Dynamic efficiency and resource productivity of oil palm smallholders in Jambi, Indonesia - a non-parametric analysis

Master Thesis

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Abstract

The master thesis assesses total resource productivity change and resource productivity change in terms of the environmental performance of Indonesian oil palm smallholders. The study relies on production data and a plot level biodiversity account of around 30 farmers, collected in three waves from 2012 to 2018. First, Data Envelopment Analysis (DEA) is used to calculate Malmquist Productivity Indices (MPI) based on usage of typical production inputs. Second, by means of a non-parametric Directional Distance Function (DDF) approach, resource productivity measures are obtained. Besides productive inputs, biodiversity loss is included as an undesirable output to additionally describe dynamic resource productivity by environmental performance change. The results indicate that (i) technical efficiency improved slightly in response to better farming practices, (ii) resource productivity decreased reflecting an acceleration of biodiversity reduction in proportion to the technical efficiency change increase. Mixed results were found for technical change: the adoption of higher yielding variaties were counteracted by the strong El Niño effects that can be found in all respective measures for the year of 2015. It is shown that the trade-off between improving conventionally measured efficiency and productivity measures including biodiversity increases over time.

Contents

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All the best,

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List of Abbreviations

BPS Badan Pusat Statistik - Indonesian National Statistics Office. 9

CPO Crude Palm Oil. 9

CRS Constant returns to scale. 31

DDF Directional Distance Function. 2, 28

DEA Data Envelopment Analysis. 17, 18

ENS Effective Number of Species. 25, 36

FFB Fresh Fruit Bunch. 4

GHG Greenhouse gas. 5

MPI Malmquist Productivity Index. 2, 28, 49

RSPO Roundtable on Sustainable Palm Oil. 14

SDG Sustainable development goals. 5

SFA Stochastic Frontier Analysis. 31

TFP Total Factor Productivity. 2, 18

TRP Total Resource Productivity. 2, 18, 21

VRS Variable returns to scale. 31

WTP Willingness to pay. 6

1 Introduction

On April 8th, 2020, during the Corona crisis, the German government passed a law on deforestation-free supply chains (Bundeskabinett, 2020). The law counteracts deforestation caused by expanding cultivation area for inter alia soy beans, cocoa and palm oil. While everybody agrees upon the need for rain forest protection, a common ground with concrete measures to tackle deforestation, is difficult to achieve.

The relevance of palm oil in the media is also reflected by a vast amount of scientific literature examining the environmental effects of palm oil production. Many studies have investigated the negative effects of land expansion on biodiversity and $CO2$ emissions.

While some political actors in western countries propose import bans for palm oil as a rash solution, it is questionable if this regulatory measure is effective and not causing negative side-effects. After all, the global demand for palm oil has risen sharply in recent years and will continue to rise in the coming years. Thus, it is very important to harvest more palm oil from the same area to save rain forests.

Without yield improvement, however, it will not be possible to increase plant productivity without clearing more rain forests. Accordingly, it is important to analyze how efficient smallholder palm oil cultivation currently is. To contribute to this, this thesis analyzes dynamic efficiency and resource productivity of smallholder palm oil cultivation in the province of Jambi, Indonesia.

It can be assumed for smallholder farmers in Jambi, that the production of palm oil is not perfectly efficient and that there is room for improvement, especially regarding the appropriate use of fertilizers, herbicides and pesticides. Yield improvements linked to productivity increase might cause a substitutive effect by hampering further deforestation.

For this study, survey data analyzing conventional agricultural production and input variables were collected and combined with species richness data. The data was gathered in three rounds in 2012, 2015 and 2018 in Jambi province, Indonesia. The main variable reflecting desirable output is the production of crude palm oil per farm. Plot size, man hours and agrochemicals are used as input variables throughout the analysis. Subsequently, a measure of undesirable output representing the reduction of the Effective Number of Species is included in the analysis.

Due to the scarcity of data it is necessary to use non-parametric methods for the analysis. Efficiency is measured via the Malmquist Productivity Index' (MPI) measurement for Total Factor Productivity (TFP) change and the directional distance function's (DDF) approach to obtain a measurement for environmental performance and therefore Total Resource Productivity (TRP) change.

With my paper I want to contribute to the existing research about palm oil and its efficiency with respect to classical and environmental production factors. If there is a way to reduce deforestation by using the available resources and inputs more efficiently, it is worth analyzing where these inefficiencies are originated.

The guiding research question of this study is: *Did the smallholder palm oil production in Jambi province, Indonesia become more efficient over time in terms of conventional efficiency and/or dynamic resource productivity?*

My hypothesis is that both conventional efficiency and resource productivity have increased over time and that the results of the analysis performed in this thesis can prove this.

2 Literature review

Prevailing media presence of palm oil and related environmental debates are mirrored in the relatively high number of scientific publications in the field of palm oil production. Leading scholars evaluate palm oil production from agricultural, biological, ecological, economic, anthropological or ethnological perspectives. For instance, many studies focusing environmental outcomes and related CO_2 emissions of transformation of lowland rain forest areas into palm oil plantations (Reijnders & Huijbregts, 2008). Although a vast amount of literature related to the topic, few studies have addressed dynamic efficiency or dynamic resource productivity in smallholder palm oil production. This master thesis addresses the outlined research gap. In this chapter the existing scientific literature concerning palm oil production is reviewed.

This chapter reviews the existing literature regarding palm oil production and is divided in four subchapters: The first part describes the physiology and different uses of the oil palm fruit, the second subchapter deals with the demand of vegetable oils. The third subchapter addresses the evolution of palm oil production over the last years, while the fourth subchapter focuses on the trade-off between palm oil and environment.

2.1 Oil palm tree

2.1.1 Oil palm tree: Physiology

To understand the high demand for and omnipresence of palm oil in the market, it is important to cast a glance at the physiology of the plant and its crop. The palm oil tree, whose scientific name is *elaeis guineensis*, can grow 20-30 meters high. They are pollinated by insects and not self-fertile. It grows best on moist and wet soils, which is why most of the trees are planted in the lowland tropics. Additionally, it can grow on very acid soils with a low pH value. However, it cannot grow in the shade. Originally, the palm oil tree stems from Western Africa, yet today most of them are found outside of Africa due to its intensive use for palm oil production. Therefore, most of the world's oil palm trees stand today in South-East Asia and partially in South America. The breeding population *deli* *dura* is mainly used for large scale palm oil production in Malaysia and Indonesia (Hayati, Wickneswari, Maizura, & Rajanaidu, 2004).

Elaeis guineensis is the most productive palm oil tree and it is able to produce around 8 - 28 bunches, each of 23 to 27kg per year, although the numbers depend strongly on the tree's age (Morcillo et al., 2013). The yields vary from 10 - 35 tonnes per hectare of fresh fruit bunch (FFB) (Ong, Mahlia, Masjuki, & Norhasyima, 2011). An average bunch contains about 65% of fruit and 22% of oil if the composition is ideal. The kernel makes up around 21% of the total fruit weight (Poku, n.d.). The main product of the production is the palm oil which can be extracted both from the *mesocarp* - the flesh of the fruit - and the kernel.

It is usually necessary to harvest the palm once every 7-10 days, as the bunches continue to grow constantly over the year. As palm oil is a tropical crop, the yields are suspect to seasonal changes: the weight of the bunch can be three times higher in wet compared to dry season (Mhanhmad, Leewanich, Punsuvon, Chanprame, & Srinives, 2011). This is due to the fact that the tree needs water to produce the crops. The composition of the fruit is also suffering seasonal changes: while the fruit is smaller in dry season, it contains higher mesocarp and kernel oil shares. The composition of fatty acids which is relevant for further processing changes as well.

Mhanhmad et al. investigated that higher accumulated rainfall and temperature lead to a higher average fruit weight and oil yield (Mhanhmad et al., 2011). The opposite is observed for the fruit share on the bunches: the higher the accumulated temperature and rainfall, the lower the fruit share.

2.1.2 Oil palm tree: Main uses

As the melting point is at around 35°C, palm oil can be used both in solid and fluid physical state. 68% of the globally produced palm oil is used for food production, 27% for industrial purposes and 5% for biofuels. The food production use mostly consists of processed food, beverages and feedstuffs for agriculture, whereas the industrial use is mostly applied in cosmetics and detergents (Noleppa, 2016).

As discussed in the beforehand section, palm oil is a very productive crop. Its yield is higher than the ones of other sources of vegetable oils, such as rapeseed, coconut or sunflower. The yield of oilseeds like soy bean is also lower. A study by Ong et al. analyzed the yields of different oil crops used for the production of biodiesel. In comparison to other oil crops, the production oil yield of palm oil is of nearly 5,950 litres per hectare, around 3,000 litres per hectare for coconut and around 1,200 litres for rapeseed (Ong et al., 2011).

The paper argues that the greenhouse gas (GHG) emissions could be reduced by palm oil based biodiesel by 62%. Thus, replacing palm oil with other vegetable oils with coconut oil or rapeseed would require a bigger cultivation area. Regional differences matter: as oil palms cannot be cultivated in temperate climate zones - in contrast to e.g. rapeseed or sunflower - all types of vegetable oil sources are relevant for meeting the future global demand. Still, a replacement of palm oil by other vegetable oil sources might exacerbate environmental problems.

2.2 Demand side

2.2.1 Palm oil demand: future prospects

The demand for palm oil is linked to the global demand for vegetable oils. Global production of vegetable oils ascended from around 160 million tons in 2012 by more than 25% to 200.2 million tons in 2019 (Colombo, Chorfi Berton, Diaz, & Ferrari, 2018). Palm oil increased its share with respect to other oil crops slightly from 34.5% in 2013 to 35.8% in 2019. The four most important oil crops in terms of vegetable oils are are palm oil, soy beans, sunflower and rapeseed. Together they produce more than 85% of the world's vegetable oils.

Vegetable oils are crucial for fulfilling the sustainable development goals (SDG) 2 (United Nations, 2020) by assuring the global food security throughout the next decades. SDG 3 also depicts the importance of fats for good health and well-being, however, the UN works for better diets by trying to replace trans-fats by less harmful fat acids in the diets. Palm oil plays an important role in that regard. As we deduced in the previous sections, it is the most productive vegetable oil in terms of surface area productivity.

In 2018, vegetable oil prices experienced a ten-year low, partially due to a slowdown in global trade. In 2020, due to the COVID-19 pandemic, demand for vegetable oils experienced a slowdown. Despite these unfavorable factors and the limited land expansion capacity for soy bean and palm oil, it is estimated that global vegetable oil production will further expand to 28 million tons by 2028 (OECD & FAO, 2020). However, the estimated growth rate for the period 2020-2029 is of 1.3% per year and therefore lower than the growth rate of the last decade. Consequently, the demand for palm oil will continue to grow beyond the next 10 years.

One of the drivers of this increased demand is Indonesia itself. Being the world's major producer of palm oil, Indonesia is pursuing a transition towards one of the countries in the world with the highest domestic uses of palm oil. A national policy to promote biofuels plays an important role in this context. By 2025, it is estimated that 51 million tonnes of Indonesian palm oil production will be needed to supply the country's worldwide and domestic demand (Khatiwada, Palmén, & Silveira, 2018).

2.2.2 Palm oil demand: influencing factors

The increasing demand for more environmentally sustainable products is putting pressure on many agricultural products whose land use is linked to environmental damage. This affects in particular palm oil or oilseeds like soy beans. Both are related to the destruction of tropical rainforests. The question is, how exactly the environmental topic influences the demand for palm oil and soy bean products. A lab experiment from Disdier et al. reveals that the willingness to pay (WTP) for different product sets which include palm oil decreases after the participants received information about health and environmental impacts of palm oil production (Disdier, Marette, & Millet, 2013). Simultaneously, the WTP for non-palm-oil products did not decrease with similar packages concerning negative health and environment information about the products.

Yet, when the participants received information about the land use of alternative vegetable oils, the WTP for palm oil products increased slightly compared to the alternative products. Thus, there is no clear demand shift or decline for palm oil products if the consumers are informed about the environmental consequences of all products.

As palm oil is often framed in the media as an ecologically incompatible product, consumers tend to mistrust Since palm oil is framed in the media as environmentally incompatible, the product has a bad reputation. However, it is usually ignored that other products also require land for cultivation and their cultivation is by no means CO_2 neutral.

There is a clear consumer preference for environmentally friendly products. However, there are only few processed oil crops with very low CO_2 emissions or high environmental compatibility. Additionally, due to its high yields, palm oil has a comparative advantage over other oil crops and thus the potential to save agricultural land. The question is, how is it possible to transform palm oil into more environmentally compatibility and how to communicate this to consumers in a credible way?

2.3 Supply side

2.3.1 Palm oil supply: evolution of Indonesian palm oil production

The demand for vegetable oils is projected to increase in the next years. The growth projection for palm oil production in Indonesia is of 1.8% per year for 2019 to 2028 which is considerably low. In contrast, production grew at a rate of 6.9% per year from 2009-2018 (OECD & FAO, 2019). In some regions, the growth potential is limited because the years of constant expansion lead to a lack of potential land cultivation area. Riau province, for example, already has 25.4% of its whole area covered with palm oil plantations (BPS Statistics Indonesia, 2019).

There is not much area left which would still be profitable to be transformed into oil palm plantations. In other regions, the landscape has not the best characteristic for palm oil plantations, e.g. in Sulawesi which is rather hilly and more attractive for other crops, such as cocoa or coffee. Despite the limited growth potential in terms of area, palm oil production grew substantially during the last two decades. In this subsection, the evolution of Indonesian palm oil production throughout the last years are described in detail.

