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RESEARCH

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Limited impacts of climatic conditions on commercial oil palm yields in Malaysian plantations

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Abstract

Background: Oil palm is a key driver of deforestation, but increasing yields in existing plantations could help meet rising global demands, while avoiding further conversion of natural habitat. Current oil palm plantations present substantial opportunities for sustainable intensification, but the potential for local yield improvements depends partly on the role of climate in determining yield.

Methods: We determine the importance of local climatic conditions for oil palm yields in 12 commercial plantations in Peninsular and East Malaysia (Borneo), during 2006–2017. We quantify relationships between climatic conditions (raw and anomalised monthly temperature and rainfall data) and yield for lag times up to 36 months prior to harvest, corresponding to key stages in oil palm fruit development.

Results: Overall, climatic conditions explained < 1% of the total variation in yield. In contrast, variation in yield among plantations accounted for > 50% of the explained variation in yield (of total $R^2 = 0.38$; median annual fresh fruit bunch yield 16.4–31.6 t/ha). The main climatic driver of yield was a positive effect of maximum monthly temperature during inflorescence development (Spearman's Rho = 0.30), suggesting that insufficient solar radiation is the main climatic constraint to yield in our study sites. We also found positive impacts of rainfall during key stages of fruit development (infloresence abortion and sex determination: Spearman's Rho 0.06 and 0.08 respectively, for rainfall anomalies), suggesting minor effects of water-limitation on yield; and a negative impact of maximum temperature during the month of harvest (Spearman's Rho – 0.14 for temperature anomalies), suggesting possible heat stress impacts on plantation workers.

Conclusions: Our findings imply a relatively minor role of climate in determining yield, and potentially substantial yield gaps in some commercial plantations in Malaysia (possibly up to ~ 50%). Thus, there appear to be substantial opportunities for improving oil palm yield in existing plantations in Malaysia, with further research needed to identify the drivers of such yield gaps.

Keywords: Oil palm, Sustainable intensification, Climate change, Malaysia, Commercial agriculture, Yield improvement

Background

Oil palm is widely cultivated across the tropics (Descals et al. 2021; Pirker et al. 2016), and the vast majority of oil palm-producing countries are currently expanding their area of oil palm agriculture (FAO, 2020c). The high yield of oil palm compared to other vegetable oil crops (~ sixfold that of rapeseed) can minimise the total land

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area required to produce a given quantity of oil (Jackson et al. 2019; Yan 2017), and results in lower per-tonne-oil impacts on biodiversity than alternative crops (Beyer and Rademacher 2021). Nevertheless, recent increases in total palm oil production have occurred through plantation expansion rather than intensification (Basiron 2007; Carter et al. 2007; de Vries et al. 2010; Jackson et al. 2019; Mohd Basri & Mohd Arif, 2009; Murphy, 2014; Woittiez et al. 2017), driving extensive tropical deforestation, and associated biodiversity loss and greenhouse gas emissions (Carlson et al. 2013; Curtis et al. 2018; Fitzherbert et al. 2008; Gaveau et al. 2014; Vijay et al. 2016). Oil palm thus presents substantial opportunities for the sustainable intensification of vegetable oil production: increasing production while reducing negative environmental impacts, which could help improve food and biofuel provisioning over coming decades (Conijn et al. 2018; McKenzie and Williams 2015; Springmann et al. 2018). Oil palm yield improvements in existing plantations could therefore play an important role in reducing the negative environmental impacts of vegetable oil production, provided they are accompanied by regulation of plantation expansion, increased environmental protection, and a reduction in consumer demand, through measures such as education to improve consumer knowledge (Conijn et al. 2018; Erb et al. 2016; Hunter et al. 2017; Lange and Coremans 2020; Springmann et al. 2018).

To improve oil palm yield where possible, and maintain productivity under climate change (Barros et al. 2014), it is essential that we understand factors determining yield, which primarily comprise climate and management practices (Woittiez et al. 2017). Optimal climatic conditions for oil palm are high temperature and high year-round rainfall (Woittiez et al. 2017), although the precise relationships between climate and yield vary according to the stage of oil palm fruit development, beginning approximately three years prior to harvest (Corley and Tinker 2016, Sects. 5.4.1, 5.5.2). In many areas of Indonesia and Malaysia, which account for over 80% of global palm oil production (FAO 2020a), current climatic conditions are near-optimal for oil palm growth (Corley and Tinker 2016, Sect. 5.5.2; Pirker and Mosnier 2015). In these countries, potential oil palm yield, defined as the maximum possible yield under optimal management (i.e., for given local conditions), is primarily determined by solar radiation, because year-round rainfall is high (Hoffmann et al. 2014; Woittiez et al. 2017), although some studies have also found water availability to be sub-optimal (Chow 1992; Puah and Sidik 2011). The impacts of climate on oil palm yield that have been identified by previous studies, according to the time-lag prior to harvest, are summarized in Table 1. Leading plantation groups in Indonesia and Malaysia have achieved annual fresh fruit bunch (FFB) yields of ~27 t/ha (6 t/ha oil yield) (Donough et al. 2009), although average annual FFB yields for 12 oil palm companies in Malaysia ranged from 16.5 to 25.4 t/ha in 2011, demonstrating substantial variation in yield (ERE Consulting Group and RSPO 2012).

Yield gaps, defined as the difference between actual crop yield and potential yield (Woittiez et al. 2017), are as low as 11% in some commercial plantations in Indonesia and Malaysia, but are generally more substantial (Hoffmann et al. 2017; Woittiez et al. 2017). Management practices to minimise yield gaps of oil palm, by maximising the actual yield, include effective control of weeds, pests and diseases; optimal planting density; effective frond pruning and regular fruit harvesting regimes; and mitigating environmental drivers of yield gaps (e.g., managing nutrient supply through fertilisation) (Woittiez et al. 2017). Oil palm yields also vary among cultivars: clones of high-yielding individuals can produce ~20–30% greater yields than standard cultivars (Kushairi et al. 2010). However, the long crop rotation period of oil palm (25–30 years) means that there are delays in planting new cultivars with improved yield (Woittiez et al. 2017), and national-level yield growth in Indonesia and Malaysia has stagnated in recent years (Hoffmann et al. 2017). Thus, it is essential that we understand the roles of climate and other factors in determining oil palm yield, in order to guide yield improvements.

In this study, we quantify the relative importance of variation among plantations (indicating a role of factors such as soil, cultivar and plantation-level management) and local climatic conditions for determining monthly FFB yields of 83 oil palm fields (median size = 70 ha, range 2.5–159 ha). We were able to obtain data from 12 commercial plantations in Malaysia, which belong to a single company, and we determine the relationships between climatic conditions (monthly temperature and rainfall) and yield. We examine monthly rainfall, minimum temperature and maximum temperature as the climatic predictors for oil palm yield in this study, because these are known to drive variation in yield, including in Southeast Asia (Chow 1992; Corley and Tinker 2016, Sects. 3.1, 5.1.1.3, 5.3.4). Low rainfall reduces yield by causing drought stress, and oil palm appears particularly sensitive to this during sex determination and inflorescence abortion (Chow 1992; Dufour et al. 1998; Legros et al. 2009a, b; Legros et al. 2009a, b). However, high rainfall can also have negative impacts on yield, through increased cloud cover, and negative impacts on insect pollination (Hoong and Donough 1998). Yield increases with temperature, because temperature both directly increases photosynthesis, and because temperature is positively correlated

Table 1 Previously detected effects of climate on yield, according to stages of oil palm fruit development

