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LETTER

CO_2 fertilization effect may balance climate change impacts on oil palm cultivation

Tim Beringer[1,*], Christoph Müller[1], Julia Chatterton[2], Michal Kulak[2], Sibyll Schaphoff[1] and Yvonne Jans[1]

[1] Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Climate Resilience, Potsdam, Germany
[2] Unilever, Safety and Environmental Assurance Centre (SEAC), Colworth Science Park, Sharnbrook, Bedfordshire, United Kingdom
[*] Author to whom any correspondence should be addressed.

E-mail: tim.beringer@pik-potsdam.de

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Abstract

Oil palm cultivation has become one of the world's most important drivers of land use change in the tropics causing biodiversity loss and greenhouse gas emissions. The impact of climate change and rising carbon dioxide (CO_2) concentrations in the atmosphere on oil palm productivity is not well understood. If environmental change leads to declining palm oil yields in existing cultivation areas, cultivation areas may expand or shift to other regions. Here we assess climate change impacts on palm oil production using an extended version of the dynamic global vegetation model with managed land, LPJmL4, and a range of climate scenarios from the inter-sectoral impact model intercomparison project. We find increasing average yields under all future climate scenarios. This contradicts earlier studies, which did not consider the potential positive effect of CO_2 fertilization. If we do not account for CO_2 fertilization, future yields also decrease in our simulations. Our results indicate the potentially large role of rising CO_2 levels on oil palm cultivation. This highlights the importance of further applied plant science to better understand the impact of climate change and elevated CO_2 levels on oil palm growth and productivity.

1. Introduction

The oil palm tree is native to West Africa and grows best in tropical climates with abundant water (Meijaard *et al* 2018), with Indonesia and Malaysia as the world's largest producers accounting for 85% of global production. Worldwide palm oil production almost tripled from 25 to 70 Mt yr^{-1} between 2000 and 2018 (FAO 2019). Palm oil demand is projected to continue to increase by 1.8% per year driven by continuously rising demand for food, biofuel, cleaning, and personal care products containing palm oil (OECD/FAO 2018).

Against this background, it is important to understand the potential impacts of climate change on the cultivation and productivity of oil palms. A major change in climatic conditions in current cultivation areas could, for example, lead to a need for relocation to other areas or adaptation measures such as irrigation. Both would have significant ecological impacts. Between 2000 and 2011, expanding oil palm cultivation triggered an additional 3.6 Mha of deforestation, releasing 2.4 $GtCO_2$ (Henders *et al* 2015). Pirker *et al* (2016) estimate that 17% and 63% of new plantations in Malaysia and Indonesia, respectively, were established on former biodiversity-rich tropical forests, and up to a third of the new areas are located on carbon-rich peat soils. Relocation could increase competition for fertile land and lead to further deforestation or displacement of other uses of agricultural land. Large-scale irrigation may drive growing competition for water and entail adverse effects such as falling groundwater tables or soil salinization (Foley 2005, Döll *et al* 2014). Due to the high productivity of the oil palm relative to other oil crops, a shift to alternatives could have even larger environmental impacts, highlighting the need to reduce yield gaps in palm oil production and ensure optimal land management for least environmental impact (Meijaard *et al* 2018, Beyer and Rademacher 2021).

At the same time, there are, so far, only a few studies that investigate the effects of climate change on the cultivation of oil palms using statistical approaches but not yet process-based vegetation modeling (Paterson *et al* 2015, 2017). These statistical methods do not account for the effects of rising carbon dioxide (CO_2) concentrations on the productivity and water use efficiency of plants. Therefore, a process-based modeling approach, accounting for the effects of temperature, water availability, CO_2 fertilization, and crop management (irrigation and harvest) is needed to refine these assessments. Process-based models use representations of biogeochemical processes such as photosynthesis, transpiration, and growth to simulate plant productivity and do not rely on observed statistical relationships that have been developed based on observations that do not include conditions expected under climate change (Cuddington *et al* 2013). We acknowledge also that process-based models require substantial amounts of observational data for process-formulation and parameterization. Despite these data limitations and associated uncertainties, we add a process-based component to the assessments of climate change impacts on oil palms, which we see as a starting point for further scientific scrutiny and understanding.

