relatively low compared to the rest of the wet season. However, except for the two months of the haze drought period, the oil palm plantations remained a sink of atmospheric CO_2. Our study site is a well-managed commercial oil palm plantation where fertilization and pest control is applied on a frequent basis. Other oil palm plantations, with less developed management practices might have lower ability to adapt to the drought and haze conditions compared to our study site.

C5: Page 2 line 17: The life cycle of oil palm is about 25 years.

R5: We agree with the referee. We updated the wording according to the referees comment: "Oil palm has high life cycle of about 25 years (Woittiez et al., 2017)…"

C6: I see NEE is first written on Page 3 line 2 in the manuscript, please define NEE or what does NEE stand for.

R6: We updated the manuscript and defined NEE (net ecosystem exchange) in its first appearance in the manuscript. NEE was defined as GPP (gross primary productivity) plus respiration. In this study we assign fluxes as positive when they are directed away from the surface.

C7: Page 3 line 26: The superscript should be put for -1 (2235 mm yr-1).

R7: We updated the paragraph.

C8: Page 3 line 25-26: I don't understand the use of climatic data from the meteorological station. If it is to show longer term data, then it is probably necessary to compare meteorological data from the site and that of the station even though they are only 29km apart. This is to show that the longer term data is relevant to the site.

R8: We updated the paragraph with the following sentences:

"A comparison of air temperature and precipitation at our study site with climate records from Sultan Thaha Airport Jambi during our study period June 2014 to July 2016 showed no significant differences in daily average air temperature ($P<0.001$) or in monthly accumulated precipitation ($P<0.001$). Therefore, we consider the long-term climate records being representative for our study location."

C9: Page 3 line 30: The superscript should be put for m2 m-2.

R9: We updated the manuscript.

C10: Page 3 line 30: The LAI was very low for the palm age. Could this be due to the large gaps because of palm leaning?

R10: We updated the paragraph with information on how LAI at the study site was derived. Palms are planted in a triangular array, with 8×8 m horizontal density and 156 palms per ha. Based on this horizontal density, an average palm height of 12 m, and 35-45 expanded leaves per palm, Fan et al. (2015) estimated a site-specific leaf area index (LAI) of 3.64 m^2 m^{-2}. Gaps in oil palms that can be created due to disturbances or extreme weather conditions was not observed in this study.

Sample measurements of LAI (unpublished data), using LAI-2200 Plant Canopy Analyzer (LI-COR Inc. Lincoln, USA) at 12 oil palm plantation plots in the Jambi province in June 2018 show average LAI of 2.7 ±0.57 SD m^{-2}. Oil palm age at the measured plots is ~18 years and horizontal density varies between 8x8 m or 9x9 m. Awal & Wan Ishak (2008) report LAI of 3.05 ±0.119 m^{-2} m^{-2} and 4.05 ±0.343 m^{-2} m^{-2} for two oil palm locations with 16 years old palms and a density of 148 palms per ha. Breure (2010) reports mean LAI of 5.97-5.51 m^{-2} m^{-2} for three 8 years old plantations with 135 palms per ha.

- *Fan, Y. et al. (2015): A sub-canopy structure for simulating oil palm in the Community Land Model (CLM-Palm): phenology, allocation and yield, Geosci. Model Dev. 8, 3785-3800.*
- *Awal, M.A. & Wan Ishak, W.I. (2008): Measurement of oil palm LAI by manual and LAI-2000 method, Asian Journal of Scientific Research 1 (1), 49-59.*
- *Breure, C.J. (2010): Rate of leaf expansion: A criterion for identifying oil palm (Elaeis guineensis Jacq.) types suitable for planting at high densities, NJAS – Wageningen Journal of Life Sciences 57, 141-147.*

C11: Page 4 line 13: The superscript should be put for...m s-1.

R11: We updated the manuscript.

C12: Page 8 line 6-9: The monthly oil palm yield does not make sense as the values are extremely high. Annual fresh fruit bunch yield can rarely achieve more than 40 t/ha on average.

R12: We agree with the referee. We reanalysed our harvest data and found an error in the calculation of monthly yield. We apologize for the error. We changed the wording with the correct monthly harvest:

"From August 2015, monthly oil palm yield declined continuously from 3.93 t ha^{-1} to its minimum of 1.05 t ha^{-1} in May 2016. Compared to the same period (Nov.-May) in the two years before and the year after the ENSO event, average yield affected by 2015-drought and haze was 32% (0.70 t ha^{-1}) lower. Considering the 2015-haze drought only, average oil palm yield 6-9 months after the beginning of the haze drought was even 50% (1.1 t ha^{-1}) lower compared to the non-ENSO years."

C13: Page 9 line 16: The word 'NDH+ should be 'NHD+

R13: We updated the manuscript.

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 updated the paragraph according to the referees comment.*

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 updated the manuscript and further developed the possible impact of aerosol particles on energy flux partitioning and CO_2 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.*
>
> *Increased aerosol concentration from biomass burning and related increase in diffuse light increase plant photosynthesis and therefore decrease the ratio of sensible to latent heat (Steiner et al., 2013). However, in our study and during the peak of the drought when forest fires started to develop in the area, we observed increase in the ratio of sensible to latent heat (Bowen ratio) which is likely due to water stress and related partial stomata closure at high VPD (Dufrene & Saugier, 1993; Oettli et al., 2018). Further, increased aerosol concentration is able to increase overall canopy photosynthesis under moderately enhanced diffuse light conditions (Knohl et al., 2008; Mercado et al., 2009; Kanniah et al., 2012) and sun-exposed leaves seem to benefit from lower VPD while shaded leaves benefit from increased diffuse light conditions (Wang et al., 2018). Although our measurements and MLRM suggest that the leaves benefitted from the increase in diffuse light conditions during the haze drought period, the high level of VPD, especially during midday, was an overall stress factor for the oil palm plantation and therefore resulted in a decrease in CO_2 uptake. At our study site, increased fraction of diffuse radiation due to biomass burning had an overall positive impact (increase in CO_2 uptake) and decreased incoming PAR a negative impact on CO_2 uptake, which is in line with the findings of Malavelle et al (2019). However, while the authors of that study 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, exceeded an optimal range of diffuse fraction (Knohl et al., 2008) and therefore inhibited a positive impact on CO_2 uptake.*

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: We updated the methods section (2.3 & 2.3.1) and the supplementary material (Table S2) accordingly to the referees' comment.

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) ~ 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) ~ 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 ~ 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(formula = NEE ~ VPD + CO2 + fdifRad + 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(formula = NEE ~ CO2 + fdifRad + 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: We updated the methods section and the supplementary materials to motivate our choice of model design.

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 and we updated the manuscript with this information.

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: We updated the paragraph in the manuscript.

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: We updated the manuscript in the methods section (2.4). 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. Seasonal differences in u, especially during night time, might impact the performance of eddy covariance gap filling. However, we found no significant differences ($P < 0.05$) in u* which could have affected the proportion of available night time data during the different meteorological periods. Therefore, we consider the applied gap filling procedure and derived flux averaging as robust and representative for the studied time periods.*

C8: bottom of p 7: define 'dim light'. Light that is 'dim' to our eyes is probably below the CO2 compensation point (because human eyes respond logarithmically to light levels).

R8: We updated the paragraph and changed the wording:

"With the continuous development of haze in September 2015 and related absence of direct sunlight the oil palm plantation seemed to compensate for the overall haze-related reduction in incoming PAR, with a jump of Amax by 13 µmol m^{-2} s^{-1} (37%) within a couple of days (Figure 4).

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 restructured the results section and added a new sub-section with the title "Evapotranspiration and turbulent heat fluxes". In this sub-section we present energy flux analyses in more detail:

Total evapotranspiration (ET) derived from eddy covariance (EC) latent heat flux (LE) measurements was 1245 ± 362 mm yr^{-1} in 2015 and 1580 ± 469 mm yr^{-1} during the reference period (Table 2), with a higher share of ET on precipitation during the reference period (77.9%) compared to 2015 (64.5%). During the non-haze drought and haze drought periods, the oil palm plantation experienced strong water loss from ET as ET was 2.5 and

1.2 times the amount of precipitation, respectively. ET was lowest during the haze drought period (Figure 5, Table 2), mainly driven by the reduction in incoming solar radiation and PAR as well as by oil palm drought and heat stress which may have triggered partial stomata closure, especially in the beginning of the non-haze drought when VPD was high (Figure 2). Conversely, partial stomata closure during high VPD as well as the absence of precipitation and related drying of the upper soil generally increased sensible heat fluxes (H) at the cost of LE and ET, reflected in the behaviour of the Bowen ratio (H/LE) (Figure 5). From the first half of the pre-drought period into the second half of the non-haze period, the Bowen ratio showed a steady but relatively small decline. However, the end of the non-haze drought and the beginning of the haze drought period mark a strong transition in the behaviour of the Bowen ratio, manifested by a strong jump, peak values of ~0.38 and average of 0.25 for approx. one month. This jump in the Bowen ratio might be related to the increasing density of the haze and related reduction in incoming PAR in combination with high VPD which decrease LE mainly via oil palm water and light stress to a greater extent than the general drying of the soil and lack of precipitation.

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 µmol m^{-2} s^{-1}.

We made this statement clear in the methods section of the manuscript (2.3.1) and 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. We updated the manuscript and changed 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.

C12: 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. CO2 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.

R12: We updated the manuscript with a discussion on the effect of elevated air temperature and VPD on oil palm compared with other tropical plants in section 4.1 as suggested by the referee.

C13: 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.

R13: 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_2 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 changed 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_2 levels beyond the temperature optimum of oil palm photosynthesis. We updated the methods section (2.3.1) and the discussion section (4.2) accordingly.

C14: 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.

R14: We updated the manuscript with a discussion on possible impact of increased ozone and aerosol concentration 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 haswas not been measured in this study but biomass burning (Kita et al., 2000), as well as nitrogen management and isoprene emissions in oil palm plantations (Hewitt et al., 2009 & 2011) are considered to significantly affect near-surface ozone concentration due to emission of ozone precursor gases. 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.*

Increased aerosol concentration from biomass burning and related increase in diffuse light increase plant photosynthesis and therefore decrease the ratio of sensible to latent heat (Steiner et al., 2013). However, in our study and during the peak of the drought when forest fires started to develop in the area, we observed increase in the ratio of sensible to latent heat (Bowen ratio) which is likely due to water stress and related partial stomata closure at high VPD (Dufrene & Saugier, 1993; Oettli et al., 2018).

Further, increased aerosol concentration is able to increase overall canopy photosynthesis under moderately enhanced diffuse light conditions (Knohl et al., 2008; Mercado et al., 2009; Kanniah et al., 2012) and sun-exposed leaves seem to benefit from lower VPD while shaded leaves benefit from increased diffuse light conditions (Wang et al., 2018). Although our measurements and MLRM suggest that the leaves benefitted from the increase in diffuse light conditions during the haze drought period, the high level of VPD, especially during midday, was an overall stress factor for the oil palm plantation and therefore resulted in a decrease in CO_2 uptake. At our study site, increased fraction of diffuse radiation due to biomass burning had an overall positive impact (increase in CO_2 uptake) and decreased incoming PAR a negative impact on CO_2 uptake, which is in line with the findings of Malavelle et al (2019). However, while the authors of that study 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, exceeded an optimal range of diffuse fraction (Knohl et al., 2008) and therefore inhibited a positive impact on CO_2 uptake.

El Niño–Southern Oscillation (*ENSO*) event reduces CO_2 uptake of an Indonesian oil palm plantation

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Abstract. The El Niño–Southern Oscillation (*ENSO*) in 2015 was one of the strongest observed in almost 20 years and set the stage for a severe drought and the emergence of widespread fires and related smoke emission over large parts of Southeast Asia. In the tropical lowlands of Sumatra, which were heavily affected by the drought and haze, large areas of tropical rainforest have been converted into oil palm (*Elaeis guineensis* Jacq.) plantations during the past decades. In this study, we investigate the impact of drought and smoke haze on the net ecosystem CO_2 exchange, evapotranspiration, yield and surface energy budget in a commercial oil palm plantation in Jambi province (Sumatra, Indonesia) by using micrometeorological measurements, the eddy covariance method, yield data and a multiple linear regression model (*MLRM*). With the *MLRM* we identify the contribution of meteorological and environmental parameters to the net ecosystem CO_2 exchange. During the initial part of the drought, when incoming shortwave radiation was elevated, net CO_2 uptake increased by 50% despite a decrease in upper-layer soil moisture by 35%, an increase in air temperature by 10% and a tripling of atmospheric vapour pressure deficit. Emerging smoke haze decreased incoming solar radiation by 35% compared to non-drought conditions and diffuse radiation became almost the sole shortwave radiation flux for two months resulting in a strong decrease in net CO_2 uptake by 86%. Haze conditions resulted in a complete pause of oil palm net carbon ~~uptake~~ accumulation for about 1.5 months and contributed to a decline in oil palm yield by 35%. With respect to ~~climate change and~~ a projected pronounced drying trend over the western Pacific during future El Niño, our model showed that an increase in drought may stimulate net CO_2 uptake while more severe smoke haze, in combination with drought, can lead to pronounced losses in productivity and net CO_2 uptake, highlighting the importance of fire prevention.