Months before harvest	Stage	Effects of climate on yield with corresponding lag time	Reference(s)
36	Frond initiated	Hypothesized: positive impact of temperature and rainfall	
33	Inflorescence initiated	Negative effect of photoperiod 33–34 months prior to harvest (Indonesia) (note that this is intercorrelated with the same effect at 9–10 months), although it is unclear whether oil palm is sufficiently sensitive to photoperiod to justify this effect (Corley & Tinker, 2016, Sect. 5.4.4.1)	Legros et al. (2009a)
~22–28	Sex determination	Positive effect of useful radiation anomaly (which was adjusted for water deficit) 24–25 months prior to harvest (Ivory Coast)	Dufour et al. (1998)
		Positive effect of soil water availability (simulated fraction of transpirable soil water) 26–27 months prior to harvest respectively (Indonesia)	Legros et al. (2009a)
		Positive effect of soil water availability (simulated fraction of transpirable soil water) and photoperiod combined at 29 months prior to harvest (Indonesia)	Legros et al. (2009a)
		Positive effect of monthly rainfall 20–24 months prior to harvest (Malaysia)	Chow (1992)
~12–19	Inflorescence development: number of spikelets and number of flowers per spikelet determined	Negative effect of water deficit anomaly 7–13 months prior to harvest (Ivory Coast)	Dufour et al. (1998)
		Positive effect of temperature anomaly 13 months prior to harvest (Malaysia)	Shanmuganathan & Narayanan (2012)
		Negative effect of monthly rainfall 13 months prior to harvest (Malaysia), although this was unexplained	Chow (1992)
		Negative effect of water deficit anomaly 7–13 months prior to harvest (Ivory Coast)	Dufour et al. (1998)
9–10	Inflorescence abortion	Negative effect of water deficit anomaly 7–13 months prior to harvest (Ivory Coast)	Dufour et al. (1998)
		Negative effect of photoperiod 9–10 months prior to harvest (Indonesia) (note that this is intercorrelated with the same effect at 33–34 months), although it is unclear whether oil palm is sufficiently sensitive to photoperiod to justify this effect (Corley & Tinker, 2016, Sect. 5.4.4.1)	Legros et al. (2009a)
		Negative effect of cumulative water balance (monthly rainfall – potential evapotranspiration) 10 months prior to harvest (Indonesia)	Legros et al. (2009b)
		Positive effect of monthly rainfall 10–11 months prior to harvest (Malaysia)	Chow (1992)
5–6	Flowering (pollination required)	Negative effect of monthly rainfall, and positive effect of sunshine hours, 6 months prior to harvest: indicates impacts of climate on pollinator activity (Sabah, Malaysia)	Hoong & Donough (1998)
0–5	Fruit development (ripening)	Positive effect of monthly rainfall and temperature with lag of 3 and 4–5 months prior to harvest respectively (Sabah, Malaysia)	Puah & Sidik (2011)
		Negative effect of monthly rainfall, and positive effect of sunshine hours, on oil to bunch ratio 0–1 months prior to harvest (Sabah, Malaysia)	Hoong & Donough (1998)

The generalised timescale and stages of fruit development follow (Corley and Tinker 2016, Sect. 5.4.1). An inflorescence develops in the axis of each frond (leaf), and some are later aborted; oil palm is harvested as fresh fruit bunches (FFB), which comprise multiple spikelets of female inflorescences. FFB yield is a function of both fruit bunch number (i.e., how many bunches are harvested in a month; note that harvesting is conducted continually), determined by sex determination and abortion, and average fruit bunch weight, determined by inflorescence development, pollination and ripening (also see Fig. 3) with solar radiation, which also increases photosynthesis (Corley and Tinker 2016, Sects. 3.1, 5.1.4.3; Harris et al. 2020). Thus, temperature impacts all stages of fruit development, although its effects are most apparent at certain key stages such as inflorescence development and fruit ripening (Puah and Sidik 2011; Shanmuganathan and Narayanan 2012).

We test the relationships between climatic conditions and yield for time-lags up to 36 months prior to harvest (which is conducted continually in plantations), to account for impacts on different stages of fruit development. We conduct analyses on both raw data for yield and climate (whilst controlling for variation and autocorrelation through space and time), and on climate and yield anomalies for each month (i.e., removing spatial variation and regular seasonal cycles from all variables prior to analysis), in order to maximise the sensitivity of our analyses for revealing relationships between climate and yield. Although Malaysia (Peninsular Malaysia and Borneo) is considered broadly 'aseasonal', it is affected seasonally by both the Northeast and Southwest monsoons, and both yield and climate show regular seasonal (within-year) fluctuations in Malaysia (Tang 2019). Yield seasonality is likely primarily driven by seasonality in climatic conditions, although oil palm physiology drives alternating periods of low and high fruiting activity, and can therefore exacerbate existing seasonal cycles (Corley and Tinker 2016, Sects. 5.4.2, 5.4.2.2, 5.4.8, 5.5.1). Relationships between oil palm yield and climatic variables could therefore be spurious correlations between similar seasonal patterns, particularly when incorporating time-lags (Corley and Tinker 2016, Sect. 5.5.2), emphasising the importance of analysing anomalised data. Hence, we examine relationships between yield and climatic variables for both raw data, and for anomalised yield and climatic variables, from which we remove regular seasonal and spatial variation (see "Methods" section). Moreover, the climate anomalies allow us to detect relationships between climate and yield at additional time-lags to the raw analyses, where lags of climatic variables 12 months apart are highly correlated. Thus, we address the following hypotheses:

1. The majority of variation in yield is due to local climatic conditions, but variation also arises from differences among the 12 oil palm plantations (owing to factors such as management practices, soil, cultivar, and pests and diseases).
2. Relationships between climatic conditions and yield are strongest at time-lags corresponding to key stages of fruit development, such as sex determination (~22–28 months prior to harvest), inflorescence development (~12–19 months), and abortion (9–10 months), of all the tested relationships at time-lags 0–36 months prior to harvest.
3. Maximum temperature has the strongest (positive) relationship with yield (comparing rainfall, minimum temperature, maximum temperature), indicating that solar radiation is the strongest climatic constraint on yield.
4. Yield is positively related to rainfall, and this relationship is stronger at higher temperatures, when oil palm is more likely to be under drought stress.
5. The relationships between climatic conditions and yield are consistent for analyses of raw and anomalised data, and we are able to detect additional patterns (for different climatic variables and/or time-lags) by analysing the anomalised data.

Methods

Study plantations

We analyse data for 12 commercial oil palm plantations in Malaysia, belonging to a single company, for which we were able to obtain data. We obtained these data under a confidentiality agreement with the oil palm company, which requires that its name is withheld. Eleven plantations are located in Peninsular Malaysia, spanning from the North (Kedah) to the South (Johor), and one is located in East Malaysia (Sabah) (Fig. 1, Table 2). All plantations are in the lowlands (median elevation within plantations 9–86 m above sea level (masl), overall median = 39 masl; Table 2). All plantations in this study are subject to the same company- and country-level management directives (e.g., principles determining pesticide and fertilizer application, replanting and harvesting schedules, worker training and management), but the application of management procedures could nonetheless vary among plantations. However, we do not expect substantial differences in management practices among plantations if management is imposed company-wide, although differences in yield could also arise due to variation in plantation-level management (e.g., availability of workers to harvest the crop, precise quantities and timings of agro-chemical applications), soil type, and the specific cultivar of oil palm planted. The data associated with the study sites include date of planting of each oil palm field, but we do not have other specific information on cultivation or management. We provide the data used in our analyses as a supplement to this article, in anonymised format (Additional files 2, 3).

Oil palm yield data

We obtained data on monthly oil palm fresh fruit bunch yield (t FFB /ha) as time-series for each of 83 oil palm 'fields' (the finest-scale level of management within