For this, we here introduce an extended version of the process-based dynamic global vegetation model with managed land LPJmL4 (Schaphoff *et al* 2018a, 2018b) capable of simulating oil palm cultivation at the global scale. We evaluate the new model features against observed oil palm yields at the national level from different world regions and different sites. Finally, we analyze the effects of future climate change on current oil palm cultivation by the end of the century using climate scenarios from five different climate models (general circulation models (GCMs)) based on four representative concentrations pathways (RCPs) that describe alternative future greenhouse gas concentration trajectories (van Vuuren *et al* 2011). Our analysis focuses on the world's largest producer countries which comprise more than 90% of global palm oil production: Indonesia, Malaysia, Thailand, and Colombia (FAO 2019), The model, however, is capable of simulating oil palm production globally and in a spatially explicit manner.

2. Methods

2.1. The LPJmL4 model

LPJmL is a process-based global crop model that provides an integrated framework to study the effects of climate change on terrestrial ecosystems. The model simulates key ecosystem processes and services including net primary productivity (NPP), carbon stocks in vegetation and soils, as well as agricultural yields and irrigation demand (Schaphoff *et al* 2018a, 2018b). Growth and productivity of natural and agricultural vegetation are consistently linked through their water, carbon, and energy fluxes which allows the model to assess a broad range of feedbacks within and impacts on the terrestrial biosphere from land-use change, CO_2 fertilization, and climate change. LPJmL represents the diversity of plant species based on a limited set of plant functional types (PFTs), i.e. generic representations of broad groupings of plant species with similar structural, physiological, and phenological characteristics. This version of LPJmL uses ten PFTs to simulate natural ecosystems, 12 annual crop functional types to simulate the cultivation of annual crop species, and three perennial bioenergy functional types to simulate dedicated energy crop plantations with perennial tree and grass species. The model has been evaluated against a broad range of observed data (Schaphoff *et al* 2018b), including crop yields (Müller *et al* 2017).

LPJmL is driven by weather, land use, and soil data at 0.5° resolution. Depending on the simulations' timeframe either observed weather conditions or scenarios from climate models are used. For this study, we used soil texture data from the harmonized world soil database (FAO/IIASA/ISRIC/ISS-CAS/JRC 2012).

2.2. Implementation of oil palms in LPJmL4

Oil palm (*Elaeis guineensis*) is a perennial evergreen crop native to the tropical rainforests of West Africa but predominantly cultivated in southeast Asia in regions with annual rainfall above 1600 mm. Due to the favorable climatic conditions in major cultivation areas, oil palm is rarely irrigated (Carr 2011).

Hoffmann *et al* (2017) and Woittiez *et al* (2017) summarize yield development in oil palm plantations that guided our implementation in LPJmL. Commercial oil palms are typically cultivated for about 25 years before they are replanted and start producing the first fruit bunches only 2–3 years after planting. Maximum yields occur between 6 and 12 years after planting. Increasing yields in the early phase are driven by increasing leaf area index and canopy closure. Oil palms can reach heights of 30 m and more but are usually replaced once they start to exceed 12 m because large trees are difficult to harvest. Heights around 12 m are typically reached after 25 years of growth (Tan *et al* 2014). The optimal temperature range for growing oil palms is between 24 °C and 28 °C (Pirker *et al* 2016).

The further development of the model presented here is based on previous work that introduced a framework for simulating tree crops in LPJmL (Fader *et al* 2015). Agricultural trees, as implemented in the model by Fader *et al* (2015) are established as larger saplings compared to trees in natural vegetation, reflecting initial growth in nurseries. In the model, agricultural trees require a few additional parameters that are not otherwise used for natural trees or annual crops. These include a parameter to define country-specific planting densities and a pre-defined

Table 1. Model parameters modified for the simulation of oil palms in LPJmL. See Schaphoff *et al* (2018a) for an overview of all model parameters and equations used; range of t_{opt_ph} is based on Tan *et al* (2017) and Corley and Tinker (2016).

