Author:
Beese, Lucy V J

Title:
Map the gap

using repeat airborne LiDAR to map the growth of oil palm across a tropical landscape.

Author:
Beese, Lucy V J

Title:
Map The Gap – Using Repeat Airborne LiDAR to Map the Growth of Oil Palm Across a Tropical Landscape.

Map The Gap – Using Repeat Airborne LiDAR to Map the Growth of Oil Palm Across a Tropical Landscape.

Lucy Beese.

A dissertation submitted to the University of Bristol in accordance with the requirements for award of the degree of Master of Science by Research in the Faculty of Life Sciences.

Biological Sciences.

September 2021.

Word count: 20,963

Abstract.

The ever-increasing demand for palm oil has led to a rapid rise in the clearing of tropical forests, particularly in areas of South East Asia. Oil palm is central to the livelihoods of many people, and it must be ensured that the production of palm oil can occur as sustainably as possible. Thus, it is essential to understand how oil palm growth varies across tropical landscapes in order to optimise yields. In this project, repeat airborne LiDAR data was used to map the height growth of over half a million individual oil palms in Malaysian Borneo over a two-year period which coincided with the 2015-16 global El Niño event. The ability of oil palms to continue growing during this period of uncharacteristically dry and hot weather was investigated, and the ecological and landscape features that contributed most to differences in growth rates across landscapes were explored. Despite the drought conditions, oil palms grew 1.61 m yr^{-1} in height on average, but growth varied substantially among individuals, with smaller oil palms exhibiting the fastest rates of height growth. Landscape features such as the distance of palms from forest edges, elevation, and terrain ruggedness all had significant effects on height growth, as did relative competition with neighbours. However, effect sizes were weak and collectively these predictors only explained a small portion of the variation in growth among individual oil palms (5%). The project also revealed opportunities for improving the efficiency and yields of oil palm agriculture, but doing so requires further work to pinpoint the factors that contribute most to driving variation in oil palm growth rates across tropical landscapes.

Covid-19 statement.

Original plans for this research were to travel to the study site in Borneo to obtain information on palm oil production and collect field data for validation. However, these activities were curtailed by the COVID-19 pandemic because of travel restrictions to Malaysia which remain ongoing. Because of this, I focussed solely on the changes in height growth of palms during the project, as I could measure these from existing LiDAR data. Information on oil production would have enriched this project as it could have allowed the results to be put into a more practical context for oil palm plantation owners and managers. This is discussed in more detail in Chapter 3 in the section 'Future Work'.

Dedication.

For my Family.

Acknowledgements.

First and foremost I have to thank my wonderful supervisor, Dr. Tommaso Jucker. I would never have had the opportunity to partake in this project if he hadn't seen potential in my work at a time when even I had begun to doubt myself. His unwavering support and encouragement allowed me to feel comfortable in knowing there was never a stupid question, and that even the most successful academics experience the trials and tribulations of being human. His support as my supervisor has been immeasurable and he truly is an inspirational academic. My thanks also extend to the whole Selva Lab team, who could always be relied on for support and kind words via the WhatsApp group, despite Covid-19 keeping us apart.

The SAFE project and the data collected by those involved in the experiment made this thesis and a wealth of other valuable works possible. The data from SAFE has been a vital part of many studies that have influenced my work and created the foundations for this thesis to be built upon. I must also give a huge thank you to the Bristol Centre for Agricultural Innovation for awarding me with the Lady Emily Smyth Studentship, that made my Master's study financially viable.

Finally, I have to thank my family. My incredible mother Jane, without her unconditional love and support I would not be where I am today, to her I owe everything. My siblings, whose good humour, caring nature, and unrivalled loyalty provide my home base, no matter how far we are apart. Joshua, who I have grown with over our academic journey together, your dedication to your work is unmatched and you continue to inspire me every day. And finally Apollo, I didn't think a little ginger kitten could play such a role in keeping me sane throughout a global pandemic while completing a thesis, alas, I was wrong.

Author's declaration.

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: Lucy Victoria Jane Beese [redacted]

DATE: 17/09/2021

Table of contents.

List of tables and figures.

Chapter 1

Chapter 2

Appendix

Chapter 1:

Introduction

1.1 Introduction.

Oil palm is a recent agricultural success story, having become one of the most globally important crops for the production of vegetable oils over the last century [1]. The ever-rising demand for palm oil over recent decades has led to an exponential rise in the clearing of natural forests to grow oil palm, particularly in areas of South East (SE) Asia [2]. With oil palm plantations covering over 19 million hectares of agricultural land [3–4], 2018 marked palm oil as the world's most traded vegetable oil. This is concerning from an ecological standpoint as oil palm plantations support a relatively low level of biodiversity and lower above-ground carbon storage compared to that found in both primary and logged forests [5–6]. Henceforth, it is essential that there is rapid and careful management of oil palm plantations to ensure that sustainable production of the crop can continue while minimising costs to the environment. In order to achieve this, it must be understood how oil palm growth and yields vary across landscapes. During a time of such rapid global change, this understanding must include an appreciation of the consequences of future conditions such as rising global temperatures and increasing frequency of extreme climate events, such as droughts in the tropics associated with El Niño [7].

The ideal for any agricultural plantation is to increase the productivity of the crop, resulting in greater yields produced per unit of land, boosting economic gain while reducing environmental disruption. However, determining areas of the landscape that vary in their efficiency for growing oil palm is inherently difficult, due to the typical vastness of the areas used for producing this crop. Thus, in order to identify the conditions required for oil palm to grow most efficiently, the optimum techniques for monitoring plant growth over vast landscapes must also be considered. This introduction starts by covering how oil palm has risen to become one of the most important crops across the globe and its implications on biodiversity, before exploring the techniques used to assess and monitor plant growth currently in practice. Current literature on the rates of oil palm growth according to a variety of drivers and how such effects may be compounded by El Niño are then discussed, and conclusions are drawn on how certain factors may affect oil palm growth based on the information currently available. Finally, the specifics of this thesis project and the intended research questions under investigation are addressed.

1.2 Oil palm; its origins and popularity.

Palm oil is produced from several palm species in the Aceraceae family, including *Attalea maripa* and *Elaeis oleifera* from South America, but the overwhelming majority of commercial palm oil production relies on several cultivars of *Elaeis guineensis* – the African oil palm. *E. guineensis* is a monoecious plant that can grow to around 20 m in height, with long pinnate leaves or fronds, that can reach up to 3-5 m in length [8]. The palm bears bunches of fruit known botanically as drupes, consisting of a hard-shelled nut (endocarp) and an orange-coloured outer pulp (mesocarp), which provides the primary source of commercial crude palm oil [9–10].

The first recorded sample of oil palm was thought to be from around 5000 BCE, but the botanical description of *E.guineensis* was produced by Jacquin in 1763 [1–3–11]. Though there has been some contention surrounding the origins of oil palm, it is now typically accepted that *E.guineensis* originated in Western Africa [12]. Traditional methods of palm oil production tended to yield poor quality oil, and thus the plant was predominantly used as a vitamin source; medicine; to produce palm wine; for its edible hearts; and for the harvesting of fronds for thatching and fencing [13]. Until the Second World War, the palm oil industry was largely centred in Africa [1] and palm groves played a large role in the African economy through the 16th century. It was in the late 1800s that improvements in oil quality were made possible by mechanised mills and regulated standards were brought into production [12]. However, attempts to introduce commercial-scale plantations in Africa during the 1800s were thwarted by issues surrounding political instability, poor infrastructure for processing and transport, internal conflict, and difficulties in obtaining land [12]. It is only more recently in the 1960s and 70s that there was a huge expansion of oil palm production in SE Asia, predominantly in Malaysia and Indonesia. Asia had an advantage over Africa with its continuous high temperatures, humidity, and high rainfall which has led to Malaysia and Indonesia producing 85% of the oil palm used today [1]. Palm oil has now become a household name, found in a vast range of products including spreads, ice creams, cooking oils, and shortenings, as well as paints, candles, chemicals, and surfactants [14]. Approximately 70% of the palm oil produced presently is used in food, and of the non-food industrial purposes, around two-thirds are used to produce biodiesel [15–16].

African oil palm has earned the name 'tree of life' owing to the fact that almost every part of the palm is useful to humans, as well as its propensity to live and flourish for many years [14]. The crop is incredibly productive, with average oil palm yields reaching 4–5 t oil ha^{-1} yr^{-1} (tons per hectare a year), around 10 times the yield of soybean oil which has been ranked second among the most productive oil crops [17–18]. Palm oil derived from the mesocarp is a reddish colour, and contains carotenoids as well as other valuable minor components such as tocotrienol antioxidants [19]. Its ability to be refined and fractionated allows the production of many different types of oil with various properties, resulting in its wide variety of uses [19]. Kernel oil is another derivative of the oil palm that can be extracted from the endosperm of the seed via pressing [15–20]. Kernel oil is composed of short-chain fatty acids and is often used in processing confectionaries due to its high lauric acid content and sharp melting profile, as well as for the production of non-edible products such as cosmetics and detergent [21]. The proteinaceous residue that is left after the extraction of kernel oil is referred to as 'cake' and can be used for animal feed, meaning that little of the oil palm goes to waste.

1.3 Socio-economic and environmental impacts of oil palm production.

The 'oil palm boom' has brought with it a variety of positive and negative social, economic, and environmental impacts, making it a very contentious and highly debated global issue (Fig. 1.1). As a huge driver of economic growth in the countries where it is produced, oil palm has been celebrated as a wonder crop, but the social and environmental impacts of this growth have also resulted in substantial criticism [15–22–24]. These effects can be complexly woven together, and an issue of this magnitude calls for careful consideration. In what is the most recent and comprehensive overview of these issues, Qaim and colleagues reviewed the 'Environmental, Economic, and Social Consequences of the Oil Palm Boom' in 2021 [15]. This section aims to give a brief overview of some of their key findings.

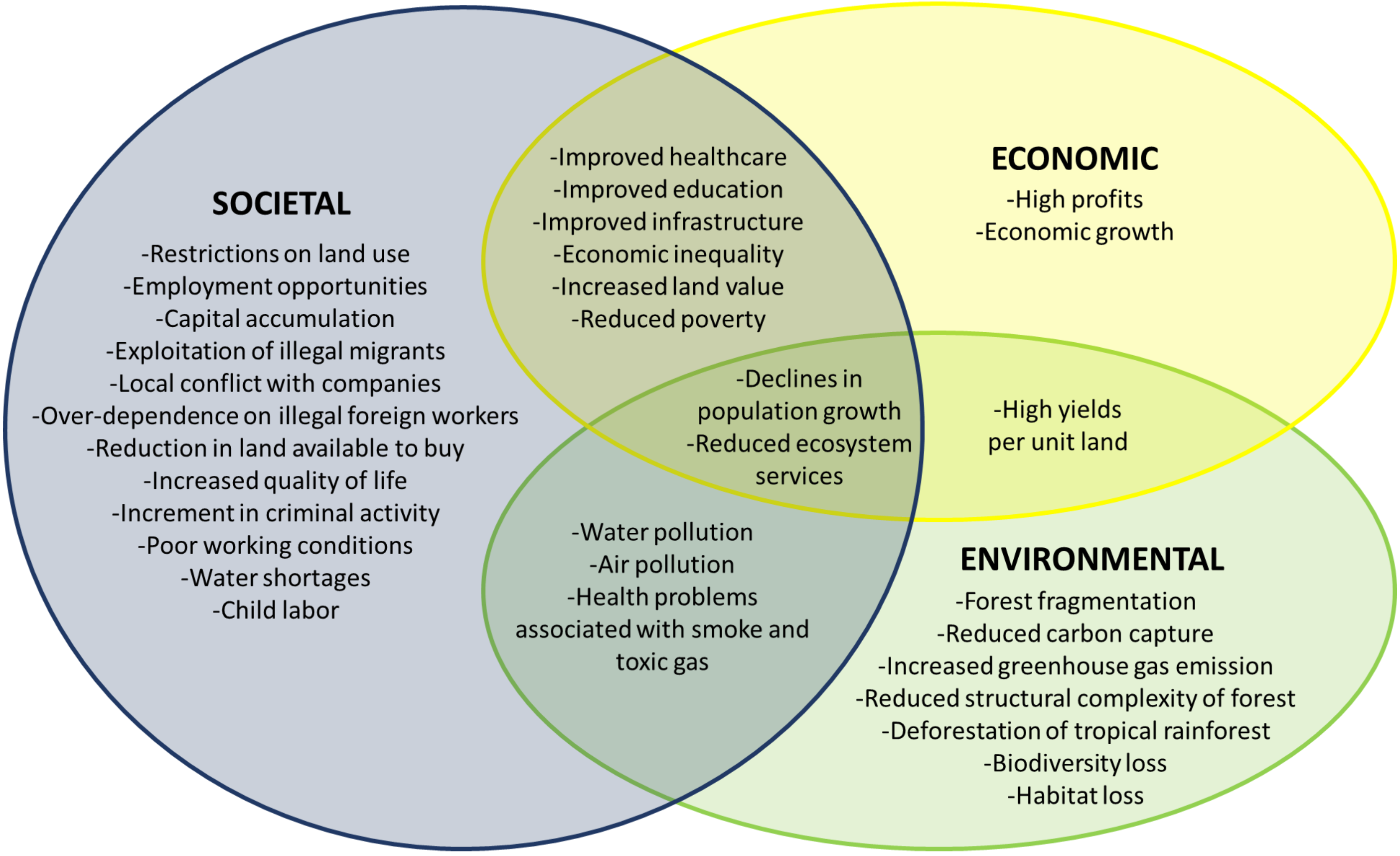

Fig. 1.1: The direct and indirect consequences of oil palm agriculture categorised into 'Environmental', 'Economical' and 'Societal' effects.

1.3.1 Economic impacts of oil palm production.

The economic effects of oil palm agriculture are significantly less documented in the scientific literature than the ecological and environmental effects, however they cannot be overlooked. Palm oil is responsible for around 10% of total national exports from Indonesia [25], and the revenue that it generates is substantial, with the international palm oil trade estimated at 30 billion US dollars in 2018 [15]. It is therefore clear that the crop contributes significantly to the quality of life for many people living in SE Asia and beyond. Indonesia and Malaysia are some of the biggest exporters of the crop and recent studies from Indonesia have indicated that oil palm leads to higher employment incomes and lower poverty rates, not just locally, but at a regional and national level [15–26–28].

It is not only large companies that are involved in oil palm agriculture, smallholder farms also have significant involvement, cultivating around 50% of global oil palm [15–29]. Studies have found a clear and consistent pattern that the livelihood of farmers is positively affected by oil palm cultivation [15–25–27]. Positive economic impacts not only include higher profits for farmers, but also improvements in infrastructure, and new employment opportunities for those looking for work [15–22–28–30–34]. This means that as well as farmers benefitting from increased income, positive effects are also found for other members of society such as laborers, those involved in the supply chain, intermediaries, traders, and small-scale processors [15].

Almost every part of the oil palm can be used for economic gain, meaning that the industry can offer a wide range of job opportunities to a diverse range of people, leading to lower overall unemployment rates [14]. Such high employment opportunities are generated through oil palm agriculture because of the multiple manual activities that contribute to its production and processing, such as the establishment and maintenance of plantations, harvesting, threshing, picking of fruits, and processing into both palm oil and kernel oil or cake [14–15–22–35–36]. Despite this, the production of oil palm is less labor-intensive than the alternative main plantation in most of these areas, the rubber tree [27–37]. This suggests that more labor can be allocated to activities such as expanding farmland or to off-farm activities, which in turn could allow the cultivation of larger areas, contributing to additional economic gains [37].

Studies focused on smallholder farm households in SE Asia have shown that the rise in income associated with oil palm agriculture contributes to the accumulation of capital, and greater expenditure on important commodities such as health and education [15–27–30–33–38–40]. A 2019 study based in Indonesia indicated that the oil palm industry was responsible for a 9% reduction in national poverty [15–28]. Despite the positive financial benefits that oil palm agriculture achieves, not everyone in the community will reap the same benefits [15–22–36–41]. To establish an oil palm plantation a considerable amount of initial capital is required, and consequently, smallholders lacking access to this may fall behind those with better access to capital. As a result, they may adopt oil palm farming more slowly and at a later time, contributing to economic inequality [15–41–42]. Any drive to reduce the extent of oil palm agriculture must account for the socio-economic knock-on effects that this will have on local populations [27].

1.3.2 Social impacts of oil palm production.

Studies from SE Asia have shown how the economic effects discussed above can result in direct positive social outcomes within the community, such as better infrastructure in rural areas, electrification, and improved healthcare facilities [15–28–31]. Kubitza and Gehrke (2018) found that an increase in economic growth led to new schools being built within local communities, which subsequently led to better education for the young population [43]. As populations gain access to better education, other shifts in society emerge as secondary benefits to this, such as changes in family planning, resulting in a decline in population growth [15–27–43]. There are evidently social and livelihood benefits from the increased economic gain and employability in developing countries, particularly when local smallholder farmers start to farm the crop themselves. However, despite the higher wages, the oil palm sector does not always offer huge improvements to welfare in terms of non-income dimensions such as food security [15–44–45].

Similarly to the economic benefits, the social results of increasing employment and improving social services remain spatially heterogeneous [25–36]. Multiple studies have documented how oil palm expansion into rural communities often leads to conflicts with large companies over land and worker rights [15–23–46–47]. Such conflicts have arisen between locals and palm oil companies due to unclear property rights over land that local communities have claimed under customary law, though they lack the formal titles [15–37–48]. When parties are willing to negotiate this may be settled through compensation and out-grower schemes, but this is not always feasible, nor undertaken in practice [15–33–47]. It is the stakeholder groups, such as the investing households, employees, and out-growers that benefit from associated socio-economic gains, while the traditional land users suffer from the restrictions, decreases in land available to buy, and the increased cost of the land that is left available to them [22]. Local villages around plantations have also been found to suffer water shortages due to redirected water flows, further increasing tensions between farmers and locals, while also being particularly concerning in terms of human health and welfare during times of drought [49].

Another social problem that has been identified in conjunction with the expansion of oil palm is the involvement of the laborers. There were reported issues as recently as 2018 concerning the use of child labor on plantations in Indonesia [50], as well as the exploitation of illegal migrants [15–34]. Poor conditions for workers are not uncommon, leading to a wealth of associated human welfare concerns [34–51]. In 2003, Wong and Anwar showed that Malaysia had one of the highest rates of illegal foreign workers in its workforce, and in the state of Sabah around 90% of the laborers in agriculture have migrated from Indonesia [52–53]. Foreign labor immigration has been key in the growth of the oil palm industry over the last thirty years in places like Kota Tinggi, Malaysia [54]. However, it has also led to strong tensions with local populations, who commonly blame immigrant workers for economic hardship and associate them with a rise in criminal activities [52–54].

Some of the negative social effects experienced by societies can also be linked to the environmental impacts of oil palm agriculture, such as the overuse of chemical fertilisers and pesticides. The presence of high volumes of agrochemicals in the landscape has detrimental effects on air and water quality [22]. Pollution in water bodies mainly occurs through an excess of fertilisers resulting in nitrate pollution which can damage the local fishing industries. As a result, the benefits that oil palm agriculture brings to a population may come at the expense of alternative socio-economic benefits that the fishing trade may offer [15–55–56]. Not only is the air quality at a detriment due to agrochemicals, but the land used to create palm plantations is typically cleared using fire, releasing smoke, toxic gases, and carbon dioxide into the environment. Furthermore established oil palm plantations can lead to increased production of haze and aerosols further diminishing air quality [57]. Poor air quality has been linked to health problems in local communities, with increases in respiratory problems and associated human mortality rates [15–58]. These effects are likely to be further exacerbated in the future due to climate change, which is expected to result in more frequent heatwaves and droughts and therefore higher risk of fires and related health problems [15–59].

1.3.3 Ecological and environmental impacts of oil palm expansion.

The abrupt rise in oil palm plantations across the globe has led to a wealth of concern in regards to the negative impacts that the clearing of primary forests has on the environment and biodiversity. In contrast to other vegetable oils, palm oil has its own set of unique problems, because it is typically grown in areas where carbon-dense tropical rainforests with high levels of biodiversity would have existed otherwise [25–60]. Between 2000 and 2017, an average of 350,000 ha of primary forest was cleared each year in Borneo, with around half of this associated with oil palm agriculture [15–25–59–61–63]. The IUCN reported in 2018 that across Malaysia, around 68% of oil palm plantations were developed at the expense of forests, while the remaining replaced other land uses including shrubland and pastures [25–61]. The loss of carbon-sequestering forests leads to a subsequent increase in the warming effect of greenhouse gases on global temperatures. This effect is particularly prominent in areas of tropical deforestation, where annual carbon emissions have been estimated to contribute ~10% of total anthropogenic greenhouse gas emissions worldwide [60]. The deforestation occurring in Borneo is a compounding force in the current effects of global climate change, leading to the increased occurrence of temperature extremes, higher maximum daily temperatures, and decreased precipitation levels [64]. Such effects have been most profound in the heavily logged areas of south and east Borneo and these impacts are exacerbated by El Niño [64].

One of the most obvious direct impacts of oil palm agriculture is the loss of habitat for wildlife, leading to declines in biodiversity and species richness. The development of oil palm plantations also leads to forest fragmentation as the portions of undisturbed land that act as sanctuaries for wildlife become increasingly smaller and isolated [65]. This exacerbates the problem of direct habitat loss, as the remaining fragments are often unhospitable because oil palm plantations can affect the habitats next to them through edge effects and pollution [66]. When oil palm is planted as a monoculture, the structural complexity and heterogeneity of a primary forest is lost and replaced with the comparatively simple structure of regularly planted crops, able to support far lower levels of biodiversity, as well as being associated with ecosystem function declines both locally and regionally [25–61–66–67]. A 2020 study showed that the oil palm monocultures have profound impacts on both invertebrate and vertebrate diversity throughout SE Asia, including numerous charismatic and endangered vertebrates endemic to Borneo such as the Bornean Orangutan and the Sunda Clouded Leopard [68–69]. To maintain biodiversity and support endemic species like these, oil palm monocultures are a poor substitute for areas of original and native tropical forests [66]. Oil palm plantations have been shown to hold fewer than half the vertebrate species of primary forest and far lower species richness than disturbed logged or secondary forests. Maintaining a high level of biodiversity is vital to sustaining functional and stable ecosystems [59–69]. The production of oil palm at this scale, and its expansion into new territories may also bring with it the threat of invasive pest species which can severely impact endemic biodiversity [69–70].

It is not just habitat loss and fragmentation that creates an unsuitable habitat for many forest specialists, but also the use of agrochemicals, irrigation practises, and human disturbance [25]. Land clearing for oil palm plantations is hugely disruptive and can result in a variety of secondary impacts such as water pollution, soil erosion, and air pollution, all of which can affect a range of ecosystem functions as well as making the habitat less viable for a range of different animals and plants [22–25]. Excessive application of fertilisers often leads to nitrate pollution of waters, in addition to which, crushed shells and fat residues (known as oil mill effluent) are often left untreated and returned to pollute water courses, affecting aquatic life further [15–56]. These effects on freshwater ecosystems are further exacerbated by higher sediment run-offs due to lower forest cover and subsequent soil erosion [25].

