GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN

Competition and yield in oil palm agroforestry: examining the 'yield penalty' of biodiversity

Hendrik Lorenz

Master's thesis at the Faculty of Forest Sciences and Forest Ecology, Georg- August University Göttingen

Supervisors

1. Prof. Dr. Dirk Hölscher
2. Dr. Alexander Röll

Hendrik.lorenz@stud.uni-goettingen.de
M.Sc. Tropical and International Forestry (TIF)
4th semester

Date of submission: 27.10.2018

Abstract

Oil palm agroforestry is proposed as a measure to tackle existing and upcoming socio-environmental challenges of conventional oil palm plantations, yet little is known about the effects of neighboring trees on oil palms. Embedded into an existing biodiversity enrichment project, this paper investigates the underlying causes of spatial and temporal yield variability among oil palms in a tree-enriched oil palm plantation in Jambi province, Sumatra. The analyses use monthly yield data (2014-2018) from oil palms within tree-enriched plots (0, 1, 2, 3 or 6 planted species), adjacent to the plots and far outside the plots (control palms). The data was used to (1) compare yield on palm level and the 'yield penalty' per area between different surrounding tree diversity levels and further palm categories; (2) identify and test yield determinants from the field of tree-to-palm and palm-to-palm competition and palm morphology by multiple linear regressions models; (3) create time series graphs and relate temporal yield amplitudes to local meteorological variables. Results show that four years after planting the trees, yield in the diversified plots is below the conventional plantation average (-28%, $p = 0.08$ and -45%, $p < 0.01$ for 3 and 6 planted tree species, respectively). The time series suggests a steady yield decline among all enriched plots throughout the period. Yet, plots with no trees planted but natural undergrowth development and suspension of artificial fertilization have shown above-average yield per area since initial palm thinning. This offers a 'low-cost' alternative to agroforestry at supposedly intermediate ecosystem functioning. Regressions on palm level confirm negative yield effects of surrounding trees and palms and show positive effects of palm crown size. A quantification of the 'yield penalty' of diversity improves transparency among the costs associated with agroforestry, which can help to reduce risks of agroforestry investments and to develop economic incentives for less ecologically destructive oil palm cultivation.

Keywords: landscape restoration, biodiversity enrichment, economic-ecological trade-off, crown projection area, competition index, tree planting

Wettbewerb und Ertrag im Ölpalmen-Agroforst: eine Untersuchung der Ertragsminderung durch Biodiversität

Zusammenfassung

Ölpalmen-Agroforstsysteme werden als ein Mittel gehandelt, um bestehende und zukünftige sozio-ökologische Folgen konventioneller Ölpalmenplantagen zu bekämpfen, obwohl bislang wenig über die Effekte von benachbarten Bäumen auf den Ertrag von Ölpalmen bekannt ist. Als Teil eines bestehenden Baumvielfaltsprojekts werden in der Arbeit die zugrundeliegenden Ursachen räumlicher und zeitlicher Ertragsvariabilität bei Ölpalmen in einer baumangereicherten Ölpalmenplantage in der Provinz Jambi auf Sumatra untersucht. Die Analyse stützt sich auf monatliche Ertragsdaten (2014-2018) von Ölpalmen innerhalb der baumangereicherten Plots (0, 1, 2, 3 oder 6 gepflanzte Arten), von Plot-angrenzenden Palmen sowie Palmen weit außerhalb der Plots (Kontrollpalmen). Die Daten wurden dazu verwendet (1) Einzelpalmenertrag und Flächenertragsminderung verschiedener umgebender Diversitätsstufen und weiterer Palmenkategorien zu vergleichen; (2) Ertragsfaktoren aus dem Bereich des Wettbewerbs Baum-Palme und Palme-Palme sowie Palmenmorphologie mithilfe multipler linearer Regressionsmodelle zu identifizieren und zu testen; (3) Zeitreihen zu erstellen und temporäre Ertragsspitzen mit lokalen meteorologischen Variablen in Verbindung zu bringen. Die Ergebnisse zeigen, dass der Ertrag in den angereicherten Plots vier Jahre nach Pflanzung der Bäume den Plantagendurchschnitt unterschreitet (-28%, $p = 0.08$ und -45%, $p < 0.01$ für 3 und 6 gepflanzte Baumarten). Die Zeitreihe deutet auf einen kontinuierlichen Ertragsrückgang durch alle Diversitätsstufen während des betrachteten Zeitraums. Jedoch waren Erträge in Plots mit keinen gepflanzten Bäumen und natürlicher Unterholzentwicklung sowie Aussetzung der künstlichen Düngung seit der anfänglichen Palmenausdünnung überdurchschnittlich. Dies bietet eine „preisgünstige“ Alternative zur Agroforstwirtschaft bei voraussichtlich mittlerem Funktionieren des Ökosystems. Die Einzelpalmen-Regressionen bestätigen negative Ertragseffekte durch umgebende Bäume sowie Palmen und zeigen positive Effekte ausgehend von Palmkronenausdehnung. Eine Quantifizierung der Ertragsminderung durch Diversität erhöht die Transparenz bezüglich der Kosten von Agroforstwirtschaft, was dazu helfen kann, die Risiken von Investitionen in Agroforstsysteme zu senken und ökonomische Anreize für einen weniger umweltzerstörenden Anbau von Ölpalmen zu entwickeln.

Schlüsselwörter: Landschafsrestaurierung, Biodiversitätsanreicherung, ökonomisch-ökologischer Trade-off, Kronenprojektionsfläche, Wettbewerbsindex, Baumpflanzung

Contents

List of tables and figures

Abbreviations

Adj. pos. 1, 2, 3	adjacent-to-plot palms on positions 1 (closest to the plot), 2 and 3
CHM	canopy height model
CRC990	Collaborative Research Centre 990
cv	coefficient of variation
DBH	diameter at breast height
DEM	digital elevation model
DSM	digital surface model
EF	expansion factor
EFForTS-BEE	Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems – Biodiversity Enrichment Experiment
FFB	fresh fruit bunch
NDVI	normalized difference vegetation index
sd	standard deviation
se%	relative standard error of the mean

Acknowledgements

I would like to offer my special thanks to my supervisors Prof. Dr. Dirk Hölscher and Dr. Alexander Roell for enabling my research stay in Indonesia and for the valuable and constructive suggestions during the planning and development of this research work, and equally to Dr. Clara Zemp for organizing and supervising my research stay in Jambi.

For their data provision, I would like to thank again Dr. Clara Zemp and previous project members for the provision of all yield data, as well as numerous palm and tree measurements; Also thank you to Watit Khokthong for the supply of all drone images and some canopy values derived from his algorithms, and finally, to CRC990 subproject Z02 for providing the climate data of Humusindo and Bungku village. I would also like to express my appreciation of the free development and provision of open source software to the respective development teams (R, QGIS, Inkscape).

Moreover, I wish to acknowledge the help of the CRC990 team in Jambi and Bogor, for their kind support in all administrative and logistical matters. Special thanks go to my assistants Ozy and Irham who supported me in the field despite partly harsh weather conditions and in the early morning hours before sunrise.

I would like to thank Johanna Gather for reviewing my manuscript and for all the helpful advices and comments! Thanks also to my study companions Johanna K., Alejandra and Lena for your input during the process and for the great time we shared in the field.

Finally, I wish to thank my family, Anne and Johanna, for sharing our family time with my thesis, for encouraging my stay in Indonesia, for joining my joy of great findings and for raising my mood whenever outcomes turned out less spectacular than hoped. Not least, I thank my parents who supported and encouraged me throughout my entire studies.

1 Introduction

The use of palm oil has experienced a global surge in popularity and caused a two-fold expansion of the agricultural oil palm (*Elaeis guineensis* Jacq.) frontier in a decade between 2007 and 2016 (FAO, 2018). Consequently, natural rain forests have been transformed into large-scale monocultural oil palm plantations (Vijay et al. 2016), with Indonesia being the most important producing country, providing 53% of the global production in 2016 (FAO 2018). On a local scale, palm oil has profited the producing farmers and is associated with several social improvements of adjacent local populations (Euler et al., 2017). However, the ongoing expansion has led to alarming losses in biodiversity and ecological functioning (Dislich et al., 2017; Fayle et al., 2010; Fitzherbert et al., 2008; Koh and Wilcove, 2008), potentially reducing overall economic welfare by decreasing ecosystem services (D. P. Edwards et al., 2014).

To minimize ecological damages while allowing the productive agricultural use of the landscape, scientists have proposed diversified agroforests (Bhagwat et al., 2008; Clough et al., 2011). Supporters of agroforestry mainly focus on the ecological and socio-economic advantages of agroforestry (Barrios et al., 2018; Jose, 2009; Reed et al., 2017; Schroth et al., 2004). Counter-arguments, on the other hand, especially concern the trade-off between productivity and ecological gain (Cannell et al., 1996; Ranganathan and de Witt, 1996) – a 'yield penalty' that has to be paid in order to increase diversity (Bhagwat and Willis, 2009). This is a likely hypothesis, given the ongoing economic yield optimization of oil palm plantations (Corley and Tinker, 2016). While several agroforestry studies have investigated a yield penalty of tree *density* in tropical agroforestry (Boreux et al., 2016; Rajab et al., 2018), only little attention has been paid to the yield effects of tree *diversity* (e.g. Nesper et al. 2017). And a very limited number of studies have linked either of these effects to oil palm (Edwards et al., 2014; Gérard et al., 2017; Gray and Lewis, 2014; Miccolis et al., 2014; Teuscher et al., 2016, 2015).

All in all, there is much speculation and little scientific evidence to date concerning the specifics of the alleged trade-off in oil palm agroforestry. Contributing to filling this research gap, the presented study investigates drivers of yield in a diversity enriched oil palm plantation in Sumatra, Indonesia. The study is linked to the long-term Biodiversity Enrichment Experiment EFForTS-BEE (Teuscher et al., 2016; www.uni-goettingen.de/de/412084.html) of the Collaborative Research Center 990 (Drescher et al., 2016). 52 tree islands of varying sizes and diversity levels with up to six planted native tree species in systematical design had been established within a conventional oil palm plantation, starting in 2013. Initial results showed that oil palm yield increased simultaneously with palm thinning and planting the trees (Gerard et al. 2017). However, it has remained unknown how the initial trend would continue.

Building on these findings, the objective of this thesis is to explain spatial and temporal variation in oil palm yield by identifying and testing different yield determining factors from the field of tree-to-palm and palm-to-palm competition, palm morphology and local meteorological patterns. The main interest lies in understanding the effects of diversity and performance of interplanted trees. Yet, also the effect of tree and palm crown projection areas and their interactions are extensively discussed to harness the role of light competition within the conventional and enriched parts of the plantation.

The analyses base upon monthly oil palm yield data (2014-2018), other existing palm and tree variables taken by members of the project, as well as several newly collected variables mostly related to crown and canopy (March 2018). Inter-categorial comparisons were conducted to examine yield on palm level and yield penalty per area between palms of different surrounding tree diversity levels and further palm categories. Moreover, multiple linear models were employed to test yield determinants from the field of tree-to-palm and palm-to-palm competition and palm morphology. Finally, time series graphs were computed and temporal yield amplitudes were related to local meteorological variables. With these analyses, the study will contribute to a better understanding of the drivers of oil palm yield in agroforestry.

2 Material and methods

2.1 Study site

The experiment is located in an oil palm plantation of PT. Humusindo Makmur Sejati (01.95° S and 103.25° E, 47 ± 11 m a.s.l.) near Bungku village in the lowlands of Jambi province, Sumatra, Indonesia with a humid tropical climate, a mean annual temperature of 26.7 C and precipitation of 2,235 mm (Teuscher et al., 2016). The plots were established in a medium-sized conventional oil palm plantation of 500 ha. The planted oil palm breed *tenera*, a high yielding cross between varieties *dura* and *pisifera*, was grown from seed and single individuals may take the phenotype of the less productive parent generation. Following the recommendations for *tenera* by the state-owned oil palm company PTPN, the seedlings were planted in a triangular grid of 9.8 m distance between all palms; resulting in approx. 120 palms ha^{-1} and row distance of 8.5 m (Hasbiuan, pers. comm.; Annex 1)[1]. The plantation is managed to a degree 'close-to-nature' because epiphytes growing on the palm stems are not removed and weeding is done only directly around the palm stems (~2 m radius). Fertilizer is applied on a regular schedule (230 kg [N], 196 kg [P], 142 kg [K] plus minerals); pesticides only rarely and in urgent cases. Palm age cannot be clearly determined. According to satellite images, the whole plantation was set up between 2001 and 2007, marking an age structure of 11 to 17 years at the time of writing (Teuscher et al., 2016). Mean palm height across the plantation is 11.9 m (total) and 5.2 m (meristem) in Feb. 2018 (own examination).

2.2 Plot design and sampling

The data used in this paper builds on existing plots from EFForTS-BEE (described in Gérard et al., 2017; Teuscher et al., 2016; description below from these sources if not stated otherwise). Following an elaborate statistical design for biodiversity-ecosystem functioning experiments (Bell et al., 2009), the experiment established 52 fenced plots ('tree islands') with systematically varying composition of up to six planted tree species (*Parkia speciosa* Hassk., Fabaceae; *Archidendron pauciflorum* (Benth.) I.C.Nielsen, Fabaceae; *Durio zibethinus* L. ex Murray, Malvacea; *Dyera costulata* (Miq.) Hook., Apocynaceae; *Peronema canescens* Jack, Verbenaceae; *Shorea leprosula* Miq., Dipterocarpaceae). The plots contain five different diversity levels (0, 1, 2, 3 or 6 planted tree species) and four different plot sizes (5 m x 5 m, 10 m x 10 m, 20 m x 20 m or 40 m x 40 m). The minimum distance between the plots is 85 m. Neither weeding nor fertilizer treatment is done within the plots, although some pruning is inevitably done as part of the monthly harvesting. The

[1] Planting information was obtained in an interview with the plantation manager Hasbiuan (Annex 1), although it contradicts the value provided by Gérard *et al.* (2017) where planting distance is cited as 9 m, resulting in 143 palms ha^{-1}.

fences also exclude cattle ranching, which is allowed for workers-owned cattle in the rest of the plantation (Hasbiuan, pers. comm.; Annex 1). Around 40% of the palms were removed in order to make space prior to planting the trees in December 2013, reducing the number of inside-plot palms to 214. The plots host an irregular number of palms because of plot sizes, relative positioning and initial thinning intensity. 31 plots contain at least one palm and 21 plots are free of palms (detailed summary: Table 5 in Annex 2). Additional 52 x 3 palms outside but near the plots ('adjacent-to-plot') are included in the yield survey and stand in different rows (mean distances: 3.5 m, 12.2 m, 21.8 m, for adj. pos. 1, 2 and 3, respectively; Gérard et al., 2017). Another 34 control palms introduced in Dec. 2016 outside the plots are managed as usual (not fenced, conventional fertilizer and weeding treatment).

A stratified sub-sample was drawn for some of the collected variables (epiphyte cover, micro-slope, girth at breast height) out of the 214 inside-plot-palms. The sample covers the 15 best performing, 15 least performing (randomly selected from the group of palms with zero yield) and additional 20 randomly selected palms from the remainder, all based on the sum of available recent and uninterrupted yield data at the time of data collection (Oct. 2017 - Feb. 2018; list of included palms: Table 6 in Annex 2). Plot 29 (40 m x 40 m; three species planted: *Archidendron pauciflorum, Durio zibethinus, Dyera polyphylla*) was chosen for another set of observations. The selection was based upon a utility analysis and further observations from the field (criteria: Table 7 in Annex 3). Plot 29 holds the largest number of palms of all plots (n = 20) at a medium high diversity level, contained the largest oil palm yield variability and hosts several successful trees, which are steadily distributed across the plot and sporadically reach to the oil palm canopy. For crown overlap measurements of control palms, we[2] included also their neighboring palms, selecting those whose crowns are overlapping or at least tangent to a control palm.

2.3 Data collection and processing of variables

2.3.1 Yield survey

The yield analyses presented in this paper used existing EFForTS-BEE yield surveys of the past 4.5 years (Jan. 2014 - June 2018). Oil palms were harvested monthly and weighed at the roadside using a digital hand scale, expressed as fresh fruit bunch (FFB) weight (kg). Inside-plot yield (aggregated on plot level: n = 31) and adjacent-palm yield (n = 156 palms) records reach back to Jan. 2014. Inside-plot palm yield (n = 214 palms), on the other hand, and control-palm yield (n = 34 palms) were successfully introduced not before Jan. 2017. One control palm was removed from the analyses due to missing data. For those analyses using inside-plot yield data before Jan. 2017

[2] Whenever referring to data collection, I use 'we' to acknowledge the joint effort by the assistants, other supporting team members and myself during the field work.

(Fig. 3, Fig. 4, Fig. 5), I weighted plot-level means of different plot categories by the number of palms per plot. Due to logistical problems, the yield survey had been suspended several times, with the largest gap of three months (complete representation of all gaps: Fig. 6 in Annex 3).

A preliminary yield analysis showed that suspended harvest saves a share of yield for the next month, thus artificially increasing the first yield observation after the suspended month. To quantify this effect, I systematically compared the values before and after survey gaps ('post-gap' and 'pre-gap' values). As pre-gap value I chose the last available harvest observation before the peak, which itself was no post-gap value. Due to sporadic yield on palm level (individual palms do not fruit every month), the palm-level data was not suitable for processing and yield means had to be used. Given the small sample size of only n = 8 gaps (n = 5, 2 and 1 for gap sizes of 1, 2 and 3 months, respectively), I pooled all inside-plot and adjacent observations (31 plots comprising 214 palms plus 156 adjacent palms) for all gap sizes with the aim to compute a general and reliable value (theoretically, there is no reason why harvest suspension should affect palm groups differently). A one-sample t-tests confirmed that the computed deviations (post-gap minus pre-gap divided by post-gap) are different from zero for the pool ($p = 0.03$; mean = 22.5%). The median of post-gap overshooting amounts to 28.72%, by which I subsequently reduced all inside-plot, adjacent and control palm post-gap yield data underlying the analyses in this paper.

2.3.2 Yield penalty calculation

Yield penalty is defined in this paper as a per-area yield reduction caused by the established tree islands and is calculated as the relative difference of control and treatment (Eqn. 1). It is different from yield on palm level because the initial palm thinning in the plots reduced the number of palms per ha and increased the production reference area per palm. Even if palms affected by thinning were overyielding, the reduced planting density could lead to reduced yields per area. For palm oil businesses, per-area effects are of particular importance because they are more related to the revenues that can be generated with a limited unit of land.

$$YP = 100 \frac{Y_{ha\ control} - Y_{ha\ thinning}}{Y_{ha\ control}} \quad \textbf{(1)}$$

YP = yield penalty (%)
$Y_{ha\ thinning}$ = per-area yield of a palm category affected by thinning
$Y_{ha\ control}$ = per-area yield of a palm category verifiably not affected by thinning

Nonetheless, yield per palm is interesting (for ecologists) to understand processes and interactions on palm level. Therefore, both types, (1) yield penalty per area and (2) yield per palm are employed for different questions in the analysis. The second part of palm categorial differences

(Fig. 2 b) and the temporal yield developments (Fig. 3 and Fig. 4 a, b, c) are based upon (1), whereas the first part of categorial differences (Fig. 2 a), the analysis of meteorological effects (Fig. 5 b) and the regression analyses to explore yield determinants (Table 3, Table 4) use type (2).

Expanding palm-level yield (kg FFB $palm^{-1}$) to yield per area (kg FFB ha^{-1}) requires expansion factors. Because of different planting densities within and around the tree islands as compared to the conventional plantation part, expansion factors are different for both categories (Eqn. 2 and Eqn. 3). An expansion factor generally requires a reference area $\mathrm{A_{palm}}$ assigned to each palm (Eqn. 4). This is less complicated for palms in far distance from the plots (control palms, adj. pos. 3 and adj. pos. 2), where the conventional planting scheme is unaffected by plot-thinning. In these cases, a single palm represents one out of approx. 120 planted palms per ha, which leads to a palm-reference area equal to the inverse of planting density ($\mathrm{A_{palm}} = \frac{1}{120}$ ha) and an expansion factor $EF_{conventional}$ equal to 120 (Eqn. 5).

$$Y_{ha\ conventional} = EF_{conventional}\ Y_{p\ conventional} \quad \mathbf{(2)}$$

$$Y_{ha\ thinning} = EF_{thinning}\ Y_{p\ thinning} \quad \mathbf{(3)}$$

$$EF_{general} = \frac{A_{ha}}{\mathrm{A_{palm}}} \quad \mathbf{(4)}$$

$$EF_{conventional} = A_{ha}\ d_{pl\ ha} = 120 \quad \mathbf{(5)}$$

$$EF_{thinning} = EF_{conventional}\left(\frac{7 - n_{cut}}{7}\right) \quad \mathbf{(6)}$$

$Y_{ha\ thinning}$	=	per-ha yield of a palm affected by thinning (all inside-plot palms and adj. pos. 1)
$Y_{ha\ conventional}$	=	per-ha yield of a palm not affected by thinning (control palms, adj. pos. 2 and 3)
$Y_{p\ thinning}$	=	per-palm yield of a palm affected by thinning
$Y_{p\ conventional}$	=	per-palm yield of a palm not affected by thinning
$EF_{general}$	=	general expansion factor
$EF_{thinning}$	=	expansion factor for palms affected by thinning
$EF_{conventional}$	=	expansion factor for palms not affected by thinning
A_{ha}	=	target area (ha)
$\mathrm{A_{palm}}$	=	reference area of one palm (ha)
$d_{pl\ ha}$	=	conventional ('original') palm planting density (ha^{-1})
n_{cut}	=	number of palms intentionally thinned within circle of $r = 12$ m around palm

However, the definition is more challenging for those palms affected by thinning (all inside-plot palms and adj. pos. 1). Using the plot size divided by the number of palms as palm reference area is not appropriate, because it gives too much power to the plot position and orientation relative to the planting scheme. In the original planting grid, a 10 m x 10 m square plot could contain 1, 2 or 3 palms, resulting in EF equal to 100, 200 or 300, respectively. Moreover, benefits for adjacent palms from reduced competition would not be reflected by the calculation. To overcome this problem of attributability, I developed an alternative approach for estimating the reference area of inside-plot palms and adj. pos. 1 by using a virtual search circle around each of these palms with a radius r = 12 m (illustration: Fig. 7 in Annex 3). Building on the uniform equilaterally triangular planting scheme, each circle is assumed to host exactly seven palms (center palm plus six neighbors). If all seven palms were present, the planting density for this palm would be equal to the conventional factor. Each missing palm, however, reduces the factor by one seventh (Eqn. 6). For example, a palm with two removed neighbors would result in $EF_{thinning}$ equal to 86.

An important role comes to the radius of the search circle. According to the planting scheme, the distance from the center palm is equally 9.8 m to all six closest neighboring palms, but buffer should be included to account for various errors during planting and measuring of the positions. Additional neighbors are included at approx. 17 m radius. The optimal radius, therefore, lies within 9.8 m and 17 m, but a higher radius increases the chance of including palms from the outer circle. I tested different radii within the range by counting the number of palms (prior to thinning) for each alternative, for all inside-plot palms. The simulation showed that relatively few changes in the frequency of included palms occur between r = 12 m and 13 m (histogram: Fig. 8 in Annex 3), the first of which I selected for the analysis.

An alternative 'opportunity cost'-approach (Gérard et al., 2017) deals with the different planting densities by subtracting the palm-level control yield from the yield of one plot for each palm removed within that plot. In order to use this approach for the above described expansion from palm level to area, it needs to be adjusted to avoid the drawback of attributability of reduced planting density. Hence, it was extended by the proposed measure of reference area estimation in Eqn. 6. In the new model (Eqn. 7), palm-level yields are reduced by the fraction of removed palms within the circle of r = 12 m and multiplied by a palm-level plantation average yield $Y_{p\ control}$, before being expanded to a hectare. Since this adapted approach faces a set of disadvantages in the new context (discussed under 4.1 Effects of tree diversity and species), it is applied only as a supplement (for comparison to the dominant approach in Fig. 4 c and more elaborated for the past 1.5 years in Fig. 13 in Annex 4).

$$Y_{ha\ thinning} = EF_{conventional}\left[Y_{p\ thinning} - Y_{p\ control}\left(\frac{7 - n_{cut}}{7}\right)\right] \quad \textbf{(7)}$$

$Y_{ha\ thinning}$	=	per-ha yield of a palm affected by thinning (all inside-plot and adj. pos. 1)
$Y_{p\ thinning}$	=	per-palm yield of a palm affected by thinning
$Y_{p\ control}$	=	per-palm yield of a palm category verifiably not affected by the tree islands
$EF_{conventional}$	=	expansion factor for palms not affected by thinning
n_{cut}	=	number of neighboring palms intentionally cut within circle of r = 12 m around palm

All yield penalties depend on the used value of control yield per area $Y_{ha\ control}$ (Eqn. 1) and the alternative approach additionally depends on control yield per palm $Y_{p\ control}$ (Eqn. 7). Results of the yield time series (Fig. 5) suggest considerable fluctuations between years, so the timeframe does matter. Averaging along an extensive timeframe will neglect the temporal variability, while a monthly mean of control yield increases the dispersion of monthly yield penalties. As a compromise, I selected the time frame for $Y_{ha\ control}$ as to be in line with the respective analysis: a 1.5-year mean for the 1.5-year comparison of palm types (Fig. 2), means of four months each in the time series (Fig. 4) and means of one year each in the four-year boxplot (Fig. 3). Control yield for the palm-level yield $Y_{p\ control}$ in the alternative approach (Eqn. 7), on the other hand, used a constant mean, computed from designated control palms of the past 1.5 years, throughout all representations. In absence of more recent information, Gérard et al. (2017) used a general plantation mean in their analysis, provided by the plantation manager.

For those analyses dating back to the 'pre-control-era', when the designated control palms were not yet in place (Fig. 3 and Fig. 4), I used the yield of adj. pos. 3 as control. This is justified by earlier project findings that indicated no spillover effect on pos. 3 palms (Gérard et al., 2017) and by findings from this paper, where (1) pos. 3 palms show almost identical yield mean and median as the designated control (Fig. 2 a) and (2) control yield levels evenly around yield of adj. pos. 3 (Fig. 4 d). On the other hand, for analyses including yield of Jan. 2017 and younger, I used the designated control.

2.3.3 Yield time series

To explain yield development by meteorological data (Fig. 5), yield is displayed as a consecutive time series since the start of yield measurement in Jan. 2014 with a temporal resolution of one month. To allow for a clear distinction of meaningful peaks and valleys, and to reduce the influence of missing values, I applied a centered rolling mean algorithm (width = 3 months) and further smoothed the curves via loess functions. Several prior analyses were conducted to set the parameters appropriately so that findings become more pronounced without generating false findings.

To show the temporal development of yield penalty (Fig. 4), I computed four-month averages of the valid observations (no roll-mean nor loess functions applied) and thereby reduced the effect of yield gaps and resulting 'post-gap' peaks.

2.3.4 Palm positions

Exact palm positions were required to compute palm-based competition indices. I used existing high-resolution copter images (Sep.-Oct. 2016; 0.004 m spatial resolution), which I strictly co-registered with the accurately georeferenced fixed wing rasters (Sep.-Oct. 2016; 0.1 m resolution) via the 'Helmert' algorithm in the georeferencer plugin of QGIS (QGIS v. 2.18; QGIS development team, 2018), using palm crown centers as ground control points (both image series collected by Khokthong, unpublished). Existing ground-based palm position data, expressed as distance to the plot fence, showed a distinctive pattern which was laid upon the raster layers to identify surveyed palms from above and update the positions. By visual identification, I updated the plot corner positions to calculate exact palm-to-fence distances.

Positions for control palms and their crown-interfering neighbors could not be identified on the drone images so that ground-based data had to be used for this purpose. We measured horizontal distances from control palms to their neighbors via measuring tape from one stem center to the next and recorded the azimuth in degrees with a Suunto compass.

2.3.5 Crown projection areas of palms and trees

While competition indices on plant level have gained wide popularity in forest science (Biging and Dobbertin, 1995; Pretzsch, 2009), the concept has, to the best of my knowledge, not yet been applied to oil palms. Consequently, methodologies to measure palm crown projection area from the ground seem unavailable in scientific literature. The method in this paper is adapted from tree crown projection area measurements (Pretzsch et al., 2015) although the palms' ragged projection contours complicate the transfer.