1 Introduction

El Niño – Southern Oscillation (*ENSO*) is a coupled ocean-atmosphere interaction phenomenon in the equatorial Pacific Ocean and one of the most distinct drivers of seasonal to interannual regional and global climate variability (Wolter & Timlin, 2011). Increasing sea surface temperatures in the eastern and central tropical Pacific Ocean are linked to increases in sea-level air pressure in the western Pacific Ocean resulting in reduced cloudiness and low precipitation over Southeast Asia (Rasmusson & Carpenter, 1981; Wolter, 1986). Generally, *ENSO* shows episodic and varying timing, frequencies and amplitudes but *ENSO* during 2015 was the strongest observed in almost 20 years (Santoso et al., 2017; Lim et al., 2017). It set the stage for a severe drought over large parts of Southeast Asia, particularly in Indonesia, which ~~favored~~favoured the emergence of widespread and mostly human-induced forest, grassland and peat fires (Betts et al., 2016).

The fires released record-breaking amounts of terrestrial-stored carbon as CO_2 into the atmosphere, with mean daily emission rate of 11.3 Tg CO_2 during September to October 2015 (Huijnen et al., 2016). The recent *ENSO* elevated Mauna Loa mean monthly CO_2 concentration for 2015 above 400 ppm for the first time in its measurement history and contributed to the highest annual CO_2 growth rate on record (Betts et al., 2016). The emitted aerosol particles from biomass burning covered large parts of Sumatra, Borneo, Malay Peninsula and Singapore for several months under a persistent pall of smoke haze.

The regions affected by the smoke haze, especially Indonesia and Malaysia, have undergone substantial land-use changes within the past two decades due to the world's hunger for cheap vegetable oil, such as palm oil (Koh et al., 2011). Oil palm (*Elaeis guineensis* Jacq.) emerged to an important cash crop due to the extensive application of palm oil in pharmaceutical, cosmetics and food industries as well as for biofuel (Koh & Ghazoul, 2008; Turner et al., 2018). Indonesia and Malaysia are the world's biggest producers of palm oil. For example, in 2016/17, the two countries contributed 56% (Indonesia) and 30% (Malaysia) to the global supply of palm oil (USDA, 2018). In 2015, oil palm plantations in the two countries combined covered 17 Million hectares (Chong et al., 2017).

Oil palm has high ~~average~~ life ~~span~~ cycle of about ~~>~~25 years (Woittiez et al., 2017) and is adapted to tropical climate with optimal mean temperature of 24-28°C, it requires frequent and sufficient precipitation of ~2000 mm yr^{-1} and high level of solar radiation (Bakoumé et al., 2013; Corley & Tinker, 2016). Oil palm shows distinct reaction to changes in atmospheric and soil parameters, with gradual symptoms of water and heat stress such as inhibited growth (Legros et al., 2009; Cao et al., 2011), snapping off leaves and drying out of fruit bunches (Bakoumé et al., 2013), reduction in yield (Caliman & Southworth, 1998; Noor et al., 2011), reduction or even pause in carbon dioxide assimilation (~~Rivera~~ Méndez et al., 2012; Jazayeri et al., 2015) and ultimately, plant death (Maillard et al., 1974).

Aerosol particles from biomass burning generally reduce the amount of sunlight reaching the surface and increase the fraction of diffuse radiation through scattering (Kozlov et al., 2014). Diffuse light conditions up to a certain level enhance plant photosynthesis and evapotranspiration through more uniform through-canopy distribution of photosynthetically active radiation (*PAR*) (Knohl & Baldocchi, 2008; Kanniah et al., 2012; Heuvelink et al., 2014). Light haze smoke intensities may therefore increase CO_2 uptake, maximum rate of photosynthesis (A_{max}) and evapotranspiration but during dense haze smoke, the effect is reversed due to the overall reduction of incoming *PAR* ~~and high share of diffuse light may strongly reduce both CO_2 uptake and evapotranspiration~~ (Yamasoe et al., 2006; Moreira et al., 2017). In addition, ambient atmospheric CO_2 increase due to local fires and burning may act as a temporary plant CO_2 fertilization which, to some extent, may offset reduced plant CO_2 uptake during dense smoke haze (Mathews & Ardiyanto, 2016).

Global warming and consequent regional climate changes, including changes in precipitation pattern and increase in the magnitude and frequency of extreme events such as drought, *ENSO* and fires (Neelin et al., 2006; IPCC, 2013; Jiménez-Muñoz et al., 2016), may severely stress oil palm plantations in the near future (Tangang, 2010; Rowland et al., 2015). It is therefore important to assess how much net ecosystem CO_2 exchange (*NEE*) would change under such conditions. Model predictions suggest more intense *ENSO* over the course of the 21st century, which may result in a general drying in the western regions of the Pacific Ocean during El Niño (Power et al., 2013; Cai et al., 2014; Kim et al., 2014; Keupp et al., 2017; Cai et al., 2018). Increasing frequency of *ENSO*-related drought in Southeast Asia has already caused a decline of 10-30% in palm oil production (Paterson et al., 2017). Projected temperature increase and water stress through enhanced *ENSO* might further decrease oil palm yield (Oettli et al., 2018) or even lead to detrimental conditions for oil palm growth in some areas in Southeast Asia (Paterson et al., 2017). On the other hand, *ENSO* is associated in Indonesia with an increase in incoming solar radiation which can increase CO_2 uptake in a tropical environment (Olchev et al., 2015). However, current studies and modelling approaches lack a holistic understanding of ecosystem response, resilience and the underlying meteorological, ecological and biological processes during extreme events, such as drought and smoke haze conditions. The *ENSO* in 2015 was the first strong climate extreme event after the major land-use conversions on Sumatra from forest into oil palm plantations but only little is known about how the *ENSO*-related severe drought and persistent smoke haze influenced oil palm monoculture.

In this study, we therefore aim to (a) quantify land-atmosphere CO_2, water vapour and turbulent heat exchange over oil palm plantation using the eddy covariance technique during the 2015-*ENSO*, (b) analyse the contribution to net ecosystem CO_2 exchange (*NEE*) of meteorological and environmental parameters using a multiple linear regression model (*MLRM*), (c) investigate the impact of a possible near-future more severe drought and smoke haze scenario on *NEE* and (d) evaluate potential changes in evapotranspiration and energy fluxes to the atmosphere. We hypothesize that (a) oil palm monoculture would reduce net ecosystem CO_2 uptake and maximum photosynthetic rate (A_{max}) during drought and haze, and (b) sensible heat fluxes would increase at the cost of evaporative cooling.

2 Materials and methods

2.1 Study site

The study site is located in a commercial oil palm plantation (1°41’35.0”S, 103°23’29.0”E, 76 m a.s.l.) in tropical lowlands of Jambi province on Sumatra island (Indonesia), approx. 25 km west-southwest of Jambi City (Figure 1). The landscape is flat with small elevation variations of approx. ± 15 m. Average mean annual air temperature during the period 1991-2011 is 26.7°C (± 0.2°C standard deviation) and mean precipitation for the same period is 2235 mm yr^{-1} (± 381 mm SD), with a dry season from June to September and two peak rainy seasons around March and December (Drescher et al., 2016). Long-term climate records are collected at Sultan Thaha Airport Jambi, approx. 29 km east-northeast of the study site. A comparison of air temperature and precipitation at our study site with climate records from Sultan Thaha Airport Jambi during our study period

May 2014 to July 2016 showed no significant differences in daily average air temperature ($P<0.001$) or in monthly accumulated precipitation ($P<0.001$). Therefore, we consider the long-term climate records being representative for our study location. The oil palm plantation covers 2186 ha and the palm seedlings were planted in the years 1999, 2002 and 2004. Our measurements are located in the section where the palms have been planted in 2002. ~~Average palm height in 2014 was 12 m and leaf area index (*LAI*) was 3.64 m^2 m^{-2} (Fan et al., 2015).~~ Palms are planted in a triangular array, with 8×8 m horizontal density and 156 palms per ha. Based on this horizontal density, an average palm height of 12 m, and 35-45 expanded leaves per palm, Fan et al. (2015) estimated a site-specific leaf area index (*LAI*) of 3.64 m^2 m^{-2}. Gaps in oil palms that can be created due to disturbances or extreme weather conditions were not observed in this study. In 2015, 144 kg ha^{-1} of Magnesium Nitrate, 575 kg ha^{-1} of NPK Granular, and 251 kg ha^{-1} of Dolomite fertilizers were applied in topdress application. The plantation is owned by Perseroan Terbatas Perkebunan Nusantara VI, Batang Hari Unit (PTPN6). Stumps of pruned oil palm leaves are densely covered with epiphytes, e.g. ferns (*Polypodiophyta*) or flowering plants (*Melastomataceae*, *Orchidaceae*), while understory vegetation is scarce due to regular application of herbicides and occasional mowing. Highly weathered Loam Acrisols soils dominate in the area (Allen et al., 2015) and mean soil carbon and nitrogen content in the plantation reach 1.12% (± 0.34% SD) and 0.08% (± 0.02% SD) (Meijide et al., 2017).

2.2 Eddy covariance measurements

Eddy covariance (*EC*) measurements to derive fluxes of sensible (*H*) and latent (*LE*) heat, ~~CO_2~~ net ecosystem CO_2 exchange (*NEE*) and water vapour (*ET*) for this study were carried out from June 2014 to July 2016. We use a LI7500A fast response open-path CO_2/H_2O infrared gas analyser (LI-COR Inc. Lincoln, USA) and a Metek uSonic-3 Scientific sonic anemometer (Metek, Elmshorn, Germany). The *EC* system measures at 10 Hz and is placed at the top of a 22 m high steel framework tower. Digital signal recording, statistical tests for raw data screening and raw data correction, spectral analysis, eddy flux calculation using EddyPro (LI-COR Inc, Lincoln, USA), post-processing such as quality flagging, removal of fluxes during stable atmospheric conditions, i.e. friction velocity ($u*$) <0.1 m s^{-1}, flux footprint analysis and gap filling of missing flux data follow standard procedures (Meijide et al., 2017). The energy balance closure for the entire study period was 0.75 ($R^2 = 0.85$).

2.3 Meteorological ad environmental parameters, oil palm yield

Above-ground measurements include air pressure (22 m above the surface), precipitation (11.5 m), wind direction (15.4 m) and wind speed (18.5, 15.4, 13 and 2.3 m), air temperature and air humidity (22, 16.3, 12.3, 8.1, 2.3 and 0.9 m), incoming and reflected photosynthetically active radiation (*PAR*) (22 m), incoming and outgoing shortwave and longwave radiation (22 m), global and diffuse radiation (22 m), and sunshine duration (22 m). Detailed information on instrument type and manufacturer for all measured parameters can be found in Meijide et al., (2017). Below-ground measurements consist of three profiles where ground heat flux (*G*) is measured with heat flux plates at 5 cm depth and soil moisture and soil temperature is measured at 0.3, 0.6 and 1 m depth, respectively. All meteorological and environmental parameters were measured every 15 s and stored as 10-

minute mean, minimum and maximum values in a DL16 Pro data logger (Thies Clima, Göttingen, Germany). Monthly oil palm yield data was provided by PTPN6 and covers the period January 2013 to April 2017.

2.4 Data analysis and statistics

The meteorological data used in this study covers the period from May 2014 to July 2016. Based on precipitation and the ratio between diffuse and global radiation (R_G), i.e. fraction of diffuse radiation (*fdifRad*), we defined four distinct meteorological periods during 2015, i.e. pre-drought, non-haze drought, haze drought, and post-haze and compared the four periods with meteorological conditions in 2014 and 2016. We consider pre-drought as the period with frequent precipitation on an almost daily basis and non-haze drought as the period when precipitation occurred only sporadically and heavy precipitation events >50 mm d^{-1} were completely absent. Haze drought period follows the non-haze drought. We defined the start of the haze drought period at the day when daily average fraction of diffuse radiation was >0.8 for more than three consecutive days. We consider the end of the haze drought period as the day when daily average fraction of diffuse radiation dropped below 0.8 for five consecutive days and when clear day-to-day variations in fraction of diffuse radiation, with day-to-day variation of >0.2 became apparent. Reference meteorological conditions cover the period May-December 2014 and January-July 2016.

To investigate the behaviour of the oil palm plantation in more detail, we defined day (6-18:30 h local time), night (19-5:30 h) and midday (10-14 h) time periods. Due to the proximity of our study site to the equator the difference in day length between summer and winter solstice is only 12 minutes. Therefore, we consider the impact of differences in day length on the fluxes and meteorological parameters as negligible.

Maximum rate of photosynthesis (A_{max}) at ecosystem scale was calculated from daily light response curve using *NEE* (Falge et al., 2001). Initially, we applied CO_2 flux partitioning of *NEE* into gross primary production (*GPP*) and respiration using (a) non-linear regression model based on Reichstein et al. (2005) and (b) CO_2 flux partitioning based on *CLM-Palm* (Fan et al., 2015) which is a sub-model within the framework of the Community Land Model (*CLM4.5*) (Oleson et al., 2013). The non-linear regression model underestimated *NEE* by 58%, on average, most likely because the model struggles to assess the temperature sensitivity of ecosystem respiration using the filtered nighttime data (Oikawa et al., 2017). *CLM-Palm* struggled to represent daily average *NEE* during the non-haze drought and haze drought periods, most likely due to the models' soil water stress function (Sellers et al., 2013) and missing plant hydraulic processes in the overarching *CLM4.5* (Oleson et al., 2013). Therefore, we decided to solely focus on *NEE* to describe the overall CO_2 flux behaviour of the oil palm plantation during the extreme events of drought and haze. However, we used the nighttime *NEE* (=respiration) as a proxy for the overall behaviour of oil palm monoculture respiration and disentangled its driving climatic variables. Seasonal differences in *u**, especially during nighttime, might impact the performance of eddy covariance gap filling. However, we found no significant differences (P<0.05) in *u** which could have affected the proportion of available nighttime data during the different meteorological periods. Therefore, we consider the applied gap filling procedure and derived flux averaging as robust and representative for the studied time periods.