The loss of both primary and secondary tropical forests associated with palm oil production also impacts a variety of other functions and services provided by forests. These ecosystem services are defined by the Millennium Ecosystem Assessment as '*the benefits that humans obtain from ecosystems…These include provisioning, regulating, and cultural services that directly affect people. They also include supporting services needed to maintain all other services…Ecosystem services affect human well-being and all its components, including basic material needs such as food and shelter, individual health, security, good social relations, and freedom of choice and action*' [71]. Forest functions affected by oil palm agriculture include carbon sequestration and storage, regeneration of soils, and nutrient cycles [25]. Depending on their age, tropical rainforests may hold up to 270 tonnes more carbon per hectare than oil palm plantations [15–24–72–73]. Consequently, even though mature oil palm plantations can store significantly more carbon aboveground than alternative oils [24], the net loss in ecosystem carbon stocks when converting tropical forests to oil palm plantations is considerable.

Despite the long list of environmental and ecological impacts associated with palm oil production, a study by Beyer and colleagues in 2020 suggests that oil palm may be the best crop to farm for oil in terms of its consequences to the environment [25]. Because of its incredibly high yields in comparison to alternative vegetable oils, a much smaller area of land is required to generate the equivalent quantity of oil. This gives oil palm the advantage of requiring less land than other lower-yielding crops, minimising the scale of the environmental impact in comparison to the alternatives [25]. Since oil palm can only be grown in tropical regions, the carbon and biodiversity impacts per hectare are greater than that of its competitors and yet, when accounting for the area requirements for oil production, oil palm represents the lowest average loss in terms of both carbon and biodiversity per tonne of oil produced [25]. Demand for vegetable oil – whether from oil palm or alternative crops – is unlikely to decrease in the future. As a result, finding ways to grow crops such as oil palm more sustainably and in ways that are less ecologically damaging is key. One way of doing this is to ensure that oil palm is grown as efficiently as possible, but to do this variation in oil palm yields and growth rates across landscapes must be understood.

1.4 Closing yield gaps to minimise environmental impacts of oil palm production.

Yield gaps represent the difference between actual yields and those that are agro-climatically attainable [25]. Simulation models have been used to calculate the maximum theoretical yields of oil palm, working out at around 18.5 t oil ha^{-1} yr^{-1}, highlighting the significant gaps between actual and theoretical yield in the oil palm industry [74]. Harvested yields rarely exceed 3 t oil ha^{-1} yr^{-1}, when estimates suggest that with improved cultivation practices and quality inputs up to 8 t oil ha^{-1} yr^{-1} could be harvested [15–20–75]. In order to keep up with the increasing demand for palm oil, the area dedicated to oil palm agriculture must be expanded, or the yield of existing oil palm plantations must increase [15]. Closing these yield gaps by sustainable means is far from simple, especially as demand is still on the rise and incentives favour increasing plantation size rather than optimising yields [25]. Consequentially, tropical rainforests are at constant threat of being expanded into.

There are two scales at which improving crop efficiency can be considered. On a large scale, 'landscape drivers' of crop growth can be investigated. This describes where growth varies across the globe due to factors such as climate -which is where the majority of research has been focussed until now. The second option is looking at palm growth at a smaller scale and deriving 'local drivers' that contribute to oil palm growth, which have received much less attention across scientific literature.

Improving the management of oil palm plantations can have a profound impact on yield, but to implement beneficial practices across large scales more agronomic research is required [15]. The idea of maintaining intact forests while simultaneously maximising the productivity of crops is often referred to as the 'land sparing' approach. The land-sparing approach typically describes high-yielding, intensified agriculture, meaning that a greater yield can be obtained from a smaller footprint of land [76]. A study in 2016 found that by optimising the management of 190 Indonesian oil palm smallholdings (e.g., better seed quality, pruning, weed management), yields could be increased by up to 65% [77]. If these approaches can have such a marked effect on productivity across smallholdings it is essential to further investigate their benefits for plantations on a commercial scale [77]. A more recent 2018 study showed that the main factors causing gaps between theoretical and realised yields in Ghana were incomplete crop harvesting and poor agronomic management, although it is likely that the factors leading to yield gaps differ among regions and climates [78].

There is of course a risk that by attempting to maximise productivity, environmental impacts of oil palm production might actually be increased, for example: through greater nitrogen use, irrigation, and pesticides. A second approach to sustainably managing agricultural landscapes is the 'land sharing' technique. Land-sharing promotes ecosystem services and environmentally friendly crop production which is crucial for conserving species that are incompatible with agriculture [76]. One such example of this is 'The Biodiversity and Ecosystem Function in Tropical Agriculture' (BEFTA) Programme [79], which aims to find ways in which increasing landscape structural complexity could increase the sustainability of oil palm agriculture without detriment to oil palm yield. A growing body of literature suggests that increased productivity does not necessarily have to come at the cost of greater environmental impacts. For instance, a 2014 study showed that oil palm yields were actually greater when planted with a cover crop and that weeding had no net positive effect on oil palm yields, suggesting that understorey vegetation does not compete strongly with oil palm for water or nutrients [80]. Similarly, other research has shown that the common practise of removing epiphytes from oil palms has no positive effect on yields [81]. In addition to potentially making oil palm plantations more biodiversity-friendly, not having to remove weeds and epiphytes also reduces labour costs, benefitting both farmers and the environment.

Numerous other local drivers affect yield, one such factor being soil type. Oil palms on sandy substrates have shown an 18-142% increase in yield compared to those of marine clay, with significant productivity increases also associated with factors such as peat maturity. The issue with the implementation of practices from findings such as these is that in many cases, the type of soil used for planting will not offer many alternative options due to limited land available to plantation owners. Additionally, one 2018 study highlighted issues with productivity losses due to poor harvesting processes, showing that yield gaps are not only due to farming techniques [82]. This highlights yet another area in the processing of palm oil used on both small and large scales that could lead to higher oil production from the same population of plants [82]. Among the landscape-driven factors that lead to yield gaps, the variety of palm selected for plantations may also contribute to increasing oil palm productivity [20–25–83]. However, growing location has a higher environmental impact than crop type does, providing one of the main reasons as to why producing oil from the most optimal areas is deemed preferable to the substitution or breeding of different types and varieties of vegetable oil [25].

The factors affecting yield discussed here are a brief overview of just some of the factors that could be driving yield gaps and are by no means exhaustive. There are a variety of other important factors that have been accounted for in more thorough reviews of oil palm and yield gaps [75–82–84]. What is evident from reviewing the literature is that better ways of mapping oil palm productivity at scale across entire landscapes is required in order to identify where yield gaps are occurring and their potential drivers.

1.5 Remote sensing and its potential for uncovering variation in oil palm productivity across landscapes.

Traditionally, ecologists have relied on hard-won field data to monitor the dynamics and growth of ecosystems such as forests and tree plantations. However, manually monitoring plant growth in the field is costly, time-consuming, and prone to error [85]. One way to get around these issues is through the use of remote sensing data. Remote sensing describes the process of measuring emitted, reflected, or back-scattered electromagnetic radiation from the Earth's surface via sensors located at a distance from the point of interest [86]. These sensors can be placed in a range of environments and include ground-based, aerial, and space-borne varieties that can be either active (emitting and detecting their own source of radiation, such as laser beams or radio waves) or passive (simply measuring natural radiation reflected off the earth's surface, such as heat or light in the visible spectrum [87]. Over the past two decades, remote sensing has revolutionised the way ecosystems are mapped, and their changes through time at broad spatial scales, as well as ushering in a new era of precision agriculture that is helping farmers to improve yields on their land [88–89].

In the context of oil palm agriculture, remote sensing imagery is being increasingly used to map the overall extent of oil palm plantations [90], as well as identifying and measuring the size of individual palms [89]. For instance, in 2014 researchers showed how high-resolution satellite imagery and traditional image processing could be used to accurately detect around 90% of individual oil palms in a plantation [91]. This was further improved upon in 2016 when Santoso and colleagues used Quickbird satellite imagery to produce around 98% accuracy [85]. In addition to high-resolution satellite imagery, another promising technology for mapping oil palms is airborne light detection and ranging (LiDAR). LiDAR is an active remote sensing technology that relies on a high-frequency laser scanner to emit 100,000s of laser beams per second and then measure the time it takes for these to hit an object and be reflected back to the scanner. In this way, LiDAR technologies can create a detailed 3D representation – or point cloud – of both the vegetation and the underlying topography. LiDAR has been used to successfully identify and estimate the height and biomass of individual oil palms in Malaysian Borneo [92]. This suggests that by using repeat LiDAR datasets collected over time, it should be possible to identify hotspots of oil palm growth across landscapes, as well as areas where growth is slower than expected – thereby mapping yield gaps at scale. Moreover, these same LiDAR data could also be used to capture landscape features that may help explain why oil palms are growing particularly well or poorly in specific locations.

1.6 Factors affecting oil palm growth rates.

There are a wide variety of intrinsic and extrinsic factors that may explain why some individual plants grow faster than others across landscapes, including genetics, local soil conditions, microclimate, pathogen prevalence, and fertiliser use. Here, a subset of landscape features that can be either directly measured or estimated from LiDAR data are investigated (Table 1). From this, the main factors that potentially affect oil palm growth in tropical landscapes are outlined and these form a basis for the analyses presented in this thesis.

Table 1: Topographic and vegetation structural attributes believed to affect oil palm growth and the metrics used to measure or investigate them. TWI= Topographic wetness index, TPI= Topographic position Index, TRI= Terrain ruggedness index.

Factors affecting oil palm growth	Corresponding LiDAR-derived metrics			
Water Availability	TWI	Distance to rivers		
Topography	TRI	TPI	Aspect	Slope
Competition	Distance to forest edge	Neighbours	Palm height	
Life stage	Palm height	Crown size	Crown volume	
Microclimate	Elevation	Distance to forest edge		

1.6.1 Topography and its influence on water availability and microclimate.

The exact location within a landscape where a plant germinates can profoundly influence its future potential for survival and growth. Topographic features such as terrain aspect, slope, elevation, and curvature can affect plant growth in a number of ways, as they influence soil structure, nutrient availability, water flow, and other local microclimatic conditions such as air temperature, humidity, and exposure to wind and solar radiation [93].

The topography of a landscape can be used to predict where water might accumulate across the region. Oil palm requires stable light and moisture supplies in order to achieve the most efficient growth and yield production. A minimum annual rainfall for the successful growth of oil palm is estimated at around 1800 mm, but in Malaysia 2000 mm per year has been found to produce optimum yields [94]. In SE Asia droughts and heatwaves are typically associated with El Niño events, where sea surface temperature increases by around 0.5 °C – peaking in December. Oil palm favours high temperatures, with anything below 18 °C inhibiting growth, but the crop is believed to be vulnerable to drought [95–96].

Droughts can lead to the immediate death of plants due to hydraulic failure, or alternatively result in a slower death through carbon starvation, or a combination of both mechanisms [97–98]. Though water limitations have been found in multiple cases to restrict the growth of oil palms there is a gap in the literature on the topographic and canopy metrics that may contribute to water stress and lead to variation in yields across landscapes [99–105]. A study by Woittiez and colleagues found that when there are water deficits >400 mm per year, yields are more than halved [75]. This indicates the importance of investigating landscape-driven information to predict the impacts of drought-related changes in growth [106].

For optimal growth of oil palms, it is thought that dry periods should not exceed a maximum of 3 months per year. An almost continuous water supply is required for their successful growth, and excessive dry periods lead to crop reduction around 10 months after the drought period due to the abortion of inflorescences, the death of existing fruit bunches, and changes in sex determination of inflorescences, increasing male skew [94]. Drought periods can additionally disturb the production and expansion of plantations as seedlings require a minimum period to establish and develop a root system before being exposed to this type of physiological stress [94]. Due to the unique vegetative structure of the leaves and stem in oil palms, there is around a three-year interval between the inflorescence and production of a mature fruit bunch. Because of this, causal links between environmental factors and fruit yield are complicated [10]. It becomes even more difficult to predict or anticipate the effects of drought on oil palm when also considering how the landscape itself will experience different levels of drought intensity due to variation in topography and its influence on local microclimates.

Sun and colleagues found that water stress not only affects growth, but also nutrient concentration, biomass partitioning, and the physiological and morphological traits of oil palms [99]. They determined that oil palm growth in drought conditions responds negatively to fertilisation and that it compounds the drought stress by dissolving the fertiliser. In this experiment, oil palms showed an ability to slow their growth and alter the way they allocated biomass between organs, with their root-to-shoot ratio increasing under water stress [99]. This highlighted that it is not only landscape features that may produce variation in the effects of drought experienced by oil palm, but that this can also be confounded by management practises.

Another study conducted by Cao and colleagues confirms the inhibition of oil palm seedling growth under water-limited conditions, however it must be appreciated that the effects on vulnerable seedlings are likely to be more severe than the effects on mature and established palms [107]. This is likely to be reflected in the vulnerability of plantations across a landscape to the effects of drought, dependent on the development stages of palms in the region and their associated water-stress tolerance. Silva's experiment in 2017 focussed on mature palms and identified the molecular reasons behind reduced growth during drought, including the decreased activity of enzymes associated with carbon metabolism such as sucrose-phosphate synthase, Rubisco, and ADP-glucose pyro-phosphorylase [108]. They investigated how two different hybrids of oil palm adjusted their carbon metabolism to cope with drought and found that although both could tolerate drought conditions, differences in the hybrids showed in their ability to adjust to the conditions [108].

Other than the effects associated with reductions in growth caused by drought, Eycott identified how drought may also cause variations in the resilience of particular ecological functions throughout oil palm agroecosystems [109]. They measured several functions including seed removal, mealworm predation, herbivory, and decomposition of leaf litter throughout the El Niño period, and determined that the ecological processes that were measured across the plantations were resilient to changes in rainfall. Their findings indicated that ecological functions could remain robust under future changes and frequency of drought periods. Despite this, what is most important from an economic perspective is that yields do not decrease with such changes. Corley and colleagues advocate that drought-tolerant varieties of oil palm are necessary to prevent yield reductions and that such selection must be completed during the drought conditions that crops will be planted in [94].

Having discussed the effects of water stress on oil palms, the extent to which landscape features affect where water is more likely to accumulate in the landscape must be appreciated to understand where palms may be most affected by drought. There are a host of reasons for variations in water availability and microclimate across a landscape, including structural attributes of vegetation such as density and terrain roughness [93–110]. One way to quantify 'roughness' within a landscape is the 'terrain ruggedness index' (TRI), which captures how jagged or flat the terrain is on average by expressing the amount of elevation difference between adjacent cells of a digital elevation grid. Rougher landscapes may be more variable in terms of soil moisture compared to flatter ones. This is because where peaks and troughs form, water is more likely to be retained in the lower regions and run-off from the elevated regions, creating pockets of wetter and drier soils even at a very localised scale.

Alongside any river over three metres wide across Sabah, 20 metre strips of riparian forest reserves border the watercourses (Sabah Water Resources Enactment, 1998). These riparian buffers are intended to improve the quality of the water by reducing runoff, maintaining hydrological processes and associated ecosystem functions, and reducing flood risks. But these areas also have the additional benefit of functioning as a reserve habitat for forest-dependent species, supporting biodiversity and landscape connectivity [111–113]. A 2021 study by Williamson and colleagues evidenced that riparian buffers 20-30m wide at each side of a river can provide a cooler and more humid microclimate than that of continuous forest, and adoption of wider buffers may bring benefits both in terms of hydrological processes and terrestrial biodiversity to the surrounding landscape [114]. Humidity is an important factor in oil palm growth, with plants requiring relative humidity to be >75% per year to maintain optimal growth. The distance of oil palms to rivers is therefore likely to influence both the microclimate that they experience, as well as the availability of water to them. TWI is another metric that can be calculated from a digital elevation model (DEM) as a proxy for soil moisture. TWI identifies areas that accumulate water flow and shows topographically dry and wet areas of land [115]. The impacts of El Niño are likely to be experienced to a higher degree in areas with low TWI, because of the existing limits on water availability, than areas that originally have wetter soils.

The topographic position index (TPI) or the curvature of the terrain refers to the difference in elevation between a particular point and the mean elevation of the surrounding area. Positive values indicate areas on ridges and negative ones denote depressions. Jucker and colleagues found that TPI strongly influenced both local air temperature and vapour pressure deficit (VPD), with ridges experiencing much drier and hotter conditions compared to gullies [93]. VPD describes the difference in moisture between the air and the amount of moisture the air can hold when it is fully saturated, and plays a strong role in driving transpiration in plants (and therefore their overall water status). Plants growing on ridges and steep slopes therefore tend to experience stronger competition for water as well as nutrients. Oil palm is most often grown where land is relatively flat due to recommendations from the 'Roundtable on Sustainable Palm Oil', 'Malaysian Palm Oil Board', and 'Standards for Oil Palm Production', that palm oil production on flat surfaces is higher [92]. However, these recommendations are often near-impossible to follow in tropical landscapes that vary considerably in their topography, leading to considerable variation in the landscape position on which different oil palms are planted.

In addition to water flow, terrain aspect and slope also influence when and for how long a particular area is exposed to the sun, thereby affecting air and soil temperature, as well as photosynthetic activity [116–117]. Intuitively, the number of hours of solar exposure will affect photosynthesis rates, with lower rates of photosynthesis resulting in lower fruit yield and vice versa. Tropical landscapes typically experience high rates of solar radiation and because plantations are mostly located on relatively flat land, aspect is not thought to be a strong determinant of growth. However, aspect does have known effects on microclimates in tropical rainforests, with eastern facing slopes having hotter and drier microclimates than those that are west-facing [114]. It has been proposed that the higher maximum temperatures on east-facing slopes are due to greater insolation from clear mornings, as local cloud cover generally develops in the afternoons [116]. It is also of interest to note that the effect of solar radiation is most prominent for maximum daily temperature, with less pronounced effects on minimum temperatures. This means that aspect and slope could play an important role in exacerbating conditions of extreme heat, such as those observed during El Niño events [118–120].

In addition to water flow and microclimate, topography can also influence local variation in soil nutrient availability. A study by De Toledo and colleagues portioned the effects of soils and topography on tree mortality and found that these were dependent on tree size. Moreover, the effect of soils and topography on tree mortality increased after storms, highlighting the importance of considering factors such as watershed morphology and wind exposure for predicting patterns of tree mortality [121]. Toledo's study found that trees on steep slopes with fertile soils, and those in sandy soils in valleys exhibited higher tree mortality rates than those on well-drained clay soils on flat terrain. This shows the importance of accounting for topography when thinking about landscape-scale variation in plant demographic rates.

Finally, the position of an oil palm in relation to areas of primary forest is also of note in terms of microclimate and not just in terms of competition. Those oil palms closest to forest edges are more likely to experience the influence of a different type of microclimate, not only since they may be experiencing edge effects, but also because they will be influenced by differences in the local climate and water availability around forest areas. Nunes and colleagues determined that canopy height reduction due to fragmentation was also affected by topography, with forests located on ridges displaying a reduced canopy height of 0.5 metres in contrast to riparian forests, and forests situated within valleys [98]. Forest canopy structure as a product of topography and microclimate can vary greatly leading to variation in micrometeorological and light conditions, for example, a closed canopy can buffer daily temperature changes, as well as wind and radiation [98].

1.6.2 Competition for light and nutrients.

Competition in plants refers to the impacts on plant growth or fitness induced by the presence of neighbours. This typically involves a reduction in resources available to the plant such as water, light, and nutrients. Because LiDAR explicitly measures vegetation density and its spatial variation, it can provide key information on how planting density and configuration affect how individual oil palms compete with one another for light and water.

There are a variety of factors that contribute to the level of competition that an oil palm will endure for light, one of the most obvious being exposure to sunlight. Within the tropical regions where oil palm is grown, there is almost a continuous supply of sunlight distributed across plantations, meaning that solar radiation is less likely to be a limiting factor to palm growth. However, not all of this light will be distributed equally across each palm in a plantation. Optimal solar exposure for oil palms has been estimated between 1,800 and 2,200 hours a year, or a minimum of 5 hours a day, every day of the year [94]. In areas where plants may differ in heights, it is the tallest palms that will be best suited to compete for sunlight, and these may form shades using their canopies over smaller, less developed stands. Yields of oil palm have been found to decrease significantly where they are shaded by other palms because of competition for light [20–122]. High levels of solar radiation are vital in terms of bunch yield, and even across the same plantations, side-rows of oil palm with less shading often produce greater yields than those in inner rows [94]. Because of this, by investigating the average heights of palms around a particular individual, researchers can get an idea of the level of competition that the palm is facing for light.

Typically, oil palms are found planted in triangular or square patterns with approximately 9 m spacing between them, a density found to be optimal in terms of competition between palms [94]. Despite this, a blanket approach to planting across a heterogenous landscape will mean that this approach may be optimal in some areas while suboptimal in others. For instance, in areas of the landscape where there is a poor ability to retain soil moisture, it may be that palms would be optimally spaced out at further distances, to allow for less competition where water is scarcer. By measuring the vegetation density within an oil palm's neighbourhood and exploring how this influences growth at different positions within the landscape (e.g., exposed ridges vs flat, low-lying areas), it would be possible to determine if planting density can be optimised to match the features of a particular landscape.

Another interesting phenomenon that may relate to competition – although likely associated with local microclimate as well – is the existence of edge effects. Edge effects are often described from the perspective of primary forest, where there tends to be increased tree mortality at the boundary of oil palm plantations. The effects of these boundaries on the palms planted at the edges of plantations have been documented far less across scientific literature. Palms at the edges of plantations will not only be competing with their oil palm neighbours, but also be competing with forest trees. Competition for nutrients, water, and light will all vary more substantially for oil palms at the edges of plantations than those at the centre of plantations, and a 2014 study by Edwards and colleagues attempted to quantify these effects [82]. One of the key concerns of oil palm growers is that plantations closer to unmanaged forests may be at risk of spill-over from pests and pathogens. Natural forest habitats have the potential to act as reservoirs of pests, parasites, invasive weeds, and disease [82]. The spill-over of biodiversity from primary forest to agricultural land therefore has the potential to cause ecosystem 'disservices' to oil palm [82–123–124]. There is also reluctance from oil palm plantation managers to incorporate areas of natural forest between plantations because this would reduce the amount of land available for growing crops, and thus incur a cost to local production as well as making the management of the crop more difficult. The issue of incorporating natural land could also potentially increase the demand for converting land elsewhere to agriculture if it is not coupled with the intensification of oil palm production [82–125].

On the other hand, retaining natural habitats such as forest fragments and riparian strips within agricultural landscapes has been advocated as a means of benefitting ecosystem services and consequentially increasing yield [82–126–132]. This has the additional benefit of providing conservation advantages to biodiversity. Results from Edwards' study indicate that proximity of palms to natural forests actually had a neutral effect on oil palm yields. Thus, even though oil palm may not benefit directly from association with natural forest, they do not seem to be inhibited either, proving there may be the potential to make landscapes more biodiversity-rich, without a consequential reduction in yield.

1.6.3 Life stage and ontogenetic effects on growth.

Because of the ontogenetic trends in growth all plants experience, an association between how growth and yield might vary with plant size -which can be used as a proxy for plant age in oil palms- can be derived [133]. Ontogeny describes the development of an organism from its earliest stages to maturity, and this relates directly to the propensity a plant has for growth. Oil palm height growth rates are fastest during the first 5-10 years after planting, before declining as plants reach their plateau in height of around 12-16 m at an age of 20-25 years [133]. Not only do palms experience less vertical growth with age but they also exhibit a marked decline in yield, especially after an age of around 20 years [134]. A study based on palms from ages 11 to 21 years found that the age of the palm displayed a negative relationship with fresh fruit bunch yield, indicating that the productivity of oil palms will decline with their development [135]. From this, It could be predicted that the taller palms grow across the landscape, the more likely it is that their growth rate and fruit production will subsequently decline.

