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Agricultural-induced deforestation emissions and drivers of agricultural land use change in Indonesia

by

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Abstract: Tropical deforestation, primarily driven by the expansion of agricultural land use, is responsible for significant global CO_2 emissions, threatening current climate goals. Indonesia experiences one of the highest deforestation rates, endangering its rich biodiversity and human health. Global demand for Indonesia's crops is a critical force behind its increasing deforestation. Recent bilateral trade data is analyzed to answer the overall research question of which nation is a primary consumer of Indonesia's crops driving deforestation emissions. Moreover, a Structural Decomposition Analysis is applied using multi-regional input-output tables to identify drivers of its agricultural land use changes. The results show that Indonesia is a net exporter of deforestation emissions. Leading importers of Indonesia's deforestation emissions are India, China and the United States, especially importing palm oil and rubber. Moreover, agricultural land use change was driven mainly by internal factors in Indonesia, like changes in final demand per capita and population growth of Indonesia. Final demand per capita accounts for the strongest driver of land use. 86 % of the increased land use results from Indonesia's final demand per capita changes, while 14 % comes from other countries (foreign trade), primarily China and India.

Keywords: Deforestation, Agricultural Trade, Land use, Structural Decomposition Analysis, Multi regional Input-Output, Indonesia

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List of Abbreviations

BEET Balance of emissions embodied in trade

BRIC Country group of Brazil, Russia, India and China

BTIO Bilateral trade input output analysis

CBA Consumption-based accounting

CO_2 Carbon dioxide

EEU Eastern European countries

EKC Environmental Kuznet Curve

EU European Union

FAO Food and Agriculture Organization of the United Nations

GHG Greenhouse gas emissions

ha Hectares

IDA Index decomposition analysis

IO Input output analysis

IPCC Intergovernmental Panel on Climate Change

JAKT Country group of Japan, Australia, South Korea and Taiwan

MRIO Multi-regional input output

Mt Metric tons - used as emission unit

NA Country group of North America including Canada, the United States and Mexico

NDCs Nationally Determined Contributions

OECD Organisation for Economic Co-operation and Development

OLS Ordinary least squares regression

PBA Production-based accounting

REDD+ Countries' efforts to reduce emissions from deforestation and forest degradation, and foster conservation, sustainable management of forests, and enhancement of forest carbon stocks

RoW Rest of the World

SDA Structural Decomposition Analysis

SDGs Sustainable Development Goals of the United Nation

TCBA Technology-adjusted consumption-based accouting

UNFCC United Nation Framework Connection on Climate Change

WEU Western European countries

WIOD World Input Output Database by Timmer, Dietzenbacher, Los, Stehrer, and De Vries (2015)

1 Introduction

The recently published final draft of the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) measures that deforestation eliminated over 420 million hectares (ha) of forest area from 1990 to 2020 (Pörtner et al., 2022). Tropical deforestation is one of the most strongest contributors. 90 % of the 420 million ha forest loss took place in the tropics (Pörtner et al., 2022). Deforestation threatens the rich biodiversity of forests and harms environmental services and the well-being of forest communities (Burgess, Hansen, Olken, Potapov, & Sieber, 2012; Pörtner et al., 2022). Moreover, deforestation brings a risk to planetary health for humanity due to the development of new diseases (Lorenz, de Oliveira Lage, & Chiaravalloti-Neto, 2021).

Moreover, alarming is the high amount of emitted CO_2 emissions resulting from deforestation and forest degradation that contributes to rising global greenhouse gas emissions (GHG), increasing the risk of threats related to global warming (Van der Werf et al., 2009). Between 2007 and 2016, GHG emissions from agriculture, forestry and other land use accounted for 23 % of all anthropogenic GHG emissions, thereby 11 % results from forestry and other land use, with most emissions from deforestation (IPCC, 2020). Forests are the natural earth's carbon storage as they sequester more CO_2 from the atmosphere than they release. Through photosynthesis, forests store CO_2 from the air in their trunk, roots and dead material such as soil for over hundreds of years. They play a significant role in the fight against climate change by reducing GHG emissions, which is crucial to slow down global warming and reaching the goals of the Paris Agreement and the 2030 Sustainable Development Goals (SDGs) of the United Nations. To reach the 1.5°C goal, deforestation needs to be reduced by 70 % until 2030 and by 95 % until 2050 (Roe et al., 2019). Moreover, forests can help to achieve SDGs such as SDG 15 (Life on Land), 1 (Poverty) and 2 (Hunger), as sustainable forest management can provide goods and services as a core business for local communities, bringing income and employment benefits and create indirect linkages to also other SDGs (Swamy, Drazen, Johnson, & Bukoski, 2018; Tegegne, Cramm, Van Brusselen, & Linhares-Juvenal, 2019). Implementing protection policies for tropical forests is crucial for reducing deforestation. To set effective policies, it is vital to understand the drivers of deforestation in the tropics . Indonesia has the third-largest tropical rainforest and is one of the species-richest countries in the world (FAO, 2020a; Paoli et al., 2010).

While many studies have focused on tropical deforestation in Amazonia, fewer studies have investigated drivers in Indonesia. Studies about Indonesia have either focused on one specific driver, such as plantations of palm oil, timber and rubber or on region-specific deforestation (Austin, Schwantes, Gu, & Kasibhatla, 2019; Kastner et al., 2021).

In the last century, globalization has increased rapidly with production outsourcing and intermediate trade flows. This shaped land-use systems in a new way (Kastner et al., 2021). As a result, Indonesia and other tropical countries are the leading agricultural producers for high-income importing countries. This trade leads to an unequal distribution of environmental degradation due to land use changes and agriculture. To the best of my knowledge, a detailed analysis of the role of foreign demand, including several agricultural products, and its effect on changes in agricultural land use in Indonesia in the context of deforestation has not yet been conducted. Therefore, I ask the first research question:

1. How much are agricultural-induced deforestation emissions embodied in Indonesia's domestic consumption versus in the consumption of other countries? I will add to this question also the questions about how these consumption patterns changed over time and which nations are the primary importers of Indonesia's crop production, causing significant deforestation emissions. Therefore, I focus on deforestation carbon emissions for the period from 2005 to 2018 in the first part of the thesis by using the data provided from Pendrill et al. (2019).

The analysis of agricultural-induced deforestation emissions of the thesis is based on the physical trade model of Kastner, Kastner, and Nonhebel (2011) and does not account for intermediate trade flows, which have become in the last half-century a critical aspect of global trade (Pendrill et al., 2019). The importance of intermediate trade flows for agricultural products can be understood when looking at the global supply chain of palm oil, which has become increasingly complex in the last decade. Indonesia is one of the biggest producers of the global palm oil market (Pacheco, Gnych, Dermawan, Komarudin, & Okarda, 2017). The global value chain of palm oil increased in complexity as palm oil is used for several different products. After harvesting, crushing the palm oil seeds and producing the plain oil in a refinery, palm oil is further globally distributed to different industries' plants to be further processed for other goods, such as cooking oil, cosmetics, processed foods, detergents and bio-diesel (Pacheco et al., 2017). Afterwards, the final good is traded to the end consumer.

To account for intermediate trade flows and determine the primary contributor behind agricultural-induced deforestation, I apply a structural decomposition analysis by using multi-regional input-output (MRIO) tables in the second part of my thesis. This approach will answer my second research question:

2. What are the drivers of Indonesia's agricultural land use changes? As data on deforestation emissions of Indonesia with a detailed division of sector-level linked to intermediate trade flows is not available, I investigate the agricultural land use change in Indonesia, which is a primary driver of deforestation (Tsujino, Yumoto, Kitamura, Djamaluddin, & Darnaedi, 2016). I extend the MRIO tables of the World Input-Output Database (WIOD) by adding data on Indonesia's agricultural land use. The WIOD of the 2016 release is only from 2000 until 2014 available (Timmer et al., 2015). For that reason, the structural decomposition analysis is applied for this period.

Answering the two above-defined research questions, I will contribute to the literature with new insights into Indonesia's agricultural-induced deforestation emissions and land use embodied in global and domestic demand. The first part of my thesis shows that the balance of deforestation emissions embodied in trade (BEET) linked to agricultural production is positive for Indonesia, meaning Indonesia is a net exporter of emissions.[1] Moreover, when comparing emissions of production embodied in export to domestic use, Indonesia's deforestation emissions embodied in domestic use accounts for 59 % of all production-based emissions. This is around 1,000 Mt higher than the emissions embodied in its exports, accounting for 41 %. The structural decomposition analysis shows, for instance, that agricultural land use was strongest driven by changes in the final demand per capita and the Leontief inverse. Thereby, Indonesia's final demand increases land use more significant than any other region. However, the consumption per capita of China and India plays an important role in increased land use as well.

The thesis is structured as follows. Section 2 provides a detailed overview of the literature related to deforestation, drivers of deforestation and emission accounting approaches. Section 4 explains the structural decomposition analysis. Results of the descriptive analysis of Pendrill et al. (2019) data and the results of the structural decomposition analysis are presented in Section 5. Section 6 discusses the results and policy implications are considered. The thesis concludes with Section 7.[2]

2 Theory and Literature Review

2.1 Deforestation and Consequences

The Food and Agricultural Organization (FAO, 2020a) defines *"deforestation as the conversion of forest to other land uses"* (p.2). The definition matters as negative forest net changes are not the same as deforestation (FAO, 2020b). The latter is the sum of total forest loss and gain in each period and does not imply that the land use changed. Land use changes imply the role of human activity, while net forest loss could also be a result of tree diseases, droughts and other factors. This thesis follows the FAO (2020a)'s deforestation definition, putting a focus on the impact of human activities on forest changes.

Decreasing forest areas leads to dangerously increasing CO_2 emissions and thus fosters climate change (Van der Werf et al., 2009). Moreover, deforestation causes the loss of biodiversity, soil degradation and higher air and water pollution and more, which has long-term consequences

[1] The term net exporter of emissions means that a country has more emissions embodied in its exports of products consumed by other nations than emissions embodied in its imports of goods from other countries. In other words, the consumption-based (CBA) emissions are lower than the production-based (PBA) emissions. CBA and PBA will be explained in Section 2.4.

[2] Supporting information for this thesis: The complete analysis of this thesis is performed using Matlab and Stata software programs. On request, a code can be provided. All figures in this thesis are intended to be viewed in colour.

(Barlow et al., 2016; Burgess et al., 2012; Foley et al., 2011; Jie, Jing-Zhang, Man-Zhi, & Zi-tong, 2002; Marlier et al., 2013). On the other hand, deforestation is associated with several harmful social consequences like the decimating of indigenous societies, the development of new diseases and a higher risk of rural conflict (Lorenz et al., 2021; Pörtner et al., 2022; Rich, 2014). In addition, forests play a significant role in sustainable food security and livelihoods and other essential products and ecosystems that a forest provides (FAO, 2020a).

Reducing global emissions and biodiversity loss is crucial not to overstep the planetary boundaries concept introduced by Rockström et al. (2009) and risk that the environmental earth systems are getting out of balance and threatening multiple goals of the 2030 Agenda from the United Nations. Maintaining tropical forests as natural carbon stocks is a relatively inexpensive method for the mitigation of climate change (DeFries, Rudel, Uriarte, & Hansen, 2010).[3] The social and environmental problems have put deforestation toward the top of the agenda of global climate policies (Burgess et al., 2012). Nevertheless, clearing forests for commercial agricultural production can also bring social-economic positive effects such as higher income and income-related benefits like education (Drescher et al., 2016). Evaluating forest area and why it changes over time is crucial to measure the progress towards the SDGs.

According to FAO (2020b), 178 million ha of the world's forests have been lost since 1990. Nevertheless, the global deforestation rate per year decreased from 1990 to 2020 (see Table 1 for deforestation rates over different decades). However, not all countries have experienced a reduction in the last decades. There are significant regional and subregional differences in deforestation rates in the world (Table 1). Most deforestation-affected areas of recent years have been in lower-income countries such as Western and Central Africa (3. row of Table 1). In contrast, higher-income countries experienced stable deforestation or even a net increase in forest areas (Tsurumi & Managi, 2014). Tropical forests were the most affected forests by deforestation (Pörtner et al., 2022).

Asia faced one has the second-highest deforestation rates between 1990 to 2000 (Table 1, 1. Column). The overall Asian deforestation rate per year was almost halved by 2015-2020. Most of this deforestation rate reduction results from Chinese action against deforestation and afforestation programs, while in South and Southeast Asia, deforestation was more extensive than the forest gain between 1990 and 2020 due to significant deforestation in Cambodia, Indonesia and Myanmar (FAO, 2020a). Over the last two decades, the literature investigating deforestation has increased rapidly. Most focus has been on the tropical forest of South America. Nevertheless, attention to other deforestation hot spots in the world is increasing. Focusing on tropical deforestation is essential for two primary reasons: First, tropical regions face the highest rate of deforestation. At the same time, they are rich in enormous biodiversity (Pörtner et al., 2022).

[3] Forest as natural carbon stock describes the stored amount of CO_2 that is absorbed from the atmosphere. The CO_2 is primarily stored in soil and living biomass and with less amount in deadwood and litter.