In this study, we assign *H*, *LE* and *NEE* as positive when they are directed away from the surface. To avoid negative values of A_{max} and for better readability, we perform sign conversion of A_{max}. All statistical analyses and graphing were performed with R version 3.1.1 (R Core Development team, 2014).

2.~~3~~ 5 Multiple Linear Regression Model

We used a multiple linear regression model (*MLRM*) (Ray-Mukherjee et al., 2014; Whittingham et al., 2006) to investigate the temporal contribution of climatic variables to observed trends in *NEE*. The first *MLRM* used in this study ~~considered~~ considers the diel averaged *NEE*, which includes both the photosynthetic and respiratory processes. We built the model including vapour pressure deficit (*VPD*), atmospheric CO_2 concentration (CO_2), fraction of diffuse radiation (*fdifRad*), wind speed (*wind*), air temperature (*tair*) and actual evapotranspiration divided by potential evapotranspiration (*ET_ET_pot*). Unless otherwise stated, the environmental variables used in this study are measured above the canopy in 22 m height. The form of the model for the 24-hour averaged *NEE* is as follows:

$$NEE = \beta_1 VPD + \beta_2 CO_2 + \beta_3 fdifRad + \beta_4 wind + \beta_5 tair + \beta_6 ET\_ET\_pot \tag{1}$$

where β is the slope. The *MLRM* parameters were estimated using the ordinary least squares method. We transformed each parameter by subtracting the mean and dividing it by the standard deviation. The transformed data has a mean zero with a standard deviation of 1. 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), and thus the goodness of fit decreased by 53 %. Therefore, we ~~We~~ did not include the intercept term in equation (1) because without the intercept the model gave a relatively high goodness of fit (see Supplement, Table S1 & Table S2). Initially, we included more parameters for the *MLRM* since we did not put a limit on the number of covariates to explain the observed *NEE*. However, we applied different case scenarios where we examined different *MLRMs* in relation to setting up the model (see sample model case scenarios in the Supplement, Table S2). In these case scenarios we included Akaike information criterion (*AIC*) scores along with the goodness of fit values to ensure the following model criteria: (a) ~~Our first criteria of the model design (equation 1) was to ensure that~~ the β's are highly statistically significant (Chatfield, 1995), (b)~~. Our second criteria of the model design (equation 1) was to choose~~ the predictors are chosen in such a way so that they are least correlated (Zuur et al., 2010), and (c) the model has high *AIC* score. In~~-~~ the initial model setup (equation 1) ~~the initial model setup (equation 1),~~ we included drought-indicators such as ~~predictors that are more closely related to drought such as~~ precipitation and soil moisture at different depths ~~,~~ but these predictors were not significant (p-value >0.1). Thus, we excluded them from the model and used only predictors which were highly significant. We also standardized the data to consider normality and non-linearity (Chen et al., 2018), but these changes reduced the goodness of fit by a large amount. Therefore, throughout this study we use the data in the original form. ~~In the initial model setup (equation 1), we included predictors that are more closely related to drought such as precipitation and soil moisture at~~

~~different depths, but these predictors were not significant (p-value >0.1). Thus, we excluded them from the model and used only predictors which were highly significant.~~

For the second *MLRM*, we focused on the midday *NEE* (10-14 h local time), which is dominated by photosynthesis and thus avoids any issues of ~~nighttime~~nighttime flux uncertainties. In this case, we used predictors for our model which were significant, i.e. incoming photosynthetically active radiation (*PARin*), *tair*, *VPD*, CO_2 and *fdifRad*. The form of the model for the day-time *NEE* is as follows:

$$NEE = \beta_1 PARin + \beta_2 tair + \beta_3 VPD + \beta_4 CO_2 + \beta_5 fdifRad + \beta_6 ET\_ET\_pot \tag{2}$$

To complement day-time *NEE*, we looked as well at night-time *NEE* (19-5:30 h local time). The ~~modeled~~modelled *NEE* for the night-time takes the following form:

$$NEE = \beta_1 tair + \beta_2 VPD + \beta_3 ET\_ET\_pot + \beta_4 tair_{12} + \beta_5 wind \tag{3}$$

For the ~~nighttime~~nighttime *NEE*, we also considered environmental variables within the canopy profile, i.e. air temperature measured at 12 m above the soil (*tair12*). In the night, soil respiration could be influenced by this environmental factor (Zhou et al., 2013). Initially, we also tested the model using soil temperature and soil moisture but these parameters were not significant.

2.~~3~~5.1 *NEE* under intensified drought and haze conditions

We used the above three *NEE* models (equations 1 to 3) based on the 2015-drought and haze conditions to investigate the impacts of intensified non-haze drought (*NHD*+) and haze drought (*HD*+) conditions on oil palm *NEE*. These two scenarios focus on the response of oil palm to short-term more extreme atmospheric conditions associated with projected more severe future *ENSO* events during the current life cycle of the oil palm plantation, which was planted 1999-2004 and is therefore in a mature stage and in the middle of its life cycle. The temperature change in the scenarios, however, reflects only short-term extreme conditions and does not consider slow long-term effects of a changing climate.~~s~~

Under intensified non-haze drought (*NHD*+) during the current rotation cycle of the oil palm plantation, we ~~expect~~ assume a short-term~~n~~ increase in *VPD*, incoming *PAR* and air temperature and a decrease in diffuse radiation. Thus, we modified the mean of the model input variables as *VPD* +20%, *fdifRad* -20%, *tair* +20%, *PARin* +20%, ET_ET_pot -20% and *tair12* +20%. Under intensified haze drought (*HD*+) we modified the mean of the environmental variables (*VPD* by +20%, CO_2 by +20%, *fdifRad* by +20%, *tair* by +20%, *PARin* by -20%, ET_ET_pot -20% and *tair12* by +20%) in the model. For both scenarios (*NHD*+ and *HD*+), however, we kept the coefficients of the input parameters constant.

3 Results

3.1 Atmospheric and environmental conditions

Strong inter-seasonal differences in precipitation pattern, air temperature and atmospheric *VPD* characterize the study period, with the year 2015 being slightly drier and warmer as during the reference periods of 2014 and 2016 (Table 1). From March 2015, both the daily mean air temperature and daily mean *VPD* showed a steady increase and reached their maxima during the haze drought period in mid-October (Figure 2). The first four months in 2015 were cooler and wetter than during the reference period (Table 1). From May until mid-September, when the non-haze drought hit the area in 2015, air temperature and *VPD* were of similar magnitudes in 2015 and the reference period but accumulated precipitation was as little as 192 mm in 2015 compared to 594 mm during the reference period (Supplement, Figure S1). Inter-seasonal differences in air temperature and in *VPD* were most pronounced from mid-September until mid-November, when haze covered the area in 2015. During that time, mean air temperature was 28.3 ± 0.8°C and mean *VPD* was 8.71 ± 2.57 hPa, which is 2.3°C and 4.98 hPa higher than during the reference period. There were sharp contrasts in soil water content (*SWC*) in 2015 between the pre-drought and haze drought period due to the absence of precipitation in the latter period. *SWC* in the upper two soil layers (30 & 60 cm) declined by 35%, respectively, while in the bottom layer (100 cm) the decline was 10% (Table 1). During the reference period, differences in *SWC* were less pronounced, with maximum decline of 26% in the upper two soil layers. Daily mean global radiation and daily mean incoming photosynthetically active radiation (*PAR*) showed strong periodical and day-to-day variations over the course of the study period. In 2015, irradiance reached its maximum during the non-haze drought period in late July and mid-August (Figure 2). After this peak, the continuous emergence of haze led to a substantial decrease in both R_G and *PAR* (Table 1). Simultaneously, fraction of diffuse radiation increased from 0.21 to 0.99 and diffuse radiation remained almost the sole shortwave radiation component for almost two months. Compared to the reference period, daily average incoming *PAR* during the haze drought in 2015 decreased by 107 µmol m^{-2} s^{-1} (-36%) while fraction of diffuse radiation increased by 0.12 (13%) (Table 1). The persistence and density of the haze in 2015 is reflected in daily average sunshine duration (Table 1). During the haze drought period, the sun was, on average, visible for 50 minutes per day, which equals to 7% within 12 hours of potential daylight (sun above the horizon). During the pre-drought, non-haze drought and post-haze period, the sun was visible for 6.7 (56%), 10 (83%) and 6 (50%) hours per day, respectively. Atmospheric CO_2 concentration during the haze drought and post-haze period in 2015 was 5% (20 ppm) and 6% (24 ppm) higher than during the reference period.

3.2 Net ecosystem CO_2-exchange, carbon accumulation and~~,~~ yield ~~and evapotranspiration~~

The oil palm plantation was a net sink of CO_2 during the study period. Mainly due to the impact of the haze period, net ecosystem CO_2 exchange (*NEE*) in 2015 (-1.79 ± 13.53 µmol m^{-2} s^{-1}) was significantly weaker (P <0.01) compared to the reference period (-2.20 ± 14.48 µmol m^{-2} s^{-1}) (Table 2). Only in the very beginning of 2015 and during the period June-September 2015, *NEE* was higher compared to the reference period (Figure 3) and CO_2 uptake showed a slight increase coinciding with the drought-related increase in incoming *PAR*. The beginning of the haze drought marks a strong transition where CO_2 uptake initially decreased with developing haze, followed by a two-month period where the oil palm plantation turned into a small source of CO_2 to the atmosphere.

Carbon accumulation by the oil palm plantation was relatively strong in the first months of 2015 and exceeded accumulation of the reference period by up to 80 g C m^{-2} (Figure 3b). During the following months until mid-June, carbon accumulation of the reference period surpassed 2015-carbon accumulation but by mid-August these differences were offset. Due to the haze from October to mid-November 2015, carbon accumulation initially paused, followed by small overall carbon loss of 10 g C m^{-2} within 40 days. After the haze, the oil palm plantation was not able to offset the pause in carbon accumulation and carbon losses during the haze and therefore, the total amount of accumulated carbon in 2015 was 152.7 g C m^{-2} (18%) lower compared to the reference period (Table 1).

Over the course of the non-haze drought, the oil palm plantation reduced its maximum rate of photosynthesis (A_{max}) (Figure 4). However, drought-related changes in meteorological and environmental conditions caused a ~~not relevant~~ minor (3%) decrease in A_{max} compared to pre-drought conditions. With the continuous development of haze in September 2015 and related absence of direct sunlight the oil palm plantation seemed to compensate for the ~~dim light conditions~~overall haze-related reduction in incoming *PAR*, with a jump of A_{max} by 13 µmol m^{-2} s^{-1} (37%) within a couple of days (Figure 4). This compensation effect of relatively high A_{max} continued over the haze drought period, with A_{max} being 4.8 µmol m^{-2} s^{-1} (18%) higher than during the non-haze drought.

Using linear regression between monthly *NEE* and oil palm yield, we found that a 6-month delay in yield showed highest R^2 of 0.36 (P<0.01) with *NEE*. Therefore, we consider the period November 2015 to May 2016 as the time when *NEE* and carbon accumulation during the non-haze drought and haze drought in 2015 were reflected in monthly oil palm yield. From August 2015, monthly oil palm yield declined continuously from ~~7950~~ 3.93 t ha^{-1} to its minimum of ~~2128~~ 1.05 t ha^{-1} in May 2016. Compared to the same period (Nov.-May) in the two years before and the year after the *ENSO* event, average yield affected by 2015-drought and haze was 32% (~~1421~~ 0.70 t ha^{-1}) lower. Considering the 2015-haze drought only, average oil palm yield 6-9 months after the beginning of the haze drought was even 50% (~~2231~~ 1.1 t ha^{-1}) lower compared to the non-*ENSO* years.

3.3 Evapotranspiration and turbulent heat fluxes

Total evapotranspiration (*ET*) derived from ~~eddy covariance (*EC*)~~ latent heat flux (*LE*) measurements was 1245 ± 362 mm yr^{-1} in 2015 and 1580 ± 469 mm yr^{-1} during the reference period (Table 2), with a higher share of *ET* on precipitation during the reference period (77.9%) compared to 2015 (64.5%). During the non-haze drought and haze drought periods, the oil palm plantation experienced strong water loss from *ET* as *ET* was 2.5 and 1.2 times the amount of precipitation, respectively. *ET* was lowest during the haze drought period (Figure 5, Table 2), mainly driven by the reduction in incoming solar radiation and *PAR* as well as by oil palm drought and heat stress which may have triggered partial stomata closure, especially in the beginning of the haze drought when *VPD* was high (Figure 2). Conversely, partial stomata closure during high *VPD* as well as the absence of precipitation and related drying of the upper soil generally increased sensible heat fluxes (*H*) at the cost of *LE* and *ET*, reflected in the behaviour of the Bowen ratio (*H/LE*) (Figure 5). From the first half of the pre-drought period into the second half of the non-haze period, the Bowen ratio showed a steady but relatively small decline. However, the end of the non-haze drought and the beginning of the haze drought period mark a strong transition in the behaviour of the Bowen ratio, manifested by a strong jump, peak values of ~0.38 and average of 0.25 for approx. one month. This jump in the Bowen ratio might be related to the increasing density of the haze and related reduction in incoming *PAR* in combination with high *VPD* which decrease *LE* mainly via oil palm water and light stress to a greater extent than the general drying of the soil and lack of precipitation.