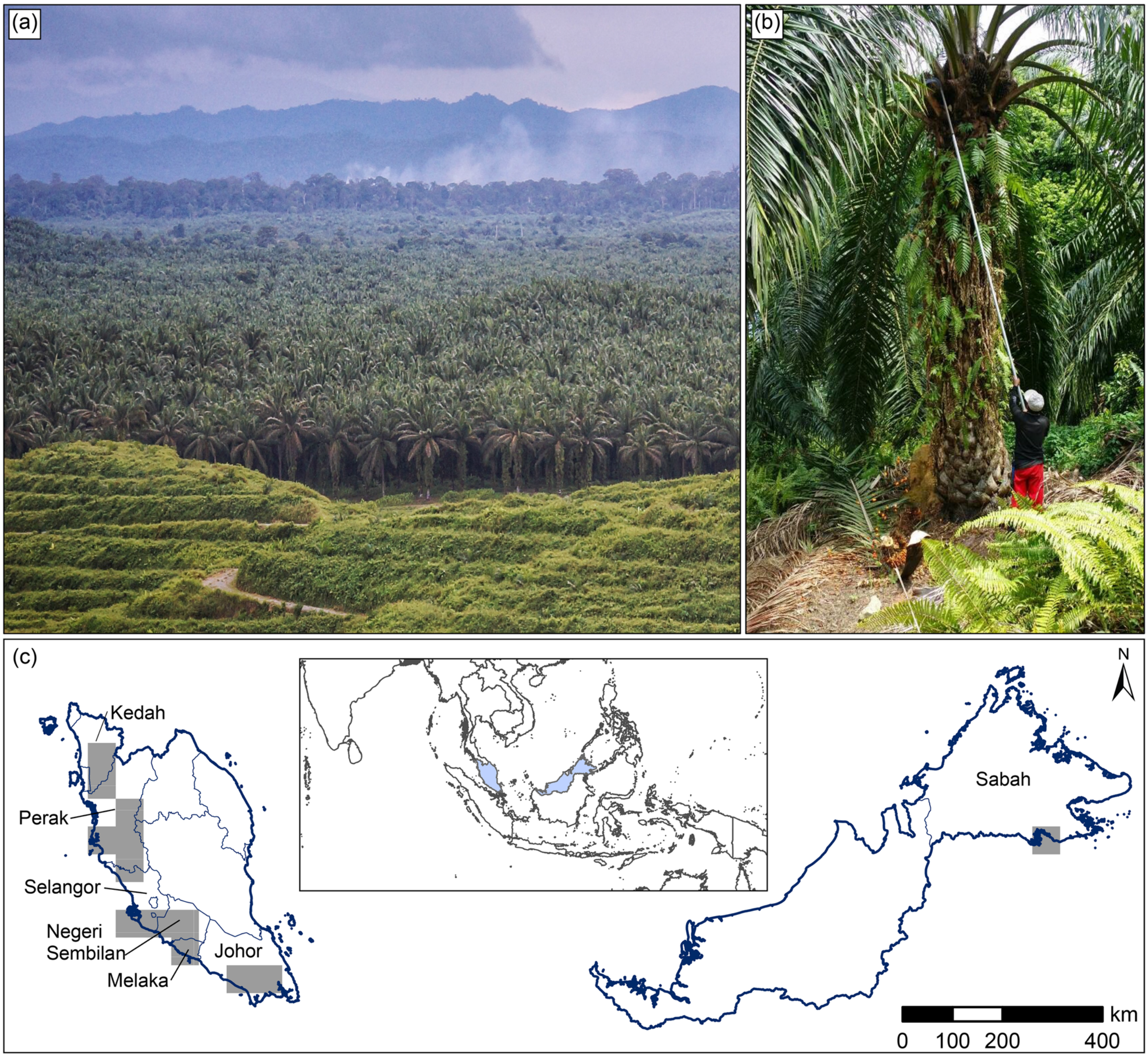

Fig. 1 Commercial oil palm cultivation in Malaysia, and locations of plantations in this study. **a** Oil palm plantation in Sabah (photo credit: Robin Hayward): terraces prepared for replanting in the foreground, mature oil palm fields in the middle ground, and remnant forest in the background. **b** Plantation worker harvesting fresh fruit bunches (FFB) in a plantation in Sabah, using a sickle on an extendable pole (photo credit: Ahmad Jelling). **c** Locations of the 83 oil palm fields (in 12 plantations) in this study. Grey grid cells (0.5 degree or ~55 km-resolution) contain the study plantations (note that we obtained the locations as point coordinates of 'divisions' within the plantations). Inset shows Malaysia (blue) within Southeast Asia. Grid cells for which we have data are shaded grey, and the states for which we have data are labelled. The grid cells in this map match those of the CRU TS temperature data used in this study (Harris et al. 2020)

a plantation; individual field size ranges 2.5–159 ha, median = 70.2 ha) across the 12 study plantations (data for 2–14 fields per plantation, median = 6 fields, as provided by the oil palm company). These time-series of monthly yield data span roughly one decade (timespans per field range from 4 years 1 month to 11 years 11 months, median = 10 years 11 months), starting in July 2006 at the earliest and finishing in June 2017 at the latest (Additional file 1: Fig. S1). The yield data were collected as the harvesting records of the oil palm fields at the study plantations. All yield data are for oil palms at least four years old, representing the regularly harvestable phases of production (Woittiez et al. 2017), and range 4–17 years since planting.

Table 2 Summary data for the oil palm plantations in this study, ranked by median annual yield

Plantation	State	N fields	Median elevation (masl)	Median annual yield (t FFB/ha)	Median palm age (years)	Maximum annual yield (t FFB /ha)	% yield in peak month	Monthly Tmax (°C)	Monthly Tmin (°C)	Monthly rainfall (mm)
1	Negeri Sembilan	5	82	16.4	8	29.6	13.8	30.6 (29.0–31.9)	22.5 (21.5–23.7)	143 (0–539)
2	Johor	3	74	18.9	9	27.2	13.6	31.2 (29.3–32.6)	23.8 (22.7–25.0)	150 (3–582)
3	Perak	10	38	20.0	10	32.7	12.4	30.0 (27.4–32.4)	23.0 (20.8–25.0)	223 (0–811)
4	Johor	2	70	20.6	9	28.3	13.2	31.0 (29.0–32.5)	23.8 (22.8–25.1)	222 (0–949)
5	Negeri Sembilan	11	40	21.1	10	24.4	13.6	31.1 (29.3–32.5)	23.3 (22.3–24.6)	135 (0–549)
6	Melaka	3	48	22.2	10	32.3	14.0	31.3 (29.9–32.7)	23.3 (22.2–24.6)	146 (0–580)
7	Kedah	5	23	22.2	11	30.5	14.6	30.8 (29.2–33.2)	22.3 (20.9–24.1)	184 (4–1070)
8	Sabah	10	24	25.3	10	43.1	11.9	30.6 (28.0–32.2)	23.1 (21.8–24.4)	166 (0–568)
9	Perak	8	86	26.2	11	32.5	13.3	28.7 (27.2–30.0)	19.9 (19.0–21.4)	144 (0–920)
10	Selangor	14	9	28.8	10	36.4	12.1	32.6 (30.7–34.2)	23.5 (22.5–24.6)	160 (0–543)
11	Perak	5	22	29.6	11	37.9	12.7	30.7 (28.5–32.5)	23.55 (22.5–25.3)	146 (0–615)
12	Selangor	7	10	31.6	9	38.2	12.1	32.4 (29.3–34.2)	23.5 (22.3–24.6)	168 (0–1338)

N fields: number of oil palm fields for which we have data; median elevation: extracted from elevation data at 30 arc-second resolution, aggregated from the Shuttle Radar Topography Mission 90 m-resolution data (Jarvis et al. 2008); median annual yield: median total annual yield for all fields at a plantation, for years for which we had data for all months in an oil palm field; median palm age: median age of oil palm for all yield datapoints included in annual yield values; % yield in peak month: mean percentage of the annual yield which is harvested in the peak yield month; monthly Tmax, Tmin and rainfall: mean and range (minimum–maximum) of all values at the timepoints of oil palm yield data for that plantation

Climate data for predictors of oil palm yield

We obtained monthly rainfall data (mm month^{-1}) from all of the oil palm plantations in this study, alongside the yield data. Rainfall was measured at rain gauges on the plantations, and provided at the management level of oil palm 'division' (signifying different groups of oil palm fields within a plantation, ranging 1–6 fields per division, median = 3 fields). The rainfall data encompass the full timespan of the yield data, and generally two decades beforehand.

We obtained monthly temperature data from the Climatic Research Unit gridded Time Series (CRU TS) version 4.04 (Harris et al. 2020), which are global gridded climate data, interpolated from local meteorological stations at 0.5 degree (55 km) resolution. We downloaded monthly minimum temperature (Tmin) and maximum temperature (Tmax) (°C; mean of each daily minimum and maximum temperature for a month respectively) as candidate predictors of oil palm yield. Note that these values do not therefore represent the absolute minimum and maximum temperatures experienced by oil palm in the study plantations.

Calculating anomalies of yield and climatic variables

We analysed raw yield and climate data (variables described above), but to improve the sensitivity of our analyses to relationships of yield with climate, and to assess the reliability of the relationships we detect for the raw variables, we also calculated standardised monthly anomalies for each of the variables (yield, rainfall, Tmax and Tmin) for analysis. Using the 56 time-series of oil palm yield data which spanned a full decade, from July 2007 to June 2017 (i.e., data for 56 oil palm fields, excluding data for 27 fields of the 83 in total, which did not fully span this period), we computed anomalies for each variable. We calculated anomalies as the difference between each value and the mean of all values for that month for each oil palm field, scaled by the standard deviation of all values for each month and field (i.e., anomalised per time-series of oil palm yield data) (see Additional file 1: Text S1 for details). The computed anomaly time-series are therefore centred at zero and do not incorporate differences in yield mean or variation among spatial locations at any spatial scale (oil palm fields, divisions or plantations) or months of the year (i.e., regular seasonal effect removed), enabling us to analyse relationships between 'unexpected' variation in climate and yield, given the month of the year and oil palm field.