The adapted method was used to estimate crown projections from the ground and via manual identification on drone images. Since ground measurements were suspected to produce higher measurement errors, the drone approach was chosen as the preferred measure for all inside-plot palms and their interfering neighbors outside the fence. Control palms and their neighbors, on the other hand, could not be identified on the images and relied on the ground approach.

For both applications, we decided for a measurement of maximum frond extension in four directions/two axes (N-S and E-W), benefitting from the approximately circular shape and enabling compatibility with previous EFForTS-BEE measurements from 2014 and 2017. Prior to decision, we also ground-tested a more ambitious setup with eight directions/four axes (N-S; E-W; NW-SE; NE-SW) in a sample of $n = 15$ palms. Radius and area estimates of the latter method were significantly lower (mean relative difference: -6% and -11% for radius and area, respectively; $p < 0.01$ for both variables in a one-sample t-test). The significant systematic difference was probably due to the smaller 'search angle' caused by the smaller segmentation, so that shorter fronds were relatively more likely to be chosen for the virtual approximation of the crown perimeter. Still, since the bias does not really affect precision (4% and 1% difference in the coefficients of variation of both approaches for radii and areas, respective), we decided in favor of the less complex alternative. Available palm crown projection estimates from previous EFForTS-BEE surveys were tested. Yet, regression results involving these variables are presented only in Annex 4 (Table 9 and Table 10) because preliminary analyses cast doubt on the consistency of past measurement methods (Fig. 10 a in Annex 3).

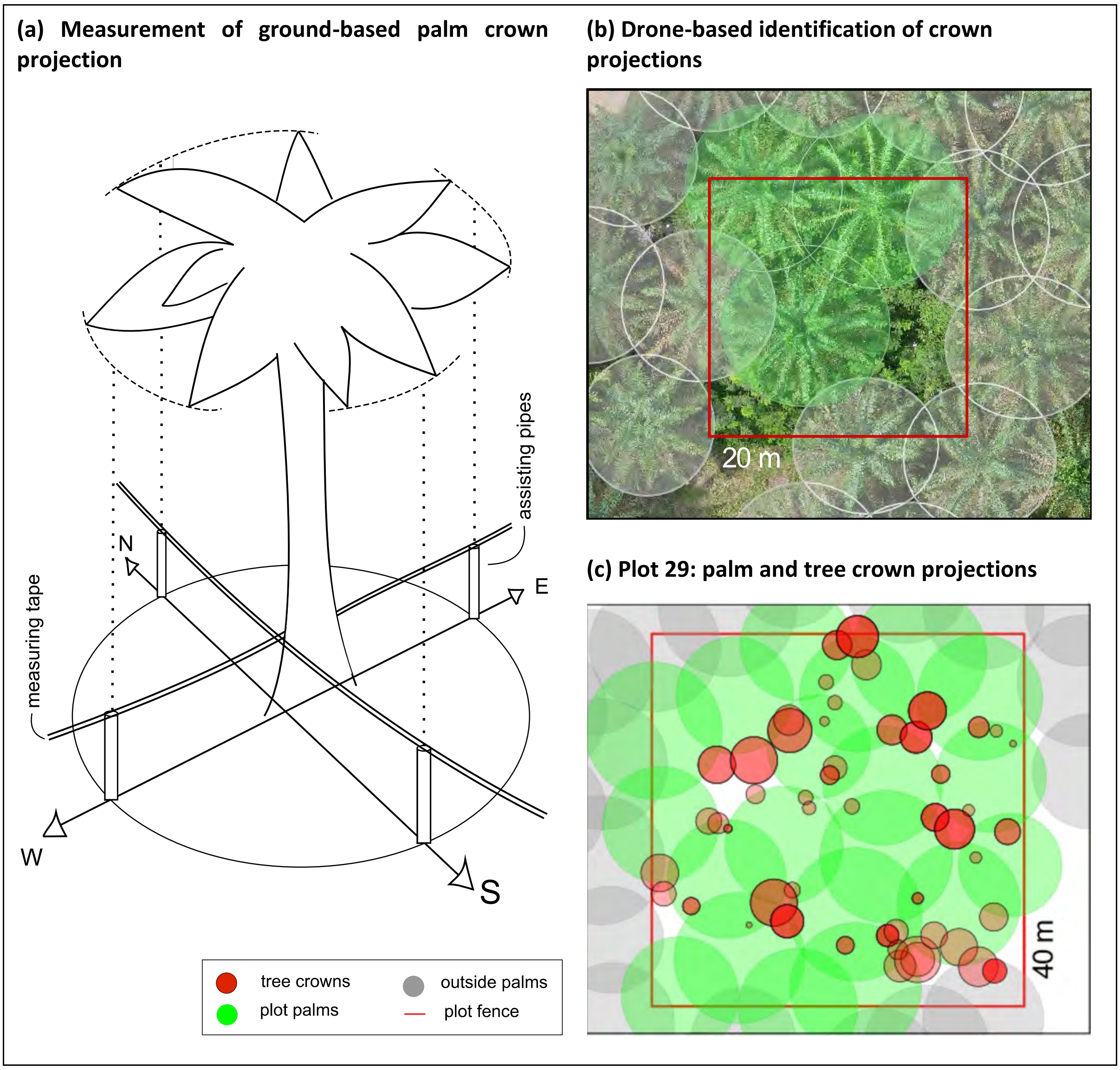

Figure 1. Crown projection area methodology and exemplary plot maps

For the ground measurements, we successively aligned the measuring tape in N-S and E-W directions via compass and used pipes which we leveled vertically to estimate the maximum crown extension (Fig. 1 a). We marked the projected points on the ground along the N-S/E-W axes tangential to the ground projection of an interpolated circular perimeter around the furthest visible frond extensions (roughly within a 45° slice of the projection ellipse). We recorded the direct horizontal line between the two pipes with the straight tape touching always the left part of the palm stem. The methodology was tested and trained before working in the field to ensure that both people identified the same points on the axes. I computed ellipses from the measurements in both directions and obtained the area of the polygons via rgdal plugin in R (Bivand et al., 2017).

Crown radii from the two axial measurements $\overline{NS}$ and $\overline{EW}$ were calculated via quadratic mean formula (Pretzsch et al., 2015).

The drone-based measurements were computed from precisely co-registered high-resolution drone images (see 2.3.4 Palm positions). Using QGIS software, I extracted crown areas by manually fitting ellipses to the maximum frond extensions. In accordance with ground measurements, the ellipses were adjustable in N-S and E-W directions. The same methodology was applied to plot-neighboring palms whose palms reached into the plot area (Fig. 1 b).

Measurement of *tree* crown projection (only in plot 29; see 2.2 Plot design and sampling) generally followed the ground-based procedure for palms. We measured all trees whose crowns interfered with at least one inside-plot palm by touching or overgrowing its fronds. To rank the possible light competition effect, we additionally recorded the tree crown density (1: 'projected leaf area covers < 1/3 of the crown projection area'; 2: 1/3 to 2/3; 3: > 2/3) and the vertical crown position relative to the palm fronds (1: 'the top of the tree touches the lower palm fronds and starts *competition from below*'; 2: 'the top of the tree is *interwoven with palm fronds* but the largest tree part is still below the fronds; 3: 'the largest tree part grows *above the fronds*'). To obtain exact crown positions for accurate modeling, we measured the horizontal palm-to-tree distance from the estimated tree crown centroid to the stem center of the palm and recorded the azimuth via a Suunto compass. For trees interfering with multiple palms, I calculated means from the resulting position data.

2.3.6 Palm and tree competition indices

Several variables reflecting competition on single palm level were computed involving neighboring palms and trees and their morphological characteristics, positions and elevations. For all plots (n = 214 palms), I computed the number of planted palms, trees and tree stem volume within six different circles (r = 5 m to 10 m) around each of the recorded palm positions. For tree variables, I used the most recent survey (Feb. 2018; collected by Zemp et al., unpublished) and, consequently, excluded trees that had died in the previous years. Stem volume was calculated from basal area and tree length (after Prodan 1965); for simplicity using a general form factor of 0.5 (Eqn. 8).

$$V = 0.5\, l\, \frac{\pi}{4}\, DBH^2 \tag{8}$$

V = tree stem volume (m^3)
l = tree stem length (m)
DBH = tree diameter at breast height (m)

Absolute and relative crown overlap areas (Eqn. 9 and 10, respectively) were calculated from crown projection areas, inspired by the influence zone concept of competition indices for trees (Bella, 1971) by constituting crown projections as influence zones and simply adding up intersecting areas. These overlaps were also used for computing the number of interfering neighbors as additional variable (included if crown overlap between center palm and neighbor > 0). Alternative ways of calculating crown projection area and the overlaps (e.g. superposed overlap by multiple palms vs. single overlap) were tested beforehand and only the most promising regressions were selected for presentation. As additional variable, I computed palm crown canopy (%) within six circles of varying size (r = 5 m to 10 m) around the palm.

$$A_{abs_p} = \sum_{i=1}^{n} (CPA_p \cap CPA_i) \qquad \textbf{(9)}$$

$$A_{rel_p} = \frac{\sum_{i=1}^{n} (CPA_p \cap CPA_i)}{CPA_p} = \frac{A_{abs_p}}{CPA_p} \qquad \textbf{(10)}$$

$$A_{rel\_wt_p} = \frac{\sum_{i=1}^{n} [(CPA_p \cap CPA_i)\, f_{ELV_i}]}{CPA_p}; \qquad \textbf{(11)}$$

$$f_{ELV_i} \coloneqq \begin{Bmatrix} 0, & ELV_p > (ELV_i + 2) \\ 0.5\,(ELV_p - ELV_i), & (ELV_i - 2) \leq ELV_p \leq (ELV_i + 2) \\ 1, & ELV_p < (ELV_i - 2) \end{Bmatrix} \qquad \textbf{(12)}$$

A_{abs} = absolute crown projection overlap area (m^2)
A_{rel} = overlap area relative to crown projection area of center palm (%)
A_{rel_wt} = relative overlap area weighted with elevation difference between palms (%)
CPA = crown projection area (m^2)
ELV = elevation of palms (topographic elevation plus palm height) (m)
p = index of center palm
i = index of neighbor palm
n = number of crown-overlapping neighbors
f_{ELV} = factor to weigh overlap areas according to elevation difference between palms

To give more weight to relatively exposed palms with overarching crowns and thereby putting more emphasis on the light aspect of competition, I included palm elevation into an additional model (Eqn. 11). It excludes overlap areas of palms with elevation difference below 2 m compared to the center palm, gives full weight to all elevations above 2 m difference and an intermediate value based on a linear function for differences within that corridor. The factor f_{ELV} in Eqn. 12, accordingly, takes values between zero and one. The elevation represents topographic elevation plus palm height, which I extracted for all palm coordinates from a digital elevation model (DEM) (Sep.-Oct. 2016; 0.02 m resolution; Khokthong, unpublished; also strictly georeferenced). To reduce the error, I computed mean values of all raster elevation values within a radius of 3 m around the supposed palm center, using R raster package (Hijmans, 2017). This procedure was found to be the best according to a trial with different radii and mean vs. max functions (comparison: Fig. 11 in Annex 3).

For light competition of trees in Plot 29, I developed an additional more specific model (Eqn. 13) to give more weight to dense crowns and pronounced interference. The two weight factors $f_{density}$ and f_{interf} (Eqn. 14) reduce the respective tree-palm crown overlaps to account for different crown densities and interference classes, respectively.

$$A_{tree\_rel\_wt_p} = \frac{\sum_{i=1}^{n}[(CPA_p \cap CPA_{tree_i})\ f_{density_i}\ f_{interf_i}]}{CPA_p}; \quad \textbf{(13)}$$

$$f_{density_i} \coloneqq \begin{Bmatrix} 0.33, & leaf\ cover < 1/3 \\ 0.66, & 1/3 \leq leaf\ cover < 2/3 \\ 1.00, & leaf\ cover \geq 2/3 \end{Bmatrix};\ f_{interf_i} \coloneqq \begin{Bmatrix} 0.33, & below \\ 0.66, & interwoven \\ 1.00, & above \end{Bmatrix} \quad \textbf{(14)}$$

$A_{tree\_rel\_wt}$	=	weighted tree crown overlap relative to palm crown projection area (%)
p	=	index of center palm
i	=	index of competing tree
n	=	number of crown-overlapping neighbors
$f_{density}$	=	factor to weigh overlap areas according to crown density
f_{interf}	=	factor to weigh overlap areas according to degree of interference with palm

Diversity indices (Shannon, Simpson, Inverse Simpson) were computed based on 2018 tree data via R package vegan (Oksanen et al., 2018).

2.3.7 Gap fractions and canopy

Gap fractions (canopy openness) were computed on plot level from hemispherical photos, taken with a Nikon D5100 SLR camera and Sigma 4.5 mm F2.8 EX DC circular fisheye lens. We moved the camera to systematically arranged spots to account for different plot sizes (5 m x 5 m and 10 m x 10 m: 1 spot in the plot-center; 20 m x 20 m: 3 spots in a triangular shape around the center; 40 m x 40 m: 6 spots in a hexagonal shape around the center), following the methodology described in Teuscher et al., 2016 (sketch: Fig. 9 in Annex 3). The camera was mounted on a tripod at 1.2 m height and leveled to face the vertical using a bubble level slotted into the flash socket with the top of the camera aligned towards North. Starting with an overexposed shot in each spot, we gradually decreased the exposure value and selected the image with highest exposure value and no peak touching the very right end of the gray value histogram (Glatthorn and Beckschäfer, 2014). Pictures were taken in non-rainy morning and evening hours to avoid distortions by overexposed sky. The images were processed using the batch processing plugin 'Hemispherical_2.0' (Beckschäfer, 2015) in Image J v.1.52e of which binarization is based upon the minimum thresholding algorithm (Prewitt and Mendelsohn, 2006).

Since these gap fractions account for all vegetation (including trees), I derived additional canopy fractions exclusively for palms by dividing the aggregated crown projection areas (derived from 2016 drone data) by the plot areas. In addition, I included existing canopy variables describing tree and palm canopy fractions, derived via algorithm (Khokthong, unpublished), also based on the drone images from 2016.

2.3.8 Height, meristem height and basal area

We collected recent height data for all palms in Plot 29, the control palms and their crown interfering neighbors via the Haglöfs Vertex IV hypsometer. We defined meristem height as the upper end of the stem, the last point to which fruits are visible, and total height as the upper point of the fronds emerging into the sky. For the remainder, we used existing EFForTS-BEE meristem height data (Feb. 2017; same methodology). Drone-based height measurements (Khokthong, unpublished) were tested as alternative measures prior to the analysis. However, the high dispersion of the data and large differences between mean or max values in circles of different size around the identified palm positions in the canopy height model (CHM) raster images suggested against their use (comparison: Fig. 12 in Annex 3).

Palm circumference was collected via measurement tape for the subsample of inside-plot palms and for all control palms, via measurement tape at breast height above the basal bulge (in line with Henson, 2006).

2.3.9 Epiphyte cover and micro slope

We measured epiphyte cover (%) for the stratified sub-sample of inside-plot palms and for the control palms looking from North towards the stem and estimating which fraction of the meristem was hidden by vital epiphytes. Micro slope (%), measured for the same sample, was expressed as maximum slope across a circle of r = 2 m around the palm center. We marked the start and end points with pipes of equal length and measured the angle via Vertex IV In angle mode, pointing through both upper tips of the pipes.

2.3.10 Meteorological data

Local meteorological data including precipitation (mm h^{-1}), global radiation (W m^{-2}) and air temperature 2 m above the ground (°C) of the plantation Humusindo and of Bungku village were provided by the Collaborative German-Indonesian Collaborative Research Center CRC 990, subproject Z02. Originally, the measurements were taken in 10 min intervals, but were supplied as hourly data where incomplete hours were removed. Whenever Humusindo measurements were not available, I replaced data gaps with measurements from the nearby climate station in Bungku village. I computed monthly mean values for solar radiation as well as temperature and upscaled precipitation from the valid observations. All series were smoothed with a loess function.

2.3.11 Expert interview

To identify further (possibly plantation-specific) yield determining factors, we conducted a semi-structured expert interview, following the suggestions provided in Bogner, Littig, & Menz (2009) with the plantation manager Hasbiuan (results in Annex 1).

2.4 Statistical analysis

2.4.1 Regression design

Linear regression analyses were conducted for all enriched plots on palm level (not per area) and on plot level to explore promising yield determinants. On palm level, I computed separate models for the full sample (n = 214 palms), for the stratified subsample (n = 50 palms), for Plot 29 (n = 20 palms), for the control palms (n = 34 palms) and for different subsets of the full sample based on distance to the plot fence (explained below). To avoid multicollinearity and support comparability, the models were computed separately for all predictors of interest. To account for temporal effects, all models were computed with a set of different yield period means as dependent variable (explained below).

For Plot 29 and the control palms, I used the simplest possible model of linear regression (Eqn. 15). For the full sample on palm level and for the stratified subsample, I performed multiple linear regressions with yield as dependent variable, explained by one independent predictor variable plus a constant set of control variables (Eqn. 16). As predictors, I tested all available variables from the field of palm-to-palm and palm-to-tree competition, palm morphology and slope. The control variables were selected based on previous hypotheses and on insights from data exploration. For example, plot size was dropped in favor of palm-to-fence distance because yield variability was found to be more dependent on the latter.

Using Eqn. 16 as a template, I computed additional mixed models to account for random effects from Plot ID on palm level, using the R package lme4 (Bates et al. 2015). Plot ID was entered as random effect with random intercept and by-$PREDICTOR$ random slope to account for possible random effects emerging from spatial proximity. The rest of the model (Eqn. 16) remained unchanged. I extracted p-values with the R package lmerTest (Kuznetsova et al., 2018), R^2-values via R package MuMIn (Barton, 2018) and cAIC values via R package cAIC4 (Saefken et al., 2018). However, across the majority of results, mixed effects showed similar results to the fixed effects models, although fits and significance levels were systematically worse. To avoid unnecessary complexity and dodge the ongoing debate about the reliability of reported p and R^2 values in mixed models (Kuznetsova et al., 2018; Nakagawa and Schielzeth, 2013), results from these models are merely provided as a supplement in Table 11 in Annex 4.

As noted above, I repeated all palm-level regressions with subsets of the data according to the distance of the palms to the fence to exclude possible boundary effects. For that purpose, palms with eight different minimum fence distances (1 m to 8 m) were successively excluded. Preliminary results suggested that especially palms beyond intermediate fence distance (*dist* > 5 m), reflecting roughly one leaf distance, show better regression fits. Therefore, results on palm level are reported for the full (*dist* = 0 m) and the restricted (*dist* > 5 m) samples. By definition, this procedure excluded all palms within plots of 5 m x 5 m and 10 m x 10 m, reducing the original number of plots from 31 to 20. Regressions of restricted samples (e.g. Plot 29) are not reported for different fence distances.

$$\widehat{YIELD}_{PALM_{kj}} = a + b\ PREDICTOR_{ij} \tag{15}$$

$$\widehat{YIELD}_{PALM_{kj}} = a + b\ PREDICTOR_{ij} + c\ div_j + d\ dist_j + plot\_ID_j \tag{16}$$

$$\widehat{YIELD}_{PLOT_{kj}} = a + b\ PREDICTOR_{ij} + c\ div_j + d\ plot\_size_j \tag{17}$$

$\widehat{YIELD}$	=	dependent variable, denoting yield on palm or plot level
PREDICTOR	=	independent predicting variable of interest
i	=	index of used predictor of interest
j	=	index of observations (palm or plot)
k	=	index of applied yield period mean
div	=	control variable denoting the number of tree species planted per plot
dist	=	control variable denoting the shortest distance of palm j from the plot fence (m)
plot_ID	=	place holder for 'Plot ID' dummy variables as control variables, and their coefficients
plot_size	=	control variable denoting plot size (m^2)
a	=	intersection point
b	=	coefficient of predictor of interest
c, d	=	coefficients of control variables

In addition to the regressions on palm level, I computed some predictors on plot level because of the plot-level nature of some variables (e.g. canopy openness and diversity) and because of the longer data availability of plot-level yield data. In accordance with regressions on palm level, a multiple linear regression approach was used for the several possible predictors, with plot size and diversity level as control variables (Eqn. 17). The diversity control was dropped for models with diversity indices as independent variable to avoid multicollinearity.

Both regression types (palm and plot level) were executed with different yield period means (Table 1). This was done to (1) include as many monthly yield observations as possible while (2) complying with natural temporal units of one year and (3) synchronizing the variables with the date of measurement of the predictor variables, which were recorded in different points between 2016 and 2018. The periods are different for plot- and palm level regressions, which is due to the late installation of the palm-level survey in Jan. 2017. These aspects lead to four different periods (Table 1), covering the past and previous year, the past four years and the past 1.5 years to keep the observations for yield on plot and palm level maximal. As depicted in the table (and discussed under 2.3.1 Yield survey), the survey was suspended several times, with max. three months consecutive suspension.

Table 1. Yield means used as dependent variables in regressions on palm and plot level.

	Yield variable	Covering period	n valid months	n missing months	Start - end of period	Missing values
PALM LEVEL	(a) past year	12 months	9	3	July 2017-June 2018	July - Sep. 2017
	(b) past 1.5 years	18 months	15	3	Jan. 2017-June 2018	July - Sep. 2017
PLOT LEVEL	(c) past year	12 months	9	3	July 2017-June 2018	July - Sep. 2017
	(d) previous year	12 months	9	3	July 2016-June. 2017	Sept., Nov., Dec. 2016
	(e) past 4 years	48 months	34	14	July 2014-June 2018	Dec. 2014; Feb., May, June, Dec. 2015; March, April, June, Sept. Nov., Dec. 2016; July-Sept. 2017

Across all regressions, I selected promising regressions for display according to the significance level (p-value) and goodness of fit (adjusted R^2). In addition, I hand-selected single ‘failed’ models of particular scientific interest. Descriptive statistics are provided for all reported predictors. No standard errors for mean values of predictors are reported on palm level because individual palms were not selected randomly which would systematically overestimate the error (Cochran, 1977). The regression assumptions were checked visually for all promising models via histograms and QQ-plots. No severe violations of the assumptions were identified.

2.4.2 Difference tests, boxplots and used software

To check for significance between groups, I used parametric or non-parametric difference-tests depending on fulfilment of the respective test assumptions. In most cases (Fig. 2 and Fig. 3), Welch tests for normality could not reject non-normality at $p < 0.05$ for many of the investigated palm categories. In these cases, I switched to non-parametric tests for all categories to maintain comparability within the graph. For boxplots, I improved the comparability of yield observations between palm categories by computing monthly yield averages within categories so that one monthly observation reflects the mean yield of all respective plots or palms within that category.

Firstly, this avoids complications from heterogeneous sample sizes (e.g. n = 3 plots with diversity level zero vs. n = 52 adjacent palms per position). Secondly, it bypasses a median of zero yield caused by many sequences of zero yield in monthly observations on palm level. Difference tests to compare monthly yield averages between different years (Fig. 3) assumed independence.

All variables and analyses were computed with R v. 3.4 (R Core Team, 2017) and QGIS v. 2.18 (QGIS development team, 2018). Graphical plots (Fig. 1 c, Fig. 2, Fig. 3, Fig. 4, Fig. 5) were produced with R package ggplot2 v. 2.2 (Wickham and Chang, 2016); Fig. 1 b via QGIS and the technical drawing (Fig. 1 a) via Inkscape v. 0.92 (Inkscape development team, 2018).

3 Results

To create an understanding of the difference between dependent yield variables used in the regression analyses on palm and plot level (not per area), Table 2 provides an overview of the descriptive statistics. Across all periods, the mean yield of inside-plot palms (Table 2 a-e) does not differ substantially, with the most accurate yield estimate (for the past four years) amounting to 219 ± 47 kg FFB $palm^{-1}$ $year^{-1}$. Due to averaging effects, standard deviations are generally less pronounced for observations on plot level than on palm level and for longer periods. For example, the coefficient of variation (*cv*) is 0.42 for the previous year as against 0.22 in the four-year period, on plot-level. Palm and plot-level means for the past year differ slightly because plot means are not weighted by the number of palms.

Table 2. Descriptive statistics of different yield period means on palm and plot level. One observation represents the yield of one palm or plot, averaged along the respective periods (a-g). The periods and values represent those used in the regressions. All yield values are expressed as kg fresh fruit bunch (FFB) $palm^{-1}$ $year^{-1}$. Standard errors are not shown for (a) and (b) to avoid overestimation from the sampling design. Plot-level observations were divided by the number of remaining palms per plot and the presented mean was not weighed by the number of palms. 'n' = number of observations (a, b, f, g = palms; c, d, e = plots); 'sd' = standard deviation; 'se%' = relative standard error of the mean (%); 'ctrl' = control palms. 'past year' = July 2017 to June 2018; 'previous year' = July 2016 to June 2017; 'past 1.5 years' = Jan. 2017 to June 2018; 'past 4 years' = July 2014 to June 2018.

		Yield period	n	Min	Max	Mean ± sd	se%
INSIDE-PLOT	PALM LEVEL	(a) past year	214	0	587	228 ± 121	-
		(b) past 1.5 years	214	0	468	197 ± 81	-
	PLOT LEVEL	(c) past year	31	65	315	225 ± 65	5.20
		(d) previous year	31	106	561	212 ± 90	7.65
		(e) past 4 years	31	113	348	219 ± 47	3.84
CTRL	PALM LEVEL	(f) past year	33	0	517	222 ± 114	51.15
		(g) past 1.5 years	33	49	367	184 ± 75	40.67

Both palm-level yield means (Table 2 a and b) contain zero-yield palms (indicated by min = 0), which comprise six individuals from five different plots in the past year, but only one individual in the past 1.5 years (not excluded from the regressions). The max value is 19% higher for the short period of palm level (587 vs. 468 kg $palm^{-1}$ $year^{-1}$) and the mean value is 16% higher, but the relative deviation (*cv*) is smaller for the long mean period (0.41 vs. 0.53).

3.1 Effects of tree diversity and species

The results indicate a significant negative effect of tree diversity on oil palm yield, which is evident from plot-level regressions (Table 3 a-d) and from a boxplot of per-area yield penalty (Fig. 2 b). The situation looks different for yield on palm level, where most inside-plot palm categories perform better than the control (Fig. 2 a). A significant effect on species level (plots with presence of particular tree species performing better or worse than the other) cannot be identified.

The plot-level regression output (Table 3 a-d) shows that tree diversity explains a part of yield variation, although not for all indices tested and at relatively low significance. The effect is negative for all tree-diversity related predictors (indicated by the negative coefficients) and across all applied yield period means. The most significant predictor is the sheer number of species (levels 0, 1, 2, 3, 6) for explaining the four-year period of yield ($R^2 = 0.10$, $p = 0.04$), followed by Shannon index ($R^2 = 0.05$, $p = 0.08$).

A comparison of recent yield data on palm level (yield mean period: past 1.5 years) for different diversity levels (Fig. 2 a3) shows that mean yields on palm level are generally lower in plots with higher diversity levels, ranging from 16.9 kg FFB $month^{-1}$ (one tree species) to 11.6 kg FFB $month^{-1}$ (six species). The means of diversity levels 0, 1 and 2 indicate a productivity per palm above plantation average (= control palm mean) as against levels 3 and 6, which produce relatively less. These differences, however, are not significant beyond 95% confidence: a two-sample Mann-Whitney test for significance between diversity level means and control mean attests the highest significance level for the overyielding of zero-species ($p = 0.08$). On the other hand, yield in the plots with six species is significantly lower than in plots with no trees planted but same thinning and suspension of weeding and fertilization (also Mann-Whitney two-sample test; $p < 0.01$).

More drastic differences between enriched plots and the control is evident from the yield penalty boxplot (Fig. 2 b3). The figure compares yield per area, expressed as a percentual difference from the control, for different diversity levels. It shows that, in contrast to yield on palm level (Fig. 2 a3), all diversity levels with one or more tree species planted suffer a yield penalty per area, because they produce relatively less than the conventional plantation average (mean: -18.3%, -18.7%, -27.6% and -45%, for 1, 2, 3 and 6 species, respectively). Yield in zero-species plots, on the other hand, almost resembles the plantation average with 3.6% positive difference from the control. The significance levels of the yield penalties tested via a one-sample Mann-Whitney test also correlate with species richness ($p = 0.21$, 0.23, 0.08 and <0.00, for 1, 2, 3 and 6 species, respectively).