The top most part of the palm – its crown – is made up of the plant's large leaves (or fronds) and reproductive structures that grow outwards from the trunk. Together, this is what is visible from airborne and satellite imagery, including LiDAR point clouds. A 2015 study by Chemura and colleagues investigated the relationship between age and crown projection area of oil palms, using object-based image analysis applied to multispectral data [136]. The crown projection areas determined from this were used in conjunction with a regression model for estimating the age of oil palms in a larger area. These data indicated that there was a strong linear relationship between the age of oil palms and their crown area, up to the age of 13 years, after which the relationship weakened [136]. This suggests that by combining information on the height of the palm and its crown area (both of which can be retrieved from LiDAR) it should be possible to accurately estimate an individual's age and life stage (e.g., immature, mature, senescing).

The crown size directly relates to the canopy cover of oil palms, which has in turn been used to estimate aboveground carbon stocks of oil palm plantations [92–137]. In an experiment aiming to compare the conditions of oil palm canopies between non-thinned and thinned plantations, thinning was not found to lead to lower palm oil yield [137]. With knowledge of the age of oil palms and surrounding forest areas, better resource utilisation and optimal management of agriculture can be informed. By making operations such as fertilisation suited to palm age more efficient, productivity can be increased, aiding the problem of increasing yield without increasing the area under production [136]. Not only this, but knowing the age of oil palm is required for assessing certification requirements for organisations such as RSPO (Roundtable on Sustainable Palm Oil), and remote sensing has the capability to assist with age estimation across larger areas [136].

Palm height, aboveground biomass, or some other metric of size also have the potential for predicting an oil palm's susceptibility to drought. Taller plants have more difficulty in transporting water to their leaves than smaller plants do, and because larger palms have subsequently larger crowns, they require greater amounts of water to meet higher transpiration demands. This potentially puts the largest palms across the landscape at higher risk of mortality or reduced growth rates during El Niño events compared to smaller palms. In saying this, larger palms will also have bigger root systems than their shorter counterparts, leading to a greater capacity for water uptake from soils. Plant height as a factor that determines mortality has been studied in depth in the case of droughts, but less so in the context of oil palm agriculture. In 2019, Stovall and colleagues tracked 1.8 million trees over 8 years, in conifer-dominated forests. Almost half of all trees over 30 m died, which was more than double the number of tree fatalities under 15 m [138]. It was determined that tree height was the single strongest predictor of mortality during extreme drought events, over maximum VPD, temperature, precipitation, available water storage, cover, and slope.

1.7 Conclusions.

A review of the literature has shown that a variety of factors with the propensity to affect oil palm growth- particularly during periods of drought -need further investigation. Creating a blanket ban on oil palm is not a feasible option for limiting the environmental consequences of oil palm agriculture, as this would have profound knock-on effects to many people's livelihoods. It is essential that the most efficient ways of growing oil palm are found, without further compromising existing primary forests that hold so much value. For such an economically important crop, it cannot be overstated how important it is to optimise its growth, both for environmental purposes as well as for economic security in developing nations. The effects on oil palm growth throughout drought at an individual plant level are under-studied, and it is necessary to identify the factors contributing to the changes that might occur in growth because of El Niño events. Creating clear and concise methods for identifying palms and tracking their growth over time using LiDAR data is also of huge importance and can give researchers valuable insight into oil palms at an individual level.

1.8 Aims and content.

The aim of this thesis is to investigate differences in the growth of oil palms during El Niño periods in Sabah. The study site is situated in Malaysian Borneo and the data investigated was collected as part of the SAFE (Sustainability of Altered Forest Ecosystem) project between 2014 and 2016. Two main questions were posed:

1) How much did oil palms grow during a period characterised by unseasonably hot and dry conditions, and how variable were growth rates across the landscape?
2) Can developmental, ecological, and landscape features be identified that explain why some oil palms grew faster than others during this two-year period?

This introduction and literature review constitute the first chapter of the thesis, and are intended to give an overview and context to the themes addressed in chapter two. Chapter two consists of an introduction, methods, results, and conclusion. It begins with a brief introduction to the context and specifics of the project. Detailed information on the methods used is then discussed, before a section outlining the results and a discussion of these with reference to existing literature. Chapter three considers chapter two in further detail, going into depth on the limitations of the project and further work required in the area. An overview is also provided of how the conclusions sit in the context of the field, and final closing remarks on the project outcomes are addressed.

Chapter 2: Using repeat airborne LiDAR to map the growth of individual oil palms in Malaysian Borneo during the 2015-16 El Niño'.

2.1 Abstract.

The ever-increasing demand for palm oil has led to a rapid rise in the clearing of tropical forests, particularly in areas of South East Asia. Oil palm is central to the livelihoods of many people, and it must be ensured that the production of palm oil can occur as sustainably as possible. Thus, it is essential to understand how oil palm growth varies across tropical landscapes in order to optimise yields. In this project, repeat airborne LiDAR data was used to map the height growth of over half a million individual oil palms in Malaysian Borneo over a two-year period which coincided with the 2015-16 global El Niño event. The ability of oil palms to continue growing during this period of uncharacteristically dry and hot weather was investigated, and the ecological and landscape features that contributed most to differences in growth rates across landscapes were explored. Despite the drought conditions, oil palms grew 1.61 m yr^{-1} in height on average, but growth varied substantially among individuals, with smaller oil palms exhibiting the fastest rates of height growth. Landscape features such as the distance of palms from forest edges, elevation, and terrain ruggedness all had significant effects on height growth, as did relative competition with neighbours. However, effect sizes were weak and collectively these predictors only explained a small portion of the variation in growth among individual oil palms (5%). The results highlight the high resilience of oil palms to climate extremes associated with El Niño events. The project also reveals opportunities for improving the efficiency and yields of oil palm agriculture, but doing so requires further work to pinpoint the factors that contribute most to driving variation in oil palm growth rates across tropical landscapes.

2.2 Introduction.

African oil palm has earned some notable accolades – including 'tree of life' [14], 'wonder crop' [139] and 'natures gift to man' [140] – as almost every part of the palm has a use, and it produces 10 times more oil per hectare than its closest competitor, soybean [17–18]. This has resulted in oil palm becoming one of the most important crops worldwide for the production of vegetable oil over the late century [14]. Nowhere is this truer than in parts of SE Asia [2], such as in Indonesia where palm oil accounts for around 10% of total national exports and is central to the livelihoods of countless people [25]. However, this rapid rise in the demand for oil palm has come at a huge environmental cost, as the expansion of the oil palm industry has led to the large-scale conversion of tropical forests to monoculture plantations. On the island of Borneo alone over 3 million ha of primary forest were cleared to make way for oil palm agriculture between 2000 and 2017, with substantial impacts on biodiversity and carbon storage [15–25–59–61–63]. Oil palm plantations have been shown to hold fewer than half the vertebrate species of primary forests and far lower species richness than disturbed logged or secondary forests [66]. This puts many of the ecosystem services provided by stable and diverse tropical landscapes at risk [59–70]. Moreover, intact tropical rainforests can hold as much as 270 tonnes more carbon per hectare than oil palm plantations [24–72–73]. Consequently, the continued expansion of oil palm agriculture is weakening the tropical forest carbon sink, which has played a key role in slowing the pace of climate change over the past half-century [15].

The solution to this challenge is not simply to ban or replace palm oil. Not only would this have huge socio-economic impacts for millions of people, but the environmental impacts of vegetable oil production would simply be displaced elsewhere, likely with worse outcomes for biodiversity and climate given how productive oil palm is compared to alternative crops [25]. Instead, it is vital to find ways to produce oil palm more sustainably. One way to do this is to increase efficiency by maximising yields – the so-called 'land sparing' approach [76–141]. Research shows that there are often significant gaps between actual and potential oil palm yields. Harvested yields rarely exceed 3 t oil ha^{-1} yr^{-1}, when estimates suggest that better cultivation practises could almost triple average yields to around 8 t ha^{-1} yr^{-1} [15–20–75]. Closing these yield gaps would be a win-win for both people and the environment, as it would allow more oil to be produced from less land. However, while some of the large-scale drivers of these yield gaps (e.g., climate, soils) are known, much less is known about what causes yields to vary locally across landscapes – the scale at which farmers can actually intervene by adapting planting strategies. For example, local factors such as topography can have a profound influence on soil water and nutrient availability, as well as on microclimatic factors such as air temperature, VPD, and solar radiation – all of which directly constrain plant growth [93]. Moreover, these same landscape features can exacerbate or dampen the effects of extreme climate events, such as the extraordinarily hot and dry conditions associated with El Niño events [98].

One of the main challenges of identifying oil palm yield gaps across tropical landscapes is the scale of the plantations, which is often vast. This makes tracking the growth rates of oil palms from the ground both logistically challenging and prohibitively expensive [1]. One solution to this challenge is to leverage remote sensing technologies to map oil palm plantations from above, an approach that is becoming increasingly popular under the banner of precision agriculture [142–143]. One particularly promising technology in this regard is LiDAR, which simultaneously captures the 3D structure of both vegetation and the underlying terrain in superb detail [142]. This makes LiDAR the ideal tool for measuring vegetation height and biomass at large scales and exploring how landscape features constrain their variation [144–146]. LiDAR data has also been used to segment and measure the size of the crowns of individual plants, including oil palms [92–147]. All of this suggests that by using repeat LiDAR surveys conducted at two or more points in time, it should be possible to track the growth of individual oil palms through time and explore how and why it varies across entire landscapes [98].

To test this idea, repeat LiDAR data acquired across an oil palm-dominated landscape in Malaysian Borneo was used to map the height growth of >500,000 individual oil palms between 2014–16. This period coincided with the global 2015-16 El Niño event, which resulted in unusually hot and dry conditions lasting multiple months across the region. Using these data, two main questions were proposed about oil palm growth and its variation across tropical landscapes:

1) How much did oil palms grow during this period characterised by unseasonably hot and dry conditions, and how variable were growth rates across the landscape?
2) Can developmental, ecological, and landscape features be identified that explain why some oil palms grew faster than others during this two-year period?

2.3 Methods.

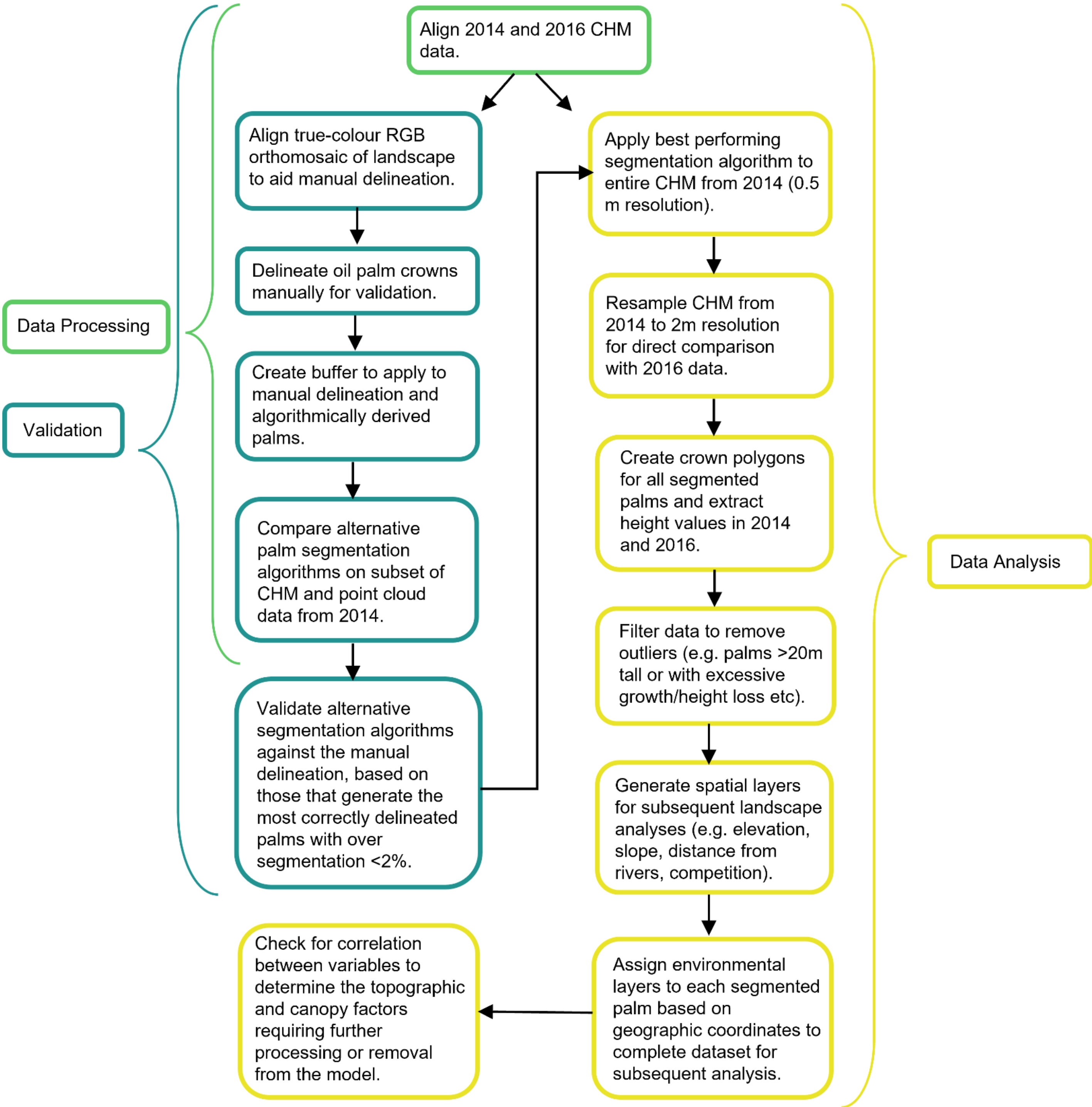

Fig. 2.1: Workflow diagram illustrating the main steps involved in processing the data, carrying out a validation of the palm segmentation routine, and the final data analysis.

2.3.1 Study area.

The data used in this project were acquired as part of the Stability of Altered Forest Ecosystems (SAFE) project, situated in the Malaysian state of Sabah, in Borneo [148]. The SAFE project is one of the largest ecological experiments in the world on biodiversity and ecosystem change in tropical forests as a result of human modification, forest degradation, and fragmentation. The region's climate is tropical, with a mean annual temperature of 26.7°C and an annual rainfall of 2,600–3,000 mm [145]. The SAFE landscape is highly fragmented and comprised of a variety of land-use types, ranging from oil palm plantations of varying ages, logged and fragmented secondary forests, and unlogged old-growth forests. This study focusses on oil palm plantations in this region spanning an area of approximately 94km^2. The site was affected by the 2015-16 global El Niño event, leading to particularly hot and dry weather spells which were especially strong towards the end of 2015 and early 2016. For more information on the logging history of the study area, see Ewers *et al.* (2011) [148].

2.3.2 2014 Data.

LiDAR data were first acquired across the SAFE landscape in November of 2014 with a Leica ALS50-II LiDAR sensor flown by NERC's Airborne Research Facility. Data were collected as a discretised point cloud with a median pulse density of 15.3 pulses per m^2 [93]. For the purposes of this study, point cloud data were classified into ground and non-ground returns with the software 'LAStools' (https://rapidlasso.com/lastools). A DEM was then fit to the ground returns to generate a 1 m resolution raster. The DEM values were then subtracted from the non-ground returns to generate a normalized point cloud from which a 0.5 m resolution CHM was generated using the pit-free algorithm described in Khosravipour *et al.* (2014) [149]. Further details of this data acquisition and processing can be found in Jucker *et al.* (2018) [145]. The DEM and CHM data are archived online and freely available at: https://doi.org/10.5281/zenodo.4020697. In addition to the LiDAR data, true-color RGB imagery was also acquired across the SAFE landscape using a Phase One iXU-RS 1000 100 MP digital camera mounted alongside the LiDAR scanner. Individual images were subsequently georeferenced, orthorectified, and stitched together into a mosaic spanning the same area as the CHM and DEM.

2.3.3 2016 Data.

The second LiDAR dataset was collected by the Global Airborne Observatory (GAO; formerly the Carnegie Airborne Observatory) [150] in April 2016 as part of a larger-scale project mapping aboveground carbon stocks across the entire state of Sabah [151]. As the goal of this project was to maximize coverage of the region to best capture spatial variation in forest structure and aboveground biomass, the flights were conducted at a higher elevation than in 2014 and the resulting point density was lower (1.1 pulses m^2 on average). The processing of the point cloud data followed a similar approach to the 2014 data described above. 'LAStools' (https://rapidlasso.com/lastools) was used to classify the point clouds into ground and non-ground returns, following which a 2 m resolution DEM and CHM were created. Further details of data acquisition and processing can be found in Asner *et al.* (2018) [151].

2.3.4 Data processing.

All subsequent data processing and analysis were carried out using a combination of QGIS [152] and R [153]. For a general overview of the workflow described below, see Fig. 2.1. First, to minimise errors due to misalignment between the two datasets, the Georeferencer plug-in in QGIS was used to manually align the 2016 CHM to the 2014 data. Following this, the full extent of the 2014 and 2016 CHMs were cropped so that only overlapping areas covering oil palm plantations were retained for further analysis (Fig. 2.2). This was achieved using a shapefile of the SAFE project landscape marking the boundary of oil palm plantations, as well as creating a shapefile marking the area of overlap between the two datasets, as the 2016 data only covered a portion of the area flown in 2014. Additionally, areas of riparian forest surrounding rivers and areas affected by cloud cover were manually delineated and removed from the CHMs.

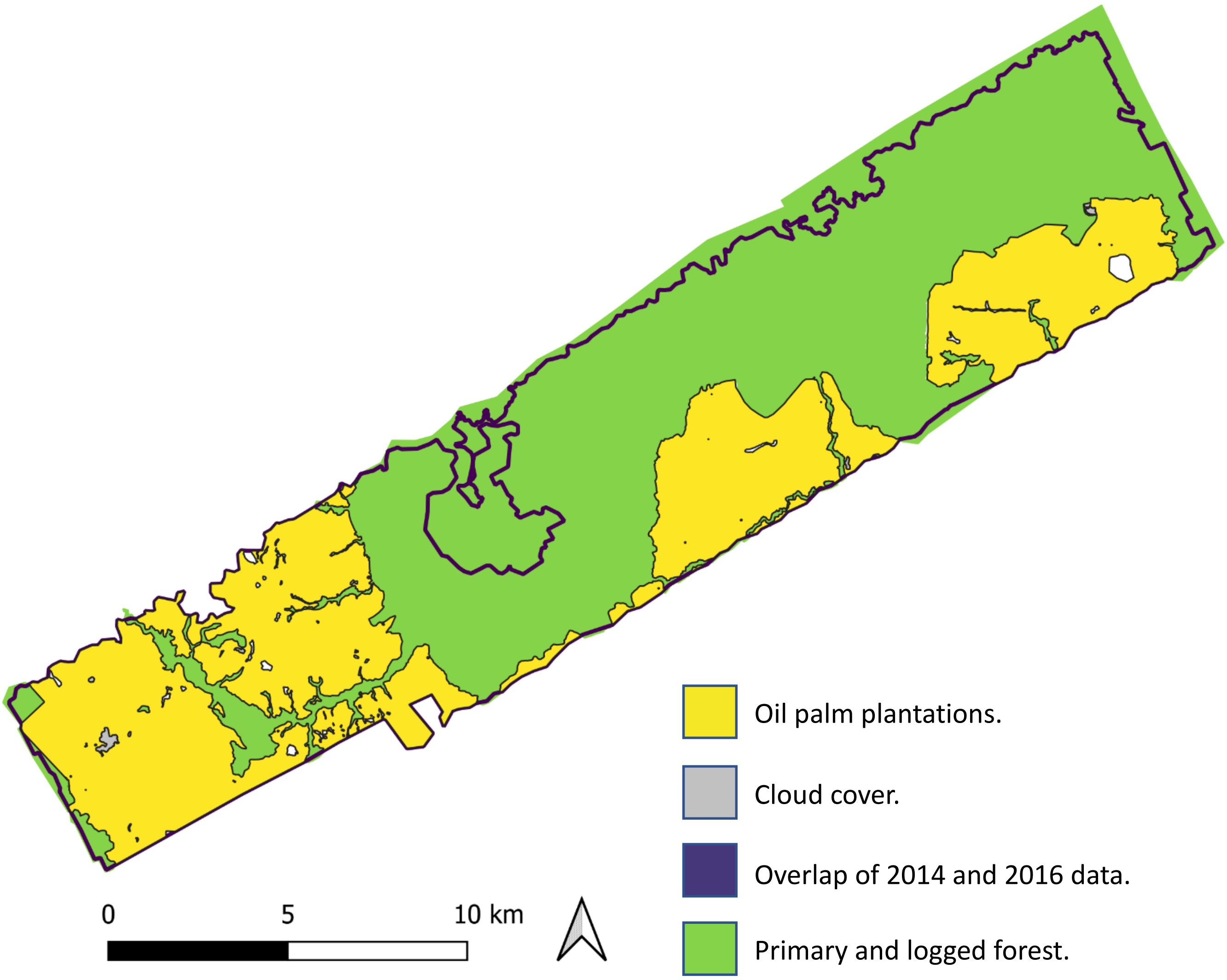

Fig. 2.2: Map of the SAFE project landscape, showing the distribution of oil palm plantations and remaining forest areas. Areas of cloud cover which were masked from the analysis are shown in grey, while the dark blue line shows the contour of the area of overlap between the 2014 and 2016 LiDAR data.

2.3.5 Creating a validation dataset.

To develop an effective approach for identifying and delineating individual oil palms from LiDAR across the entire SAFE landscape, a validation dataset was created that would allow a comparison of the accuracy of different crown segmentation approaches. An area of 4.5 ha straddling the boundary between a mature and young oil palm plantation was chosen (Fig. 2.3). Using both the RGB imagery and 2014 CHM data, all oil palm crowns within this area were manually delineated. A 5 m buffer was then applied to the area and any oil palms falling within it were removed, to avoid including individuals with crowns falling partially outside the extent of the imagery. This left a total of 409 manually delineated oil palms to assess the accuracy of the crown delineation algorithms (Fig. 2.3). These were further grouped into young (< 6 m tall, n = 177) and mature oil palms (>= 6 m tall, n = 232), in order to determine how delineation accuracy might vary among size classes.

To identify individual oil palm crowns the *lidR* package in R was used [154]. This involved first using a local maximum filter (LMF) algorithm to locate the tops of individual palms and then applying the *itcSegments* algorithm to delineate the border of their crowns [147]. This approach was applied to both the point cloud and CHM data from 2014 and has been used successfully in the past to map individual oil palms from LiDAR [92]. The LMF algorithm allows the user to specify a window size across which to search for local maxima (i.e., palm crowns), which were varied between 6-10 m. This range was chosen as oil palms were planted approximately 8-9 m apart on average. The accuracy of the various segmentation routines were assessed by comparing the computer segmented crowns to those manually delineated by hand and calculating (i) the number of correctly segmented palms, (ii) the number of omitted palms (i.e., those which the algorithm failed to detect) and (iii) the number of over segmented palms (i.e., those which the algorithm incorrectly split into two or more palms). The primary goal was to keep the number of over-segmented palms as low as possible, as this would otherwise introduce a source of pseudoreplication in subsequent analyse. Therefore, an upper threshold of 2% over segmented palms was set, above which the algorithm was deemed too imprecise. Based on this preliminary analysis, the segmentation was run on the CHM rather than the point cloud data, as accuracy was comparable while being computationally much faster on the CHM (see Results section for details).