Table 1: Deforestation rate by Region and Subregion between 1990 to 2020

Region/Subregion	1990-2000	2000-2010	2010-2015	2015-2020
	Deforestation (1,000 ha/year)			
Eastern and Southern Africa	1,781	2,2240	2,116	2,199
Northern Africa	461	442	330	316
Western and Central Africa	1,854	1,631	1,998	1,899
Total Africa	4,096	4,314	4,444	4,414
East Asia	399	353	369	170
South and Southeast Asia	3,689	2,232	2,460	1,958
Western and Central Asia	82	99	96	107
Total Asia	4,170	2,684	2,925	2,235
Total Europe	88	92	201	69
Caribbean	3	2	23	5
Central America	228	222	142	168
North America	740	475	253	263
Total North and Central America	972	699	428	436
Total Oceania	655	662	458	42
Total South America	5,837	6,667	3,354	2,953
World	15,818	15,117	11,801	10,150

Source: Data from FAO (2020a)

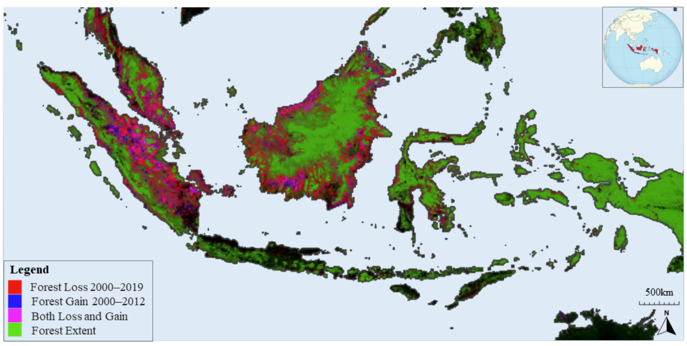
Second, many tropical forests are located in countries with less strong governance being unable to protect their forests, increasing the risk of illegal and unsustainable deforestation (Burgess et al., 2012).

2.2 Deforestation in Indonesia

Several reasons motivate to focus on deforestation in Indonesia. In the world, Indonesia has the third most significant area of tropical rainforest, which accounts for 92 million ha in 2020 (FAO, 2020a). This is 2 % of the world's forest area (FAO, 2020a). However, between 2010 and 2020, Indonesia had an average deforestation rate of -753,000 ha per year (FAO, 2020a). Indonesia experiences one of the highest rates of deforestation in the tropics. Only Brazil and the Democratic Republic of the Congo had higher rates worldwide for the same period (FAO, 2020a).

Figure 1 shows a map of Indonesia with forest gain (blue), loss (red) and forest extent (green) from 2000 until 2019. The map is conducted from satellite images of the data set of Hansen et al. (2013). First, the large green highlighted areas show the extensive amount of Indonesia's forests. Being aware that forest loss does not always have to be due to deforestation, according to FAO (2020a), the map shows that forest loss is a countrywide problem happening on several islands of Indonesia. Zarin et al. (2016) analyze further the satellite images of Hansen et al. (2013) for Indonesia and argue that most of its tree loss is resulting from plantation harvest, which accounts as a factor of deforestation. Country-wide deforestation makes it interesting to study deforestation at a country level.

Figure 1: Forest Loss and Gain between 2000 to 2019 in Indonesia. Author's construction based on satellite images of Hansen et al. (2013).



Indonesia is one of the species-riches countries. Unfortunately, extensive deforestation leads to a dangerous risk of biodiversity loss (Barlow et al., 2016). Vijay, Pimm, Jenkins, and Smith (2016) investigate the effect of deforestation driven by the palm oil industry on biodiversity loss in the five most affected countries between 1989 to 2013. They find high risk for biodiversity loss in all five countries, including Indonesia.

Furthermore, the study of Austin et al. (2018) shows that its high rate of deforestation results in Indonesia being one of the highest emitters of greenhouse-gas emissions worldwide. Burgess et al. (2012) state that the fast deforestation rate has put Indonesia once as the third-largest emitter of greenhouse gases behind the United States and China. Moreover, Marlier et al. (2015) find that the burning of organic peat soils linked to Indonesia's deforestation leads to higher air pollution, negatively affecting humans' health. Without policy measures to slow down deforestation, emissions will further increase in the future, as factors like positive economic growth and population growth will cause further deforestation. Indonesia has the fourth-largest population in the world, with an annual growth rate of 1.07 % in 2020 (World Bank, 2014d). The government aims to a rapid economic development strategy to lift people out of poverty, as in 2014, 11 % of Indonesia's population was still living below the poverty line (Aji, 2015). However, this strategy risks increasing deforestation and higher emissions due to higher pressure on land conversion. From 1990 to 2019, the cropland area of Indonesia already increased by 60 %, putting Indonesia in the sixth position of the countries with the largest cropland area (FAO, 2021). Indonesia's government is already aware of the increased risk to its ecosystems and environment. However, the importance and size of the agriculture sector for Indonesia's economy and labour market challenges a fast sustainable transition (World Bank, 2021). The contribution of its agriculture sector (13 %) to the national gross domestic product has slightly decreased in the last three years. Nevertheless, it still accounts for the third-largest contributor (World Bank, 2021). Moreover, 29 % of Indonesia's total employment is working in the agriculture sector. This share decreased from 2000 from 45 %, nevertheless remains still very important for the labour market (World Bank, 2014a).

Several events related to Indonesia's deforestation motivate this thesis to focus on the period from 2000 until 2018. At the beginning of the 21st century, Indonesia's government promoted large oil-palm plantations, developed on several islands. In 2008, Indonesia surpassed Malaysia in palm oil production and is now the world's largest producer (Shigetomi, Ishimura, & Yamamoto, 2020). Rapid deforestation happened between 2000 and 2016, which peaked around 2016 (Global Forest Watch, 2020). In the last years, deforestation of primary forests has declined. Simultaneously, an international and local network of NGOs, local actors and agencies was established, protesting against commodity-driven deforestation (T. K. Rudel, Defries, Asner, & Laurance, 2009). In 2011, the government implemented the Indonesia Forest Moratorium, which should protect 21 million ha of peatland and 44 million ha of the primary forest while at the same time slowing down the palm oil plantation expansion (USDA Foreign Agricultural Service, 2011). In order to support the Moratorium and protect even more forest areas, it is essential to identify the latest causes of deforestation in Indonesia and the responsible actors by answering the two aforementioned research questions of whose consumption of agricultural products is driving Indonesia's deforestation.

2.3 Drivers of Deforestation

As primary drivers of tropical deforestation are often similar, and to extend the relatively small literature on Indonesia's deforestation, this thesis reveals and discusses several general and not only Indonesia-specific drivers of tropical deforestation in this section. This section provides an overview of general forces such as economic growth and focuses on the role of agricultural production and underlying forces of domestic and international agricultural demand.

2.3.1 Deforestation and Environmental Kuznets Curve

The regional differences in deforestation rates with higher rates in lower-income countries raised the question if the economic growth of countries is related to deforestation. The general relationship between economic development and environmental degradation is known under the Environmental Kuznets Curve (EKC). Environmental economists derived the EKC from the general Kuznets Curve, which Kuznets (1955) attempted to describe the relationship between income inequality and economic growth over time. The EKC examines environmental degradation instead of inequality. The literature on deforestation has also examined the EKC's hypothesis of a possible inverted U-shaped relationship between deforestation and economic growth.

Indonesia's government's ambitious economic growth strategy risks further deforestation, leading to harmful consequences. However, in the case of an EKC for deforestation, it may be expected that with further economic growth, deforestation starts to decline. The theory of EKC can provide possible explanations. Evidence of EKC would tell if we can learn about the extensive environmental degradation of higher-income countries in their past and try to implement more sustainable strategies for growth to flatten the EKC without affecting the development of lower-income countries.

First, the following on the general understanding of EKC: In the early 1990s, Grossman and Krueger (1991) argued that the relationship between the level of air pollution and economic development follows an inverted U-shaped relationship. Grossman and Krueger (1991) looked thereby at the per capita pollution and income in the context of the North America Free Trade Agreement, suggesting that the pollution increases with higher income per capita until a certain threshold, from which onwards pollution continues to decrease. Following literature has built on this theory, arguing that until a threshold level of income, further economic development can be reached without further increasing environmental degradation. A significant implication is that multiple environmental indicators of environmental degradation for the EKC can be examined, such as carbon emissions, biodiversity loss, and deforestation. The World Bank's World Development Report 1992, in which environmental protection is linked to income development, had given a significant push to find confirmation of the EKC (Shafik & Bandyopadhyay, 1992; World Bank, 1992). Even with stronger criticism on the importance of the EKC (Stern, 2004), the EKC as a theoretical concept of explaining environmental degradation over time remains central.

According to the literature, economic growth has three effects on environmental degradation: scale, composition, and technique effects (Brock & Taylor, 2005) The scale effect implies that as the economy grows, the degree of environmental damage will increase (i.e. deforestation). Economies heavily depend on agriculture in the early stages of economic development (pre-industrial periods). However, the amount of land needed per capita is less efficient with lower technological progress. This means that environmental degradation is unavoidable. Moreover, with positive population growth, the demand for converting forests to agricultural and grazing land increases, enhancing deforestation (Tsurumi & Managi, 2014). In favour of the EKC for deforestation also speaks the role of forest products as an energy source in pre-industrialized countries. With economic development, wood is substituted with other energy sources and decreases the deforestation rate (Cropper & Griffiths, 1994). The composition effect states that when real income rises, the composition of production shifts between industries that cause different degrees of environmental degradation as a shift from agricultural to industrial or service, i.e. structural change. The technology impact occurs when sectors of the economy use improved production technologies to minimize ecological damage. With further economic development, agricultural technologies improve the efficiency of land use per capita, implying that even with further population growth, not necessarily more land is needed (Cropper & Griffiths, 1994). However, it must be noted that land use per capita depends not only on agricultural technological progress but also on consumption changes per capita (FAO, 2017).

Another explanation for the decline in environmental degradation after a certain threshold of income is the idea that the environmental quality is a luxury good and the demand for a more sustainable economy increases with higher income (Tsurumi & Managi, 2014).

The earlier literature about EKC for deforestation found mixed evidence. Shafik (1994) and Koop and Tole (1999) found no statistically significant evidence supporting the EKC for deforestation. In contrast, Cropper and Griffiths (1994) and Ehrhardt-Martinez, Crenshaw, and Jenkins (2002) confirmed the inverted U-shaped relationship. Literature from the 21st century tried to bring greater clarity into this debate. However, mixed results remain.

Using annual agricultural land use changes as a proxy for deforestation, Barbier (2004) found no statistically significant relationship between land use changes and income per capita. Looking at the period from 1990 until 2000 and considering institutional variables as indicators for economic development, Ferreira (2004) supports that there is no EKC for deforestation. Looking at satellite pictures from a more recent period of 2001 and 2010 for 128 countries, Leblois, Damette, and Wolfersberger (2017) also argue against the existence of a deforestaion EKC. Using the same satellite data but only considering 95 countries from 1999 to 2014, Andree, Spencer, and Chamorro (2019) find supporting evidence with a turning point of US$3,000 income per capita. It seems that regional heterogeneity drives the results when investigating a deforestation EKC.

Accounting for potential regional variation, Bhattarai and Hammig (2001) analyze the EKC for tropical deforestation in a study of 66 countries in Latin America, Africa and Asia between 1972 to 1991. Their results strongly support evidence of a U-shaped relationship between deforestation and income per capita for Latin America and Africa. In contrast, a reversed pattern is shown in Asia. Bhattarai and Hammig (2001) also show that improvements in institutions can significantly reduce deforestation and seems to be more critical for the rate of deforestation than income. A slightly more extended period from 1972 to 2003 is considered by Chiu (2012). Chiu (2012) looks at 52 lower-income countries and uses a panel smooth transition regression model, which supports the findings of Bhattarai and Hammig (2001) for the existence of the EKC in the context of deforestation. A more recent study by Caravaggio (2020) examines a panel data set of 55 years and 114 countries divided into low, middle and high-income countries. The article evaluates this sample in a static and dynamic manner. The findings support an EKC for deforestation. Hence, Caravaggio (2020) argues that deforestation is likely to increase in lower-income countries and more substantial effort is needed to slow down environmental degradation and reach earlier the turning point.

Evidence for the deforestation EKC in Indonesia has also been found by Waluyo and Terawaki (2016) from 1962 until 2007. They estimate an income turning point of US$990. This national income per capita level was surpassed in 2002 in Indonesia (World Bank, 2014b) and is lower than the above-mentioned turning point of Andree et al. (2019). Evidence of a deforestation EKC in Indonesia is also supported by findings of Adila, Nuryartono, and Oak (2021), who look at 32 Indonesia's provinces.

An explanation for the mixed results could be the different dependent variables used as a proxy for deforestation and the regional differences regarding the income effect. Nevertheless, the empirical models in the literature have also changed over time from static to more dynamic approaches. Moreover, Bhattarai and Hammig (2001) and Babier and Burgess (2008) highlight the significant influence of political institutions, which might be somewhat more important than the income effect per se, even if good institutions are highly correlated with higher income per capita. Finally, the debate about the EKC is complicated by the lack of data for a more extended period of forest cover (Caravaggio, 2020). However, providing clarity in this debate remains further research and is not the focus of this thesis. For effective government measures against tropical deforestation to flatten a potential EKC, the knowledge about the relationship between economic growth and deforestation is essential. More critical is the understanding which economic drivers of tropical deforestation play a key role, which will be analyzed in the next

Section.