Determining time-lags of climatic predictors of oil palm yield for inclusion in models

To identify the most important candidate climatic predictors (i.e., climatic variable at a specific time-lag) of oil palm yield for inclusion in our statistical models, we assessed the Spearman rank correlations between each of our candidate climatic variables (rainfall, Tmax and Tmin) and oil palm yield, for time-lags of 0–36 months prior to harvest (see "Results" section "Correlations between climatic predictors and oil palm yield at different lags prior to harvest"). We selected candidate climatic predictors with high correlations with yield relative to other time-lags, at time-lags that correspond to key stages of oil palm fruit development, whilst avoiding inclusion of inter-correlated predictors in the models (Table 1, Fig. 3; see Additional file 1: Text S2 for details). Based on these selection criteria, we selected Tmax and rainfall at a 14-month time-lag (Spearman's Rho correlation with raw yield = 0.30 and − 0.15 respectively), corresponding to oil palm inflorescence development, and rainfall at a 10-month time-lag (Spearman's Rho correlation with raw yield = 0.08), corresponding to inflorescence abortion, as candidate climatic predictors of raw oil palm yield (Fig. 3). As candidate predictors of yield anomalies, we included the anomalies of these three predictors (Tmax and rainfall at a 14-month time-lag, and rainfall at a 10-month time-lag), to test the robustness of their relationships with yield to the removal of regular seasonal fluctuations from the data. We also included three climatic anomaly predictors which suggested additional relationships between climate and yield: Tmax anomalies at the month of harvest (Spearman's Rho with yield anomalies = − 0.14), suggesting impacts of temperature on harvesting; and rainfall and Tmin anomalies at 29 months prior to harvest (Spearman's Rho with yield anomalies = 0.08 and 0.12 respectively), corresponding to sex determination (Fig. 3; Additional file 1: Text S2).

Modelling the impacts of spatial variation and climatic variables on oil palm yield

To quantify the relationships between raw climatic predictors and oil palm yield, and the degree of spatial variation in oil palm yield (among- and within plantations), we fitted Generalized Additive Mixed Models (GAMMs) using the 'gamm' function in the R package *mgcv* version 1.8-31 (Wood 2011). We conducted this analysis on our full dataset of monthly data for 83 oil palm fields (9731 data points in total, excluding two outliers; Additional file 1: Text S3). To quantify among-plantation differences in oil palm yield, we tested the importance of plantation as a random intercept for model fit, as well as the impact of additionally including a random intercept for 'field within plantation.' To quantify relationships between raw climatic conditions and yield, we fitted both linear and quadratic terms for all three candidate climatic predictors of yield (Tmax at a 14-month lag, rainfall at a 14-month lag, and rainfall at a 10-month lag) in our initial full model. We did this because yield is likely to peak at particular values for each predictor (Corley and Tinker 2016, Sects. 3.1, 3.2), and our exploratory analyses suggested that the relationships of these climatic variables with yield were non-linear (Additional file 1: Fig. S8). We included an interaction term between Tmax and rainfall, with a 14-month lag, to test for changing plant–water relations under different temperatures. In addition, we fitted smoothers to control for oil palm age and seasonality (cyclic smoothers of months of the year), and we fitted an autoregression-moving average error structure to account for temporal autocorrelation between data points from the same yield time-series (i.e., in the same oil palm field). To obtain homoscedasticity and normality of residuals, we found that we needed to square-root transform the response variable (yield); we then proceeded with selection of the optimal model for GAMMs of square-root yield with a Gaussian error function and identity link. In total, we fitted 51 model permutations to find the optimal error structure (autoregression-moving average parameters and random effects of plantation/field), and 44 permutations to find the optimal fixed effects (age of oil palm in field, seasonality, and climatic variables) (Additional file 1: Text S3). We provide the R code analysing raw yield and climatic variables in Additional file 4.

To quantify the relationships between climate and yield anomalies, we fitted Generalized Additive Models (GAMs), also using the 'gamm' function in the R package *mgcv* (Wood, 2011). We conducted this analysis on the full anomaly dataset of 56 oil palm fields spanning exactly one decade, with a total of 6,719 datapoints. In the initial full model, we included linear effects for six climatic anomaly predictors (Tmax and rainfall at a 14-month lag, rainfall at a 10-month lag, Tmax at a 0-month lag, and Tmin and rainfall at a 29-month lag), and interaction terms between the two pairs of temperature and rainfall variables at the same time-lag (Tmax and rainfall at a 14-month lag, and Tmin and rainfall at a 29-month lag). These models were similar to the GAMMs of raw yield but did not include random effects to account for spatial variation or smoothers to account for seasonality, because these had been removed from the anomalised data, and we only allowed for linear relationships between climatic predictors and yield anomalies (Additional file 1: Text S4). We provide the R code analysing anomalised yield and climatic variables in Additional file 5.

Results

Summary of oil palm yield in the study plantations

All of the plantations in this study had median annual yield > 16 t FFB/ha and all but one had maximum annual yields > 25 t FFB/ha, which are values typical of commercial plantations but probably not close to optimal yield, which is likely to be > 30 t FFB/ha in many of the plantations (ERE Consulting Group and RSPO 2012; Hoffmann et al. 2017; Woittiez et al. 2017) (Fig. 2; Table 2). The highest mean annual yield of a plantation (31.6 t FFB/ha) was roughly double that of the lowest (16.4 t FFB/ha), highlighting substantial variation in yield among plantations (Table 2, Fig. 2), and suggesting substantial variation in plantation yield gaps. This variation among plantations accounted for the majority of spatial variation in modelled monthly yield, because median monthly yield values were generally similar among oil palm fields within each plantation (generally within ~ 0.3 t FFB/ha of each other; Additional file 1: Fig. S11). Concurrently, including a random intercept for oil palm field in addition to plantation did not improve model fit (Additional file 1: Text S3). Whilst our final GAMM of raw oil palm yield included a strong effect of oil palm age (increasing sharply from 4-year-old palms to a peak at 8–9 years, followed by a gradual decline; Additional file 1: Fig. S12), median oil palm age was generally similar across the plantations and therefore does not appear to be a major driver of the differences in yield among plantations (Table 2).

Monthly oil palm yield varied among months of the year, showing regular seasonal variation, which differed among plantations. The mean proportion of annual yield that was harvested in the peak yield month ranged 11.9–14.6% across all plantations, which indicates some seasonality in yield in each plantation (values above 8.33% indicate greater seasonal variation, i.e., more than one-twelfth of yield is obtained in the most productive month), although to a varying degree, which appears to relate partly to location (Table 2). The final GAMM of raw oil palm yield included seasonal fluctuations (cyclic cubic regression spline across months of the year) for 11 of the 12 plantations (one plantation was fitted with no seasonal variation), which differed among the plantations (Fig. 2). All fitted splines included a single peak in yield across the year, which was generally between July and September (Fig. 2).

Relative importance of climatic conditions and plantation-level factors for explaining variation in oil palm yield

The final GAMM of raw climatic variables and oil palm yield explained almost 40% of variation in the monthly yield values (approximate R^2 of 0.38; Additional file 1: Table S9). When compared to the full final model, a model without any plantation terms explained less than half of the variation (approximate $R^2 = 0.18$; Additional file 1: Table S9), highlighting that differences among oil palm plantations accounted for the majority