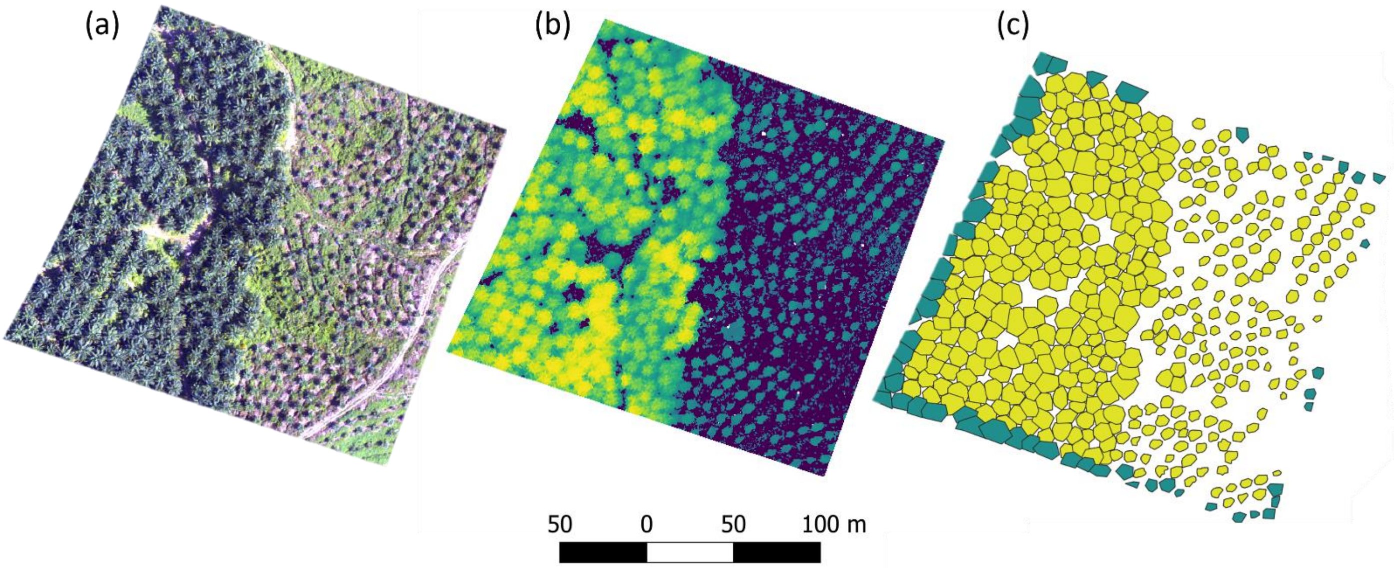

Fig. 2.3: Manually delineating oil palms to create a validation dataset for individual oil palm segmentation. RGB imagery (a) and CHM data (b) from 2014 were used to manually delineate individual oil palm crowns in an area of approximately 4.5 ha. Crowns falling within a 5 m buffer from the edge of this area were excluded (teal polygons in c), leaving a total of 409 manually delineated crowns for training and validating algorithms (yellow polygons in c).

2.3.6 Calculating height growth of individual oil palms across the SAFE landscape.

The best performing segmentation routine was used to automatically identify individual oil palm crowns across the entire 2014 CHM. To calculate height change between 2014 and 2016, the 2014 CHM was resampled to 2 m to match the resolution of the 2016 data. The polygons of the individual oil palm crowns were then overlayed onto the CHMs from 2014 and 2016 and the maximum height value of pixels falling within each polygon was extracted. Finally, to calculate the height change (in m yr^{-1}) of each oil palm the height in 2014 was subtracted from that of 2016 and this was divided by the time interval between surveys (1.417 years).

As part of this process, any crowns < 2 m in height and with a crown area < 9 m^2 in 2014 (the size of the smallest palm that was manually delineated in the validation dataset) were excluded from the analysis. To filter out possible outliers (e.g., remnant plants left within the landscape which would have mistakenly been counted as oil palms, or oil palms which died between surveys), any individual > 20 m in height (which is an upper limit for oil palms) and those which exhibited a percentage height change of ≤ 0 % or ≥ 200% (calculated as $\frac{H_{2016}-H_{2014}}{H_{2014}} \times 100$) were also excluded. In total, this filtering step removed only a small fraction of the total number of segmented oil palms.

2.3.7 Drivers of local-scale variation in oil palm height growth.

To explore the factors that could explain variation in oil palm growth rates across the landscape, data was assembled on a range of features linked to topography, ecological context, and plant development stage. First, using the 2014 DEM a number of terrain metrics were calculated that have been shown to capture variation in hydrology, soil water availability, nutrients, local microclimate, and exposure to sun and wind [93]. These included terrain elevation, slope, aspect, TRI, TPI, and TWI. Prior to calculating these metrics, the DEM was aggregated to a resolution of 10 m to smooth out any local artifacts and speed up subsequent computations. TWI was then calculated using the *dynatopmodel* package in R, while all other predictors were derived using the *raster* package [155]. Following this step, aspect values were cosine transformed to obtain a variable ranging in value between -1 (corresponding to north-facing slopes) and 1 (south-facing) [156].

In addition to these topographic metrics, a shapefile of rivers across SAFE was used to calculate the distance from rivers for all oil palms using the *sf* package in R [157]. Similarly, the distance to the closest forest edge from each oil palm was calculated to test whether changes in microclimate, soil structure and pathogen loads related to proximity to intact forests might affect oil palm growth. To further test the effects of planting configuration and competition for light, the 2014 CHM was used to calculate the mean canopy height in a 20 m radius around each oil palm and regressed against the palms' height. The residuals of this model were used as an indicator of whether a given individual experiences stronger or weaker competition than expected based on its size (hereafter referred to as relative competition effect). Finally, as a measure of plant developmental stage, the crown volume of each oil palm was derived by multiplying the crown area by the palms' height in 2014 [158].

To determine how well each of these predictors contributes to explaining variation in oil palm growth across the landscape multiple regression was used. To avoid issues with multicollinearity, Pearson's correlation coefficients (ϱ) were calculated between all model predictors prior to model fitting. Any that exceeded $\varrho > \pm 0.5$ were excluded from the analysis. Based on this, the following predictors were retained in the regression model: crown volume, relative competition effect, distance to the forest edge, ground elevation, TWI, TRI, and aspect. The response variable – height change – was log-transformed to normalise the model residuals, while all model predictors were scaled to have a mean of 0 and standard deviation of 1 to allow their effect sizes to be directly comparable. As a post-hoc test of collinearity among model predictors, the variance inflation factors for the fitted model were calculated and confirmed as < 2 for all predictor variables [159].

2.4 Results.

2.4.1 Accuracy of oil palm segmentation.

For the individual oil palm segmentation, a window size of 9 m proved the best compromise between minimising over-segmentation while also ensuring as few individuals as possible were omitted by the algorithm (Fig. 2.4). This proved to be the case regardless of the initial size of the palm or the input data (point cloud or CHM). Using this approach applied to the CHM, 65.8% of manually delineated oil palms were correctly segmented while over-segmentation was kept to 1.7%. The segmentation accuracy was greater for small palms < 6 m in height (84.8%), whereas for mature individuals it was only 51.3%. The accuracy of the segmentation algorithm was almost identical when applied to the point cloud data (see Table S1 in the Appendix), but was substantially slower. Therefore, the segmentation of the whole landscape was run using the CHM data as input.

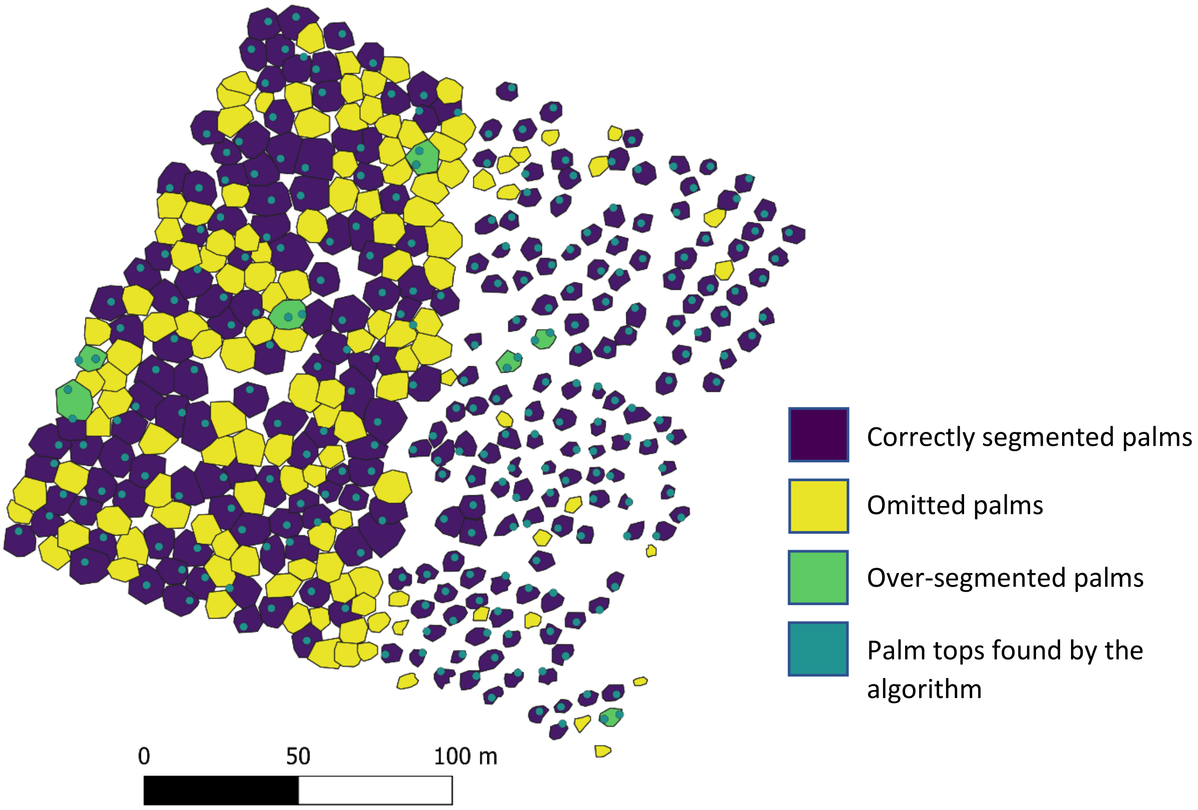

Fig. 2.4: Accuracy of oil palm automatic segmentation using the CHM and window size of 9, against manually delineated palm crowns on a section of 409 palms in the landscape. Correctly segmented oil palms represent those where a single individual was found within a manually delineated polygon, over segmented palms are ones where more than one individual was found within a manually delineated polygon, and omitted palms are ones where no individual was found within a manually delineated polygon.

2.4.2 Oil palm height growth and its variation.

After applying the data quality filters described in the Methods, a total of 550,566 oil palms across the SAFE landscape were delineated and their height growth measured. There was a significant difference in the mean height of palms in 2014 (7.94 m) and their height in 2016 (10.32 m) (t = -295.79, $P < 0.0001$), with palms growing an average of 1.61 m yr^{-1} between the two LiDAR flights. However, there was considerable variability in the rate of height growth across the study area, with 90% of values ranging between 1.00 m yr^{-1} (5^{th} percentile) to 3.90 m yr^{-1} (95^{th} percentile). Height growth rates varied significantly depending on the initial size of oil palms in 2014 ($t = 81.87$, $P < 0.0001$), with smaller individuals (< 6 m in height) growing an average 1.69 m yr^{-1}, while larger ones (> 6 m in height) grew 1.56 m yr^{-1} (Fig. 2.5).

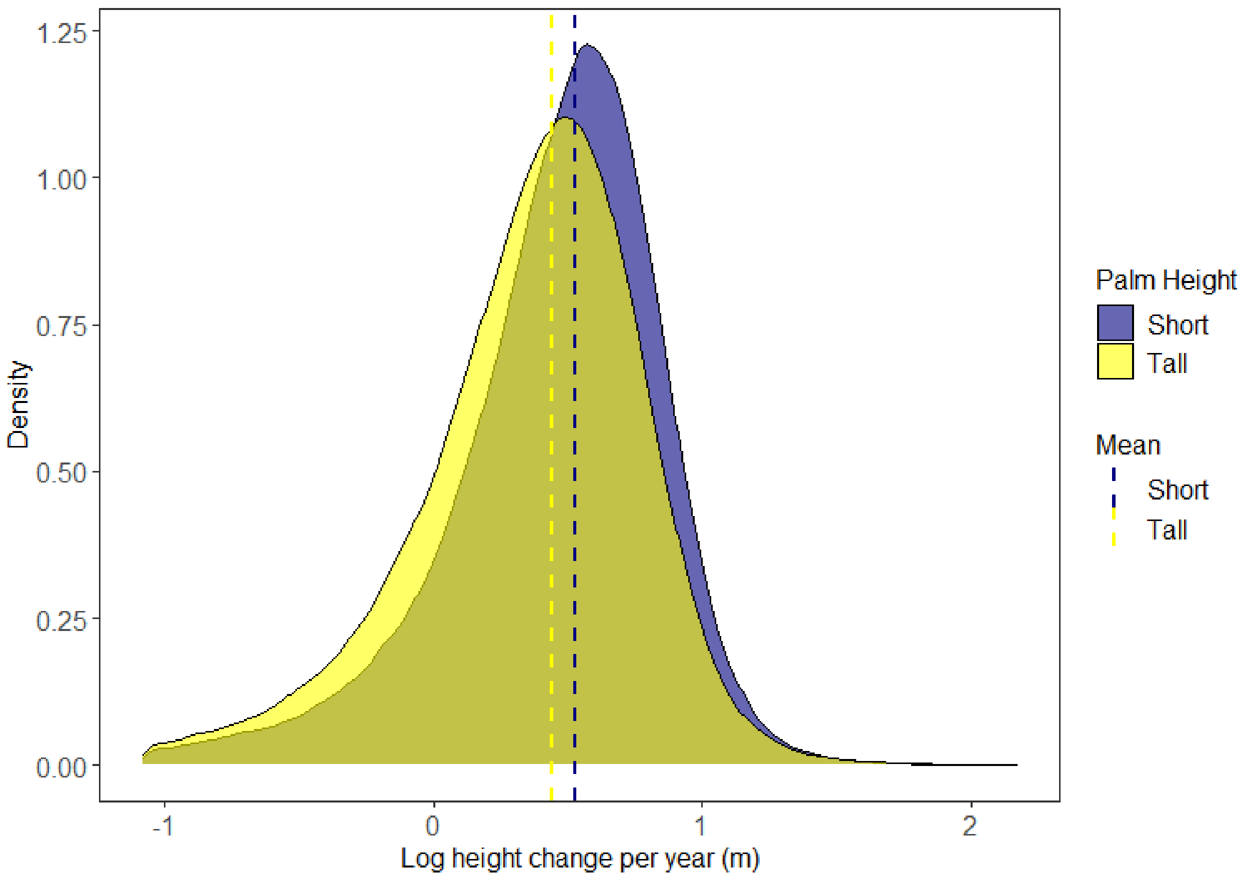

Fig. 2.5: Comparison of the distribution of height growth per year (log-transformed) of short (< 6 m in height in 2014) and tall oil palms (>= 6 m in height in 2014). Dashed vertical lines indicate the mean values for each group.

2.4.3 Drivers of spatial variation in oil palm height growth across the landscape.

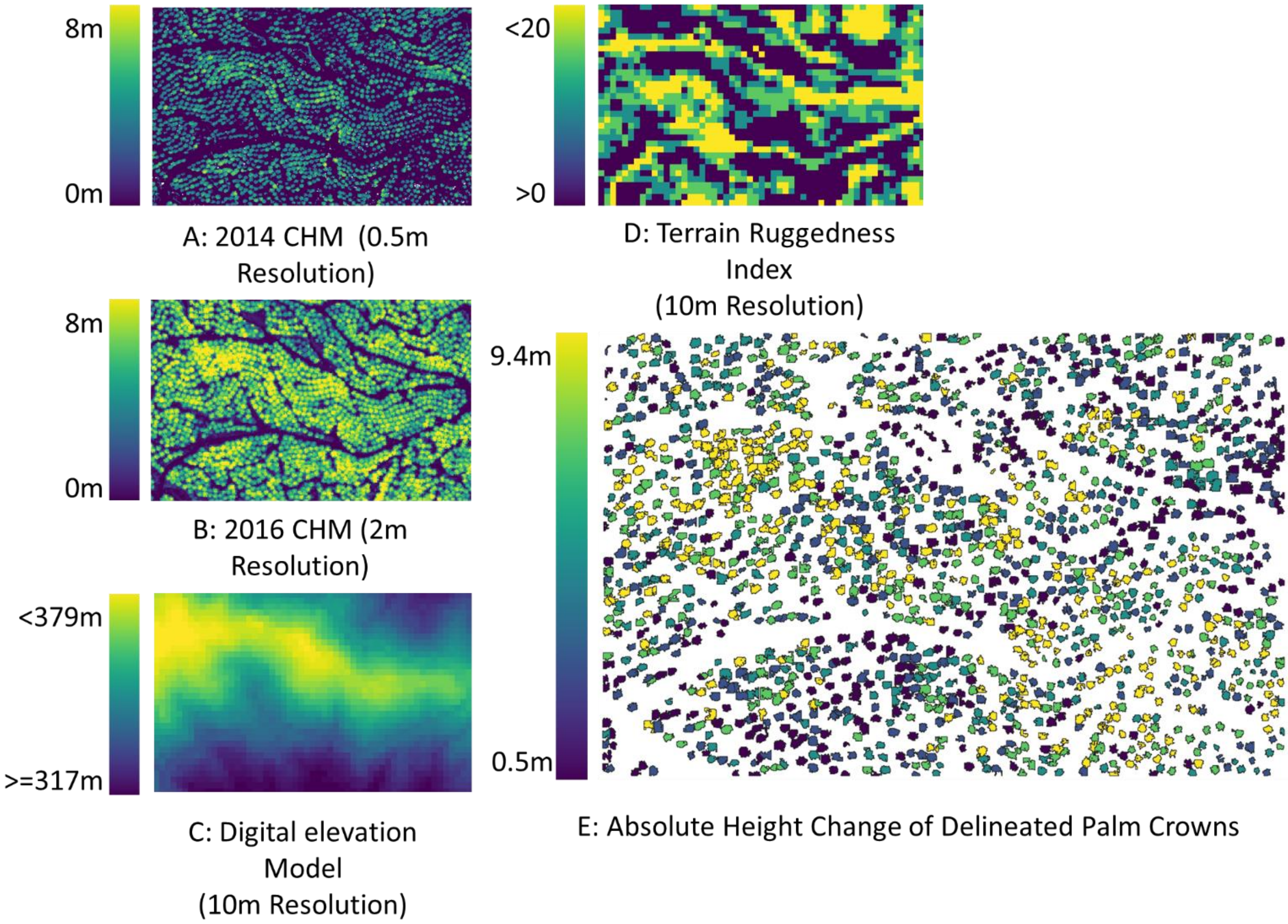

Fig. 2.6: Maps of a subset of the SAFE landscape showing variation in oil palm canopy height in both 2014 (A) and 2016 (B), and how this maps on to the digital elevation model (C) and terrain ruggedness index (D). The bottom right-hand panel (E) shows the segmented oil palms within this area, colour-coded by their height growth rate, ranging from low (blue) to high (yellow).

Between LiDAR data collected in 2014 and 2018, the heights of palms in the landscape changed significantly (Fig. 2.6). Of the predictors included in the multiple regression model, all but TWI and aspect emerged as statistically significant (Fig. 2.7). Initial crown volume emerged as the single strongest predictor of height growth, with mature oil palms with large crown volumes exhibiting slower rates of height growth on average than younger palms with smaller crown volumes. Distance from forest edges was the second strongest predictor of height growth, with palms planted closer to forest edges growing more quickly than those further away. By contrast terrain elevation, relative competition effect, and TRI were all positively correlated with oil palm height growth rates. However, despite being statistically significant, the effect size of these predictor variables was generally low and together they only explained 5% of the variation in oil palm height growth rates across the SAFE landscape.

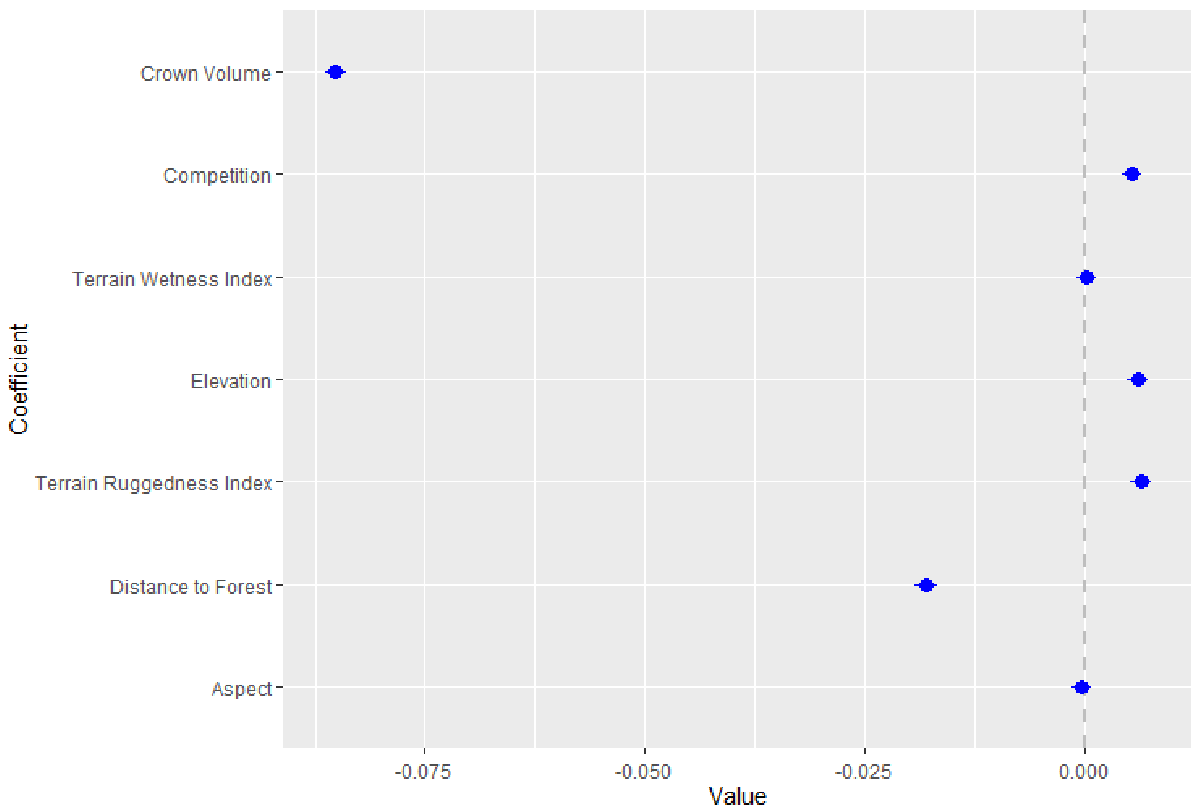

Fig. 2.7: Standardised regression coefficients (± 95% confidence intervals) for all predictor variables included in the multiple regression model [160].