2.3.2 Agricultural-driven Deforestation

Various human activities drive deforestation: Agricultural land expansion, shifting cultivation practices, infrastructure and urban development, forestry production and forest fires (Austin et al., 2019). These factors have been grouped in the literature into three main drivers: Conversion of the forest into pasture and cropland, collecting of fuelwood and the harvesting of logs (Cropper & Griffiths, 1994). Population growth is emphasized as an indirect and underlying driver of the three primary factors. This thesis focuses on the drivers of agricultural land expansion, such as final demand per capita and population and the role of agricultural trade, since tropical forest loss is primarily driven by agricultural-induced deforestation (FAO, 2017; Gibbs et al., 2010).

Since the 1990s, the agriculture sector structure shifted from small-scale subsistence farmers to more commercialized exporting agriculture in Southeast Asia and Latin America (Curtis, Slay, Harris, Tyukavina, & Hansen, 2018; T. K. Rudel et al., 2009). This shift also includes the transition from small farmers inducing deforestation to capitalized, larger and well-organized companies driving deforestation in Southeast Asia, including Indonesia (T. K. Rudel et al., 2009). With the further economic development of tropical countries, Fischer and Heilig (1997) predicted that the area of cultivated land is likely to increase by over 47 % by 2050, with deforestation and wetland conversion accounting for about 66 % of the new agricultural land.

Figure 2: Primary Deforestation Drivers between 2001 to 2020 in Indonesia. Source: Global Forest Watch (2020), Author's Construction.

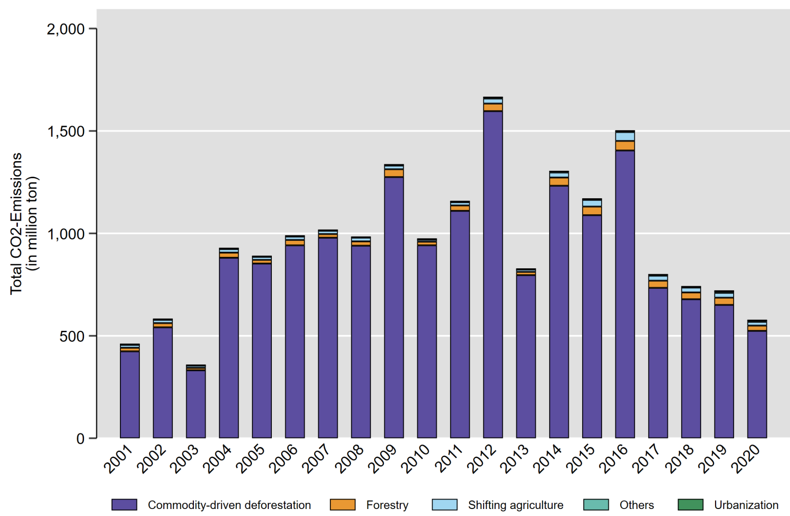


Figure 2 shows that most of Indonesia's deforestation emissions are driven by commodity-driven deforestation, i.e. commercial agriculture. Other factors like forestry, shifting agriculture and urbanization play compared to commodity-driven deforestation a minor role.

Cross-country and country-specific studies investigated significant drivers of deforestation in Indonesia in the last two decades, supporting the general finding that agricultural production is indeed the primary driver in Indonesia. A common approach in analyzing deforestation drivers is examining satellite images over time. This approach views high spatial resolution pictures from satellites and classifies them into different land use categories. Austin et al. (2019) examine satellite images of Indonesia with 12 different land use categories between 2001 to 2016.[4]. The use of satellite data brings the advantage that one does not have to rely on national statistics, which are often not complete, especially in tropical countries of the Global South, and are often only available in aggregated form. Another advantage is that one has country-specific data and can also compare different regions within the country. Austin et al. (2019) find that between 2001 and 2016, the primary drivers of Indonesia's deforestation were large-scale palm oil and timber plantations. Palm oil-induced deforestation reached a peak from 2008 to 2009. During this time, it almost accounted for up to 40 % of the total deforestation in Indonesia (Austin et al., 2019). However, deforestation due to conversion to grassland also increased strongly, particularly at the end of the study period. On the smaller islands of Indonesia, small-scale plantations and agriculture are the primary causes of deforestation (Austin et al., 2019).

A regional perspective of Indonesia is also taken by Gaveau et al. (2016), who find that the deforestation due to palm oil plantations strongly increased after 2005. Before 2005, many palm oil plantations were developed on already "cleared degraded land". He focuses on Indonesia's island Borneo, arguing that the palm oil industry is the most significant driver of deforestation. Besides palm oil, Warren-Thomas, Dolman, and Edwards (2015) argue that the development of rubber plantations contributes to deforestation in Indonesia and elsewhere in Southeast Asia and is strongly driven by global demand. The impact of the driver grassland, crop production and small-scale agriculture motivates the topic of this thesis to look closer into which agricultural products are causing deforestation emissions and analyze in the second part of this thesis what drivers are lying behind the agricultural land use change in Indonesia.

2.3.3 Population Growth

Population growth increases the pressure on the expansion of agricultural land use. Thereby, increasing agricultural land use can lead to more extensive deforestation. According to the FAO (2017) global population is predicted to grow to around 10 billion by 2050, increasing the demand for agricultural products. Many researchers are concerned about the unprecedented pressure on the earth's land and the impact of deforestation in countries such as Indonesia (Godfray et al., 2010; Tilman, Balzer, Hill, & Befort, 2011). Discussing the role of population growth on deforestation becomes crucial for understanding the driving forces behind the agricultural land

[4]The 12 categories used by Austin et al. (2019) are palm oil plantation, timber plantation, other large-scale plantations, grassland, small-scale agriculture, small-scale mixed plantation, small-scale palm oil plantation, mining, fish pond, logging road, secondary forest and others

expansion. The theory of population growth and deforestation is based on the well-known argument of Malthus that population growth increases the pressure on agricultural land (Cropper & Griffiths, 1994). In a modern context of literature, Malthus' argument is interpreted that "geometric" population growth can exceed "arithmetic growth", i.e. subsistence, leading to the consequence that environmental degradation will be inevitable due to the constraints of environmental resources like lands (Shandra, 2007). However, with structural change and technological improvements, population growth does not necessarily have to create pressure on land, adapting the Malthusian theory (Cropper & Griffiths, 1994). In recent years, a related question to this relationship arose whether the changes in consumption per capita might put higher pressure on agricultural land use than on population growth. In the second part of my thesis, I consider both factors, the final demand per capita and population, to investigate to what extent these are drivers of agricultural land use change in Indonesia.

According to DeFries et al. (2010), the increasing world population puts pressure on the food supply and land, leading to a more robust conversion of forest areas to agricultural land. Their argument support early findings in the literature that population growth enhances tropical deforestation (Ehrhardt-Martinez et al., 2002; T. Rudel & Roper, 1997; Shandra, 2007). However, regional heterogeneity in whether population growth is a significant driver exists. Allen and Barnes (1985) investigated drivers of deforestation in 39 countries in Asia, Africa and Latin America from 1968 to 1978 by using an ordinary least squares (OLS) regression. Their findings support the argument that population growth is a significant driver of deforestation due to the indirect link of agricultural expansion. However, being aware of the limitations of OLS regression not to be able to investigate causal relationships, these findings need to be interpreted with caution. Adjusting the limitations of OLS, Cropper and Griffiths (1994) use a fixed-effect model with data from 1961 to 1988 from 64 lower-income countries in Asia, Africa and Latin America and find, in contrast, no significant correlation between population growth and the rate of deforestation. They only find a significant relationship between these two variables for the rural population in Africa. Nevertheless, a more recent study by DeFries et al. (2010) finds opposite results that population growth as a cause is mostly driven by urban population growth and not by rural population growth. But DeFries et al. (2010) focus on the period of 2000 to 2005 at 41 countries of the tropics. Due to the differences in their data sample, the two different results of Cropper and Griffiths (1994) and DeFries et al. (2010) studies cannot be compared directly. The heterogeneity of the relationship can also be seen in the study of Bhattarai and Hammig (2001), which shows that the impact of population on annual deforestation rates differs depending on the sample region for 1972-91. They find a significant negative effect of population growth on deforestation in Latin America (-0.041***) and Africa (-0.02***), while it is a reversed effect in Asia (0.24***) from 1972 to 1991, meaning that population growth is correlated with decreasing deforestation in Latin America and Africa and increasing deforestation in Asia.

More recent data from the period 2001 until 2010 for lower-income countries by Leblois et al. (2017) found a statistically significant positive effect of population density on deforestation when a static model is used. However, the effect of the population remains only significant for the lower-income countries in Africa (0.774***) and Latin America (8.141**). In contrast, no significant effect is found in Asia and the Pacific (5.827). Leblois et al. (2017) findings contradict the results of the earlier study by Bhattarai and Hammig (2001). It could be that differences in the country coverage can explain the difference in the results or that the correlation has changed over time, as Bhattarai and Hammig (2001) study an earlier period. Moreover, Leblois et al. (2017) look at population density instead of population growth, which could also lead to the contrary results.

Results of the current literature suggest that the impact of the own population of Asian countries, including Indonesia, on their deforestation risk might be less relevant than in other regions of the world (T. K. Rudel et al., 2009). Jha and Bawa (2006) highlight that other reasons than population growth must play a more critical role in Indonesia's high deforestation rates. They refer to the role of trade openness as a driver.

Besides population growth, changes in the consumer preferences for agricultural products can further increase or decrease the demand for cultivated land (FAO, 2017). The FAO (2017) highlights that the individuals of lower- and middle-income countries experience a dietary change towards higher amounts of consumed meat, fruits and vegetables due to income growth and thereby increasing the risk for deforestation additionally to population growth. Analyzing different agricultural production scenarios to achieve a zero-deforestation world in 2050, Theurl et al. (2020) argue that changes in human diets remain the most critical factor, e.g. changing from a high meat to a plant-based diet. Some agricultural products, like meat, dairy and palm oil, especially in Indonesia, lead to a higher level of deforestation than other products. This implies that deforestation due to agricultural expansion is also driven by the choice of products that are consumed. Trying to reduce this pressure, firms, governments and private consumers have been choosing to implement and consume more products with eco-certification labelled products in recent years, which certify goods that have been produced without causing deforestation (Dauvergne & Lister, 2010). Literature defines this consumer shift as eco-consumerism. However, the effectiveness against deforestation is not apparent yet (Dauvergne & Lister, 2010). Most of the studies focus on the consumer choice of palm-oil-free products. Dauvergne and Lister (2010) argue that forest certification is only in some places practical, and the potential of eco-consumerism is generally overestimated.

To briefly summarize, agricultural production is affected by population growth and consumption per capita. Therefore, I will control for these two factors in the SDA when answering the second research question (see Section 4).

Literature about Indonesia's agricultural-induced deforestation has primarily focused on subregions, like Borneo, single crops (e.g. palm oil production) or specific forest types (e.g. peatland forests). However, almost no studies have analyzed agricultural products' primary consumers and trading partners inducing land expansion and deforestation in Indonesia. As own population growth could not be identified as an underlying factor of deforestation for several Southeast Asian countries, including Indonesia, scholars suggest that global demand of other countries could drive agricultural-induced deforestation (Jha & Bawa, 2006; T. K. Rudel et al., 2009). Hence, the role of agricultural trade and global demand will be discussed in the next Section.

2.3.4 Agricultural Trade and Global Demand

Increasing global trade volume of agricultural products has constantly shaped transformations of land use systems since the industrial revolution (Brolin & Kander, 2020). Since 1950, the land use systems changed further into a dynamic system which industrialized and globalized patterns, in part due to the "Great Acceleration" (Brolin & Kander, 2020; Kastner et al., 2021). Following standard trade theories can help understand the pressure of global trade on tropical land. A higher level of trade openness increases agricultural commodities' export production in countries with a comparative advantage in agricultural production resources (Abman & Lundberg, 2020).

The share of specific agricultural commodities in total agricultural trade has shifted over time. For instance, while grains remain as one of the most critical shares of agricultural traded products, in recent years, the share of specific cash crops, like palm oil, grew rapidly, which led to several harmful consequences in many tropical land systems such as Indonesia's (Kastner et al., 2021).

Two general trends in agricultural trade arose in the last half-century and can be divided into spatial and crops pattern. First, the spatial distribution of agricultural trade is mainly formed by trade from either low-densely populated regions to higher populated regions or from lower-income countries to higher-income countries. Second, around 60 % of traded calories and around 44 % of proteins come from only five traded crops: Soybean, wheat, maize, sugar and palm oil (Kastner et al., 2021). As stated earlier, Indonesia arose as one of the major exporting countries for some of these crops, particularly palm oil.

Studies from the early 21st century investigating the effect of trade openness on deforestation could not clarify the impact of trade on deforestation. For example, Frankel and Rose (2005) employ a cross-section analysis for 41 countries (including Indonesia) for the year 1990 and find no statistically significant results when applying an OLS regression. Also, Van and Azomahou (2007) cannot find significant effects of trade openness by using a fixed-effect model and a panel data set of 59 lower-income countries from 1971 to 1994. However, more recent studies were able to find evidence supporting the theory that agricultural trade causes deforestation. Tsurumi and Managi (2014) apply a dynamic model using a data set containing 142 countries over the period 1990 to 2003. They find that higher levels of trade openness increase the deforestation rate in non-OECD countries while it decreases the deforestation rate in OECD countries. Tsurumi and Managi (2014) link their findings back to the second explanation of the EKC, the composition effect. They argue that trade openness affects the composition of industries due to the comparative advantage of a country. A shift in the composition of industries can increase deforestation if land use extensive industries are growing due to the composition effect in a country (industry shift). When testing empirically for the EKC, Tsurumi and Managi (2014) find no statistically significant relationship that confirms the EKC for deforestation in either OECD or non-OECD countries. They argue that trade openness may be a stronger driver than income effects per se, and thus, there is no statistically significant effect supporting an EKC.