~~This observed difference was driven by the absence of precipitation during the non-haze drought period, which increased the overall share of sensible heating at the cost of *ET* (Bowen ratio) (Figure 5). In addition, oil palm drought and heat stress may have triggered partial stomata closure, which further decreased *ET* towards the end of the non-haze drought. The reduction in incoming solar radiation and *PAR* during the haze drought further decreased *ET*.~~

3.~~3~~ 4 Drivers of net ecosystem CO_2-exchange

Modelled *NEE* from our *MLRM* simulated a small positive effect on *NEE* during the non-haze drought, with an increase in CO_2 uptake by 0.32 µmol m^{-2} s^{-1}, and a negative effect on *NEE* during the haze drought, with a decrease in CO_2 uptake by 0.99 µmol m^{-2} s^{-1} (Figure 6, Supplement Table ~~S4~~S5). Modelled *NEE* is in good agreement with the measured *NEE*, i.e. for midday (10-14 h local time), ~~nighttime~~nighttime (19-5:30 h) and average *NEE* (0-24 h) the model explains 98%, 94% and 83%, respectively, of the temporal variability in the measured *NEE*. Overall, the relative change of meteorological and environmental parameters during the non-haze drought and haze drought caused a more pronounced response of *NEE* in the latter period compared to non-drought and non-haze conditions, especially during midday (Figure 6).

During the non-haze drought, changes in radiation components were the main predictors of changes in midday *NEE*. Higher incoming *PAR* increased CO_2 uptake while at the same time, this gain in CO_2 uptake was compensated by the negative impact of decreasing fraction of diffuse radiation (Figure 6, Supplement Table ~~S4~~S5). However, this estimated effect of the changes in irradiance on *NEE* was clearly small compared to the negative effects of dim light conditions during the haze drought where a reduction in incoming *PAR* resulted in strong decrease in CO_2 uptake (Figure 6). Further, the effect of incoming *PAR* and fraction of diffuse radiation on midday *NEE* was reversed during the haze drought compared to the non-haze drought and the decrease in fraction of diffuse radiation contributed to higher midday CO_2 uptake but these positive effects were almost offset completely by the decrease in incoming *PAR*.

Increasing *VPD* had a negative impact on midday *NEE* (decrease in CO_2 uptake), while the increase in air temperature had a positive impact on midday *NEE* (increase in CO_2 uptake). Oil palm drought stress, manifested in a general decrease in ET/ET_{pot} (Table 2), was less severe during the non-haze drought compared to the haze drought period, resulting in a slightly more pronounced decrease in CO_2 uptake during the latter period (Figure 6). The observed changes in atmospheric CO_2 concentrations during the non-haze drought and haze drought suggest that the oil palm might respond via photosynthesis and stomata behaviour to the elevated atmospheric CO_2 levels. However, rising atmospheric CO_2 concentration had no fertilization effect for the oil palm plantation, in contrary, the increase in CO_2 concentration contributed to a decrease in CO_2 uptake (Figure 6).

During both non-haze drought and haze drought, the change in ~~nighttime~~nighttime (19-5:30 h) air temperature above the canopy was the main predictor of changes in ~~nighttime~~nighttime *NEE* (respiration). The increase in air temperature tended to increase respiration. This was more pronounced during the haze drought compared to the non-haze drought (Figure 6, Supplement Table ~~S4~~ S5 & ~~S5~~S6).

3.~~4~~ 5 *NEE* under intensified drought and haze conditions

Our two model projections, where we increased the effects of non-haze drought and haze drought conditions based on the 2015-drought and haze conditions, showed that increased non-haze drought conditions (*NHD+*) enhanced CO_2 uptake while increased haze drought (*HD+*) weakened CO_2 uptake and might even promote CO_2 release (Figure 7, Supplement Table ~~S6~~S7). Daily average (24-hour) CO_2 uptake in *NHD+* was increased by 2.25 µmol m^{-2} s^{-1} compared to the 2015-non-haze drought conditions. *NHD+* might enhance midday CO_2 uptake and ~~nighttime~~nighttime respiration, which increased by 6.52 µmol m^{-2} s^{-1}, 1.59 µmol m^{-2} s^{-1}, respectively, mainly due to the effect of a high air temperature in *N~~D~~HD+* which is also the main predictor of daily average, midday and ~~nighttime~~nighttime *NEE* (Supplement Table S7~~6~~). Incoming *PAR* is the dominant light parameter for *NEE* and increases in incoming *PAR* in *NHD+* are able to offset the modelled negative impact of decreased fraction of diffuse radiation on *NEE*. This is contrary to what the model suggested for the 2015-non-haze drought reference conditions where we observe that the increase in incoming *PAR* was not able to offset the negative impacts on *NEE* due to decreased fraction of diffuse radiation. Similar to *NHD+*, air temperature in the increased haze drought scenario (*HD+*) was the main predictor of *NEE* and contributed to a high midday and daily average (24-hour) CO_2 uptake and also to a high ~~nighttime~~nighttime respiration (Figure 7, Supplement, Table ~~S7~~S8). However, the negative effects of *HD+* offset the positive effects of increased air temperature. Daily average (24-hour) CO_2 uptake and midday CO_2 uptake in *HD+* were decreased by 0.85 µmol m^{-2} s^{-1}, 4.51 µmol m^{-2} s^{-1}, respectively, while ~~nighttime~~nighttime ecosystem respiration was increased by 2.53 µmol m^{-2} s^{-1}. Incoming *PAR* in *HD+* remains the dominant light parameter on midday *NEE* and its decrease cannot be offset by the positive effects of increased fraction of diffuse radiation. In *HD+*, midday *VPD* is of less relative importance on *NEE* as compared to the reference haze drought conditions. As already observed in the 2015-haze drought model output, increased CO_2 concentration in *HD+* does not act as an additional fertilization for the oil palm plantation. In contrast, the negative impact of increased CO_2 concentration on *NEE* becomes the dominant predictor of *NEE* in *HD+*. Our two scenarios indicate that increased drought stress, reflected by decreasing ET/ET_{pot}, has more pronounced negative impact on *NEE* in *HD+* compared to *NHD+*. However, oil palm seems to be relatively resistant against drought since the overall impact of changes in ET/ET_{pot} on *NEE* was relatively small in both scenarios.

4 Discussion

4.1 Oil palm response to drought and haze conditions

Oil palm has exceptionally high photosynthetic efficiency compared to most of the vascular plants (Apichatmeta et al., 2017) but this efficiency comes with a downside: Oil palm, like many other tropical plants, shows a distinct reaction to changes in atmospheric and soil parameters, with gradual symptoms of water and heat stress which directly affect photosynthesis and evapotranspiration as well as fruit bunch development and yield (Bakoumé et al., 2013; Paterson et al., 2013). During our study period, we observed that accumulated annual precipitation 2015 and during the reference period was on the lower limit of reported optimum precipitation range for oil palm (Pirker et al., 2016). However, oil palm requires minimum precipitation of 100 mm per month to avoid drought stress (Corley & Tinker, 2016). This was not fulfilled in September 2014, from June to October 2015, and in January 2016. ~~S~~Previous studies report a strong correlation between *NEE* and soil moisture ~~conditions~~ (Méndez et al., 2012; Cha-um et al., 2013), with declining CO_2 assimilation under dry conditions. In our study, however, we found no strong correlation between *NEE* and soil moisture conditions, and between *NEE* and ET/ET_{pot} during the non-haze drought and haze drought period. This might be explained by the relatively stable soil moisture conditions in deeper layers (100 cm) of the oil palm plantation which, compared to the upper layers (30 and 60 cm) showed only a moderate decrease during both non-haze drought and haze drought (Table 1). Oil palm ~~i~~seems to be able to uptake water from deep soil and store the water in the trunk during night, supporting water use during peak hours of photosynthesis (Niu et al., 2015; Meijide et al., 2017). Therefore, the relatively moderate decrease in soil moisture in deeper soil layers might have had a limited effect on *NEE*.

~~which suggests that oil palm was relatively resistant against drying soil.~~

Temperature increase and related heat stress is another factor which might negatively affect the growth of oil palm (Oettli et al., 2018). Our analysis did not support this finding because during the non-haze drought the effect of increasing temperature on *NEE* was almost negligible. During the haze drought, higher air temperature had a positive impact on CO_2 uptake although the haze period experienced the highest air temperature during the entire study period. Changes in temperature and moisture availability also impact oil palm ecosystem respiration. Matysek et al. (2018) observed high heterotrophic carbon loss from drained peat soils in a Malaysian oil palm plantation during the dry season and Sigau & Hamid (2018) found similar behaviour in Malaysian rubber and oil palm plantations on drying Haplic Nitisols soils but both studies report only minor impact of increased soil temperature on soil respiration. Autotrophic respiration, however, tends to decrease with increasing leaf temperature (Slot et al., 2014). In our study, the increase in air temperature tended to increase nighttime ecosystem respiration and therefore might also lead to higher day time respiration during the non-haze drought and haze drought period.

Oil palm, such as other tropical plant species, seems particularly susceptible to changes in atmospheric *VPD* (Dufrene & Saugier, 1993; Cunningham, 2005; Lamade & Bouillet, 2005; Wahid et al., 2005; Bayona-Rodríguez & Romero, 2016; Mathews & Ardiyanto, 2016) with high levels of *VPD* causing partial closure of stomata and limiting photosynthesis and transpiration. Our *MLRM* and measurements are in line with these findings and high levels of *VPD* had a stronger impact on *NEE* during the haze drought period compared to the non-haze drought period. ~~Dufrene & Saugier (1993) found that *VPD* >17 hPa had a strong negative impact on CO_2 fluxes of oil palm. On a daily basis, this threshold was not reached during the non-haze drought which is likely to explain why *NEE* during that period seemed to be rather unperturbed by the steady increase in *VPD*. The haze drought, however, showed a different picture and *VPD* close to this reported threshold exerted a strong impact on *NEE*, with overall decrease in CO_2 uptake.~~ To a certain extent, oil palm is capable to adjust its stomatal regulation to short-term periods of ~~relatively low~~ moderate *VPD* and ~~low~~ soil water deficit by increasing its maximum rate of photosynthesis (A_{max}) (Dufrene & Saugier, 1993; Apichatmeta et al., 2017). However, during the non-haze drought and haze drought those two environmental parameters exerted only little impact on A_{max} and changes in irradiance seemed to be the dominant driver of A_{max}.

Oil palm grows in regions with high solar flux densities (Barcelos et al., 2015) and it is able to strategically optimize its photosynthesis to light conditions, with pronounced diurnal effects and maximum efficiency before or at about midday (Apichatmeta et al., 2017). In our study, measurements and *MLRM*-results showed strongest response of oil palm *NEE* to drought, haze and changes in irradiance during midday. Due to the reduction of incoming *PAR* for almost two months, the haze was a major and persistent disturbing factor for oil palm *NEE* and A_{max}. The initial increase in diffuse light conditions and its positive impact on A_{max} and *NEE* cannot compensate for the reduction in incoming *PAR*. Therefore, the observed pause in carbon accumulation and even small carbon release during the haze drought could have been prevented since without the haze, the oil palm plantation would have remained a sink of CO_2 during that period.

Changes in oil palm yield are one direct consequence of varying nutrient, meteorological and climatic conditions (Sun et al., 2011; Mathews & Ardiyanto, 2016; Oettli et al., 2018). Prolonged drought and nutrient limitation does not only affect carbon accumulation via photosynthesis but leads to abortion of female inflorescences and failing bunch yield (Bakoumé et al., 2013). ~~Oil palm yield in 2016, and its initial sharp drop by the end of 2015 can therefore be related to the drought and haze conditions.~~ In an oil palm plantation in Central Kalimantan (Indonesia) dense haze from peat fires resulted in poor quality of the fruit bunches and in low oil palm extraction rates (Mathews & Ardiyanto, 2016). Fertilization under water stress conditions has negative impact on oil palm growth and may further reduce oil palm yield while fertilization during well-watered conditions promotes oil palm growth and yield (Sun et al., 2011). At our study site, fertilizers are applied at the end of the wet season (April-May) and in 2015, precipitation was still sufficiently high to maintain well-watered soil conditions during the fertilization. ~~Here,~~ Oil palm yield in 2016, and its initial sharp drop by the end of 2015 can therefore be related to the drought and haze conditions and ~~.~~ the haze was the driving stressor. S~~and s~~imilar to the effects of haze on *NEE*, without the haze oil palm yield might not have experienced such a sharp decline.

Short-term elevated CO_2 exposure on oil palm seedlings (Ibrahim et al., 2010; Jaafar & Ibrahim, 2012) and on mature oil palm (Henson & Harun, 2005) have shown that elevated CO_2 concentration promote plant growth due to elevated rates of photosynthesis and reduced water loss by transpiration. To our knowledge, no comprehensive study has investigated the complex interplay of elevated CO_2 concentrations, increased temperature and decrease in radiation in oil palm. Mathews & Ardiyanto (2016) speculate that short-term elevated levels of CO_2 under haze conditions and related potentially strong stomatal opening may offset for the lack of irradiance and related shorter timing of stomatal opening. Based on leaf gas exchange measurements in trees, Urban et al., (2014) come to a contradiction that low irradiance is incapable to activate stomatal opening since plants exposed to elevated CO_2 levels require higher stomatal activation energy. From our results, it is highly doubtable that elevated CO_2 exposure during the haze had any fertilization effect. On the contrary, increasing atmospheric CO_2 concentration acted as an additional stress factor for oil palm and decreased CO_2 uptake.

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 was not measured in this study but biomass burning (Kita et al., 2000), as well as nitrogen management and isoprene emissions in oil palm plantations (Hewitt et al., 2009 & 2011) are considered to significantly affect near-surface ozone concentration due to emission of ozone precursor gases. 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.