2.5 Discussion.

These findings demonstrate that oil palms were able to grow over the two-year period between 2014-2016 despite experiencing drought conditions as a result of El Niño. Palms varied in their ability to grow according to particular factors in the environment such as topographic and canopy differences, however, the ability of these landscape features to explain variation in growth rates was minimal. The strongest predictor of palm growth over the time period was the initial size of palms, with those that were initially larger growing significantly more slowly in height than those that were initially smaller. A similar negative relationship between distance to forest edge was also found, with growth tending to decline with increasing distance to the forest edge. Furthermore, the results highlighted a positive relationship of palm growth with the relative competition effect, TRI, and elevation, and a non-significant relationship with both TWI and aspect.

2.5.1 Growth during El Niño events.

It is reasonable to predict that the most growth over the two years would be expected in areas where conditions were most favourable for oil palms. Because of the drought coinciding with this period, it was also likely that water stress would be one of the greatest pressures on palms, and thus areas of the landscape where water accumulated to a greater extent may indicate where palms could be expected to display the highest levels of growth. Factors such as the distance of oil palms to rivers, and the elevation of the terrain have an impact on both the microclimate that plants experience, as well as the availability of water or wetness of the soil. In oil palm, water deficits can affect growth, dependant on genotype and drought stress severity [99–108–161–163]. With rising global temperatures and increasing frequency of El Niño events and drought [7] it is expected that oil palms with less access to water, such as those further from rivers or on elevated, hilly terrain may suffer more in terms of the energy that they could put into vertical growth.

There was extensive variation in the extent that palms grew across the landscape, likely due to differences in stress severity as a result of topographic variation in the landscape as discussed below. However, what is clear from the results is the fact that oil palms across the landscape did grow during this period, suggesting a strong resilience of the palms to cope with drought. This is a highly important finding for oil palm agriculture as it suggests that increasing frequency of severe climatic conditions and global change will have little effect on the production of oil palm, boding well in terms of the economic and social impacts that would be inflicted on many SE Asian populations [15–25–26–43–82]. Despite the fact that this resilience is highlighted, it must be done so tentatively as the study did not take into account delayed effects of drought on oil palm growth, which would require longer-term monitoring of the palms. What is important to take into consideration is the fact that El Niño and drought periods differ in their severity, and this particular case cannot be used as a definitive outcome for palms in all cases of drought. The extent that a palm is pushed to its physiological limits in terms of water stress will heavily depend on the maximum temperatures reached and the length of these stress periods [97–98–105]. With an appreciation of this caveat it is reasonable to hope that in drought periods that are similar to, or less severe than the 2014-2016 El Niño events in SE Asia, oil palms will be able to show this resilience in the face of climatic stress.

It was also predicted that palms at a later life stage, would experience slower growth than smaller palms at an earlier stage in their development due to propensity for growth declining with development due to effects induced by life stage and ontogeny. By far, the strongest predictor of palm growth in the study was the initial size of palms, with taller palms growing significantly more slowly than those palms that were initially shorter. The ability that oil palms can grow has been found to decline with age and crown volume was used in this study as a proxy for life stage or age [133]. The results here are consistent with the finding that palm changes in height and age are highly correlated with one another [133–164].

2.5.2 Spatial variation in growth.

The growth of palms varied substantially across the landscape (Fig. 2.6), however the predictors that were tested in the analysis did not explain a large amount of this variation (5%). Spatial variations in levels of competition for resources other than water, such as nutrients and light are also likely to have affected palm growth. Palm growth varied positively with the relative competition that oil palms experienced, which indicates the resources that exert the most pressure on palms. Had oil palm growth exhibited a negative relationship with relative competition it may have suggested that there was intense competition for nutrients and water, thus palms could not access what they need to grow efficiently. However, since height increased with relative competition, it shows that palms were dedicating their energy to vertical height growth, indicating that the most important resource that palms were competing for was likely to be light. This is because when there is more competition for light than nutrients and water, such as cases where competing neighbours are taller, it may be expected that greater vertical growth would be observed in plants, as they attempt to compete with their taller neighbours for access to light. Despite this, competition does not seem to have a very large effect in determining growth, possibly due to the way oil palms have been planted, and the high levels of light exposure that Borneo receives. This is likely to mean that oil palms have been planted at a distance whereby they are not experiencing a great amount of competition for light, showing that plantation arrangements are relatively successful at the ~9 m planting interval used across this landscape. The light levels across the landscape and hence resulting competition were even less likely to vary substantially across the landscape due to the relative flatness of the terrain.

The negative relationship between palm growth and a palms distance from forest edge was interesting, as it goes against the concept that the agricultural ideal of 'monoculture' is ideal for palm growth [82–165]. It is typically thought that proximity to primary forest could be a source of pests and disease, and plantations of large monoculture between them are most agriculturally productive [82–166]. This does not seem to be the case in what has been observed from this experiment. It could be that proximity to primary forest is a better predictor of water availability than the metrics used as proxies for access to soil moisture, but alternatively it may suggest that the increased biodiversity around oil palms closer to primary forest offers them a growth advantage that was not anticipated such as increased soil nutrients from increased bacterial diversity and microbial biomass [82–166]. This finding could offer a way of both increasing productivity while also reducing the negative impacts of oil palm agriculture on the environment by encouraging the use of ecologically beneficial practices. The introduction of more unmanaged forest in and around plantations, or even the addition of intercropping techniques could increase palm yield while also creating wildlife corridors and more areas of refuge for native wildlife. This would also have the benefit of creating a more structurally complex landscape, beneficial to a variety of animals and plants [82–126–132]. What is interesting is that when the growth of oil palms is compared to the growth of forest under regeneration from heavy logging in the same region, the forest continued to grow despite higher evaporative demand, except when it was located close to oil palm plantations. These edge effects were experienced up to 300m from plantations which suggests that the oil palms were likely better competitors than plants in the surrounding forest [98].

Variation in topography constrains a range of factors likely to affect palm growth, ranging from local nutrients, hydraulic conditions, soil structure, to other local microclimatic conditions such as air temperature, humidity, and exposure to wind and solar radiation [93]. Elevation is known to affect microclimatological factors such as air temperature and humidity through changes in atmospheric pressure or exposure to wind and solar radiation, whereby increasing elevation relates to increased VPD and decreased temperatures [93–120]. Here, elevation of palms across the landscape exhibited a positive relationship with palm growth. The effects of elevation were relatively weak, probably due to the fact that the palms were across a fairly flat landscape, and there were not necessarily any extremely high elevations whereby temperature would have cooled enough to affect growth. Nevertheless, palms growing at higher elevations grew faster than those at lower elevations, and this may be related to competition for light. At higher elevations, light availability may likely be slightly greater than at low elevations, whereby palms may experience some shading effects from crowns of palms situated at higher elevations [20–122]. This is an interesting finding as it could be expected that areas of lower elevation- such as valleys- would have better access to water due to an accumulation in the soils from run-off. If water had been a restricting factor to growth the opposite trend to that which was observed may have been found within the results.

TRI gives an idea of the localised roughness of the landscape. Where it is higher there are more differences between the land where a palm is planted, and the land directly surrounding it. Rougher landscapes may be variable in terms of the wetness of soils than flatter landscapes due to localised peaks and troughs across a small scale. The positive relationship between TRI and palm growth reveals that palms are likely to benefit from more rugged terrain than a smoother landscape. This is an interesting finding in terms of plantation management, as often landscapes are flattened before plantations are established, to make access for heavy machinery and crop management more simple. These findings could advocate that flattening the land is actually negatively impacting palm growth and thus save managers large amounts of labour and money, as well as reducing the use of CO_2 emitting machinery across landscapes for plantation establishment.

Although it was anticipated that water availability would be one of the greatest predictors of palm growth across the landscape during El Niño events, TWI did not prove to be a significant predictor. Despite the drought period, water availability and wetness of soils did not appear to affect the vertical growth of palms over the two years. This could indicate that a water minimum threshold was not reached, whereby the effects of drought may have been observed, however it could also indicate that TWI was not the best proxy to use for water available to oil palms. The most likely explanation though is that these palms are resilient to periods of drought once they have established to at least 2 m tall, though the long-term impacts of water stress and the response to different durations of the period would also need investigating.

The aspect of slopes where palms were planted also did not exert a significant pressure on oil palm growth. This is most likely because the landscape was relatively flat, and due to the location being equatorial, most palms experienced a similar level of solar exposure per day, not accounting for competition. Aspect may exert more of a pressure in regions further from the equator or those with more varied, hilly landscapes.

2.5.3 Limitations and future work.

As the predictors only explained around 5% of the large degree of variation observed in palm growth over the two years, further work must take place to identify those factors which are most important in predicting the variation. The results suggest that other factors which were not captured in the model were driving variation in growth. The range of different potential predictors that were not accounted for is vast, and planning an experiment that accounts for the majority of all potential sources of variation in growth would require a wide and detailed review of the literature. Some drivers worth investigating may be differences in fertiliser use which were not accounted for in this study, or perhaps different cultivars planted across the landscape [167–168]. A more robust survey of predictors could be investigated over the same landscape to try and account for the high levels of variation by including drivers such as these in the model, along with other factors like soil type and pest prevalence [167–169–170].

An important factor that was not taken into account during this study was spatial autocorrelation. Spatial autocorrelation describes how palms that are spatially closer together will experience similar conditions, and thus some predictor variables are likely to correlate between them. Spatial correlation is therefore likely to result in an overestimation of certainty in fitted model parameters. However, there are difficulties in fitting a spatial model to data on a scale this large. Future studies which aim to look at individual palms across a large scale must derive a way of accounting for spatial autocorrelation that may occur when fitting a model. One such way of doing this would be to use the coordinates of palms as a predictor in the model or another approach such as auto covariate models, or dividing the landscape and fitting spatial models based on generalised least squares regression [171].

The experiment could also be improved methodologically by achieving better segmentation of crowns in the landscape. Though the validation showed that over-segmentation could be limited in the analyses, this meant there were a substantial number of omitted palms across the landscape. Fine-tuning the algorithm could better delineate crowns, and thus could have resulted in a greater sample size, demonstrative of a greater proportion of the population. The fitting of a random forest model or general additive model instead of the more simple linear regression could also be useful in the future in order to look at predictors more flexibly. In terms of distributing these findings as advice to plantation owners and management, it may have been a good idea to measure oil production from palms, rather than vertical height growth. Despite vertical height growth being a proxy for aboveground carbon and yield, precise conversion of the experimental data to such metrics may make the outcome more obvious in the context of plantation management.

Finally, it must also be determined which topographic and canopy structural factors influence oil palm growth under 'normal' climactic conditions (i.e., non-El Niño years) and which instead only influence growth under conditions of drought. Doing this would require collecting or sourcing additional LiDAR data from years that were not affected by El Niño events. Similarly, it is also worth looking into different lengths and severity of drought periods as a form of meta-analysis, as it may be that there is a limit of temperature and humidity whereby effects are only observed past a particular stress threshold.

2.5.4 Conclusions.

The experiment indicated that oil palms in Malaysian Borneo are resistant to drought, and do not suffer declines in growth during extreme climatic periods such as El Niño. What is interesting to note is that water did not seem to be a limiting factor in palm growth even over drought periods. The greatest predictor of oil palm growth was the initial size of the palm, with larger palms growing more slowly than shorter ones, likely due to differences in life stage and development. Differences across spatial scales, did have an impact on the rate of palm growth, but the effects were minimal. From this, it can be assumed that regardless of variation within the landscape, oil palms grow successfully during drought and are likely to be resilient in the face of climate change.

Chapter 3: Discussion and conclusions.

3.1 Aims and Approach

In recent decades, demand for oil palm has continued to rise, putting increasing pressure on tropical forest ecosystems that are essential for both biodiversity conservation and climate change mitigation[1–2–5–6]. Therefore, there is a growing demand for accurate and effective monitoring of oil palm plantations that allows converted lands to be used as efficiently as possible to reduce pressure on natural ecosystems. Moreover, with increasing global temperatures as a result of anthropogenic impacts on the earth's atmosphere, there is also an urgent need to understand how resilient crops like oil palm will be under new climatic regimes, such as the warmer and drier conditions associated with El Niño events [7].

Of the vegetable oils, oil palm is the most efficient crop, suggesting that it is a more environmentally friendly option than its alternatives [17–18]. It is not a feasible option to completely eliminate the use of oil palm, as it is now a staple of many people's livelihoods. This highlights the necessity to find the most productive ways of growing oil palm without further compromising existing primary forests. Previous work has focussed on identifying climatic conditions under which oil palm grows most efficiently, providing evidence for where in the world oil palm should be planted. However, there has been a gap in the scientific research in identifying local drivers of variation in oil palm growth at the individual palm level across landscapes. A review of the current scientific literature on the topic indicated that particular local drivers had the propensity to affect oil palm growth, and that these effects may be confounded during periods of drought.

In this project, methods were developed for identifying palms across vast landscapes and tracking their growth over time using repeat LiDAR data. For the first time at this scale, the growth of palms over time was tracked and analysed in order to understand how it varied with a range of topographic and canopy structural metrics during a period of anomalously warm and dry conditions. Using LiDAR data obtained from the SAFE project in Malaysian Borneo [148], alternative segmentation algorithms were compared on a subset of CHM and point cloud data from 2014. The best performing segmentation algorithm was then applied to the entire landscape and the height growth of ~550,000 palms over a two-year period coinciding with the 2015-16 El Niño event in SE Asia was calculated. Finally, a multiple regression model was fitted to the data to determine if features such as terrain slope, distance from rivers, distance from forest edges, and relative competition could assist in explaining why some oil palms grew faster than others across during this period.

3.2 Summary of main findings.

The findings from this project determined that oil palms were able to grow over the two years between 2014-2016 despite experiencing drought conditions as a result of El Niño climatic events. On average oil palms grew 1.6 m yr-1 between the two LiDAR surveys. However, there was substantial variation in growth rates, which ranged from 1.0 m yr-1 (5th percentile) to 3.9 m yr-1 (95th percentile). Variations in their ability to grow according to particular factors in the environment such as topographic and canopy differences were observed, however the effects of the variation were minimal. The greatest predictor of palm growth over the period was the initial crown volume of palms, with those that were initially larger growing significantly less than those that were initially smaller. The results also highlighted a positive relationship between competition for light, TRI and elevation with palm growth. Furthermore, distance to forest edge exhibited a negative relationship with change in palm height, as growth tended to decline with increasing distance to the forest edge. It was therefore concluded from the results that oil palms could continue to grow during extreme conditions and that growth rates varied across the landscape. However, the results could not convincingly explain the reasons as to why growth varied across the landscape, as the majority of variation was not explained by the predictors that were investigated.

The study also highlights a relatively fast and simple approach to deriving individual palms across a large landscape and segmenting them into individual palm crowns. A validation of the methods showed that this could be achieved with a minimum amount of over-segmentation (<2%) while maintaining a fairly high proportion of correctly segmented palms (65.8%). The project demonstrated how repeat LiDAR data can be used effectively to track aspects of landscapes over time, and that it can be completed with a high level of detail. The fact that the oil palms across the landscape grew during this period, suggests a strong resilience of the palms to cope with drought. This is a highly important finding for oil palm agriculture as it suggests that increasing frequency of severe climatic conditions and global change will have little effect on the production of oil palm, boding well in terms of the economic and social impacts that would be inflicted on many SE Asian populations [2–6].

3.3 Limitations and possible solutions.

Although oil palm's resilience in the face of drought is highlighted, it is done so tentatively as there were several limitations present in the analysis. The first of these limitations was the accuracy of palm segmentation and crown delineation. The experiment could be improved methodologically by achieving better segmentation of crowns across the landscape. Though the segmentation was validated to confirm that the most accurate technique for crown delineation was used, around 34.2% of palms were not correctly identified according to the manual delineation. Assessments of the performance of a variety of crown delineation methods and algorithms from LiDAR data have shown that different algorithms segment a highly varied number of crowns with different characteristics [172–173]. As in the 2019 study by Aubry-Kientz *et al*., a comparative assessment of a variety of individual crown segmentation techniques could potentially be completed, including algorithms such as AMS3D [174–175], itcSegment [147], Graph-Cut [176], Profiler [177–178] and SEGMA [179], to identify the best performing algorithm for oil palms. Considerable differences in the algorithms' ability to detect large and small crowns have been found [172], suggesting that the validation that was completed- whereby large and small palm crowns were separated- would be advisable to use in an algorithm comparison as well.

In the individual tree crown delineation comparison from Aubry-Kientz *et al*., the segmentation methods that were based on point cloud data (AMS3D and Graph-Cut) were more accurate than those based on CHMs. This finding was reflected in the validation though the CHM-derived data was used rather than the point cloud data which yielded slightly more accurate results for palms in the landscape. This was due to time and computer processing constraints for this project, as point cloud data took substantially longer to segment than CHM data. In contrast, other studies have found that methods based on local maxima detection from a CHM using variable-sized moving windows are the best performing, and these differences are likely due to variation in crown shape and density [173]. There are not any known studies at present that have focused solely on testing algorithms for the identification of oil palm, which would be a key step in finding the best performing algorithm for this study. Some recent studies have shown the benefits of combining approaches using the CHM for the identification of potential apices or crowns, and the point cloud data for refining the delineation [172–180–181]. With unlimited time and processing power available, utilising the data derived from the point cloud to delineate palms could have been useful in improving the accuracy of delineation. Despite this there was only a difference of around 3% incorrectly segmented palms between cloud and CHM data, so it is not expected that vast improvements in crown delineation accuracy would be observed from this alone, and thus it should be used in combination with comparisons of different algorithms.

The main limitation faced in the delineation of tree crowns was the speed at which the algorithms ran on the vast scale of the data. The computer processing took upwards of ~90 hours and the landscape had to be divided into 18 separate sections for the delineation to run smoothly. One important issue to factor into an algorithm/method comparison would be the speed at which it runs. For instance, some methods may be much slower and not scalable, and thus missing some crowns may be an acceptable compromise for speed. A compromise between speed and accuracy should be factored into choosing the best algorithm for delineation. Other methods that may be suitable for oil palm delineation could be to use crown geometry to identify specific patterns or shapes, this is likely a better method to use in a relatively uniform oil palm plantation than in landscapes such as tropical forests [172]. The issue with allowing a large number of omissions in palm crown detection is that it could introduce bias into the analysis. Missed crowns may just mean that there was lower replication but if the palms missed show systematic differences to those that have been segmented there may be a cause for concern. This could potentially be tested using a reference dataset to determine whether bias has been introduced, and adjust the algorithm accordingly to compromise between omissions in the data and over-segmentation.

Another limitation is how the data was filtered to remove outliers. In the analysis, palms where the height had decreased between 2014 and 2016 were filtered out, under the justification that this would be theoretically impossible, and that the analysis was focused on investigating height growth. However, this does have the implication of introducing some bias into the analysis as it is very likely that some palms with negative height change values are due to measurement errors. Due to the nature of oil palm fronds, it is justifiable to assume that LiDAR may have collected data from the top of the palm fronds in 2014 that it then missed in 2016. This measurement error could have occurred in the opposite time scale as well, whereby fronds missed in 2014 may have been reported in 2016, yet this error was not accounted for. The filtering step could be potentially refined by assigning an arbitrary value of negative height change, based on the typical length of crown fronds, that should be retained in the results. This would account for negative height changes as a result of missed fronds in the LiDAR data collection. Maximum height change could also have been filtered by determining a maximum threshold of growth possible over the survey period, from literature based on palms grown in ideal conditions. Though there was an upper limit of palms 20 m tall and a percentage height change limit of 200%, palms showing growth up to 13 m were still included in the analysis which is theoretically highly unlikely. Alternatively, there are several other ways of removing outliers that could be tested, with the potential to provide a more objective and justifiable alternative to filtering the data than the methods used. By removing the filtering steps used in the data processing steps, and instead looking at a boxplot of the logged changes in tree height, potential outliers within the data could be detected. From this, a Rosner test could be used on the potential outliers to help determine those that were true outliers and those which were not, without automatically disregarding any negative values. Other methods of outlier detection could include a log transformation of absolute height change and subsequent Z-Score analysis.

In terms of the validation, there is also the issue that the manual delineation that was used as the 'true' crown segmentation for justification of the segmentation, was not actually completely representative of the true crown segmentation. The manual delineation was carried out with great care, cross-referencing CHMs from both 2014 and 2016 with RGB imagery of the palms. However, the delineation was subject to human error whereby palms may have been over-segmented or omitted by accident. This would mean that choosing the best method of segmentation according to how many palms matched up with the manual delineation may not be truly representative of the method that was actually most descriptive of the landscape. To have improved this, using a known piece of land whereby palms had been manually counted and measured in the field could have ensured greater accuracy, however, this would have implemented great logistical issues for this project. If the study site could've been accessed, field measurements of palms could have been taken to check against the manually delineated crowns to improve the accuracy of the reference dataset [172].

The issue of human error in the manual delineation of palm crowns also extends to the generation of shapefiles used to section out the landscape, such as riparian river zones and cloud anomalies. There likely remained anomalous areas in the data set due to factors such as cloud cover, but the majority of these should have been accounted for within the filtering stage of the data processing. It is also likely that when delineating areas of riparian forest around rivers, some oil palms would also have been included in the 'riparian forest' zones, and potentially some non-oil palm vegetation may have been included in the analysis. Manually delineated shapefiles could be improved through the use of RGB imagery to cross-reference delineations from CHMs, adding to data processing time but possibly increasing the accuracy of delineation. Though this factor could have introduced some error in the results, with such a large sample size these effects would likely be very small and most likely buffered out.

Differences in the resolution and general acquisition parameters of the two datasets could be an important source of error. LiDAR estimates can be affected by point density but were not accounted for in the analysis [182]. To identify errors associated with point density, two areas in the landscape where point density in 2014 was the same but in 2016 it was variable, could have been found. By comparing the height change rates in these two areas it could then be determined whether the area with low point density in 2016 showed lower growth than the one with high point density, and to what degree they varied. Biases arriving from differences in the point density could then be accounted for by only using areas of the landscape where point density in 2016 was high, as in Nunes *et al*., (2021). Alternatively, point density in 2016 could have been included as a predictor in the model. The point density in 2014 was relatively homogeneous, while in 2016 it was more variable. By including point density as a predictor in the model, this variation in the estimated growth rates could be accounted for. Higher point density increases the likelihood of detecting the tops of the crowns and thus increases the possibility of observing a greater change in height. As both the resolution and point density of the 2016 data were lower than the 2014 data, here the results air on the side of conservative, and it is more likely that true growth was slightly greater than was estimated.