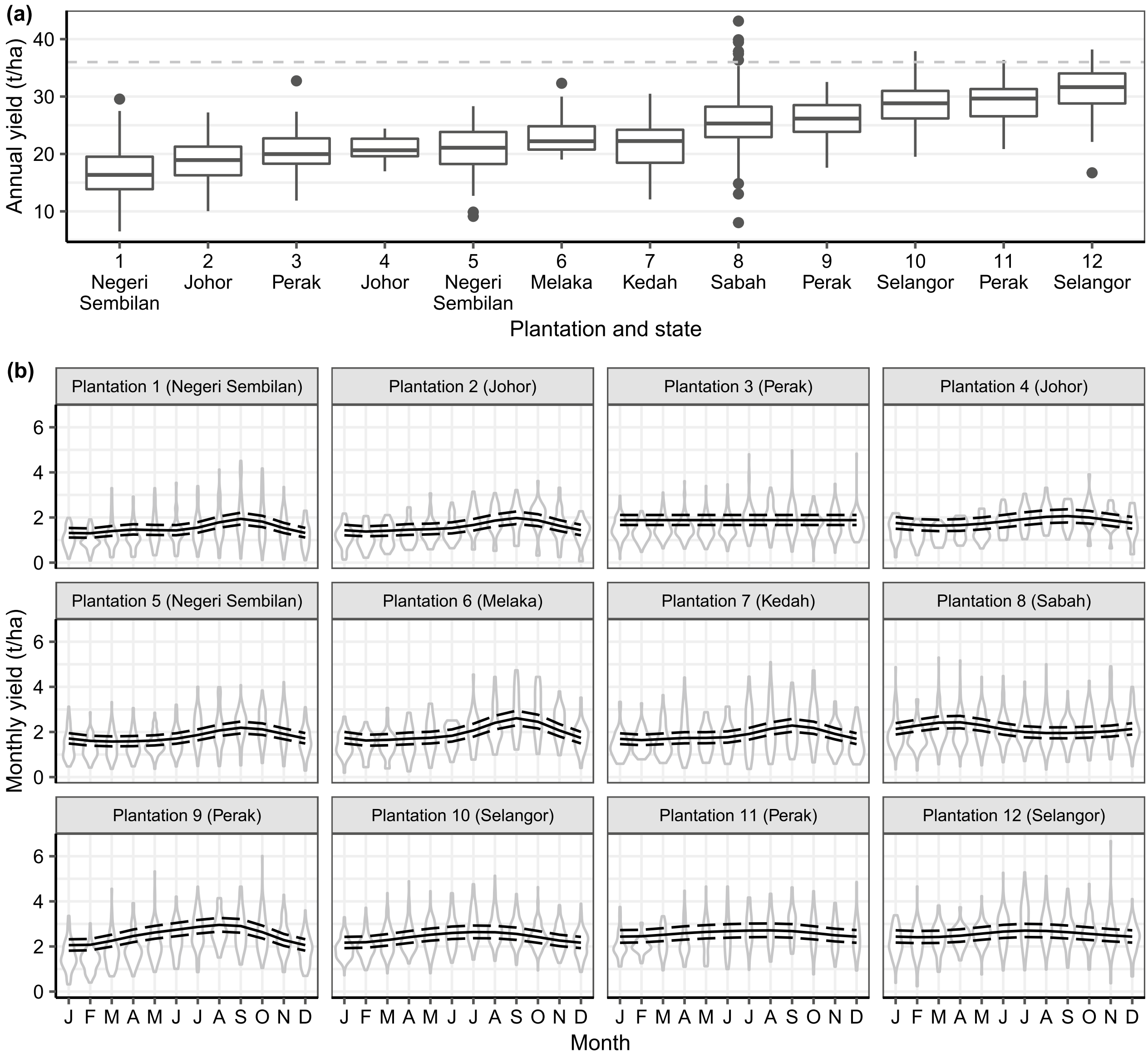

Fig. 2 Variation in oil palm yield among study plantations, with plantations ranked by median annual yield. **a** Boxplots of annual yield for each full year of harvest in each oil palm field, by plantation. Dashed grey line represents potential annual yield for many coastal areas in Malaysia (36 t/ha), after Hoffmann et al. (2014). Boxplot centre lines show the median, lower and upper hinges show the first and third quartiles respectively, whiskers extend to the maximum and minimum values within 1.5 × inter-quartile range, and outliers are plotted individually. **b** Monthly oil palm yield in each plantation, including regular seasonal fluctuations. Solid and dashed black lines show predicted monthly yield values from the final GAMM of raw yield and climatic variables (mean and 95% confidence intervals). The predictions incorporate both cyclic cubic regression splines of seasonality fitted across months per plantation, and random intercepts fitted for each plantation, with all other numeric predictors held at the median value, and were back-transformed from a square-root transformation for plotting. Grey violin plots show distribution of actual monthly yield data for each month in each plantation

of explained variation in yield. In contrast, the climatic predictors explained < 1% of the total variation in yield, but smoothers for seasonal fluctuations (cyclic pattern across months of the year) per plantation and for oil palm age had slightly greater importance (reduction of ~ 7–9% in the approximate R^2 value when these predictors were omitted, compared to full model; Additional file 1: Table S9). In line with these findings, the final GAM of climate and yield anomalies explained only 9% of variation in the monthly yield anomalies (approximate R^2 of 0.09; Additional file 1: Table S9), highlighting that only a small fraction of 'unexpected'

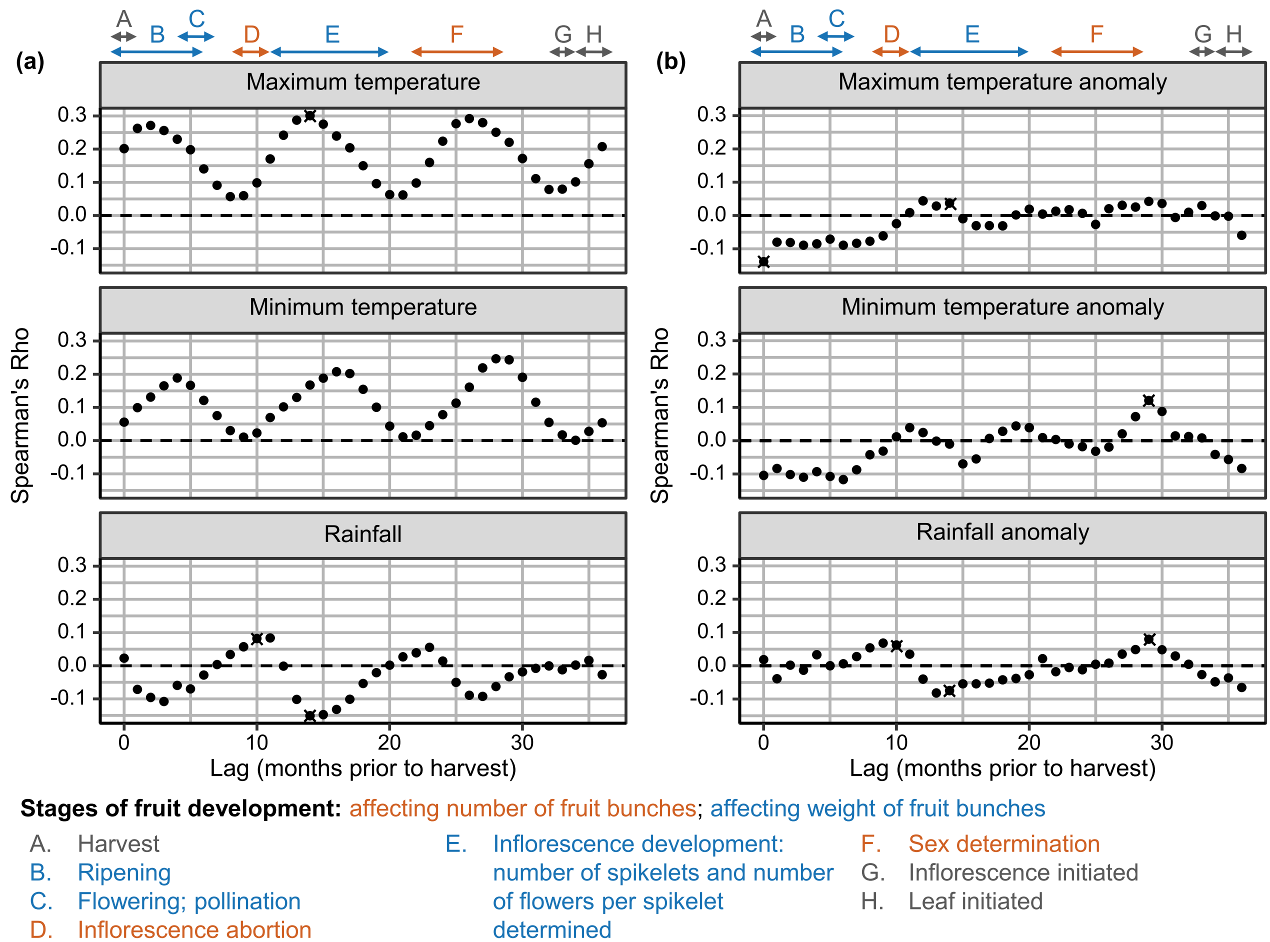

Fig. 3 Correlations between climatic variables and oil palm yield by time-lag, with corresponding fruit development stages. **a** Correlations between raw climatic variables and raw oil palm yield; **b** correlations between climatic variable anomalies and yield anomalies. Crosses denote climatic predictors (i.e., climatic variables at a specific time-lag) included in the statistical models of yield. We selected climatic predictors for inclusion in the models from their high correlations with yield relative to other time-lags, at time-lags which correspond to key stages of oil palm fruit development, but avoided inclusion of inter-correlated predictors in the models (see Additional file 1: Text S2 for details). Stages of fruit development follow Corley and Tinker (2016, Sect. 5.4.1). See Table 1 for a summary of existing studies which have detected effects of climate at stages of oil palm fruit development

variation in oil palm yield (for a given month at a given oil palm field: the anomaly values) was due to factors that we were able to account for ('unexpected' variation in climatic conditions, and oil palm age).