Indonesia and Malaysia are the two biggest palm oil producing countries: they produce over 80% of global palm oil which represents around 30% of the volume of all vegetable oils. As the data set which is used for this thesis' analysis

Figure 1: Palm oil production volume in Indonesia over time (BPS Statistics Indonesia, 2019)

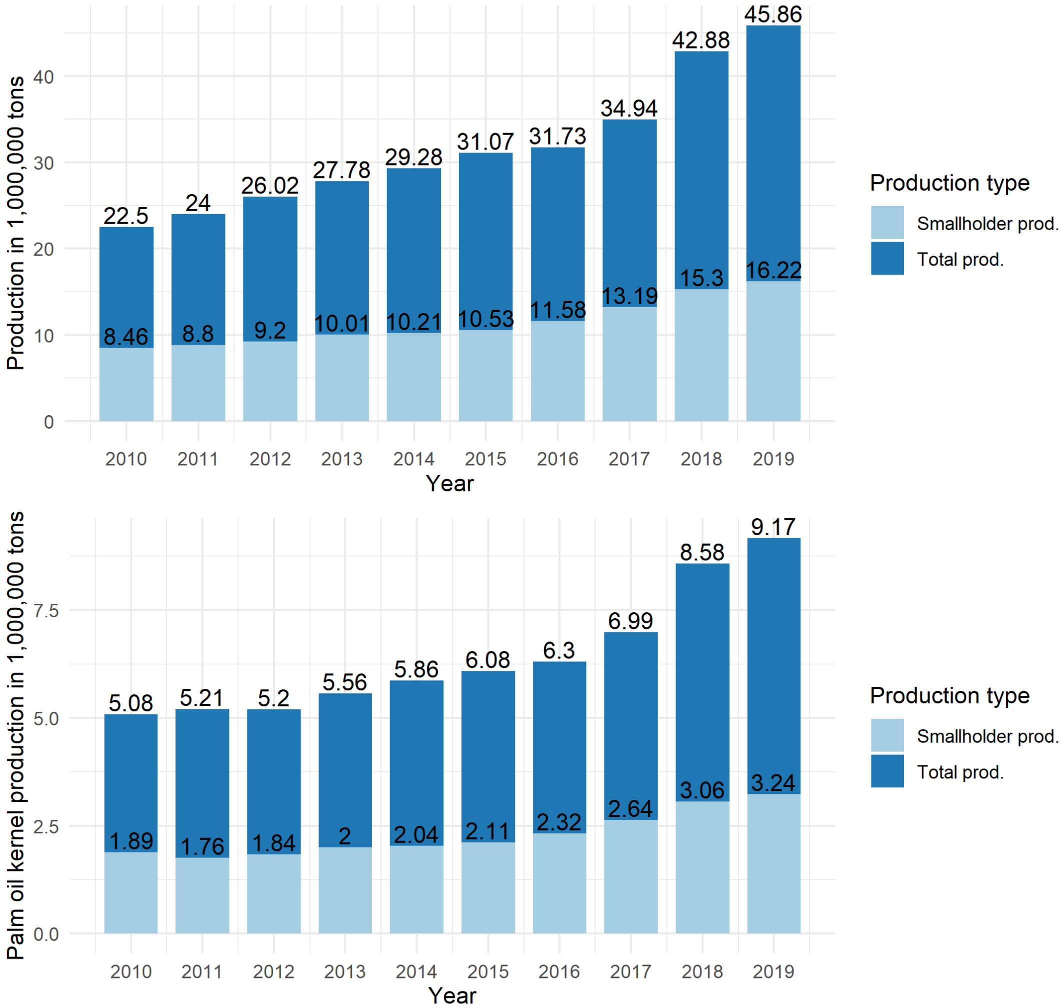
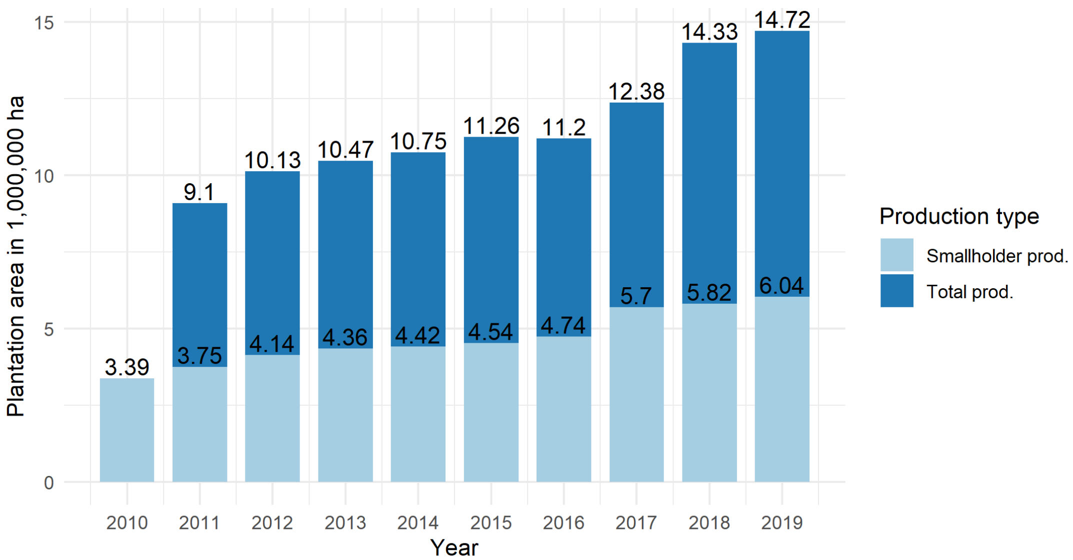


Figure 2: Palm oil plantation area in Indonesia over time (BPS Statistics Indonesia, 2019)



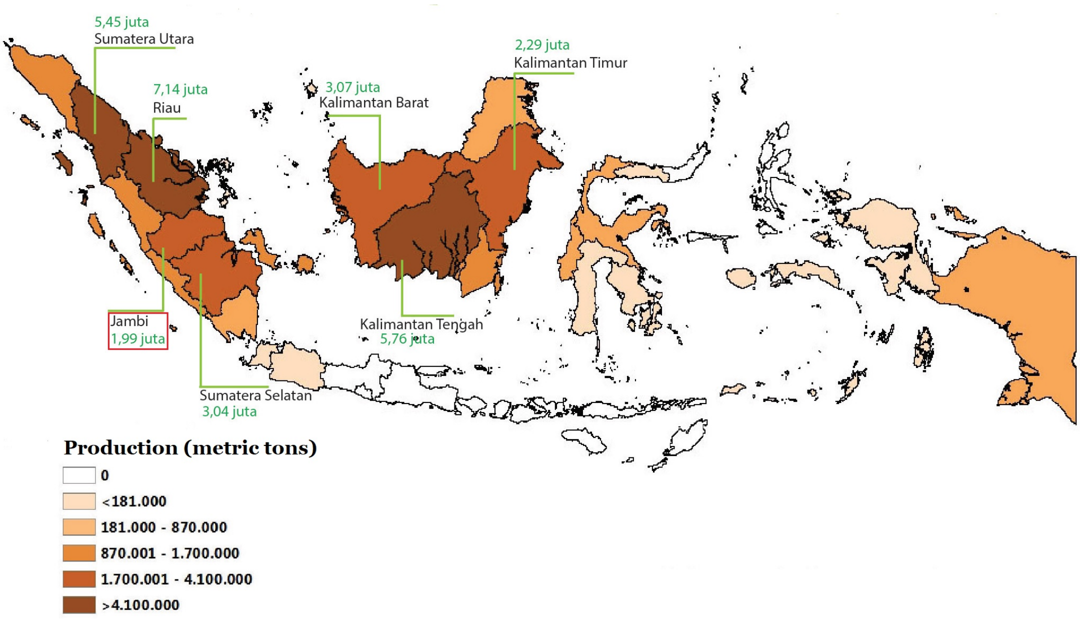
comes from Indonesia, it is worth examining the evolution of palm oil production on a national scale over the last years: Figure 1 depicts crude palm oil (CPO) production in the upper graph and palm oil kernel production in the lower graph. As illustrated in the upper graph, CPO production more than doubled from 22.5 million tons in 2010 to 45.9 million tons in 2019. Out of this number, around 35% are accounted to smallholder production. This share remained relatively constant over time, as the smallholder share in 2010 was at 37%. Thus, both large private enterprises and smallholders increased their production at a very high growth rate during the last 10 years.

A similar picture is drawn when looking at the lower graph in figure 1. It depicts the evolution of palm oil kernel production in Indonesia during the last 10 years. The most striking difference to the other figures is the smaller proportion of smallholder production, which was 26.3% of total production of 9.17 million metric tons in 2019. This is one of the reasons why smallholder production is not as productive as large-scale production: Many palm oil kernels are not processed as effectively by the smaller mills as the kernels of large-scale production. As we have seen before, the kernel oil is especially relevant for industrial uses. Improving practices in kernel production has the potential to further improve smallholder incomes in the future.

Another production type which is included in non-smallholder production in these figures is the production of state-owned companies. In 2013, they produced 9% of Indonesia's palm oil and represented 7% of the Indonesian palm oil land use (Daemeter Consulting, 2015). They used to play an important role in the process of developing the economic activity in former remote areas, but as both private companies and smallholders are now dividing the market among themselves, state-owned companies will continue to play minor roles in comparison to the quickly growing private sector.

The available data concerning palm oil production and cultivation area varies according to the institution that collects and provides it. The *FAO* has other production numbers than *USDA* or *Badan Pusat Statistik Indonesia (BPS)*. I finally decided in favor of the Indonesian national bureau of statistics (BPS) data because it provides numbers concerning both large estate and smallholder palm

Figure 3: Palm Oil Fruit Bunch Production per Indonesian Province, 2018. *Source: BPS Indonesia, 2018*



Note: 1 Juta = 1 million

oil production.

Figure 2 shows the total oil palm plantation area and its smallholder share over the last 10 years. The current total plantation area increased is 14.2 million hectares which equals more than one third of the total area of Germany. Of this area, 6.04 million hectares - or 19.4 % - are owned by smallholder farmers (BPS Statistics Indonesia, 2019). As in the previous figures, the smallholder share remained constant over the years, while the total plantation area extended significantly. There are two possible explanations for that reduction:

1. The illegal expansion of small-scale cultivation areas was not reported and is therefore not included in the official statistics of the Indonesian statistics office BPS.

2. Since several small-scale farmers increase their plot size over time, they are no longer counted as such after surpassing a certain threshold. This would also explain the strong increase of large-scale cultivation area in the respective years from 2016 to 2018.

Figure 3 shows the distribution of palm oil fruit bunch production per province in 2018, the year of the last data collection for this study. It can be observed that most of the production takes place on the islands of Sumatra and Borneo. The three provinces with the highest palm oil production are North Sumatra, Riau and Central Kalimantan. Together, they produced 50.5% of Indonesia's CPO in 2018.

Regarding Jambi province, its 721,403 hectares represented 13.4% of the entire Indonesian palm oil cultivation area in 2013. Of all provinces, it ranks 7 out of 23 Indonesian palm oil producing provinces. Compared to the overall Indonesian smallholder share of 34.5%, Jampi province has one of the highest smallholder shares in terms of palm oil production area with 62%. This emphasizes that smallholder palm oil production is not only a fringe phenomenon but a substantial part of the province's economic activity. This fact makes the results of this study even more relevant. The mean plot size of smallholders is 2.6 hectares in Jambi province, slightly above average. The average plot size of our sample figures of our sample are similar, as shown in chapter 4.

2.3.2 Palm oil supply: increasing production and farmers' income

Many scholars agree on the trade-off between increasing farmers' income through oil palm cultivation and the negative environmental effects on biodiversity and CO_2 emissions. In this subsection, the income side of this trade-off is examined.

Today, 6 million people are directly employed in the palm oil industry in Indonesia. This number has grown continuously during the last years. If the sector continues to grow as it has been growing until now, the sector could employ more than 20 million people in 2045 (Purnomo et al., 2020). The increased attraction of the sector for smallholders and day labourers indicates an economic incentive expressed by a considerably high expected income.

Kubitza et al. (2018) elaborate that in Jambi province, palm oil cultivation practice has significant positive effects on farmers' livelihoods. This is mirrored in total consumption expenditures being significantly higher in palm oil cultivating households than in non-cultivating households. Cultivating households were also able to save labour time through their economic activity related to palm oil and reallocate this time to non-farm economic activities, thereby increasing their income further. Meanwhile, no significant spillover effects by cultivation on neighbouring, non-cultivating households were found - neither positive nor negative ones (Kubitza, Krishna, Alamsyah, & Qaim, 2018).

Santika et al. (2019) find mixed results concerning the impact of expanding palm oil plantation practices on objective and material well-being in Kalimantan from 2000 to 2014. More accurately, those villages who already relied on market-oriented economic activities are more likely to profit from the introduction of palm oil plantations. The opposite finding was made for those villages with a high natural forest cover and which were mainly relying on subsistence farming. In addition, socioeconomic inequality increased for many villages, as well as environmental issues, such as a deteriorated natural hazard prevention (Santika et al., 2019).

2.3.3 Palm oil supply: *El Niño*

With regard to figure 1, it is evident that the production growth rate decelerated between 2015 and 2016. This is attributed to the fluctuation in temperature between the Pacific ocean and the surrounding atmosphere. This weather phenomenon is called *El Niño*. It causes a hotter, dryer weather in several areas in South-East-Asia. It is estimated that for the 2015/16 *El Niño* wave in Malaysia, FFB yields dropped by 10-16% and thus, CPO production by 8-14% (Azlan et al., 2016).