Table 3. Results of linear regressions on plot level for three different yield periods. Adjusted R^2, p-values and coefficients ('coef.') are presented for multiple linear regressions between a yield mean per plot as dependent variable, one of the independent predictors (a-i) and control variables (plot tree diversity level (dropped for a-d) and plot size). 'Past year' = July 2017-June 2018; 'previous year' = July 2016-June 2017; 'past four years' = July 2014-June 2018. Descriptive statistics are shown for independent variables. Shannon, Simpson and Inverse Simpson include less observations because they are not defined for zero-species plots. Significance levels are indicated by * (p < 0.1), ** (p < 0.05), *** (p < 0.01).

	INDEPENDENT VARIABLE		DESCRIPTIVE STATISTICS			REGRESSION RESULTS					
						Past year		Previous year		Past four years	
	Name	Unit	n	Mean ± sd	se%	R^2	Coef.	R^2	Coef.	R^2	Coef.
DIVERSITY	(a) number of species	-	31	1.8 ± 1.4	14.2	0.04*	-14.8	-0.02	-12.2	0.10**	-12.5
	(b) Shannon index	-	28	0.8 ± 0.4	9.9	-0.02	-33.5	-0.02	-37.2	0.05*	-36.0
	(c) Simpson index	-	28	0.5 ± 0.2	8.6	-0.05	-45.0	-0.04	-33.6	-0.03	-43.9
	(d) Inverse simpson index	-	28	2.1 ± 0.9	8.0	-0.01	-15.2	-0.03	-14.1	0.03	-14.9
CANOPY	(e) Non-palm crown area plot share	(%)	31	19.9 ± 12.5	11.2	0.01	0.1	0.11**	3.0	0.16	1.1
	(f) Tree canopy area plot share	(%)	31	15.5 ± 9.7	11.3	0.01	0.2	-0.04	-1.0	0.07	-0.1
	(g) Gap fraction	(%)	31	12.5 ± 9.1	13.1	0.02	0.9	-0.05	0.7	0.07	0.2
	(h) Palms removed per area	(ha^{-1})	31	61.1 ± 20.9	6.1	0.02	-0.4	-0.05	0.3	0.08	-0.4
	(i) Max. slope across plot	(%)	31	8.8 ± 9.1	18.6	0.07	1.9	-0.05	-0.7	0.07	-0.3

An alternative 'opportunity cost'-calculation method of yield penalty per area (Fig. 13 a in Annex 4) shows a very similar pattern to Fig. 2 b and no substantial differences in the mean of inside-plot palms. Yet, if both calculation methods are compared (Fig. 13 b in Annex 4), it is evident that the alternative method proposed inspired by Gérard et al. (2017) relatively underestimates yield penalty of low diversity levels (0, 1 and 2 tree species planted) and relatively overestimates yield penalty of high diversity levels (3 and 6 species planted).

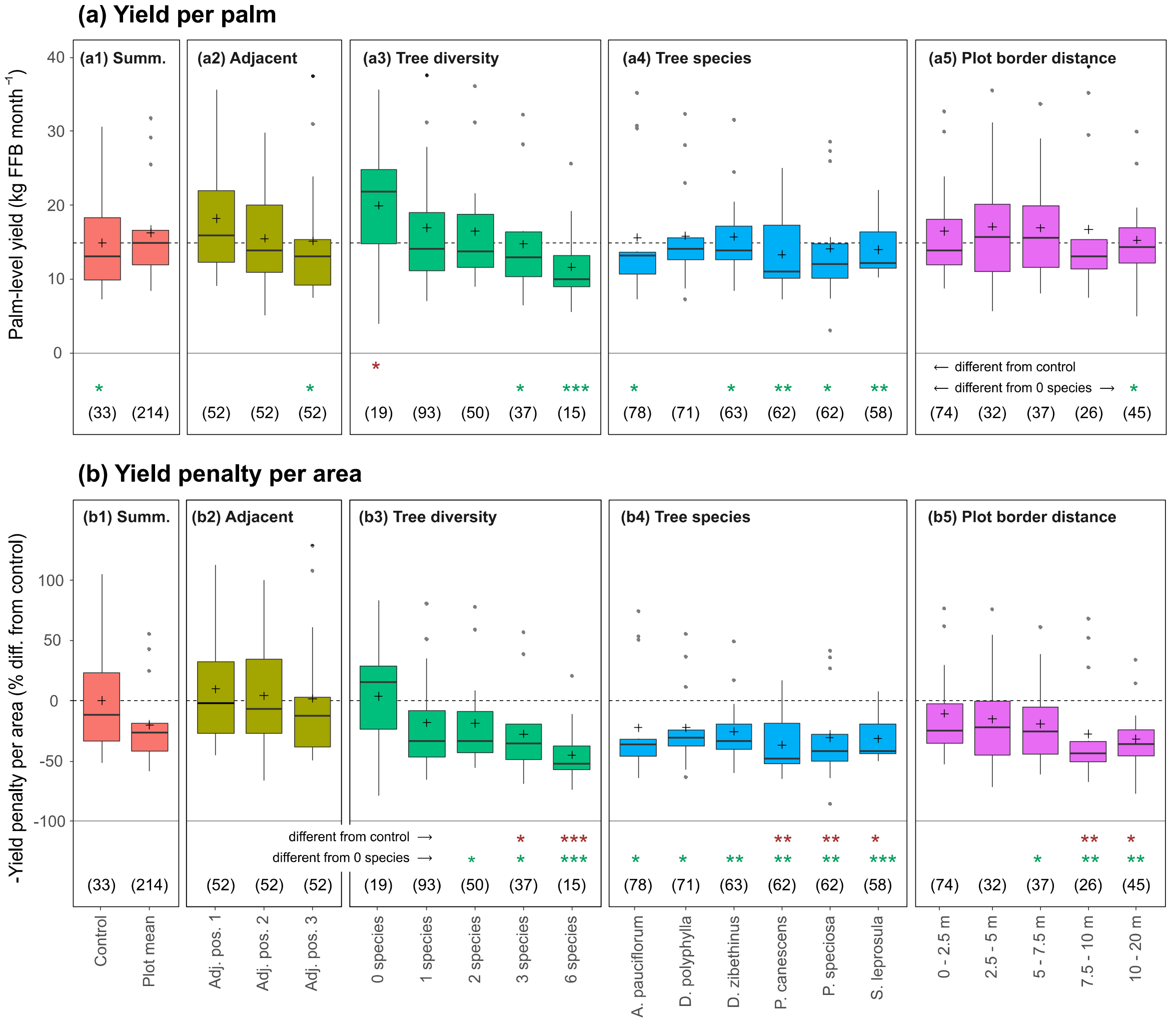

Figure 2. Yield on palm level and yield penalty per area for selected palm categories. One observation relates to one month averaged within the respective palm category. The control used to compute percentual differences in (b) is averaged over the past 1.5 years (Jan. 2017 - June 2018). Negative values in (b) indicate yield penalties. 'Adj. pos' = position index of adjacent-to-plot palms; 'FFB' = fresh fruit bunch; horizontal bar = median; '+' = mean; dashed horizontal line = mean of control palms; 'plot mean' includes all inside-plot palms as shown in (a3) and (b3), weighted by the number of palms per plot. '*' top row = Mann-Whitney test for difference from control. '*' bottom row = Mann-Whitney test for difference from zero-species plots. Bracketed values = number of palms involved in the monthly means. Significance levels are indicated by * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

A palm-level comparison of the role of particular planted species on yield (Fig. 2 a4) is inconclusive (Kruskall-Wallis test for differences between the groups: $p = 0.48$). Although some of the species are significantly different from zero-species plots, none of the species indicates significant over- or underyielding compared to the control beyond 90% significance. Per-area yield penalties show a similar pattern of the different species means compared to one another (Fig. 2 b4). Mean yield of all species is below the control, but not all yield penalties are significant. In accordance with Fig. 2 a4, differences between the groups are not significant (Kruskall-Wallis: $p = 0.45$).

To investigate the role of plant nitrogen fixation, the species were additionally categorized into plots with presence of leguminous specimens (*Parkia speciosa* and *Archidendron pauciflorum*) against the remainder, forming groups of n = 16 plots and n = 110 palms with Fabaceae presence and n = 12 plots and n = 88 palms for non-Fabaceae presence. In fact, mean yield in leguminous plots is slightly lower (14.9 vs. 15.8 kg FFB $month^{-1}$ on palm level and -23.5% vs. -21.4% relative difference from control yield per area, for leguminous vs. other, respectively). Yet, differences between the groups are not significant, neither for yield on palm level, as indicated by a two-sample Mann-Whitney test ($p = 0.13$), nor for yield penalty ($p = 0.26$)

3.2 Effects of tree performance and tree-to-palm competition

Independent of tree diversity, the growth performance and density of trees around single palms was found to show significant negative effects on yield averages from different periods. This is evident from the regression results on palm level with different estimators of tree-performance (Table 4 a-e).

The two models with observations from Plot 29 (Table 4 a-b) use overlaps of tree crown projection areas with palm crowns as sole predictors and thereby approach the role of light competition imposed by trees. The relative tree crown overlap area (the sum of the overlap areas of all trees in one palm, divided by the crown projection area of the palm; Table 4 a) is the best identified predictor ($R^2 = 0.34$; $p < 0.01$) of yield among the past year. It shows the best goodness of fit of all presented models on plot or palm level and is also the best predictor of all tested variables for yield in Plot 29 (generally, regression results are better for the individual Plot 29 than for individual palms across all plots; further Plot 29 regression results in Table 9 in Annex 4). A more sophisticated tree crown overlap variable (Table 4 b) weighs the tree overlaps according to intensity of interference and crown density, which narrows competition effects down to light competition. Yet, it does not improve the fit nor the significance ($R^2 = 0.12$; $p = 0.13$ for the past year).

Table 4. Results of linear regressions on palm level for two different periods (inside-plot). Adjusted R^2, p-values and coefficients ('coef') are presented for multiple linear regressions between a yield mean per palm (past year or past 1.5 years) as dependent variable, one of the independent predictors (a-m) and a set of control variables (plot tree diversity level, minimum distance between palm and fence and plot ID as dummy variables. The number of palms ('n') differs with sample type ('all'= all inside plot palms from all 31 plots; 'P29' = Plot 29; 'sub' = stratified subsample. Distance ('dist.') to the fence ('-'= no exclusions; '>5'= exclude palms within 5 m fence distance). One yield observation is the mean of 9 (past year) and 18 (past 1.5 years) valid monthly observations with max. three months subsequent gaps. Significance indicated by * (p < 0.1), ** (p < 0.05), *** (p < 0.01).

	INDEPENDENT VARIABLE			DESCRIPTIVE STATISTICS			REGRESSION RESULTS			
							Past year		Past 1.5 years	
	Name	Unit	Sample	n	Fence dist. (m)	Mean ± sd	R^2	Coef.	R^2	Coef.
TREE COMPETITION	(a) Relative tree crown overlap in palm	(%)	P29	20	-	13.48 ± 8.74	0.34***	-9.2	0.26**	-5.4
	(b) Weighted rel. tree crown overlap	(%)	P29	20	-	7.05 ± 6.98	0.12	-6.9	0.11	-4.3
	(c) Number of trees within 5 m radius	(ha^{-1})	all	214	-	925.8 ± 754.9	0.02	0.0	0.05	0.0
				108	>5	1029.2 ± 804.9	0.16*	-0.1	0.16	-0.1
	(d) Tree basal area within 5 m radius	(m^2 ha^{-1})	all	214	-	1.4 ± 1.7	0.04*	-15.1	0.08**	-11.2
				108	>5	1.6 ± 1.8	0.16**	-19.5	0.19**	-15.4
	(e) Tree stem volume within 5 m radius	(m^3 ha^{-1})	all	214	-	5.1 ± 7.3	0.04*	-3.3	0.07**	-2.3
				108	>5	5.8 ± 8.1	0.16*	-3.7	0.18**	-2.8
PALM MORPHOLOGY	(f) Elliptic palm crown projection area (drone 2016)	(m^2)	all	214	-	120.8 ± 22.4	0.06***	1.1	0.10***	0.9
				108	>5	121.3 ± 22.3	0.23***	2.0	0.29***	1.6
	(g) Mean palm crown radius (drone 2016)	(m)	all	214	-	6.2 ± 0.6	0.06***	45.4	0.11***	36.5
				108	>5	6.2 ± 0.6	0.23***	78.7	0.30***	63.4
	(h) Meristem height (2017)	(m)	all	213	-	5.4 ± 0.9	0.04**	24.3	0.07**	16.3
				108	>5	5.4 ± 0.9	0.15*	27.5	0.17*	20.0
PALM COMPETITION	(i) Absolute crown overlap in palm	(m^2)	all	213	-	45.2 ± 34.5	0.03	0.5	0.06	0.4
				108	>5	39.2 ± 30.4	0.16*	1.2	0.18**	0.9
	(j) Weighted relative palm crown overlap	(%)	all	214	-	24.0 ± 18.2	0.02	0.1	0.05	0.0
				108	>5	22.3 ± 17.1	0.13	0.1	0.15	-0.1
SITE AND EPIPHYTES	(k) Epiphyte cover along meristem	(%)	sub	50	-	8.5 ± 5.5	0.09	2.3	0.24	2.4
	(l) Max. slope 2 m radius around palm	(%)	sub	50	-	38.5 ± 27.8	0.09	-0.4	0.23	0.1
	(m) Fence distance	(m)	all	214	-	5.8 ± 4.7	0.03	-1.1	0.06	-0.8

Further predictors related to tree-competition are the number of trees, their aggregated basal area and stem volume, all recorded within a radius of 5 m around the palm (Table 4 c-e; further radii reported in Table 10, Annex 4). Basal area and stem volume perform similarly well at medium to high significance levels for yield of the past 1.5 years ($R^2 = 0.19$; $p = 0.02$ and $R^2 = 0.18$; $p = 0.03$, for palms > 5m fence distance, respectively). The number of trees is not as significant ($R^2 = 0.16$; $p = 0.10$) for the same period and sample.

3.3 Spillover and plot boundary effects

Spillover effects in the experimental setup describe yield differences between adjacent-to-plot palms and the plantation average caused by influences from the tree islands. Plot-boundary effects, on the other hand, mean that palms within the islands may behave differently in close distance to the fence caused by influences from outside the plots. Both effects, again, depend upon the mode of comparison, yield per palm or per area. Comparisons on palm level (Fig. 2 a2 and Fig. 5 b) do provide evidence for a positive spillover, while per-area differences (Fig. 2 b2 and Fig. 4 d) are rather undecisive. Boundary effects behave oppositely: they are non-identifiable on palm level (Fig. 2 a5 and as independent variable in the regressions, Table 4 m), but quite pronounced on a per-area scale (Fig. 2 b5).

Starting with spillover, yield levels of adjacent palms in the palm-level boxplot for yield of the past 1.5 years (Fig. 2 a2) are higher with closer distance to the plot (22.1%, 4.1% and 1.7% higher mean yield compared to the control, from plot-closest to furthest, respectively). None of these alleged spillovers are significant ($p = 0.20$, 0.68, 0.87, respectively). Supporting evidence is provided by the time series of the ‘climate’ chart (Fig. 5 b), which reveals substantial differences, especially between adj. pos. 1 and pos. 3 in the first two years of the series (the difference between pos. 2 and pos. 3 does not appear as pronounced in the graph).

Yet, findings from yield per area (Fig. 2 b2) indicate that the overperformance of pos. 1 disappears if the yield measure compensates for the reduced planting density, which seems to affect also the surroundings of the adjacent palms (mean relative overperformance of adj. pos. 1, 2 and 3 is reduced to 9.7%, 4.1% and 1.7%, respectively). Further evidence comes from the yield penalty time series (Fig. 4 d), which neither gives an obvious indication for higher yield in adj. pos. 1 and 2. Rather, both categories fluctuate around the yield level of pos. 3, sometimes below and sometimes above the reference. Jointly with all other shown categories, both adjacent positions 1 and 2 show initially increased yield (Jan.-Oct. 2014), directly after opening the canopy. The designated control introduced as late as Jan. 2017 levels evenly around adj. pos. 3, which further justifies its use as a reference variable.

To unravel possible diversity effects among spillover, yield penalty per area among adjacent palms on pos. 1 was additionally computed for different plot diversity levels. Monthly means from the past 1.5 years do not differ significantly across diversity levels (Kruskall-Wallis test: p = 0.38). Yet, there is a tendency of higher mean values for higher diversity levels, expressed as relative difference from the control (-12.2%, -2.1%, 26.8%, 18.4%, 36.2% for 0, 1, 2, 3, 6 planted species, respectively). Still, none of the groups' spillovers are significant (one-sample Mann-Whitney test: p = 0.36, 0.80, 0.21, 0.52, 0.27, respectively).

For boundary effects, the boxplot of yield on palm level (Fig. 2 a5) generally shows almost no difference between yield of palms in neither of the five investigated border-distance classes (0-2.5 m, 2.5-5 m, 5-7.5 m, 7.5-10 m, 10-20 m). Rather, all yields are slightly above, but close to the plantation average. This is different for yield per area (Fig. 2 b5), which shows higher median and mean yield penalties (mean values: -10.9%, -15.5%, -19.4%, -27.9% and -32.1%, from close to far) as well as increasing significance for palms at further fence distances (p = 0.21, 0.20, 0.10, 0.04, 0.02, from close to far). A Kruskall-Wallis test for significant differences among the group, however, is inconclusive (p = 0.30).

In the regression analyses on palm level, the proximity of inside-plot palms to the plot fence as predictor of interest with plot size and diversity level as control (Table 4 m) showed no significant effect (n = 214; R^2 = 0.06; p = 0.53 for 1.5 years of yield). Yet, several of the other investigated yield predictors seem to be affected by distance. Table 4 shows that the smaller sample, restricted to inside-plot palms with distance > 5 m to the fence, improves correlations for some predictors (e.g. crown projection area, crown radius and meristem height). Also, it contributes significantly to several of the independent variables as control variable in the multiple model. Generally, 51% of the palms are excluded by this definition, reducing the sample from 214 to 108 palms and excluding 11 of the original 31 plots. Despite the systematic exclusion of big plots, the descriptive statistics of both variables do not show severe differences.

3.4 Temporal yield development

The temporal analysis brings evidence of a steady yield decline in the treatment plots, which is stronger for higher diversity levels. This is brought forward by monthly grouped data, which was split into four subsequent years to make reliable statements about inter-group and inter-annual differences (Fig. 3) and further supported by time series of relative yield performance (Fig. 4).

Fig. 3 shows the development of relative per-area yield (= negative yield penalty) over the past four years, expressed as the relative difference from the control (adj. pos. 3 used as control), for three diversity levels (0, 3 and 6 planted tree species). The mean relative yield performance of these categories has decreased compared to the control throughout the whole period, which means that yield penalties of all depicted diversity levels have increased. In year four, mean of the relative yield is 60.2, 25.4 and 42.8 yield penalty percentage points lower for diversity levels 0, 3 and 6, respectively, compared to year one. Despite the mean differences, a Kruskall-Wallis test across all presented categories and years ($p < 0.01$) with subsequent Tukey HSD, however, attests inter-annual significance (not shown in Fig. 3) beyond 90% only for zero species (year one to four: $p = 0.06$) and six species (year one to four: $p = 0.02$).

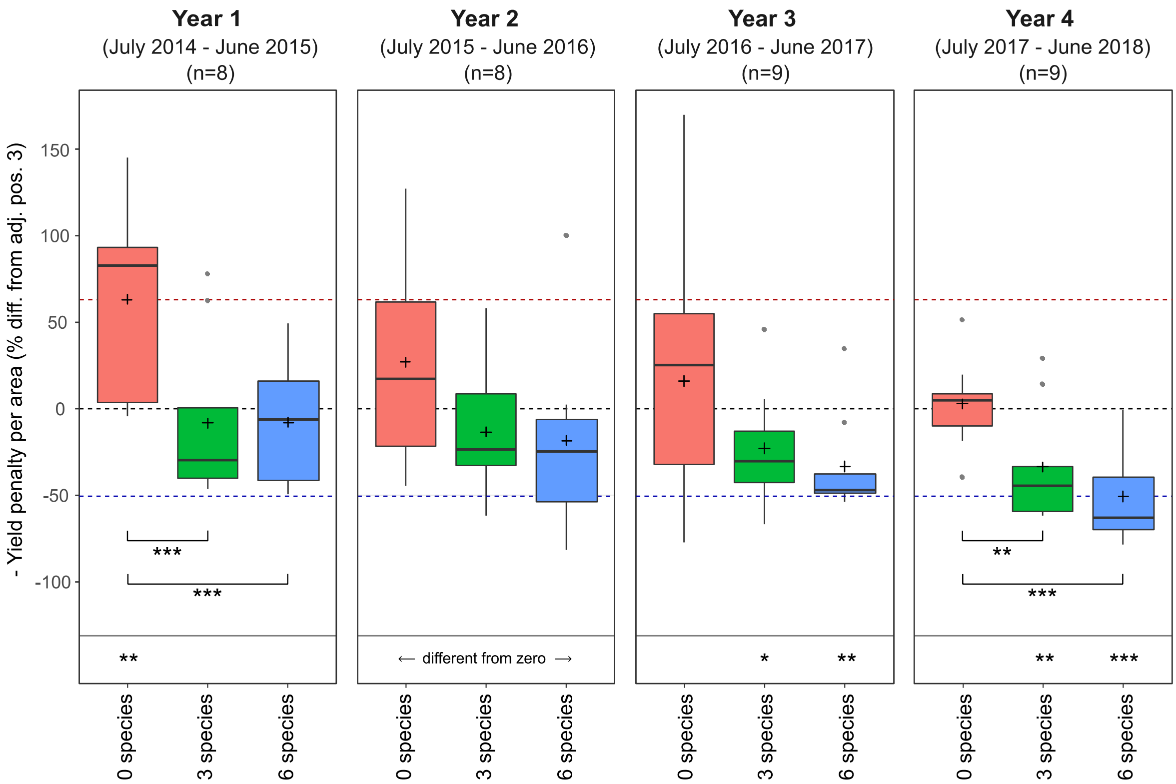

Figure 3. Yield penalty per area across four years, for diversity levels zero, three and six. Shown is the relative yield difference from the 'control', where control is defined as the mean of adj. pos. 3 within each year. One observation relates to one month of yield averaged within each palm category. Negative values indicate yield penalties. Horizontal bar = median; '+' = mean; dashed horizontal lines: above = year-one mean of zero-species plots, below = year-four mean of six-species plots; center = control mean. Bracketed 'n'-values denote the number of months included in the annual boxes. '*' below brackets = result of Tukey HSD post-hoc test across all palm categories and years, following a significant Kruskall-Wallis test-result ($p < 0.01$). Differences between the years are not marked. '*' in the bottom row = results of one-sample Mann-Whitney tests. Significance levels are indicated by * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

Noteworthy is that zero-species plots have, despite the unconventional treatment, performed above average in all years, until yield per area came close to neutral in year four (significantly higher than the control only in year one, as suggested by a significant result of a Mann-Whitney test, $p = 0.04$). On the other hand, plots with three or six species planted have constantly suffered a yield penalty per area (where especially the last year is significantly below plantation average ($p = 0.02$ and $p < 0.01$, respectively). The gap between three and six species seems to grow slightly

(-0.4 percentage points in year one vs. 17.0 percentage points in year four), although the difference is not significant in neither of the years (p = 0.16 in year four). Intra-annual differences between diversity levels are only significant in year one and four, both times indicating that zero-species plots perform relatively better than both other categories.

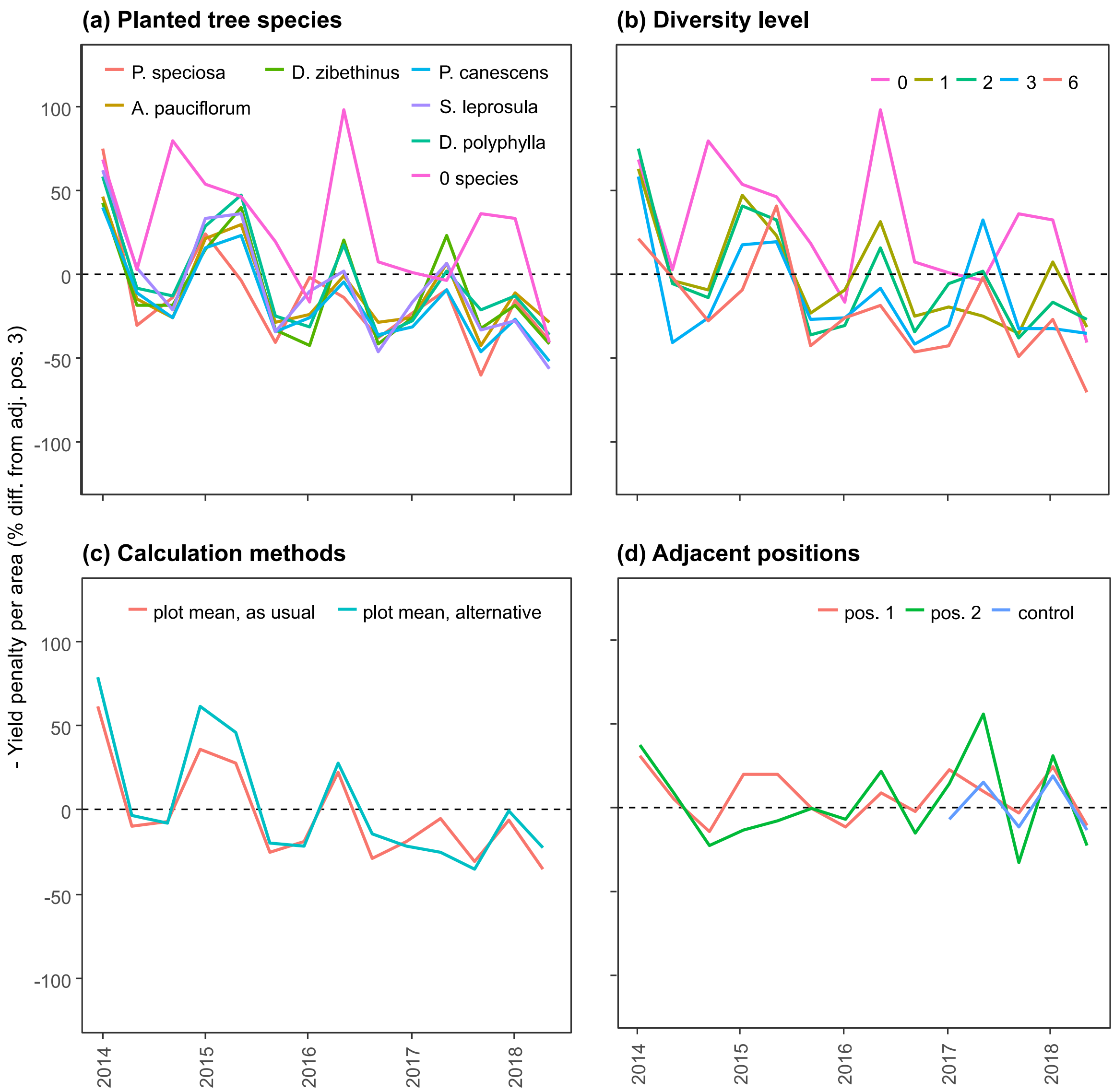

Figure 4. Time series of yield penalties per area for selected palm categories (2014-2018). Shown are triannual means of the relative yield difference from the 'control' per palm category. Control is defined as the mean of adj. pos. 3 within each triannual period. Data gaps in the series imply a different number of included months per period, but the same number across palm categories within each period. Negative values indicate yield penalties. Dashed horizontal line = control mean. 'plot mean, as usual' in (c) equals the calculation method applied in (a), (b) and (d) and the rest of the presented analyses in the paper. 'plot mean, alternative' is an adapted opportunity cost method inspired by Gérard et al. (2017). Both plot means include all inside-plot palm categories as shown in (b), weighted by the number of palms per plot.