Parameter	Description	Value
Allom2	Allometry parameter 2	20
Allom3	Allometry parameter 3	0.4
E_{max}	Maximum water transport capacity of oil palm (mm/day)	6
HR	Harvest ratio: share of net primary productivity allocated to fruits during fruit production phases	0.3
H_f	Years of growth before first harvest	3
k_{est}	Tree density on plantation (trees/ha)	140
t_{opt_ph}	lower and upper limit of temperature optimum for photosynthesis (°C)	24, 28

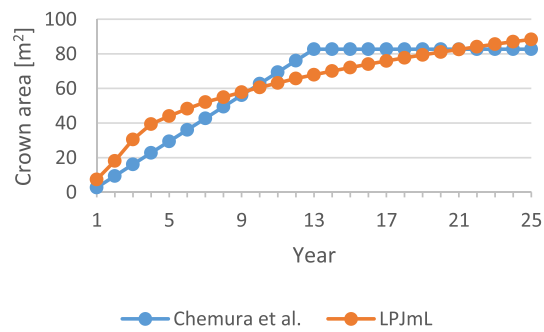

Figure 1. Growth of oil palm crown area simulated by LPJmL and estimated from satellite images (Chemura *et al* 2015).

tree-specific parameter that determines the number of years over which the trees need to grow before they are harvested for the first time. After this period without harvest, a fixed share of the plant's NPP is continuously allocated to the fruits, referred to as the harvest ratio (HR; Fader *et al* 2015). We make use of the same modeling principles to simulate oil palms, which were not included in the set of agricultural trees presented by Fader *et al* (2015).

We parameterized oil palms as tropical broadleaved evergreen agricultural trees, using initial parameters from the tropical broadleaved evergreen PFT, as parameterized in the model for natural ecosystems. Several plant parameters were revised to represent physiological and morphological characteristics of oil palms (table 1).

Following the ISIMIP modeling protocol (Rosenzweig *et al* 2014, Frieler *et al* 2017), we did not use land use information to prescribe the locations of oil palm plantations, but simulated oil palm cultivation on all grid cells. To calculate yields and changes in productivity over time in current growing regions we used land use data from the spatial production allocation model (SPAM) database (You *et al* 2017).

A central adaptation of the agricultural trees model for the representation of oil palms was made by changing the allometry parameters. Allometric rules in LPJmL prescribe the carbon allocation to different plant compartments and hence their relative sizes. Contrary to other trees, oil palms develop large crowns early and at smaller heights. The original parameterization of the tree PFTs in LPJmL provides for a gradual increase in size with growth. In the simulation, this would result in small oil palms forming only small leaf masses and correspondingly low productivity. Against this background, we have adapted two allometry parameters (allom2 and allom3) so that the ratio of tree height to crown size now follows a logarithmic function instead of an exponential function. This means that oil palm PFTs develop large crowns at smaller heights. Following the data in Chemura *et al* (2015), the allometry parameters have been selected so that the simulated oil palms develop a maximum crown area of about 90 m^2 over one growing cycle of 25 years (figure 1). Although non-linear growth processes as simulated by a process-based model such as LPJmL typically do not result in linear increases of individual plant parts, the magnitudes of the changes agree well with the linear model of Chemura *et al* (2015). We also used data reported for an Indonesian oil palm plantation site in Fan *et al* (2015) to refine the calibration of the allometry parameters.

We also adapted parameters related to oil palm physiology. Carr *et al* (2011) cite experimental studies that investigated the water balance of oil palms and found maximum transpiration rates between 5.5 and 6.5 mm d^{-1}. Here we use an average value of 6 mm d^{-1} (parameter E_{max}).

Tan *et al* (2014) present estimates of biomass development in different parts of oil palms based on allometric equations from Corley and Tinker (2003). According to their calculations, fruit biomass is on average about 30% of total biomass in oil palms over a lifetime of 25 years. Accordingly, we set the corresponding parameter HR to 0.3 which means that 30% of NPP is allocated to fruits once fruit development begins, three years after planting, as defined by parameter H_f.

Typical planting densities for oil palm on commercial plantations range between 120 and 150 palms per hectare (Woittiez *et al* 2017). Here we simulate plantations with 140 trees per hectare (parameter k_{est}). Fire is actively used on palm oil plantations for land clearing, before and between cultivation cycles, to remove brush, or eliminate pests during crop cycles

(Cattau *et al* 2016). Earlier studies estimate that fires occur in 2% to 20% of all plantation areas each year depending on drought, soil conditions as well as certification status of plantations (Cattau *et al* 2016, Carlson *et al* 2018). We assume a global value of 5% for tree mortality from crown damage due to fire, to represent managed plantations across all soil and climate conditions in oil palm cultivation areas (parameter r_{CK}, see Schaphoff *et al* 2018a).