The World Food Programme states that the drought caused by the phenomenon substantially increased food insecurity in affected areas. Those households who depend on agricultural wage labor suffered a reduction of at least 30% in production and therefore in income (Webb & Wadhwa, 2016). The data is mostly collected in Eastern Indonesia, namely in Sulawesi, Jawa and Nusa Tunggara, however, Sumatra and Kalimantan are also strongly affected by *El Niño*. It is reasonable to suggest that strong decreases in palm oil yield caused by *El Niño* affect the efficient use of input factors in the farmers' agricultural practices. Therefore, *El Niño* can be considered as an external shock for this study, which mainly affects the 2015 wave data.

2.4 Palm oil and environment

2.4.1 Palm oil and environment: Description of the problem

Between 2004 and 2013, vegetable oil production increased globally by 4.5% on average per year(Oettli, Behera, & Yamagata, 2018). So far, most of the rise in production is obtained by expanding the cultivation area. Therefore, palm oil is one of the major triggers of rain forest destruction in South-East Asia (Imai, Furukawa, Tsujino, Kitamura, & Yumoto, 2018). Today, rain forest destruction, biodiversity loss and increased CO_2 emissions are associated with expanding palm oil cultivation.

Many people profited from the increase in palm oil production by higher incomes. However, the expansion of palm oil implied a massive land use change and the clearing of large areas that beforehand were mainly covered by areas of high tree density - if not by intact rain forests. This circumstance anticipates one of the main results of the existing literature concerning palm oil: there is a clear trade-off between economic prosperity - implying an increased well-being of many farmers and companies - and the preservation of the environment.

Sayer et al. (Sayer, Ghazoul, Nelson, & Klintuni Boedhihartono, 2012) describe palm oil as a highly profitable crop which has stimulated economic growth in several countries and therefore contributed to the alleviation of poverty. Additionally, palm oil plantations in a landscape mosaic can contribute to biodiversity conservation. And that these schemes are mostly found in smallholder farms where plantations are less extensive.

Smallholder systems can retain more diverse landscape matrices which have the potential to retain more of the original biodiversity. These considerably diverse production landscapes also might represent a less hostile environment for animals which permit them to move. In fact, the

The central statement of Sayer et al. (2012) outlines four truths about palm oil that, according to the authers, should be recognized prior to any meaningful discussion about the topic:

1. demand for oil palm is increasing and continues to do so due to a growing and more affluent global population

2. in humid lowland tropics, palm oil is one of the most profitable crops
3. more $C0_2$ is stored by oil palm plantations than by any other agricultural alternative in humid lowland tropics
4. in comparison to rain forests, native biodiversity in palm oil plantations is substantially lower.

In Indonesia, most of the plantations are administered by large corporations. However, the share of independent smallholder farmers is around 40% and its share continues to increase over time (Feintrenie, Chong, & Levang, 2010). This is partly attributable to stronger limitation of land acquisitions by big corporations and to the increasing potential of conversion of smallholders' farmland into palm oil plantations. Illegal slash-and-burn practices (S&B) also play an important role in this context. This is, among other things, due to the fact that decentralized smallholder conversion practices are more difficult to monitor by the state than those of big corporations.

Ketterings et al. (1999) analyzed the structure and motives of S&B practices in Bungo department within Jambi province, Indonesia. They have pointed out that better accessibility to land is the main driver of illegal S&B, since 51% of the farmers mention it as a motive. Additionally, 23% of the farmers report that the ash which functions as a fertilizer is the main motive of S&B, 18% of them indicate that the fire would improve the soil structure. Further drivers are the removal of weeds and trees because they compete with the main crop and the fact that S&B reduces the occurrence of diseases, pests and fungus (Ketterings, Tri Wibowo, van Noordwijk, & Penot, 1999).

2.4.2 Palm oil and environment: Certification

While the smallholders try to compete with large corporations in the market, the social and environmental performance of their products is far from being optimal. In this context, European and North American importers increase demand for certified palm oil, e.g. by WWF's Roundtable on Sustainable Palm Oil (RSPO). Today, about 19% of the palm oil production is RSPO certified (RSPO, 2019). Additionally, the Indonesian government created the Indonesian

Sustainable Palm Oil certificate which is mandatory for all producers (Jelsma, Schoneveld, Zoomers, & van Westen, 2017). However, it is widely criticized for applying less rigid standards than RSPO and hereby undermining the already existing private standards. After all, one can say that there are significant certification attempts to make palm oil production more sustainable.

Despite these attempts, the existing literature suggests that conservation schemes such as RSPO are mostly ineffective in achieving their conservation objectives (Ruysschaert & Salles, 2014). In their study area around North Sumatra, it was examined that the amount of the premium paid by the firms to the farmers for RSPO certified plantation practices is too low. The economic loss is higher than this premium and unless the farmers attached a high value on ethical and environmental issues, there is no incentive to apply the RSPO practices.

In Germany, the Forum for Sustainable Palm Oil (FONAP) is trying to change the use of palm oil in German industry to RSPO certified palm oil. Hence, there are significant attempts from the Indonesian state, its public administrations and international stakeholders to make palm oil production more environmentally sustainable and less detrimental for rain forests.

2.4.3 Palm oil and environment: Yield improvements

Previous subsections and figure 2 pointed out that the increase in palm oil production was preliminarly obtained by expanding the cultivation area. However, as available and accessable land has become scarcer during the last years, especially in Indonesia and Malaysia, an increasing importance will be attached to yield improvements on the area which is already used for cultivation. So far, production per unit of area did increase over the years, but at a low scale: on average, it increased by 0.148% per year from 2009 to 2018. From 2009 to 2015, yields increased by 2.8%, yet after 2015, yields decreased again and today they are at the same level than in 2014. This is another indicator for the *El Niño* effects on palm oil production. Yields in Indonesia were reported to be 3.8 tonnes of CPO per hectare which is substantially lower than the Malaysian yield of 4.5 tonnes per hectare (Khatiwada et al., 2018). This number indicates that the weather conditions of both countries are similar and there is significant room for yield improvement on the Indonesian side.

Still, yield improvements in palm oil production are usually not a matter of days or weeks. Due to the design of the plantations including the distancing between the trees cannot be changed once it is installed, yield improvements can only be achieved by:

- best farming practices
- agrochemicals including fertilizers, herbicides and pesticides
- in some cases, irrigation

As mentioned before in subsection 2.3.3, *El Niño* extends extremely dry seasons and makes rainfall more unstable which is proven to affect yields negatively. Thus, irrigation would be needed to compensate the low rainfall. Thus, it can be assumed that these strong effects on productivity also affect the efficient use of resources. Although one would assume that farmers always have a high incentive to economize their resources as much as they can, it is also possible that an external shock makes farmers more sensitive for the inputs they are using. After all, agrochemicals are costly and an expected future decrease in revenue would lead to less expected purchasing power. This would lead to more carefully applied inputs for production.

Villoria et al. (2013) found that in a scenario of increasing productivity of primary and intermediate inputs, oil palm production in Indonesia and Malaysia increased by 39% using the same amount of land. Isolated, local TFP growth may lead to a slight increase of deforestation. However, thanks to the global increase of TFP, these deforestation effects are counteracted. Moreover, a net forest reversion and a reduction of greenhouse gas emissions are further consequences of this global increase. The paper concludes that global increases in crop productivity would be an effective tool for preserving rain forests from transformation in Indonesia and Malaysia (Villoria, Golub, Byerlee, & Stevenson, 2013) .

Soliman et al. (2016) analyzed production data from a survey conducted among palm oil smallholders in West and South Sumatra. They conclude that efficiency of smallholders is far from being at an optimal level. However, the main factors leading to these inefficiencies are not yet well understood by the existing literature (Soliman, Lim, Lee, & Carrasco, 2016). For their analysis, the authors applied a two-stage data envelopment analysis (DEA). The same method is used for this analysis. Subchapter 5.1 describes it in detail. The results of the study also show that an average yield improvement of 65% would be possible in palm oil production. Particularly, if the use of fertilizers and herbicides were less excessive, more targeted and therefore more efficient. After all, these inputs represent a considerable Additionally, better pruning and weeding practices as well as the adaption of industry-supported scheme management had significantly positive effects on yields and efficiency.

The use of palm oil has greatly expanded in recent years, often at the expense of the rain forest. The demand for palm oil will continue to rise in the coming years and production will increase accordingly. According to current data, the yields are still in need of improvement. The next chapters of this study will lay the groundwork for investigating how the trade-off between smallholder yields and environmental protection has developed in Jambi, Indonesia during the last years.

3 Theory

The study aims to analyze the dynamics of efficiency and resource productivity in palm oil production in Jambi, Indonesia from 2012 to 2018. In this chapter the theoretical framework of the analysis is built. The first part of this chapter discusses the relevance and the scope of analyzing efficiency in the case of palm oil smallholders. The second part introduces the Farrell Efficiency which is the theoretical basis of the Data Envelopment Analysis (DEA). The third and final part deals with the concept of Total Resource Productivity (TRP), an extension of Total Factor Productivity (TFP) which allows for the inclusion of biodiversity loss as a source of undesired output.

3.1 The scope of efficiency

Why is efficiency important? Investopedia defines efficiency as *a level of performance that describes using the least amount of input to achieve the highest amount of output*. Thus, to save resources it is crucial to understand the reasons why some producers are not efficient in their production. In contrast, productivity describes an increased output for a given amount of inputs. A profit-oriented businessman or farmer would most likely seek to maximize both. Increased productivity usually accompanies increased efficiency, but they can also counteract. While productivity decreases, efficiency can increase. This might be the case when resources suddenly become scarcer, as e.g. through an external shock - whereby farmers need to use their scarce inputs as careful - or efficient - as possible.

The underlying assumptions for both efficiency and productivity include the idea of the *Homo Oeconomicus*. It implies a perfectly rationally acting market actor. More precisely, every market actor is able to oversee the whole market and takes his decisions with perfect information about the long-term consequences of his actions. This idea is not above any doubt. Subdisciplines of economic science such as behavioral economics, institutional economics and political economy and ecological economics expand the neoclassical framework and allow for actors who do not act perfectly rationally. In this sense, behavioral economics admits that human perceptions are systematically affected by biases and cognitive limitations, while ecological economics considers the environment as an endogenous factor which should be included in economic calculations (Urbina & Ruiz-Villaverde, 2019).

In a corporate environment, such as a factory or a service company, there is no problem with assuming rationally acting market participants. After all, they have employees whose purpose is to observe the market and optimize the firm's processes. However, in the context of small-scale agriculture, the businesses are usually too small to fulfill this condition. It seems sensible to assume profit-orientation in these businesses for the farmers to arrive at a certain level of wealth and economic stability. Still, it is questionable if they would follow the profit maximizing logic of reinvesting and expanding their businesses once they have a good harvest. It is more likely that after a good harvest the time spent with friends and family is rather maximized instead. Thus, in the context of small-scale farming it is clearly problematic assuming no preference for future and present revenues as in neoclassical theory. It is probably the small farmers themselves who know best how they should allocate their working and leisure time. Additionally, it is likely that they know their own plot best, which is why one should be particularly careful when drawing conclusions about farming practices which appear as inefficient.

Although, as just stated, the concept of efficiency is by no means uncontroversial, the advantages of an efficiency analysis outweigh the disadvantages. In fact, the efficiency analysis of smallholder farmers concerning resource use contributes to the aforementioned transdisciplinary field of ecological economics. In this respect the inclusion of nonmarket resources such as loss of biodiversity can be seen as an approach to internalize environmental externalities in economic calculations. In relation to small-scale palm oil cultivation, these results can be helpful in identifying how more environmentally friendly technologies can be applied.

Furthermore, the understanding of the influencing factors of imperfect efficiency can make it possible to reduce the spill of resources and therefore combat avoidable land expansion. It may help us to understand the characteristics of farmers which apply best practices in their production. In that way, the results of the efficiency analysis can lead to improved policy advice. However, the results from the subsequent parts have to be interpreted with caution. Small-scale farming is multifaceted and the results must be placed in the appropriate context.

3.2 Farrell efficiency

The assumption of perfect rationality which have been discussed in the last part is partially loosened by Farrell to form the basis of individual efficiency calculations. Farrell's model allows for inefficiently acting individuals (Farrell, 1957) - which is an important extension of the neoclassic model - and the basis of efficiency calculations in a non-parametric framework.

The Farrell (1957) approach to efficiency analysis extends Robert Solow's work about productivity and efficiency (Solow, 1957). While Solow was focusing on the macroeconomic dimension of factor productivity, Farrell's work concerning efficiency is mainly focused on the micro level. The main contributions are: 1. the definition of efficiency and productivity; 2. the way to calculate a benchmark technology and the respective efficiency measures (Førsund & Sarafoglou, 2002).

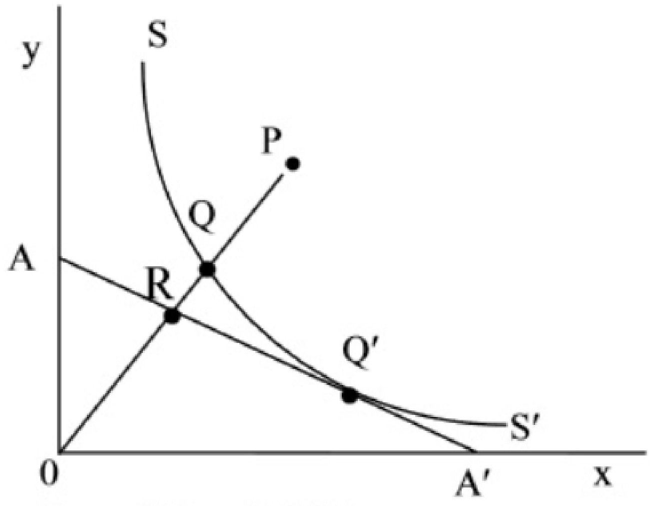
One of the novelties with regard to the existing neoclassical production theory is the aforementioned granting of the possibility of inefficient operations. Figure 4 shows the definition of Farrell efficiency graphically. Within that figure, x and y represent two different input coefficients. Constant returns to scale are assumed for this case. The SS' curve describes the unit isoquant representing the frontier technology. It contains the various input combinations that a perfectly efficient firm can employ to produce a unit of output. The point O describes the origin, while Q represents a 100% efficient firm and P a firm with an inefficient input combination. The line AA' shows the price ratio of the two production factors.