A further temporal analysis with higher temporal resolution of four months (Fig. 4 a-d) shows the development of yield penalty per area for selected oil palm groups between Jan. 2014 and June 2018. It is evident that all inside-plot palm categories (Fig. 4 a-c) have shown a general downward trend since 2014. At the start of the survey, all inside-plot palms performed substantially better than the control, while all of them ended in 2018 with a similarly high deficit (= yield penalty).

The species plot (Fig. 4 a) gives no indication for a systematic difference in performance between plots of different species, except the plots with no planted trees stand out by their superior performance throughout most of the periods. The diversity graph (Fig. 4 b) further supports this over-performance. The highest peak occurs around July 2016, when zero-species yield is 98% higher than adj. pos. 3. The remaining diversity levels appear to be stacked with higher yield for higher diversity level across many seasons, especially between 2016 and 2017 and in 2018.

The different calculation methods (Fig. 4 c) depict the development of two different yield calculations of all inside-plot palms combined, 'plot mean, as usual' and 'plot mean, alternative', the first of which is applied consistently as the measure for yield penalty throughout this paper. The latter is offered as an alternative (inspired by Gérard et al., 2017), for comparison. The two graphs comprise all palms inside the plots, across all possible diversity levels. Independent of the method used, the graphs show that inside plot palms have outperformed the control in many periods at the beginning of the survey despite the general downward trend. Both methods are not systematically different. In the year between mid-2014 and mid-2015, the alternative predicts substantially higher over-yielding, whereas it relatively overestimates the yield penalty in the first half of 2017.

Also noteworthy is the cyclic pattern of peaks and vales, which repeats annually with one peak in each year, for all plots with diversity level bigger or equal to one and both adjacent positions. Plots with diversity level zero, on the other hand, exhibit a less regular pattern.

3.5 Meteorology-induced seasonal effects

The yield development since start of the experiment in 2014 holds a rather irregular pattern, which is only sporadically correlated with findings from the meteorological data series. This result is derived graphically from the composed yield and 'climate' figure (Fig. 5 a-c), which maps three meteorological variables (solar radiation, temperature 2 m above the ground and precipitation) on a joint time scale with all adjacent and inside-plot palm yield means.

The meteorological graphs (Fig. 5 a and c) suggest that all three variables are generally synchronized: radiation levels are substantially lower during the two dry periods (in July and around Feb.) and temperature and precipitation follow an inverse relationship, where precipitation peaks occur almost simultaneously with temperature lows. Precipitation exhibits a pronounced dry season with a minimum during July, and a second period of relatively low rainfall, although substantially less pronounced, from Jan. to Feb. The second half of 2015, coinciding with the global El Niño phenomenon, shows anomalies in all curves with a global low in precipitation, a lack of the typical temperature minimum, and a global minimum in solar radiation (all around Aug. 2015). The rainy season after El Niño started one to two months later than usual but maintained a high level of precipitation along the whole season, so the usual dry period around Feb. almost skipped 2016.

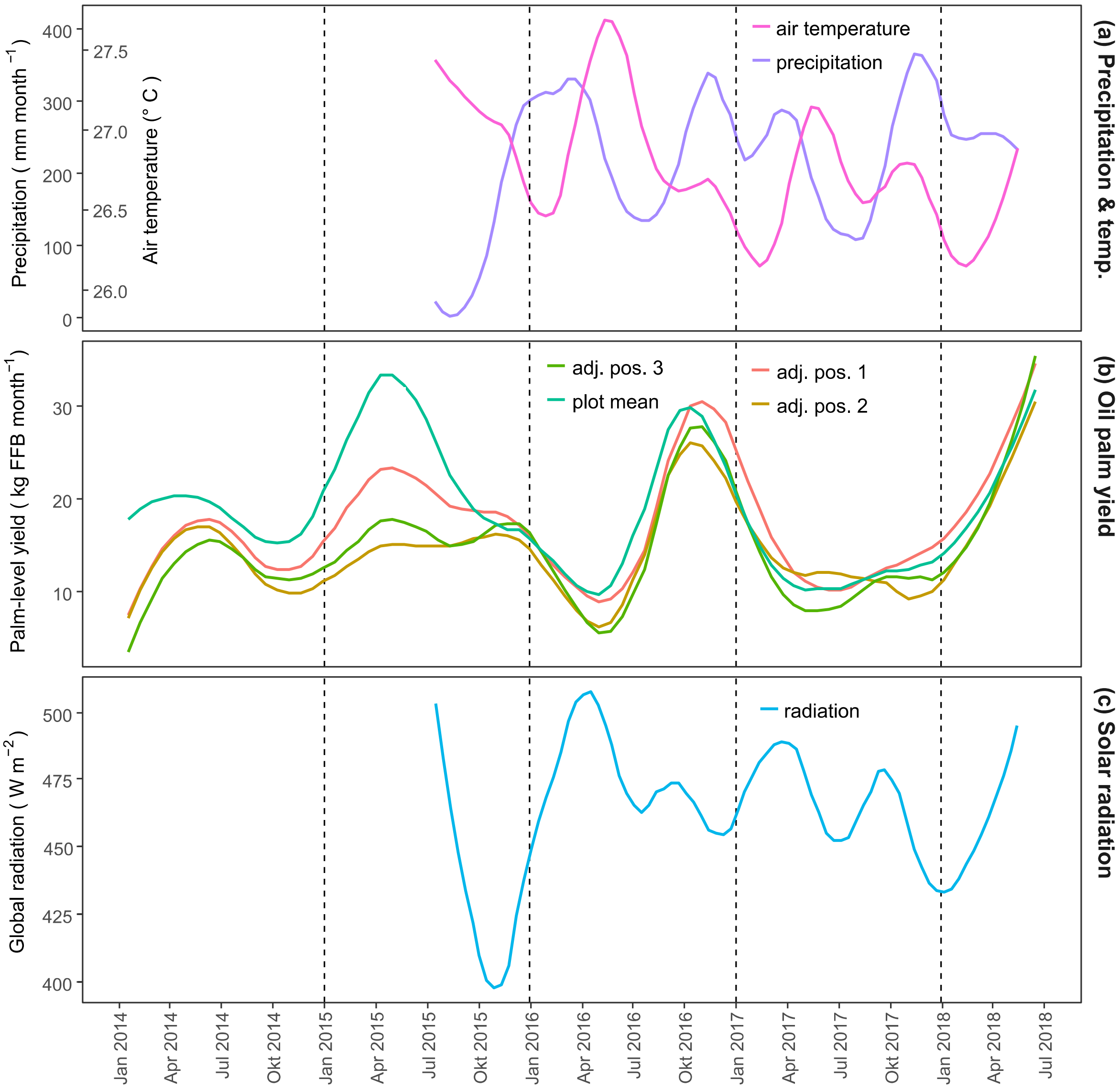

Figure 5. Time series of oil palm yield and selected meteorological variables (2014-2018). Graphed are **(a)** monthly sum of precipitation and mean of air temperature 2 m above ground; **(b)** oil palm yield per palm of different palm categories ('adj. pos.' = position index of adjacent-to-plot palms; 'FFB' = fresh fruit bunch; 'plot mean' refers to the weighted mean of all inside-plot palms; **(c)** monthly mean of ground-measured global radiation from daily means (11 am - 6 pm). All meteorological observations were derived from ten-minute measurements at Humusindo climate station; missing values were replaced with data from Bungku village climate station if available. Ten-minute observations were subsequently scaled to daily level (incomplete hours were dropped) and to monthly level. Meteorological data is available from July 2015 to May 2018 and yield data from Jan. 2014 to June 2018. A data gap in (a) and (b) between Aug. and Oct 2016 was filled with 2017 values from the same months. The yield series were smoothed by a rollmean algorithm; additional loess functions were applied to all series. Dashed lines mark the beginning of the year.

The yield variables on palm level (Fig. 5 b) are generally synchronized among each other, although a regular cyclic pattern across the years cannot be certainly identified, because the number of maxima, minima and their timings, as well as the relative heights of these features, differ throughout the years. A single peak in 2014 (July) is followed by two peaks in 2015 (April and Dec.), a single peak in 2016 (Nov.), a very weak peak in 2017 (around Oct.) and a strong recent surge during the first half of 2018 (until July and possibly continuing). The general course of yield on palm level shows substantial differences between palm types in the first years. Inside-plot palms initially produce the highest yield, followed by adj. pos. 1. The lowest ranks take adj. pos. 2 and 3. Where no systematic difference can be observed. During the past two years, the differences among the palm categories have become rather meaningless – a finding, which is also in line with non-significant differences between inside-plot mean and adjacent palms in Fig. 2.

A temporal dependence between meteorological data and yield cannot be determined unambiguously from the graph and requires further input of the plant physiological processes. However, a rather regular time lag is suggested to lie between start of the double-peaked rainy season and the relative yield peaks, amounting to around 15 months for the yield-peaks in 2016 and 2017. Depending on the further rise after July 2018, it could be again 15 months, although all three peaks are very different in their amplitude. The periods between the severe El Niño drought in 2015 to the yield minima in 2016 and 2017 are around 12 and 23 months, respectively, where yield drops to roughly one third of the recorded maxima.

3.6 Effects of crown size and canopy cover

Crown projection-related variables are among the most successful yield predictors, associating a larger crown with higher yield, which is evident from the regression results on palm level (Table 4 f and g). Plot-level canopy effects, on the other hand, are less evident from regression findings (Table 3 e-h).

Among the different tested measures of crown projection area (various geometric approximations, drone and ground-based), the manually derived drone-based measure for elliptical crown projections (Table 4 f) shows the best correlation, which is most significant in the restricted sample at > 5 m fence distance ($R^2 = 0.29$; $p < 0.01$ for yield of the past 1.5 years and the drone data from 2016). According to this linear model, a crown area expansion by 1 m^2 is associated with a yield increase by 1.60 kg $palm^{-1}$ $year^{-1}$. The significance in the full sample (n = 214) is equally good, but the goodness of fit to the linear model is substantially worse ($R^2 = 0.10$; $p < 0.01$).

Noteworthy is that the crown radius (approximately equal to the maximum leaf length; Table 4 g) derived from the same drone data explains yield even better than crown area ($p < 0.01$; $R^2 = 0.30$) in the past 1.5 years. Both drone-based predictors perform better for the extended yield period, which comes close to the date when drone images were taken (Sep.-Oct. 2016). Tests of further crown projection areas or radii based upon ground-based crown measurements of 2017 (not in the table) are significant with a slightly worse fit (best result: $R^2 = 0.27$; $p < 0.01$ and 0.26; $p < 0.01$ for the past 1.5 years with radii and elliptic crown projection, respectively).

Canopy effects on plot level (Table 3 e-h) were also tested with a variety of variables, derived from ground-based measures (hemispherical images and crown projections) and drone-based measures (extracted for trees, palms and canopy openness via algorithm by Khokthong, unpublished, and for palms via manually defined crown projection areas). Of all attempts, the only significant correlation was derived from the manually derived drone-based area of non-palm-crown-cover (Table 3 e) with previous year's yield data (which includes the period when drone images were taken) across all plots ($R^2 = 0.11$; $p = 0.04$; positive effect). This suggests higher yield for plots with lower oil palm fraction among the canopy. However, neither the area fraction covered by trees, nor the number of thinned palms per area, nor the gap fractions from ground-taken hemispherical images (Table 3 f-h) reveal significant correlations among any of the yield period means.

3.7 Effects of palm height, basal area, stem epiphyte cover and slope

Meristem height as yield predictor, recorded in 2017, is most significant in the full sample across all inside-plot palms (Table 4 h; $R^2 = 0.03$, $p = 0.03$ for the past year). The best linear fit, however, is found in the distance-restricted model ($R^2 = 0.17$; $p = 0.05$ for the past 1.5 years), where 1 m meristem height increment is found to increase annual FFB yield by 20 kg per palm. The descriptive data (*sd* = 0.9; *cv* = 17%) indicates, despite a large range of 4.6 m, a fairly homogenous canopy structure across the plantation. Height regression data from Plot 29 (Table 9 in Annex 4) provides evidence that meristem height is a more promising predictor for palms on specific sites ($R^2 = 0.28$; $p = 0.02$).

Palm basal area, tested for a sub-sample of 25 inside-plot palms, shows no significant effect (best model: $R^2 = 0.00$; $p = 0.13$). Control palms, on the other hand (Table 8 in Annex 4), do exhibit a more significant effect of basal area ($n = 33$; $R^2 = 0.10$; $p = 0.08$; positive effect for the same period). A tested relationship between basal area and crown projection area, however, is not significant ($R^2 = 0.06$; $p = 0.17$ for control palms).

Epiphyte cover (Table 4 l), measured as percentage covering the meristem (mean = 39% across the sub-sample), shows a considerable variation (*cv* = 0.72), but is no useful yield predictor ($R^2 = 0.23$; $p = 0.93$ for the past 1.5 years).

Slope entered the regression analyses on plot and palm level as maximum slope across the entire plot (Table 3 i) and as maximum micro-slope across a diameter of 4 m through the palm stem (Table 4 k), respectively. Both measures showed no significant effect ($R^2 = 0.06$; $p = 0.20$ and

$R^2 = 0.03$; $p = 0.56$ for macro and micro slopes and yield of the past year, respectively). Control palms (Table 8 in Annex 4) neither give any hint for an effect of micro slope ($R^2 = 0.01$; $p = 0.62$ for the same period).

3.8 Effects of palm-to-palm competition

Potential yield determinants from the category palm-to-palm competition try to explain yield by the influence of neighboring palms, as compared to morphological predictors that merely base upon morphological features of the center palm itself. The regression results suggest, despite some significant findings, that competition indices are no better predictors than variables of palm morphology.

Several measures were developed to account for competition influence of neighboring palms, most of which fell below expectations. The absolute aggregated area of crown overlapping in one palm (Table 4 i) as the only predictor exceeding 95% significance explains yield of the past 1.5 years in the distance-restricted sample ($R^2 = 0.18$; $p = 0.02$). The linear model suggests a yield decline by 1 kg palm^{-1} year^{-1} per additional crown overlap of 1 m^2. Further crown overlap indices, based upon all combinations of variables, were generally poor in significance and fit. This includes a variety of measurements (ground- and drone-based from different years), calculation methods (elliptic or circular projection; including and excluding multiple overlaps; expressed as absolute or relative projection area), influence radii (radius of own crown projection vs. ten different radii between 1 m and 10 m), and fence distances (0 m and 5 m).

Especially the attempt to derive a more exact index by weighing overlaps by their relative elevation and dividing by the center palm's crown area (Table 4 j) did not succeed (best result: $R^2 = 0.15$; $p = 0.17$ for the distance-restricted sample of the past 1.5 years). Further evidence for no systematic influences of crown overlap indices is provided by results from the control palm regressions, where crown overlap is neither a good predictor ($R^2 = 0.07$; $p = 0.16$ for relative crown overlap and yield mean of the past 1.5 years). The mere count of palm competitors within circles around a palm with varying radius (4 m-14 m; Table 10 in Annex 4) did not yield many significant results, none of which show better results than the absolute crown overlap. Noteworthy is that the highest significance is found for a radius of 14 m ($R^2 = 0.09$; $p < 0.01$) with a negative influence, yet the subsequent significance ranks are taken by smaller circles ($r = 4$ m and $r = 5$ m) and indicate a negative direction ($R^2 = 0.07$; $p = 0.04$ for both circles); all values reported for the unrestricted sample and the past 1.5 years.

4 Discussion

4.1 Effects of tree diversity and species

The results provide evidence for a yield penalty of tree diversity, indicated by a negative effect of the plot-level regressions with diversity level as predictor (Table 3) and a significant test result for the difference between yield in plots of high diversity and control palms (Fig. 2). Throughout other agroforestry studies, there is no general answer to the effects of tree diversity. In contrast to negative yield effects in agroforestry (e.g. Blaser et al., 2017), many systems also reportedly profit from tree diversity or show at least a neutral effect (Clough et al., 2011; Miccolis et al., 2014; Nesper et al., 2017).

Although differences in physiology make it difficult to compare oil palm agroforestry to agroforestry of other crops, I argue that the yield penalty should be interpreted as a *net* effect of both hampering and supportive aspects, where the negative effects on yield over-compensate the positives. Furthermore, I hypothesize that the supposedly strongest advantage of diversity, the resilience aspect, could not demonstrate its real strength because major ecological crises were absent in the region during the time of observation. Unfortunately, there are, to my knowledge, no comparable studies from other experiments systematically investigating the effect of trees within a conventional oil palm plantation. The presented findings can, hence, not be generalized and should be regarded as the effect of the presented design with a limited number of species and plots. Finally, yield is not the only aspect to the debate of land use systems beside many economic and ecological considerations (Shanmugam and Babu, 2017; Silvertown, 2015).

The negative aspects of tree diversity can be explained by the intermediate role of diversity. Many advantages of diversity seem to benefit the trees rather than palms, which raises the overall competitiveness and impacts of trees against palms. Indeed, there is evidence for tree overyielding in plots with high tree diversity (Zemp, unpublished; see 4.4 Temporal yield development). Obviously, the investigated oil palm plantation is strongly influenced by this tree-related competition. Competition between palms and trees is generally for water, nutrients and light (Gérard et al., 2017), where water plays a major role during dry seasons or droughts (Corley and Tinker, 2016; Oettli, Behera and Yamagata, 2018; see 4.5 Meteorology-induced seasonal effects) and is supposedly the most important cause of competition. Nutrients, on the other hand, are likely sufficiently abundant, at least in close distance to the conventionally treated palms (see 4.3 Spillover and plot boundary effects). Light competition is a more recent effect since individual trees have started to grow into the palm canopy (see 4.2 Effects of tree performance and tree-to-palm competition).

In contrast to the negative effects, which have a simple cause, the potential benefits are more versatile and require further explanation. In terms of overall ecosystem productivity, the diverse system is likely to be the most productive. Due to complementarity, selection and resilience, it may even exceed the productivity of a monoculture in terms of biomass: below ground complementarity may enhance resource partitioning or even resource facilitation (Ewel, Celis and Schreeg, 2015). Above ground complementarity may increase overall light interception because diverse systems occupy more space with their crowns and enhance intra- and inter-species structural variability (Pretzsch and Schütze, 2016). Also, inter-species competition leads to the selection of the best suited species for a given spot (Pretzsch, 2014). Finally, diverse systems are supposedly more resilient, show a reduced susceptibility to competitive invasive shrubs and stabilize ecosystem processes during extreme biotic and abiotic conditions (Hooper et al., 2005; Rembold et al., 2017; Tscharntke et al., 2011).

Although these advantages seem to show effect on the growth of trees, they obviously fail to improve palm yield or at least to overcompensate the disadvantages brought against palms by yield reducing aspects of diversity. Still, especially the resilience aspect is frequently cited as advantageous on the crops in diversified systems, particularly to reduce the risk of insect pests via supporting the development of animal predators (Dassou and Tixier, 2016). Indeed, trunk-borers and defoliating caterpillars are known to reduce oil palm yield by up to 80% and 90%, respectively (Dislich et al., 2017). Especially birds, bats, ants and spiders are likely to serve as control agents against these insects (Koh, 2008; Maas et al., 2016; Niu et al., 2015; Offenberg, 2015). These pests, however, have not occurred during the presented time series of the past 4.5 years. The last insect pest in the region, which substantially threatened oil palm succession and required insecticide treatment reportedly occurred in 2001 (Hasbiuan, pers. comm.; Annex 1). In general, defoliating insect pests have reportedly not posed a major thread to crops in the Jambi region till now (Denmead et al., 2017), which is why diversity failed to show its strongest benefits within the particular time frame.

Another realistic potential benefit of tree diversity for palms lies in pollination. The oil palm is a monecious plant and does not frequently self-pollinate. Wind pollination does not always suffice, which is why insect pollination is required to avoid laborious manual pollination by humans (Corley and Tinker, 2016). Insect pollination is mainly facilitated by a single weevil species and a support or introduction of further native pollinators is desirable for risk reduction (Foster et al., 2011) and could be hosted by the newly gained diversity. The dependence on pollinators ('bees and butterflies') was mentioned as especially important for the particular plantation by its manager (Hasbiuan, pers. comm.; Annex 1).

Given the proposed benefits of pollination and pest control, advantages of both monoculture and agroforest could be combined and the yield penalty could be avoided by maintained adjacent forest reserves or fragments close to conventional plantations. The effect of such remnants on yield, however, is still under debate. On the one hand some studies identified a spillover-effect of potentially pest-regulating animal species into an oil palm plantation from nearby forest fragments (e.g. Lucey *et al.*, 2014; Gray *et al.*, 2016). Yet, these animals do not necessarily improve oil palm yield, as shown by studies investigating benefits from ants, birds, and bats in the same study region (Denmead et al., 2017), of adjacent intact forests (F. A. Edwards et al., 2014) and of adjacent riparian forest fragments (Gray et al., 2016).

To avoid negative financial consequences of the yield penalty on business while maintaining agroforestry, the produce of the non-palm specimens could be harvested, marketed and their production combination could be economically optimized (Mercer et al., 2014; Schneider et al., 2017). Timber can also be a profitable source of agroforest revenues (de Sousa et al., 2016; Khasanah et al., 2015). Additional marketable products were also among the original selection criteria of tree species for the experiment (Teuscher et al., 2016). However, none of the individuals have yet reached economic maturity to allow for harvesting. Finally, oil palm yield is just one aspect when talking about the advantages of different land use systems. It is generally conceivable that positive external effects of the diverse system outweigh the negative effects on private revenues via monetization of societal benefits of ecosystem services. These could be internalized via governmental market intervention (Shanmugam and Babu, 2017). And after all, there are even non-business related and non-economic arguments to the debate (Silvertown, 2015).

Yield per area in the plots with tree diversity level zero is not significantly different from the control (Fig. 2 b). This finding is particularly remarkable given the distinct treatments as compared to the control plots, which are the initial thinning of palms and a suspension of weeding treatment and fertilizer application. However, the neutral result does not imply that no effects arise from the different treatments. More likely is that, in accordance with notes on the high diversity plots (stated above), the finding is again a net-effect composed of several potential positive and negative effects originating from different light regimes, diversity and density of ground cover plants, and competition and availability of nutrients and water.

Ground cover plants are presumably more developed inside the treatment plots, where palms were endowed with a diverse vegetative undergrowth around their stems (EFForTS-BEE undergrowth survey is pending), which is removed in the control plots. On the one hand, ground cover plants can be even more competitive for light and nutrients than trees, despite their lower height, and could imply palm yield declines, as has been found for other agroforestry systems. For example, a study of cocoa agroforestry found especially herbs to significantly reduce cocoa yield, whereas trees showed a neutral effect (Clough et al., 2011). Although cocoa and oil palm agroforests are admittedly little comparable due to different demands. On the other hand, ground cover offers the advantage of improved soil features, fostering nutrient and water retention, mitigating erosion and offering further ecosystem functions (Nearing et al., 2005; Schipanski et al., 2014). Not least, the ability to host additional animal individuals and species could potentially affect the yield outcome by regulating pests and facilitating pollination (see above). For example, a study by Nájera and Simonetti (2010) found a three-fold higher bird richness in oil palm plots with undergrowth as compared to the weeded control. Generally, those undergrowth species are preferred that place low nutrition demands (to avoid strong competition as e.g. by *Imperata cylindrica*) and ideally fix nitrogen (Rosenstock et al., 2014; Woittiez et al., 2017).

The effect of fertilizer suspension could be a plausible factor contributing to the net effects. Whether these differences are substantial because of above and below ground exchange with the outside plot area remains unknown (see 4.3 Spillover and plot boundary effects). More research for this aspect of oil palm agroforestry is desirable.

The initial palm thinning, which reduced the planting density by around 40%, is most likely associated with a *positive* yield effect. Despite the obvious effect of less contributing individuals to a yield per area, the contrary effect of higher availability of nutrients, water and light per palm probably overcompensates the losses – a thought featured by the previous EFForTS-BEE yield study (Gérard et al., 2017). Indeed, this effect is confirmed by the difference of yield per palm and yield per area in Fig. 2: adj. pos. 1 and palms in plots with diversity level zero outperform the control on palm level. Yet, when yields are expressed per area, mean values of both categories almost resemble the plantation average.

The high yield level in a low planting density also raises the question whether the currently applied planting density of 120 palms ha^{-1} is optimal, a question previously raised by Gérard *et al.* (2017) who argued for a reduction of planting density based on the initial yield overshooting in the experiment between 2015 and 2016. The planting scheme across the plantation was set following a recommendation for the use of *tenera* seedling variety, by the state-owned oil palm company PTPN (Hasbiuan, pers. comm.; Annex 1). The number of plants per ha in this scheme is already 16% lower than proposed by the generally recommended FAO-scheme (FAO, 1977). The conducted thinning is in line with a density study proposing initially high planting densities followed by systematic thinning optimal temporal yield development (Nazeep et al., 2008). Reduced palm densities (and resulting low canopy cover) increases the importance of understory functions for preventing erosion and retaining nutrients (Nearing et al., 2005). A quantification of the optimal density in this experiment would among other aspects require better knowledge of the surrounding light conditions of the adjacent palms.

From an ecologist's perspective, a system with comparable yield and higher diversity and resilience is pareto superior. Therefore, I propose the natural management of undercover vegetation, including herbs and shrubs as a viable mainstream alternative to planting trees, to overcome the trade-off between maintaining ecosystem services and the oil palm yield penalty. Trees still have advantages for ecosystem functioning, e.g. by their vertical structural diversity (Schulze et al., 2001), but the maintenance of a diversified natural understory is offered as a compromise that will eventually provide sufficient habitat for pollinating and pest-regulating animals and enhances soil quality. Attention should be given, however, to upcoming results from undergrowth diversity research (Sachsenmeier, unpublished), which compare understory plant diversity between treatment and control plots. More insights into the effect of palm thinning and fertilizer treatment in oil palm agroforestry would be equally desirable and further research is also necessary on the management cost of such systems, which is usually higher than for the conventional alternative (Blaser et al., 2017).

The yield effects on tree *species* level and species category are not significant (Fig. 2). Theoretically, palm yield performance could be determined on species level if the above noted advantage of complementarity was optimal for the unique combination of oil palm and tree species. Indeed, soil properties are known to respond to the introduction of particular species in agroforestry systems (Guillemot et al., 2018) and attempts have been made to optimize the selection of agroforestry tree species for particular systems (German et al., 2006). Special expectations in this experiment were held for the plots where N_2-fixing specimens from Fabaceae family (*Parkia speciosa* and or *Archidendron pauciflorum)* had been planted. A study across agroforestry systems in different climates estimated a mean nitrogen [N]-supply by leguminous trees in agroforestry systems of 246 kg [N] ha^{-1} (Nygren et al., 2012) – providing 16 kg more than artificially applied to the conventional part of the plantation (Teuscher et al., 2016). Above all, tree-originated nitrogen is proposed to be more effective than artificial supply (Leakey, 2014).

About the reasons why the theoretical nitrogen effects are not reflected by yield findings can only be speculated. Previous studies showed that legume-based N_2 fixation in agroforestry varies greatly by species and soil nitrogen content (Rosenstock et al., 2014). Possibly, the soil is already swamped with nitrogen from the surrounding conventionally managed plantation, presumably because the high ground vegetation cover captures nitrogen-rich runoff water and indicating that nitrogen is not a limiting factor for oil palm yield. Alternatively, the nitrogen provision by trees is perhaps not yet provided in relevant quantities because of low tree age. Both hypotheses suggest further pedological research.

The area-based yield penalty is relatively robust towards different calculation methods, but the 'alternative method' (inspired by Gerard et al., 2015) relatively overestimates yield penalties

among high diversity levels. Although both methods were based on the new area expansion approach (counting the removed palms within a circle of r = 12 m), they differ by the value of yield per palm which is subtracted proportionally to the number of removed palms. The 'alternative approach' uses average yield from the conventional plantation, whereas the 'usual approach' uses average yield from within that particular plot. Therefore, the alternative approach declares relatively higher yield penalties whenever palm-level averages within plots are below the plantation average. These effects are not justified in the context of area expansion because they base on the false assumption that removed palms would produce plantation average yield.