2.3. Model evaluation

To validate the model performance under current climate, we used gridded daily mean temperature and cloud cover information from the CRU TS 3.23 climatology dataset (Harris *et al* 2014) and precipitation data from the GPCC Full Data Monthly Product Version 7 (Schneider *et al* 2015), using an internal weather generator to convert monthly observational weather data to daily data. We evaluated simulated yields using data from FAO (2019) for Indonesia, Malaysia, Thailand, and Colombia, whereas the model parameterization is based on oil palm physiology and management information derived from literature and combined with observations from an Indonesian plantation site (section 2.2).

For comparison with yield statistics, simulated gridded yield data have been aggregated as area-weighted national means over current palm oil cultivation areas using land use data for the year 2005 from the SPAM 2005 version 3.2 (You *et al* 2017).

For conversion of LPJmL data from units of carbon to fresh fruit bunches (FFB) we use a carbon content value of 60% per dry weight (Fan *et al* 2015) and a dry-to-wet weight ratio of 53% (Hoffmann *et al* 2014).

2.4. Projections of yields into the future

For the simulations of oil palm cultivation and yields under climate change we used climate scenarios from the inter-sectoral impact model intercomparison project (ISIMIP) fast track initiative as used in the ISIMIP fast track simulations (Rosenzweig *et al* 2014, Warszawski *et al* 2014). This dataset provides daily, bias-corrected, gridded climate data at 0.5° resolution from five different GCMs (Hempel *et al* 2013): HadGEM2-ES (Jones *et al* 2011), IPSL-CM5A-LR (Dufresne *et al* 2013), MIROC-ESM-CHEM (Watanabe *et al* 2011), GFDL-ESM2M (Dunne *et al* 2013a, 2013b), and NorESM1-M (Bentsen *et al* 2013, Iversen *et al* 2013). From each GCM we used climate scenarios based on all four RCPs (van Vuuren *et al* 2011) corresponding to mean changes in global surface air temperature in the late 21st century relative to the 1986–2005 reference period of 1 °C (RCP2.6), 1.8 °C (RCP4.5), 2.2 °C (RCP6.0) and 3.7 °C (RCP8.5) (IPCC 2014). Atmospheric CO_2 concentrations ($[CO_2]$) are prescribed following the corresponding RCP trajectories reaching 420, 538, 669, and 935 ppm by 2100 in RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. For counterfactual scenarios to quantify the effect of CO_2 fertilization, we keep $[CO_2]$ static after 2000 at 370 ppm.

3. Results

3.1. Evaluation of the model

3.1.1. Oil palm yields

Figure 2 shows a comparison of simulated oil palm yields with FAOSTAT yield data (FAO 2019) for the main producer countries. Yields from LPJmL simulations and yield statistics were averaged over the years 1991–2010 to reduce the influence of inter-annual climate variability and data errors. Yield statistics are subject to considerable uncertainty, making it difficult to assess how well these data are suitable for comparison with model results. For example, data from the National Federation of Oil Palm Growers of Colombia reports national oil palm yields of 15.4 tFFB ha^{-1} for the years 2012–2016 (Fedepalma 2017). This value is much closer to the 15.8 tFFB ha^{-1} simulated by LPJmL than the 19 tFFB ha^{-1} from FAO (2019) for the same period.

We also used yield time series from the Malaysian Palm Oil Board[3] (MPOB) and FAOSTAT (FAO 2019) to evaluate the interannual variability of the simulated oil palm yields. For a time series covering the years 2002–2015 we find that simulated yields follow the observed trends closely; however, simulated yields are less variable (figure 3). The root mean squared errors between the three time series are 0.58 FFB ha^{-1} (MPOB vs LPJmL), 1.16 FFB ha^{-1} (FAOSTAT vs LPJmL), and 1.09 FFB ha^{-1} (MPOB vs FAOSTAT) confirming the closer agreement between our model and the yield statistics from the MPOB.