Increased aerosol concentration from biomass burning and related increase in diffuse light increase plant photosynthesis and therefore decrease the ratio of sensible to latent heat (Steiner et al., 2013). However, in our study and during the peak of the drought when forest fires started to develop in the area, we observed increase in the ratio of sensible to latent heat (Bowen ratio) which is likely due to water stress and related partial stomata closure at high *VPD* (Dufrene & Saugier, 1993; Oettli et al., 2018).

Further, increased aerosol concentration is able to increase overall canopy photosynthesis under moderately enhanced diffuse light conditions (Knohl et al., 2008; Mercado et al., 2009; Kanniah et al., 2012) and sun-exposed leaves seem to benefit from lower *VPD* while shaded leaves benefit from increased diffuse light conditions (Wang et al., 2018). Although our measurements and *MLRM* suggest that the leaves benefitted from the increase in diffuse light conditions during the haze drought period, the high level of *VPD*, especially during midday, was an overall stress factor for the oil palm plantation and therefore resulted in a decrease in CO_2 uptake. At our study site, increased fraction of diffuse radiation due to biomass burning had an overall positive impact (increase in CO_2 uptake) and decreased incoming *PAR* a negative impact on CO_2 uptake, which is in line with the findings of Malavelle et al (2019). However, while the authors of that study 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, exceeded an optimal range of diffuse fraction (Knohl et al., 2008) and therefore inhibited a positive impact on CO_2 uptake.

~~ed~~4.2 ~~Future *ENSO* projections, oil palm response~~Short-term response of oil palm to changed climatic conditions and adaptation strategies

Paterson et al., (2015) report that increasing frequency of drought in Southeast Asia has already caused a decline of 10-30% in palm oil production. Our study supports the findings of Dufrene & Saugier (1993) and Apichatmeta et al. (2017) that short-term drought conditions and elevated irradiance under the current or potentially amplified ENSO conditions may be beneficial for oil palm growth since we observe an increase in CO_2 uptake during the non-haze drought despite relatively high *VPD* and low soil moisture content. Our scenario of increased non-haze drought (*NHD*+) suggests that drought conditions may enhance CO_2 uptake to a certain extent, mainly due to increased incoming *PAR* and increased air temperature. However, our scenario does not consider a temporal prolongation of the drought or a constant increase in temperature associated with elevated temperatures as a result of global rising CO_2 levels. ~~,~~ We only considered changes in the magnitude of the atmospheric and environmental parameters under the current climate conditions which we expect to be rather constant for the current life cycle of the oil palm plantation. Therefore, we cannot rule out that this modelled positive effect of *NHD*+ on CO_2 uptake can be maintained if drought conditions remain over a longer period but the relatively weak impact of ET/ET_{pot} on *NEE* suggests that oil palm is relatively resistant to drought.

The reduced irradiance due to fire-induced haze is another stressor for oil palm since it occurs during those periods when the oil palm plantation is already negatively affected by drought and heat. Similar to *NHD*+, we did not include temporal changes in the length of the increased haze drought scenario (*HD*+) but we see that *HD*+ may amplify the negative impacts on oil palm *NEE*. Changes in ozone and aerosol concentrations caused by biomass burning have not been measured in our study but it is very likely that both had an additional negative impact on *NEE* (decrease in CO_2 uptake) which we are quantitatively not able to capture with our *MLRM*. Nevertheless, ~~N~~n~~Future n~~egative impacts of *ENSO*-related droughts on oil palm productivity, carbon sequestration, growth and yield ~~might~~ are ~~therefore~~ ~~be~~ strongly coupled with the temporal and spatial occurrence of fire-induced haze and its ancillary effects such as reduced incoming *PAR*, as well as air pollution of increased ozone and aerosol concentration.

It has been shown that fertilized mature commercial oil palm plantations transpire more water than tropical rainforests due to high productivity (Manoli et al., 2018), thus making them more prone to the effects of droughts (Bakoumé et al., 2013). Adaptation strategies, such as short-term irrigation or the establishment of irrigation ditches may dampen the drought-related impacts in oil palm plantations but aggravate the depletion of natural water reservoirs (Manoli et al., 2018). Elongated periods of drought, as shown in this study, increase sensible heating at the cost of evapotranspiration, resulting in surface warming. Oil palm plantations have a strong potential to further amplify air heating during droughts since they are hotter and dryer as compared to tropical rainforest and rubber monocultures even during non-El Niño years (Hardwick et al., 2015; Meijide et al., 2018). Covering vast areas of tropical lowlands of Sumatra and Borneo, oil palm plantations have already caused an increase in land surface temperature (Sabajo et al., 2017).

State-of-the-art process-based land surface schemes, such as the Community Land Model (*CLM4*.5) (Oleson et al., 2013; Fan et al., 2015), are powerful tools to address ecosystem surface energy balance, hydrological processes and carbon-nitrogen biogeochemistry (Oleson et al., 2013; Fan et al., 2015). Although these models are well-developed and widely-used, they fail to include smoke haze as an environmental parameter affecting ecosystem behaviour. In this study, we used a simple multi linear regression model (*MLRM*) to assess the impact of haze drought on oil palm productivity and developed an increased haze scenario (*HD*+). With this simple model we were able to show strong site-specific negative response of oil palm to haze drought. These specific results of oil palm behaviour during drought and haze conditions might be useful to parameterize models, such as *CLM* and even applicable to other ecosystem and land-use types.

5 Conclusions

In this study, we investigate the impact of drought and smoke haze on the net CO_2 exchange, evapotranspiration, yield and surface energy budget in a commercial oil palm plantation. We found that drought and smoke haze conditions, with related increase in atmospheric *VPD* and air temperature, and changes in light conditions are major disturbing factors for the oil palm plantation. ~~Drought conditions increased sensible heating at the cost of evapotranspiration while strong smoke haze resulted in a complete pause of carbon accumulation for 1.5 months with subsequent decline in oil palm yield. In general, our~~Our measurements and *MLRM* showed that the strong haze amplified the negative effects of the drought. It is very likely that without the haze, the negative impact on CO_2 fluxes, carbon accumulation and yield would have been less pronounced. Although micrometeorological measurements in oil palm plantations become more and more frequent, there is still a substantial lack of air quality measurements, e.g. ozone or aerosol concentration. In our study, smoke haze may have substantially increased ozone and aerosol concentration which both further negatively impact the oil palm plantation. Fire-preventing measures such as sustainable land management, stricter law enforcement and sanctioning, strategic hazard planning and awareness-raising on the effects of fires on oil palm yield but also on air quality and health may help to mitigate the negative effects of drought. Further, incorporating smoke haze as an environmental stress factor into regional or global model approaches may foster more accurate estimations of ecosystem CO_2, energy and water vapour flux behaviour during such extreme meteorological events and may allow a more holistic viewpoint of possible adaptation strategies and hazard-prevention caused by *ENSO*.

Code and data availability

The code and data used in this study are available on GitHub (https://github.com/CbioST/ENSO_OilPalm).

Author contribution

The original idea of the paper was suggested by Alexander Knohl (AK), Ana Meijide (AM) and Christian Stiegler (CS) and discussed and developed by all authors. AM performed the field work and CS performed the data analysis. Ashehad Ashween Ali (AA) and CS developed the model code, run the simulations and performed the model analysis. CS prepared the manuscript with contributions from all co-authors.

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Figures

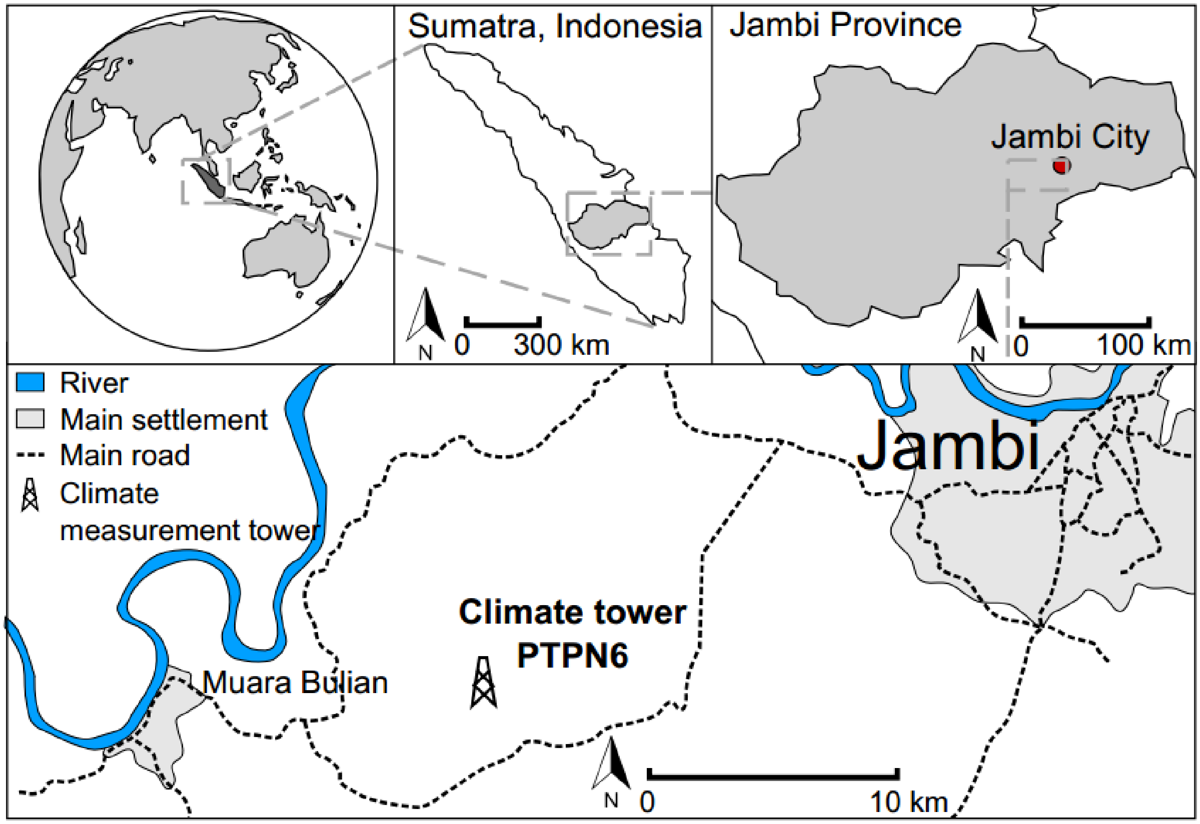

Figure 1: Map and location of the study site and climate measurement tower at PTPN6 oil palm plantation, approx. 15 km south-west of the city of Jambi (Sumatra, Indonesia)

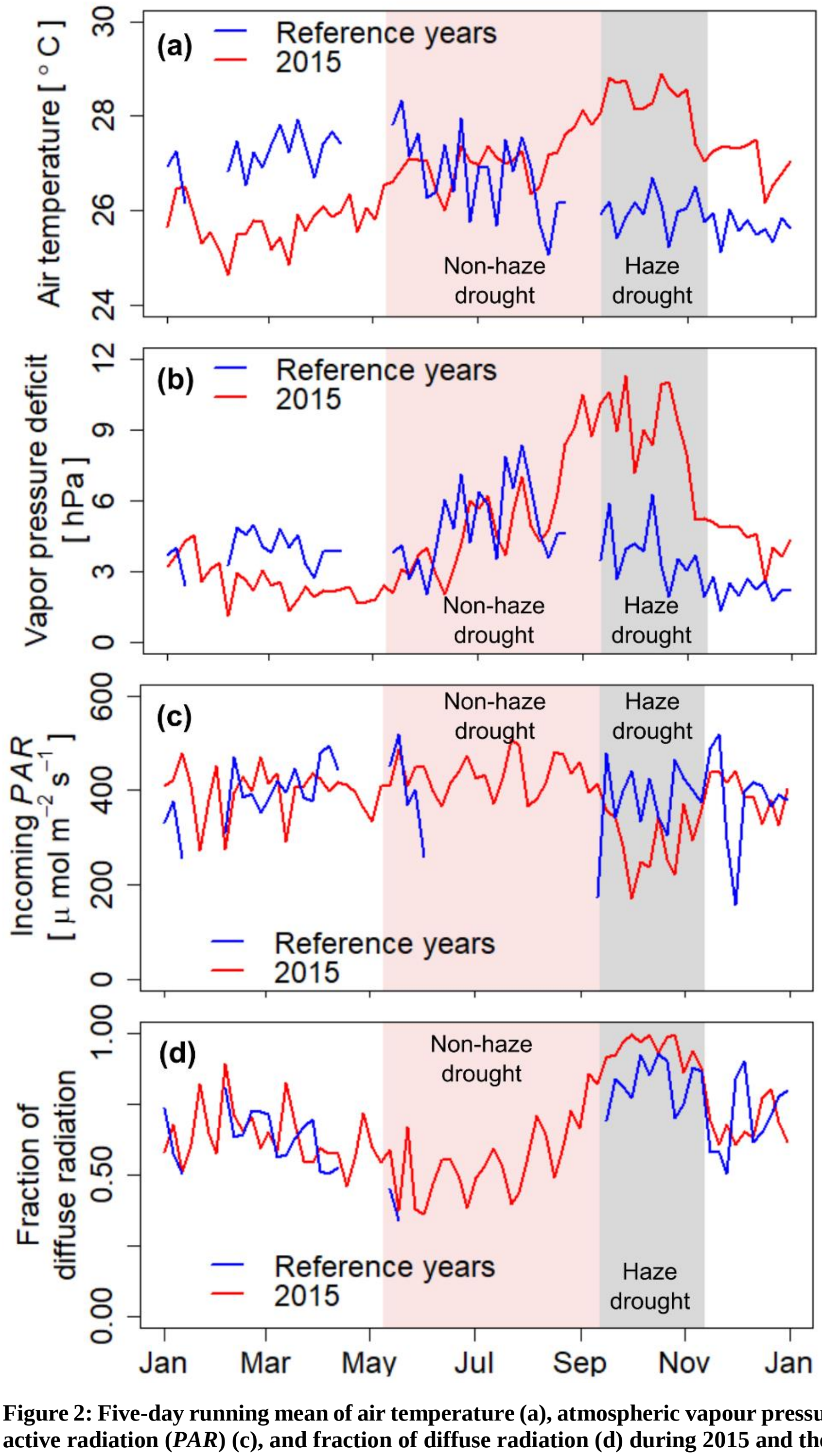

Figure 2: Five-day running mean of air temperature (a), atmospheric vapour pressure deficit (*VPD*) (b), incoming photosynthetically active radiation (*PAR*) (c), and fraction of diffuse radiation (d) during 2015 and the reference time period. Shaded areas in red and grey mark the non-haze drought and the haze drought period in 2015, respectively.