The definitions for deriving the individual efficiency types are as follows:

- OQ/OP shows the *technical efficiency* of firm P. It describes the inputs needed assuming best practice to produce the optimal observed output in terms of each input. With perfect efficiency, the term takes the value 1 or 100%.

- $\frac{OR}{OQ}$ describes the price efficiency. Note that point Q might be technically efficient but it only achieves perfect price efficiency at the point Q', where the unit isoquant is tangent to the price ratio AA'

Figure 4: Farrell efficiency with two input types



Source: Farrell, 1957

- $\frac{OR}{OP} = \frac{OQ/OP}{OR/OQ}$ describes the *overall efficiency*, which is the production cost for the event that technical and price efficiency are both achieved. In other words, it is defined as the *technical efficiency* divided by the *price efficiency* (Farrell, 1957).

The next step is a piecewise linear envelopment of the data as the most pessimistic specification of the frontier. The idea is that the resulting unit isoquant lies as close to the observations as possible (Førsund & Sarafoglou, 2002). In this way, the distribution of the data spots is taken into account for the calculation of each efficiency type. However, there are many different approaches to pursue the linear programming which would give us the frontier function we are looking for.

The Farrell efficiency is the basis of DEA and in connection with panel data, of the MPI. Both are used to draw conclusions about the productivity of the smallholders of our sample using conventional production variables.

3.3 Total Resource Productivity

One of the fundamental theoretic frameworks of the analysis carried out in this thesis is the Total Resource Productivity (TRP) approach. The approach is an expansion of the Total Factor Productivity approach by Robert Solow (Solow, 1957). According to Solow the output shift $\Delta Q/Q$ in an economy is described as

$$\frac{\Delta Q}{Q} = \alpha * \frac{\Delta K}{K} + \beta * \frac{\Delta L}{L} + \frac{\Delta A}{A} \tag{1}$$

where

$$Q = F(K, L; t) \tag{2}$$

and where $\Delta K/K$ represents the shift of capital and $\Delta L/L$ the shift of man hour from one period to another. t is a placeholder for time and allows for technical change in Q. α and β denote the relative shares of capital and labor respectively. Rearranging equation 1 by $\Delta A/A$, we obtain an index measure for technical change:

$$\frac{\Delta A}{A} = \frac{\Delta Q}{Q} - \alpha * \frac{\Delta K}{K} - \beta * \frac{\Delta L}{L} \tag{3}$$

What Solow initially calls technical change was hence defined as *Total Factor Productivity*. Its function is to measure the portion of output - or the increase in productivity - which cannot be explained by the amount or proportion of inputs. However, TFP only includes marketable factors. Nonmarket resources such as water, air and biodiversity are not captured by TFP as well as other externalities.

Total Resource Productivity is an approach to expand Total Factor Productivity by accounting for nonmarket resources. After all, natural resources play a central role in many productions and they are as scarce as labour or capital. Thus, its use entails true opportunity costs (Gollop, Swinand, & G., 2001). With regard to the measurement of TRP, there are several approaches. Gollop and Swindon (2001) propose both a producer- and a welfare-based model combines with the calculation of production possibility frontiers. Unfortunately, the C01 data set which is used for the analysis does not provide sufficient information to replicate this method. Still, an idea which was indeed used by Gollop and Swindon is the inclusion of a source of undesired output into the calculations. The same will be included in this analysis in the form of biodiversity loss to obtain results for dynamic resource productivity in palm oil production in Jambi, Indonesia.

In this chapter, the necessity to analyze palm oil production with regards to efficiency was highlighted. Subsequently, one of the most renowned approaches to calculate efficiency was introduced, the Farrell efficiency. The methodology of this analysis is based on this approach. Finally, the concepts of Total Factor Productivity and Total Resource Productivity were outlined - both measures are of paramount importance when comparing the results in chapter 6.

4 Data

4.1 C01 sample

This chapter describes the summary statistics and the collection method of the data set used for the analysis. The data set is based on a total of 96 observations, divided into the three survey waves 2012, 2015 and 2018.

4.1.1 C01 sample: Number of observations and survey method

All the present data were collected within the *Collaborative Research Centre 990: Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems*. The C-group particularly analyzes the human dimensions of land use transformation from rain forest into rubber and palm oil plantations. Its database consists of nearly 800 households in around 100 villages in five regencies of Jambi province. However, the C01 group only consists of a smaller subsample.

Table 1: Observations used for the analysis

	Wave			
	2012	2015	2018	Total
No. of observations including rubber	199	221	219	639
No. of observations before restriction	37	44	45	126
No. of observations after restriction	27	35	34	96

Table 1 gives an overview about the total number of C01 observations. The second and third row report only those observations who were collected at palm oil plots. As some input, plant richness or size data is missing, the sample had to be further restricted to those observations reported in the third row. A detailed report over which households are reported in which year is attached in the appendix in table 6.

Most of the production variables such as agrochemical use and CPO production were collected by a questionnaire in each wave. Besides, the C01 project group collected plant richness and biodiversity data in the respective fields. For this purpose, a 5*5-meter square was staked out at the same spot on the field at each data collection wave. The exact position of the field was determined with

GPS data. On these squares, the number of different species and the number of individuals of each of these species were surveyed. Both figures are used to receive measures of biodiversity, such as the Shannon Index and the Effective Number of Species (ENS).

While the number of observations is relatively small, it is necessary to apply methods which are suitable for small samples. For instance, if no normally distributed error terms can be assumed, it is not possible to apply a classic linear model. The use of non-parametric methods is appropriate for the present data set since they do not assume a functional form or a normal distribution of the error terms. The methods that are used throughout this research to obtain results regarding dynamic efficiency and resource productivity are presented in detail in chapter 5.

4.1.2 Descriptive statistics of input and output variables

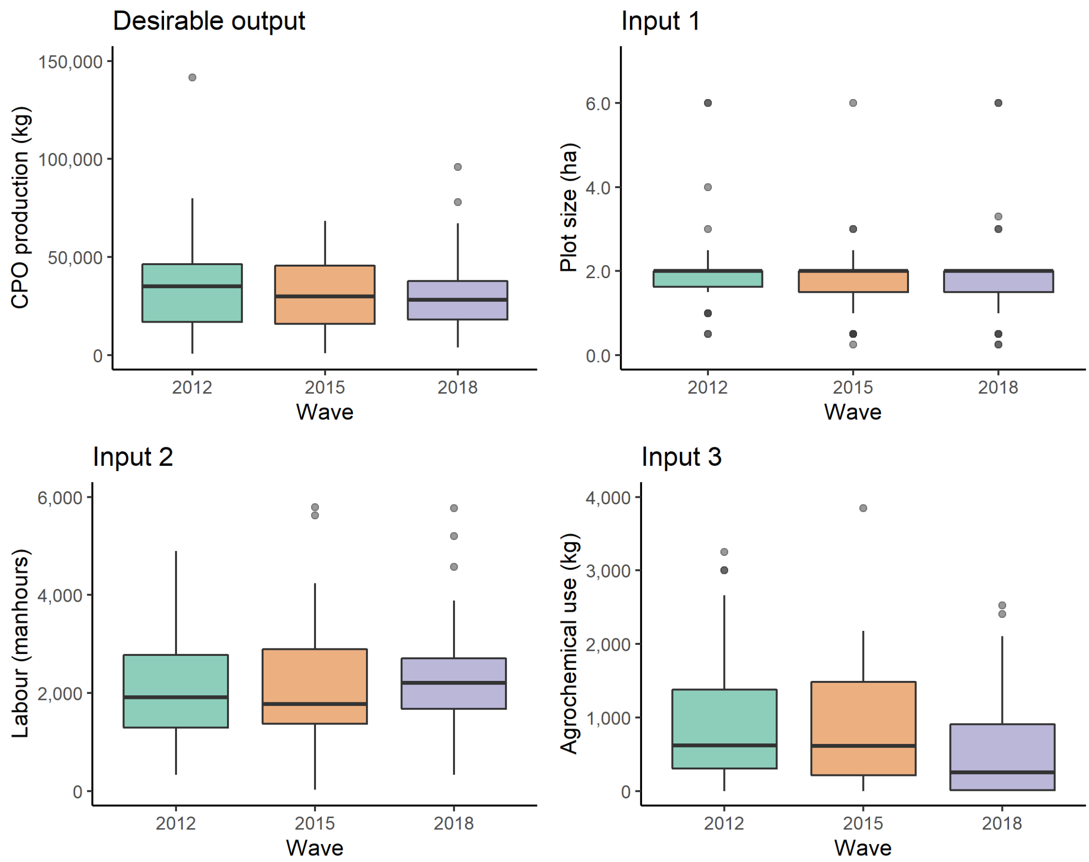
Summary statistics of the input and output variables used for the analysis of palm oil production in Jambi, Indonesia are reported in table 2. Note that the average CPO production decreased by 27.6% from 40,050kg in 2012 to 29,002kg in 2018. Median figures also decreased from 32,820kg in 2012 to 27,300kg in 2018. Thus, there is a substantial decrease in CPO production.

The input variables *agrochemical use*, *labour* and *plot size* are the ones used as input factors in our model. Agrochemical use sums up the use of fertilizers, pesticides and herbicides. It is measured in metric kilograms. Labour describes man hours and the plot size represents the cultivation area. Concerning the dynamics of these input variables, there is another substantial decrease over the period: the average man hour employed in production decreased by 24.9% from 3,152h in 2012 to 2,368h in 2018.

Figure 5 shows the evolution of the production variables illustrated by one box plot per year of observation. Most of the median figures represented by the bar in the middle of the plot decreased over time, except labour which decreased from 2012 to 2015 and increased again in 2018.

While there could be multiple explanatory approaches for the substantial reduction of CPO production in the sample, the principal reason is most probably

Figure 5: Evolution of production variables



due to a shift in climatic conditions caused by *El Niño*. Its effects have already been described in subchapter 2.3.3. As its impacts are supposed to be particularly strong on the 2015 wave, the largest decline of CPO production took place from 2012 to 2015. However, as the first and third quartile converge in the third plot, the lower production has further consolidated in 2018. Additionally, the amount of agrochemicals used for palm oil production has also decreased in the sample: the average agrochemical use decreased by 46.5% from 1,479kg in 2012, and by a similarly high rate from 919kg in 2015 to only 570kg in 2018.

There is a data problem regarding the plot size: since the cultivation areas are rather small, the figures were strongly rounded in the survey. Therefore, 49 out of 96 observations report a plot size of 2, although many of them are certainly only close to 2 and not exactly 2 hectares. As figure 5 illustrates, the median remains at 2 hectares of plot size and there is little change in these dimensions. After all, the plot size cannot be changed easily. Accordingly, the median remained constant at 2 hectares.

Table 2: Summary figures on input and output variables

	Wave	Min.	1st quartile	Median	Mean	3rd quartile	Max.	Std. deviation
Production (CPO in kg)								
	2012	38	16,860	32,820	40,048	46,360	191,184	38,659
	2015	960	15,075	27,900	34,238	45,600	204,000	33,194
	2018	3,000	18,000	27,300	29,002	36,000	96,000	20,717
Agrochemical use (in kg)								
	2012	1	233	624	1,062	1,479	3,252	1,045
	2015	1	204	613	919	1,437	6,000	1,143
	2018	2	15	253	570	698	2,523	743
Labour (in hours)								
	2012	9	1,290	2,014	3,152	3,425	31,008	5,168
	2015	25	1,404	1,960	2,356	2,900	7,830	1,689
	2018	48	1,676	2,269	2,368	2,704	5,772	1,217
Plot size (in hectares)								
	2012	0.25	1.62	2.00	2.38	2.00	12.00	2.10
	2015	0.25	1.38	2.00	2.15	2.00	12.00	1.93
	2018	0.25	1.50	2.00	1.94	2.00	6.00	1.22

5 Methodology

Unlike other research projects, in our case the distinction between theory and methodology is not straightforward. The Data Envelopment Analysis implies both a theoretical and a methodological concept. By means of the DEA it is possible to obtain measures of technical change and efficiency for samples that are either too small or whose error terms are not normally distributed. Both apply to our case. The following chapter describes the reasoning behind the choice and the fundamental points of the method which is used to derive the results of our analysis.

The first subchapter describes the assumptions, procedures and distinctions of the Data Envelopment Analysis (DEA). In the second subchapter the Malmquist Productivity Index (MPI) is introduced, which allows DEA based calculations for panel data. The last part deals with the construction of a Directional Distance Function (DDF) that includes a source of unwanted outputs in the DEA calculation.

5.1 Benchmarking with Data Envelopment Analysis

5.1.1 Assumptions

The two main underlying sources for this chapter are *An introduction to efficiency and productivity analysis* by Coelli et al. (1998) and *Benchmarking with DEA, SFA, and R* by Bogetoft & Otto (2011).

The first term which is relevant for this study is *benchmarking*. Its underlying idea is the systematic comparison of the economic performance of one firm against another firm (Bogetoft & Otto, 2011). Two of the methods for *benchmarking* which can be applied to a data set similar to ours are the *Stochastic Frontier Analysis* and the *Data Envelopment Analysis*. Both rely on econometric methods and mathematical programming.