Using new collected high-resolution spatial data on forest loss, Leblois et al. (2017) investigate cross-country drivers of tropical deforestation from 2001 until 2010. Their study shows that countries with more forest-covered land face a more significant risk of deforestation caused by trade than countries with smaller forest areas. Abman and Lundberg (2020) look at the effect of regional trade agreements of 189 countries between 2001 and 2012 and find that a higher level of openness of trade increases deforestation significantly. Nevertheless, this study also faces limitations as the period for studying regional trade agreements is relatively short. The number of regional trade agreements has largely increased since the end of the 1980s (World Bank, 2018), which means that the event of joining a regional trade agreement of the earlier years is not accounted for, which could bias the results. As Abman and Lundberg (2020) use an event study methodology, a more extended period before the event of interest can help to estimate more precisely.

A shortcoming of studies including extensive coverage of countries is that it does not allow for understanding country-specific trade patterns as driver for deforestation.

López and Galinato (2005) analyze structural relationships as country-specific drivers of deforestation in Brazil, Indonesia, Malaysia and the Philippines. While in Brazil and the Philippines, trade openness increases forest area, in Indonesia and Malaysia, trade of agricultural products leads to a higher conversion of forest to agricultural land use. One explanation for this result is the difference in commodity export policies. The country study of Indonesia by Tsujino et al. (2016) shows the different intensity of primary drivers over periods. From 1970 to the mid-1990s, global demand, population growth and a transmigration policy enhanced deforestation as the cultivation of, among others, rice increased. From the mid-1990s to 2015, the global demand for timber and palm oil from Indonesia increased strongly and incentived non-sustainable land expansion and uncontrolled deforestation.

Literature shows that agricultural production and trade are primary factors for deforestation in Indonesia (DeFries et al., 2010; Leblois et al., 2017; López & Galinato, 2005). However, studies including agricultural trade as a driver often use linear regression models. However, linear regression approaches do not allow for accounting for intermediate trade flows and analyzing who are trading partners and consumers of the traded products, causing deforestation. To implement effective policy measures, it is vital to discuss which agricultural products are driving deforestation and who is consuming it because of the importance of global demand for Indonesia's deforestation. Nevertheless, knowledge about the consumers of these products is not enough to fight against deforestation. In addition, it needs to be agreed on who bears the responsibility. In the literature and on political agendas and conferences, there is no explicit agreement about dividing the responsibility between producers and consumers and stakeholders of the whole value chain. A brief overview of this debate in the literature is provided in the following, to which also the discussion of this thesis will refer in Section 6.

2.4 Producer and Consumer Responsibility of Deforestation

In 2015, Indonesia committed to the Paris Agreement with the ambition to reduce emissions from 2020 to 2030 by 29 % unconditionally and up to 41 % conditionally against the business as usual scenario (Dhewanthi, 2021). The government also states the awareness of Indonesia's role in protecting the high level of biodiversity and tropical rainforest by reducing deforestation and clearing primary forests. Accounting for national emissions for evaluating the NDCs of countries has raised a significant debate in the literature of emission accounting, as there is sizeable technical difficulty and uncertainty in measuring emissions (Vaidyula & Hood, 2018). Most literature on emission accounting focuses on the emissions embodied in the energy sector. However, the same emission accounting methods can also be applied to emissions embodied in deforestation and other so-called satellite accounts.

With increasing global trade flows and outsourcing of agricultural production to some particular countries, such as Indonesia, the global demand for crops from the tropics is increasingly driven by global demand (Kastner et al., 2021). Thus, the question established who is responsible for deforestation and deforestation emissions in the tropics. Several approaches to sharing responsibility regarding environmental pressure between producers and consumers have developed recently. It can be generally distinguished between full-responsibility approaches, which mean that one party, i.e. producer or consumer, is taking the full responsibility as well as shared and value-added based responsibility approaches, to name a few. First, the value-added-based responsibility allocates the environmental footprint along the global value chain to the responsible actors regarding their share of value-added within the particular supply chain (Pinero, Bruckner, Wieland, Pongrácz, & Giljum, 2019). Following this accounting approach, certain countries and sectors hold higher or less responsibility than they would have compared to using full accounting approaches (Pinero et al., 2019). Second, the shared producer and consumer responsibility also divided the responsibility of each transaction to the supplier and partly to the consumer of a commodity (Gallego & Lenzen, 2005). Gallego and Lenzen (2005) suggest that instead of following a full responsibility approach, the burden of the (environmental) production footprint should be allocated among all stakeholders of a supply chain and the demand for the product, taking their contribution into account. Moreover, a relatively new accounting scheme at the national level has been developed by Dietzenbacher, Cazcarro, and Arto (2020). With their emission responsibility allotment (ERA) system, nations are allocated credit or penalties based on whether their trade reduced or increased global GHG emissions. Nevertheless, this scheme is more suited to measure overall mitigation effects at a country level rather than specific stakeholders. The results of the ERA scheme compared to CBA are quite similar (Dietzenbacher, Cazcarro, & Arto, 2020).

The discussion about producer and consumer responsibility is increasing and is gaining more weight on political agendas. This thesis captures only the producer nation Indonesia and other final demand nations (consumers) as actors. The chosen country-level data and methodology will not allow allocating to all stakeholders active in the supply chain of Indonesia crops. Thus, the three full-responsibility approaches will be discussed in more detail in the following.

First, production-based accounting (PBA, also called territorial responsibility) accounts for all emissions embodied in a country's production. This traditional approach is used in the official carbon reports of the UN Framework Connection on Climate Change (UNFCCC) (Peters, Minx, Weber, & Edenhofer, 2011). With the increase in global and intermediate trade due to outsourcing of production processes, many high-income countries have stagnated or experienced a decrease in emissions when measured with PBA (Peters et al., 2011). In contrast, the production-based emissions of countries in the Global South have increased. These patterns from the energy-related emissions can also be linked to emissions of deforestation (Pendrill et al., 2019). With the increasing outsourcing of the leading agricultural products like grains, soybeans, palm oil and beef from higher- to lower-income countries (Kastner, Erb, & Haberl, 2014), methods accounting for deforestation emissions should include the role of international trade as well. Outsourcing deforestation risk may also explain why for higher-income countries, at least in some regions, an EKC of deforestation was found.

Kander, Jiborn, Moran, and Wiedmann (2015) argue that an emissions accounting approach should fulfill three significant conditions: *"First, it should be responsive to factors that nations can influence, for example, the level and composition of their consumption, and their domestic carbon efficiency (sensitivity). Second, countries should not be able to reduce their national carbon footprints in ways that contribute to increased global carbon emissions (monotonicity). Third, the sum of national emissions for all countries should equal total global emissions (additivity)" (p.431).* The literature has widely discussed the criticism of PBA not fulfilling these conditions. PBA faces the risk that countries avoid their responsibility regarding their NDCs to reduce emissions by not accounting for the imported emissions embodied in their consumption as these products were produced elsewhere. Thus, PBA demonstrates the risk of carbon leakage across borders (Davis & Caldeira, 2010).[5] To overcome the limitations of PBA, two other full-responsibility approaches have been introduced as alternatives: Consumption-based accounting (CBA), recently complemented with the technology-adjusted consumption-based accounting (TBCA) and the income-based environmental responsibility. CBA (i.e. upstream responsibility) accounts for all emissions that are embodied in the consumption of goods to the consumer, which means that domestically produced emissions minus the emission embodied in exports of a country are accounted plus the emissions embodied in the imports of the same country (Marques, Rodrigues, Lenzen, & Domingos, 2012). The income-based environmental or downstream responsibility is similar to CBA. However, it measures the emissions generated downstream in a global value chain to the final demand and allocates the responsibility to the actors who are gaining an income from selling/producing the good that the emissions are accounted for (Marques et al., 2012). Marques et al. (2012) argue that actors earning an income are benefiting from emitting emissions when selling a good, and therefore, they could compensate for the environmental pressure and should take the responsibility. These approaches are full-responsibility allocations as well. However, researchers have introduced various PBA, CBA, and income-based accounting combinations. A review can be seen by Rodrigues, Domingos, and Marques (2010). Nevertheless, CBA and income-based accounting do not satisfy these three conditions (sensitivity, monotonicity, additivity), as they only fulfill the first condition.

Kander et al. (2015) address two major weaknesses of the CBA regarding climate policies. First, because all export-related emissions are passed on to end consumers, CBA does not consider changes in the carbon efficiency of export industries. Second, CBA fails to account for specific specializations and trade. Thereby, international trade can increase the global emissions but can also contribute to a more carbon-efficient production at a global scale if emission-intensive products are outsourced to countries that use renewable energy sources and have higher levels of emission efficiency (Kander et al., 2015). To account for differences in national carbon efficiency (sensitivity) in the export sectors of countries, Kander et al. (2015) introduce the TCBA. TCBA is similarly constructed as CBA, with the significant difference that the export emissions are not weighted to the national average intensity, rather than calculated with the global average carbon intensity of the regarding sector (Kander et al., 2015).[6]

The technological adjustments for CBA are less relevant for accounting for deforestation emissions embodied in trade, as their emissions result from the conversion from forests to agri-

[5]Carbon leakage describes the process in which a country committed to climate goals of international agreements such as the Kyoto protocol is reducing its GHG emissions due to outsourcing its production to a country that is not-committed and then imports the products again for the domestic use (Peters & Hertwich, 2008).

[6]In theory, the TCBA aims to hold all three conditions under the assumption that there is an equal substitution at the global market average carbon intensity (Baumert, Jiborn, Kander, & Kulionis, 2022). However, this assumption does not often hold in practice, as dynamics effects and price elasticities are not considered. Nevertheless, Baumert et al. (2022) suggest that, despite its shortcoming in terms of dynamic impacts, the TCBA is a good compromise since the additivity criterion is met, which is critical to ensuring that global emissions reductions are achieved even if all nations accomplish their NDCs.

cultural land. Thus there is no technological efficiency that can be directly improved. However, if emissions from agricultural production would also be linked to crops inducing deforestation, technological adjustments could be made, for example, through the use of pesticides or fertilizers.

The discussion of producer and consumer responsibility shows the importance of emissions accounting in the context of global trade. To ensure countries are not ignoring their responsibility regarding their consumption of imported agricultural products that are inducing deforestation elsewhere, CBA is a preferred approach to measure deforestation emissions embodied in trade and reduce the risk of emission leakage linked to deforestation according to Pendrill et al. (2019). Even if many deforestation-affected countries, including Indonesia, joined the UNFCC program REDD+[7], there is still evidence that emission leakage is happening, as not all tropical hot spots of deforestation are covered by the REDD+ (Streck, 2021).

Discussing the trade pattern of Indonesia's crops linked to deforestation to answer the defined research questions is closely linked to the debate about producer and consumer responsibility. Few studies have tried to understand what role global demand has for deforestation responsibility and who producers and consumers are.

Literature studying deforestation emissions embodied in international trade is relatively small, and some of them face limitations regarding their data sample and methodology. Saikku, Soimakallio, and Pingoud (2012) look for Brazil and Indonesia for the year 2007. According to them, in 2007, 15 % of Indonesia's total agricultural land was used for exports. But their study focusing on only 2007 gives no insights into broader and long-term trends. Additionally, they do not link their results to end consumers.

Kastner et al. (2011) are using a physical (non-monetary) bilateral trade model while looking at land and water use embodied in trade. They also include intermediate trade flows between countries but not between sectors. They analyze a case study of soybean land use and Austria's consumption. The bilateral trade data set was further extended in Kastner et al. (2014), in which they aggregate over 200 countries into eleven regions to follow agricultural products to the end-consumer. However, both studies do not include the linkage to deforestation in their analysis. Building upon that physical model, Henders, Persson, and Kastner (2015) look at a period from 2000 until 2011 for seven countries but only four commodities. They found that soybeans, palm oil, wood products, and beef are responsible for 40 % of tropical deforestation in the seven countries, including Indonesia. Thereby, one-third of it was cultivated for exports in 2011, which increased from accounting for only a fifth in 2000.

Saikku et al. (2012), Kastner et al. (2014) and Henders et al. (2015) only look at some countries and years. Moreover, they do not consider a multi-regional perspective of trade and

[7]REDD+ stands for the effort of countries to "reduce emissions from deforestation and forest degradation, and foster conservation, sustainable management of forests, and enhancement of forest carbon stocks" was established by the UNFCC in 2007. Participating countries are unable to avoid their responsibility for causing deforestation elsewhere (Streck, 2021).

include deforestation. The drawback of not accounting for intermediate trade flows between sectors is an issue that analyses using MRIO tables try to solve (Stadler et al., 2018). The criticism of not accounting for intermediate trade flows between sectors underestimates the total amount of the environmental degradation consumed by some countries. For example, some deforestation embodied in agricultural products from country A are going through intermediate trade flows into country B's manufacturing sector and are further processed and traded to country C. However, the model of Kastner et al. (2011) is not measuring deforestation embodied in other sectors through intermediate trade flows from country A to C and thus underestimates C's consumed amount of deforestation and overestimates B's amount.

Karstensen, Peters, and Andrew (2013) is one of the first who uses a MRIO model from the Global Trade Analysis Project (GTAP) to investigate the international supply chains of soybeans and cattle meat as a driver of Brazilian deforestation. They find that around 30 % of carbon emissions are embodied in the exports from Brazil and that China and Russia are leading importers.