3.2. Oil palm yields under climate change

Figure 4 shows changes in simulated mean oil palm yields between 1971–2000 and 2070–2099 on current cultivation areas, determined using SPAM (You *et al* 2017), in major producer countries averaged over all climate scenarios. The simulations include CO_2 fertilization and assume no change in irrigated areas or management in the future as well as no irrigation water constraints on current irrigation areas. Yields increase in all countries under all climate scenarios. On average across all countries, yields increase by 16%, 31%, 39%, and 50% under RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. The range of modeled yields in simulations based on different climate models increases in the higher emission scenarios.

Figure 5 shows maps of relative and absolute yield increases under RCP2.6 and RCP8.5, respectively, calculated from the difference between average values for 1971–2000 and 2070–2099. Simulated

[3] http://bepi.mpob.gov.my/index.php/en/statistics/yield.html.

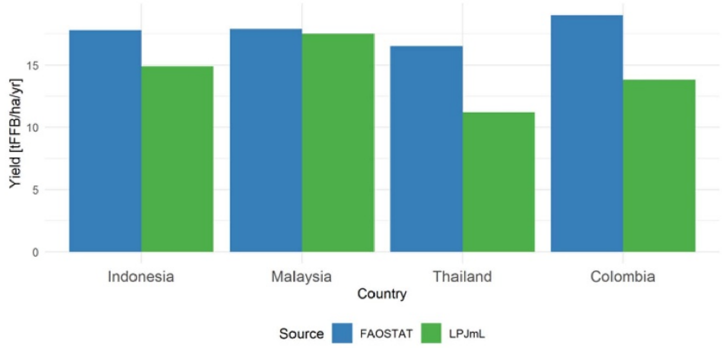

Figure 2. Comparison of simulated and observed oil palm yields (tonnes of fresh fruit bunches per hectare per year) from four main countries for 1991–2010. Country values based on LPJmL simulations are area-weighted national averages using cultivation areas within a country according to the SPAM land use data as weights. We considered the four countries that provide more than 90% of global palm oil supply.

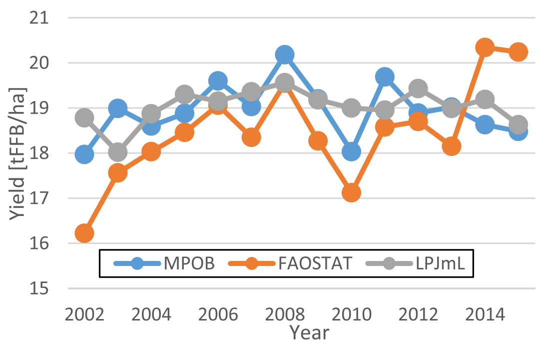

Figure 3. Comparison of observed and simulated oil palm yields in FFB ha^{-1} in Malaysia. Yield statistics were retrieved from the Malaysian Palm Oil Board (MPOB) (http://bepi.mpob.gov.my/index.php/en/statistics/yield.html) and FAOSTAT (FAO 2019).

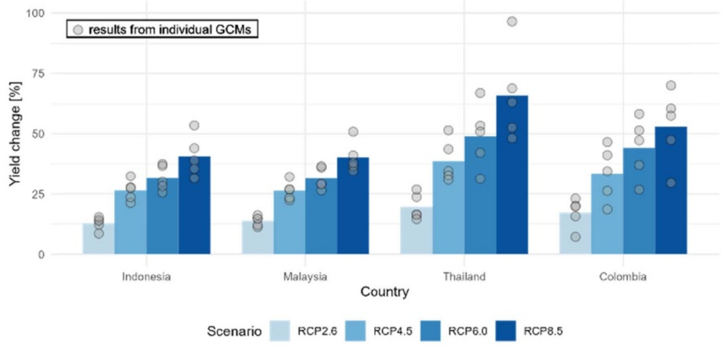

Figure 4. Relative changes in oil palm yields in percent on current cultivation areas up to the end of the century under the four greenhouse gas emissions pathways. Changes are calculated from the difference between average values over all climate models from the baseline (1971–2000) and future (2070–2099) periods relative to the baseline period. Simulations include CO_2 fertilization and assume constant (current) shares of irrigated areas (0.2% of currently cultivated oil palm) and no irrigation water constraints over time on irrigated areas. Points show results of individual simulations based on the climate scenarios from the different climate models.