Furthermore, the yield time series (Fig. 5 b) shows that even palms in the conventional plantation part (adj. pos. 3) contain substantial volatility. It is, therefore, questionable if a long-term plantation average should be used to subtract opportunity costs to account for removed palms (as proposed by Gérard et al., 2017, and taken on in this paper). On the other hand, using current (monthly) plantation averages widens the general dispersion and increases the propensity to create negative yield values.

In their original approach, Gérard et al. (2017) calculate net plot-effect by adding spillover changes to inside-plot changes and subtracting the above mentioned plantation average yields for removed palms. Since the resulting plot effects verifiably depend on plot size, the method could be labeled 'per-island approach'. The general advantage of the 'usual approach' piloted in this paper is that palm categories (inside-plot palms vs. adjacent positions) can be evaluated separately and per area which facilitates an expansion to larger islands or a total conversion of plantation to agroforestry (see 4.3 Spillover and plot boundary effects).

4.2 Effects of tree performance and tree-to-palm competition

Tree growth performance showed the highest effect on yield via competing crown projection areas. Aggregated tree basal area and stem volume showed substantially less effect; the number of trees had little impact on yield. All investigated measures are above-ground indices for the trees' competitiveness and materialize the above noted competition for water, light and nutrients. Below-ground competition is indirectly included in these models because crown projection area could as well be a proxy for a tree's influence zone (Bella, 1971), which potentially considers above and below ground competition. Unfortunately, this bond also aggravates a quantification of the light effect. Further research on the direct below-ground competition via roots could improve the understanding of palm-to-tree competition. Previous agroforestry research presents evidence that tree interplanting not only alters the canopy structure, but has the potential to reshape below ground root occurrence of the crop species (Rajab et al., 2018). Tree dominance as a yield determining factor is likely to become even more important in the future with intensifying tree dominance, especially because trees within agroforestry are known to grow faster due to surrounding fertilization (Khasanah et al., 2015).

The negative effect of crown overlap shows that light competition by trees has started. This, however, is relativized by the low explaining capacity of the weighed crown overlap (Table 4 b): crown density and interference class do not improve the model and suggest that the light aspect is not yet decisive for competition. Further evidence for this hypothesis is provided by the identified non-relationship of yield and tree share among the canopy (Table 3 f). While tree canopy share appeared to be important in selected plots with strong tree growth, it was no overall predictor of palm yield in 2016, when the used drone images were taken. Further aspects of the link between tree performance and yield are discussed in Section 4.4 Temporal yield development.

The non-contribution of the number of trees contradicts other studies (e.g. Teuscher *et al.*, 2015) who found a relationship between the number of trees per ha and yield, yet not by a linear regression. Improving the functional form could potentially be advantageous. In general, tree differentiation in height, crown and root extension in the field is likely to have proceeded during the last years, causing heterogeneity in the impacts of trees on palms. Thus, the mere counting of trees may not be an appropriate measure at the time of analysis.

4.3 Spillover and plot boundary effects

There is no (substantial) spillover effect of yield per area, but mean spillover in adj. pos. 1 increases with diversity level in the adjacent plots. The previous project results by Gérard et al. (2017) suggested to have found significantly positive spillover-effect on adjacent pos. 1 palms. Indeed, adj. pos. 1 showed increased mean yield (not significant) also in this study. Yet, the finding can be re-evaluated with the applied measure of yield penalty per area, where the mean overperformance becomes even smaller, far from being significantly different from the control.

The per-area approach gives more meaning to the spillover, because remaining effects are less likely the effect of reduced planting density. Although not significant, the relatively high yield among palms adjacent to plots of high diversity provides first (weak) evidence of a ‘true’ spillover caused by adjacent tree diversity. A hypothetical explanation is provided by the above-mentioned advantages of diversity, in this case pollination and pest-control provide likely explanators.

Palms show higher yield penalties per area at high distances to the fence and significant negative effects in several regression models on palm level. Some models show better correlations when close-to-fence-palms are excluded. A potentially influential cause of boundary effects regards the suspension of fertilizer inside the plots. Whether the non-fertilizing effect is really that important remains, however, debatable. The conventionally managed palms receive, among other treatments, chicken manure, which is dispensed as bags placed next to the palm stems whose contents slowly dissolve and enter the ground (Hasbiuan, pers. comm.; Annex 1). During heavy rain events, nutrients could easily enter the plot via surface runoff or via below-ground leaching. The relatively high ground cover share within the plots reduces surface runoff, especially in plots surrounded by steep slopes, and the improved water infiltration may help to capture water and nutrients from the entering surface streams (Corley and Tinker, 2016; Mathews et al., 2007). Also, palm-roots, especially of palms near the plot boundary, may extend to the outer area by their far-reaching horizontal root system, as far as 25 m from the stem (Corley and Tinker, 2016; Jourdan et al., 2000). Thus, palms within plots of all sizes could technically use their roots to consume nutrients from the outside and fertilizing of oil palms within plantations increases yield regardless of the planting density (Nazeep et al., 2008).

A further influence regards the absence of shrubs and trees outside the fence, which is why border palms face 'hybrid' competition influences: the plot-facing side faces considerable above and below ground competition from non-weeded vegetation; while from the other side only palms are competitors. It appears logical that the observed yield predictors work best for palms with 'pure' treatment. The reason for different results on palm- vs. area-level (Fig. 2 a5 and b5) is that palms in the plot center have relatively more removed palms within their neighborhood, which mathematically reduces their yield by the used area-expansion approach. Given the indifference on palm level, it is reasonable to assume that yield penalties plateau after a certain distance and do not further decrease towards centers of even bigger tree islands.

Both analyzed effects from the tree island back to the plantation (spillover) and vice versa (boundary) are important aspects to the debate of the optimal island size in the context of yield penalty per area. The number of adjacent palms changes with island size (Gérard et al., 2017), yet spillover effects of yield per area across tree diversity levels are almost neutral so that calculations do not need to distinguish between conventional plantation and island-adjacent palms, regardless of the island size. Following this perspective, yield penalty would increase linearly with island size. A question about frequency and size of islands could, therefore, be decided upon ecological and/or arguments from business to the debate.

Yet aggravating this conception, yield penalties seem to increase to the center of big islands (not significantly) and plateau around 7.5 m distance to the boundary. This information can be used to derive yield penalty in quadratic islands as a function of island size. The marginal yield penalty increases after size 7.5 m^2, when the first palms exceed 7.5 m boundary distance. If FFB yield maximization in an agroforest was the only concern, this would advocate many small islands below 7.5 m edge length. Yet, island sizes come with different ecological benefits and (presumably) with different management costs. A weighing of these aspects to optimize island size requires transparency over the preferences within a particular system.

4.4 Temporal yield development

Yield penalty increases with growing tree age and more drastically in plots with high tree diversity (Fig. 3). In the current tree development stage, none of the trees have reached maturity; they are all still growing and accumulating biomass. Therefore, reduced yield and increased yield penalty can be directly attributed to enhanced competition between trees and palms. Yield reduction in high diversity plots is strongest because trees are especially prospering in these plots. Indeed, project findings suggest overyielding of trees in high-diversity plots (Zemp, unpublished). Also, explorative analyses with the tree performance measures used in this paper show that both mean basal area and standing volume are highest with diversity level 6, followed by 1, 3 and 2 while the ranking of surviving individuals follows the order of diversity level 1, 3, 6 and 2, respectively – suggesting that natural thinning by tree competition is in full motion. Exceptional tree productivity in the high diversity plots can be explained by a number of ecological advantages of mixed species systems over monocultures (discussed in Section 4.1 Effects of tree diversity and species).

All inside palms and adjacent palms on pos. 1 and 2 initially outperform the control. The initial relative over-performance was already identified by Gérard *et al.*(2017) who analyzed data from April 2015 to March 2016. Fig. 4 c shows that the last period when inside-plot palm yield per area outperformed the control occurred between 2015 and 2016, exactly falling into their observed period and further supporting their findings. Also, the ever since occurring downward trend had already been forecasted as a hypothesis in their paper. Reason for the initial surge is most likely the opening of the canopy, which increased nutrient, water and light availability per palm (Gérard et al., 2017).

4.5 Meteorology-induced seasonal effects

Radiation, temperature and precipitation show an irregular pattern between July 2015 and beginning of 2016. The presented 'climate' and yield time series are dominated by the El Niño extreme weather event in 2015 with severe effects on climate conditions across Indonesia. The event caused a pronounced dry season starting in mid-June, followed by one of the most severe wild fires in past decades between July and October (Field et al., 2016). The fires burnt a total area of 123.000 ha land Jambi province alone (Tacconi, 2016). As a result, the atmosphere was covered in haze, until the plumes were transported transnationally (Mead et al., 2018). The presence of haze is likely to have caused the minimum in solar radiation around Aug. and Oct. 2015 (Fig. 5 a) because emitted radiation is reflected or absorbed by the haze particles rather than being transmitted through the atmosphere and reaching the ground (Liu et al., 2014). The subsequent rise in radiation levels coincides with the disappearance of the fires and haze. The more or less systematic co-appearance of solar radiation and rainfall throughout the series can be explained by radiation-absorbing atmospheric aerosols (Ramanathan et al., 2001), which are removed from the atmosphere by washout and rainout effects, related to clouds or precipitation, respectively (Budiwati et al., 2016).

The yield time series shows an irregular pattern and, if any, a rather complex response to meteorological variables (Fig. 5). On the one hand, the irregular pattern is at least in part attributable to the effect of smoothing, giving relatively more priority to the extreme amplitudes of the 2015 El Niño effects. It shall be mentioned again that the time series could still be influenced by the data gaps and manipulated yield records after these gaps. Yet, the visible peaks proved quite robust towards different treatments of loess and post-gap manipulation. Indeed, oil palm yield is subject to a complex response to climate by several internal and external processes, which has been shown in several previous studies (Corley and Tinker, 2016). Existing theories from literature can be applied to the presented time series and patterns can be attributed to preceding climate events, attributing the yield minima of 2016 and 2017 to the El Niño drought of 2015, caused by inflorescence abortion and sex ratio, respectively (as explained below). To provide a quantification in terms of a 'yield penalty of El Niño' is not possible because of uncertainty in both yield and meteorological measurements and, above all, a general lack of understanding of the cycles of influenced physiological processes.

In scientific literature, it is agreed upon that weather and climate substantially affects oil palm yield – although effects are difficult to trace because various plant components and physiological stages in the development of fruits are concerned and because the possible effects require several months to years to materialize (Corley and Tinker, 2016; Henson, 1998; Oettli et al., 2018). Especially the early stages of fruit production are affected, causing delays in the yield response of up to 35 months, which corresponds to the period between inflorescence initiation and fruit ripening. Given this complexity, research has ever since struggled with identifying the time lag and determining the corresponding direction of the effect (both positive and negative effects are possible). This is further aggravated by general annual yield cycles that exist even without substantial climatic variability, as well as by interdependent factors causing feedback oscillations (Corley and Tinker, 2016). The underlying physiological processes of fruit determination have been investigated by several studies, which are only sporadically accessible. The following findings are based upon the extensive review by Corley and Tinker (2016) if not stated otherwise.

Mathematically, oil palm FFB yield can be raised by increasing the bunch weight or the number of bunches per palm, where bunch number is generally more variable and is more likely to explain climate-induced annual cycles. On plant physiological level, bunch weight is determined by the number of flowers per spikelet, the share of fruit set, the weight per fruit and the non-fruit components of the bunch. Bunch number is determined by sex ratio, inflorescence initiation rate, abortion rate and bunch failure rate.

Related to weather and climate, the most promising direct determinants are, according to the review, abortion rate of inflorescences, sex ratio, and initiation rate of inflorescences (all three unfavorably influenced by water stress and extreme radiation), see also Woittiez *et al.* (2017). They correspond to time lags of around 10, 25 and 35 months until the time of harvest, respectively (subject to broad variability). Albeit, times vary substantially between phenotypes, climatic zones and sites. An indirect and external determinant is pollination (influencing the fruit set and influenced by all climatic developments via creating enabling conditions for pollinators). Finally, an indirect internal determinant is the general fruiting activity (influencing all physiological processes and itself influenced by various physiological effects of different climate events). Against all expectations, yield is not optimal if all processes are optimized individually. While a more pronounced fruit set is known to increase fruit weight almost linearly, bunch number and bunch weight are most likely negatively correlated. Temperature plays a less important role on yield. Only extremes beyond the optimal temperature of less than 40° C seem to have an effect, when leaf stomata are closed to limit evaporation in times of water stress. For example, Hong and Corley (1976) found a 50% reduced photosynthesis rate at 40° C as compared to the optimal temperature.

Applying the understanding of the physiological effects onto the (irregular) yield pattern can retrace the implications of El Niño on the palms. The identified intervals of 12 and 23 months between the El Niño drought and the yield minima in 2016 and 2017, respectively, roughly correspond to the above noted lags for the rate of inflorescence abortion (10 months) and determination of sex ratio (25 months). These results are generally in line with experience by the plantation manager who stated that drought effects generally materialize in the following year after the event (Hasbiuan, pers. comm.; Annex 1). By end of this year, 35 months after the 2015 drought, it will be possible to see if yield was additionally altered via decreased inflorescence initiation rate.

4.6 Effects of crown size and canopy cover

Both crown projection area and radius show significant yield effects (Table 4 f and g). While crown projection measurement has become a common method in forestry to determine a tree's competitiveness (Bella, 1971; Grote, 2003; Pretzsch, 2009), to predict the diameter at breast height (DBH; Verma et al., 2014), or to determine tree space requirements (Pretzsch et al., 2015), it has, to the best of my knowledge, rarely been applied to palms. Apparently, only few studies have used this measure for establishing drone-based age models (Chemura et al., 2015), and for airborne identification of single palms (Shafri et al., 2011). No study could be found that links oil palm crown projection area to yield. The rationale behind using 2D projections of palm crowns could be either an above-ground proxy for leaf area – which itself is an accepted yield determinant via the potential of accumulating sugars via photosynthesis (Corley et al., 1971; Hardon et al., 1969) – or it could be a hypothetical below-ground proxy for the influence zone as used in competition indices (e.g. Bella, 1971) linked to the root system and the access to nutrients and water.

As was shown by Chemura, van Duren and van Leeuwen (2015), palm crown projection area increases linearly with age, until palms reach their final crown area. Generally, it is unclear whether palms further expand their crowns after reaching the alleged crown maximum in year ten (Corley and Tinker, 2016; Hardon et al., 1969). If that was the case, crown area would only serve as a proxy for age, which has advantages when estimating palm age from above, but is not superior to ground-based height measurements. With 11-17 years estimated palm age across the plantation, the differences between crown areas could still be attributed to age differences. However, crown extension is known to be influenced also by site conditions and especially linked to planting density (Gerritsma and Soebagyo, 1999). Another counter-indication is provided by an adapted multiple regression controlling for meristem height, which shows that palm age further contributes to explaining the variation (a model with yield means from Jan. 2017 to July 2018 as dependent variable, ground-based elliptical crown area measured in 2017 as predictor and meristem height measured in 2017 as control is significant in both predictors and the overall model; $p < 0.01$).

Noteworthy is that the area is no better predictor than the radius. This fact may be explained by the palms' distinctive crown morphology and a resulting general inaccurate estimation of circular palm crown projection areas. As compared to trees, the palm's fronds extend radially from the meristem to the outside. This implies that the center part of the crown, where fronds are more likely to overlap, is more densely covered. The outer part, however, (as can be seen in Fig. 1 a) shows an increased distance between the fronds and exposes gaps between the leaves. Crown projection areas that base on the maximum frond extension (as I have done in this analysis) always overestimate the effective crown area by these gaps and introduce bias. Larger crown areas have presumably larger gaps, but to which proportion remains unknown. The inaccurate circular shape is therefore no better proxy than the mean length of the outer fronds, which corresponds to the radius of the circular projection area. In fact, crown radius has already been used as explaining variable in photosynthesis-related research. For example, it serves as proxy for rachis length and thereby shows a close relationship to light interception (Germer, Jörn; Sauerborn, 2004).

A related methodological problem is the definition of the crown perimeter. For a given frond length, the largest 2D projection is obtained if the fronds extend parallel to the ground, building a 90° angle between outer frond and stem. Field observations have shown that fronds in this angle have already lost their strengths and are most likely over-mature or already dry, presumably not contributing to photosynthesis and introducing further bias to the estimation. To reduce bias in the measurements, I propose to use normalized difference vegetation index (NDVI) compatible imagery and develop algorithms to extract non-circular shaped areas of the fresh fronds.

There is a weak but significant positive relationship between the area of non-palm crown cover and yield on plot-level (Table 3 e). This finding suggests that yield per palm is potentially higher with larger spaces surrounding the palms. It is a further support for the hypothesis of non-optimal plant spacing (see Section 4.1 Effects of tree diversity and species). However, because of the unknown plot-level nutrient demand and availability, as well as rooting structure specific to the EFForTS-BEE experiment, it cannot be clarified whether this effect is caused by reduced competition for light, nutrients or water. The fact that only the previous year's yield can be explained by the date of measurements in 2016 shows that palm crown canopy across the plots is not a constant.

The non-significant regression results of several canopy related variables, such as the algorithm-determined palm canopy and tree canopy fractions as well as the number of thinned palms per area, cast doubt on the identified effect. After all, this category of plot-level predicting variables may be too imprecise to make accurate predictions because the space fillings outside the fence are not considered and may influence the growth of adjacent inside palms and particularly distort the values of small plots.

Gap fraction does not explain palm yield. In contrast to the non-palm crown cover (above), gap fraction describes the percentage of sky visible through the canopy from the ground (Glatthorn and Beckschäfer, 2014). The non-relationship is best explained by the character of the variable: it includes both trees and palms and does not distinguish between the shares of tree canopy (negative yield effect) and palm canopy (positive yield effect). In contrast, initial results by EFForTS-BEE did show a significant relationship between gap fraction and yield (Gérard et al., 2017). Although based on the same gap fraction methodology, the results are little comparable due to the meanwhile undergrowth and tree development – amongst others evident by the higher gap fraction values in the former survey (27% ± 15% vs. 12% ± 9% mean ± *se%* in 2014 and 2018, respectively).

Despite the difficult attributability, there are some occurrences commonly associated with gap fractions, such as precipitation and wildlife, both of which could potentially influence yield, although – admittedly – only indirectly. Free fall of rain through the canopy limits the amount of water intercept by the canopy and may increase soil moisture below the canopy – a small effect which loses importance with high rainfall intensities (Hasselquist et al., 2018). Similarly, throughfall may enhance erosion (Nearing et al., 2005). Also, wildlife is reportedly linked to gap fraction (Yue et al., 2015). It is conceivable that certain pollinating insects profit from open light regimes. Notwithstanding, also defoliating insects are reportedly more abundant under open canopies and could cause an opposite effect (Basset et al., 2001). The complexity of several opposing indirect effects suggests that gap fraction in oil palm agroforestry is generally no suitable yield predictor.

4.7 Effects of palm height, basal area, stem epiphyte cover and slope

The relationship between yield and palm height is weak, but significant. In accordance with findings from literature, there is no simultaneous increase of yield and height throughout a palm's growth period (Corley and Tinker, 2016). Therefore, it is plausible that the linear fit was the cause of poor regression results. More evidently, palm height is determined by age in a linear relationship (Henson and Dolmat, 2003) and age itself is a viable yield predictor – a strategy used in previous project results, where height showed a strong yield effect at $p < 0.01$ and $R^2 = 0.84$ in a multiple regression model (Gérard et al., 2017).

Literature findings suggest, depending on agroclimatic zones, an almost linear oil palm yield increase during the first ~8-14 years with a decline starting after year ~16-22 and a plateauing of up to ~8 years (Corley and Tinker, 2016; Mahamooth et al., 2011). The plantation manager mentioned an earlier productivity peak (year 8) with a narrower corridor (years 5 - 12) for the present site and *tenera* variety conditions (Hasbiuan, pers. comm.; Annex 1). The functional form of linear regressions is henceforth not suitable for older palms. The weak functional fit of the meristem height regression in this paper ($R^2 = 0.04$) and the given age structure of 11-17 years across the plantation give an indication that some palms have not reached maturity of productivity.

A second reason for the poor regression fit could derive from the reportedly low variation in palm age and height, coupled with relatively high measurement errors from the measurement via Vertex hypsometer. A study on measurement accuracy found a relative standard deviation of the random component of the error as high as 30% of the true height for this method (Larjavaara and Muller-Landau, 2013). This error is much bigger than the meristem deviation itself (meristem height cv = 17%). I observe that the EFForTS-BEE meristem survey could be made more accurate by alternative measurement devices or via several repeated measurements to mitigate the random error.

Epiphyte cover along the meristem does not significantly affect oil palm yield. This finding is completely in line with an existing study, which equally reported no effect of epiphyte removal on oil palm yield (Prescott et al., 2015). However, there are good arguments why epiphytes could benefit oil palm yield. The manager of plantation Humusindo speculated about epiphyte cover as a potential refuge for ants serving as pest control against defoliating caterpillars (Hasbiuan, pers. comm.; Annex 1). This effect could not be confirmed by the authors who found no significant difference of ant quantity between plots with intact and removed epiphytes. Also, as discussed in previous sections, the plantation has not yet experienced a severe pest to promote the advantages of pest control.

Palm basal area shows no effect on palm yield. Generally, little research has been conducted on the effect of oil palm stems on yield. While palm basal area, measured above the basal bulge, is known to be more or less constant throughout the adult palm life, it can adapt to different environments in the early years (Corley and Tinker, 2016). For example, diameters are reportedly smaller with higher planting densities (Henson, 2006). It is possible that trunk features show intermediate yield effects if trunk characteristics are correlated with other oil palm features. This influence could go both ways: While big stems may be necessary to support extensive crowns or to store nutrients (Henson, 2006), they could also hinder crown or fruit development if nutrients are used to a great extent for stem construction. Since trunk volumes are rather unaffected by planting densities (Henson, 2006), individuals with thinner diameter may show stronger growth in height and secure better light access. Findings from control palms suggest, however, that palm basal area and crown size are not significantly related so that the hypothesis of basal area influencing yield cannot be confirmed for this experiment. This marks a substantial difference to trees, where stem and crown projections are tightly linked (Grote, 2003; Shimano, 1997; Verma et al., 2014).

The slopes around palms and across plots show no effect on palm yield. The non-contribution of maximum slope measured across the plots in the experiment was already described by Gérard *et al.* (2017) and can now be confirmed for the extended time frame. Micro slope measured across a 2 m radius around the palm, on the other hand, was introduced as a new and promising variable for the sub sample of inside-plot palms and control palms. Generally, slope in oil palm plantations is seen as potentially yield reducing especially for steep slopes because of lower sun exposure (depending on aspect, they receive either morning or evening sun), overlapping fronds, erosion of nutrients, land slips leading to thinner soil, limited root extension and anchorage (Paramananthan, 2013). On bare soils, all these effects reportedly reduce yield by 10-30% on slopes of 2-7° and can almost be neutralized by proper soil conservation (Woittiez et al., 2017). Consequently, the reason why no slope effects can be observed is likely due to the vegetation cover, which is abundant inside the plots and also covers the major share of the conventional part of the plantation, except circular weeding areas roughly 2 m around the palm stems.

4.8 Effects of palm-to-palm competition

Prediction performance of palm-to-palm competition indices was found to be generally poor. A literature search shows no scientific reports about competition-based yield prediction of oil palms or palms in general, on individual plant level. Although some palm-level simulators have been developed, they focus rather on physiological properties of the palm of interest, excluding the effects of neighboring competitors (e.g. Van Kraalingen, Breure and Spitters, 1989).

However, competition indices are a successful and common tool in the prediction of tree growth (Biging and Dobbertin, 1995; Larocque and Alfaro, 2016; Pretzsch, 2009). In this thesis, I tried to adapt concepts of common tree indices and adjust them to predict oil palm yield by morphological features of neighboring palms. The poor significance levels and fits yielded by the analysis suggest that the used attempt was largely unsuccessful, supposedly because the goals and circumstances of both approaches are structurally different: tree competition indices are used to predict a tree's performance in terms of plant growth, while palm competition analysis would try to estimate fruit yield. Even for trees, the prediction of fruit yield is a complex puzzle because the optimization of biomass does not necessarily lead to more fruit (Costes et al., 2006). Also, tree competition frequently bases upon diameter at breast height or basal area as proxy for a tree's dominance – a measure not applicable to palms due to the absence of secondary thickening (Corley and Tinker, 2016). A further exacerbating factor is that palm morphological features show little variability across the largely even-aged monocultural plantation (Table 4), whereas tree-based competition indices are often applied to uneven-aged or mixed stands (Pretzsch, 2014, 2009) where a higher structural diversity supports the process of identifying correlations.

Tree-related 2D competition indices essentially rely upon a combination of DBH or basal area of trees within a certain range and sometimes the distance of the trees, for example entering as the inverse in the model (e.g. the frequently cited distance-weighted DBH ratio by Hegyi, 1974; further indices e.g. reviewed by Biging and Dobbertin, 1995). The influences of different competitors are most often simply added up, or in some cases this sum is related to features of the tree of interest.

The approach of weighed crown projection overlaps applied in the analysis of this paper was considered most promising for the application on palms given the availability of crown projection data. The approach was adapted from Bella (1971), who introduced the frequently cited concept of circular influence zones, which are either determined by above-ground (crown projection overlap) or below-ground (root system) space requirements. The additional factor of DBH ratio to Bella's formula was tried to be overcome by a meristem ratio or elevation ratio, both equally unsuccessful. This, again, could be the result of inaccurate height measurements, where the measurement error exceeds height variability.

Because of the generally poor responses to the basic models, more advanced models were not tested and exponential factors such as those proposed by Bella (1971) were not developed. However, given the large varieties of approaches tested in this paper and the homogeneity of morphological features across palms in even-aged plantations, it is doubtable if any competition index could be developed to satisfyingly explain yield on palm level. More success is likely achieved in the field of tree-to-palm competition (see 4.2 Effects of tree performance and tree-to-palm competition) where existing concepts could be applied more easily. Another attempt could be made with more sophisticated 3D models as proposed for trees (Pretzsch, 2009). Also better knowledge about root extension could be helpful to improve the modeling of below-ground competition entering in the influence zone approach (Bella, 1971).

4.9 Limitations and way forward

Some of the limitations of this study were mentioned in the methods and discussion chapters, the most important of which are summarized below. Building on those, I propose improvements of existing surveys and proposals for future research in the subsequent sections.

4.9.1 Limitations of the analysis and used data.

The primary limitation of the analyses is caused by gaps in the yield survey. As discussed above, the months directly after suspended harvest show increased yield because some bunches are accumulated for later harvest. Although all 'post-gap' yield values were systematically reduced, it remains uncertain how these manipulations effect the result. Especially the time series are prone to temporal inter-monthly yield differences. The ambiguous effect of weather and climate could in part be caused by fluctuations from these effects. Generally, it was assumed that gaps do not affect the relative yield level between palm categories (e.g. inside-plot vs. adjacent) because both categories are theoretically affected equally. However, it is possible that outside-plot palms are more likely to be harvested (illegally) during EFForTS-BEE harvest suspension. This goes along with Fig. 6 b in Annex 3, where inside-plot yield shows on average substantially higher peaks after harvest suspension than adjacent palms.

A further limitation is the result of the sampling design. Due to random positioning of the plots and palm thinning, only 31 of the total 52 plots contain palms and could be used in the yield analyses. Despite several palms within these plots, plot categories build on a very limited number of randomly selected positions. For example, there are 3, 13, 8, 5 and 2 plots for diversity levels 0, 1, 2, 3 and 6, respectively.

As mentioned earlier, all used measurements face, partly considerable, measurement errors. Even if the expected measurement value is not different from the true population mean (unbiasedness), high measurement errors cause problems for the regression analyses on palm level. This is especially severe if the population is relatively homogenous (e.g. meristem height across the even-aged oil palm plantation) and the corresponding measurement errors relatively high. Thus, some of the regressions likely would have shown better fits and significance levels under better measurements. Generally affected are all measures that use palm position data because drone-derived coordinates could be subject to geographic distortion even after concise georeferencing.