Correlations between climatic predictors and oil palm yield at different time-lags prior to harvest

Raw yield was positively correlated with both Tmax (Spearman's Rho 0.05–0.30) and Tmin (0.0–0.25) for all time-lags up to 36 months prior to harvest (Fig. 3a). In contrast, the correlations between raw yield and rainfall ranged between positive and negative values across all time-lags examined (− 0.15 to 0.08; Fig. 3a). However, all three of these predictors had seasonal autocorrelation (patterns of 12-month cycles, Additional file 1: Fig. S5), and their correlations with yield showed substantial fluctuations around an approximate annual cycle, so interpretation of the correlations between raw variables and yield at different lag times is not straightforward. Nevertheless, the strongest correlation coefficients between raw climate and yield were for time-lags corresponding to key stages of oil palm fruit development, which have irregular durations and do not correspond to an annual cycle: sex determination, inflorescence development and abortion (Fig. 3; Table 3).

The correlations between climate and yield anomalies were consistently weaker than those for the raw

Table 3 Directions and rank importance of relationships of main effect climatic predictors with yield

Stage	Climatic variable (main effect)	Relationship with yield		Rank importance among main effect climatic predictors (1 is most important)	
		Raw data	Anomalised data	Raw data	Anomalised data
Sex determination (29-month lag prior to harvest)	Tmin		Positive		1
	Rainfall		Positive		4
Inflorescence development (14-month lag prior to harvest)	Tmax	Quadratic (positive, plateauing)	Positive	1	3
	Rainfall	Negative	Negative	3	6
Inflorescence abortion (10-month lag prior to harvest)	Rainfall	Quadratic (peak at 460 mm monthly rainfall)	Positive	2	5
Harvest (no lag)	Tmax		Negative		2

Note that we included three main effect climatic predictors in the GAMM of raw data and six in the GAM of anomalised data (see "Methods" section). We determined relative predictor importance based on change in approximate R^2 on predictor removal for the raw data, and relative effect sizes for the anomalised data (see Additional file 1: Tables S8, S9)

variables, but their relative strength did not follow the same pattern as the raw variables (Additional file 1: Fig. S3), enabling us to investigate additional effects of climate not detectable from the raw data. One of the strongest correlation coefficients for rainfall anomalies with yield was during sex determination (at a time-lag of 29 months: Spearman's Rho = 0.08), which was undetectable from the raw data. Moreover, the correlations between temperature and yield anomalies varied from weak negative to weak positive values (Tmax Spearman's Rho − 0.14 to 0.04, Tmin − 0.12 to 0.12), suggesting that variation in temperature does not have a consistently positive relationship with yield at all time-lags (Fig. 3b), but that this is masked by high autocorrelation in the raw temperature data (Additional file 1: Fig. S5).

Effects of temperature on oil palm yield

We found that Tmax, with a time-lag of 14 months prior to harvest, was the most important climatic predictor in our GAMM of raw oil palm yield (Table 3). As temperature showed greater seasonal and spatial (among-plantation) variation than rainfall, it is unsurprising that it was more important in explaining

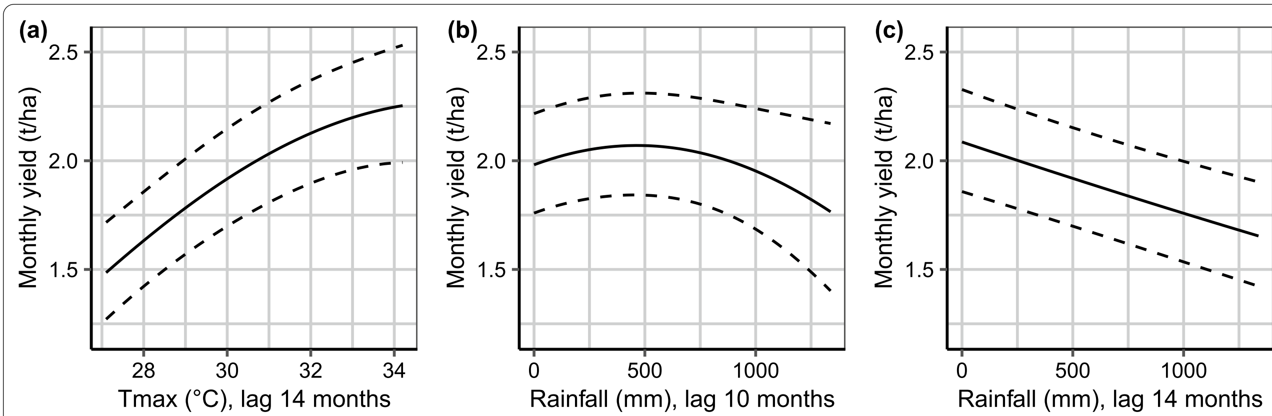

Fig. 4 Expected yield for the main effect climatic predictors in the final GAMM modelling raw yield: **a** Tmax at a 14-month time-lag prior to harvest; **b** rainfall at a 10-month time-lag; **c** rainfall at a 14-month time-lag. The yield values in these plots were predicted with all other numeric predictors in the model (the two other climatic predictors and oil palm age) held at the median value in the dataset. Yield values and 95% confidence intervals (denoted by dashed lines) were back-transformed from the square-root scale for plotting. These were fitted with a GAMM which also included smoothers for seasonality per plantation and oil palm age (Fig. 2, Additional file 1: Fig. S12), plantation as a random intercept, and an autocorrelation-moving average error structure of order $p = 4$, $q = 4$ (Additional file 1: Table S5)

variation in raw oil palm yield (Additional file 1: Fig. S4). The weak fitted relationship between raw yield and Tmax was positive and quadratic, with yield increasing at a slowing rate as Tmax increased (Fig. 4a). With the other predictors held at median values, a 1 °C increase in Tmax from 28 to 29 °C drives a 9.2% increase in yield, but a 1 °C increase in Tmax from 33 to 34 °C drives only a 2.2% increase in yield. This time-lag corresponds to the period of inflorescence development when the number of spikelets and number of flowers per spikelet are determined, and would therefore affect yield by altering FFB weight (Table 1, Fig. 3). This relationship is robust to the removal of seasonal autocorrelation, because we also found a positive relationship between Tmax and yield anomalies at this time-lag (Table 3; Fig. 5), although it was not the most important climatic anomaly predictor for yield anomalies (Table 3). In contrast to the raw data, analyses of anomalies showed that the most important predictors of yield were Tmin with a lag of 29 months, followed by Tmax at the month of harvest (Figs. 3, 5; Table 3). Thus, temperature also appears to influence yield by affecting sex determination (affecting the proportion of female inflorescences and thus fruit bunch number), and by affecting the last weeks of fruit development or harvesting (Fig. 3).

Effects of rainfall on oil palm yield, and its interaction with temperature

We detected weak positive effects of rainfall on oil palm yield in both the raw yield and anomaly analyses at certain key stages of oil palm fruit development. Rainfall at a time-lag of 10 months prior to harvest was the second-most important climatic predictor of raw oil palm yield (Table 3), with an optimum monthly rainfall of 460 mm resulting in 4.5% greater yield compared to 0 mm monthly rainfall, when the other predictors are at median value (Fig. 4b). The anomaly analyses supported this positive effect of rainfall during inflorescence abortion (10-month time-lag), and additionally during sex determination (29-month time-lag), which correspond to the two stages of fruit development responsible for determining total number of fruit bunches (Figs. 3, 5, Table 3).

However, we detected a weak negative relationship between raw yield and rainfall at a 14-month lag prior to harvest, with each increase in rainfall of 500 mm month^{-1} conferring a decrease in yield of 8–9% (Fig. 1c), supported by the anomalised data at this