yields were averaged over all climate models. Under both RCPs, relative yield changes are found in Eastern Africa, Northern Thailand, the Philippines, and Central America. Absolute yield changes differ between RCP2.6 and RCP8.5 reflecting the stronger CO_2 effect in the latter. In RCP2.6 yields increase homogeneously by up to 5 tFFB ha^{-1} yr^{-1} on current oil palm plantation areas, In RCP8.5, the highest yield increases of 5–10 tFFB ha^{-1} yr^{-1} occur in Malaysia, Indonesia, and the Philippines while other areas remain in the same range as in RCP2.6.

To better understand the effects of increased [CO_2] on palm oil yields under climate change, we conducted additional simulations using the climate

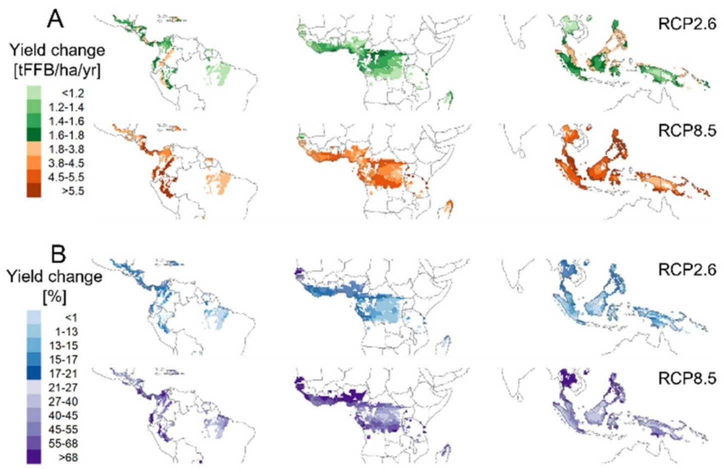

Figure 5. Maps of absolute (A) and relative (B) yield increases under RCP2.6 and RCP8.5. All maps show the difference between 1971–2000 and 2070–2099 periods averaged over all climate models.

change scenarios but prescribing a constant CO_2 level of 370 ppm after the year 2000. Without additional CO_2 fertilization, average yields across all climate scenarios decrease in all countries considered. In our simulations, we found that the negative effects of climate change on oil palm yields are more than compensated by the CO_2 fertilization effect. Figure 6 shows the potential relative yield changes for the end of the century compared to today for all scenarios with and without CO_2 fertilization. Note that the scenarios assuming no CO_2 fertilization are not plausible but only serve to quantify the size of the CO_2 fertilization effect.

4. Discussion

Oil palm cultivation is a driver of biodiversity loss (Fitzherbert *et al* 2008) and greenhouse gas emissions (Miettinen *et al* 2017) and its continued expansion is therefore a cause for concern. However, while a shift to alternative oil crops, all of which are less productive, may increase land use change emissions still further (Meijaard *et al* 2018, Beyer and Rademacher 2021), closing palm oil yield gaps and optimizing location of new production, including consideration of the future effects of climate change, can reduce impacts (Lam *et al* 2019).

Previous studies have applied statistical methods to estimate changes in the climatic suitability of oil palm cultivation under climate change and found decreasing suitability towards the end of the century, especially in Malaysia and Indonesia (Paterson *et al* 2015, 2017). As discussed above, it is unclear if the statistical relationships between current climate conditions and oil palm productivity will remain the same under climate change (Cuddington *et al* 2013). Furthermore, the model used by Paterson *et al* (2015, 2017) did not account for the effect of rising [CO_2] on plants. To our knowledge, no measurements of the effects of elevated [CO_2] on oil palm yields and palm oil quality have been published, but positive yield responses to rising [CO_2] are likely (Woittiez *et al* 2017). Ibrahim *et al* (2010) measured growth of oil palm seedlings under elevated [CO2] and found large increases in net photosynthesis and water use efficiency. It remains unclear how this will affect fruit productivity over the lifetime of palms in plantations.

This effect thus explains the difference between our results and the findings of previous studies that did not take the CO_2 fertilization effect into account and found widespread decreasing oil palm suitability under climate change.