4.9.2 Proposal for improvements of existing surveys in the experiment

Given the several implications of data gaps in the yield survey, the most important recommendation is to grant a strict continuity of the monthly yield survey. The improved data quality will allow to analyze less obvious effects, such as different yield behavior of palm categories in response to drought: do diverse plots show an increased resilience towards negative effects of drought? I also recommend breaking the yield survey down to bunch level so that the development of bunch weight and bunch number can be compared and assessed individually. This will allow for more specific conclusions on past meteorological influences because both components are affected by different conditions.

As described above, ground-based palm meristem height values contain a considerable measurement error if they are done with the Vertex hypsometer. The use is aggravated by substantial sound interference of surrounding insects which hinder the measurements in strongly affected positions and generally cast doubt on some values. I therefore propose to switch the meristem height surveys to direct height measurement via telescope poles. The measurement of ground-based total height is not very helpful because total height depends on the angle and length of the recent emerging frond. Also, the dense plantation canopy does not always allow for a clear view on the upper fronds of one palm. Yet, these challenges can be overcome if palm height is extracted from a valid canopy height model (CHM), which is currently available for only few of the plots. An accurate digital surface model (DSM), which is a by-product of the CHM, could be used for a more systematic assessment of micro-slope (roughly $r = 2$ m around the palm).

Ground-based crown projection measurements, if continued, should put emphasis on a clear definition of the methodology and proper training of the assistance. Data exploration has shown that these measurements are considerably affected by small inattentiveness. In general, crown projection measurements seem more promising if they are extracted from co-registered drone images. Drone images could be taken periodically (e.g. annually) so that inter-annual differences give insight into detailed crown changes in response to crown-competing trees. Yet, the above-mentioned aspect of unsuitability of the circular shape to approximate leaf coverage casts doubt on the general measure. A drone-based survey of NDVI-compatible imagery could improve the automated extraction of non-circular and photosynthetically relevant crown shapes.

4.9.3 Proposal for further studies in the experiment

The identified trend of decreasing yield in diversified plots is likely to continue in the future. But especially the pest control and resilience aspects had not opportunity to prove their potential benefit. This suggests, on the one hand, to reconduct selected (time series) analyses from this paper in the future. When yield series are more coherent and reliable, I propose to conduct more sophisticated time series analyses, especially cross-correlations of yield and tree performance series and yield and meteorological data series.

As mentioned throughout the discussion, yield penalties are likely a net-effect of several positive and negative influences. Given the numerous aspects included in the experiment, it is becoming increasingly difficult to disentangle single effects. Especially the aspect of fertilization could potentially be a negative effect. Hence, I propose a systematic investigation of soil nutrient composition inside the plots along a gradient of distance to the fence. The series should distinguish between plots with presence and absence of trees from Fabaceae family to get a better understanding of tree nitrogen fixation.

Finally, attention should be paid to the business-relevance of the findings from the experiment: the profitability of the proposed agroforestry. Beyond the mere assessment of fruit bunch yield, profitability assessments require transparency of all associated costs and benefits. Especially the costs are likely to increase with agroforestry due to thinning, tree-planting and perhaps increased harvesting. But also benefits could increase by the harvest of side-products or if palm oil from agroforestry can be marketed at higher prices. Therefore, I propose a systematic financial analysis of the system as further research, including time series of the workers and the management personnel.

4.10 Synthesis

The study investigated several palm and tree related yield influences on a spatial and temporal level. The following aspects highlight the most important findings.

(1) There is a net yield penalty per area of tree diversity affecting yield in oil palm agroforestry, which is positively correlated with the species richness of planted trees. The negative effect is directly linked to the presence and performance of trees, which are more dominant in plots with higher diversity. The competitive character of trees is accounted for especially by the tree crown, stem volume and basal area, which suggests that tree growth will further reduce palm yield in the future. Proposed benefitting aspects of tree diversity such as pollination or resilience, if existing, play only a minor role. An effect on single species level cannot be identified, nor does the presence of leguminous trees show a measurable effect. Little studies have been conducted on the yield effect of tree species in oil palm agroforestry, suggesting further research and a systematic review.

(2) A 'low-cost' alternative for increasing diversity is provided by a system with reduced oil palm planting intensity and suspended weeding so that a natural (non-tree) undergrowth can develop between the palms. This conclusion can be drawn from the finding that yield per area in plots with no planted trees are not significantly different from the plantation average. The plots were thinned before the experiment and ever since weeding was suspended so that a vast understory could develop. Also, epiphytes growing on palm stems proved not to affect yield. However, if the provision of undergrowth and epiphytes is generally superior in ecological terms (e.g. water infiltration or habitat functions) requires further investigation.

(3) The yield penalty of tree diversity does not allow for straightforward conclusions on land use. More importantly, the judgement whether a system comparable to the one investigated should be implemented depends upon the cost related to yield penalty, the intermediary ecosystem services provided by the system and society's (intrinsic) valuation of these services.

(4) Predicting yield via crown competition of neighboring palms shows significant effects but is more complicated and less effective than a prediction by mere morphological features of the palm of interest, such as height and crown. The use of crown projection areas of palms, as practiced in this study, faces methodological difficulties. As a more effective and efficient alternative, it is suggested to use the ground projection of maximum leaf length (equal to the radius of a circular crown projection).

5 Conclusions

The presented study provides evidence that competition by trees in an oil palm plantation reduces oil palm yield per area, confirming the hypothesis of a yield penalty in oil palm agroforestry. The effect is stronger in plots with more species planted, which can be explained by enhanced tree performance in diversified plots. Four years after planting the trees, this yield penalty amounts to 45% in plots with six tree species planted and 28% in plots with three tree species planted. Nonetheless, the negative ecological effects of oil palm monocultures require a land use change with agroforestry being a promising concept. The presented quantification of yield penalty creates transparency among revenue streams in diversified oil palm plantations, which can help to improve business plans, reduce uncertainties related to investments in oil palm agroforestry and reduce financing costs. Even more importantly, it can help to calculate optimal subsidies to governmentally support forest landscape restoration. The presented findings will hopefully encourage further research in the field of yield in oil palm agroforestry that will further contribute to balancing the trade-off between oil palm returns and ecological functioning.

References

Barrios, E.; Valencia, V.; Jonsson, M.; Brauman, A.; Hairiah, K.; Mortimer, P.E.; Okubo, S., 2018. Contribution of trees to the conservation of biodiversity and ecosystem services in agricultural landscapes. *Int. J. Biodivers. Sci. Ecosyst. Serv. Manag.* 14, 1–16.

Barton, K., 2018. MuMIn: multi-model inference. URL https://cran.r-project.org/package=MuMIn

Basset, Y.; Charles, E.L.; Hammond, D.S.; Brown, V.K., 2001. Short-term effects of canopy openness on insect herbivores in a rain forest. *Guyana. J. Appl. Ecol.* 38, 1045–1058.

Bates, D.; Maechler, M.; Bolker, B.; Walker, S.; Christensen, R.H.B.; Dai, B.; Grothendieck, G., 2015. lme4: mixed-effects models using "Eigen" and S4. URL https://cran.r-project.org/web/packages/lme4/index.html

Beckschäfer, P., 2015. Hemispherical_2.0 - Batch processing hemispherical and canopy photographs with ImageJ – User Manual [WWW Document]. URL https://www.researchgate.net/publication/274011723_Hemispherical_20_-_Batch_processing_hemispherical_and_canopy_photographs_with_ImageJ_-_User_Manual

Bell, T.; Lilley, A.K.; Hector, A.; Schmid, B.; King, L.; Newman, J.A., 2009. A linear model method for biodiversity–ecosystem functioning experiments. *Am. Nat.* 174, 836–849.

Bella, I., 1971. A new competition model for individual trees. *For. Sci.* 364–372.

Bhagwat, S.A.; Willis, K.J., 2009. Conservation in oil-palm landscapes. *Conserv. Biol.* 23, 245–246.

Bhagwat, S.A.; Willis, K.J.; Birks, H.J.B.; Whittaker, R.J., 2008. Agroforestry: a refuge for tropical biodiversity? *Trends Ecol. Evol.* 23, 261–267.

Biging, G.S.; Dobbertin, M., 1995. Evaluation of competition indices in individual tree growth-models. *For. Sci.* 41, 360–377.

Bivand, R.; Keitt, T.; Rowlingson, B., 2017. rgdal: bindings for the "geospatial" data abstraction library. URL https://cran.r-project.org/package=rgdal

Blaser, W.J.; Oppong, J.; Yeboah, E.; Six, J., 2017. Shade trees have limited benefits for soil fertility in cocoa agroforests. *Agric. Ecosyst. Environ.* 243, 83–91.

Bogner, A.; Littig, B.; Menz, W., 2009. Interviewing experts, Interviewing experts. Palgrave Macmillan, London.

Boreux, V.; Vaast, P.; Madappa, L.P.; Cheppudira, K.G.; Garcia, C.; Ghazoul, J., 2016. Agroforestry coffee production increased by native shade trees, irrigation, and liming. *Agron. Sustain. Dev.* 36.

Budiwati, T.; Setyawati, W.; Tanti, D.A., 2016. Chemical characteristics of rainwater in Sumatera , Indonesia , during 2001 – 2010. *Int. J. Atmos. Sci.* 2016, 1–11.

Cannell, M.G.R.; Van Noordwijk, M.; Ong, C.K., 1996. The central agroforestry hypothesis: The trees must acquire resources that the crop would not otherwise acquire. *Agrofor. Syst.* 34, 27–31.

Chemura, A.; van Duren, I.; van Leeuwen, L.M., 2015. Determination of the age of oil palm from crown projection area detected from WorldView-2 multispectral remote sensing data: The case of Ejisu-Juaben district, Ghana. *ISPRS J. Photogramm. Remote Sens.* 100, 118–127.

Clough, Y.; Barkmann, J.; Juhrbandt, J.; Kessler, M.; Wanger, T.C.; Anshary, A.; Buchori, D.; Cicuzza, D.; Darras, K.; Putra, D.D.; Erasmi, S.; Pitopang, R.; Schmidt, C.; Schulze, C.H.; Seidel, D.; Steffan-Dewenter, I.; Stenchly, K.; Vidal, S.; Weist, M.; Wielgoss, A.C.; Tscharntke, T., 2011. Combining high biodiversity with high yields in tropical agroforests. *Proc. Natl. Acad. Sci.* 108, 8311–8316.

Cochran, W.G., 1977. Sampling techniques, 3rd ed. John Wiley & Sons, New York, Chichester, Brisbane and Toronto.

Corley, R.H.V.; Hardon, J.J.; Tang, Y.; Tan, G., 1971. Analysis of growth of the oil palm (Elaeis guineensis Jacq.) I. Estimation of growth parameters and application in breeding. *Euphytica* 20, 307–315.

Corley, R.H.V.; Tinker, P.B., 2016. The Oil Palm. John Wiley & Sons, Chichester, UK.

Costes, E.; Lauri, P.E.; Regnard, J.L., 2006. Analyzing fruit tree architecture: implications for tree management and fruit production. *Hortic. Rev. (Am. Soc. Hortic. Sci).* 32, 1–61.

Dassou, A.G.; Tixier, P., 2016. Response of pest control by generalist predators to local-scale plant diversity: A meta-analysis. *Ecol. Evol.* 6, 1143–1153.

de Sousa, K.F.D.; Detlefsen, G.; de Melo Virginio Filho, E.; Tobar, D.; Casanoves, F., 2016. Timber yield from smallholder agroforestry systems in Nicaragua and Honduras. *Agrofor. Syst.* 90, 207–218.

Denmead, L.H.; Darras, K.; Clough, Y.; Diaz, P.; Grass, I.; Hoffmann, M.P.; Nurdiansyah, F.; Fardiansah, R.; Tscharntke, T., 2017. The role of ants, birds and bats for ecosystem functions and yield in oil palm plantations. *Ecology* 98, 1945–1956.

Dislich, C.; Keyel, A.C.; Salecker, J.; Kisel, Y.; Meyer, K.M.; Auliya, M.; Barnes, A.D.; Corre, M.D.; Darras, K.; Faust, H.; Hess, B.; Klasen, S.; Knohl, A.; Kreft, H.; Meijide, A.; Nurdiansyah, F.; Otten, F.; Pe'er, G.; Steinebach, S.; Tarigan, S.; Tölle, M.H.; Tscharntke, T.; Wiegand, K., 2017. A review of the ecosystem functions in oil palm plantations, using forests as a reference system. *Biol. Rev.* 92, 1539–1569.

Drescher, J.; Rembold, K.; Allen, K.; Beckschäfer, P.; Buchori, D.; Clough, Y.; Faust, H.; Fauzi, A.M.; Gunawan, D.; Hertel, D.; Irawan, B.; Jaya, I.N.S.; Klarner, B.; Kleinn, C.; Knohl, A.; Kotowska, M.M.; Krashevska, V.; Krishna, V.; Leuschner, C.; Lorenz, W.; Meijide, A.; Melati, D.; Nomura, M.; Pérez-Cruzado, C.; Qaim, M.; Siregar, I.Z.; Steinebach, S.; Tjoa, A.; Tscharntke, T.; Wick, B.; Wiegand, K.; Kreft, H.; Scheu, S., 2016. Ecological and socio-economic functions across tropical land use systems after rainforest conversion. *Philos. Trans. R. Soc. B Biol. Sci.* 371, 20150275.

Edwards, D.P.; Tobias, J.A.; Sheil, D.; Meijaard, E.; Laurance, W.F., 2014. Maintaining ecosystem function and services in logged tropical forests. *Trends Ecol. Evol.* 29, 511–520.

Edwards, F.A.; Edwards, D.P.; Sloan, S.; Hamer, K.C., 2014. Sustainable management in crop monocultures: The impact of retaining forest on oil palm yield. *PLoS One* 9, e91695.

Euler, M.; Krishna, V.; Schwarze, S.; Siregar, H.; Qaim, M., 2017. Oil Palm Adoption, Household Welfare, and Nutrition Among Smallholder Farmers in Indonesia. *World Dev.* 93, 219–235.

FAO, 2018. FAOSTAT. Online statistical service. Food and Agriculture Organization of the United Nations [WWW Document]. URL faostat.fao.org (accessed 10.27.18).

FAO, 1977. Better farming series. The oil palm [WWW Document]. URL http://www.fao.org/docrep/006/t0309e/t0309e00.HTM (accessed 10.27.18).

Fayle, T.M.; Turner, E.C.; Snaddon, J.L.; Khen Chey, V.; Chung, A.Y.C.; Eggleton, P.; Foster, W.A., 2010. Oil palm expansion into rain forest greatly reduces ant biodiversity in canopy, epiphytes and leaf-litter. *Basic Appl. Ecol.* 11, 337–345.

Field, R.D.; van der Werf, G.R.; Fanin, T.; Fetzer, E.J.; Fuller, R.; Jethva, H.; Levy, R.; Livesey, N.J.; Luo, M.; Torres, O.; Worden, H.M., 2016. Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought. *Proc. Natl. Acad. Sci.* 113, 9204–9209.

Fitzherbert, E.B.; Struebig, M.J.; Morel, A.; Danielsen, F.; Brühl, C.A.; Donald, P.F.; Phalan, B., 2008. How will oil palm expansion affect biodiversity? *Trends Ecol. Evol.* 23, 538–545.

Foster, W.A.; Snaddon, J.L.; Turner, E.C.; Fayle, T.M.; Cockerill, T.D.; Farnon Ellwood, M.D.; Broad, G.R.; Chung, A.Y.C.; Eggleton, P.; Khen, C.V.; Yusah, K.M., 2011. Establishing the evidence base for maintaining biodiversity and ecosystem function in the oil palm landscapes of South East Asia. *Philos. Trans. R. Soc. B Biol. Sci.* 366, 3277–3291.

Gérard, A.; Wollni, M.; Hölscher, D.; Irawan, B.; Sundawati, L.; Teuscher, M.; Kreft, H., 2017. Oil-palm yields in diversified plantations: Initial results from a biodiversity enrichment experiment in Sumatra, Indonesia. *Agric. Ecosyst. Environ.* 240, 253–260.

German, L.A.; Kidane, B.; Shemdoe, R., 2006. Social and environmental trade-offs in tree species selection: A methodology for identifying niche incompatibilities in agroforestry. *Environ. Dev. Sustain.* 8, 535–552.

Germer, Jörn; Sauerborn, J., 2004. Solar radiation below the oil palm (Elaeis guinensis Jacq.) canopy and its impact on the undergrwoth species composition. *Plant.* 80, 13–27.

Gerritsma, W.; Soebagyo, F.X., 1999. An analysis of the growth of leaf area of oil palms in Indonesia. *Exp. Agric.* 35, 293–308.

Glatthorn, J.; Beckschäfer, P., 2014. Standardizing the protocol for hemispherical photographs: Accuracy assessment of binarization algorithms. *PLoS One* 9, 1–19.

Gray, C.L.; Lewis, O.T., 2014. Do riparian forest fragments provide ecosystem services or disservices in surrounding oil palm plantations? *Basic Appl. Ecol.* 15, 693–700.

Gray, C.L.; Simmons, B.I.; Fayle, T.M.; Mann, D.J.; Slade, E.M., 2016. Are riparian forest reserves sources of invertebrate biodiversity spillover and associated ecosystem functions in oil palm landscapes? *Biol. Conserv.* 194, 176–183.

Grote, R., 2003. Estimation of crown radii and crown projection area from stem size and tree position. *Ann. For. Sci.* 60, 393–402.

Guillemot, J.; le Maire, G.; Munishamappa, M.; Charbonnier, F.; Vaast, P., 2018. Native coffee agroforestry in the Western Ghats of India maintains higher carbon storage and tree diversity compared to exotic agroforestry. *Agric. Ecosyst. Environ.* 265, 461–469.

Hardon, J.J.; Williams, C.N.; Watson, I., 1969. Leaf area and yield in the oil palm in malaya. *Exp. Agric.* 5, 25–32.

Hasselquist, N.J.; Benegas, L.; Roupsard, O.; Malmer, A.; Ilstedt, U., 2018. Canopy cover effects on local soil water dynamics in a tropical agroforestry system: Evaporation drives soil water isotopic enrichment. *Hydrol. Process.* 32, 994–1004.

Hegyi, F., 1974. A simulation model for managing jack pine stands, in: Growth Models for Tree and Stand Simulation. Proceedings of Meetings in 1973. IUFRO, pp. 74–90.

Henson, I.E., 2006. Measuring and modelling oil palm trunk growth. *Oil Palm Bull.* 52, 1–24.

Henson, I.E., 1998. Notes on oil palm productivity. II. An empirical model of canopy photosynthesis based on radiation and atmospheric vapour pressure deficit. *J. Oil Palm Res.* 11, 25–28.

Henson, I.E.; Dolmat, M.T., 2003. Physiological analysis of an oil palm density trial on a peat soil. *J. Oil Palm Res.* 15, 1–27.

Hijmans, R.J., 2017. raster: geographic data analysis and modeling. URL https://cran.r-project.org/package=raster

Hong, T.K.; Corley, R.H. V., 1976. Leaf temperature and photosynthesis of a tropical C3 plant, Elaeis guineensis. *MARDI Res. Bull.* 4, 16–20.

Hooper, D.U.; Chapin, F.S.; Ewel, J.J.; Hector, A.; Inchausti, P.; Lavorel, S.; Lawton, J.H.; Lodge, D.M.; Loreau, M.; Naeem, S.; Schmid, B.; Setälä, H.; Symstad, A.J.; Vandermeer, J.; Wardle, D.A., 2005. Effects of biodiversity on ecosystem functioning: A consensus of current knowledge. *Ecol. Monogr.* 75, 3–35.

Inkscape development team, 2018. Inkscape. URL www.inkscape.org

Jose, S., 2009. Agroforestry for ecosystem services and environmental benefits: An overview. *Agrofor. Syst.* 76, 1–10.

Jourdan, C.; Michaux-Ferrière, N.; Perbal, G., 2000. Root system architecture and gravitropism in the oil palm. *Ann. Bot.* 85, 861–868.

Khasanah, N.; Perdana, A.; Rahmanullah, A.; Manurung, G.; Roshetko, J.M.; van Noordwijk, M., 2015. Intercropping teak (Tectona grandis) and maize (Zea mays): bioeconomic trade-off analysis of agroforestry management practices in Gunungkidul, West Java. *Agrofor. Syst.* 89, 1019–1033.

Koh, L.P., 2008. Birds defend oil palms from herbivorous insects. *Ecol. Appl.* 18, 821–825.

Koh, L.P.; Wilcove, D.S., 2008. Is oil palm agriculture really destroying tropical biodiversity? *Conserv. Lett.* 1, 60–64.

Kuznetsova, A.; Bruun Brockhoff, P.; Haubo Bojesen Christensen, R., 2018. lmerTest: tests in linear mixed effects models. URL https://cran.r-project.org/package=lmerTest

Larjavaara, M.; Muller-Landau, H.C., 2013. Measuring tree height: A quantitative comparison of two common field methods in a moist tropical forest. *Methods Ecol. Evol.* 4, 793–801.

Larocque, G.R.; Alfaro, R.I., 2016. Ecological forest management handbook, Applied Ecology and Environmental Management. CRC Press, Boca Raton, Florida.

Leakey, R.R.B., 2014. The role of trees in agroecology and sustainable agriculture in the tropics. *Annu. Rev. Phytopathol.* 52, 113–133.

Liu, Y.; Goodrick, S.; Heilman, W., 2014. Wildland fire emissions, carbon, and climate: Wildfire-climate interactions. *For. Ecol. Manage.* 317, 80–96.

Lucey, J.M.; Tawatao, N.; Senior, M.J.M.; Chey, V.K.; Benedick, S.; Hamer, K.C.; Woodcock, P.; Newton, R.J.; Bottrell, S.H.; Hill, J.K., 2014. Tropical forest fragments contribute to species richness in adjacent oil palm plantations. *Biol. Conserv.* 169, 268–276.

Maas, B.; Karp, D.S.; Bumrungsri, S.; Darras, K.; Gonthier, D.; Huang, J.C.C.; Lindell, C.A.; Maine, J.J.; Mestre, L.; Michel, N.L.; Morrison, E.B.; Perfecto, I.; Philpott, S.M.; Şekercioğlu, Ç.H.; Silva, R.M.; Taylor, P.J.; Tscharntke, T.; Van Bael, S.A.; Whelan, C.J.; Williams-Guillén, K., 2016. Bird and bat predation services in tropical forests and agroforestry landscapes. *Biol. Rev.* 91, 1081–1101.

Mahamooth, T.N.; Gan, H.H.; Kee, K.K.; Goh, K.J., 2011. Water requirements and cycling of oil palm. *Agron. Princ. Pract. oil palm Cultiv.* 89–144.

Mathews, J.; Yong, K.K.; Nurulnahar, B.E., 2007. Preliminary investigation on biodiversity and its ecosystem in oil palm plantation. *Int. Palm Oil Congr. Biotechnol. Sustain. Conf.* 1112–1158.

Mead, M.I.; Castruccio, S.; Latif, M.T.; Nadzir, M.S.M.; Dominick, D.; Thota, A.; Crippa, P., 2018. Impact of the 2015 wildfires on Malaysian air quality and exposure: A comparative study of observed and modeled data. *Environ. Res. Lett.* 13, 044023.

Mercer, D.E.; Frey, G.E.; Cubbage, F.W., 2014. Economics of agroforestry, in: Handbook of Forest Resource Economics. pp. 188–209.

Miccolis, A.; Vasconcelos, S.S.; Castellani, D.C.; Kato, O.R.; Carvalho, W.R.D.; Silva, A.C.D., 2014. Oil palm and agroforestry systems: coupling yields with environmental services, an experiment in the Brazilian Amazon., in: World Congress on Agroforestry Delhi 2014. Compendium of Abstracts. pp. 114–115.

Nájera, A.; Simonetti, J.A., 2010. Can oil palm plantations become bird friendly? *Agrofor. Syst.* 80, 203–209.

Nakagawa, S.; Schielzeth, H., 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods Ecol. Evol.* 4, 133–142.

Nazeep, A.T.M.; Tang, M.K.; Loong, S.G.; Shahar, S.A.B.S., 2008. Varible density plantings for aoil palms (Elaeis guineensis) in peninsular malaysia. *J. Oil Palm Res.* 61–90.

Nearing, M.A.; Jetten, V.; Baffaut, C.; Cerdan, O.; Couturier, A.; Hernandez, M.; Le Bissonnais, Y.; Nichols, M.H.; Nunes, J.P.; Renschler, C.S.; Souchère, V.; Van Oost, K., 2005. Modeling response of soil erosion and runoff to changes in precipitation and cover, in: Catena. pp. 131–154.

Nesper, M.; Kueffer, C.; Krishnan, S.; Kushalappa, C.G.; Ghazoul, J., 2017. Shade tree diversity enhances coffee production and quality in agroforestry systems in the Western Ghats. *Agric. Ecosyst. Environ.* 247, 172–181.

Niu, F.; Röll, A.; Hardanto, A.; Meijide, A.; Köhler, M.; Hendrayanto; Hölscher, D., 2015. Oil palm water use: Calibration of a sap flux method and a field measurement scheme. *Tree Physiol.* 35, 563–573.

Nygren, P.; Fernández, M.P.; Harmand, J.M.; Leblanc, H.A., 2012. Symbiotic dinitrogen fixation by trees: An underestimated resource in agroforestry systems? *Nutr. Cycl. Agroecosystems* 94, 123–160.

Oettli, P.; Behera, S.K.; Yamagata, T., 2018. Climate based predictability of oil palm tree yield in Malaysia. *Sci. Rep.* 8, 2271.

Offenberg, J., 2015. Ants as tools in sustainable agriculture. *J. Appl. Ecol.* 52, 1197–1205.

Oksanen, J.; Blanchet, F.G.; Friendly, M.; Kindt, R.; Legendre, P.; McGlinn, D.; Minchin, P.R.; O'Hara, R.B.; Simpson, G.L.; Solymos, P.; Stevens, M.H.H.; Szoecs, E.; Wagner, H., 2018. vegan: Community Ecology Package. URL https://cran.r-project.org/package=vegan

Paramananthan, S., 2013. Managing marginal soils for sustainable growth of oil palms in the tropics. *J. Oil Palm Environ.* 4, 1–16.

Prescott, G.W.; Edwards, D.P.; Foster, W.A., 2015. Retaining biodiversity in intensive farmland: Epiphyte removal in oil palm plantations does not affect yield. *Ecol. Evol.* 5, 1944–1954.

Pretzsch, H., 2014. Canopy space filling and tree crown morphology in mixed-species stands compared with monocultures. *For. Ecol. Manage.* 327, 251–264.

Pretzsch, H., 2009. Forest Dynamics, Growth and Yield. Springer, Berlin, Heidelberg.

Pretzsch, H.; Biber, P.; Uhl, E.; Dahlhausen, J.; Rötzer, T.; Caldentey, J.; Koike, T.; van Con, T.; Chavanne, A.; Seifert, T.; Toit, B. du; Farnden, C.; Pauleit, S., 2015. Crown size and growing space requirement of common tree species in urban centres, parks, and forests. *Urban For. Urban Green.* 14, 466–479.

Pretzsch, H.; Schütze, G., 2016. Effect of tree species mixing on the size structure, density, and yield of forest stands. *Eur. J. For. Res.* 135, 1–22.

Prewitt, J.M.S.; Mendelsohn, M.L., 2006. The analysis of cell images. *Ann. N. Y. Acad. Sci.* 128, 1035–1053.

Prodan, M., 1965. Holzmesslehre. Sauerländer's, Frankfurt A.M.

QGIS development team, 2018. QGIS Geographic Information System. URL https://www.qgis.org

R Core Team, 2017. R: A language and environment for statistical computing. URL https://www.r-project.org/

Rajab, Y.A.; Hölscher, D.; Leuschner, C.; Barus, H.; Tjoa, A.; Hertel, D., 2018. Effects of shade tree cover and diversity on root system structure and dynamics in cacao agroforests: The role of root competition and space partitioning. *Plant Soil* 422, 349–369.

Ramanathan, V.; Crutzen, P.J.; Kiehl, J.T.; Rosenfeld, D., 2001. Aerosols, cimate, and the hydrological cycle. *Science (80-.).* 294, 2119–2124.

Ranganathan, R.; de Witt, C.T., 1996. Mixed cropping of annuals and woody perennials: an analytical approach to productivity and management, in: Ong, C.K., Huxley, P. (Eds.), Tree-Crop Interactions. pp. 25–49.