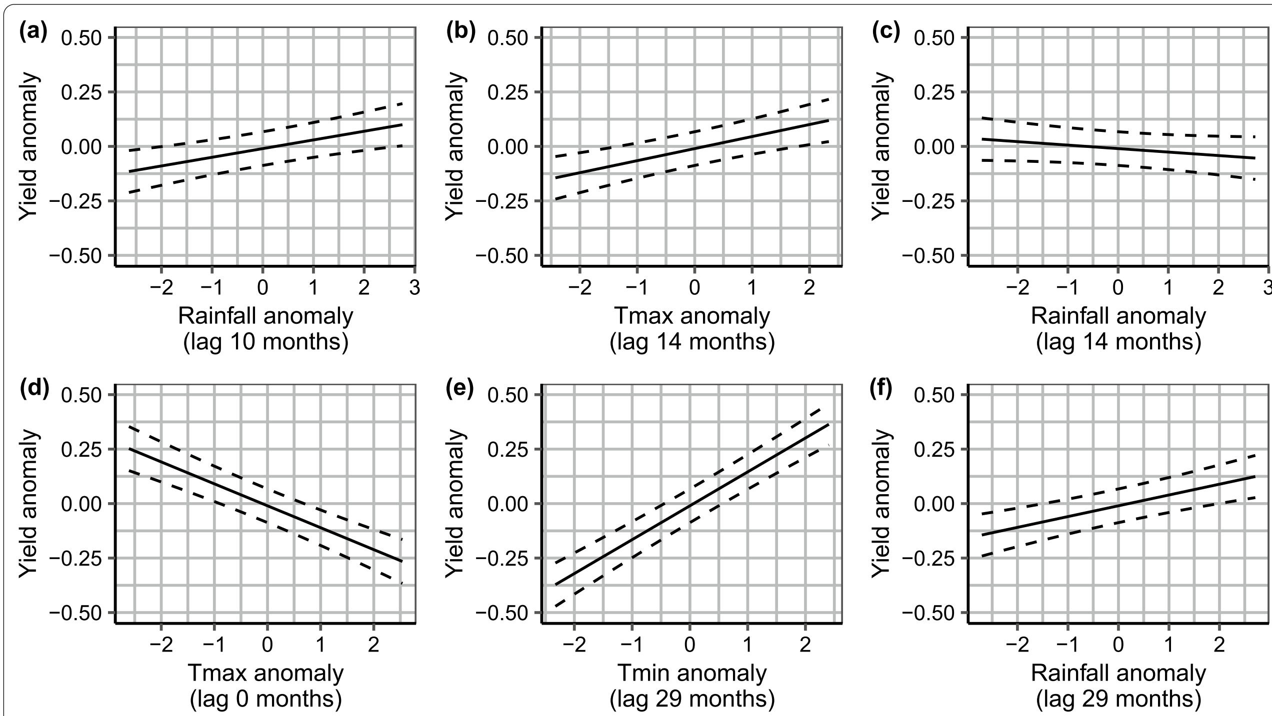

Fig. 5 Expected yield anomaly values and 95% confidence intervals for the main effects of the six climatic anomaly predictors in the final GAM modelling yield anomalies: **a**–**c** predictors which were also included in the final GAMM modelling raw oil palm yield, as raw climatic variables (see Fig. 4); **d**–**f** predictors which were only included in the anomaly analyses. The yield anomaly values in these plots were predicted with all other climate anomaly predictors held at zero, and oil palm age held at the median value in the dataset. See Additional file 1: Table S8 for final model coefficients; and see Additional file 1: Fig. S12 for the fitted smoother of oil palm age and yield anomalies

time-lag (Table 3; Fig. 5). Thus, high rainfall, or a correlate such as cloud cover, appears to reduce the number of spikelets and/or the number of flowers which develop per spikelet (Table 1, Fig. 3). The interaction between rainfall and Tmax at this time-lag (14 months prior to harvest) predicts the highest yield from the driest, hottest months (Additional file 1: Fig. S13). However, the interaction between Tmax and rainfall 14 months prior to harvest differs for the anomalies: increasing rainfall has a strong positive effect on yield under higher temperatures (Additional file 1: Fig. S14), suggesting that water availability was sometimes sub-optimal in this study. The interaction between rainfall and Tmin anomalies at a 29-month time-lag prior to harvest suggests that the positive response of oil palm yield to rainfall anomalies is weakest under warmer temperatures, which could represent a spurious relationship, or further suggest that water limitations at our study sites are generally minimal (Additional file 1: Fig. S15).

Discussion

Oil palm yield varied substantially among the 12 commercial plantations in this study, with only minor effects of climatic variables, refuting our first hypothesis that the majority of explained variation in yield is due to climatic conditions. Nevertheless, we detected varied impacts of both temperature and rainfall on yield at time-lags corresponding to key stages of fruit development, with a greater effect of temperature than rainfall in our analyses of both raw and anomalised yield. In light of our findings, we discuss the expected yield gaps at our study sites, and the climatic drivers of oil palm yield that we detected. We briefly address the potential drivers of differences in yield among plantations, the implications of our findings for expected impacts of climate change on yield, and the potential for sustainable intensification of commercial oil palm production in Malaysia.

Current yield gaps

We found that differences among plantations were the primary source of variation in oil palm yield, with the mean annual yield of the least-productive plantation only half of that of the most-productive plantation. Hoffmann et al. (2014) estimated that the potential annual FFB yield of coastal areas in Malaysia was generally 36 t FFB/ha, which is over double the lowest plantation annual yield in this study, and suggests that only ~60% of the potential yield is currently achieved in the majority of plantations in this study. However, estimated potential yield varies substantially across Malaysia (9–48 t FFB/ha) (Hoffmann et al. 2014), so it is possible that the actual yield gap in the plantations in this study is considerably lower (or higher). This is in line with previous research suggesting that 44–63% of potential yield is achieved for the whole of Malaysia (depending on potential yield estimation) (Fischer et al. 2014). Nevertheless, Hoffman et al. (2017) estimated that four plantations in Malaysia and Indonesia achieved 67–89% of their potential yield, suggesting that the plantations in this study have large yield gaps. Overall, yield gaps for oil palm in Malaysia appear substantial. In combination with potentially weak expected impacts of climate change on average oil palm yield, given the minor role of climate in determining yield that we identified (see section below "Implications for expected changes to yield in Malaysia under climate change"), our findings suggest that there is considerable potential to improve oil palm yield in Malaysia in existing plantations. As Malaysia has the highest national-level palm oil productivity of any country (FAO 2020b), yield gaps in other countries are likely to be even more substantial, highlighting a strong potential for oil palm yield improvements globally. Although we identified a number of effects of climate on yield in this study, we were unable to explain a large proportion of the variation in raw oil palm yield ($R^2 = 0.38$), highlighting the need for further research into drivers of yield gaps both in Malaysia and elsewhere (such as the role of soil, pests, pathogens, pollination and oil palm cultivar: see section below "Variation in oil palm yield among plantations").

Likely importance of solar radiation for oil palm yield

We found that Tmax was the most important climatic variable for raw oil palm yield, with positive correlations of Tmax and Tmin with raw yield at all time-lags. Tmax and solar radiation are closely correlated (Harris et al. 2020), so our findings are in line with existing literature, suggesting that solar radiation is the most important climatic variable for oil palm yield in Southeast Asia (Hoffmann et al. 2014; Woittiez et al. 2017). We also found a positive effect of Tmin anomaly during sex determination, which is a probable correlate of 'useful radiation', representing increasing capacity for photosynthesis, previously identified as having a positive effect at this developmental stage (Dufour et al. 1998). The importance of solar radiation in determining yield could have determined the shape of the relationships of Tmax, rainfall, and their interaction, with yield during inflorescence development, where the hottest, driest months appear to have the greatest yield (Additional file 1: Fig. S13).

Water limitation at our study sites

Our findings suggest that plant-water relations vary by stage of oil palm fruit development, because we detected both weak positive and negative effects of rainfall on yield, suggesting that water is limiting to yield at our study sites by affecting only certain developmental stages. We found positive relationships between rainfall and yield at time-lags corresponding to determination of the number of FFB produced (sex determination, at a 29-month lag prior to harvest, found for anomalies; and inflorescence abortion, at a 10-month lag prior to harvest, found for both raw variables and anomalies), previously identified as sensitive to water availability in Southeast Asia (Dufour et al. 1998; Legros et al. 2009a, b; Legros et al. 2009a, b). Thus, our findings support previous research suggesting that water stress reduces photosynthesis and thus the carbohydrates available for fruit development, triggering a high ratio of male inflorescence initiation and/or high abortion rates, possibly with selective abortion of female inflorescences (Corley and Tinker 2016, Sects. 5.4.4.1, 5.4.4.2, 5.4.5.3).

However, we also identified a negative relationship between rainfall and yield during inflorescence development (at a time-lag of 14 months prior to harvest, for both raw variables and anomalies), which has previously been identified in Malaysia (Chow 1992). We are not aware of an explanation for this negative relationship, which contrasts with the evidence for water-limited yield during sex determination and abortion. Like temperature, rainfall is a correlate of solar radiation, through increased cloud cover (and thus lower solar radiation) when rainfall is higher (Harris et al. 2020). Our results thus suggest that during inflorescence development, when the number of spikelets per inflorescence, and the number of flowers per spikelet are determined (i.e., corresponding to the 14-month time-lag, see Table 1), solar radiation is more strongly limiting than water availability. This also suggests that both soil moisture and air humidity were sufficiently high at our study sites to prevent stomatal closure and thus support inflorescence development (Corley and Tinker 2016, Sects. 5.3.3.2, 5.3.4; Henson and Harun 2005).

We did not detect some relationships between rainfall and yield that have been identified previously; for example, Hoong and Donough (1998) identified a negative relationship between yield and rainfall six months prior to harvest, attributed to negative impacts of rainfall on pollination. Overall, relationships between rainfall and yield appear complex and variable through time, highlighting the need for ongoing research examining the effects of water availability on yield at different stages of oil palm fruit development.