The main assumptions about the analyzed firms for *DEA* are

1. Free disposability: a farmer can produce less output with more input

2. Convexity: any weighted average of production plans is feasible.

3. Returns to scale: scaling and rescaling is possible. The strongest assumption is that there are constant returns to scale, meaning $\gamma \geq 1$.

4. Additivity and replicability: if a production plan is feasible, so is its sum.

In a classic economic analysis, perfect efficiency of all firms is assumed. The advantages of Farrell efficiency and the DEA is that imperfect actors can be assumed. In contrast to SFA, DEA does not imply a certain distributional pattern of the farmers' efficiencies. Additionally, no functional form is assumed. Accordingly, the method is non-parametric. Instead, a frontier function is estimated based on the most efficiently producing units in the sample. The outcome of the DEA depends not only on the input and output quantities vectors, but also on the fine adjustment of the index, e.g. regarding the RTS orientation.

The advantage of this measure is clearly that despite the limited size of a sample, meaningful conclusions can be made regarding the evolution of productivity and efficiency. One of the main drawbacks is that non-parametric methods such as the DEA lead to results that cannot be extrapolated to other contexts.

5.1.2 Minimal extrapolation

A special feature of DEA is how the technology approximation is built. It uses, as mentioned before, mathematical programming.

The first step in DEA is to estimate the technology of each firm. It is done by applying the *minimal extrapolation principle* which means that T* is the smallest subset of a data matrix which satisfies the aforementioned assumptions. (Bogetoft & Otto, 2011)

In the following, the idea of minimal extrapolation and its combination with the concept of Farrell efficiencies are combined.

$$
\begin{aligned}
T^*(\gamma) =& \{(x,y) \in \mathbb{R}^m_+ \times \mathbb{R}^n_+ | \ \exists \lambda \in \Lambda^K(\gamma) : x \geq \sum_{k=1}^{K} \lambda^k x^k, \ y \leq \sum_{k=1}^{K} \lambda^k y^k\} \\
& where \\
\Lambda^K(crs) =& \{\lambda \in \mathbb{R}^K_+ | \sum_{k=1}^{K} \lambda^k free\} = \mathbb{R}^K_+
\end{aligned} \tag{4}
$$

where $T^*(\gamma)$ describes an estimated technology set which is obtained under the principles of minimal extrapolation. x represents a set of inputs of length m and y a set of outputs of length n. Both are expressed by real and positive numbers. The same mathematical set is the smallest possible set which contains the data which fulfill the aforementioned assumptions. The letter γ serves as a placeholder for a model which implies a set of assumptions, as we have formulated above. The assumptions made for our model employ the use of constant returns to scale. The use of *CRS*, again, allows full convexity and rescaling in the model and therefore requires the largest of all possibly implied technologies (Coelli, Rao, & Battese, 1998).

However, the larger the technologies, the more optimistic we are in granting improvement potential to each firm. This also makes the firms appear less efficient in the model than with e.g. *VRS*.

$$E^p = E((x^p, y^p); T*) = \min\{E \in \mathbb{R}_+ | (Ex^p, y^p) \in T*\} \tag{5}$$

5.1.3 Obtaining efficiency scores by mathematical optimization

Equation 5 combines the minimal extrapolation problem with the method to obtain Farrell efficiency scores. E describes the Farrell efficiency of the firm p. x^p is a set of inputs of firm p which can produce a set of output y^p.

$$\begin{gathered}
\min_{E,\lambda^1,\ldots,\lambda^K} E \\
s.t. \\
x_i^p \geq \sum_{k=1}^{K} \lambda^k x_i^k, i = 1, ..., m \\
y^p \leq \sum_{k=1}^{K} \lambda^k x_j^k, j = 1, ..., n \\
\lambda \in \Lambda^K(\gamma).
\end{gathered} \tag{6}$$

In equation 6 the term $T^*(\gamma)$ from equation 4 is inserted and results in a minimization problem. As a result of this mathematical optimization procedure, we obtain an input efficiency for each firm p.

The main modification that has to be done for extracting results for output efficiency is to change the mathematical optimization from a minimization to a maximization problem. The technology, i.e. the input and output sets remain unchanged. Thus, the relationship between the two efficiencies is $F = \frac{1}{E}$, where F describes the output efficiency.

As described by Coelli (1998), the DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface - or *frontier* - including all the data points. Each data point representing a decision making unit, in our case palm oil farmers. In contrast to the Stochastic Frontier Analsis (SFA), the surface's form is not imputed but completely determined by the most efficient data points in the distribution (Coelli et al., 1998). Consequently, the efficiency value of these farmers is exactly 1.0 or 100%.

In order to apply a DEA, it must ultimately be decided whether

- there are constant CRS or variable returns to scale (VRS) and
- there is input or output orientation.

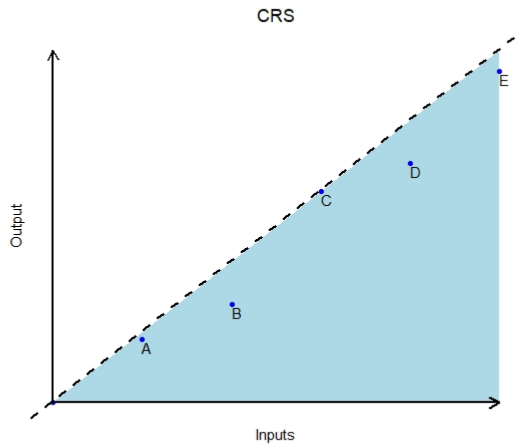
5.1.4 Returns to scale

To perform a DEA, a distinction must be made between VRS and CRS. Variable returns to scale consist of constant, increasing and decreasing returns to scale. By intuition, the application of this distinction within the DEA makes sense for our data. However, the CRS assumption is more commonly used and the interpretation of its outcomes is less complicated. Therefore, there is a trade-off between the accuracy of the method and the meaningfulness of its results. The correct procedure is to run a test over all our observation and test for its returns to scale. This will be done in chapter 6.

Figure 6 depicts the construction of a frontier based on the CRS orientation. It draws a straight line based on the two most efficient data points, in this case A and C who thus represent 100% efficiency. The efficiency figures of the remaining data points are calculated based on the distance to the illustrated CRS frontier. These can take values from 0 to 1, or 0% to 100%.

Figure 7 depicts the construction of a frontier based on the VRS orientation. The frontier is again based on the most efficient data points, but it is no straight

Figure 6: Hypothetical data distributed with respect to their efficiency under CRS hypothesis.



Source: Coelli et al., 1998

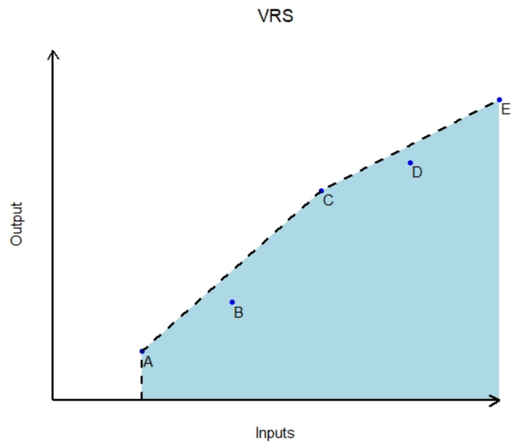
line. Thus, its functional form fully depends on the data points in the sample. However, it is concave by definition. Due to this fact, B reports, as in figure 6, imperfect efficiency.

An analysis was pursued concerning efficiency change of banks in Czech Republic from 2001 to 2011 by Repková (2013). It was pointed out that by applying a Dynamic DEA the results between CRS and VRS differed. The average efficiency under CRS orientation ranged from 80% to 92%, while under it ranged from 90% to 98% under VRS orientation (Repková, 2013). These findings indicate that it is possible by applying the same method with different orientations on the same data may lead to different results. Yet, both results point at least at the same direction. Thus, for the context of analyzing dynamic resource productivity of palm oil production in Jambi, Indonesia it might be sensible to test which returns to scale type to apply to our sample. In subchapter 6.1 the sample is therefore tested with regard to its returns to scale.

5.2 Malmquist Productivity Index

So far, we established the assumptions and chose the appropriate method for the analysis of dynamic efficiency and resource productivity. Farell efficiencies and the DEA do not take the panel structure of the data set into account because they are cross-sectional measures. Therefore, another method is needed to generate results for panel data. In order to capture the efficiency change over time, the

Figure 7: Hypothetical data distributed with respect to their efficiency under VRS hypothesis.



Source: Coelli et al., 1998

DEA based Malmquist Productivity Index (MPI) is the appropriate measure.

The basic figure of the framework is the DEA based efficiency $E^i_{s,t}$ as it was obtained in the beforehand subchapter. Again, i is an index number for the individual firms, s and t describe two points in time, t subsequent to s.

The calculation of the index is described by:

$$Mq^s = \frac{E(t,s)}{E(s,s)} \tag{7}$$

$$Mq^t = \frac{E(t,t)}{E(s,t)} \tag{8}$$

The Mq stands for the Malmquist index for each point in time s and t. It is simply the division of the Farrell efficiency scores in each point in time. Thus, if there is an efficiency increase in one period with respect to the other, the MPI will return a number which is greater than 1. As there is no preference of one period over the other, there are two possible directions of the efficiency change: from s to t, as in Mq^s and from t to s, as in Mq^t. The MPI is obtained by calculating the geometric mean of these two:

$$Mq(s,t) = \sqrt{Mq^s * Mq^t} = \sqrt{\frac{E(t,s)}{E(s,s)} * \frac{E(t,t)}{E(s,t)}} \tag{9}$$

However, so far we neglected a central figure which interferes with the outcome of the MPI. We need to take the general change of technology of one period with respect to the other into account. This general efficiency change is described by $EC(s,t)$ in the following equation:

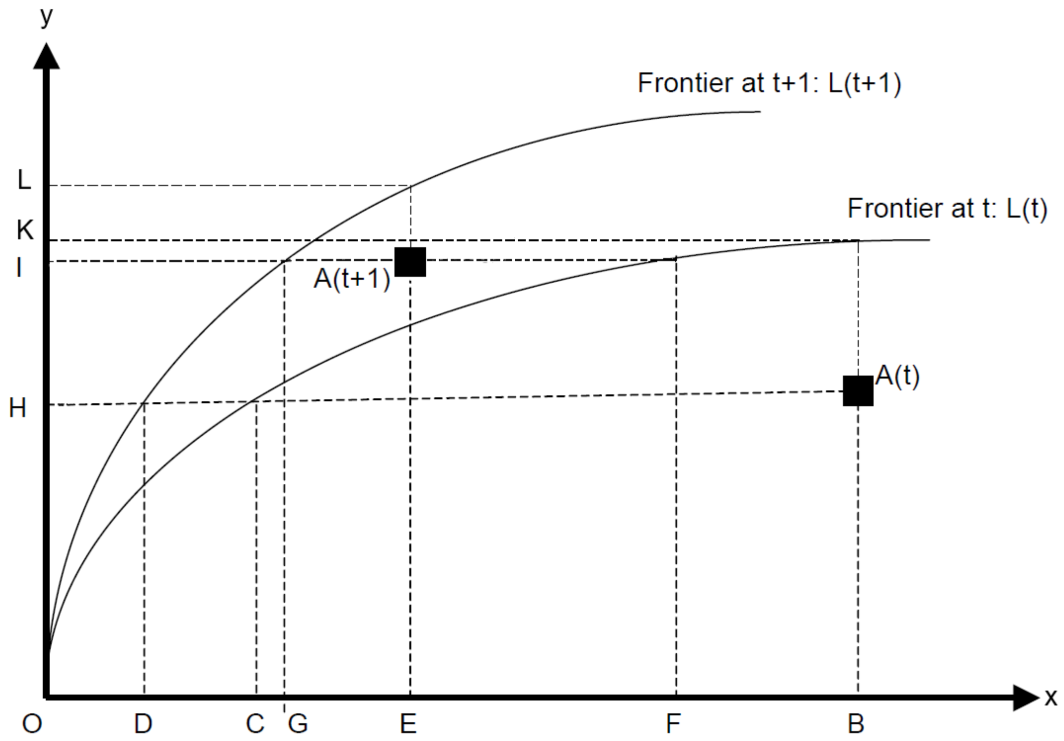
$$Mq(s,t) = \underbrace{\frac{E(t,t)}{E(s,s)}}_{EC(s,t)} * \underbrace{\sqrt{\frac{E(t,s)}{E(t,t)} * \frac{E(t,t)}{E(s,t)}}}_{TC(s,t)} \tag{10}$$

Both can be counteracting or additive. When interpreting the MPI, it is important to analyze both figures separately in order to arrive at a meaningful conclusion.

Figure 8 shows the decomposition of the MPI into technical change and technical efficiency change (Emrouznejad & Thanassoulis, 2010). Technical change refers to a change in innovation that affects the entire sample. Technical efficiency change describes the efficiency of the individual actors in relation to the benchmarkt technology, also known as *catch up*. Let x denote a level of input and y a level of output. For this graph, one input and one output are assumed, although multiple inputs and outputs could be employed generating a similar picture. Two production function depict the amount of output which can be produced for a given amount of input. $L(t)$ depicts the production frontier for period t and $L(t+1)$ for period $t+1$. According to Färe et al. (1994) the change of total productivity of a unit can be decomposed in the general shift of the efficient boundary(Färe, Grosskopf, Norris, & Zhang, 1994; Emrouznejad & Thanassoulis, 2010).