Another important factor that was not taken into account during the study was spatial autocorrelation. Linear models such as that used in this analysis assume that all observations are independent of each other. The problem here is that in spatial data such as the position of oil palms in the landscape, those observations that are spatially closer together will experience similar conditions. Thus individuals with closer spatial proximity to each other are more likely to exhibit similar behaviors than what may be assumed by chance and thus do not fit the assumption of independence. Spatial autocorrelation is therefore likely to result in an underestimation of uncertainty in the fitted model parameters [98–183]. To test for spatial correlation in the data 'Moran's I' could have been calculated for the residuals in the model and subsequent significance test for spatial autocorrelation in the residuals completed. Plotting a semi-variogram of the model could have also been used to confirm predictions about spatial autocorrelation. However, there is difficultly in fitting a spatial model to data on a scale this large as it is a very computationally intensive process. One solution to this issue would be to sub-sample the landscape to reduce the volume of data, repeating the randomisation routine numerous times to adequately capture the full extent of the data. This would allow fitting models that explicitly account for the spatial structure of the data, such as those that can be fit through maximum likelihood estimation using the *nmle* function in R [98].

What is important to take into consideration is the fact that El Niño and drought periods differ in their severity, and this particular case cannot be used as a definitive outcome for palms in all cases of drought. The 2015/2016 El Niño event across Borneo was relatively weak [98–184]. The highest temperatures reached were in the March of 2016 where temperatures exceeded the long-term average of preceding non-drought years by 2.1 °C [98]. The extent that a palm is pushed to its physiological limits in terms of water stress will heavily depend on the maximum temperatures reached and the length of these stress periods [7–9]. It must be appreciated that different responses may be observed with differing levels of water stress and temperature.

3.4 Future work.

Complications during the completion of this thesis meant that travel to Borneo to visit the study site was not feasible. Originally, plans were to visit Sabah in order to obtain some data on oil production. As this was impossible, the focus of the study was moved onto height growth alone. In terms of distributing the findings as advice to plantation owners and management, it would have been more practical to measure oil production from palms, rather than vertical height growth. Despite vertical height growth being able to act to some extent as a proxy for aboveground carbon and yield, precise conversion of the experimental data to such metrics could have made the findings more applicable in the context of plantation management. In a 1998 experiment, researchers recorded oil extraction rates at factories and determined that short-term impacts of haze and drought had a significant negative effect on oil extraction rates [185]. Future works could take a similar approach to determine an outcome that is more applicable to industry usage than vertical height growth of palms.

This work indicated that oil palm growth rates do vary substantially across the landscape, suggesting that if this could be explained, yields could be markedly improved. The predictors used in the analysis fail to explain a large quantity of these variations, suggesting that other factors were at play and were not captured in the model. The range of factors that could be responsible for this variation is vast, indicating that more research needs to be conducted into resolving what the greatest predictors of oil palm growth actually are. Possible drivers that were most obviously missing from the analysis were factors such as fertiliser use, soil type, cultivation type, and pest management. Though not for this landscape specifically, these factors have been investigated previously, so potential further work could include a meta-analysis of the importance of different predictors on oil palm growth or yield, as well as actual field measurements of such factors across the SAFE landscape.

The multiple linear regression that was used in the analysis has the advantage of being fast to run and easy to interpret. However, relying on linear models does limit the extent to which the data can be exploited. First, by definition, linear models are limited to representing linear relationships between variables (although more complex relationships can be expressed through data transformation). Second, multiple regression models assume that predictor variables are independent of one another, something which is rarely true in real-world data. This means that to limit the degree of correlation between predictors (and avoid multicollinearity, which biases parameter estimates), certain predictor variables must be excluded from the analysis based on their correlated nature. Alternative modelling approaches such as random forest models or general additive models (GAMs) provide much more flexibility when it comes to accounting for correlated predictors and allowing for non-linear relationships between response and explanatory variables. Their downside is that the results are less straightforward to interpret in ecological terms. Moreover, they can also suffer from overfitting and are much more computationally intensive to run. Nonetheless, if this work was taken further to identify other drivers of variation in growth and see if a higher proportion of the variation could be explained, the assumptions of the linear regression may no longer be met and a different model may be necessary.

This work could also be extended by determining the above-ground carbon density (ACD) of oil palms across the landscape, and the changes in this over drought periods, with methods similar to that of Nunes and colleagues in 2017 [92]. At the level of individual trees, oil palm aboveground biomass (AGB) can be derived as the dry mass in kg for each palm from its height (H) in meters and the following equation [186]:

$$AGB = 37.47 \times H + 3.6334$$

A carbon content conversion factor of 0.47 can then be applied, following the methods of Martin and Thomas (2011) [92–187]. LiDAR-derived maps of ACD could be used to quantifying the effects of oil palm agriculture on greenhouse gas emissions, the development of carbon prediction models would open doors to making the industry more environmentally sustainable [92].

The study took place over a relatively short time period in relation to the lifespan of oil palms. Oil palm is a fast-growing crop, so two years would have been enough time for differences in growth to actually be observed. However, the results did not take into account the delayed effects of drought on oil palm growth, which would require longer-term monitoring of the palms. Effects of drought on oil palm yields are known 6-12 months after a long dry season, and effects on height growth may display similar delayed effects [188]. Thus effects from drought in the early 2015 period may have been observed by the time 2016 data was collected, but the highest temperatures and VPD of the period were during March 2016 [98], meaning that by the second LiDAR flight palms may not have displayed any resulting effects. If more recent data after the last LiDAR flight in 2016 could be sourced, the work could be extended by examining findings from a longer time series of data. Future works could involve actually carrying out more of these LiDAR flights across the SAFE landscape, but they could even take advantage of high-resolution satellite imagery or structure from motion data to estimate changes in palm height over time. Additional surveys of the region are vital to investigate the effects of the worst period of drought during that time, and whether potential delayed drought-induced effects, affected the plantations.

3.5 Conclusions.

This experiment indicates that oil palms in Malaysian Borneo are resistant to drought, and do not suffer arrested growth during extreme climatic periods such as El Niño. One of the most interesting findings is that water does not seem to be a limiting factor in palm growth even over drought periods. The greatest predictor of oil palm growth by far was the initial size of the palm, with taller palms growing more slowly than shorter ones, likely due to differences in life stage and development. Oil palm growth rates vary substantially across the landscape, suggesting that if this could be explained, yields of palm oil could be substantially improved. However, the predictors tested in this analysis explained little of the variation.

Particular factors in the landscape that have a positive relationship with palm growth have highlighted that there may be scope to improve palm growth while also benefitting the environment. Increases in palm growth associated with competition for light, proximity to forest edges, and proximity to rivers may indicate that palms can grow as well or better when intercropped, or in closer association with natural primary or riparian forest, in a land-sharing style approach to plantations. Furthermore, identifying that elevation and TRI relationships positively correlated with oil palm growth may connote that land does not have to be flattened before planting for palms to grow well, and that plantation management could save a great deal of expense, labor, and disruption to the environment by refraining from such practices and maintaining existing variation in the topology of the landscape.

This study aimed to address the following two questions:

1) How much did oil palms grow during this period characterised by unseasonably hot and dry conditions, and how variable were growth rates across the landscape?

2) Can developmental, ecological, and landscape features be identified that explain why some oil palms grew faster than others during this two-year period?

The study has allowed these two questions to be answered thoroughly, as well as providing a range of suggestions for improvements to the experiment and further work:

1) Oil palm grew on average 1.67 m yr-1 between LiDAR flights in 2014 and 2016. There was considerable variability in the rate of height growth across the study area, with 90% of values ranging between 1.00 m yr-1 (5th percentile) to 3.90 m yr-1 (95th percentile).
2) The greatest predictor of oil palm growth was the initial size of the palm, with shorter palms growing more quickly than taller palms. Increases in palm growth were also associated with greater competition for light, smaller distances to forest edges, higher elevations, and greater terrain ruggedness. Despite this, the effect size of these predictor variables was generally low and together they only explained ~5% of the variation.

This project has indicated that regardless of differences across the landscape oil palms do grow successfully under drought conditions and are likely to be resilient in the face of climate change. Oil palm growth is highly variable across landscapes, and with more work into the most important factors predicting this variation, there is the opportunity to greatly increase yields. There is also potential scope for improving plantation practices that could increase yield while simultaneously reducing the level of environmental damage caused across the landscape.

Appendix.

Table S1: Accuracy of the segmentation algorithm and its variation depending on the initial size of oil palms (< 6 m vs >= 6 m), the input data (CHM vs point cloud), and the window size (6-10 m). Correctly segmented oil palms represent those where a single individual was found within a manually delineated polygon, over segmented palms are ones where more than one individual was found within a manually delineated polygon, and omitted palms are ones where no individual was found within a manually delineated polygon.

Data	Palm Size	Window size	Correctly segmented palms (%)	Over segmented palms (%)	Omissions (%)
CHM	All	8	69.44	4.16	26.41
CHM	All	9	65.77	1.71	31.78
CHM	All	10	61.86	0.49	37.65
CHM	Small	8	87.57	3.39	2.82
CHM	Small	9	84.75	1.69	6.78
CHM	Small	10	80.79	0.56	11.86
CHM	Large	8	55.60	5.17	39.22
CHM	Large	9	51.29	1.72	46.98
CHM	Large	10	47.41	0.43	52.16
Cloud	All	8	67.48	4.16	28.36
Cloud	All	9	68.22	0.98	30.81
Cloud	All	10	59.17	0.24	40.59
Cloud	Small	6	81.92	3.95	7.91
Cloud	Small	7	84.18	0.56	9.04
Cloud	Small	8	80.79	0.00	12.43
Cloud	Large	8	57.33	7.33	35.34
Cloud	Large	9	54.74	1.72	43.53
Cloud	Large	10	48.71	0.43	50.86

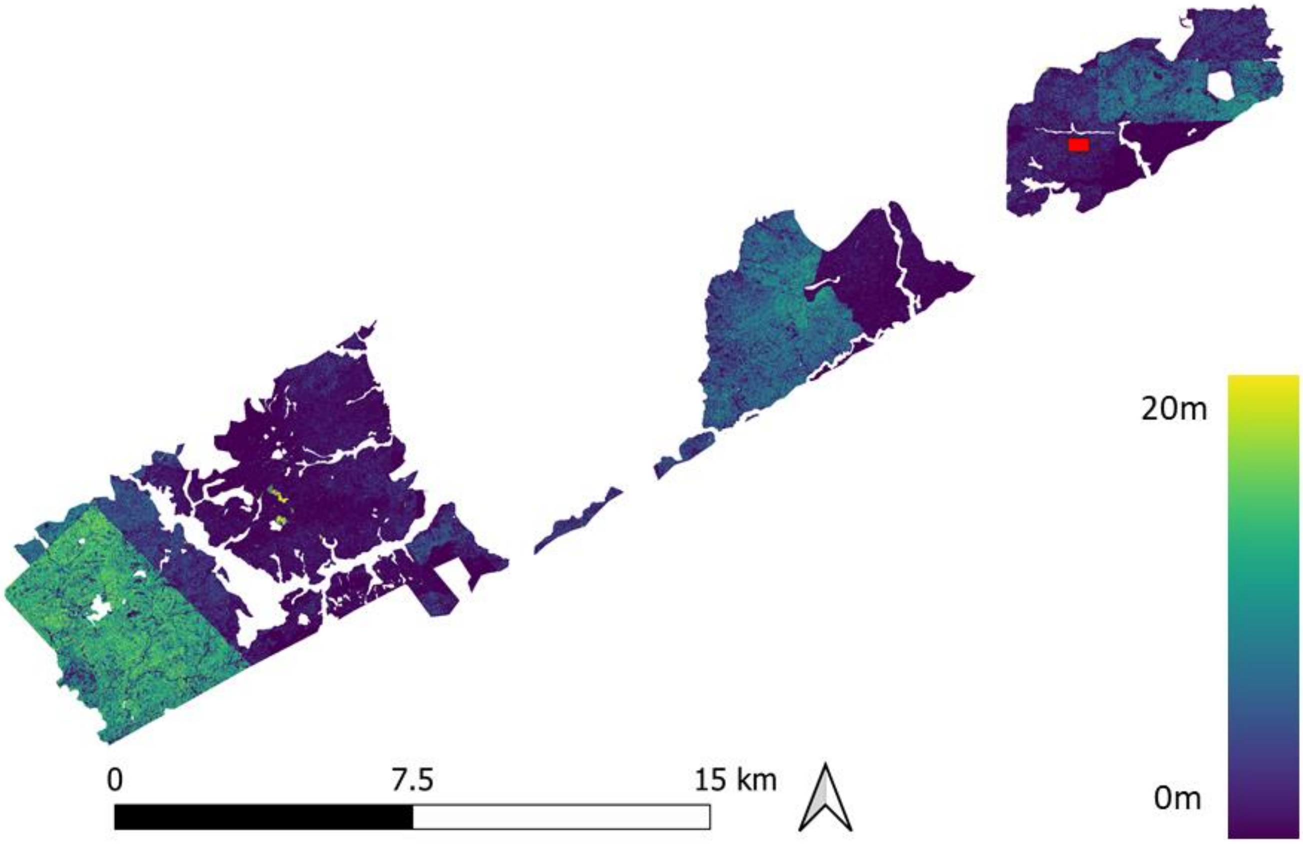

Figure S1: Canopy height model of all 2014 LiDAR data used in the analysis. The small red box indicates the section of the landscape that Fig. 2.6 is derived from.

References.

1. S. Mayes, *The History and Economic Importance of the Oil Palm* (Cham: Springer, 2020).
2. A. Brad, A. Schaffartzik, M. Pichler, & C. Plank, Contested territorialization and biophysical expansion of oil palm plantations in Indonesia. *Geoforum*, **64** (2015) 100–11. https://doi.org/10.1016/j.geoforum.2015.06.007.
3. M. Ithnin & A. Kushairi, *The Oil Palm Genome* (London: Springer, 2020).
4. A. Kushairi, S. K. Loh, I. Azman, E. Hishamuddin, M. Ong-Abdullah, Z. B. M. N. Izuddin, G. Razmah, S. Sundram, & G. K. A. Parveez, Oil palm economic performance in Malaysia and r&d progress in 2017. *Journal of Oil Palm Research*, **30** (2018) 163–95. https://doi.org/10.21894/jopr.2018.0030.
5. J. M. Lucey, G. Palmer, K. L. Yeong, D. P. Edwards, M. J. M. Senior, S. A. Scriven, G. Reynolds, & J. K. Hill, Reframing the evidence base for policy-relevance to increase impact: a case study on forest fragmentation in the oil palm sector. *Journal of Applied Ecology*, **54** (2017) 731–6. https://doi.org/10.1111/1365-2664.12845.
6. A. D. Ziegler, J. Phelps, J. Q. Yuen, E. L. Webb, D. Lawrence, J. M. Fox, T. B. Bruun, S. J. Leisz, C. M. Ryan, W. Dressler, O. Mertz, U. Pascual, C. Padoch, & L. P. Koh, Carbon outcomes of major land-cover transitions in SE Asia: Great uncertainties and REDD+ policy implications. *Global Change Biology*, **18** (2012) 3087–3099. https://doi.org/10.1111/j.1365-2486.2012.02747.x.
7. G. Wang, W. Cai, B. Gan, L. Wu, A. Santoso, X. Lin, Z. Chen, & M. J. McPhaden, Continued increase of extreme El Ninõ frequency long after 1.5 C warming stabilization. *Nature Climate Change572*, **7** (2017) 568–572. https://doi.org/10.1038/NCLIMATE3351.
8. G. Prasanna Kumar, M. V. B. Venu, B. Kalyana Babu, G. Ravichandran, & R. K. Mathur, Identification of oil palm fruit forms using SNP based CAPS marker among the Tenera/ Tenera (T X T) crossed progeny. *International Journal of Oil Palm*, (2018) 21.
9. M. J. Balick, Amazonian Oil Palms of Promise: A Survey. *Economic Botany*, **33** (1979) 11–28.

10. M. K. V. Carr, The water relations and irrigation requirements of oil palm (Elaeis guineensis): A review. *Experimental Agriculture*, **47** (2011) 629–652. https://doi.org/10.1017/S0014479711000494.

11. W. D. Raymond, The oil palm industry. *Trop Sci*, **3** (1961) 69–89.

12. I. E. Henson, A Brief History of the Oil Palm. *Palm Oil: Production, Processing, Characterization, and Uses*, (2012) 1–29. https://doi.org/10.1016/B978-0-9818936-9-3.50004-6.

13. C. W. S. Hartley, *The Oil Palm (Elaeis guineensis Jacq.)* (New York: Longman Scientific and Technical, 1988).

14. Okolo C, Okolo E, Nnadi A.L, Obikwelu F.E, Obalum S.E, & Igwe C.A, The Oil Palm (Elaeis guineensis Jacq): Natures Ecological Endowment to Eastern Nigeria. *Agro-Science Journal of Tropical Agriculture, Food, Environment and Extension*, **18** (2019) 48–57. https://doi.org/10.4314/as.v18i3.9.

15. M. Qaim, K. T. Sibhatu, H. Siregar, & I. Grass, Environmental, Economic, and Social Consequences of the Oil Palm Boom. **12** (2020) 321–344. https://doi.org/10.1146/annurev-resource-110119.

16. P. Westcott, *USDA agricultural projections to 2019.* (DIANE Publishing, 2010).

17. C. Yuen May, M. Ah Ngan, C. Kien Yoo, R. Abdul Majid, A. Yap Kian Chung, H. Lau Lik Nang, C. Sit Foon, Y. Chee Liang, P. Chiew Wei, N. Mei Han, & Y. Basiron, Palm Diesel: Green and Renewable Fuel from Palm Oil. *Palm Oil Developments*, **23** (2005) 3–7.

18. S. Sumathi, S. P. Chai, & A. R. Mohamed, Utilization of oil palm as a source of renewable energy in Malaysia. *Renewable and Sustainable Energy Reviews*, **12** (2008) 2404–2421. https://doi.org/10.1016/j.rser.2007.06.006.

19. P. T. Gee, Analytical characteristics of crude and refined palm oil and fractions. *European Journal of Lipid Science and Technology*, **109** (2007) 373–379. https://doi.org/10.1002/ejlt.200600264.

20. R. V. H. Corley & P. B. Tinker, *The Oil Palm* (John Wiley & Sons, 2008).

21. N. L. H. M. Dian, R. A. Hamid, S. Kanagaratnam, W. R. A. Isa, N. A. M. Hassim, N. H. Ismail, Z. Omar, & M. M. Sahri, Palm oil and palm kernel oil: Versatile ingredients for food applications. *Journal of Oil Palm Research*, **29** (2017) 487–511. https://doi.org/10.21894/jopr.2017.00014.

22. K. Obidzinski, R. Andriani, H. Komarudin, & A. Andrianto, Environmental and social impacts of oil palm plantations and their implications for biofuel

production in Indonesia. *Ecology and Society*, **17** (2012). https://doi.org/10.5751/ES-04775-170125.

23. O. Pye, Commodifying sustainability: Development, nature and politics in the palm oil industry. *World Development*, **121** (2019) 218–228. https://doi.org/10.1016/j.worlddev.2018.02.014.

24. J. Sayer, J. Ghazoul, P. Nelson, & A. Klintuni Boedhihartono, Oil palm expansion transforms tropical landscapes and livelihoods. *Global Food Security*, **1** (2012) 114–119. https://doi.org/10.1016/j.gfs.2012.10.003.

25. R. Beyer, A. Durán, T. Rademacher, P. Martin, C. Tayleur, S. Brooks, D. Coomes, P. Donald, & F. Sanderson, The environmental impacts of palm oil and its alternatives. *BioRxiv*, (2020). https://doi.org/10.1101/2020.02.16.951301.

26. J. B. Dib, V. v Krishna, Z. Alamsyah, & M. Qaim, Land-use change and livelihoods of non-farm households: The role of income from employment in oil palm and rubber in rural Indonesia. *Land Use Policy*, **76** (2018) 828–838. https://doi.org/10.1016/j.landusepol.2018.03.020.

27. C. Kubitza, V. v Krishna, Z. Alamsyah, & M. Qaim, The Economics Behind an Ecological Crisis: Livelihood Effects of Oil Palm Expansion in Sumatra, Indonesia. *Human Ecology*, **46** (2018) 107–116. https://doi.org/10.1007/s10745-017-9965-7.

28. R. B. Edwards, E. Edmonds, P. Burke, L. Cameron, W. Falcon, D. Gollin, G. Hadiwidjaja, N. Karachiwalla, E. Luttmer, R. Naylor, P. Novosad, B. Resosudarmo, ama Shenhav, C. Snyder, R. Sparrow, S. Sumarto, & D. Suryadarma, *Export agriculture and rural poverty: evidence from Indonesian palm oil* (Hanover, Germany: Dartmouth College, 2019).

29. D. Byerlee, W. P. Falcon, & R. Naylor, *The Tropical Oil Crop Revolution: Food, Feed, Fuel, and Forests* (Oxford University Press, 2017).

30. L. Feintrenie, W. K. Chong, & P. Levang, Why do Farmers Prefer Oil Palm? Lessons Learnt from Bungo District, Indonesia Sustainable Oil Palm Production View project Laurène Feintrenie Cirad-La recherche agronomique pour le développement. *Small-scale forestry*, **9** (2010) 379–396. https://doi.org/10.1007/s11842-010-9122-2.

31. M. Gatto, M. Wollni, R. Asnawi, & M. Qaim, Oil Palm Boom, Contract Farming, and Rural Economic Development: Village-Level Evidence from Indonesia. *World Development*, **95** (2017) 127–140. https://doi.org/10.1016/j.worlddev.2017.02.013.

32. J. Obado, Y. Syaukat, & H. Siregar, *THE IMPACTS OF EXPORT TAX POLICY ON THE INDONESIAN CRUDE PALM OIL INDUSTRY* (2009).

33. L. ; Rist, L. ; Feintrenie, & P. Levang, The livelihood impacts of oil palm Smallholders in Indonesia. *Biodiversity and conservation*, **19** (2010) 1009–1024. https://doi.org/10.3929/ethz-b-000016972.

34. R. L. Naylor, M. M. Higgins, R. B. Edwards, & W. P. Falcon, Decentralization and the environment: Assessing smallholder oil palm development in Indonesia. *Ambio*, **48** (2019) 1195–1208. https://doi.org/10.1007/s13280-018-1135-7.

35. M. van Noordwijk, M. Susswein, T. P. Tomich, C. Diaw, & S. Vosti, *Land Use Practices in the Humid Tropics and Introduction to ASB Benchmark Areas* (Bogor, Indones: ICRAF, 2001).

36. T. Santika, K. A. Wilson, S. Budiharta, E. A. Law, T. M. Poh, M. Ancrenaz, M. J. Struebig, & E. Meijaard, Does oil palm agriculture help alleviate poverty? A multidimensional counterfactual assessment of oil palm development in Indonesia. *World Development*, **120** (2019) 105–117. https://doi.org/10.1016/j.worlddev.2019.04.012.

37. V. Krishna, M. Euler, H. Siregar, & M. Qaim, Differential livelihood impacts of oil palm expansion in Indonesia. *Agricultural Economics (United Kingdom)*, **48** (2017) 639–653. https://doi.org/10.1111/agec.12363.

38. K. T. Sibhatu, Oil Palm Boom and Farm Household Diets in the Tropics. *Frontiers in Sustainable Food Systems*, **3** (2019) 75. https://doi.org/10.3389/fsufs.2019.00075.

39. W. Alwarritzi, T. Nanseki, & Y. Chomei, Impact of Oil Palm Expansion on Farmers' Crop Income and Poverty Reduction in Indonesia: An Application of Propensity Score Matching. *Journal of Agricultural Science*, **8** (2016). https://doi.org/10.5539/jas.v8n1p119.