Stadler et al. (2018) presents an extension of several environmental accounts, including three different categories of agricultural land use, to the MRIO tables of the EXIOBASE. Moreover, the land use data are allocated across the EXIOBASE sectors, which allows to also account for intermediate trade flows that are missing in the approach of Kastner et al. (2014). However, Kastner et al. (2014) do contribute to the literature with their model as they account for several agricultural products 56 and cover more bilateral trade flows of different countries from the FAOSTAT compared to Stadler et al. (2018), who combine the crops into nine larger categories.

The recent study by Pendrill et al. (2019) contributes to the literature by not only focusing on 106 tropical and subtropical countries but also by comparing data on deforestation embodied in trade from the physical trade model of Kastner et al. (2014) to the results using the MRIO tables of EXIOBASE 3 database of Stadler et al. (2018). They find that in the physical trade model 29 % CO_2 emissions of deforestation embodied in agricultural products belong to exported goods (i.e. 0.8 $GTCO_2$ yr-1). The MRIO model shows that this share increases to 39 % (1.0 $GtCO_2$ yr-1), which is due to intermediate trade between sectors. Following the trade flows to the consumer countries, most deforestation emissions are embodied in the imports to Europe, China and the Middle East. Pendrill et al. (2019) also refer to the discussion about a PBA or CBA approach and argue in favour of the CBA to include deforestation emissions into the national accounting of emissions of the consumer countries.

Even if Pendrill et al. (2019) also take a look into Indonesia's products contributing to larger shares of deforestation emissions embodied in export, a detailed analysis of Indonesia's products linked with deforestation emissions embodied in trade is missing. To address the gap in the literature, this thesis will answer the first research question of how much deforestation emissions are due to agricultural crop production embodied in Indonesia's consumption and in international demand and who are the main importers as well as the second research question, which factors are determining driving Indonesia's agricultural land use.

2.5 Hypotheses and Contribution

According to the findings of the previously discussed literature, I arrive at the following testable hypotheses:

1. Hypothesis Analyzing deforestation emission data linked to trade will show that palm oil embodies the most deforestation emissions in Indonesia from the period of 2005 to 2018, while the foreign demand for palm oil is larger than Indonesia's demand.

2. Hypothesis Deforestation emissions embodied in export demand for agricultural products in Indonesia is larger than the emissions embodied in its imports; thus, Indonesia's balance of emissions embodied in trade (BEET) is positive and Indonesia is a net exporter of deforestation carbon emissions.

3. Hypothesis Looking at the drivers of agricultural land use change in Indonesia between 2000 to 2014, final foreign demand per capita and population drive more strongly agricultural land use expansion than Indonesia's final demand or other factors of the decomposition.

Testing for these hypotheses, I will contribute to the literature in different aspects: First, I will use Indonesia's agricultural trade pattern data to analyze embodied deforestation emissions. Thereby, I use emission accounting approaches like PBA and CBA to arrive at the BEET for the total of agricultural products and the top 13 emission-intensive products. Second, I contribute to the literature by adding agricultural land use data as of Indonesia's satellite account to the WIOD tables of the 2016 release. These Input-Output tables are then used for a structural decomposition analysis of five factors from 2000 until 2014 to investigate which factor is driving agricultural land use changes in Indonesia, the most prominent driver of Indonesia's deforestation — which has been, for the best of my knowledge, not being investigated yet.

3 Data and Data Limitations

3.1 Carbon Emissions from Deforestation

To investigate the first research question, I will analyze the data provided by Pendrill et al. (2019).[8] They link tree cover loss information from the spatial data set by Hansen et al. (2013)

[8]The data set is available online under https://zenodo.org/record/4250532. The latest update 13-01-2022 is used.

and forest carbon stocks data by Zarin et al. (2016) to different crop categories from the FAO (2017).[9]

When combining these data, Pendrill et al. (2019) obtain a new data set that includes deforestation emissions from 56 different agricultural crops. Pendrill et al. (2019) provide deforestation emissions, including and excluding emissions from peatland draining. As peatland draining releases a significant amount of soil-stored CO_2 in Indonesia and thereby contributes to Indonesia's high emissions, I use for my descriptive analysis the variable of deforestation emissions, including peatland draining.

After creating the data set of deforestation emissions linked to several crops, Pendrill et al. (2019) trace the embodied deforestation emissions along global supply chains to the nations of consumption by using a) the physical trade model of Kastner et al. (2011) and b) the monetary MRIO model of the EXIOBASE 3 database of Stadler et al. (2018). The advantages and disadvantages of both models have already been discussed in Section 2.4. Briefly, the physical trade model does not account for intermediate industry trade flows and, therefore, can under- and overestimate the embodied emissions for consumer and producer countries. The MRIO model takes intermediate trade flows into account. However, Stadler et al. (2018) have only nine commodity groups, while the physical model separates into 56 crop categories. Pendrill et al. (2019) (p.8) argues that these two models are "complementary information", as the physical trade model can help to investigate upstream actors like companies and governments to reduce deforestation in the direct value chains. In contrast, the MRIO model can give insights about downstream actors to understand the underlying drivers of deforestation emissions better. Being aware of a bias in using the embodied emissions in trade of the physical trade model, I decided to choose the data linked by the physical trade model to have a more detailed overview of the different traded crops. However, the bias of missing intermediate trade flows means that the descriptive results need to be interpreted with caution. As a robustness check, I will also use data from the MRIO model by Stadler et al. (2018) to see if the results mainly differ.

3.2 World Input Output Database (WIOD)

For the second part of the thesis, SDA is applied, explained in Section 4. Because of the advantages of a MRIO model, I use the harmonized MRIO tables of WIOD from the 2016 release by Timmer et al. (2015). The WIOD consists of IO tables from 2000 until 2014 in current and previous-year-prices of US Dollars for 43 countries, included are all 28 EU members and 15 major economies and emerging markets and a model that accounts for the rest of the world (RoW).[10]

[9] Hansen et al. (2013) analyze global land satellite data with a high spatial resolution of 30 meters to identify forest gain and loss between 2000 and 2012. This data set is later extended for a longer period. Moreover, Zarin et al. (2016) are analyzing carbon stocks of several tropical forests and estimating the impact on tropical deforestation in terms of released carbon emissions.

[10] The countries included are all 28 EU member states (status July 1, 2013, thus the UK is included). Moreover, Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Norway, Russia, South Korea, Switzerland,

The WIOD tables cover 56 sectors that are classified to the International Standard Industrial Classification Revision 4 (ISIC Rev. 4). For measuring the changes in the SDA, the current price tables are being used to account for the data at time 0, while the previous-year-price tables give the data at time 1. The 44 regions m and 56 sectors n lead to the following matrix dimension $\mathrm{mn} \times \mathrm{mn} = 2464 \times 2464$. The WIOD tables also include five different categories of final consumption expenditure (i.e. final demand) for each region: by households, by non-profit organizations serving households, by government, gross fixed capital formation and changes in inventories and valuables. These five categories result in a final demand matrix $\mathbf{f}$ of $\mathrm{mn} \times \mathrm{m}5$. A country's final demand can be summed up into an aggregated final demand matrix of $\mathrm{mn} \times \mathrm{m}$.[11]

There are also other MRIO databases, such as GTAP, Eora, and EXIOBASE3. The WIOD 2016 database has some shortcomings regarding the amount of data that is covered. GTAP, EORA and EXIOBASE 3 cover longer periods and more regions and GTAP and EXIOBASE 3 also cover more sectors. However, GTAP is not publicly available, and EORA and EXIOBASE3 are not converted in constant (i.e. previous-year prices). Using non-constant prices in the SDA would lead to the problem of not looking at pure volume changes, as changes in the values could also be due to changes in prices without changes in the trade flows. Dietzenbacher, Kulionis, and Capurro (2020) explain the intuition why constant prices matter (see their work for more details). Deflating MRIO tables can be a long process as purchasing power parity (PPP) index data for each industry and year needs to be collected to convert into constant prices. The availability of previous-year prices is the main reason for choosing the WIOD tables. Moreover, Indonesia as country of interest is included in the WIOD as well as European countries, the USA, China and India, which were already mentioned by the literature to be important trading partners of Indonesia (Pendrill et al., 2019). For these reasons, the WIOD tables are the preferable database for my thesis.[12]

3.3 Agricultural land use

As a direct indicator of deforestation emissions per industry of Indonesia is not available to link to the WIOD's 56 sectors intermediate trade flows, agricultural land use is taken as a proxy for an environmental account variable. I use the agricultural land for crops and permanent pasture in 1000 ha from Indonesia's EORA 26 national table for each year. Using agricultural land use changes as a proxy for deforestation has also been conducted by other researchers, for example, Barbier (2004), who is investigating drivers and the existence of an EKC of deforestation, and Franco-Solís and Montanía (2021), who study the drivers of deforestation in Brazil, Argentina

Taiwan, Turkey and the USA are included as major other economies.

[11] A simplified example of the structure of a WIOD table is added in the Appendix B.1.

[12] In addition, several studies have compared SDA results with different MRIO databases. Comparing EORA, WIOD and GTAP, Owen, Steen-Olsen, Barrett, Wiedmann, and Lenzen (2014) find that WIOD and GTAP have pretty similar results, and differences in the Leontief inverse can explain differences to EORA. In general, it can be concluded that variations are relatively minor (Dietzenbacher, Kulionis, & Capurro, 2020).

and Paraguay applying SDA. The original data of agricultural trade for crops and permanent pasture is from the FAO (2017). However, the EORA 26 national table of Indonesia already provided the information in more aggregated sector level of 77 sectors (Lenzen, Kanemoto, Moran, & Geschke, 2012), which allow to match it with the 56 sectors of the WIOD tables.[13] The data is stored in a row vector of $1 \times mn$, for which the values of all other countries m and their sectors n (excluding Indonesia) are set to 0 to only account for land use changes in Indonesia. Most tropical deforestation primarily results from the land conversion from forest to agricultural land use (Kastner et al., 2021). Also, in Indonesia, large parts of deforestation are due to crop production such as palm oil, which leads to the assumption that understanding the drivers of agricultural land use changes, will also help to understand the changes of deforestation in Indonesia (Austin et al., 2019). Nevertheless, the data can only reflect changes in land use for total crop and pasture production, which does not allow to identify if land use is changing due to specific crops such as palm oil production, which has a significantly large share in Indonesia (Gaveau et al., 2016). It remains open for future research to link deforestation data with higher crop resolution to the WIOD tables or to use the linked data of Pendrill et al. (2019) to the MRIO tables of EXIOBASE3 and convert them into constant or previous-year-prices.

3.4 Population

Data of population for the period 2000 until 2014 for the SDA were collected from the Penn World Table version 10.0 (Feenstra, Inklaar, & Timmer, 2015). To calculate the population of the rest of the world (RoW), I subtracted from the total world population the sum of the population of the 43 WIOD countries.

4 Methodology

This section explains the methodology behind the structural decomposition analysis, which constitutes the second part of this thesis. The first part of this thesis is a detailed descriptive analysis. The steps of the descriptive analysis are explained when presenting the results.

[13] For matching the right sectors I used the detailed sector explanations of UN DESA (2008). An overview of the matched sectors can be seen in the Appendix B.1. One problem in matching EORA land use data per industry to the WIOD sector classification is the unequal division of EORA sector into sub-sectors in the National Tables of Indonesia. The challenge can be better understood by looking at the table: Certain sectors such as the agricultural, food production and mining sectors are more fragmented in EROA than in WIOD, leading on the one hand to the 77 instead of 56 sector classifications. On the other hand, especially in the service sector, some sectors are broken down in more detail by WIOD, which is why the broader categories of EORA would, in theory, need to be broken down before matching. However, since the land use variable is 0 for these sectors, of which WIOD is more detailed, I have assumed that the WIOD categories should also be set to 0. The assumption seems reasonable because if the larger category of EORA is 0, all smaller sub-categories must be 0, which means the subdivided categories of WIOD are 0.

4.1 Additive Structural Decomposition Analysis

There are two primary decomposition analyses: structural decomposition analysis (SDA) and index decomposition analysis (IDA). The latter one uses country- or sector-level data and is often applied by researchers who want to analyze a footprint (e.g. emissions) in a particular consumption sector like transportation (Su & Ang, 2012). In contrast, SDA uses an input-output model, looking at the whole economy. [14] In this thesis, I apply the additive SDA variant, which is more commonly used in environmental studies than the multiplicative variant and easier to interpret (Lan, Malik, Lenzen, McBain, & Kanemoto, 2016).

Only few papers are applying SDA to analyze the changes in agricultural land use, and none of them have been focusing on Indonesia, to the best of my knowledge. Cai et al. (2020) study the drivers of changes in agricultural land use in China, using SDA. Franco-Solís and Montanía (2021) are applying SDA to investigate dynamics behind agricultural land use variations in Argentina, Brazil and Paraguay. Thereby traditional input-output analysis has to be extended by so-called environmental accounts to include environmental factors like agricultural land use. There are three main concepts in the environmentally adjusted input-output (IO) analysis: The Single-Region IO, the bilateral trade IO model and the Multi-Region IO (MRIO) (Xu & Dietzenbacher, 2014). The differences between the three models are in the treatment of imported intermediate products and the assumptions made regarding technology and environmental footprint, i.e. emissions (Xu & Dietzenbacher, 2014). The advantage of the MRIO is that it captures the whole global supply chain as well as the feedback effects (Xu & Dietzenbacher, 2014). Therefore, the literature mostly agrees that MRIO models are the most appropriate. However, one disadvantage is their vast demand for global trade data.