The point $A(t)$ represents an arbitrary input output bundle for period t and $A(t+1)$ for the subsequent period $t+1$. When assuming input orientation, the ratio OC/OB represents a measure of input based efficiency. This measure, by logic, is between 0 and 1. If point $A(t)$ lies on the frontier, the efficiency measure would equal 1 or 100% input-oriented efficiency. Thus, for $A(t)$ which is not 100% input efficient, the same amount of output at H could be achieved by reducing the inputs and moving from point B to point C.

Figure 8: Malmquist Productivity Index and its decomposition (Emrouznejad & Thanassoulis, 2010)



When assuming output orientation, however, the approach is similar but this time, moving vertically: the ratio OH/OK represents a measure of output oriented efficiency. For the same amount of employed inputs at B, it would be possible to produce the output level K instead of H.

5.3 Measuring dynamic resource productivity

5.3.1 Measuring dynamic resource productivity: Effective number of species

To calculate the DDF accordingly, this measure is converted so that its loss can serve as a measure of undesirable output. The aim is to obtain a figure which reflects the loss of α diversity. This subchapter gives a brief introduction to what dimensions of biodiversity exist and which one is used for the further analysis in this thesis. Subsequently, the calculation of the ENS is explained.

When referring to rain forest destruction, what one usually has in mind is the destruction of trees and plants. Nonetheless, biodiversity includes a lot more factors than only the quantity of plants on one land unit. This measure is called plant richness. Beyond plant richness, biodiversity includes soil biodiversity which reflects the variability among living organisms - visible and invisible ones, such as fungi, bacteria, protozoa or nematodes (FAO, 2020).

Depending on the size of the examined area, we speak of α, β and γ-diversity. The α-diversity refers to the diversity in one particular biotope or habitat. The β-diversity is the ratio between regional and local species diversity, thus it examines a wider scale while γ-diversity describes and compares the diversity of whole ecosystems, e.g. rain forests in different regions. By definition, α and β diversity are multiplied to γ diversity(Jost, 2006):

$$\alpha * \beta = \gamma \tag{11}$$

In our case, we are not able to attempt a description of β or γ-diversity with only one variable describing plant richness in the dataset. However, α-diversity can be derived with this data.

One method to represent α is by counting the species. The problem with the mere counting of species such as through the species richness (SR) figure is that it values particularly rare species disproportionately high. On the other hand, measures such as the Simpson diversity index - which is similarly constructed as the Shannon index for γ diversity - assign a disproportionately high value to common species. A compromise between both is the effective number of species (ENS), as it does not overrate neither extremely common nor extremely rare species (Dalheimer, Brambach, Yanita, Kreft, & Brümmer, 2020; Jost, 2006). It is calculated by the exponential of the Shannon Index for α diversity:

$$ENS = \exp(-\sum(\log p_i * p_i) \tag{12}$$

With p representing the relative abundance of a species i. The lower the value of the ENS, the lower the α diversity on the plot. In the data set used for this study the ENS ranges from 1.33 to 9.8, the average ENS of the sample is 4.89. However, this equation still needs to be converted into a source of undesirable output. The expression that is ultimately used to calculate the distance function is

$$Y_{undesirable} = \frac{1}{\exp(-\sum(\log p_i * p_i)} \tag{13}$$

or

$$Y_{undesirable} = ENS^{-1} \tag{14}$$

The equation finally describes the loss of alpha diversity by the inverse of the ENS. This term can eventually be used as a source of undesired output for the construction of a DDF.

5.3.2 Measuring dynamic resource productivity: Directional Distance Function

The method which is used in this thesis to include a source of undesirable output is the directional distance function (DDF). By using this method it is possible to add an environmental component to the efficiency calculation. In this study, the ENS is used as a source of undesirable output.

Let D_O denote the Shepard output distance functions which is used in the MPI to represent technology:

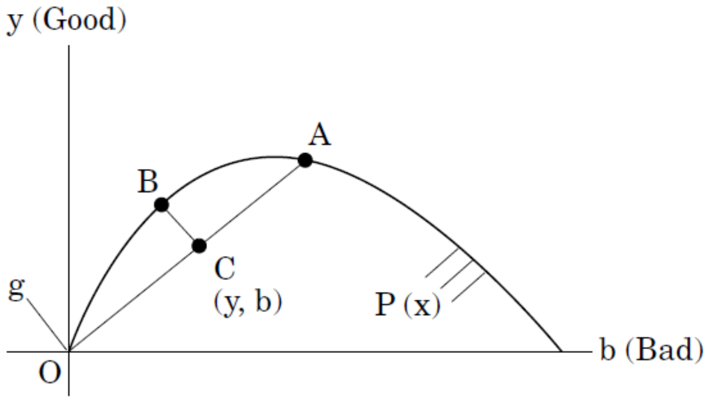
$$D_O(x, y, b) = \inf\{\theta : (\frac{(y, b)}{\theta} \in P(x)\} \tag{15}$$

where x represents a set of inputs, y represents desirable output and b represents bad or undesirable output and $P(x)$ the output set (Chung, Färe, & Grosskopf, 1997). Although we have two types of output, this function maximizes desirable and undesirable output simultaneously. However, what we are looking for is a function that maximizes the desired output while minimizing the undesired output. For this purpose, the function must be redefined as follows:

$$\overrightarrow{D}_O(x, y, b) = \sup\{\beta : ((y, b) + \beta g \in P(x)\} \tag{16}$$

where g represents a directional vector which determinate the scale of both output types, e.g. $g = (-b, y)$ for b being undesirable and y being desirable output. Likewise, while still assuming free disposability of inputs and desirable

Figure 9: Directional distance functions



Source: Chung, Färe & Grosskopf, 1997

output, for the source of undesirable output, weak disposability is assumed.

To illustrate the approach more clearly, figure 9 provides a graphical explanatory approach. Again, y denotes desirable output, b denotes undesirable output and $P(x)$ the output set. A depicts the boundary of $P(x)$, C represents an arbitrary point of imperfect efficiency. The classical Shepard's distance function used for the calculation of the MPI would result in an efficiency ratio which equals the value OC/OA. In contrast, the DDF moves in the direction of the boundary and results in point B which yields the distance ratio BC/Og. This means that the DDF effectively moved towards more desirable and less undesirable output according to the directional vector g (Chung et al., 1997).

Likewise, the relationship between the Shepard's and the directional distance function can be defined as

$$\overrightarrow{D}_O(x, y, b; y, b) = (\frac{1}{D_O(x, y, b)}) - 1 \tag{17}$$

or

$$D_O(x, y, b) = \frac{1}{1 + \overrightarrow{D}_O(x, y, b)} \tag{18}$$

assuming that $g = (y, b)$.

The results of the DDF can be described as a measure of environmental performance. As there is only one source of undesirable output included, the approach is not far-reaching enough and it contains too few biodiversity measures to describe *environmental efficiency*. However, it is quite possible to speak of a fair representation of dynamic resource productivity in the context of environmental performance.

This chapter responded to the characteristics of the data set by explaining why non-parametric methods are suitable for an analysis of efficiency and resource productivity. Subsequently, the assumptions and procedures for calculating a DEA were explained. To address the panel structure of the data, the DEA based MPI was explained and graphically illustrated. Finally, the concept of DDF was used to determine dynamic resource productivity, which adds a source of undesirable output to the MPI calculation.

6 Results

In chapter 5, the two main non-parametric approaches to calculate efficiency scores were introduced. The MPI calculating a TFP measure reflecting conventional efficiency change and the DDF calculating environmental performance change as a measure of dynamic resource productivity. In this chapter, both methods are applied to the restricted palm oil production data set that was introduced in chapter 4. This chapter is divided into five subsections: In the first subchapter, the MPI results are outlined. In the third subsection, the ENS that was introduced in subchapter 5.3.1 added as an undesired output to the model and efficiency results are calculated the DDF approach. Finally, both MPI and dynamic resource productivity results are discussed in view of the research questions and some policy advices are derived from the results.

6.1 Returns to scale test

In subchapter 5.1.4 it was pointed out that for any DEA calculation, either constant or variable returns to scale (RTS) need to be assumed. Simar and Wilson (2002) elaborated a test for RTS. The two main test statistics for the test are defined as follows by the authors:

$$\hat{S}_{1n}^{crs} = n^{-1} \sum_{i=1}^{n} \frac{\hat{D}_n^{crs}(x_i, y_i)}{\hat{D}_n^{vrs}(x_i, y_i)} \tag{19}$$

$$\hat{S}_{4n}^{crs} = Med\{\hat{D}_n^{crs}(x_i, y_i)\}_{i=1}^{n} / Med\{\hat{D}_n^{vrs}(x_i, y_i)\}_{i=1}^{n} \tag{20}$$

Where the input x can produce an output y. D represents a Shepard's output distance function. Equation 19 describes a mean of ratios $\hat{S}_{1n}^{crs}$, while equation 20 describes a ratio $\hat{S}_{2n}^{crs}$ of the medians. The authors clarify that medians and trimmed means are used rather than arithmetic means.

Table 3 shows the results of the test for constant and non-increasing RTS. $\hat{\mathrm{W}}_{4.5}$ is based on equation 19 and $\hat{\mathrm{W}}_{4.8}$ on equation 20. Both the $\hat{\mathrm{W}}_{4.5}$ and the $\hat{\mathrm{W}}_{4.8}$ test statistic do not reject the null hypothesis of non-increasing RTS. Furthermore, $\hat{\mathrm{W}}_{4.5}$ does not reject the null hypothesis of constant RTS. Taking both test results into account, it might be concluded that constant returns to scale can be correctly

Table 3: Returns to scale test

	(1)	(2)
Test for non-increasing RTS	0.81	-0.035
Test for constant RTS	0.645	-0.074*

Note : * H_0 rejected; (1) = $\hat{W}_{4.5}$ test statistic;
(2) = $\hat{W}_{4.8}$ test statistic

assumed for further analysis and therefore used for the calculation of the MPI and DDF in the following parts.

6.2 Malmquist Productivity Index, technical change and technical efficiency

Table 4: MPI results

Period	2012-2015		2015-2018		2012-2018	
Measure	Median	Mean	Median	Mean	Median	Mean
MPI	0.930	1.512	1.083	1.245	0.956	3.137
Technical change	1.063	1.278	0.954	0.956	1.123	1.219
Technical efficiency change	1.000	1.189	1.050	1.345	0.952	2.524
Observations	23		30		22	

Based on the methodologies described in subchapter 5.1 and 5.2, this subchapter points out the results of the Malmquist Productivity Index (MPI). The production function which is used for the calculation of the DEA based MPI consists of:

A source of desirable output:

- Crude palm oil production measured in kilograms per year

Three input variables:

- Agrochemicals measured in kilograms
- Labour measured in man hours
- Plot size measure in hectares

The MPI results consist of three scores: the general Malmquist-Productivity Index, a score for technical efficiency change and a score for technical change. The general MPI score can be interpreted as Total Factor Productivity (TFP). The mean and median numbers of these three figures are shown in table 4. Output orientation and CRS were assumed to calculate the results.

The first interesting finding is that there is a significant gap between the mean and median figures. There are two ways to explain the heterogeneity of median and mean results:

1. The number of observations is not constant. Only 18 observations are available as a complete time series in all three waves. Still, for the 2015-2018 period there are 30 observations. Consequently, the disparity between mean and median is not as high as in this period for the general MPI and for technical change.

2. As the sample is small, each observation which is reported - or left out - in one wave has a strong influence on the mean and the median of each measure. The average figures might be distorted by outliers.

The average TFP change from 2012 to 2015 is 1.512 which means that the average efficiency increased by 50.1% in 2015 with respect to 2012. In 2018, the average increase of TFP was 24.5% with respect to 2015. For the period from 2012 to 2018, TFP increased strongly on average, while the median figure was contracting. This indicates that the distribution of the data of this period is skewed. The average numbers of technical change and efficiency change show an overall increase for the same period. However, the median figures only show an increase of 12.3% for technical change, while technical efficiency decreased slightly by 4.8%.

Technical efficiency change was positive throughout all the average figures: It grew by 18.9% from 2012 to 2015 and by 34.5% from 2015 to 2018. Only the median value indicates a slight reduction in technical efficiency for the period from 2015 to 2018. The innovation shift or technical change figures are more ambivalent: the average technical change increased by 27.8% for the period from 2012 to 2015, but both median and arithmetic mean for the period from 2015 to

2018 show a decline. This could be possibly explained by lagged or persistent *El Niño* effects.

The results are varied. However, it can be said for technical efficiency that the development in recent years has been predominantly positive. Furthermore, the average TFP change is positive, which summarizes that the evolution of the conventionally measured efficiency in the sample was positive.