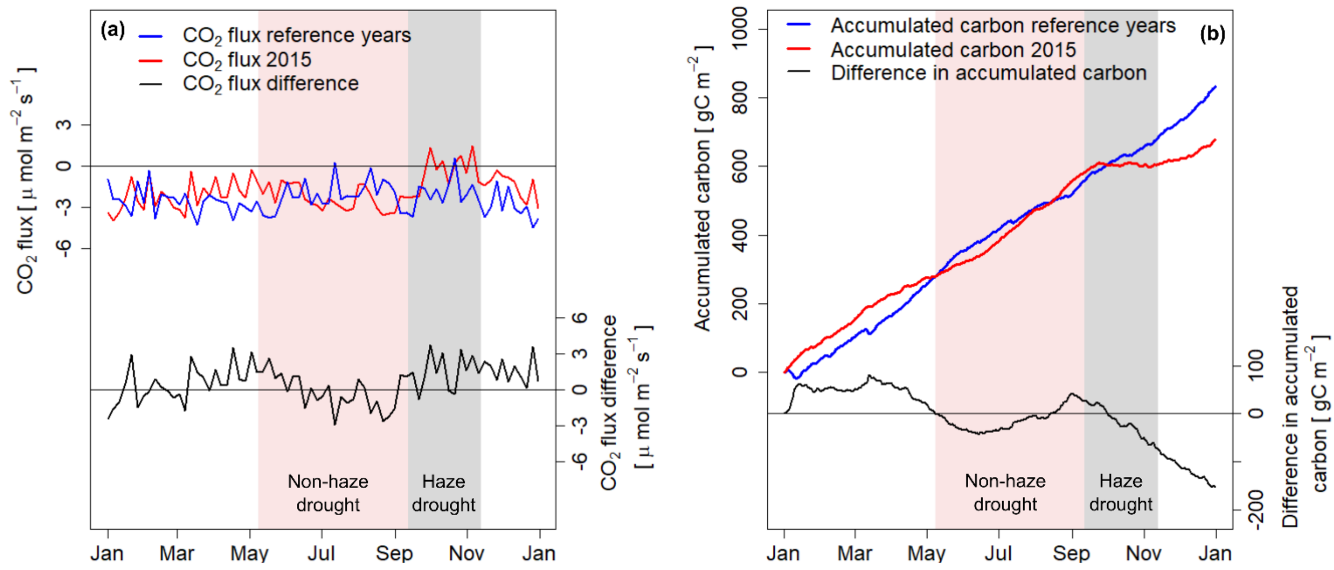

Figure 3: (a) Five-day running mean of net ecosystem CO_2-exchange (*NEE*) during 2015 and the reference time period and five-day running mean of CO_2 flux difference (2015 minus reference time period). (b) Accumulated carbon uptake derived from CO_2 fluxes during the period 2015 and the reference time period, and differences in accumulated carbon between the two periods (2015 minus reference time period). Shaded areas in red and grey mark the non-haze drought and the haze drought period in 2015, respectively.

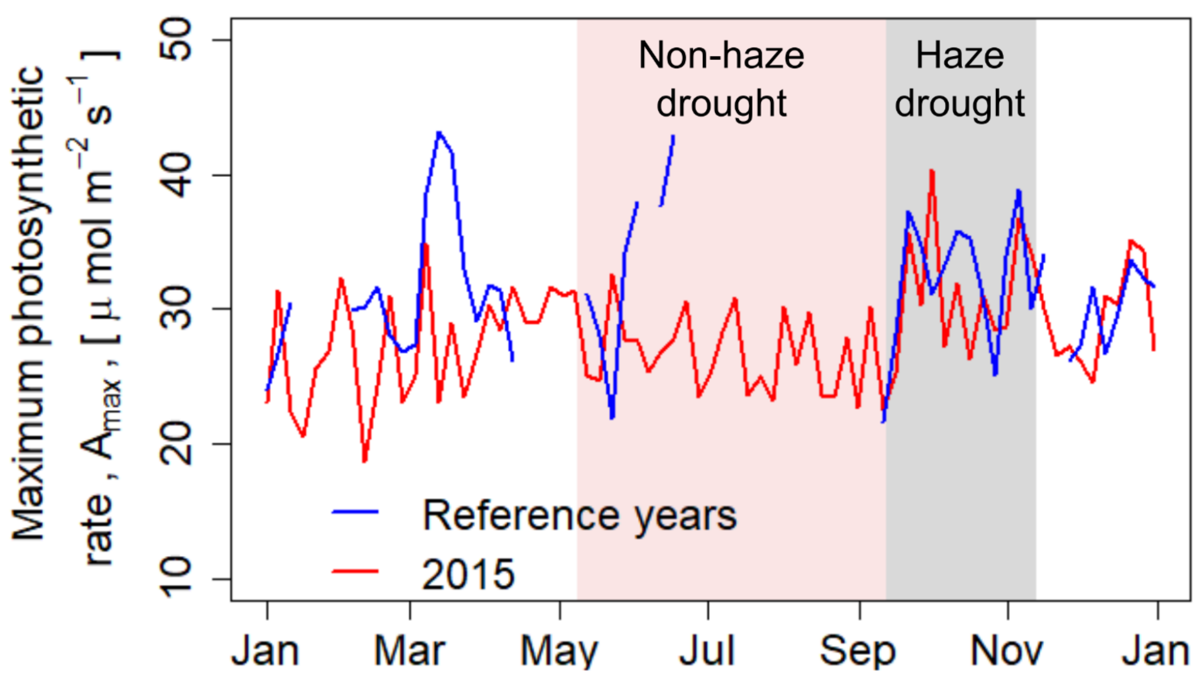

Figure 4: Five-day running mean of maximum rate of photosynthesis (A_{max}) during 2015 and during the reference time period. Sign convention has been performed to avoid negative values of A_{max}. Shaded areas in red and grey mark the non-haze drought and the haze drought period in 2015, respectively.

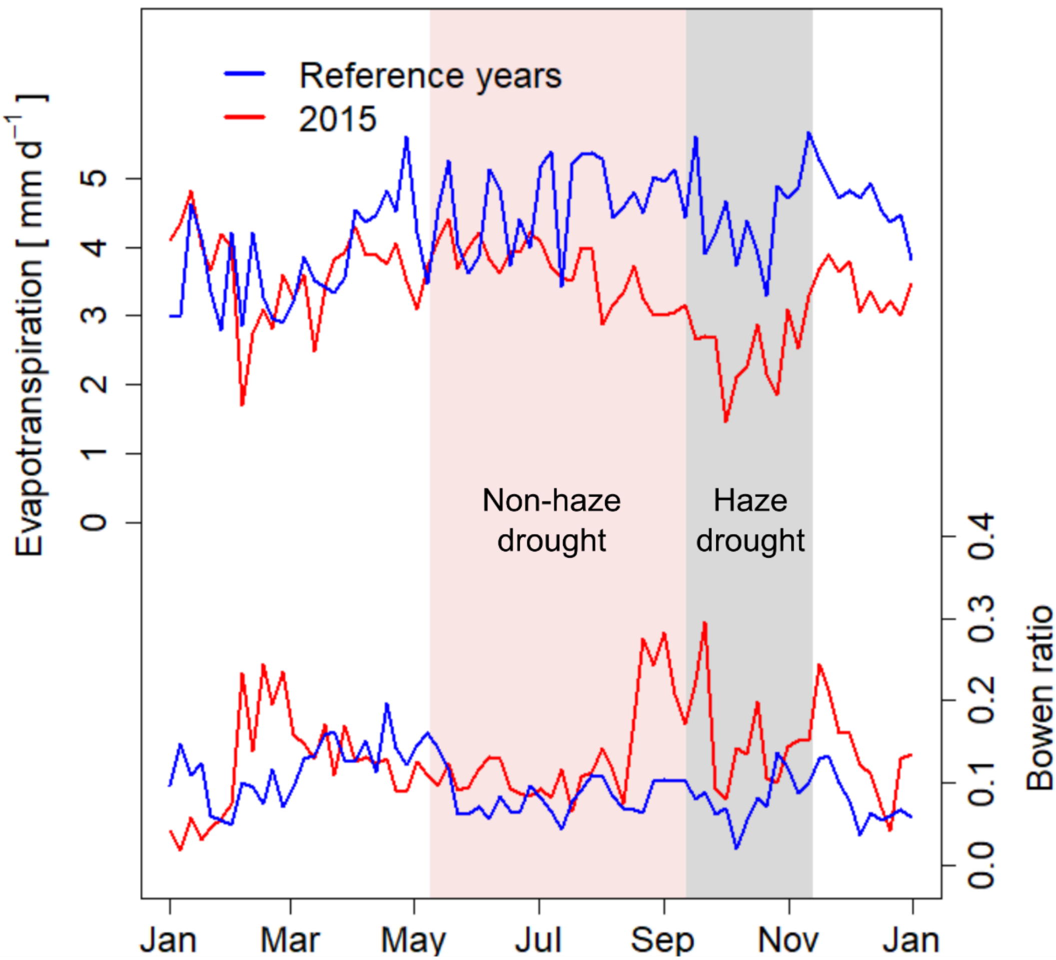

Figure 5: Five-day running mean of daily evapotranspiration and ratio of sensible to latent heat fluxes (Bowen ratio) during 2015. Shaded areas in red and grey mark the non-haze drought and the haze drought period in 2015, respectively.

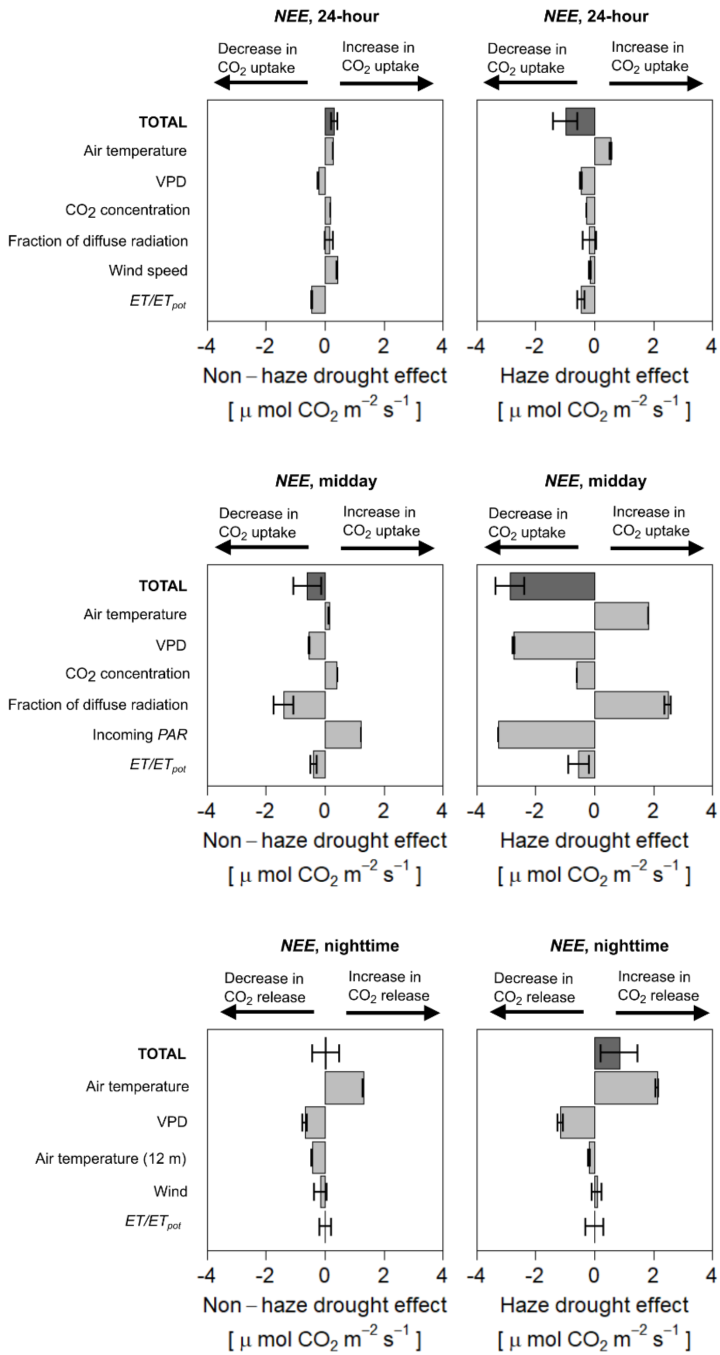

Figure 6: Contribution and effect of meteorological and environmental parameters during the non-haze drought and haze drought period on 24-hour (upper), midday (middle) and ~~nighttime~~nighttime (lower) net ecosystem CO_2 exchange (*NEE*) compared to non-drought and non-haze conditions using Multiple Linear Regression Model (*MLRM*). Error bars show the standard error.