Another critical factor to consider when conducting SDA is how prices are recorded (Dietzenbacher, Kulionis, & Capurro, 2020). To compare year-to-year changes, both MRIO tables need to be in constant prices. For these two reasons, I use the MRIO database WIOD that is available in current and previous-year prices (more details about the data and MRIO tables can be found in Section 3) (Timmer et al., 2015).

A detailed technical explanation of SDA can be seen in the Appendix A2. Nevertheless, a primary explanation is given here. The standard Leontief equation of a MRIO model with m countries and n sectors looks like the following:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f} \tag{1}$$

where $\mathbf{x}$ is the output vector with the dimensions of $\mathrm{mn} \times 1$; $\mathbf{A}$ is a $\mathrm{mn} \times \mathrm{mn}$ matrix of technical coefficients, in which the coefficient $\mathrm{a}_{\mathrm{ij}}^{\mathrm{rs}}$ gives the input from a sector i of country r

[14] To get a clear understanding of structural decomposition analysis, knowledge about input-output analysis is recommended or better required. The textbook of input-output analysis by Miller and Blair (2009) gives a detailed overview of input-output analysis and SDA.

to one monetary unit of output of sector j in the country s ; **I** is the identity matrix with the same dimensions of **A**; **L** represents an economy's total requirements matrix (mn × mn). An element l_{ij}^{rs} depicts the direct and indirect change of the good needed of sector i of country r that is required for one more unit of final demand in sector j country s; **f** is a matrix (mn × m) depicting the total final demand per each of the 44 regions.[15]

The agricultural land use footprint in Indonesia from production over a period can be derived from the Leontief equation 1 as:

$$\mathbf{q} = \mathbf{eLf} \tag{2}$$

where **q** is the total agricultural land use and **e** is the agricultural land intensities $e = d/x$, resulting from the row vector of **d** (1 × mn) as direct agricultural land use per sector (physical units) divided by the output **x** per regarding sector (monetary units).

SDA's essential point is that changes in **q** are divided into changes in its factors, leading to a comprehensive total of effects from all changes in agricultural land use throughout a specific period (Lan et al., 2016). But the current three factors of expression 2 can be further decomposed. For example, changes in the final demands could result from various driving sources, such as the total level of final demand could change, or variations in the relative shares of expenditure on products in the final demand sector might be driving the overall change in final demand (so-called final-demand mix) (Miller & Blair, 2009). It could also be that the relative importance of different final demand categories (e.g. final demand per household, government spending, exports and others) explain the changes in final demand. To investigate the changes in final demand further and their effect on changes of **q**, SDA is applied, leading to a further break down of the equation 2 to the following (Lan et al., 2016):

$$\mathbf{q} = \mathbf{eLGyp} \tag{3}$$

where the total final demand **f** can be further divided into the three sub-drivers: **G** showing the mix of final demand and denotes the final demand structure effect and is arrived from $G = f * g^{-1}$, where g is the total final demand vector per country (1x44), which is each column sum of the f matrix; **y** is the level of final demand per capita, which is g/p; and **p** depicts the total population at a country level. Not all possible decomposing steps of the final demand **y** has been conducted in this thesis, as further decomposition is possible, remaining open for further research.

A next step, in theory, would be that the total change in the Leontief inverse can be further divided into two segments: one related to technological changes within each sector (as repre-

[15] In the WIOD, **f** consists out of m × 5 categories of final demand. The five final demand categories were combined into the total final demand per country.

sented in changes in the direct input coefficients matrix A) and the other with variations in the product composition within each sector (Miller & Blair, 2009). Technology changes can reflect several different aspects; for instance, production recipes can change, relative price changes can cause substitution or economies of scale can reduce the inputs per unit of output in a sector (Miller & Blair, 2009).

However, due to the complexity of this step, the further decomposition of the Leontief inverse matrix remains open for future research and will only be addressed with a theoretical interpretation in the results (Section 5) and Appendix C.1.

Considering that the total land use at time 0 is $\mathbf{q}^0$ and a year later 1 as $\mathbf{q}^1$, and the change of total land use is $\Delta \mathrm{q} = \mathrm{q}^1 - \mathrm{q}^0$, changes of the five drivers can be written as following exhaustive sum (Kulionis & Wood, 2020):

$$\Delta \mathbf{q} = \Delta \mathbf{e} + \Delta \mathbf{L} + \Delta \mathbf{G} + \Delta \mathbf{y} + \Delta \mathbf{p} \tag{4}$$

- where Δe is the agricultural land use intensity effect (efficiency), which measures the impact of increasing or decreasing land use intensity on consumption-based land use;
- ΔL denotes the combined effect of a) changes in the trade structure of intermediate inputs and b) changes in the overall production technology of an economy regarding the country of production;
- ΔG measures the effect of changes in land use due to variations in the composition of final demand;
- Δd is the effect of final demand level per capita, also called the affluence effect and measures changes in the overall final demand per capita;
- Δp accounts for the population effect and measures changes in the total number of a country's population (Kulionis & Wood, 2020).

Dietzenbacher and Los (1998) have investigated the non-uniqueness problem of SDA, meaning there is no unique way to decompose a factor's change into the changes of the drivers. Decomposing into five factors lead to a number of 5! decompositions. Dietzenbacher and Los (1998) provide the solution that the simple average of two so-called polar decompositions can be taken, which is approximated the average of all decompositions of 5!. For that reason, I take the simple average of the two polar decompositions in this thesis. An example of a two polar decomposition is shown in the Appendix A2.

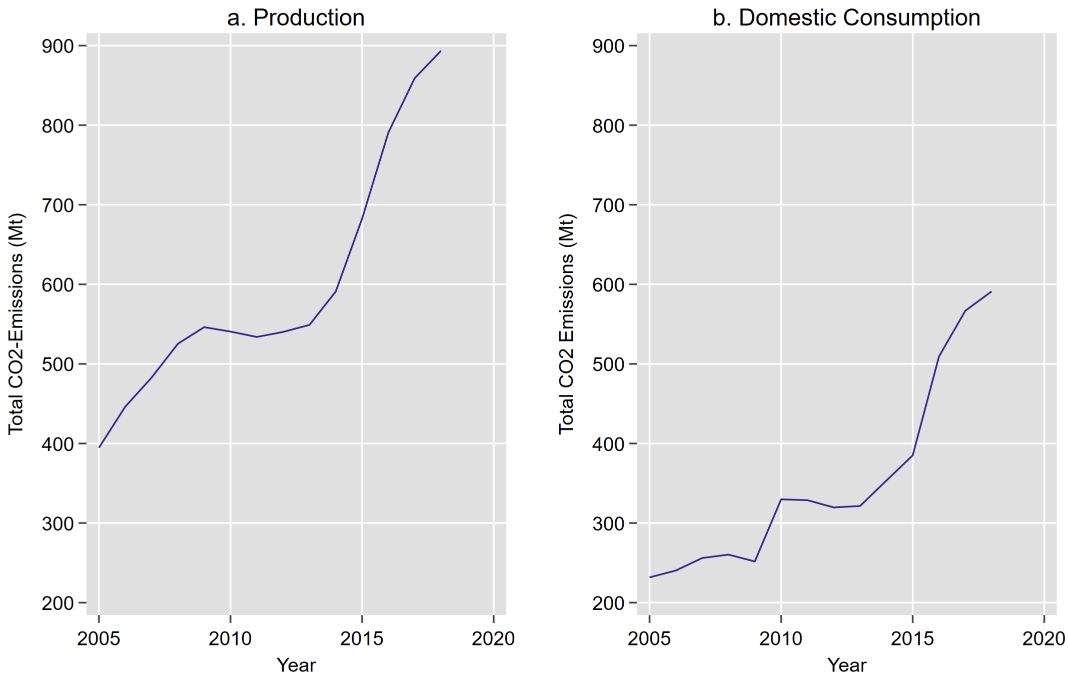
5 Empirical Analysis

5.1 Results of Descriptive Analysis of Agricultural Products inducing Deforestation Emissions

In the following section, I describe the development of deforestation emissions from 2005 to 2018 in Indonesia. I focus on 13 agricultural products that capture almost 95 % of all deforestation emissions embodied in Indonesia's agricultural production. For a better overview within the graphs, I have dropped countries with deforestation emissions embodied in their consumption of less than 10 Mt for palm oil and rubber and less than 5 Mt for coconuts. However, this means there are more importing countries with a minimal share of imports than shown. Looking at the total amount of deforestation emissions caused by agricultural production in Indonesia, the left graph of Figure 3 shows an increasing trend over the last years, which slows down between 2009 and 2013 and then starts to increase more intensely after 2014. The slowdown after 2009 may result from the Forest Moratorium established in 2011 by Indonesia's government, which was implemented to protect forest areas from deforestation. In contrast, the graphs show a sharper increase in deforestation emissions after 2013. Long-term positive effects of the Moratorium might be questioned and can, at least regarding these results, not be identified. It is worth noting that the results regarding the effect of the Moratorium can not capture causality.

Indonesia's deforestation emissions embodied in domestic use (shown in the right graph of Figure 3) also display a positive trend, which has increased rapidly after 2015. There was a slight decrease between 2010 and 2013, but the decrease was merely temporary.

Figure 3: Deforestation Emissions embodied Indonesia's Agricultural Production and in its Domestic Use between 2005 - 2018

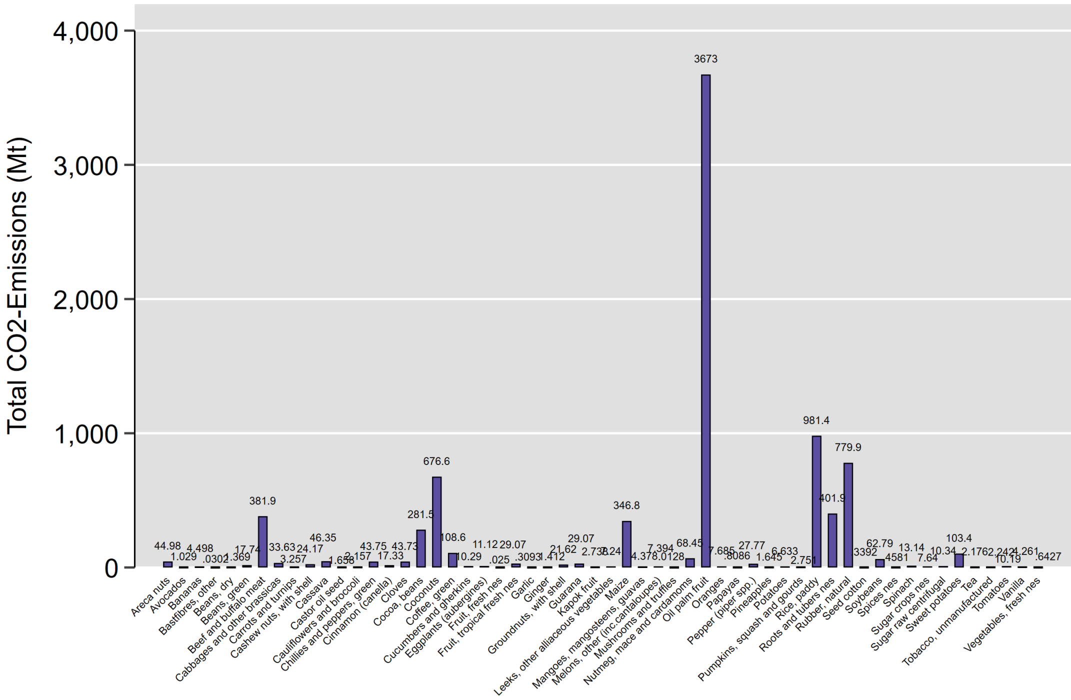


Next, I analyze the overall importers. Over the entire period, India is one of the largest importers of Indonesia's deforestation emissions, accounting for all agricultural products, with 545 Mt of CO_2 emissions (see Appendix A Figure A.1). China (430 Mt) and the USA (284 Mt) follow. Japan (157 Mt) and Pakistan (139 Mt) import less but are still among the top five importers. Of the Western European countries, only Germany (121 Mt), Italy (90 Mt) and the Netherlands (88 Mt) are among the top ten importers of deforestation emissions.[16]

In the next step, I calculate the sum of deforestation emissions per product for the whole period to understand which crops induced the most emissions during the whole time. The results are depicted in Figure 4.

[16]To see whether they are significant changes in which nations are the leading importers, I also investigate the time trends of each importer, accounting for the sum of imports of all crops. The graphs can be seen in the Appendix A.2. Nevertheless, no exceptional results stand out.

Figure 4: Total Deforestation Emissions by Indonesia's Agricultural Products of period between 2005 - 2018



Deforestation due to the production of the palm oil fruit contributes to increased CO_2 emissions by far more than the other crops, with a total of 3,673 Mt. The products rice (981 Mt), natural rubber (779 Mt) and coconuts (676 Mt) are following. These four products account for about 43 % of the total CO_2 emissions embodied in the production. The results are in line with the literature that palm oil and rubber are significant contributors of commercial agricultural production to Indonesia's deforestation (Gaveau et al., 2016; Pendrill et al., 2019; Warren-Thomas et al., 2015).