Although rising [CO_2] is likely to have positive effects on productivity, there may be other biogeochemical processes that hinder the ability of the plant to exploit the additional CO_2 supply. Future changes in productivity will largely depend on the extent to which plant-internal biogeochemical processes hinder each other, thus making it impossible for the plant to exploit the increasing availability of a resource such as CO_2 (White *et al* 2016). For example, nitrogen availability may not support yield gains despite rising [CO_2]. The role of sink and source limitations is not well known for most crops and no quantitative analysis for oil palms yet has been published, so large uncertainties remain. So although higher [CO_2] will generally allow higher rates of photosynthesis, this may not necessarily translate into higher rates of fruit development. Until direct measurements for oil palms are available, the exact implications of CO_2 fertilization on palm oil yields under climate change will remain uncertain.

The use of climate scenarios adds a layer of uncertainty to our simulations. The ISIMIP archive includes only a subset of all climate simulations produced for the Coupled Model Intercomparison

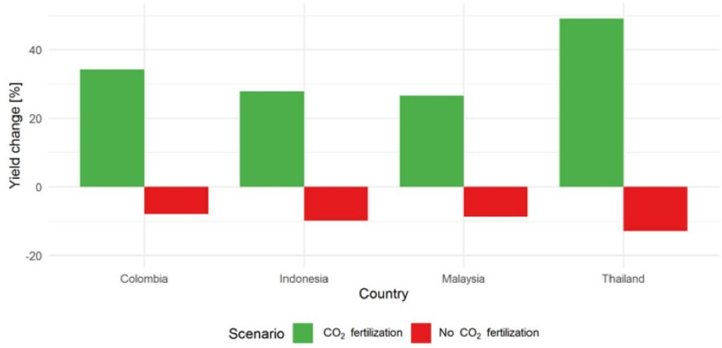

Figure 6. Comparison of relative yield changes between current (1971–2000 mean) and future conditions (2070–2099 mean) averaged over all RCP climate scenarios with (CO_2 fertilization) and without the effects of elevated [CO_2] on plant productivity and water use efficiency (No CO_2 fertilization). All yield simulations assumed only rainfed cultivation of oil palms. The No CO_2 fertilization scenario is not plausible and only serves the purpose of quantifying the size of the CO_2 fertilization effect.

Project (CMIP) and hence covers only about 75% of the full range of future projections for temperature and 55% for precipitation (McSweeney and Jones 2016). In addition, extreme events and the El Niño-southern oscillation (ENSO) as well as potential shifts in their variability and spatial patterns under climate change are generally not well represented in GCMs (Bellenger *et al* 2014, Maraun 2016). However, climate anomalies related to ENSO can have a strong impact on oil palm productivity. In Indonesia, for example, droughts typically occur during El Niño events, which additionally favor the occurrence of forest fires. The combined effects of reduced water availability and haze-related decreases in solar radiation at the surface contributed to 35% losses in oil palm yields during 2015 (Stiegler *et al* 2019). El Niño events are expected to increase in frequency and severity under climate change which would favor yield-reducing conditions in this region. Days with very high temperatures will also become more frequent in the future. However, the daily average climate data we use here are unable to capture extreme temperatures that prevail for only minutes to hours during a day. Carr (2011) describes a critical maximum air temperature threshold of 32 °C–33°C above which oil palms rapidly close their stomata, limiting photosynthesis and hence fruit production. All climate models used here simulate increasing frequencies of days with high temperatures during this century. In the RCP8.5 scenarios from GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC-ESM-CHEM, for example, the proportion of the days where maximum temperatures exceed 33 °C increases from 12% to 79% on average between 2006–2035 and 2070–2099 on current oil palm cultivation areas in Indonesia (figure 7). For Malaysia, the GCMs show an increase from 2% to 57%. According to Carr (2011), these results indicate that higher temperatures limiting oil palm productivity may become an important factor in the coming decades, However, Pirker *et al* (2016) assume that areas with average annual temperatures of up to 38 °C are suitable for oil palm plantations indicating that the upper temperature limit of oil palm cultivation is not yet well understood.