Role of seasonality in determining yield

The relationships between climate and yield anomalies were weaker overall than those of the raw variables, suggesting that the main influence of climate on yield at the plantations in this study is through regular seasonal variation, although it is not possible to determine whether the stronger correlations of raw variables were valid or spurious. The importance of Tmax with a time-lag of 14 months may be artificially inflated in our analyses of raw yield, because its seasonal peak coincides with 14 months prior to the seasonal peak in yield. In addition, previous findings suggest that the majority of FFB yield variation (both overall and seasonally) is determined by FFB number (Corley and Tinker 2016, Sects. 5.4, 5.4.7; Donough et al. 2009), whereas the 14-month time-lag of the most important climatic variables for raw yield (Tmax and rainfall) corresponds to oil palm inflorescence development, determining FFB weight (Table 1, Fig. 3). Moreover, the relative importance of different time-lags in the analyses of climate and yield anomalies (rather than the raw variables) was more in-line with previous research findings, because: (i) developmental stages that determine number of FFB were highly important for yield (sex determination and inflorescence abortion; Fig. 3); and (ii) climatic conditions during developmental stages affecting FFB weight were also important for yield (inflorescence development), but to a lesser degree (Corley and Tinker 2016, Sects. 5.4, 5.4.7; Donough et al. 2009). Thus, relationships between climate and yield anomalies may have been more accurate representations of the impacts of climatic variation on yield, and the importance of Tmax may have been artificially inflated in the raw data. Alternatively, it is possible that Tmax is the primary driver of seasonality in yield at our study sites, owing to high year-round rainfall but stronger seasonal variation in temperature, unlike more rainfall-driven seasonality in other tropical locations (Corley and Tinker 2016, Sect. 5.5.2). The relationships between climate and yield anomalies could have been weaker than those of raw variables because a single anomaly value can correspond to a range of raw climate or yield values, introducing noise into climate-yield relationships (Additional file 1: Fig. S3), and because we used fewer data points in the anomaly analyses than the raw variables.

Variation in oil palm yield among plantations

We found that the majority of variation in yield that we could explain was due to differences among plantations, but we were unable to examine the environmental and management factors that could have driven this variation. These factors could have included oil palm cultivar, effectiveness of plantation-level management, pests and pathogens, soil type and properties, local topography and pollination efficiency (Barcelos et al. 2015; Murphy 2014; Teo 2015; Woittiez et al. 2017). Previous studies have also identified management as the most important determinant of yield among plantations and/or fields, rather than environmental factors (Euler et al. 2016; Hoffmann et al. 2017). The plantations in this study would be expected to be subject to the same company-wide management directives, but it is possible that the application of these directives varied among plantations. Frequency of harvesting is a key determinant of yield, because long harvesting intervals reduce the total ripe FFB harvested by allowing some to rot, and labour available for harvesting is limited in Malaysia (Cock et al. 2016; Donough et al. 2009; Euler et al. 2016; Murphy 2014). The state of Sarawak, in East Malaysia, has reported 15% yield losses owing to rotting of unharvested FFB (Murphy 2014). However, we found that the most productive plantation had yields about twice those of the least productive plantation (Table 2), which is considerably greater than the state-wide yield loss of 15%. The differences in yield among plantations in this study therefore likely arose from a combination of management and environmental factors other than climate. Investigating the effects of a range of environmental and management factors on yield should be a key priority for future research.

Implications for expected changes to yield in Malaysia under climate change

We found weak effects of climatic conditions on yield overall, so our ability to infer likely impacts of climate change on oil palm yield is limited. We briefly speculate on the implications of some climatic effects that we detected.

Our finding that raw yield increases with Tmax suggests that increasing temperatures will benefit yield, although our study only encompasses a limited range of Tmax (~27–34 °C), well below the heat stress threshold of ~38 °C (Corley and Tinker 2016, Sects. 3.1, 5.4.3). Paterson et al. (2015) estimated that much of western Peninsular Malaysia would exceed the oil palm heat stress threshold by 2100, although this will not be exceeded in central, eastern and southern Peninsular Malaysia, nor in Malaysian Borneo. Thus, the impacts of future temperature increase on oil palm yield in Malaysia do not seem substantial, but are highly uncertain, as future projected temperatures (particularly during heat waves) will be considerably greater than those currently experienced (Barros et al. 2014).

We found a negative relationship between Tmax and yield anomalies at the month of harvest, which could suggest impacts of heat stress on workers during harvesting, which would likely worsen with climate change. Oil palm FFB, which generally weigh 15–20 kg, are almost exclusively harvested by manual labour (Fig. 1; Donough et al. 2009; Murphy 2014), which is likely to be more difficult and less efficient if workers suffer heat stress at higher temperatures. We did not expect a negative impact of temperature at this time-lag based on our knowledge of oil palm fruit development, because oil palm fruit ripen until the point of harvest, and higher temperatures aid ripening (Hoong and Donough 1998; Corley and Tinker 2016, Sects. 3.1, 5.5.3.3), although it is possible that higher temperatures drive water loss from the FFB and thus reduce harvested weight. Thus, there may be a number of overlooked negative impacts of climate change on oil palm yield.

We detected evidence that yield is partially limited by water availability, through increased inflorescence abortion and a greater proportion of male inflorescences under lower rainfall, which suggests that future periods of low-rainfall, particularly drought events, will drive periods of low oil palm yield. El Niño Southern Oscillation (ENSO) droughts are expected to increase in frequency and intensity in Malaysia over the coming century, although mean annual precipitation is projected to undergo minimal change (Barros et al. 2014; Cai et al. 2014; Tangang et al. 2017). Thus the periodic reduction in oil palm yield corresponding to ENSO cycles (~2–7 years) is likely to be exacerbated under climate change (Caliman and Southworth 1998; Oettli et al. 2018; Tangang et al. 2017). Nevertheless, increasing atmospheric carbon dioxide concentration is projected to increase oil palm water-use efficiency (Corley and Tinker 2016, Sect. 17.3.1), so overall impacts of climate change on plant-water relations and oil palm yield are unclear (Wang et al. 2012).

Potential for sustainable intensification of oil palm in Malaysia

We identified large differences in yield among plantations, suggesting substantial yield gaps. Depending on the cause(s) of these differences, it is possible that yield could be improved considerably in many plantations in this study, potentially facilitating productivity increase without further land-use change. In theory, such yield improvements could help conserve rainforest in Southeast Asia and other tropical regions (Byerlee et al. 2014; Castiblanco et al. 2013; Greenpeace, 2012; Vijay et al. 2016; Wilcove et al. 2013). However, improving crop yields can lead to greater incentives for expansion, owing to higher returns from land-use change (Byerlee et al. 2014; Carrasco et al. 2014), particularly if markets are elastic (i.e., demands increase as the price decreases) (Hertel 2012). Given that global demand for vegetable oils is increasing (OECD/FAO 2019), effective governance and incentives to preserve natural habitat are essential for reducing land-use change driven by oil palm expansion, alongside improving productivity.

Conclusions

We found that variation in oil palm yield in commercial plantations of a single company in Malaysia is largely due to differences among plantations. We detected a number of weak impacts of climatic conditions on yield, suggesting that productivity is greater at higher temperatures, and that yield has varied responses to rainfall, depending on the stage of fruit development, although higher temperatures may have negative impacts on manual harvesting. Our findings suggest that yield gaps in commercial oil palm plantations in Malaysia are substantial, so there could be considerable potential for increased palm oil production in many existing plantations, although further research would be required to examine multiple environmental and management factors driving these potential yield gaps. We therefore conclude that there is likely considerable potential for oil palm production in Malaysia, and other oil palm-producing countries, to increase in existing plantations.

Abbreviations

CRU TS: Climate Research Unit Time Series; ENSO: El Niño Southern Oscillation; FFB: Fresh fruit bunch; GAM: Generalized additive model; GAMM: Generalized additive mixed model; Tmax: Maximum temperature; Tmin: Minimum temperature.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s43170-022-00127-1.

Additional file 1. Supplementary text, figures and tables.

Additional file 2. Climate and yield data.

Additional file 3. Metadata for climate and yield data.

Additional file 4. R code for raw data analysis.

Additional file 5. R code for anomalized data analysis.

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Author contributions

SF, JKH and HK conceived the study. SF conducted the analyses with inputs from CJM and JKH, and led the writing of the manuscript. All authors contributed critically to drafts and finalized the text. All authors read and approved the final manuscript.

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Availability of data and materials

The oil palm yield and rainfall data analysed during this study are included in this published article and its additional files. The temperature data analysed in this study are available at http://data.ceda.ac.uk//badc/cru/data/cru_ts/.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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