6.3 Dynamic resource productivity

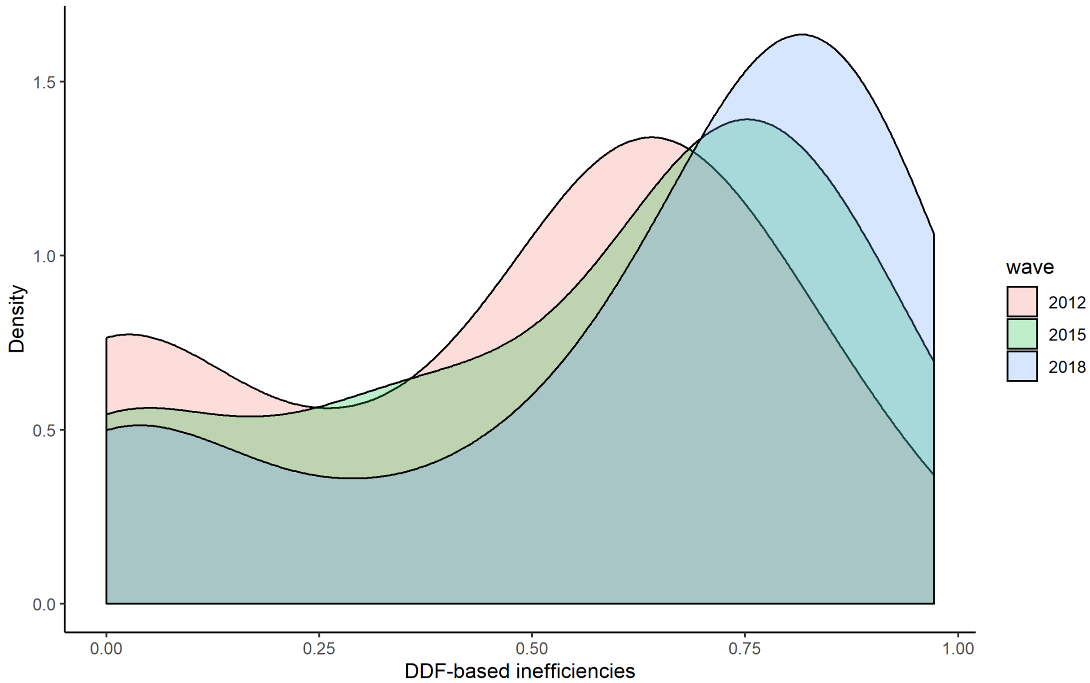
6.3.1 Dynamic resource productivity: Measurement of environmental performance

The MPI results in table 4 showed that TFP change was positive during the observation period. Yet, the average technical change was negative from 2012 to 2015 and it was therefore outweighed by the positive technical efficiency change in the same period. In this subchapter, the measurement of dynamic efficiency is extended by including an undesirable output. The results of the DDF are measured by the variable *environmental performance*, which is an indicator of resource productivity.

Initially, a DDF is constructed with the same three input variables as beforehand: plot size, labour and agrochemical use. As before, CPO production is included as a source of desirable output. Additionally, a source of undesirable output, indicated by ENS^{-1}, represents the loss of biodiversity on the plots. The results of the DEA performed with the DDF approach are reported in table 7.

Partly due to the small data set of 98 observations over three waves, the results are quite heterogeneous. Thus, it is reasonable to use as many different forms of data visualization to arrive at meaningful conclusions. Figure 10 shows that the inefficiency distribution of the three waves is harmonic, as none of the three distributions draws a strongly differing picture. The distribution shifted slightly to the right each year and therefore towards a higher average inefficiency or lower environmental performance. Furthermore, it becomes evident that the scores are not normally but binomially distributed, since two peaks for each kernel density curve can be observed. This skew distribution also pulls the mean further away from the median.

Figure 10: Density of inefficiencies per wave



Note: Inefficiency = 1 - environmental performance

An overview about the complete results of the DDF calculation per household is provided in the appendix in table 7. To anticipate the central result: the average level of environmental performance decreased over the years. In 2012, the average environmental performance was 0.55 or 55%. In 2015, it declined to 0.542 and in 2018 it further decreased to 0.385. Thus, the average environmental performance decreased by a similar rate in each wave. The median figures draw a similar picture: the median inefficiency level started at 0.553 in 2012 and increased by 20% to 0.664 in 2015. Subsequently, the median inefficiency further increased to 0.764 in 2018. However, the environmental performance reduction decelerated by 25%.

The two columns on the right-hand side display the growth rates of the inefficiency scores for each household from one wave to the subsequent one. The fourth column shows the growth rate for each household from 2012 to 2015. 17 household could be included in this calculation. This is partially attributable to less observations in 2012 and partially due to an increase of inefficiency from a level of 0 which makes the result incalculable. For instance, the households 415 and 460 report an infinite growth due to this circumstance. For that reason, they

Table 5: Stationary MPI and environmental performance

Year	MPI	ENVPERF	Obs.
2012	0.8003647	0.4855515	23
2015	0.6199037	0.4296506	30
2018	0.6556536	0.3879536	30

Note: MPI = Malmquist Productivity Index indicator for Total Factor Productivity; ENVPERF = Environmental performance

are not included in the calculation of the average growth rate - which is 0.294. Implicating that the environmental performance of the households declined by 29.4% on average.

Regarding the individual figures, only two out of 17 households, namely 387 and 488, report a decreased inefficiency - or increased environmental performance - for that period. 14 households report an environmental performance decline.

With reference to the changes from 2015 and 2018, a similar picture is drawn. Out of 23 households, 5 report a decreasing inefficiency and thereby increasing environmental performance. 18 households increased their inefficiency and decreased their environmental performance. Two of them reported a level of zero inefficiency for 2015, which is why they were not included in the calculations. The five remaining values are 0 which means that these households remained constant in terms of environmental performance.

The mean growth rate of DDF based inefficiency is 0.143 from 2015 to 2018. However, the median growth rate is only 6.9% - or 2.3% per year. 10 observations did not report a decreasing environmental performance for this period - substantially more than from 2012 to 2018. The results of the DDF calculation show that the environmental performance from 2012 to 2018 was consistently negative. We will discuss this further in the next subchapters.

6.3.2 Dynamic Resource Productivity: Combination, comparison and interpretation of MPI and DDF results

Up to this point it was shown that the evolution of technical efficiency over the observation periods was positive and that technical change increased from 2012 to 2015 and subsequently had a slightly negative development from 2015 to 2018.

In this subchapter these results are compared to the results of dynamic resource productivity that were calculated in subchapter 6.3.1.

Initially, table 5 depicts the mean non-dynamic - or stationary results of the MPI and environmental performance. The results outline the starting point in terms of efficiency in each year of observation. The MPI based measure of TFP is shown in the second column. They are interpreted as the level of Total Factor Productivity in each year of observation. Evidently, TFP decreased significantly from 0.8 or 80% in 2012 to 0.62 in 2015. In 2018, the TFP level recovered slightly and increased to 0.656 or 65.6% efficiency in terms of TFP.

The third column of table 5 portrays the score of environmental performance or total resource productivity. In both periods the figures decreased at a relatively constant rate: from 2012 to 2015 environmental performance decreased by 13.3% from 0.486 to 0.429. In 2018, it decreased by another 10.76% with regard to 2015 and achieved a level of 0.388 - or 38.8% of environmental performance. Hence, there is evidence for a negative evolution of resource productivity measured by environmental performance over the entire observation period.

While technical change and the general MPI were more fluctuative, it was already shown in table 4 that the average technical efficiency increased continuously. Therefore, the developments of technical efficiency and resource productivity can be described as divergent. This could be a sign for a trade-off that is growing over time between both figures.

Figure 11 and 12 depict the change of TFP and the respective growth of environmental performance of the palm oil farmers for the periods 2012 to 2015 and 2015 to 2018. The numbers imply the farmers' household IDs. Figure 13 shows the same measurements for the whole observation period from 2012 to 2018. The dashed lines represent the thresholds of a positive (> 1.0) or negative (< 1.0) change of either measure. Thus, the data points which are in the lower left quadrant report negative TFP change and a negative change of environmental performance. The data points in the upper right quadrant report positive TFP and environmental performance change, while the data points in the lower right quadrant report a positive TFP change and a negative environmental performance growth rate. The same axis scaling was chosen for each graph to ensure the comparability. The continuous line serves as an indicator for the direction of the correlation of both measures. It is based on a linear model calculation.

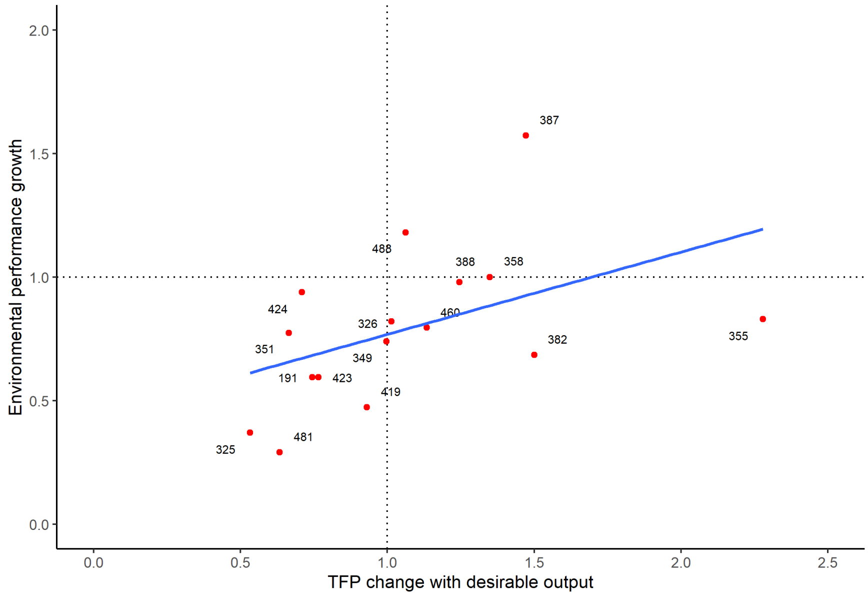
It has to be noted that due to the unbalanced panel the quantity of data points on each graph differs. To be sure that the results are not distorted by the additional households of the unbalanced panel, the same graphs were written with a sample restricted to households of the balanced panel. As a result, the direction of the correlations did not change, by which it was decided to include the *unbalanced* households in the graph. Additionally, some outliers distorted the results and were therefore excluded.

In figure 11 most of the data points are in the lower left quadrant which means that the change of both measures was preliminarly negative. However, farmers reporting a less negative TFP change also tend to perform less negatively in terms of environmental performance. For this period, it seems that an improvement of TFP compatible with the improvement of environmental performance. However, most of the data points are located in the lower left quadrant and thus undergo a negative development for this period in terms of TFP and environmental performance.

In figure 12, there is no significant relationship between both measures. Improvements in TFP are independent of improvements in environmental performance. The slope of the correlation line is not steep enough to assume the direction of the slightly positive correlation to be significant. In the period of 2012 to 2015, most of the data points report a negative change in terms of environmental performance. Regarding TFP change there is a divided picture: about half of the farmers report a positive TFP change and the other half a negative change.

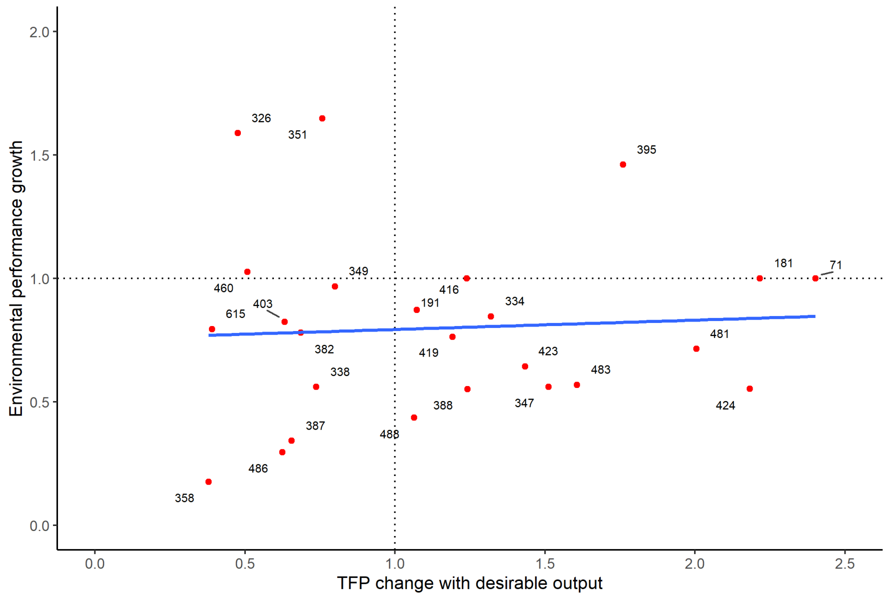
The most striking result is depicted in figure 13. For the whole observation period from 2012 to 2018, there is a clear negative correlation between TFP and environmental performance change. Again, the majority of the farmers reported a negative environmental performance change, while 8 out of 18 farmers reported a positive TFP change. Not a single household reported a positive change in both measurements. It can be concluded that there is a clear trade-off between TFP change and environmental performance change for the entire observation period.

Figure 11: Environmental performance growth and Total Factor Productivity change from 2012 to 2015



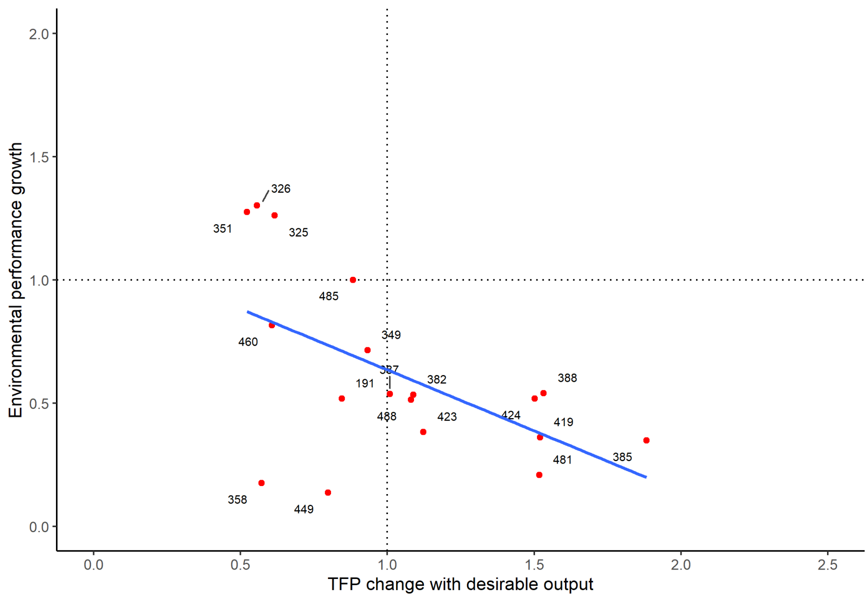
Note: Number of observations: 16

Figure 12: Environmental performance growth and Total Factor Productivity change from 2015 to 2018



Note: Number of observations: 25

Figure 13: Environmental performance growth and Total Factor Productivity change from 2012 to 2018



Note: Number of observations: 18

6.4 Discussion

6.4.1 General discussion

To answer the research question, the results obtained so far will be discussed in this subchapter. Firstly, I will elaborate on the implication that the obtained results have on current farming practices. Secondly, and before arriving at the final conclusion, I derive some policy advices from said results.