The version of LPJmL used here applies the 'strong optimality' hypothesis by assuming that depending on season and canopy position, Rubisco activity and nitrogen content variability maximize net carbon assimilation at the leaf level (Sitch *et al* 2003). This means that nitrogen deficiency cannot be accounted for in the simulations. Oil palms are typically cultivated with intensive fertilization because oil palms require large quantities of potassium, as well as nitrogen, phosphorus, magnesium, and boron to replace the nutrients removed with yields and maintain high levels of productivity (Woittiez *et al* 2017). As such, the model's inability to account for nitrogen limitation should not lead to distorted simulation results. In general, the lack of available yield data from individual oil palm plantations and for longer time periods remains a major obstacle for model parameterization and validation. Country-level data obscure regional differences and thus allow localized extreme events or their effects on palm oil yields to disappear in the averaged values. Against this background, we consider our work as a first step towards improved model-based climate impact analyses for oil palms. Further model improvements including the use of daily maximum temperature values could be implemented in LPJmL to better represent the impacts of high and extreme temperatures and drought on oil palm productivity once the underlying processes are better understood.

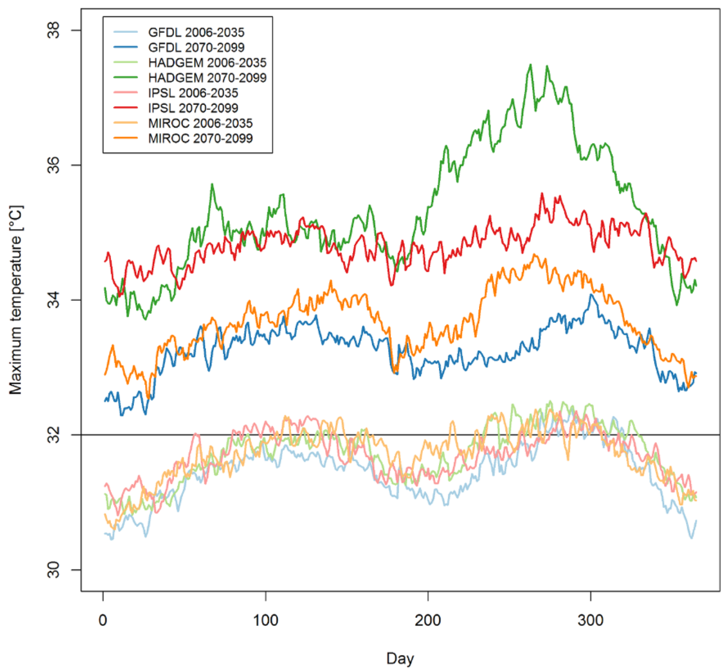

Figure 7. Average maximum daily temperatures on current oil palm cultivation areas in Indonesia during 2006–2035 and 2070–2099 simulated by GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC-ESM-CHEM under the RCP8.5 emission scenario. Data from the ISIMIP fast-track archive.

5. Conclusion

Despite the high demand for palm oil and its environmental impacts, little is known about the effects of climate change on growth and productivity of oil palms. Oil palms are not yet included in free air CO_2 enrichment experiments, which allow the study of the effects of elevated [CO_2] on plants and ecosystems growing under natural conditions, so the long-term effect of high [CO_2] is unknown. While our model adequately reproduces oil palm growth and historical yield levels in major producer countries as well as the experimental effect of elevated [CO_2] observed in oil palm seedlings, the general lack of data from experiments and observations on key aspects of oil palm responses to changes in climate conditions, means that model evaluation is difficult. For this reason, the results of our long-term projections need to be interpreted with caution.

More applied plant science is necessary to better understand the impact of climate change on oil palm growth and productivity, effects of drought severity and timing on fruit development, and the effects of elevated [CO_2] on photosynthesis and water use efficiency. These data are needed to further improve and fully test vegetation models like LPJmL. Better understanding of future climate impacts on oil palm yields is urgently needed, not least to estimate future land requirements of palm oil production and associated GHG emissions. Improved knowledge of management options relating to water and nutrients will also help to optimize sustainable plantation management, close yield gaps, and identify regions where the development of climate-resilient varieties may become necessary.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: 10.5281/zenodo.7804431.

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ORCID iDs

Tim Beringer https://orcid.org/0000-0002-5567-8738
Christoph Müller https://orcid.org/0000-0002-9491-3550

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