40. R. Cramb & G. N. Curry, *Oil palm and rural livelihoods in the Asia-Pacific region: An overview* (Blackwell, Cambridge, 2012). https://doi.org/10.1111/j.1467-8373.2012.01495.x.

41. J. F. Mccarthy, The Journal of Peasant Studies Processes of inclusion and adverse incorporation: oil palm and agrarian change in Sumatra, Indonesia. *The Journal of peasant studies*, **37** (2010) 821–850. https://doi.org/10.1080/03066150.2010.512460.

42. M. Colchester, *Palm oil and indigenous peoples in South East Asia* (Forest Peoples Programme, 2011).

43. Kubitza, Christoph, Gehrke, & Esther, Why does a labor-saving technology decrease fertility rates? Evidence from the oil palm boom in Indonesia. *Human Ecology*, **46** (2018) 107–116.

44. S. Mingorría, G. Gamboa, B. Martín-López, & E. Corbera, The oil palm boom: Socio-economic implications for Q'eqchi' households in the Polochic valley, Guatemala. *Environment, Development and Sustainability*, **16** (2014) 841–871. https://doi.org/10.1007/s10668-014-9530-0.

45. A. Castellanos-Navarrete, W. v. Tobar-Tomás, & C. E. López-Monzón, Development without change: Oil palm labour regimes, development narratives, and disputed moral economies in Mesoamerica. *Journal of Rural Studies*, **71** (2019) 169–180. https://doi.org/10.1016/j.jrurstud.2018.08.011.

46. W. Overbeek, M. Kröger, & J. F. Gerber, An overview of industrial tree plantations in the global South Conflicts, trends and resistance struggles. *Environmental Justice Organizations, Liabilities and Trade Report*, **3** (2012).

47. A. Andrianto, H. Komarudin, & P. Pacheco, Expansion of oil palm plantations in Indonesia's frontier: Problems of Externalities and the Future of Local and Indigenous Communities. *Land*, **8** (2019) 56. https://doi.org/10.3390/land8040056.

48. D. Fitzpatrickt, Disputes and Pluralism in Modern Indonesian Land Law. *Yale J. Int'l L.*, **22** (1997) 171.

49. J. Merten, A. Röll, T. Guillaume, A. Meijide, S. Tarigan, H. Agusta, C. Dislich, C. Dittrich, H. Faust, D. Gunawan, & J. Hein, Water scarcity and oil palm expansion: social views and environmental processes. *Ecology and Society*, **21** (2016).

50. T. M. Li, After the land grab: Infrastructural violence and the "Mafia System" in Indonesia's oil palm plantation zones. *Geoforum*, **96** (2018) 328–337. https://doi.org/10.1016/j.geoforum.2017.10.012.

51. A. Hervas, Land, development and contract farming on the Guatemalan oil palm frontier. *The Journal of Peasant Studies*, **46** (2019) 115–141. https://doi.org/10.1080/03066150.2017.1351435.

52. H. Abdul-Rahman, C. Wang, L. C. Wood, & S. F. Low, Negative impact induced by foreign workers: Evidence in Malaysian construction sector.

Habitat International, **36** (2012) 433–443. https://doi.org/10.1016/j.habitatint.2012.03.002.

53. A. Kassim, *Cross-Border Movement of Foreign Workers in Malaysia: A Comparative Analysis* (2005).

54. D. Wong & T. Anwar, Migran Gelap: Indonesian migrants in Malaysia's irregular labour economy. *Unauthorized Migration in Southeast Asia*, (2003) 169–227.

55. P. M. Fearnside, Transmigration in Indonesia: Lessons from Its Environmental and Social Impacts. *Environmental management*, **21** (1997) 553–570. https://doi.org/10.1007/s002679900049.

56. I. Comte, F. Colin, J. K. Whalen, O. Grünberger, & J.-P. Caliman, Agricultural practices in oil palm plantations and their impact on hydrological changes, nutrient fluxes and water quality in Indonesia: a review. *Advances in Agronomy*, **116** (2012) 71–124. https://doi.org/10.1016/B978-0-12-394277-7.00003-8.

57. J. A. Pyle, N. J. Warwick, N. R. P. Harris, M. R. Abas, A. T. Archibald, M. J. Ashfold, K. Ashworth, M. P. Barkley, G. D. Carver, K. Chance, J. R. Dorsey, D. Fowler, S. Gonzi, B. Gostlow, C. N. Hewitt, T. P. Kurosu, J. D. Lee, S. B. Langford, G. Mills, S. Moller, A. R. Mackenzie, A. J. Manning, P. Misztal, M. S. M. Nadzir, E. Nemitz, H. M. Newton, L. M. O'Brien, S. Ong, D. Oram, P. I. Palmer, L. K. Peng, S. M. Phang, R. Pike, T. A. M. Pugh, N. A. Rahman, A. D. Robinson, J. Sentian, A. A. Samah, U. Skiba, H. E. Ung, S. E. Yong, & P. J. Young, The impact of local surface changes in Borneo on atmospheric composition at wider spatial scales: Coastal processes, land-use change and air quality. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **366** (2011) 3210–3224. https://doi.org/10.1098/rstb.2011.0060.

58. F. H. Johnston, S. B. Henderson, Y. Chen, J. T. Randerson, M. Marlier, R. S. DeFries, P. Kinney, D. M. J. S. Bowman, & M. Brauer, Estimated global mortality attributable to smoke from landscape fires. *Environmental Health Perspectives*, **120** (2012) 695–701. https://doi.org/10.1289/ehp.1104422.

59. C. Dislich, A. C. Keyel, J. Salecker, Y. Kisel, K. M. Meyer, M. Auliya, A. D. Barnes, M. D. Corre, K. Darras, H. Faust, B. Hess, S. Klasen, A. Knohl, H. Kreft, A. Meijide, F. Nurdiansyah, F. Otten, G. Pe'er, S. Steinebach, S. Tarigan, M. H. Tölle, T. Tscharntke, & K. Wiegand, A review of the ecosystem functions in oil palm plantations, using forests as a reference system. *Biological Reviews*, **92** (2017) 1539–1569. https://doi.org/10.1111/brv.12295.

60. V. Vijay, S. L. Pimm, C. N. Jenkins, & S. J. Smith, The Impacts of Oil Palm on Recent Deforestation and Biodiversity Loss. *PLOS ONE*, **11** (2016) e0159668. https://doi.org/10.1371/JOURNAL.PONE.0159668.

61. E. Meijaard, J. Garcia-Ulloa, D. Sheil, S. A. Wich, K. M. Carlson, D. Juffe-Bignoli, & T. M. Brooks, Oil palm and biodiversity: A situation analysis by the IUCN Oil Palm Task Force. (2018).

62. D. L. A. Gaveau, D. Sheil, Husnayaen, M. A. Salim, S. Arjasakusuma, M. Ancrenaz, P. Pacheco, & E. Meijaard, Rapid conversions and avoided deforestation: examining four decades of industrial plantation expansion in Borneo. *Scientific Reports*, **6** (2016) 1–13. https://doi.org/10.1038/srep32017.

63. L. P. Koh & D. S. Wilcove, Cashing in palm oil for conservation. *Nature*, **448** (2007) 993–994. https://doi.org/10.1038/448993a.

64. S. Chapman, J. Syktus, R. Trancoso, A. Salazar, M. Thatcher, J. E. M. Watson, E. Meijaard, D. Sheil, P. Dargusch, & C. A. McAlpine, Compounding impact of deforestation on Borneo's climate during El Niño events. *Environmental Research Letters*, **15** (2020) 084006. https://doi.org/10.1088/1748-9326/AB86F5.

65. S. A. Abdullah & N. Nakagoshi, Forest fragmentation and its correlation to human land use change in the state of Selangor, peninsular Malaysia. *Forest Ecology and Management*, **241** (2007) 39–48. https://doi.org/10.1016/J.FORECO.2006.12.016.

66. E. B. Fitzherbert, M. J. Struebig, A. Morel, F. Danielsen, C. A. Brühl, P. F. Donald, & B. Phalan, How will oil palm expansion affect biodiversity? *Trends in Ecology & Evolution*, **23** (2008) 538–545. https://doi.org/10.1016/J.TREE.2008.06.012.

67. S. H. Luke, A. D. Advento, A. A. K. Aryawan, D. N. Adhy, A. Ashton-Butt, H. Barclay, J. P. Dewi, J. Drewer, A. J. Dumbrell, Edi, A. E. Eycott, M. F. Harianja, J. K. Hinsch, A. S. C. Hood, C. Kurniawan, D. J. Kurz, D. J. Mann, K. J. Matthews Nicholass, M. Naim, M. D. Pashkevich, G. W. Prescott, S. Ps, Pujianto, D. Purnomo, R. R. Purwoko, S. Putra, T. D. S. Rambe, Soeprapto, D. M. Spear, Suhardi, D. J. X. Tan, H.-H. Tao, R. S. Tarigan, R. Wahyuningsih, H. S. Waters, R. H. Widodo, Whendy, C. R. Woodham, J.-P. Caliman, E. M. Slade, J. L. Snaddon, W. A. Foster, & E. C. Turner, Managing Oil Palm Plantations More Sustainably: Large-Scale Experiments Within the Biodiversity and Ecosystem Function in Tropical Agriculture (BEFTA) Programme. *Frontiers in Forests and Global Change*, **2** (2020) 75. https://doi.org/10.3389/FFGC.2019.00075.

68. C. M. Yule, Loss of biodiversity and ecosystem functioning in Indo-Malayan peat swamp forests. *Biodiversity and conservation*, **19** (2010) 393–409. https://doi.org/10.1007/s10531-008-9510-5.

69. S. Dhandapani, N. T. Girkin, S. Evers, K. Ritz, & S. Sjögersten, Is Intercropping an Environmentally-Wise Alternative to Established Oil Palm Monoculture in Tropical Peatlands? *Frontiers in Forests and Global Change*, (2020) 70. https://doi.org/10.3389/FFGC.2020.00070.

70. S. Dhandapani, K. Ritz, S. Evers, & S. Sjögersten, Environmental impacts as affected by different oil palm cropping systems in tropical peatlands. *Agriculture, Ecosystems & Environment*, **3** (2019) 70. https://doi.org/10.1016/J.AGEE.2019.02.012.

71. S. Percy, J. Lubchenco, F. Almeida, P. Armsworth, A. Bennett, K. Ebi, J. Ehrmann, J. Griffith, P. Kumar, S. Pagiola, G. Prickett, D. Richards, R. Tinto, J. Rivera, V. Thompson, A. Wenblad, & G. Yohe, *Millennium ecosystem assessment, M.E.A.* (Washington, DC: Island press, 2005).

72. A. Katayama, T. Kume, H. Komatsu, T. M. Saitoh, M. Ohashi, M. Nakagawa, M. Suzuki, K. Otsuki, & T. O. Kumagai, Carbon allocation in a Bornean tropical rainforest without dry seasons. *Journal of plant research*, **124** (2013) 505–515. https://doi.org/10.1007/s10265-012-0544-0.

73. L. Khoon Kho, M. Rudbeck Jepsen, & K. Lip Khoon, Carbon stock of oil palm plantations and tropical forests in Malaysia: A review. *Singapore Journal of Tropical Geography*, **36** (2015) 249–266. https://doi.org/10.1111/sjtg.12100.

74. J.-C. A. Combres, B. B. Pallas, L. A. Rouan, I. C. Mialet-Serra, J.-P. D. Caliman, S. A. Braconnier, J.-C. A. Soulié, & M. A. Dingkuhn, Simulation of inflorescence dynamics in oil palm and estimation of environment-sensitive phenological phases: a model based analysis. *Functional Plant Biology*, **40** (2012) 263–279. https://doi.org/10.1071/FP12133.

75. L. S. Woittiez, M. T. van Wijk, M. Slingerland, M. van Noordwijk, & K. E. Giller, Yield gaps in oil palm: A quantitative review of contributing factors. *European Journal of Agronomy*, **83** (2017) 57–77. https://doi.org/10.1016/J.EJA.2016.11.002.

76. I. Grass, J. Loos, S. Baensch, P. Batáry, F. Librán-Embid, A. Ficiciyan, F. Klaus, M. Riechers, J. Rosa, J. Tiede, K. Udy, C. Westphal, A. Wurz, & T. Tscharntke, Land-sharing/-sparing connectivity landscapes for ecosystem services and biodiversity conservation. *People and Nature*, **1** (2019) 262–272. https://doi.org/10.1002/PAN3.21.

77. T. Soliman, F. K. S. Lim, J. S. H. Lee, & L. R. Carrasco, Closing oil palm yield gaps among Indonesian smallholders through industry schemes, pruning, weeding and improved seeds. *Royal Society Open Science*, **3** (2016) 160292. https://doi.org/10.1098/RSOS.160292.

78. T. Rhebergen, T. Fairhurst, A. Whitbread, K. E. Giller, & S. Zingore, Yield gap analysis and entry points for improving productivity on large oil palm plantations and smallholder farms in Ghana. *Agricultural Systems*, **165** (2018) 14–25. https://doi.org/10.1016/J.AGSY.2018.05.012.

79. W. A. Foster, J. L. Snaddon, A. D. Advento, A. A. Agung, H. Barclay, J. P. Caliman, C. Kumiawan, D. J. Kurz, D. J. Mann, M. Naim, & D. P. Pujianto, The biodiversity and ecosystem function in tropical agriculture (BEFTA) project. *The Planter*, **90** (2014) 581–591.

80. B. Samedani, A. S. Juraimi, S. A. S. Abdullah, M. Y. Rafii, A. A. Rahim, & M. Anwar, Effect of cover crops on weed community and oil palm yield. *International Journal of Agriculture and Biology*, **16** (2014).

81. G. W. Prescott, D. P. Edwards, W. A. Foster, & C. W. Graham Prescott, Retaining biodiversity in intensive farmland: epiphyte removal in oil palm plantations does not affect yield. *Ecology and Evolution*, **5** (2015) 1944–1954. https://doi.org/10.1002/ece3.1462.

82. F. A. Edwards, D. P. Edwards, S. Sloan, & K. C. Hamer, Sustainable Management in Crop Monocultures: The Impact of Retaining Forest on Oil Palm Yield. *PLOS ONE*, **9** (2014) e91695. https://doi.org/10.1371/JOURNAL.PONE.0091695.

83. F. Zulkefli, S. Syahlan, & M. F. A. Aziz, Negatives Impact Faced by Oil Palm Estate Management in managing Foreign Workers: A Case Study. *International Journal of Academic Research in Business and Social Sciences*, **8** (2018). https://doi.org/10.6007/IJARBSS/v8-i9/4863.

84. M. P. Hoffmann, C. R. Donough, S. E. Cook, M. J. Fisher, C. H. Lim, Y. L. Lim, J. Cock, S. P. Kam, S. N. Mohanaraj, K. Indrasuara, P. Tittinutchanon, & T. Oberthür, Yield gap analysis in oil palm: Framework development and application in commercial operations in Southeast Asia. *Agricultural Systems*, **151** (2017) 12–19. https://doi.org/10.1016/J.AGSY.2016.11.005.

85. H. Santoso, H. Tani, & X. Wang, A simple method for detection and counting of oil palm trees using high-resolution multispectral satellite imagery. *International journal of remote sensing*, **37** (2016) 5122–5134. https://doi.org/10.1080/01431161.2016.1226527.

86. J. Roughgarden, S. W. Running, & P. A. Matson, What does remote sensing do for ecology? *Ecology*, **72** (1991) 1918–1922. https://doi.org/10.2307/1941546.

87. N. Camarretta, P. A. Harrison, T. Bailey, B. Potts, A. Lucieer, N. Davidson, & M. Hunt, Monitoring forest structure to guide adaptive management of forest restoration: a review of remote sensing approaches. *New Forests*, **51** (2020) 573–596. https://doi.org/10.1007/s11056-019-09754-5.

88. Y. Cheng, L. Yu, Y. Xu, H. Lu, A. P. Cracknell, K. Kanniah, & P. Gong, Mapping oil palm extent in Malaysia using ALOS-2 PALSAR-2 data. *International Journal of Remote Sensing*, **39** (2018) 432–452. https://doi.org/10.1080/01431161.2017.1387309.

89. W. Li, R. Dong, H. Fu, & L. Yu, Large-Scale Oil Palm Tree Detection from High-Resolution Satellite Images Using Two-Stage Convolutional Neural Networks. *Remote Sensing*, **11** (2018) 11. https://doi.org/10.3390/RS11010011.

90. J. Miettinen, D. L. A. Gaveau, & S. C. Liew, Comparison of visual and automated oil palm mapping in Borneo. *International Journal of Remote Sensing*, **40** (2019) 8174–8185. https://doi.org/10.1080/01431161.2018.1479799.

91. P. Srestasathiern & P. Rakwatin, Oil Palm Tree Detection with High Resolution Multi-Spectral Satellite Imagery. *Remote Sens*, **6** (2014) 6. https://doi.org/10.3390/rs6109749.

92. M. H. Nunes, R. M. Ewers, E. C. Turner, & D. A. Coomes, Mapping Aboveground Carbon in Oil Palm Plantations Using LiDAR: A Comparison of Tree-Centric versus Area-Based Approaches. *Remote Sensing*, **9** (2017) 816. https://doi.org/10.3390/RS9080816.

93. T. Jucker, S. R. Hardwick, S. Both, D. M. O. Elias, R. M. Ewers, D. T. Milodowski, T. Swinfield, & D. A. Coomes, Canopy structure and topography jointly constrain the microclimate of human-modified tropical landscapes. *Global Change Biology*, **24** (2018) 5243–5258. https://doi.org/10.1111/gcb.14415.

94. W. Verheye, *Growth and production of Oil Palm* (UNESCO-EOLSS Publishers, 2010).

95. P. J. van Mantgem, N. L. stephenson, J. C. Byrne, L. D. Daniels, J. F. Franklin, P. Z. Fule, M. E. Harmon, A. J. Larson, J. M. smith, A. H. Taylor, & T. T. Veblen, A.Bracher. *Nat. Rev. Mal. Cell Biol*, **28** (2005) 512. https://doi.org/10.1126/science.1129450.

96. C. D. Allen, A. K. Macalady, H. Chenchouni, D. Bachelet, N. Mcdowell, M. Vennetier, T. Kitzberger, A. Rigling, D. D. Breshears, E. H. Hogg, C. D. Allen,

A. K. Macalady, H. Chenchouni, D. Bachelet, N. Mcdowell, M. Vennetier, T. Kitzberger, A. Rigling, D. D. Breshears, T. Hogg, P. Gonzalez, R. Fensham, Z. Zhangm, J. Castro, N. Demidova, J.-H. Lim, G. Allard, S. W. Running, A. Semerci, & N. Cobb, A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *Forest ecology and management*, **259** (2010) 660–684. https://doi.org/10.1016/j.foreco.2009.09.001ï.

97. S. Sevanto, N. G. McDowell, L. T. Dickman, R. Pangle, & W. T. Pockman, How do trees die? A test of the hydraulic failure and carbon starvation hypotheses. *Plant, Cell & Environment*, **37** (2014) 153–161. https://doi.org/10.1111/PCE.12141.

98. M. H. Nunes, T. Jucker, T. Riutta, M. Svátek, J. Kvasnica, M. Rejžek, R. Matula, N. Majalap, R. M. Ewers, T. Swinfield, R. Valbuena, N. R. Vaughn, G. P. Asner, & D. A. Coomes, Recovery of logged forest fragments in a human-modified tropical landscape during the 2015-16 El Niño. *Nature Communications*, **12** (2021). https://doi.org/10.1038/s41467-020-20811-y.

99. C. Sun, H. Cao, H. Shao, X. Lei, & Y. Xiao, Growth and physiological responses to water and nutrient stress in oil palm. *African Journal of Biotechnology*, **10** (2013) 10465–10471. https://doi.org/10.4314/ajb.v10i51.

100. M. Weih, Evidence for increased sensitivity to nutrient and water stress in a fast-growing hybrid willow compared with a natural willow clone. *Tree Physiology*, **21** (2001) 1141–1148. https://doi.org/10.1093/TREEPHYS/21.15.1141.

101. C. J. Song, K. M. Ma, L. Y. Qu, Y. Liu, X. L. Xu, B. J. Fu, & J. F. Zhong, Interactive effects of water, nitrogen and phosphorus on the growth, biomass partitioning and water-use efficiency of Bauhinia faberi seedlings. *Journal of Arid Environments*, **74** (2010) 1003–1012. https://doi.org/10.1016/J.JARIDENV.2010.02.003.

102. D. Steffens, B. W. Hütsch, S. Schubert, T. Losak, & T. Eschholz, Water logging may inhibit plant growth primarily by nutrient deficiency rather than nutrient toxicity. *Plant Soil and Environment*, **51** (2005) 545. https://doi.org/10.17221/3630-PSE.

103. P. Karageorgou, E. Levizou, & Y. Manetas, The influence of drought, shade and availability of mineral nutrients on exudate phenolics of Dittrichia viscosa. *Flora - Morphology, Distribution, Functional Ecology of Plants*, **197** (2002) 285–289. https://doi.org/10.1078/0367-2530-00042.

104. R. Munns, Comparative physiology of salt and water stress. *Plant, Cell and Environment*, **25** (2002) 239–250. https://doi.org/10.1046/j.0016-8025.2001.00808.x.

105. T. C. Hsiao, Plant Responses to Water Stress. *Annual review of plant physiology*, **24** (2003) 519–570.

106. J. S. Powers, G. V. G., T. J. Brodribb, N. B. Schwartz, D. Pérez-Aviles, C. M. Smith-Martin, J. M. Becknell, F. Aureli, R. Blanco, E. Calderón-Morales, J. C. Calvo-Alvarado, A. J. Calvo-Obando, M. M. Chavarría, D. Carvajal-Vanegas, C. D. Jiménez-Rodríguez, E. M. Chacon, C. M. Schaffner, L. K. Werden, X. Xu, & D. Medvigy, A catastrophic tropical drought kills hydraulically vulnerable tree species. *Global Change Biology*, **26** (2020) 3122–3133. https://doi.org/10.1111/GCB.15037.

107. H.-X. Cao, C.-X. Sun, H.-B. Shao, & X.-T. Lei, Effects of low temperature and drought on the physiological and growth changes in oil palm seedlings. *African Journal of Biotechnology*, **10** (2016) 2630–2637. https://doi.org/10.4314/ajb.v10i14.

108. P. A. Silva, V. S. Cosme, K. C. Rodrigues, K. S. Detmann, F. M. Leão, R. L. Cunha, R. A. F. Buselli, F. M. DaMatta, & H. A. Pinheiro, Drought tolerance in two oil palm hybrids as related to adjustments in carbon metabolism and vegetative growth. *Acta physiologiae plantarum*, **39** (2017) 58. https://doi.org/10.1007/s11738-017-2354-4.

109. A. E. Eycott, A. D. Advento, H. S. Waters, S. H. Luke, A. A. K. Aryawan, A. S. Hood, M. Naim, S. Ps, Pujianto, D. Purnomo, T. D. S. Rambe, Soeprapto, Suhardi, R. S. Tarigan, R. Wahyuningsih, R. H. Widodo, J.-P. Caliman, J. L. Snaddon, W. A. Foster, & E. C. Turner, Resilience of ecological functions to drought in an oil palm agroecosystem. *Environmental Research Communications*, **1** (2019) 101004. https://doi.org/10.1088/2515-7620/AB48DA.