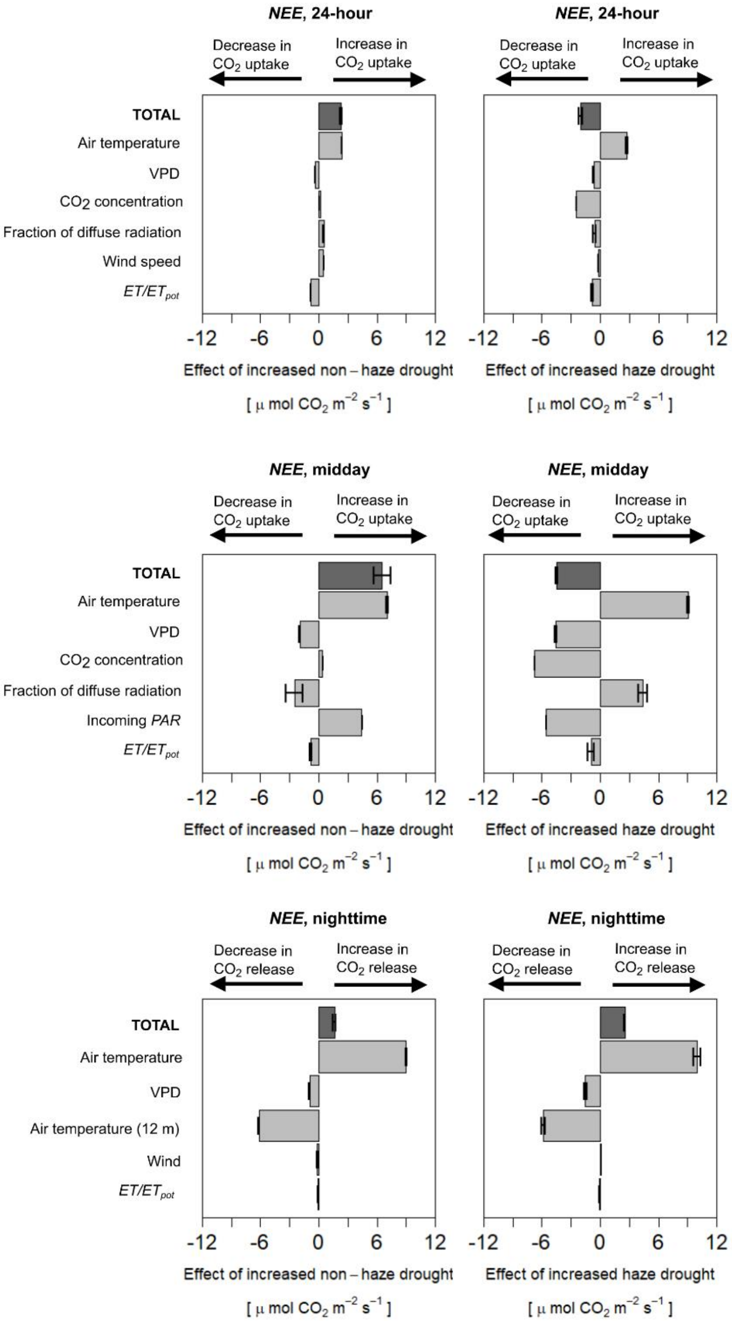

Figure 7: Contribution and effect of meteorological and environmental parameters considering increased non-haze drought (*NHD*+) and increased haze drought (*HD*+) scenario on 24-hour (upper), midday (middle) and ~~nighttime~~nighttime (lower) net ecosystem CO_2 exchange (*NEE*) using Multiple Linear Regression Model (*MLRM*). Error bars show the standard error.

Tables

Table 1: Meteorological parameters (daily mean ± SD, or accumulated for precipitation and carbon) derived from 30-minute averages or sums during pre-drought, non-haze drought, haze drought and post-haze period in 2015, for the entire year 2015 and the reference period (May 2014-December 2014, January 2016-July 2016).

Period	Air temperature [°C]	Precipitation [mm]	~~Vapor~~Vapour pressure deficit (*VPD*) [hPa]	Soil moisture, 30 cm depth [vol%]	Soil moisture, 60 cm depth [vol%]	Soil moisture, 100 cm depth [vol%]	Incoming *PAR* [µmol m^2s^{-1}]	Fraction of diffuse radiation	Sunshine duration [hours d^{-1}]
Pre-drought (128 days)	25.7 ± 0.7	1003	2.53 ± 1.25	32.5 ± 1.8	31.9 ± 1.4	32.3 ±0.8	396.9 ± 105.0	0.67 ± 0.19	6.7 ± 6.9
Drought (127 days)	27.1 ± 0.7	192	5.30 ± 2.60	27.9 ± 4.3 [A)]	26.8 ±4.3 [B)]	27.1 ±2.9	432.0 ± 70.6	0.57 ± 0.18	10.0 ± 7.1

Haze (61 days)	28.3 ± 0.8	127	8.71 ± 2.57	18.1 ± 1.5	17.5 ± 0.2	24.4 ±0.1	293.2 ±97.3	0.95 ± 0.07	0.8 ± 3.2
Post-haze (49 days)	27.1 ± 0.9	608	4.30 ± 1.45	23.4 ± 1.3 [C)]	20.6 ±1.9 [C)]	26.8 ±2.1	393.8 ± 111.0	0.71 ± 0.17	6.0 ± 6.8
2015	26.8 ± 1.2	1930	4.76 ± 2.96	27.2 ±6.1	26.4 ±6.2	28.4 ±3.6	391.4 ± 104.7	0.69 ± 0.21	6.8 ± 7.2
Reference period	26.5 ± 1.1 [D)]	2030	4.0 ± 2.0 [D)]	28.3 ± 1.7 [E)]	29.9 ± 1.8 [F)]	25.5 ± 2.0 [E)]	397.6 ± 103.6 [G)]	-	-

A) no data 26.07.-06-09.2015, B) no data 05.08.-06.09.2015, C) no data 14.12.-31.12.2015, D) no data 30.08.-0.09.2014, 12.01.04.02.2016, 14.04.-11.05.2016, E) no data 31.05.-10.09.2014, 01.01.-04.02.2016, 14.04.11.05.2016, F) no data 31.05.-10.09.2014, 01.01.-11.02.2016, 14.04.-11.05.2016, G) no data 31.05.-08.09.2014, 12.01.-04.02.2016, 14.04.-11.05.2016

Table 2: Net CO_2 flux, maximum rate of photosynthesis (A_{max}), accumulated carbon, atmospheric CO_2-concentration, Bowen ratio, evapotranspiration (ET) and actual ET divided by potential ET (ET/ET_{pot}) (daily mean ± SD, or accumulated for precipitation and carbon) derived from 30-minute averages or daily average (A_{max}, Bowen ratio) during pre-drought, non-haze drought, haze drought and post-haze period in 2015, for the entire year 2015 and the reference period May 2014-December 2014, January 2016-July 2016.

Period	Net CO_2 flux (net ecosystem exchange) [µmol m^{-2} s^{-1}]	Maximum rate of photosynthesis (A_{max}) [µmol m^{-2} s^{-1}]	Accumulated carbon [g C m^{-2}]	CO_2 concentration [ppm]	Bowen ratio	Evapotranspiration (ET) (mm d^{-1})	ET/ET_{pot}
Pre-drought (128 days)	-2.10 ± 12.91	27.4 ± 8.1	278.6 ± 81.8	416 ± 29	0.12 ± 0.10	3.6 ± 4.9	0.55 ± 0.11
Drought (127 days)	-2.33 ± 14.07	26.6 ± 5.1	306.8 ± 91.1	412 ± 25	0.13 ± 0.13	3.7 ± 4.8	0.45 ± 0.09
Haze (61 days)	-0.33 ± 12.70	31.4 ± 8.3	23.0 ± 5.5	429 ± 26	0.16 ± 0.14	2.5 ± 3.5	0.45 ± 0.07
Post-haze (49 days)	-1.41 ± 14.50	29.1 ± 6.6	69.1 ± 20.0	429 ± 29	0.14 ± 0.14	3.4 ±4.6	0.48 ± 0.11
2015	-1.79 ± 13.53	28.0 ± 7.2	676.6± 199.2	418 ± 28	0.13 ± 0.12	3.4 ± 4.6	0.49 ± 0.11
Reference period	-2.20 ± 14.48	31.8 ± 8.4 [G)]	829.3 ± 242.3	407± 30	0.09 ± 0.05	4.3 ± 5.5	0.59 ± 0.15

G) no data 31.05.-08.09.2014, 12.01.-04.02.2016, 14.04.-11.05.2016

Supplement

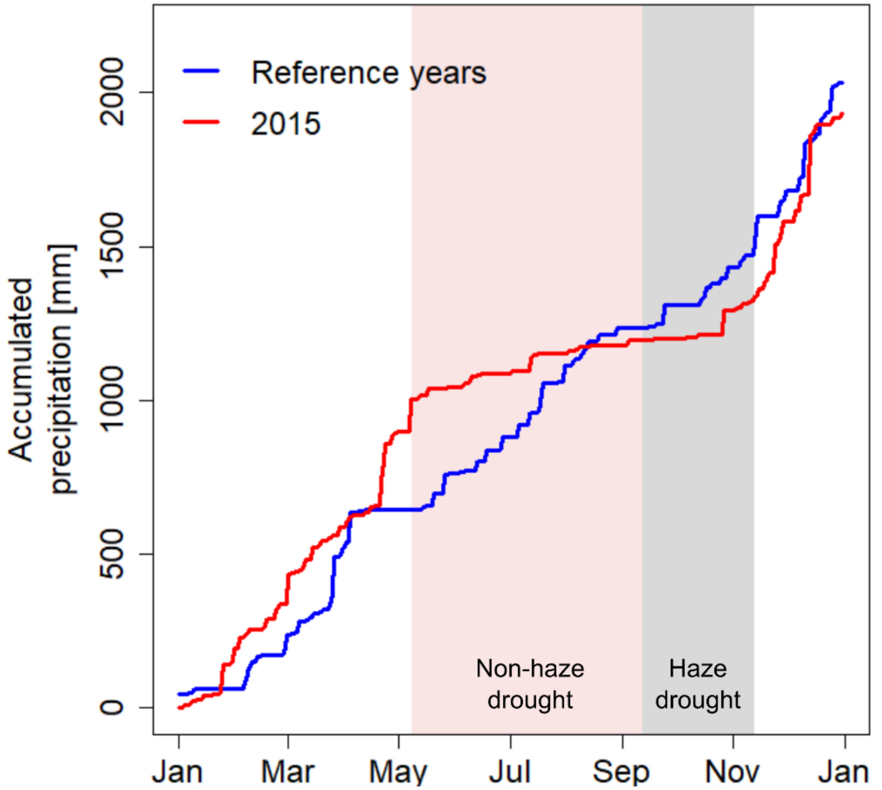

Figure S1: Accumulated precipitation in 2015 and during the reference time period. Shaded areas in red and grey mark the non-haze drought and the haze drought period in 2015, respectively.

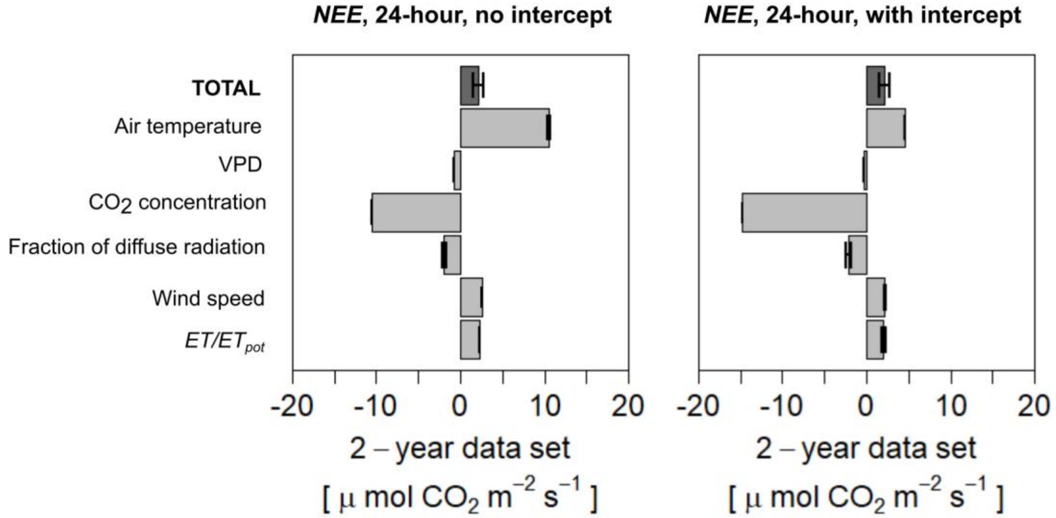

Figure S2: Comparison of Multiple Linear Regression Model (*MLRM*) results without (left) and with (right) intercept on 24-hour net ecosystem CO_2 exchange (*NEE*) during the entire study period (2014-2016). Error bars show the standard error.

Table S1: Contribution (± standard error) of meteorological parameters (predictors) on net ecosystem CO_2 exchange (*NEE*) derived from multiple linear regression model (*MLRM*) during different time periods (full 2-year study period, non-haze drought, haze drought, and non-haze & non-drought conditions). Negative values indicate CO_2 uptake for 24-hour *NEE* and midday *NEE*, and CO_2 release for night time *NEE*. If not otherwise stated, measurement height is 22 m above the surface.