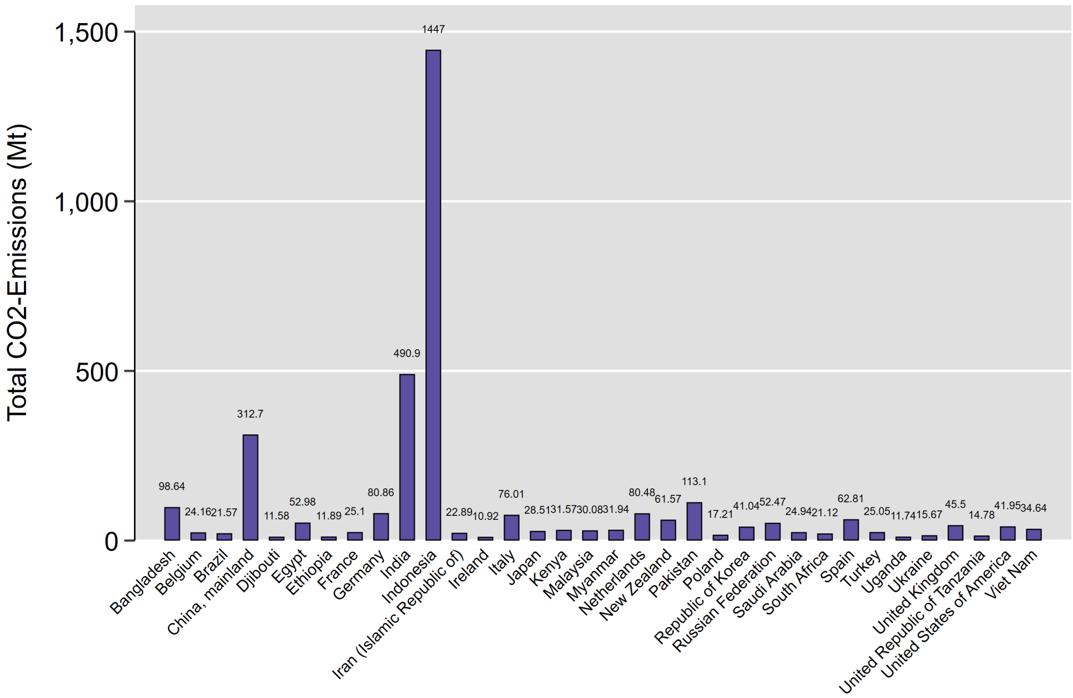
In the following step, I looked at the respective consumers for these four emission-intensive products. 2,226 Mt CO_2 deforestation emissions due to the production of the palm oil fruit are embodied in international export. In contrast 1,446 Mt CO_2 emissions are embodied in domestic use (see Table 2, Col. 1). These findings support the 1. hypothesis. Most of these emissions are embodied in trade with India (490 Mt), followed by China (310 Mt). This is followed by smaller economies such as Pakistan (110 Mt) and Bangladesh (99 Mt). Among the top 10 importers in terms of deforestation emissions of palm oil fruit are also Western European countries such as Germany (81 Mt), Netherlands (80 Mt), Italy (76 Mt) and Spain (63 Mt). At the end of the top ten is New Zealand, with 62 Mt embodied CO_2 emissions due to deforestation in the import of palm oil fruit.

Table 2: Deforestation Carbon Emissions (in Mt) of 13 Crops

Commodity	Export	Domestic use	DE-EE	PBA	Import	CBA	BEET
Total	3,429.752	4,945.771	1,516.019	8,375.522	69.923	5,015.693	3,359.829
Rice, paddy	.187	981.255	981,067	981.442	1.66	982.914	-1.472
Oil palm fruit	2,226.597	1,446.678	-779.919	3,673.275	.226	1,446.904	2,226.371
Rubber, natural	666.856	113.014	-553.842	779.870	.202	113.216	666.654
Coconuts	77.859	598.694	520.835	676.553	.012	598.706	77.847
Beef & buffalo meat	.276	381.643	381.343	381.919	5.423	387.066	-5.147
Roots & tubers	53.273	348.619	295.347	401.892	.006	348.625	53.267
Maize	1.366	345.469	344.103	346.836	4.207	349.676	-2.841
Cocoa, beans	173.626	107.83	-65.796	281.456	5.537	113.366	168.089
Sweet potatoes	.32	103.066	102.747	103.3855	.001	103.066	0.319
Coffee, green	78.039	30.531	-47.508	108.570	.134	30.666	77.905
Spices	52.063	16.383	-35.680	68.445	.001	16.383	52.062
Soybeans	.382	62.407	62.025	62.789	20.179	82.586	-19.797
Fruit tropical, fresh	.2	28.871	28.671	29.071	.005	28.876	0.195

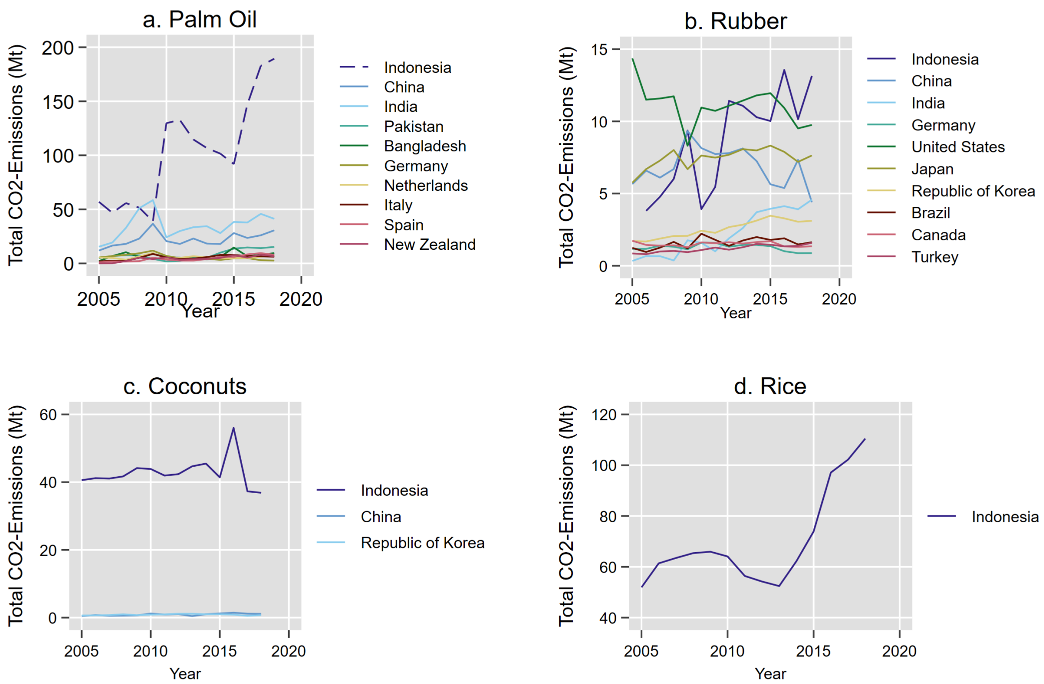
DE-EE = Emissions embodied in domestic use - emissions embodied in exports.
Each value is the sum of the whole period;
Spices include Nutmeg, mace and cardamoms.

Figure 5: Deforestation Emissions by Consumers of Palm Oil between 2005 to 2018



Looking at the time-trend for the embodied deforestation emissions of these ten consumer countries, Figure 6 shows that the amount embodied in the domestic use of Indonesia has fluctuated but in total increased over time. In contrast, the total deforestation emissions embodied in the trade of the palm oil fruit per year decreased slightly for India. Most of the other importers have only small marginally changes, which are not changing the overall picture significantly.

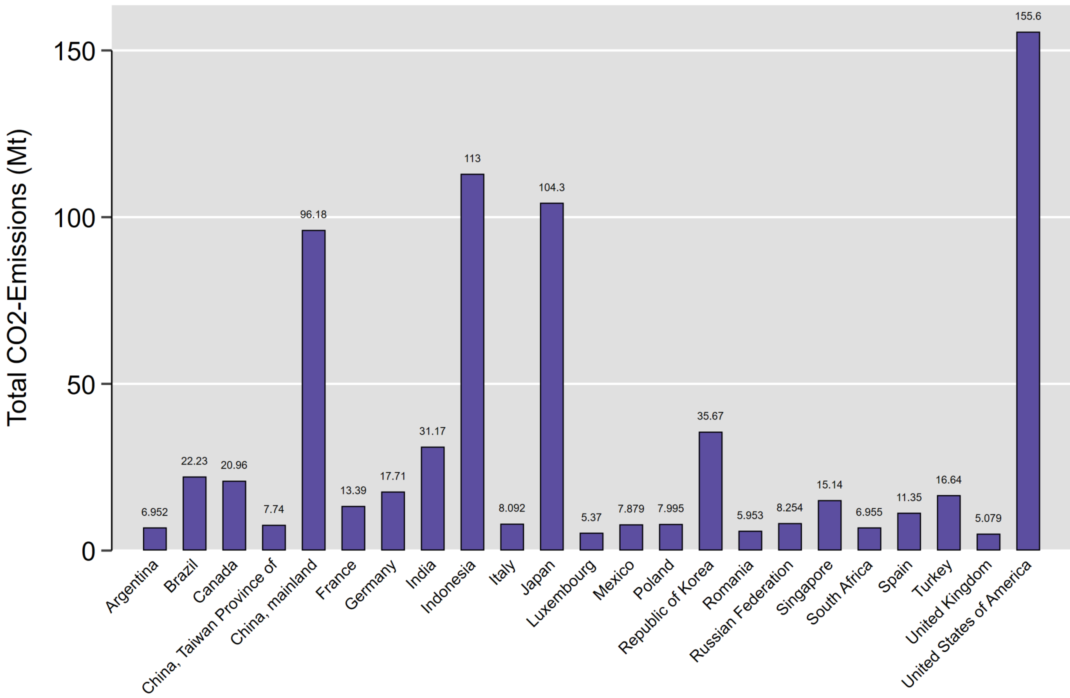
Figure 6: Total Deforestation Emissions by Consumers of 4 crops between 2005 to 2018



Rice is over 99 % domestically consumed and thus does not contribute significantly to CO_2 emissions due to deforestation embodied in international trade (see Table 2). Significant is the substantial increase since 2013 (see Figure 6). As this increase is mostly driven by domestic consumption, it could be that either overall population growth or increasing consumption per capita is driving the increase in deforestation emissions due to rice production.

Deforestation due to natural rubber production contributes as the third-largest deforestation driver of Indonesia's deforestation emission. Similar to palm oil fruit, the total emissions embodied in export (666 Mt) outweigh the emissions embodied in domestic use (113 Mt) (see Table 2). The United States, with 160 Mt, is the number one regarding the embodied deforestation emission in the imports of natural rubber over the whole period (see Figure 7). Indonesia (110 Mt), Japan (100 Mt) and China (96 Mt) are the following. However, since 2016, Indonesia has caught up. It is now the top consumer, while the emissions by consumption of the United States decreased until 2009, with a sharp drop during the Financial Crisis and stagnated since 2010 (measured in deforestation emissions, see Figure 6). Countries such as South Korea, Brazil, India, Canada, Germany and Turkey have around 36 to 17 Mt CO_2 emissions due to deforestation by rubber production embodied in their imports.

Figure 7: Deforestation Emissions by Consumers of Rubber between 2005 to 2018



Around 88 % (598 Mt) of the total deforestation emissions embodied in the production of coconuts are for domestic use, while 22 % (77 Mt) are embodied in the export of coconuts (see Table 2). China and South Korea are leading importers with around 12 Mt CO_2 emissions embodied. They are followed by the United States, Germany and Malaysia (see Figure 8). Over time, there were only significant changes for Indonesia, depicted as a sharp spike between 2015 and 2016 (see Figure 6).

Figure 8: Total Deforestation Emissions by Consumers of Coconuts between 2005 to 2018

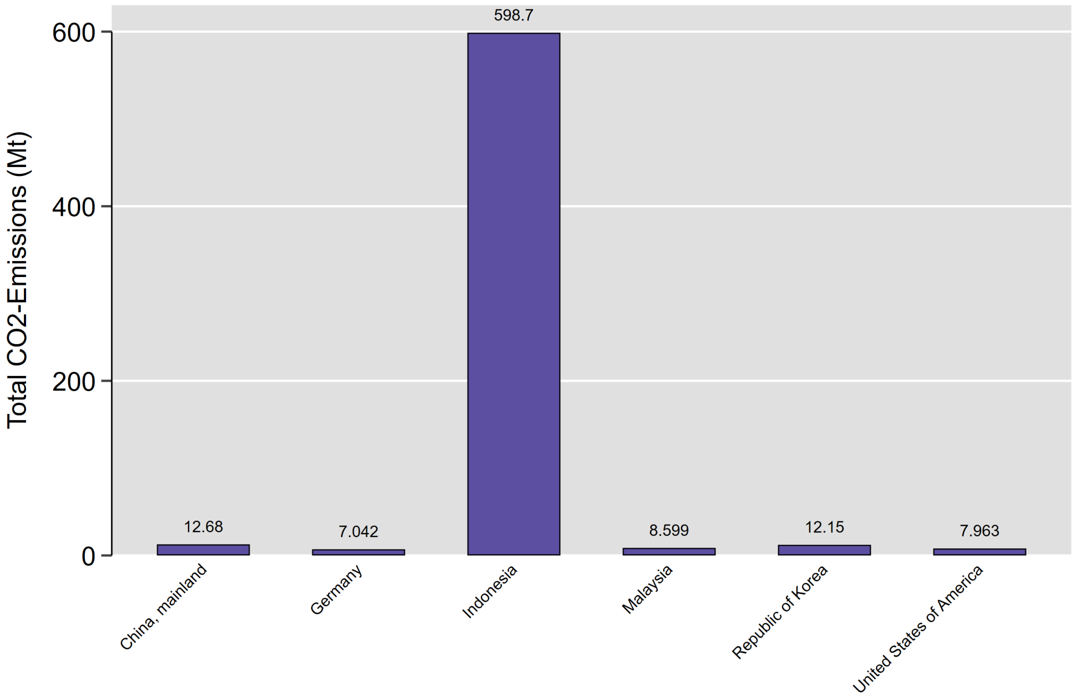


Table 2 shows the CO_2 emissions (Mt) due to Indonesia's deforestation through the production of 13 crops embodied in export and domestic use, which is accounted with the PBA approach in column 4. The overall production emissions embodied in domestic use are larger than the emissions embodied in Indonesia's exports. Table 2 also depicts Indonesia's imported emissions of the same products from elsewhere to be able to measure the CBA and arrive at BEET, which is PBA - CBA. The first row gives the total CO_2 emissions due to agricultural-induced deforestation. Only 13 of the 56 crops are depicted here, which means the sum of the 13 products will not equal the total amount. However, these 13 products' total emissions contribute almost 95% to the total emissions embodied in production.