Reed, J.; van Vianen, J.; Foli, S.; Clendenning, J.; Yang, K.; MacDonald, M.; Petrokofsky, G.; Padoch, C.; Sunderland, T., 2017. Trees for life: The ecosystem service contribution of trees to food production and livelihoods in the tropics. *For. Policy Econ.* 84, 62–71.

Rembold, K.; Mangopo, H.; Tjitrosoedirdjo, S.S.; Kreft, H., 2017. Plant diversity, forest dependency, and alien plant invasions in tropical agricultural landscapes. *Biol. Conserv.* 213, 234–242.

Rosenstock, T.S.; Tully, K.L.; Arias-Navarro, C.; Neufeldt, H.; Butterbach-Bahl, K.; Verchot, L. V, 2014. Agroforestry with N2-fixing trees: Sustainable development's friend or foe? *Curr. Opin. Environ. Sustain.* 6, 15–21.

Saefken, B.; Ruegamer, D.; with contributions from Sonja Greven; Kneib, T., 2018. cAIC4: Conditional Akaike Information Criterion for "lme4". URL https://cran.r-project.org/package=cAIC4

Schipanski, M.E.; Barbercheck, M.; Douglas, M.R.; Finney, D.M.; Haider, K.; Kaye, J.P.; Kemanian, A.R.; Mortensen, D.A.; Ryan, M.R.; Tooker, J.; White, C., 2014. A framework for evaluating ecosystem services provided by cover crops in agroecosystems. *Agric. Syst.* 125, 12–22.

Schneider, M.; Andres, C.; Trujillo, G.; Alcon, F.; Amurrio, P.; Perez, E.; Weibel, F.; Milz, J., 2017. Cocoa and total system yields of organic and conventional agroforestry vs. monoculture systems in a long-term field trial in Bolivia. *Exp. Agric.* 53, 351–374.

Schroth, G.; Harvey, C.A.; da Fonseca, G.A.B.; Gascon, C.; Vasconcelos, H.L.; Izac, A.-M.N., 2004. Agroforestry and biodiversity conservation in tropical landscapes. Island Press, Washington, Covelo, London.

Schulze, C.H.; Linsenmair, K.E.; Fiedler, K., 2001. Understorey versus canopy: patterns of vertical stratification and diversity among Lepidoptera in a Bornean rain forest, in: Plant Ecology. pp. 133–152.

Shafri, H.Z.M.; Hamdan, N.; Saripan, M.I., 2011. Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery. *Int. J. Remote Sens.* 32, 2095–2115.

Shanmugam, R.T.; Babu, S.C., 2017. Incorporating social and sustainability aspects into economics of agroforestry: a case study from South India. *J. Sustain. Dev.* 1, 20–31.

Shimano, K., 1997. Analysis of the relationship between DBH and crown projection area using a new model. *J. For. Res.* 2, 237–242.

Silvertown, J., 2015. Have ecosystem services been oversold? *Trends Ecol. Evol.* 30, 641–648.

Tacconi, L., 2016. Preventing fires and haze in Southeast Asia. *Nat. Clim. Chang.* 6, 640–643.

Teuscher, M.; Gérard, A.; Brose, U.; Buchori, D.; Clough, Y.; Ehbrecht, M.; Hölscher, D.; Irawan, B.; Sundawati, L.; Wollni, M.; Kreft, H., 2016. Experimental biodiversity enrichment in oil-palm-dominated landscapes in Indonesia. *Front. Plant Sci.* 07, 1–15.

Teuscher, M.; Vorlaufer, M.; Wollni, M.; Brose, U.; Mulyani, Y.; Clough, Y., 2015. Trade-offs between bird diversity and abundance, yields and revenue in smallholder oil palm plantations in Sumatra, Indonesia. *Biol. Conserv.* 186, 306–318.

Tscharntke, T.; Clough, Y.; Bhagwat, S.A.; Buchori, D.; Faust, H.; Hertel, D.; Hölscher, D.; Juhrbandt, J.; Kessler, M.; Perfecto, I.; Scherber, C.; Schroth, G.; Veldkamp, E.; Wanger, T.C., 2011. Multifunctional shade-tree management in tropical agroforestry landscapes - A review. *J. Appl. Ecol.* 48, 619–629.

Van Kraalingen, D.W.G.; Breure, C.J.; Spitters, C.J.T., 1989. Simulation of oil palm growth and yield. *Agric. For. Meteorol.* 46, 227–244.

Verma, N.K.; Lamb, D.W.; Reid, N.; Wilson, B., 2014. An allometric model for estimating DBH of isolated and clustered Eucalyptus trees from measurements of crown projection area. *For. Ecol. Manage.* 326, 125–132.

Wickham, H.; Chang, W., 2016. ggplot2: create elegant data visualisations using the grammar of graphics. URL https://cran.r-project.org/package=ggplot2

Woittiez, L.S.; van Wijk, M.T.; Slingerland, M.; van Noordwijk, M.; Giller, K.E., 2017. Yield gaps in oil palm: A quantitative review of contributing factors. *Eur. J. Agron.* 83, 57–77.

Yue, S.; Brodie, J.F.; Zipkin, E.F.; Bernard, H., 2015. Oil palm plantations fail to support mammal diversity. *Ecol. Appl.* 25, 2285–2292.

Annex

Annex 1 (plantation manager interview)

Interviewer: Hendrik Lorenz (B11)
Interviewee: Hasbiuan (Plantation manager PT. Humusindo
Translator: CRC assistant Irham
Location: PT Humusindo office
Time: 14:00-15:45
Date: 24.03.2018

- Oil palm yield determining factors
  - Age
    - Most productive ages: years 5-12
    - Palm productivity peaks in year 8
    - Cutting and replanting after 25 years
    - Plantations with rotation > 30 years are normally non-commercial/non-company owned because economically not optimal
  - Leaf cutting
    - Pruning only to make harvest easier
    - Pruning every 8 months
    - Target number of leaves per palm: 42-44
    - Further pruning reduces yield (less leaves, less photosynthesis)
  - Cattle
    - Cattle is brought by workers and weeding is allowed in the whole plantation ('natural process')
    - Cattle supposedly increases productivity (free fertilizer); But same amount of fertilizer is applied in areas with much cattle
  - Genetic quality
    - Seedlings came from own nursery
    - The variety used is called *tenera* and obtained by crossing *dura* and *pisifera*
    - Around 10% of the progenies will be undesired *dura* or *pisifera* types and should be removed during three selection steps in nursery
    - Sometimes these undesired varieties find their way into the plantation
  - Planting density/light competition
    - Leaf competition (dense planting) increases height growth (undesirable because it makes harvesting more expensive)
    - Planting distance in Humusindo: 9.8 * 9.8 * 9.8 m (triangle)
    - 120 trees ha^{-1}. Following PTPN's recommendation for *tenera* seedlings
    - Normal planting density in other plantations is 130 trees ha^{-1}
  - Bark loss
    - No impact on yield and is no problem.
  - Epiphytes on the palm stem
    - Do not damage the stem; no parasites
    - They host ants which help to reduce the population of leaf-damaging caterpillars
  - Pests/diseases
    - Leaf damaging caterpillar 'ulat ati' was a big problem in 2001
      - 1st try: manually collect caterpillars from the palms
      - 2nd try: introduce natural predators (ants)
      - 3rd try: fogging of palm crowns (water plus insecticide)
      - Today: only few caterpillars per plot
      - no intention to eradicate caterpillars: They become butterflies and help to pollinate the palms
    - Now: biggest problem are rats that eat the fruits
      - Two times per year: systematic rat poisoning

            - No intention to eradicate rats (important to maintain ecological equilibrium/food chain)
        - Ganoderma fungus (no big problem)
    - Fertilization
        - Fertilization according to schedule with different treatments (Urea, inorganic fertilizer, …), in general: every month
        - Sometimes, fertilizer is not available in the store. Then it will be delayed.
        - Too much fertilization can make the fruit fall down before it is ripe.
    - Weeding around palm stems
        - Only to 'control' fertilizer and to mark palms which have already been fertilized
    - Precipitation/drought/ENSO
        - Rain is important for oil palm. In general: More rain, more fruit
        - Too much rain can reduce yield because of limited pollination
        - Drought does not damage the palms but reduces yield in the following year (this year's yield is determined by last year's climate)
        - Last drought in Humusindo was in 2015
    - Optimal location, flooding and slope
        - Highest yield if plants are flooded regularly but only 1-3 days (more weight per bunch)
        - Longer flooding reduces height growth and reduces yield
        - Only in swampy areas, palms are planted on small plateaus to avoid long-term flooding
        - Pak Hasbi does not know how yield changes along a slope
    - Pollination
        - Best pollinators: bees (but have been declining in recent years)
        - Also butterflies
- Individuals with zero yield in the plantation
    - Some individuals are of undesired variety *tenera* or *dura*
    - If the amount of these individuals exceeds 1ha^{-1} they are managed (cut)
    - Other individuals go through a 'trek period', a phase of zero yield. Usually 3 months; 5 months trek period is impossible
- Yield per plant
    - 8 fruits year^{-1} palm^{-1} (no difference between in-plot and outside)
    - 152 kg tree^{-1} year^{-1} average
    - 1.5 t ha^{-1} month^{-1} average
- Harvesting cost
    - Only more expensive if palms too high
    - Not more expensive in slopes
- Yield, price and quality
    - No higher prices for different fruit qualities
    - Low-quality fruits (under- or over-mature) will be rejected by the factory
    - Price changes daily/weekly; no agreed-upon fixed price
    - Fruits are sorted in Humusindo before taken to the factory
    - (from different source): current price per kg delivered to the factory around 1.700 Rupiah
- Plantation data
    - Plantation area Humusindo: 500 ha
    - 130 workers (including harvesters, drivers, operators, …)
    - Workers exclusively from Indonesia
- Other
    - All plots in Humusindo: Mostly planted at the same time
    - In whole plantation: Planting year 2004 is right now the most productive plant generation
    - Bigger companies obtain higher yields per palm because of scientific optimization
- Pak Hasbi's whishes towards science
    - Pak Hasbi is concerned that higher planting distances may reduce overall yield but would be grateful if someone could find out the optimal distance
    - How to make oil palms productive beyond the optimal age?
    - How to reduce the height-growth of the palms to decrease harvesting cost?
    - Also interest in trees: Can trees be planted without reducing the yield?

Annex 2 (composition of plots and samples)

Table 5. Properties of diversity enriched plots. Listed are all 31 plots from the EFForTS-BEE experiment, which host at least one palm within their boundaries. 'petai' = *Parkia speciosa*; 'jenkol' = *Archidendron pauciflorum*; 'durian' = *Durio zibethinus*; 'jelutung' = *Dyera polyphylla*; 'sungkai' = *Peronema canescens*; 'meranti' = *Shorea leprosula.*

	Edge length (m)	Number of palms	Palm thinning (%)	Palm yield (kg FFB year^{-1})	Plot ID	Planted tree species
0 SP.	10	1	50	113	37	-
	20	1	75	251	10	-
	40	16	30	297	35	-
1 SPECIES	10	1	50	348	20	jenkol
	20	2	50	259	12	durian
	20	2	50	236	15	jenkol
	20	2	60	222	17	meranti
	20	2	50	198	30	sungkai
	20	3	50	242	38	jelutung
	20	3	40	205	51	petai
	40	13	35	215	1	petai
	40	12	40	269	5	jenkol
	40	11	42	250	43	durian
	40	14	30	181	45	sungkai
	40	15	32	219	49	meranti
	40	13	38	272	52	jelutung
2 SPECIES	10	1	50	194	32	durian, meranti
	10	1	50	144	34	jenkol, jelutung
	20	2	60	253	3	durian, jelutung
	20	1	67	241	36	petai, meranti
	20	5	29	197	47	jenkol, sungkai
	40	11	42	239	24	durian, sungkai
	40	12	29	243	26	jelutung, meranti
	40	17	32	185	46	petai, jenkol
3 SPECIES	10	1	50	187	9	petai, jenkol, jelutung
	20	1	75	172	2	petai, durian, meranti
	20	4	43	215	33	jenkol, jelutung, sungkai
	40	11	42	173	7	petai, sungkai, meranti
	40	20	29	196	29	jenkol,durian, jelutung
6 SP.	20	3	40	185	19	petai, jenkol, durian, jelutung, sungkai, meranti
	40	15	35	173	23	petai, jenkol, durian, jelutung, sungkai, meranti

Table 6. List of palms included in the stratified subsample of inside-plot palms. The sample includes (a) 15 palms randomly drawn from the group of palms with zero recorded yield (sum of yields during the reference period Oct. 2017-Feb. 2018 which represented the present period of non-interrupted yield at the time of sampling), (b) the 15 palms with highest yield, and (c) 20 randomly drawn palms from the palms not included in (a) or (b) and yield not zero.

Sample stratum	n	Included palms and plots ('P')
(a) Zero yield	15	7004 (P1); 7007 (P1); 7030 (P7); 7044 (P15); 7076 (P26); 7081 (P26); 7091 (P29); 7098 (P29); 7102 (P29); 7175 (P46); 7178 (P46); 7179 (P47); 7193 (P49); 7197 (P49); 7209 (P52)
(b) Highest yield	15	7040 (P9); 7041 (P10); 7066 (P24); 7071 (P24); 7080 (P26); 7084 (P26); 7089 (P29); 7121 (P35); 7124 (P35); 7141 (P43); 7146 (P43); 7190 (P49); 7191 (P49); 7200 (P51); 7203 (P52)
(c) Random (non-zero)	20	7018 (P5); 7022 (P5); 7025 (P5); 7064 (P24); 7065 (P24); 7078 (P26); 7085 (P26); 7086 (P26); 7100 (P29); 7104 (P29); 7108 (P30); 7120 (P35); 7131 (P35); 7155 (P45); 7159 (P45); 7182 (P47); 7183 (P47); 7205 (P52); 7213 (P52); 7214 (P52)

Annex 3 (methodology supplements)

Table 7. Utility analysis for the selection of a plot for detailed tree crown analysis. Examined were all big plots (40m x 40m). To increase the explaining capability of the intended crown competition measurements, the set of favorable criteria was composed of different quantitative criteria related to palm abundance and yield (expressed as kg $palm^{-1}$ $year^{-1}$, including data between Jan. 2017 and Feb. 2018; columns 5-7) and qualitative observations on the growth and distribution of trees and topography. Ranks were built for the quantitative criteria and averaged with equal weights. The analysis led to the selection of Plot 29, ranking first in the quantitative part and showing good conditions in the field. Field observations were made in March 2018. 'n' = quantity; 'sd' = standard deviation.

Plot ID	Palm yield	n tree species (rank)	n palms (rank)	Yield range (rank)	Yield sd (rank)	Mean rank (rank)	Qualitative field observations
29	151	3 (2)	20 (1)	370 (1)	97 (1)	**1.3 (1)**	few but dominant trees, steady slope but small river in plot
26	203	2 (3)	12 (8)	309 (2)	82 (3)	**4.0 (2)**	not enough trees, mainly shrubs
49	121	1 (4)	15 (4)	252 (5)	79 (4)	**4.3 (3)**	very few and small trees; different crown shapes
52	118	1 (4)	13 (6)	272 (3)	78 (6)	**4.8 (4)**	not many trees most of which are small; steady slope
43	204	1 (4)	11 (11)	262 (4)	90 (2)	**5.3 (5)**	topography very heterogeneous. Few dominant trees; many small
35	209	0 (5)	17 (2)	228 (8)	67 (10)	**6.3 (6)**	no species planted; mainly bushes
1	114	1 (4)	13 (7)	218 (9)	78 (5)	**6.3 (6)**	too much bamboo and other non-tree interfering plants
46	106	2 (3)	17 (3)	205 (10)	57 (11)	**6.8 (7)**	few trees and many oil palms without tree crown interference
24	164	2 (3)	11 (12)	248 (6)	77 (7)	**7.0 (8)**	many dominant trees, but conditions in each palm too similar
5	169	1 (4)	12 (9)	241 (7)	75 (8)	**7.0 (8)**	too many trees, equal shape and distribution too similar among palms
45	129	1 (4)	14 (5)	186 (12)	71 (9)	**7.5 (9)**	few trees reaching palm canopy; flat terrain; homogeneous topography
23	132	6 (1)	12 (10)	165 (13)	41 (13)	**9.3 (10)**	many and big trees with favorable distribution across plot
7	133	3 (2)	11 (13)	197 (11)	55 (12)	**9.5 (11)**	many trees at mainly low height; many shrubs

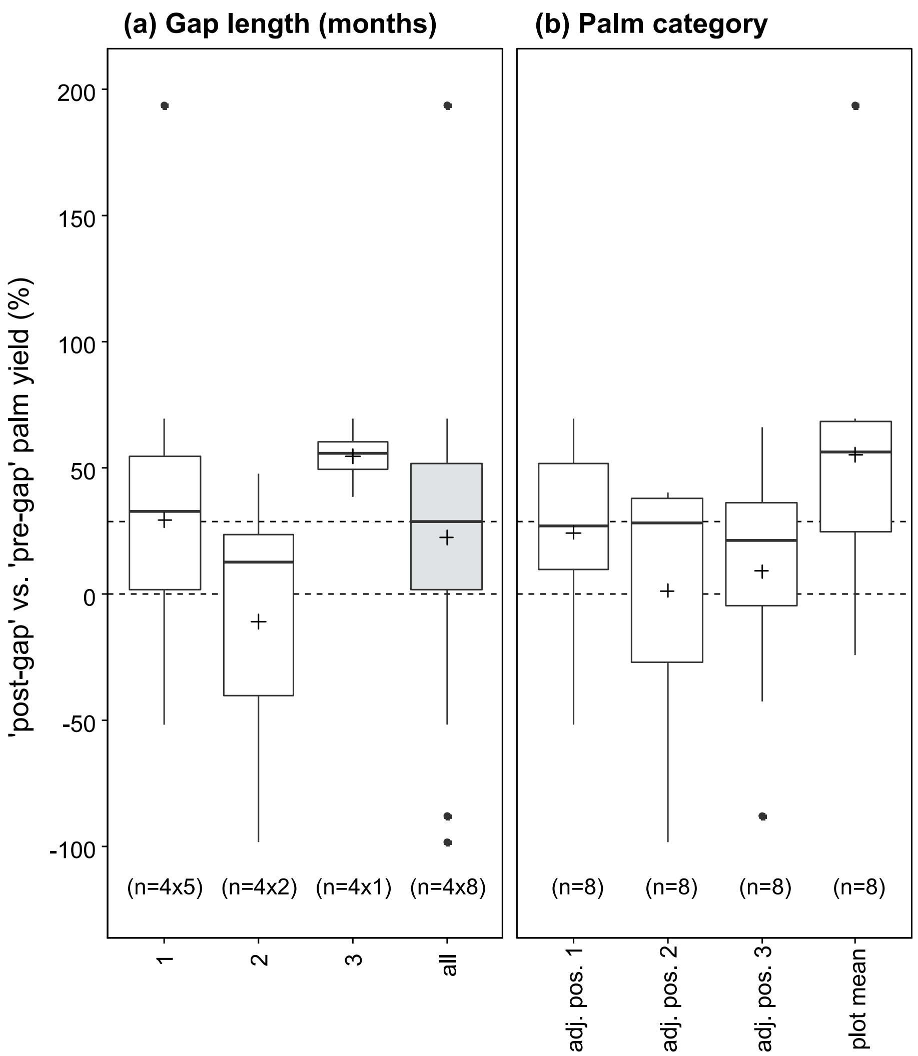

Figure 6. Boxplot of oil palm yield before and after harvest suspension. The plots compare monthly fresh fruit bunch (FFB) yield after harvest suspension (‘post-gap’) with the latest yield value before suspension (‘pre-gap’), which itself was not a post-gap value of a previous suspension. The index (vertical axis) is calculated as ‘post-gap’ minus ‘pre-gap’ divided by ‘post-gap’. Horizontal bar = median; '+' = mean; horizontal lines: below = no change (0 %); above = median of all palm groups (shaded box) over all gap sizes (= 28.72 %), by which all ‘post-gap’ observations were actually reduced in all analyses of all palm categories (including control palms) throughout the paper. In brackets: number of observations ((a): one observation per each of the four palm categories times 5, 2 and 1 observations per gap size of 1, 2 and 3 months, respectively; (b): one observation per gap.

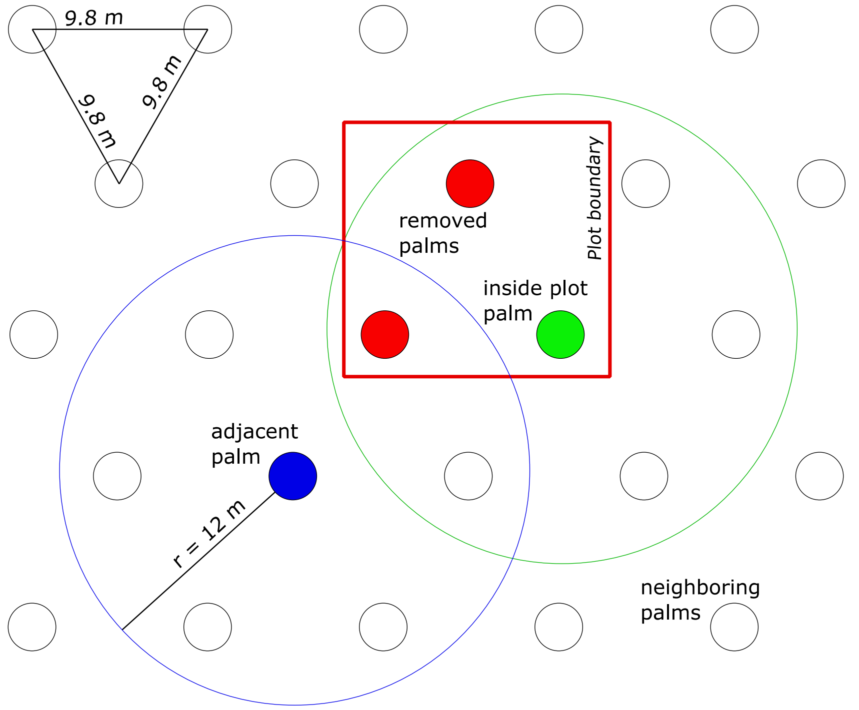

Figure 7. Sketch of the method to estimate the reference area for oil palm yield expansion.

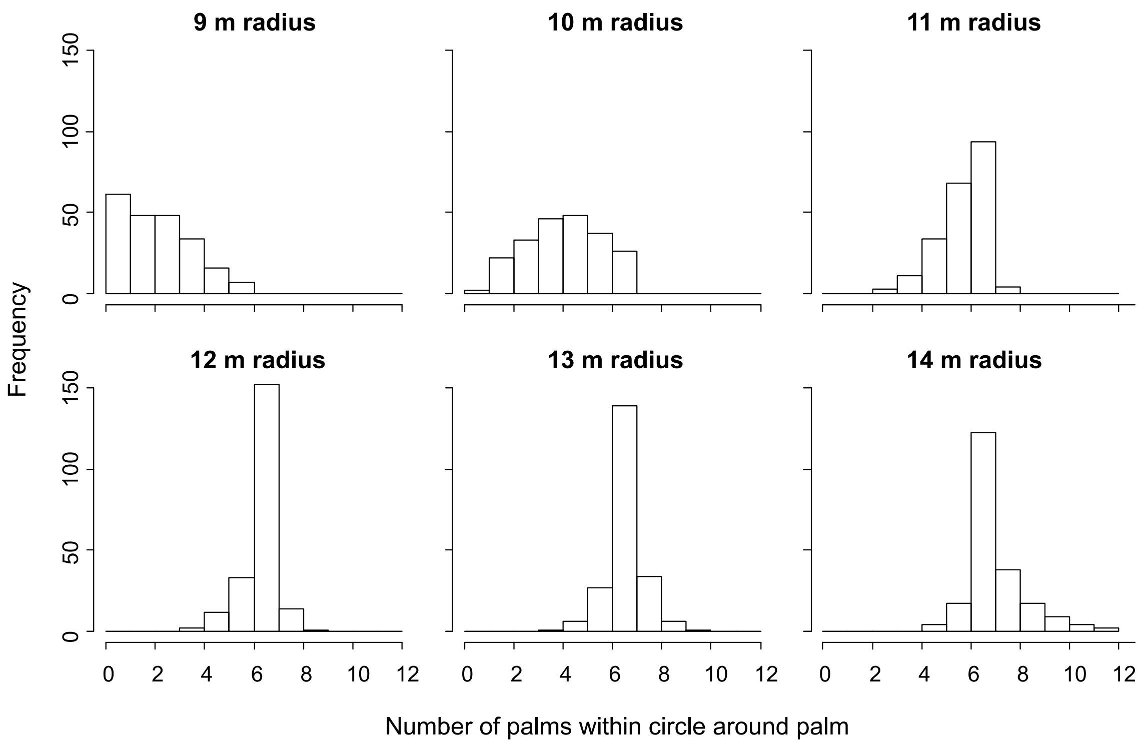

Figure 8. Histograms of palms within circles around inside plot palms. The histogram shows the number of palms prior to thinning within circles of different sizes, including the center palm. If planting density (9.8 m x 9.8 m to all six neighboring palms) was as planned, exactly seven palms would be within the circles of all presented histograms. Errors from measurement, planting and modelling, however, cause a deviation from the plan. The optimal radius is r = 12 m because it shows the highest frequency for the intended number of seven palms.

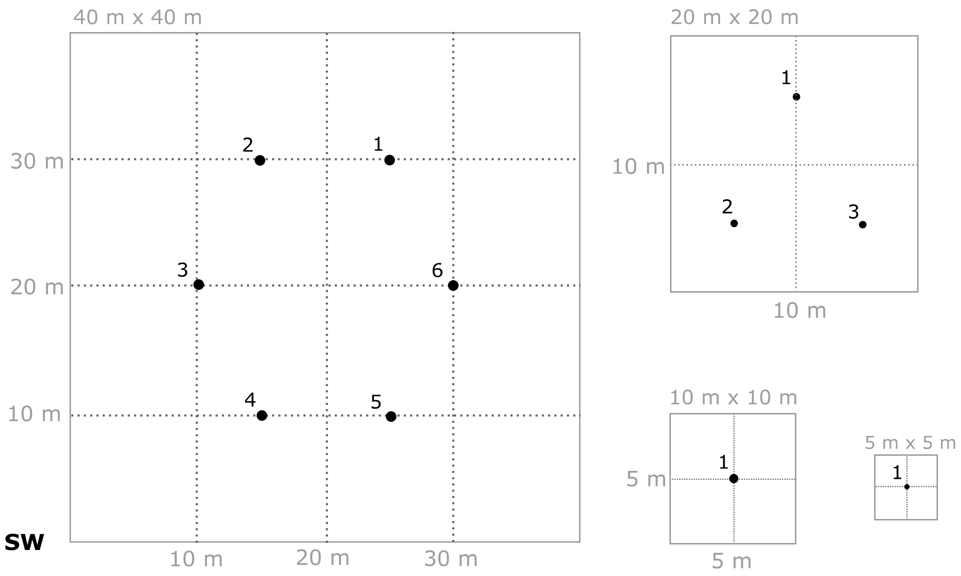

Figure 9. Design of hemispherical photos for different plot sizes. Gap fractions are averaged across the different positions per plot. Design adopted from Gerard et al. (2016).