110. S. R. Hardwick, Interactions between vegetation and microclimate in a heterogeneous tropical landscape. (2015).

111. L. B. Marczak, T. Sakamaki, S. L. Turvey, I. Deguise, S. L. R. Wood, & J. S. Richardson, Are forested buffers an effective conservation strategy for riparian fauna? An assessment using meta-analysis. *Ecological Applications*, **20** (2010) 126–134. https://doi.org/10.1890/08-2064.1.

112. C. McDermott, B. W. Cashore, & P. Kanowski, *Global environmental forest policies: an international comparison. Earthscan.* (Earthscan, 2010).

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

114. J. Williamson, E. M. Slade, S. H. Luke, T. Swinfield, A. Y. C. Chung, D. A. Coomes, H. Heroin, T. Jucker, O. T. Lewis, C. S. Vairappan, S. J. Rossiter, & M. J. Struebig, Riparian buffers act as microclimatic refugia in oil palm landscapes. *Journal of Applied Ecology*, **58** (2021) 431–442. https://doi.org/10.1111/1365-2664.13784.

115. M. Różycka, P. Migoń, & A. , Michniewicz, Topographic Wetness Index and Terrain Ruggedness Index in geomorphic characterisation of landslide terrains, on examples from the Sudetes, SW Poland. *Zeitschrift für geomorphologie, Supplementary issues*, **61** (2017) 61–80. https://doi.org/10.1127/zfg_suppl/2016/0328.

116. J. M. B. Smith, Vegetation and Microclimate of East- and West-Facing Slopes in the Grasslands of MT Wilhelm, Papua New Guinea. *The Journal of Ecology*, **65** (1977) 39. https://doi.org/10.2307/2259061.

117. S. Paramananthan, Journal of Oil Palm &The Environment An official publication of the Malaysian Palm Oil Council (MPOC) Managing Marginal Soils for Sustainable Growth of Oil Palms in the Tropics. *Journal of Oil Palm & The Environment*, **4** (2013) 1–16. https://doi.org/10.5366/jope.2013.1.

118. T. R. McVicar, T. G. van Niel, L. T. Li, M. F. Hutchinson, X. M. Mu, & Z. H. Liu, Spatially distributing monthly reference evapotranspiration and pan evaporation considering topographic influences. *Journal of Hydrology*, **338** (2007) 196–220. https://doi.org/10.1016/J.JHYDROL.2007.02.018.

119. J. D. Fridley, Downscaling Climate over Complex Terrain: High Finescale (<1000 m) Spatial Variation of Near-Ground Temperatures in a Montane Forested Landscape (Great Smoky Mountains). *Journal of Applied Meteorology and Climatology*, **48** (2009) 1033–1049. https://doi.org/10.1175/2008JAMC2084.1.

120. S. Z. Dobrowski, A climatic basis for microrefugia: the influence of terrain on climate. *Global Change Biology*, **17** (2011) 1022–1035. https://doi.org/10.1111/J.1365-2486.2010.02263.X.

121. J. Julio De Toledo, W. E. Magnusson, C. v Castilho, & H. E. M. Nascimento, How much variation in tree mortality is predicted by soil and topography in Central Amazonia? *Forest Ecology and Management*, **262** (2011) 331–338. https://doi.org/10.1016/j.foreco.2011.03.039.

122. B. Phalan, E. B. Fitzherbert, S. Rafflegeau, M. J. Struebig, A. Verwilghen, S. A. Bhagwat, & K. J. Willis, Conservation in oil-palm landscapes. *Conservation Biology*, **23** (2009) 244–246.

123. W. Zhang, T. H. Ricketts, C. Kremen, K. Carney, & S. M. Swinton, Ecosystem services and dis-services to agriculture. *Ecological Economics*, **64** (2007) 253–260. https://doi.org/10.1016/J.ECOLECON.2007.02.024.

124. C. Kremen, N. M. Williams, & R. W. Thorp, Crop pollination from native bees at risk from agricultural intensification. *Proceedings of the National Academy of Sciences*, **99** (2002) 16812–16816. https://doi.org/10.1073/PNAS.262413599.

125. R. E. Green, S. J. Cornell, J. P. W. Scharlemann, & A. Balmford, Farming and the fate of wild nature. *Science*, **307** (2005) 550–555. https://doi.org/10.1126/SCIENCE.1106049.

126. D. A. Landis, S. D. Wratten, & G. M. Gurr, Habitat Management to Conserve Natural Enemies of Arthropod Pests in Agriculture. *http://dx.doi.org/10.1146/annurev.ento.45.1.175*, **45** (2003) 175–201. https://doi.org/10.1146/ANNUREV.ENTO.45.1.175.

127. A.-M. Klein, I. Steffan-Dewenter, & T. Tscharntke, Fruit set of highland coffee increases with the diversity of pollinating bees. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, **270** (2003) 955–961. https://doi.org/10.1098/RSPB.2002.2306.

128. T. H. Ricketts, G. C. Daily, P. R. Ehrlich, & C. D. Michener, Economic value of tropical forest to coffee production. *Proceedings of the National Academy of Sciences*, **101** (2004) 12579–12582. https://doi.org/10.1073/PNAS.0405147101.

129. L. P. Koh, Can oil palm plantations be made more hospitable for forest butterflies and birds? *Journal of Applied Ecology*, **45** (2008) 1002–1009. https://doi.org/10.1111/J.1365-2664.2008.01491.X.

130. T. Tscharntke, C. H. Sekercioglu, T. v. Dietsch, N. S. Sodhi, P. Hoehn, & J. M. Tylianakis, Landscape constraints on functional diversity of birds and insects in tropical agroecosystems. *Ecology*, **89** (2008) 944–951. https://doi.org/10.1890/07-0455.1.

131. J. M. Woltz, R. Isaacs, & D. A. Landis, Landscape structure and habitat management differentially influence insect natural enemies in an agricultural landscape. *Agriculture, Ecosystems & Environment*, **152** (2012) 40–49. https://doi.org/10.1016/J.AGEE.2012.02.008.

132. R. Chaplin-Kramer, M. E. O'Rourke, E. J. Blitzer, & C. Kremen, A meta-analysis of crop pest and natural enemy response to landscape complexity. *Ecology Letters*, **14** (2011) 922–932. https://doi.org/10.1111/J.1461-0248.2011.01642.X.

133. K. Pang Tan, K. Devi Kanniah, & A. Philip Cracknell, International Journal of Remote Sensing On the upstream inputs into the MODIS primary productivity products using biometric data from oil palm plantations On the upstream inputs into the MODIS primary productivity products using biometric data from oil palm plantations. *International Journal of Remote Sensing*, **35** (2014) 2215–2246. https://doi.org/10.1080/01431161.2014.889865.

134. J. P. Monzon, M. A. Slingerland, S. Rahutomo, F. Agus, T. Oberthür, J. F. Andrade, A. Couëdel, J. I. Rattalino Edreira, W. Hekman, R. van den Beuken, F. Hidayat, I. Pradiko, D. K. G. Purwantomo, C. R. Donough, H. Sugianto, Y. L. Lim, T. Farrell, & P. Grassini, Fostering a climate-smart intensification for oil palm. *Nature Sustainability*, **4** (2021) 595–601. https://doi.org/10.1038/S41893-021-00700-Y.

135. Z. Binti Mat Sharif, N. Binti Mohd Taib, & M. Sallehuddin Bin Yusof, Study on handing process and quality degradation of oil palm fresh fruit bunches (FFB). *IOP Conference Series: Materials Science and Engineering*, **203** (2017) 012027. https://doi.org/10.1088/1755-1315/37/1/012037.

136. A. Chemura, I. van Duren, & L. M. van Leeuwen, Determination of the age of oil palm from crown projection area detected from WorldView-2 multispectral remote sensing data: The case of Ejisu-Juaben district, Ghana. *ISPRS Journal of Photogrammetry and Remote Sensing*, **100** (2015) 118–127. https://doi.org/10.1016/J.ISPRSJPRS.2014.07.013.

137. W. Khokthong, D. C. Zemp, B. Irawan, L. Sundawati, H. Kreft, & D. Hölscher, Drone-Based Assessment of Canopy Cover for Analyzing Tree Mortality in an Oil Palm Agroforest. *Frontiers in Forests and Global Change*, (2019) 12. https://doi.org/10.3389/FFGC.2019.00012.

138. A. E. L. Stovall, H. Shugart, & X. Yang, Tree height explains mortality risk during an intense drought. *Nature Communications*, **10** (2019) 1–6. https://doi.org/10.1038/s41467-019-12380-6.

139. P. Gillespie, The challenges of corporate governance in Indonesian oil palm: opportunities to move beyond legalism? *Asian Studies Review*, **36** (2012) 247–269. https://doi.org/10.1080/10357823.2012.685447.

140. Malaysian Palm Oil Council, *Palm Oil: Tree of Life. Malaysian Palm Oil Council Official Report 3.* (2007).

141. B. Phalan, Reconciling Food Production and Biodiversity Conservation: Land Sharing and Land Sparing Compared BIOFRAG View project Migratory Bird

Conservation in Asia View project. *Science*, **333** (2011) 1289–1291. https://doi.org/10.1126/science.1208742.

142. D. J. Mulla, Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, **114** (2013) 358–371. https://doi.org/10.1016/J.BIOSYSTEMSENG.2012.08.009.

143. R. P. Sishodia, R. L. Ray, & S. K. Singh, Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sensing 2020, Vol. 12, Page 3136*, **12** (2020) 3136. https://doi.org/10.3390/RS12193136.

144. T. Jucker, B. Bongalov, D. F. R. P. Burslem, R. Nilus, M. Dalponte, S. L. Lewis, O. L. Phillips, L. Qie, & D. A. Coomes, Topography shapes the structure, composition and function of tropical forest landscapes. *Ecology Letters*, **21** (2018) 989–1000. https://doi.org/10.1111/ELE.12964.

145. T. Jucker, G. P. Asner, M. Dalponte, P. G. Brodrick, C. D. Philipson, N. R. Vaughn, Y. Arn Teh, C. Brelsford, D. F. R. P. Burslem, N. J. Deere, R. M. Ewers, J. Kvasnica, S. L. Lewis, Y. Malhi, S. Milne, R. Nilus, M. Pfeifer, O. L. Phillips, L. Qie, N. Renneboog, G. Reynolds, T. Riutta, M. J. Struebig, M. Svátek, E. C. Turner, & D. A. Coomes, Estimating aboveground carbon density and its uncertainty in Borneo's structurally complex tropical forests using airborne laser scanning. *Biogeosciences*, **15** (2018) 3811–3830. https://doi.org/10.5194/BG-15-3811-2018.

146. G. P. Asner & J. Mascaro, Mapping tropical forest carbon: Calibrating plot estimates to a simple LiDAR metric. *Remote Sensing of Environment*, **140** (2014) 614–624. https://doi.org/10.1016/J.RSE.2013.09.023.

147. M. Dalponte & D. A. Coomes, Tree-centric mapping of forest carbon density from airborne laser scanning and hyperspectral data. *Methods in Ecology and Evolution*, **7** (2016) 1236–1245. https://doi.org/10.1111/2041-210X.12575.

148. R. M. Ewers, R. K. Didham, L. Fahrig, G. Ferraz, A. Hector, R. D. Holt, V. Kapos, G. Reynolds, W. Sinun, J. L. Snaddon, & E. C. Turner, A large-scale forest fragmentation experiment: the Stability of Altered Forest Ecosystems Project. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **366** (2011) 3292–3302. https://doi.org/10.1098/rstb.2011.0049.

149. A. Khosravipour, A. K. Skidmore, M. Isenburg, T. Wang, & Y. A. Hussin, Generating pit-free canopy height models from airborne LiDAR. *Photogrammetric Engineering and Remote Sensing*, **80** (2014) 863–872. https://doi.org/10.14358/PERS.80.9.863.

150. G. P. Asner, D. E. Knapp, J. Boardman, R. O. Green, T. Kennedy-Bowdoin, M. Eastwood, R. E. Martin, C. Anderson, & C. B. Field, Carnegie Airborne Observatory-2: Increasing science data dimensionality via high-fidelity multi-sensor fusion. *Remote Sensing of Environment*, **124** (2012) 454–465. https://doi.org/10.1016/J.RSE.2012.06.012.

151. G. P. Asner, P. G. Brodrick, C. Philipson, N. R. Vaughn, R. E. Martin, D. E. Knapp, J. Heckler, L. J. Evans, T. Jucker, B. Goossens, D. J. Stark, G. Reynolds, R. Ong, N. Renneboog, F. Kugan, & D. A. Coomes, Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo. *Biological Conservation*, **217** (2018) 289–310. https://doi.org/10.1016/J.BIOCON.2017.10.020.

152. QGIS Development Team, QGIS Geographic Information System. *Open Source Geospatial Foundation Project*, (2016).

153. R Core Team, R: A Language and Environment for Statistical Computing. (2020).

154. J.-R. Roussel, D. Auty, N. C. Coops, P. Tompalski, T. R. H. Goodbody, A. S. Meador, J.-F. Bourdon, F. de Boissieu, & A. Achim, lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sensing of Environment*, **251** (2020). https://doi.org/10.1016/j.rse.2020.112061.

155. P. Metcalfe, K. Beven, & J. Freer, Dynatopmodel: implementation of the dynamic topmodel hydrological model. (2018).

156. B. Blonder, S. Both, D. A. Coomes, D. Elias, T. Jucker, J. Kvasnica, N. Majalap, Y. S. Malhi, D. Milodowski, T. Riutta, & M. Svátek, Extreme and Highly Heterogeneous Microclimates in Selectively Logged Tropical Forests. *Frontiers in Forests and Global Change*, **1** (2018) 5. https://doi.org/10.3389/FFGC.2018.00005.

157. E. Pebesma, Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, **10** (2018). https://doi.org/10.32614/RJ-2018-009.

158. T. Jucker, J. Caspersen, J. Chave, C. Antin, N. Barbier, F. Bongers, M. Dalponte, K. Y. van Ewijk, D. I. Forrester, M. Haeni, S. I. Higgins, R. J. Holdaway, Y. Iida, C. Lorimer, P. L. Marshall, S. Momo, G. R. Moncrieff, P. Ploton, L. Poorter, K. A. Rahman, M. Schlund, B. Sonké, F. J. Sterck, A. T. Trugman, V. A. Usoltsev, M. C. Vanderwel, P. Waldner, B. M. M. Wedeux, C. Wirth, H. Wöll, M. Woods, W. Xiang, N. E. Zimmermann, & D. A. Coomes, Allometric equations for integrating remote sensing imagery into forest monitoring programmes. *Global Change Biology*, **23** (2017) 177–190. https://doi.org/10.1111/GCB.13388.

159. J. Fox & S. Weisberg, *An {R} Companion to Applied Regression* (Sage publications, 2019).

160. J. P. Lander, coefplot: Plots Coefficients from Fitted Models. R package version 1.2.7. (2021).

161. S. Cha-um, T. Takabe, & C. Kirdmanee, Osmotic potential, photosynthetic abilities and growth characters of oil palm (*Elaeis guineensis* Jacq.) seedlings in responses to polyethylene glycol-induced water deficit. *African Journal of Biotechnology*, **9** (2013) 6509–6516. https://doi.org/10.4314/ajb.v9i39.

162. S. Cha-Um, T. Takabe, & C. Kirdmanee, Physio-Biochemical Responses of Oil Palm (Elaeis guineensis Jacq.) Seedlings to Mannitol-and Polyethylene Glycol-Induced Iso-Osmotic Stresses. *Plant Prod. Sci*, **15** (2012) 65–72.

163. Y. D. Rivera Mendez, A. L. Moreno Chacon, & H. Romero, Biochemical and physiological characterization of oil palm interspecific hybrids (elaeis oleifera x elaeis guineensis) grown in hydroponics. *Acta Biologica Colombiana*, **18** (2013) 465–472.

164. A. P. Cracknell, K. D. Kanniah, K. P. Tan, & L. Wang, Evaluation of MODIS gross primary productivity and land cover products for the humid tropics using oil palm trees in Peninsular Malaysia and Google Earth imagery. *International journal of remote sensing*, **34** (2013) 7400–7423. https://doi.org/10.1080/01431161.2013.820367.

165. L. Feintrenie, S. Schwarze, & P. Levang, Are Local People Conservationists? Analysis of Transition Dynamics from Agroforests to Monoculture Plantations in Indonesia. *Ecology and Society*, **15** (2010).

166. S. Salaheen & D. Biswas, Organic Farming Practices: Integrated Culture Versus Monoculture. *Safety and Practice for Organic Food* (Academic Press, 2019), pp. 23–32. https://doi.org/10.1016/B978-0-12-812060-6.00002-7.

167. L. S. Woittiez, S. R. I. Turhina, D. Deccy, M. Slingerland, M. van Noordwijk, & K. E. Giller, Fertiliser application practices and nutrient deficiencies in smallholder oil palm plantations in Indonesia. *Experimental Agriculture*, **55** (2019) 543–559. https://doi.org/10.1017/S0014479718000182.

168. S. Manjit, K. Martiadi, E. F. Rambe, ZULKASTA. Sinuraya, ABDUL. Aziz, A. Hasyim, & M. Sharma, Withdrawal of fertiliser and its impact on the nutrient status, growth and production of previously fertilised oil palm. *Planter*, **90** (2014) 399–417.

169. S. A. Ruslan, F. M. Muharam, D. Omar, Z. D. Zulkafli, & M. P. Zambri, Development of geospatial model for predicting Metisa plana's prevalence in Malaysian oil palm plantation. *IOP Conference Series: Earth and Environmental Science*, **230** (2019) 012110. https://doi.org/10.1088/1755-1315/230/1/012110.

170. P. Sundararaju & K. Ratnakaran, Factors influencing the prevalence of the root-lesion nematode, Pratylenchus coffeae on oil palm (Elaeis guineensis Jacq.). *Indian Journal of Nematology*, **32** (2002) 16–19.

171. C. F. Dormann, J. M. McPherson, M. B. Araú jo, R. Bivand, J. Bolliger, G. Carl, R. G. Davies, A. Hirzel, W. Jetz, W. Daniel Kissling, I. Kü hn, R. Ohlemü ller, P. R. Peres-Neto, B. rn Reineking, B. Schrö der, F. M. Schurr, R. C. Wilson F Dormann, & Á. M. B Araújo, Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography*, **30** (2007) 609–628. https://doi.org/10.1111/j.2007.0906-7590.05171.x.

172. M. Aubry-Kientz, R. Dutrieux, A. Ferraz, S. Saatchi, H. Hamraz, J. Williams, D. Coomes, A. Piboule, & G. Vincent, A Comparative Assessment of the Performance of Individual Tree Crowns Delineation Algorithms from ALS Data in Tropical Forests. *Remote Sensing*, **11** (2019) 1086. https://doi.org/10.3390/RS11091086.

173. L. Eysn, M. Hollaus, E. Lindberg, F. Berger, J.-M. Monnet, M. Dalponte, M. Kobal, M. Pellegrini, E. Lingua, D. Mongus, & N. Pfeifer, A Benchmark of Lidar-Based Single Tree Detection Methods Using Heterogeneous Forest Data from the Alpine Space. *Forests*, **6** (2015) 1721–1747. https://doi.org/10.3390/F6051721.

174. A. Ferraz, S. Saatchi, C. Mallet, & V. Meyer, Lidar detection of individual tree size in tropical forests. *Remote Sensing of Environment*, **183** (2016) 318–333. https://doi.org/10.1016/J.RSE.2016.05.028.

175. A. Ferraz, F. Bretar, S. Jacquemoud, G. Gonçalves, L. Pereira, M. Tomé, & P. Soares, 3-D mapping of a multi-layered Mediterranean forest using ALS data. *Remote Sensing of Environment*, **121** (2012) 210–223. https://doi.org/10.1016/J.RSE.2012.01.020.

176. J. Williams, C.-B. Schönlieb, T. Swinfield, J. Lee, X. Cai, L. Qie, & D. A. Coomes, Three-dimensional Segmentation of Trees Through a Flexible Multi-Class Graph Cut Algorithm (MCGC). *IEEE Transactions on Geoscience and Remote Sensing*, **1** (2019) 1–23.

177. H. Hamraz, M. A. Contreras, & J. Zhang, Vertical stratification of forest canopy for segmentation of understory trees within small-footprint airborne LiDAR

point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, **130** (2017) 385–392. https://doi.org/10.1016/J.ISPRSJPRS.2017.07.001.

178. H. Hamraz, M. A. Contreras, & J. Zhang, A robust approach for tree segmentation in deciduous forests using small-footprint airborne LiDAR data. *International Journal of Applied Earth Observation and Geoinformation*, **52** (2016) 532–541. https://doi.org/10.1016/J.JAG.2016.07.006.

179. B. St-Onge, F.-A. Audet, & J. Bégin, Characterizing the Height Structure and Composition of a Boreal Forest Using an Individual Tree Crown Approach Applied to Photogrammetric Point Clouds. *Forests*, **6** (2015) 3899–3922. https://doi.org/10.3390/F6113899.

180. L. I. Duncanson, B. D. Cook, G. C. Hurtt, & R. O. Dubayah, An efficient, multi-layered crown delineation algorithm for mapping individual tree structure across multiple ecosystems. *Remote Sensing of Environment*, **154** (2014) 378–386. https://doi.org/10.1016/J.RSE.2013.07.044.

181. C. Paris, D. Valduga, & L. Bruzzone, A Hierarchical Approach to Three-Dimensional Segmentation of LiDAR Data at Single-Tree Level in a Multilayered Forest. *IEEE Transactions on Geoscience and Remote Sensing*, **54** (2016) 4190–4203. https://doi.org/10.1109/TGRS.2016.2538203.

182. T. Gobakken & E. Næsset, Assessing effects of laser point density, ground sampling intensity, and field sample plot size on biophysical stand properties derived from airborne laser scanner data. *https://doi.org/10.1139/X07-219*, **38** (2008) 1095–1109. https://doi.org/10.1139/X07-219.

183. P. Ploton, F. Mortier, M. Réjou-Méchain, N. Barbier, N. Picard, V. Rossi, C. Dormann, G. Cornu, G. Viennois, N. Bayol, A. Lyapustin, S. Gourlet-Fleury, & R. Pélissier, Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications*, **11** (2020) 1–11. https://doi.org/10.1038/s41467-020-18321-y.

184. C. Burton, S. Rifai, & Y. Malhi, Inter-comparison and assessment of gridded climate products over tropical forests during the 2015/2016 El Niño. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **373** (2018). https://doi.org/10.1098/RSTB.2017.0406.

185. J.-P. Caliman & A. Southworth, Effect of drought and haze on the performance of oil palm. *IOPRI international oil palm conference : Commodity of the past, today, and the future.*, (1998).

186. P. S. Thenkabail, N. Stucky, B. W. Griscom, M. S. Ashton, J. Diels, B. van der Meer, E. Enclona, & B. van der Meer, Biomass estimations and carbon stock calculations in the oil palm plantations of African derived savannas using IKONOS data. *International Journal of Remote Sensing*, **25** (2004) 5447–5472. https://doi.org/10.1080/01431160412331291279.

187. A. R. Martin & S. C. Thomas, A reassessment of carbon content in tropical trees. *PloS one*, **6** (2011). https://doi.org/10.1371/JOURNAL.PONE.0023533.

188. V. K. Boken, A. P. Cracknell, & R. L. , Heathcote, *Monitoring and Predicting Agricultural Drought: A Global Study* (Oxford University Press, 2005).