	Predictor [μmol m^{-2} s^{-1}], full 2-year study period								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	***ET/ET_{pot}***	**Incoming *PAR***	**Total**
NEE, 24-hour	-10.50 (± 0.06)	-	-2.61 (± 0.12)	1.94 (± 0.54)	10.54 (±0.01)	0.73 (± 0.03)	-2.23 (±0.44)	-	-2.13 (± 1.18)
NEE, midday (10-14 h)	-34.48 (± 0.12)	-	-	6.86 (± 1.06)	30.30 (± 0.01)	6.87 (± 0.06)	-2.47 (± 1.67	-14.68 (± 0.001)	-21.32 (± 2.93
NEE, night time (19-5:30 h)	37.70 (± 0.29)	-28.37 (± 0.30)	-1.17 (± 0.58)	-	-	-0.98 (± 0.10)	0.51 (± 0.76)	-	7.69 (± 2.03)

	Predictor [μmol m^{-2} s^{-1}], non-haze drought								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	***ET/ET_{pot}***	**Incoming *PAR***	**Total**

NEE, 24-hour	-10.65 (± 0.05)	-	-2.96 (± 0.11)	1.82 (± 0.40)	10.39 (± 0.01)	0.85 (± 0.02)	-1.97 (± 0.39)	-	-2.51 (± 0.96)
NEE, midday (10-14 h)	-34.40 (± 0.10)	-	-	-5.50 (± 0.65)	29.94 (± 0.01)	7.00 (± 0.04)	-2.26 (± 1.46)	-15.96 (± 0.001)	-21.18 (± 2.26)
NEE, night time (19-5:30 h)	38.48 (± 0.32)	-28.69 (± 0.32)	-1.30 (± 0.28)	-	-	-1.39 (± 0.06)	0.51 (± 0.47)	-	7.61 (± 1.45)

Predictor [μmol m^{-2} s^{-1}], haze drought

	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	***ET/ET_{pot}***	**Incoming *PAR***	**Total**
NEE, 24-hour	-10.94 (± 0.01)	-	-2.39 (0.03)	2.13 (0.19)	10.86 (± 0.001)	1.09 (± 0.004)	-1.96 (± 0.12)	-	-1.20 (± 0.35
NEE, midday (10-14 h)	-36.09 (± 0.10)	-	-	-9.39 (± 1.13)	30.95 (± 0.01)	9.20 (± 0.03)	-2.10 (± 0.97)	-11.49 (± 0.0004)	-18.92 (± 2.24)
NEE, night time (19-5:30 h)	39.31 (± 0.23)	-28.44 (± 0.0.25)	-1.07 (± 0.35)	-	-	-1.87 (± 0.03)	0.51 (± 0.24)	-	8.44 (± 1.11)

Predictor [μmol m^{-2} s^{-1}], non-drought and non-haze conditions

	Air temperature	Air temperature (12 m)	Wind speed	Fraction of diffuse radiation	CO_2 concentration	Vapor pressure deficit	*ET/ET_{pot}*	Incoming *PAR*	Total
NEE, 24-hour	-10.38 (± 0.05)	-	-2.55 (± 0.10)	1.96 (± 0.65)	10.57 (± 0.003)	0.63 (± 0.04)	-2.42 (± 0.34)	-	-2.19 (± 1.19)
NEE, midday (10-14 h)	-34.26 (± 0.12)	-	-	-6.91 (± 1.33)	30.33 (± 0.01)	6.46 (± 0.08)	-2.65 (± 1.67)	-14.76 (± 0.001)	-21.78 (± 3.21)
NEE, night time (19-5:30 h)	37.19 (± 0.31)	-28.25 (± 0.31)	-1.14 (± 0.69)	-	-	-0.71 (± 0.20)	0.51 (± 0.86)	-	7.60 (± 2.36)

Table S2: Case scenarios (Case 1-Case 5) of different *MLRMs* and summary of case scenarios with Akaike information criterion (*AIC*) score and model goodness of fit.

Case 1: *lm(formula = scale(NEE) ~ scale(VPD) + scale(CO2) + scale(fdifRad) + scale(wind) + scale(Tair))*

Coefficients:	**Estimate**	**Std. Error**	**t-value**	**Pr (>|*t*|)**
(Intercept)	*-0.112342*	*0.05100*	*-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*

Case 2: *lm(formula = scale(NEE) ~ 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 ~ 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	1.753	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(formula = NEE ~ VPD + CO2 + fdifRad + 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(formula = NEE ~ CO2 + fdifRad + 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	021	none	490
3	0.74	none	808
4	0.20	Temperature, *VPD* [0.8 to 0.9]	801
5	0.21	none	798

AIC scores differed 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.

Table S3~~2~~: Multiple Linear Regression Model (*MLRM*): Statistics of midday (10-14 h local time), night time (19-5:30 h) and 24-hour averaged environmental parameters. If not otherwise stated, measurement height is 22 meter above the surface.

Parameter (midday)	**Estimate**	**SE**	**t-value**	**P-value**
Incoming PAR	-0.01	0.00	-12.44	<0.001
Air temperature	-1.15	0.14	-8.50	<0.001
Vapor pressure deficit	0.56	0.07	7.98	<0.001
CO_2 concentration	0.08	0.01	9.09	<0.001
Fraction of diffuse radiation	-9.98	1.20	-8.29	<0.001
ET/ET_{pot}	-5.58	1.90	-2.94	<0.001
Parameter (night time)	**Estimate**	**SE**	**t-value**	**P-value**
Air temperature	1.50	0.17	8.68	<0.001
Vapor pressure deficit	-0.35	0.06	-6.07	<0.001
ET/ET_{pot}	1.65	0.45	3.67	<0.001
Air temperature (12 m)	-1.14	0.17	-6.52	<0.001
Wind speed	-0.88	0.34	-2.59	<0.01
Parameter (24-hour)	**Estimate**	**SE**	**t-value**	**P-value**
Vapor pressure deficit	0.12	0.06	2.11	0.04
CO_2 concentration	0.03	0.01	2.80	0.01
Fraction of diffuse radiation	2.18	1.22	1.79	0.08
Wind speed	-1.70	0.27	-6.31	<0.001
Air temperature	-0.39	0.12	-3.15	<0.001
ET/ET_{pot}	-4.33	0.99	-4.39	<0.001

Table S4~~3~~: Multiple Linear Regression Model (*MLRM*): Correlations of midday (10-14 h local time), night time (19-5:30 h) and 24-hour averaged environmental parameters. If not otherwise stated, measurement height is 22 meter above the surface.

Midday	Incoming PAR	Air temperature	Vapor pressure deficit	CO_2 concentration	Fraction of diffuse radiation	ET/ET_{pot}
Incoming PAR	1.00	0.55	0.56	-0.42	-0.82	-0.28
Air temperature	0.55	1.00	0.89	-0.22	-0.33	-0.52
Vapor pressure deficit	0.56	0.89	1.00	-0.18	-0.30	-0.53
CO_2 concentration	-0.42	-0.22	-0.18	1.00	0.33	0.14
Fraction of diffuse radiation	-0.82	-0.33	-0.30	0.33	1.00	0.16
ET/ET_{pot}	-0.28	-0.52	-0.53	0.14	0.16	1.00

Night time	Air temperature	Vapor pressure deficit	Air temperature (12 m)	Wind speed	ET/ET_{pot}
Air temperature	1.00	0.71	0.76	0	-0.01
Vapor pressure deficit	0.71	1.00	0.44	0.24	-0.02
Air temperature (12 m)	0.76	0.44	1.00	0.04	-0.03
Wind speed	0	0.24	0.04	1.00	-0.06
ET/ET_{pot}	-0.01	-0.02	-0.03	-0.06	1.00

24-hour	Vapor pressure deficit	CO_2 concentration	Fraction of diffuse radiation	Wind speed	Air temperature	ET/ET_{pot}
Vapor pressure deficit	1.00	0.05	-0.14	0.25	0.76	-0.62
CO_2 concentration	0.05	1.00	0.29	-0.30	0.09	0.13
Fraction of diffuse radiation	-0.14	0.29	1.00	-0.22	-0.19	0.25
Wind speed	0.25	-0.30	-0.22	1.00	-0.09	-0.14
Air temperature	0.76	0.09	-0.19	-0.09	1.00	-0.69
ET/ET_{pot}	-0.62	0.13	0.25	-0.14	-0.69	1.00

Table S54: Effect of meteorological parameters (predictors, ± standard error) on net ecosystem CO_2 exchange (*NEE*) during non-haze drought conditions derived from multiple linear regression model (*MLRM*). Negative values indicate decrease in CO_2 uptake for 24-hour *NEE* and midday *NEE*, and increase in CO_2 release for nighttime *NEE*. If not otherwise stated, measurement height is 22 m above the surface.

	Predictor [µmol m^{-2} s^{-1}]								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	***ET/ET_{pot}***	**Incoming *PAR***	**Total**
NEE, 24-hour	0.26 (± 0.01)	-	0.41 (± 0.01)	0.14 (± 0.25)	0.18 (± 0.0002)	-0.22 (± 0.02)	-0.45 (± 0.04)	-	0.32 (± 0.23)
NEE, midday	0.14 (± 0.02)	-	-	-1.40 (± 0.68)	0.39 (± 0.001	-0.54 (± 0.0003)	-0.39 (± 0.21)	1.20 (± 0.0003)	-0.60 (± 0.95)
NEE, nighttime (19-5:30 h)	-1.29 (± 0.02)	0.44 (± 0.01)	0.1 (± 0.41)	-	-	0.68 (± 0.14)	0 (± 0.39)	-	-0.02 (± 0.91)

Table S6~~5~~: Effect of meteorological parameters (predictors, ± standard error) on net ecosystem CO_2 exchange (*NEE*) during haze drought conditions derived from multiple linear regression model (*MLRM*). Negative values indicate decrease in CO_2 uptake for 24-hour *NEE* and midday *NEE*, and increase in CO_2 release for nighttime *NEE*. If not otherwise stated, measurement height is 22 m above the surface.

	Predictor [μmol m^{-2} s^{-1}]								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	**ET/ET_{pot}**	**Incoming *PAR***	**Total**
NEE, 24-hour	0.55 (± 0.05)	-	-0.16 (± 0.07)	-0.17 (± 0.46)	-0.29 (± 0.003)	-0.46 (± 0.04)	-0.46 (± 0.22)	-	-0.99 (± 0.84)
NEE, midday	1.83 (± 0.02)	-	-	2.48 (± 0.20)	-0.62 (± 0.001)	-2.74 (± 0.05)	-0.55 (± 0.70)	-3.27 (± 0.001)	-2.86 (± 0.97)
NEE, nighttime (19-5:30 h)	-2.12 (± 0.08)	0.19 (± 0.06)	-0.07 (v 0.33)	-	-	1.16 (± 0.17)	0	-	-0.84 (± 1.25)

Table S7~~6~~: Effect of meteorological parameters (predictors, ± standard error) on net ecosystem CO2 exchange (NEE) during increased non-haze drought (NHD+) scenario derived from multiple linear regression model (MLRM). Negative values indicate decrease in CO2 uptake for 24-hour NEE and midday NEE, and increase in CO2 release for nighttime NEE. If not otherwise stated, measurement height is 22 m above the surface.

	Predictor [µmol m^{-2} s^{-1}]								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	**ET/ET_{pot}**	**Incoming *PAR***	**Total**
NEE, 24-hour	2.39 (± 0.02)	-	0.41 (± 0.003)	0.50 (± 0.13)	0.18 (± 0.00003)	-0.39 (± 0.01)	-0.84 (± 0.04)	-	2.25 (± 0.17)
NEE, midday	7.02 (± 0.16)	-	-	-2.50 (1.71)	0.39 (± 0.001)	-1.94 (± 0.08)	-0.84 (± 0.17)	4.40 (± 0.001)	6.52 (± 1.80)
NEE, nighttime (19-5:30 h)	-8.99 (± 0.13)	6.18 (± 0.08)	0.15 (± 0.06)	-	-	0.96 (± 0.13)	0.10 (± 0.04)	-	-1.59 (± 0.29)

Table S8~~7~~: Effect of meteorological parameters (predictors, ± standard error) on net ecosystem CO_2 exchange (*NEE*) during increased haze drought (*HD*+) scenario derived from multiple linear regression model (*MLRM*). Negative values indicate decrease in CO_2 uptake for 24-hour *NEE* and midday *NEE*, and increase in CO_2 release for nighttime *NEE*. If not otherwise stated, measurement height is 22 m above the surface.

	Predictor [µmol m^{-2} s^{-1}]								
	Air temperature	**Air temperature (12 m)**	**Wind speed**	**Fraction of diffuse radiation**	**CO_2 concentration**	**Vapor pressure deficit**	***ET/ET_{pot}***	**Incoming *PAR***	**Total**
NEE, 24-hour	2.74 (± 0.13)	-	-0.16 (± 0.01)	-0.60 (±0.28)	-2.46 (± 0.01)	-0.68 (± 0.03)	-0.85 (± 0.19)	-	-2.01 (± 0.38)
NEE, midday	9.05 (± 0.21)	-	-	4.36 (± 0.87)	-6.80 (± 0.01)	-4.58 (± 0.23)	-0.97 (± 0.68)	-5.57 (± 0.003)	-4.51 (± 0.16)
NEE, nighttime (19-5:30 h)	-9.98 (± 0.76)	5.88 (± 0.36)	-0.07 (± 0.02)	-	-	1.54 (± 0.26)	0.10 (± 0.06)	-	-2.53 (± 0.10)