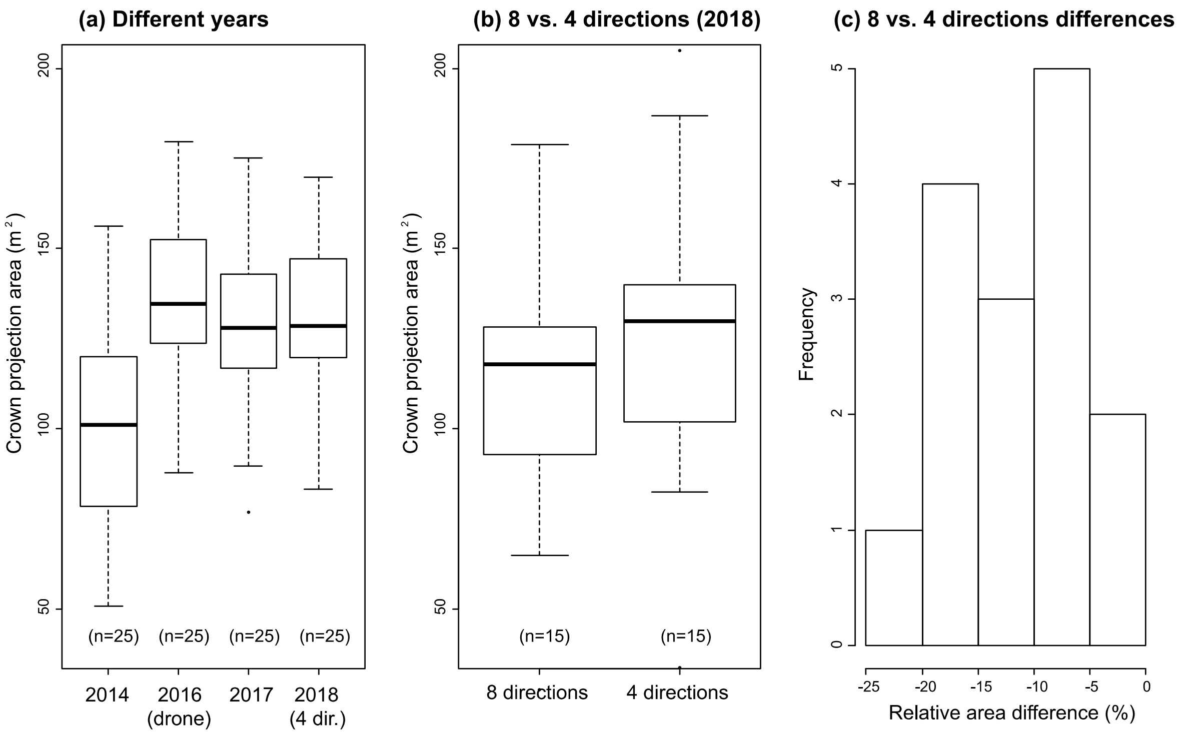

Figure 10. Comparison of different palm crown area measurements and methods. (a) shows crown projection area estimates for measurements of different years, where 2014, 2017 and 2018 were measured from the ground and 2016 derived manually from drone images. **(b)** compares two different measurements along 8 directions (4 axes: N-S, E-W, NE-SW, NW-SE) vs. 4 directions (2 axes: N-S, E-W). **(c)** is a histogram of the relative difference of the two methods in (b), calculated as (8 dir. - 4 dir.)/ 4 dir. All areas were calculated via the quadratic mean formula (Pretzsch et al., 2015). Palms represent a sub-sample of inside-plot palms. All Measurements within (a) and (b and c) were done on the same set of palms. Bars inside the boxes show the median. 'n'-values in round brackets give the number of observations (= measured palms).

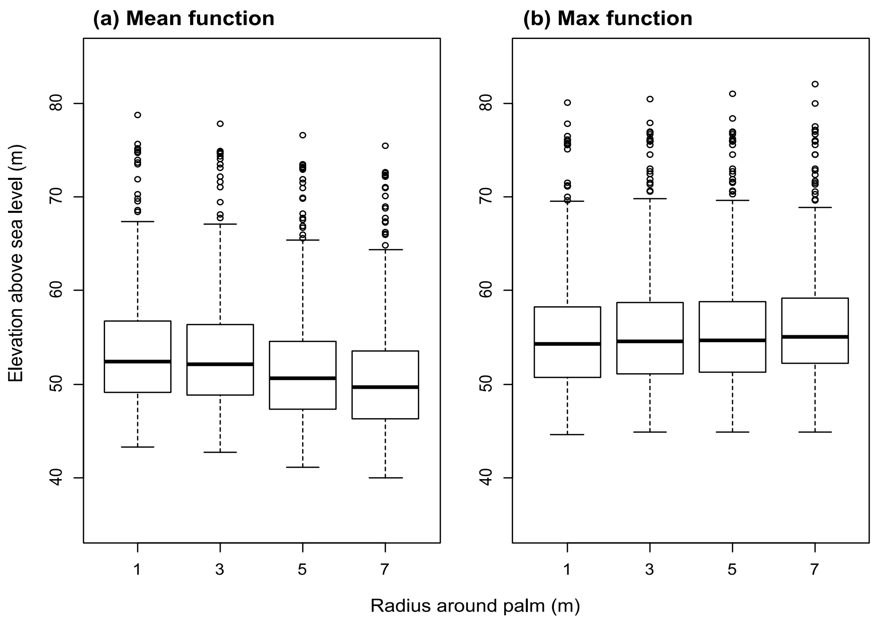

Figure 11. Comparison of different elevation values extracted from the DEM. The plots show values extracted from a digital elevation model (DEM) within circles of different size around the palm positions. Observations denote all inside-plot palms with defined raster values (n = 213). **(a)** is computed from a mean of all raster values within the circle and **(b)** from the highest pixel values. Bars inside the boxes show the median. Source of the DEM: Khokthong, unpublished. DEM spatial resolution = 0.02 m. Bars inside the boxes show the median.

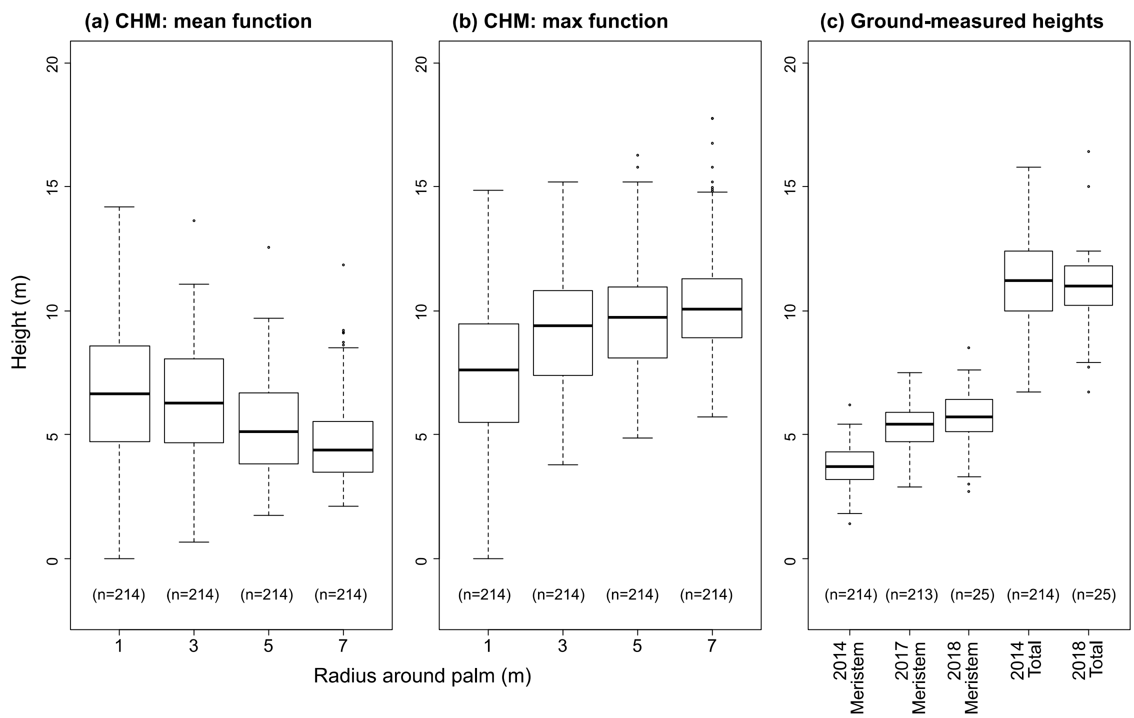

Figure 12. Comparison of different drone and ground-measured palm height values. (a) and **(b)** show canopy height values extracted from a drone-based canopy height model (CHM) recorded in 2016. Pixel values were extracted from within circles of differing radius around the palm positions. **(c)** Compares ground-measured meristem and total height values from different years, including all available measurements. All observations are from inside-plot palms. Source of the CHM: Khokthong, unpublished. CHM spatial resolution = 1 m. Bars inside the boxes show the median.

Annex 4 (additional results)

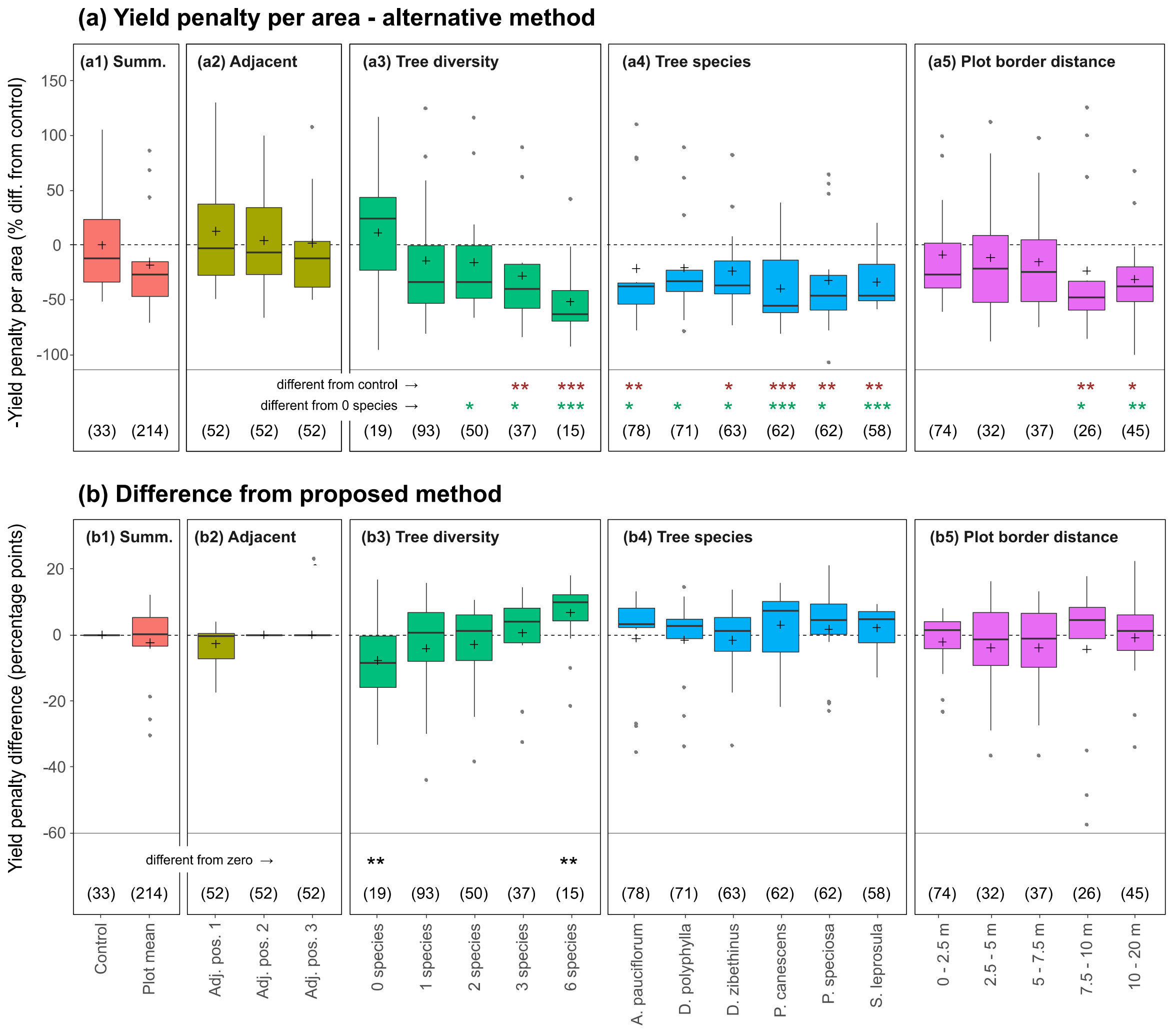

Figure 13. Alternative estimation method of yield penalty per area. The method subtracts plantation average yield to account for removed palms in the surroundings of palms influenced by thinning (adapted from Gérard et al., 2017). Thereby, it represents an alternative to the method applied throughout the other analyses presented in this paper. One observation relates to one month of yield averaged within the respective palm category over the past 1.5 years (Jan. 2017 - June 2018). Negative values in **(a)** denote yield penalties; **(b)** is the difference between both methods, computed as the 'usual approach' minus (a). Positive values in (b) show that the estimate for yield per area in (a) is lower. The control used to compute percentual differences in (b) was computed as a mean over the past 1.5 years (Jan. 2017 - June 2018). The same control values were subtracted to compensate removed palms. 'Adj. pos' = position index of adjacent-to-plot palms. 'FFB' = fresh fruit bunch. Horizontal bar = median; '+' = mean. Dashed horizontal line = mean of control palms. '*' (a) top row: One-sample Mann-Whitney test; '*' (a) bottom row: Mann-Whitney test for difference from zero-species plots. '*' (b): one-sample Mann-Whitney test. Bracketed values: number of palms involved in the monthly means. Significance levels are indicated by * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

Table 8. Results of linear regressions on palm level of control palms. Adjusted R^2, p-values and coefficients ('coef.') are presented for single linear regressions on palm level between a yield mean (past year or past 1.5 years) as dependent variable, and one of the independent predictors (a-k). One yield observation is the mean of 9 (past year) and 18 (past 1.5 years) valid monthly observations with max. three months subsequent gaps. 'Past year' = July 2017-June 2018; 'Past 1.5 years' = Jan. 2017-June 2018; 'sd' = standard deviation; 'se%' = relative standard error of the mean. Significance indicated by * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

	INDEPENDENT VARIABLE		DESCRIPTIVE STATISTICS			REGRESSION RESULTS			
						Past year		Past 1.5 years	
	Name and year of measurement	Unit	n	mean ± sd	se%	R^2	Coef.	R^2	Coef.
PALM MORPHOLOGY	(a) Total height (2018)	(m)	32	11.9 ± 1.5	2.27	0.06	-17.2	0.10*	-15.1
	(b) Meristem height (2018)	(m)	32	5.2 ± 0.9	2.88	0.00	4.5	0.02	-13.6
	(c) Total height (2016)	(m)	33	14.4 ± 3.2	3.81	0.04	7.4	0.01	2.8
	(d) Meristem height (2016)	(m)	33	5.0 ± 0.7	2.59	0.01	17.1	0.01	-9.8
	(e) Elliptic crown projection area (2018)	(m^2)	33	129.7 ± 22.2	2.98	0.01	-0.5	0.01	-0.3
	(f) Crown projection radius (2018)	(m)	33	6.4 ± 0.5	1.40	0.01	-25.4	0.01	-13.3
	(g) Basal area (2018)	(m^2)	33	0.5 ± 0.1	4.35	0.10*	379.1	0.10*	255.9
COMPETI-TION	(h) Absolute crown overlap (2018)	(m^2)	32	123.5 ± 83.1	11.89	0.02	-0.2	0.07	-0.2
	(i) Relative crown overlap (2018)	(%)	32	1.0 ± 0.7	12.63	0.01	-19.3	0.07	-28.4
SLOPE & EPI-	(j) Epiphyte cover along stem (2018)	(%)	32	32.7 ± 26.3	14.21	0.02	0.5	0.00	0.1
	(k) Slope 2 m around palm (2018)	(%)	32	13.1 ± 12.0	16.30	0.01	1.0	0.00	0.1

Table 9. Results of linear regressions on palm level of Plot 29. Adjusted R^2, p-values and coefficients ('coef.') are presented for single linear regressions on palm level between a yield mean (past year or past 1.5 years) as dependent variable and one of the independent predictors. One yield observation is the mean of 9 (past year) and 18 (past 1.5 years) valid monthly observations with max. three months subsequent gaps. 'Past year' = July 2017-June 2018; 'Past 1.5 years' = Jan. 2017-June 2018; 'sd' = standard deviation. Significance levels are indicated by * (p < 0.1), ** (p < 0.05), *** (p < 0.01).

	INDEPENDENT VARIABLE		DESCRIPTIVE STATISTICS	REGRESSION RESULTS			
				Past year		Past 1.5 years	
	Name	Unit	Mean ± sd	R^2	Coef.	R^2	Coef.
PALM COMPET.	Elevation-weighted absolute crown overlap	(m^2)	59.5 ± 43.7	0.00	0.1	0.00	0.1
	Elevation-weighted relative crown overlap	(%)	0.4 ± 0.3	0.00	2.3	0.00	11.0
PALM CROWN PROJECTION	Elliptic crown area (drone-based, 2016)	(m^2)	139.0 ± 20.0	0.09	2.1	0.16*	1.9
	Elliptic crown area (ground-based, 2017)	(m^2)	128.5 ± 19.5	0.01	0.8	0.06	1.2
	Elliptic crown area (ground-based, 2018)	(m^2)	132.9 ± 21.8	0.06	1.5	0.13	1.5
	Crown radius (drone-based, 2016)	(m)	6.6 ± 0.5	0.10	89.6	0.17*	79.6
	Crown radius (ground-based, 2017)	(m)	6.4 ± 0.5	0.01	32.8	0.06	47.5
	Crown radius (ground-based, 2018)	(m)	6.5 ± 0.5	0.06	61.6	0.13	61.9
HEIGHT VARIABLES	Meristem height (2017)	(m)	5.5 ± 0.9	0.13	53.9	0.23**	47.7
	Meristem height (2018)	(m)	5.5 ± 1.5	0.27**	47.3	0.28**	32.0
	Total height (drone, 2016)	(m)	8.8 ± 2.5	0.00	-2.7	0.00	-0.3
	Total height (2018)	(m)	10.3 ± 1.5	0.27**	48.3	0.33***	36.1
SITE & EP.	Epiphyte cover (meristem)	(%)	27.6 ± 28.8	0.00	0.0	0.03	0.5
	Slope, r=2m around palm	(%)	9.5 ± 5.4	0.12	8.3	0.18*	6.7
TREE VARIABLES: AGGREGATED IN CIRCLE AROUND PALM	Tree abundance (r=4m)	-	4.0 ± 1.8	0.13	-27.7	0.09	-15.0
	Tree abundance (r=6m)	-	10.1 ± 3.1	0.05	-10.3	0.03	-5.1
	Tree abundance (r=8m)	-	17.9 ± 5.8	0.13	-8.5	0.07	-4.3
	Tree abundance (r=10m)	-	25.9 ± 8.0	0.17*	-7.1	0.10	-3.6
	Tree basal area (r=4m)	(m^2)	27.8 ± 33.8	0.13	-1.5	0.07	-0.7
	Tree basal area (r=6m)	(m^2)	85.2 ± 56.4	0.17*	-1.0	0.20**	-0.7
	Tree basal area (r=8m)	(m^2)	213.3 ± 125.4	0.10	-0.3	0.06	-0.2
	Tree basal area (r=10m)	(m^2)	347.7 ± 186.3	0.17*	-0.3	0.08	-0.1
	Tree stem volume (r=4m)	(m^3)	22.9 ± 25.0	0.14	-2.0	0.08	-1.0
	Tree stem volume (r=6m)	(m^3)	62.1 ± 37.5	0.18*	-1.6	0.20**	-1.1
	Tree stem volume (r=8m)	(m^3)	142.8 ± 77.4	0.11	-0.6	0.06	-0.3
	Tree stem volume (r=10m)	(m^3)	230.8 ± 121.3	0.16*	-0.5	0.08	-0.2
TREE CROWN OVERLAP	Absolute overlap	(m^2)	17.4 ± 10.3	0.30**	-7.3	0.18*	-3.9
	Relative overlap	(%)	13.5 ± 8.7	0.34***	-9.2	0.26**	-5.4
	Crown intensity-weighted absolute overlap	(m^2)	9.0 ± 8.3	0.08	-4.6	0.06	-2.7
	Crown intensity-weighted relative overlap	(%)	7.1 ± 7.0	0.12	-6.9	0.11	-4.3

Table 10. Additional results of linear regressions on palm level (inside-plot). Adjusted R^2, p-values and coefficients ('coef.') are presented for single linear regressions on palm level between a yield mean (past year or past 1.5 years) as dependent variable, and one of the independent predictors. One yield observation is the mean of 9 (past year) and 18 (past 1.5 years) valid monthly observations with max. 3 months subsequent gaps. 'Past year' = July 2017-June 2018; 'Past 1.5 years' = Jan. 2017-June 2018; 'sd' = standard deviation; 'n' = number of observations 'CHM' = canopy height model. Significance levels are indicated by * ($p < 0.1$), **($p < 0.05$), *** ($p < 0.01$).

	INDEPENDENT VARIABLE		**DESCRIPTIVE STATISTICS**		**REGRESSION RESULTS**			
					Past year		**Past 1.5 years**	
	Name	**Unit**	**n**	**Mean ± sd**	**R^2**	**Coef.**	**R^2**	**Coef.**
PALM CROWN PROJECTION	Elliptic crown area (drone-based, 2016)	(m^2)	214	120.81 ± 22.41	0.06***	1.1	0.10***	0.9
	Elliptic crown area (ground-based, 2017)	(m^2)	214	109.49 ±20.16	0.06***	1.3	0.11***	1.1
	Crown radius (drone-based, 2016)	(m)	214	6.17 ± 0.57	0.06***	45.4	0.11***	36.5
	Crown radius (ground-based, 2017)	(m)	214	5.89 ± 0.54	0.06***	51.9	0.12***	43.5
PALM HEIGHT (DRONE, 2016)	CHM (max within r=1m)	(m)	213	7.46 ± 2.59	0.03	5.0	0.05	2.6
	CHM (max within r=3m)	(m)	214	9.17 ± 2.27	0.03	7.1	0.07*	6.1
	CHM (max within r=5m)	(m)	214	9.69 ± 2.18	0.04*	11.0	0.08**	9.2
	CHM (mean within r=1m)	(m)	213	6.66 ± 2.49	0.04*	7.7	0.06	3.9
	CHM (mean within r=3m)	(m)	214	6.36 ± 2.07	0.05**	12.7	0.07*	7.1
	CHM (mean within r=5m)	(m)	214	5.33 ± 1.81	0.06***	19.5	0.09***	12.6
NUMBER OF PALMS WITHIN CIRCLE AROUND PALM	Number of palms (r=4m)	-	214	0.00 ± 0.07	0.05**	268.9	0.07**	165.6
	Number of palms (r=6m)	-	214	0.01 ± 0.12	0.03	57.9	0.06	49.5
	Number of palms (r=8m)	-	214	0.32 ± 0.65	0.03	-28.2	0.06	-15.1
	Number of palms (r=10m)	-	214	2.20 ± 1.32	0.02	3.7	0.05	0.5
	Number of palms (r=12m)	-	214	3.88 ± 0.98	0.02	-6.4	0.06	-10.1
	Number of palms (r=14m)	-	214	4.49 ± 1.31	0.07***	-27.9	0.09***	-17.0
	Number of palms touching the crown	-	214	2.60 ± 1.46	0.03	6.4	0.05	0.2
TREE VARIABLES: AGGREGATED IN CIRCLE AROUND PALM	Number of trees (r=4m)	-	214	4.62 ± 3.93	0.02	1.6	0.05	1.6
	Number of trees (r=6m)	-	214	10.51 ± 8.35	0.03	2.1	0.06	1.6
	Number of trees (r=8m)	-	214	17.78 ± 14.15	0.03	1.4	0.05	0.8
	Number of trees (r=10m)	-	214	26.24 ± 20.83	0.02	0.7	0.05	0.4
	Number of trees (r=12m)	-	214	35.57 ± 28.36	0.02	0.6	0.05	0.2
	Number of trees (r=14m)	-	214	45.57 ± 36.61	0.02	0.3	0.05	0.1
	Tree basal area (r=4m)	(m^2)	214	0.01 ± 0.01	0.02	-98.5	0.05	380.8
	Tree basal area (r=6m)	(m^2)	214	0.02 ± 0.02	0.03	-997.8	0.06	-606.6
	Tree basal area (r=8m)	(m^2)	214	0.04 ± 0.04	0.02	-264.1	0.05	-129.4
	Tree basal area (r=10m)	(m^2)	214	0.06 ± 0.06	0.03	-311.1	0.05	-137.3
	Tree basal area (r=12m)	(m^2)	214	0.09 ± 0.12	0.03	-106.8	0.06	-70.1
	Tree basal area (r=14m)	(m^2)	214	0.11 ± 0.14	0.03	-82.0	0.06	-59.7
	Tree stem volume (r=4m)	(m^3)	214	0.02 ± 0.03	0.02	-37.0	0.05	119.0
	Tree stem volume (r=6m)	(m^3)	214	0.07 ± 0.09	0.03	-232.4	0.06	-129.2
	Tree stem volume (r=8m)	(m^3)	214	0.14 ± 0.17	0.03	-65.2	0.05	-20.4
	Tree stem volume (r=10m)	(m^3)	214	0.23 ± 0.27	0.03	-82.6	0.05	-30.3
	Tree stem volume (r=12m)	(m^3)	214	0.36 ± 0.52	0.03	-28.4	0.06	-16.9
	Tree stem volume (r=14m)	(m^3)	214	0.46 ± 0.62	0.03	-23.0	0.06	-14.5

Table 11. Results of mixed-model regressions on palm level (inside-plot). R^2 (R package MuMIn), p-values (R package lmerTest), conditional AIC (R package cAIC4) and coefficients ('coef.') (R package lme4) are presented for mixed regression models between a yield mean per palm (past year or past 1.5 years) as dependent variable, one of the independent predictors, plot ID as random effect with random intercept and by-independent predictor random slope, and a set of control variables entered as fixed effects (plot tree diversity level, minimum distance between palm and fence. The number of palms ('n') differs with sample type ('all'= all inside plot palms from all 31 plots; 'sub' = stratified subsample. Distance ('dist.') to the fence ('-'= no exclusions; '>5'= exclude palms within 5 m fence distance). One yield observation is the mean of 9 (past year) and 18 (past 1.5 years) valid monthly observations with max. three months subsequent gaps. 'Past year' = July 2017-June 2018; 'Past 1.5 years' = Jan. 2017-June 2018; 'sd' = standard deviation. Significance indicated by * (p < 0.1), ** (p < 0.05), *** (p < 0.01).

	INDEPENDENT VARIABLE			DESCRIPTIVE STATISTICS		REGRESSION RESULTS					
						Past year			Past 1.5 years		
	Name	Unit	Sample	n	Mean ± sd	R^2	cAIC	Coef.	R^2	cAIC	Coef.
TREE COMPETITION	Number of trees within 5 m radius	(ha^{-1})	all	214	925.78 ± 754.94	0.04	2672	0.0	0.04	2503	0.0
	Tree basal area within 5 m radius	(m^2 ha^{-1})	all	214	1.40 ± 1.71	0.07**	2656	-14.1	0.07***	2481	-10.8
	Tree stem volume within 5 m radius	(m^3 ha^{-1})	all	214	5.09 ± 7.30	0.07**	2657	-3.1	0.07**	2482	-2.3
PALM MORPHOLOGY	Elliptic palm crown projection area (drone 2016)	(m^2)	all	214	120.81 ± 22.41	0.08***	2652	1.1	0.07**	2476	0.7
	Mean palm crown radius (drone 2016)	(m)	all	214	6.17 ± 0.57	0.09***	2650	47.1	0.08**	2475	27.8
	Meristem height (2017)	(m)	all	213	5.36 ± 0.90	0.06**	2644	23.1	0.06*	2475	15.0
PALM COMPETITION	Absolute crown overlap in palm	(m^2)	all	214	45.20 ± 34.46	0.04	2660	0.5	0.04	2487	0.2
	Weighted relative palm crown overlap	(%)	all	214	24.03 ± 18.15	0.03	2660	-0.1	0.03	2495	-0.2
SITE AND EPIPHYTES	Epiphyte cover along meristem	(%)	sub	50	38.50 ± 27.82	0.03	649	0.5	0.04	603	0.7
	Max. slope 2 m radius around palm	(%)	sub	50	8.47 ± 5.48	0.05	649	3.9	0.03	603	3.1
	Fence distance	(m)	all	214	5.83 ± 4.69	0.04	2663	-0.7	0.03	2487	-0.8

Declaration of authorship

I hereby assure that this thesis was exclusively made by myself and that I have used no other sources and aids then the ones enlisted.

27.10.2018

Hendrik Lorenz