Subchapter 6.3.2 showed that the MPI measurement for TFP change and environmental performance increasingly diverged over time. Normally, one would assume that if TFP develops positively, resource productivity would also develop in the same direction. The results have shown, this is not the case. Referring to the research question, no clear answer can be found in view of these figures.

In terms of technical change and technical efficiency described by the measures of the MPI, the development was positive. Thus, the hypothesis of improving dynamic efficiency can be verified in terms of conventional output. While technical change was positive from 2012 to 2015, it was negative from 2015 to 2018. Evidently, there was a negative technology shift during that period. This is especially relevant since the *El Niño* effects were already captured in the observations from

2015. Simultaneously, the average technical efficiency increased between 2012 and 2015 and incrementing even steeper from 2015 to 2018.

Regarding resource productivity, from 2012 to 2015, the environmental performance decreased by 29.4% and subsequently by 14.3%. The hypothesis of improving dynamic resource productivity in palm oil production in Jambi, Indonesia cannot be confirmed, at least given the information provided by the present data. There can be many reasons for this. The first suspicion is that the inclusion of the ENS as undesirable output is mainly responsible for the negative evolution of resource productivity. However, this is contradicted by the fact that the ENS decreased strongly from 2012 to 2015 but increased again in 2018. It is possible that the resource productivity decline was mainly triggered by the decline of the technical change in the period from 2015 to 2018.

As mentioned above, the gap between technical efficiency and resource productivity has widened over the observed period. In this context it is important to consider that the CPO production declined significantly from 42,683 kg in 2012 to 30,772 kg in 2018. The efficiency divergence in the context of a reduced production could be interpreted as a more careful input use by the farmers. Furthermore, the average figures of man hour and agrochemical use decreased over time, especially from 2012 to 2015. This seems logical due to a less extensive use of agrochemicals being usually one of the consequences of employing less man hours.

Regarding the increased scarcity of resources, one could think of three potential settings:

1. input prices increased while the farmers' purchasing power remained constant or decreased slightly

2. the farmers' purchasing power decreased while input prices remained the same

3. both, input prices and farmers' incomes decreased simultaneously

The data of this study does not allow for the confirmation of any of these potential trajectories. However, the fact that CPO production decreased heavily makes the second hypothesis most likely. *El Niño* has reportedly hit the Indonesian palm oil production and this exogenous shock resulted in a decline in palm oil production - and consequently, the reduction in farmers' incomes (Azlan et al., 2016).

Another way to interpret the findings is by assuming that palm oil farming could have lost importance for smallholders, as farming conditions worsened due to *El Niño*. After all, smallholders might seek alternative sources of income the event that they expect a worse harvest in the future. Consequently, this would be reflected by reduced employment of man hour per farmer, as it is the case in our sample. As shown by table 2, man hours decreased from 2012 to 2015 but subsequently remained at the same level until 2018. It is possible that a strong reduction in man hour was caused by worse harvests connected to El Niño and then never picked up again, although it cannot be conclusively proven by the analysis. By anticipating worse harvests, farmers looked for alternative sources of income to ensure their livelihoods. Once these are found, the opportunity costs of reallocating all of the farmers' labour time in palm oil farming might be lower than upholding a more diversified set of activities. After all, man hour and agrochemical figures did not recover in 2018 when the weather conditions were more favorable for production.

One of the central conclusions that can be drawn out of the results is the reaffirmation of the trade-off between factor productivity and resource productivity. According to the results of this analysis, both measures diverged over time. Therefore, one of the questions raised by the obtained results is how one is able to increase productivity, technical efficiency and resource productivity at the same time? While a positive development of these three did not coincide in the case of this study, it might be possible to bring them together. As it was also mentioned in chapter 2, major yield improvements could be achieved by applying best practices and utilizing agrochemicals in a more targeted manner (Azlan et al., 2016).

6.4.2 Discussion: policy implications

In the last part of the discussion, I discuss some approaches of bringing together increased technical efficiency and environmental performance.

Not only this study has raised questions about the efficiency scope of some current smallholder oil palm farming practices. As elaborated before, there are figures that indicate an improvement potential of 65% regarding palm oil yields (Soliman et al., 2016). Although the study pursued in this thesis may not verify the same figures, mainly due to data limitations - it has become clear that there is indeed a lot of room for enhancing production. One example for this is the increase of technical efficiency despite the reduction in CPO production. While production decreased, the farmers reduced the use of almost all their input factors. Arguably, this is one of the reasons why their production has become more efficient: the more targeted and the less excessive the use of e.g. fertilizers, the better the results. Thus, it might be sensible to introduce or improve existing training approaches for the appropriate use of fertilizers, herbicides, pesticides and irrigation schemes. This would most likely further improve the plots' technical efficiency.

Intercropping might be a viable option which can be considered to increase biodiversity in palm oil production. Additionally, it might even have positive effects on yields. There is some evidence that appropriate types of intercropping are beneficial for palm oil growth in early stages and thus lead to higher yields (Dissanayake & Palihakkara, 2019). This finding is not very intuitive, as one might argue that other plants on the same plot might absorb nutrients and sunlight which is necessary for the oil palms to grow. However, when considering that due to climate change there are more days of excessive heat and sunshine, increased tree shade might have positive effect on oil palm growth. Likewise, certain plants have the ability to increase the soil's fertility and facilitate water storage. Both might help to further boost oil palm yield. Additionally, as already described in subchapter 2.4, palm oil can have a positive impact on biodiversity if it is embedded in a landscape mosaic (Santika et al., 2019).

Another positive aspect for smallholder farming is that intercropping provides an additional source of income which might be particularly pertinent while the oil palms do not yield any crops yet. There is evidence that intercropping maximizes land use, stabilizes yields and profit and increases food security in smallholder households (Nchanji, Nkongho, Mala, & Levang, 2016).

While the data and the results of this thesis are not extensive enough to draw concrete conclusions about existing approaches to enhance environmentally friendly palm oil production, it is appropriate to mention them. For example, some RSPO certification requirement include training approaches and best practices concerning appropriate and targeted input use. Furthermore, it includes the preservation of especially protected plant and animal species on the plantations. Therefore these practices would most likely have a positive effect on resource productivity, as the ENS is positively influenced by the preservation of highly protected species.

One could also think about introducing ecosystem service payments to remunerate smallholder farmers for deforestation-free cultivation. This can be done either through a national or international fund. Finally, RSPO certification is also relatively expensive and many smallholders lack the economic incentive to cultivate palm oil sustainably.

6.4.3 Discussion: limitations, scope of the contribution and outlook

The main contribution of this analysis is to combine the DEA based methods of MPI and DDF with data regarding smallholder palm oil production. Including a variable which reflects environmental damage into economic calculations can be an effective way to internalize environmental externalities. Another important contribution to this analysis is provided by the panel structure, which has shown that resource productivity has decreased noticeably over time.

Further research with similar methods can be carried out, in which several biodiversity measures are included in the productivity calculations. Especially the inclusion of increased CO_2 emissions as a source of undesirable outputs could be considered. This would allow a better representation of the real environmental damage.

The main limitation for the significance of the results is clearly the sample size. Although it is quite possible to relate the results to the entire small-scale palm oil cultivation in Jambi, the degrees of freedom in a data set with less than 100 observations are too few to reliably estimate e.g. linear regressions. One approach to circumvent this problem could be to bootstrap the sample, which is beyond the scope of this thesis. However, this would enhance the validity of the results. Another weakness is that DEA does not allow global comparison of the results because they are non-parametric and therefore result in different values in each sample.

Furthermore, a larger data set which includes not only information about resource productivity but also information on farmers' income and wealth would allow us to draw further conclusions about the trade-offs between environmental protection and wealth creation.

7 Conclusion

This study aimed to analyze the dynamics of efficiency and resource productivity in smallholder palm oil production in Jambi, Indonesia from 2012 to 2018. Based on the results of the methodologies used for the analysis, the development of resource productivity was negative over the period of the study. However, according to conventional efficiency measures the development was positive during the same period. Accordingly, the answer to the research question depends on which measures are weighted more heavily.

When mainly focusing on technical efficiency change, its evolution from 2012 to 2018 was predominantly positive. Technical change - or innovation enhancement - however, partly decreased, which is possibly related to the *El Niño* climate phenomenon. What becomes clear is that the trade-off between environmental performance and technical efficiency seems to increase over time.

Additionally, the results indicate that the trade-off between efficiency improvement in terms of a conventional production set and efficiency including environmental measures is increasing over time. Accordingly, one could consider policy approaches to reconcile the development of both variables.

Furthermore, the results raised the question if the impact of *El Niño*, which was only supposed to bed in 2015, have a lasting effect on smallholder oil palm farming practices. Both CPO production and the use of inputs such as agrochemicals and man hours suffered a heavy decline and have not recovered in 2018. These effects could partly explain the diverging of technical efficiency and resource productivity over the survey period. However, the data used in the study is not sufficient to illustrate this conclusively.

This thesis contributes to the existing literature concerning the efficiency analysis of smallholder palm oil production. Additionally, the inclusion of a source of undesirable outcome reflecting α-biodiversity loss contributes to the existing literature regarding the internalization of environmental externalities.

The discussion has shown that several policies are conceivable to reduce the trade-off between conventional and environmentally sensitive efficiency: Intercropping with a diversified landscape mosaic; smallholder training on the correct application of fertilizers, herbicides and pesticides; payment of ecosystem services.

All these strategies can promote both the yield of palm oil production and the biodiversity in the fields.

Palm oil is the most productive of all vegetable oil sources. Its multiple uses contribute very much to the nutrition and supply of the world population. Accordingly, the demand and production of palm oil will continue to increase in the coming years. However, the question after decades of slash-and-burn expansion is how can palm oil cultivation be made more compatible with ecological sustainability in the future? Policy makers must urgently address this question. This study has provided some food for thought.

A Appendix

Table 6: Panel households

	Household ID	2012	2015	2018
1	40	1	1	1
2	71	0	1	1
3	181	0	1	1
4	191	1	1	1
5	325	1	1	1
6	326	1	1	1
7	334	0	1	1
8	338	0	1	1
9	342	0	1	1
10	347	0	1	1
11	349	1	1	1
12	351	1	1	1
13	354	1	1	0
14	355	1	1	1
15	358	1	1	1
16	379	1	1	0
17	382	1	1	1
18	385	1	0	1
19	387	1	1	1
20	388	1	1	1
21	395	0	1	1
22	403	0	1	1
23	415	1	1	0
24	416	0	1	1
25	419	1	1	1
26	423	1	1	1
27	424	1	1	1
28	449	1	0	1
29	460	1	1	1
30	467	0	1	1
31	481	1	1	1
32	483	0	1	1
33	485	1	0	1

34	486	1	1	1
35	488	1	1	1
36	495	1	1	0
37	515	1	0	1
38	615	0	1	1
39	629	1	1	0

Table 7: DDF based inneffieciencies per wave; growth rates between the waves

HHID	Inef. 12	Inef. 15	Inef. 18	Growth 12-15	Growth 15-18
40	0.834	0.972	0.972	0.166	0.000
71	-	0.963	0.963	-	0.000
181	-	0.908	0.908	-	0.000
191	0.812	0.888	0.903	0.094	0.016
325	0.503	0.816	0.373	0.624	-0.543
326	0.655	0.717	0.550	0.095	-0.232
334	-	0.452	0.537	-	0.187
338	-	0.372	0.648	-	0.742
342	-	0.664	0.000	-	-
347	-	0.696	0.830	-	0.192
349	0.681	0.765	0.772	0.122	0.010
351	0.680	0.752	0.592	0.107	-0.213
354	0.580	0.000	-	-	-
355	0.677	0.732	0.000	0.082	-
358	0.000	0.000	0.825	0.000	Inf
379	0.551	0.846	-	0.537	-
382	0.652	0.762	0.814	0.168	0.069
385	0.305	-	0.758	-	-
387	0.650	0.450	0.812	-0.308	0.806
388	0.651	0.659	0.812	0.012	0.233
395	-	0.315	0.000	-	-
403	-	0.267	0.397	-	0.485
415	0.000	0.414	-	Inf	-
416	-	0.741	0.741	-	0.000
419	0.614	0.818	0.861	0.332	0.053
423	0.467	0.684	0.797	0.464	0.165
424	0.285	0.329	0.630	0.155	0.914

449	0.000	-	0.864	-	-
460	0.000	0.205	0.185	Inf	-0.101
467	-	0.000	0.000	-	0.000
481	0.237	0.778	0.842	2.283	0.081
483	-	0.597	0.771	-	0.292
485	0.000	-	0.000	-	-
486	0.916	0.000	0.704	-	Inf
488	0.838	0.808	0.917	-0.035	0.134
495	0.553	0.612	-	0.107	-
515	0.000	-	0.912	-	-
615	-	0.000	0.206	-	Inf
629	0.000	0.000	-	0.000	-
Median	**0.553**	**0.664**	**0.764**	**0.122**	**0.069**
Mean	**0.450**	**0.542**	**0.615**	**0.294**	**0.143**

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