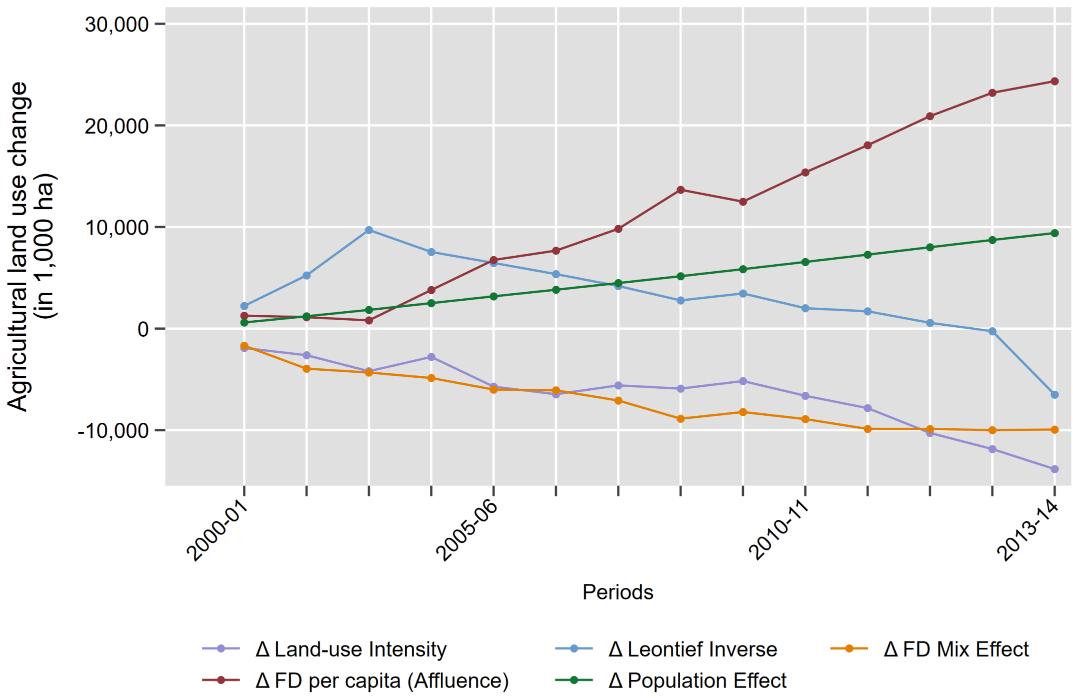
The BEET is for 6 out of 13 crops positive in sign, which means Indonesia is a net exporter of CO_2 emissions due to agricultural-induced deforestation (Col. 6). For the crops rice, beef and buffalo meat, maize and soybeans, the BEET are negative, indicating that Indonesia is a net importer of emissions for these crops. The total BEET is, with 3,359.829 Mt, positive, and Indonesia is a net exporter of agricultural-induced deforestation CO_2 emissions from 2005 until 2018, supporting the 2. hypothesis. After all, it should be noted that in the later years, Indonesia's demand increased more strongly compared to foreign consumers, meaning that the sign of the BEET could change in the future.

5.2 Results of Structural Decomposition Analysis

The results of the five-factor decomposition of annual changes in agricultural land use in Indonesia between 2000 to 2014 are depicted in Figure 9 and 10. Figure 10 shows the cumulative annual changes. The contribution of the five factors differs from year to year in their size of impact and their sign. Over the whole period, agricultural land use increased by 3,494 (in 1,000 ha) in Indonesia (see Appendix Table A.1). The land use increased especially from 2002 to 2004 and 2006 until 2009, while a large decrease was experienced in the latest period from 2013 to 2014.

Figure 9: 5 Factor Decomposition of Indonesia's Agriculture Land-use Change

Figure 10: Cumulative Change of 5 Factor Decomposition of Indonesia's Agriculture Land-use Change



The interpretation of the results of SDA can be understood as a *counterfactual* effect and the answer to the question of how land use changes if only one factor changes while the others remain constant. This interpretation design should be kept in mind for the following interpretations.

Changes in land use intensity decreased overall agricultural land use. Thus, it has been taken effort from Indonesia's actors, e.g. policymakers, farmers or others, to improve the efficiency of agricultural production. However, only between 2006 to 2007 and between 2008 to 2009 the change in land use intensity increases land use (Figure 9).

The interpretation of changes from the Leontief Inverse is more difficult in this analysis, as it combines the two effects of the trade structure effect and the production technology effect. The pure 'Leontief effect' or spill-over effect without further decomposition gives the effect of land use changes due to a change in the use of input (monetary) per each unit of output of the economy. Miller and Blair (2009) describe the changes of the Leontief as the economy-wide technology effect. The results show that changes in the Leontief Inverse strongly increased agricultural land use in Indonesia until 2003. Afterwards, changes in the Leontief Inverse decreased the overall agricultural land use - except for the period 2008-2009 (Figure 9). The negative effect of the Leontief Inverse could correspond to a decrease in the use of input per unit of the output (monetary) (Moghayer & Hu, 2013). The significant positive effect of changes of the Leontief Inverse, in the beginning, is balancing out the more minor negative changes from 2004 to 2013. However, the large negative effect of changes in the Leontief Inverse between 2013 to 2014 drives the cumulative effect negative (Figure 10).

Unfortunately, in the scope of this thesis, it is not possible to say if the changes of the Leontief Inverse are driven by changes in the trade structure or changes in technology production. Therefore, further decomposition of the Leontief Inverse, more specific of the A matrix with technical coefficients, would be necessary, which remains open for future research. Nevertheless, I provide a small theoretical interpretation of what changes in one of these two decompositions of the Leontief Inverse would mean if only one is driving the Leontief Inverse changes while the other remains unchanged.

First, it could be that changes in the trade structure drive the Leontief Inverse changes. In other words, changes in the intermediate input structures of different sectors of the whole economy explain changes in land use. Following the interpretation of Kulionis and Wood (2020), the positive effect of changes in the Leontief Inverse at the beginning of the study period could mean that the intermediate trade structure is shifted to countries that are more land use intensive. Second, changes in the technology of overall production (independent of the production country) could drive the changes in the Leontief Inverse and thus affect Indonesia's agricultural land use. This could be, for example, through efficiency gains in agriculture.

Changes in the final demand mix effect are relatively small and decrease in its size over time compared to some other drivers (e.g. Leontief Inverse, Affluence) (Figure 9). The final demand mix effect is mostly negative, except for the period from 2008 to 2009. In other words, variations in the composition of final demand are decreasing the agricultural land use in Indonesia (Figure 10).

The effect of changes in consumption per capita (affluence) is primarily positive. Besides the Leontief Inverse effect, the affluence effect is the strongest driver of all five factors. The positive effect of final demand per capita could mean that people's consumption per capita increases for agricultural products grown in Indonesia (Figure 9).

In contrast to the sign of the other effects, the impact of consumption per population is constantly positive during the whole time and mostly the same in its size (Figure 9). Therefore, the final demand changes of population, i.e. population growth, is increasing the agricultural land use in Indonesia is not surprising according to the literature. More interesting, however, is which country's population is driving the final demand and whose changes in consumption per capita play a significant role in agricultural land use. Therefore, I take a deeper look into the final demand per capita and population effect to analyze how it changed by different regions.

Figure 11, 12 and 13 shows the effect of changes of final demand per capita and population from 2000 until 2014 by different regions (i.e. Western Europe (WEU), Eastern Europe (EEU), North America (NA), Brazil, Russia, India and China (BRIC) and Japan, Australia, Korea and Taiwan (JAKT)).[17]

[17] In more detail, the 43 countries (indicated by their ISO-codes) have been grouped into following regions,

In both cases, final demand per capita and population of Indonesia are the strongest drivers (see graph a. in both Figures 11 and 13). Over the period between 2000 and 2014, 84 % of the total final demand impact (cumulative sum) on the increase of land use accounts for Indonesia's final demand per capita, while 14 % is explained by other world regions (Figure 11a).

To provide a better overview of the development of final demand per capita and population by different regions, I show the same graph without Indonesia on the right-hand side of the Figures 11 and 13 as well as showing only the final demand per capita for BRIC countries in Figure 12. Figure 11b shows the striking increase in per capita consumption of the BRIC countries. Also, changes in final demand per capita of RoW have a mostly cumulative increasing positive effect on land use in Indonesia. Higher-income countries' (i.e. WEU, EEU, JAKT, NA) consumption per capita experienced a minor drop during the Financial Crisis. However, changes were mainly constant primarily in size and the effect of these regions is less robust than of the regions BRIC and RoW. Taking a closer look at the effect of changes in the final demand per capita of the BRIC countries, Figure 12 depicts the significant land use enhancing impact of China and India over the time. The descriptive analysis has shown that China and India are among the largest importers of deforestation emissions due to agricultural products. Even if there is no clear link between agricultural land use change and the descriptive results based on the deforestation emissions data, one could suggest that BRIC's consumption per capita drives agricultural land use change and may explain the increasing CO_2 emissions from deforestation embodied in agricultural trade from Indonesia to, e.g. China and India.

In Figure 13b the results of the SDA show that land use changes due to variations in the total population are affected mainly by the population of the RoW (besides Indonesia). Minor positive effects also come from changes in the population of North America and BRIC, while almost no effect results from the change in Eastern Europe's population.

while RoW and Indonesia (IDN) remains as one region: **WEU** = AUT BEL CHE FRA DEU DNK ESP NDL GBR IRL ITA LUX NOR PRT SWE; **EEU** = BGR CYP CZE EST FIN GRC HRV HUN LTU MLT POL ROU SVK SVN; **NA** = USA CAN MEX.

Figure 11: Changes in Final Demand per capita by Region

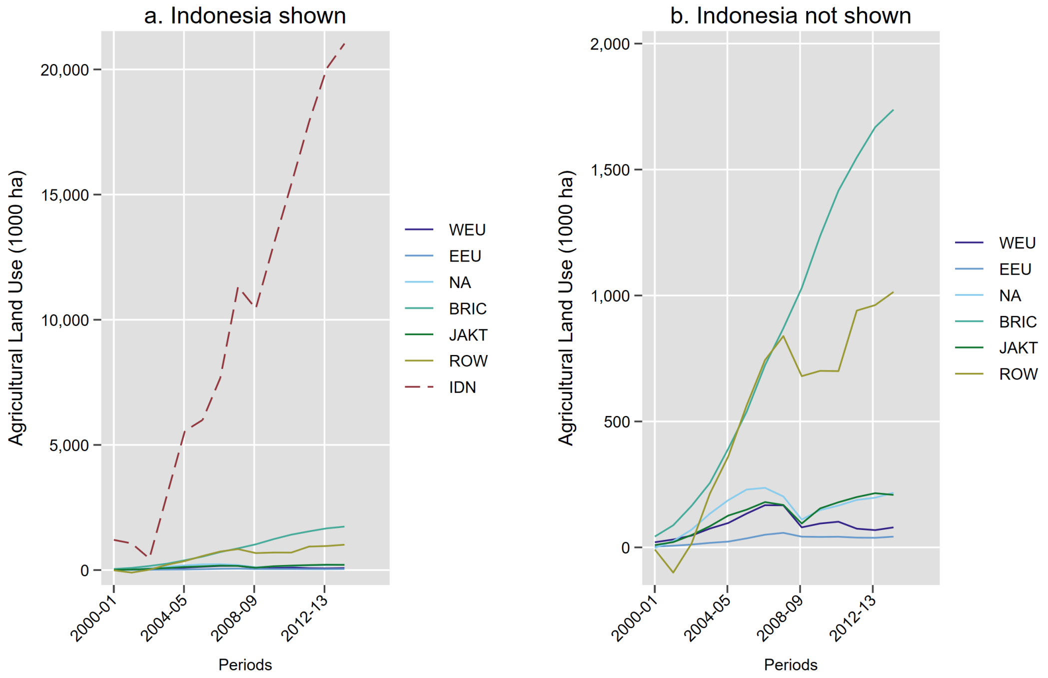


Figure 12: Changes in Final Demand per capita by BRIC

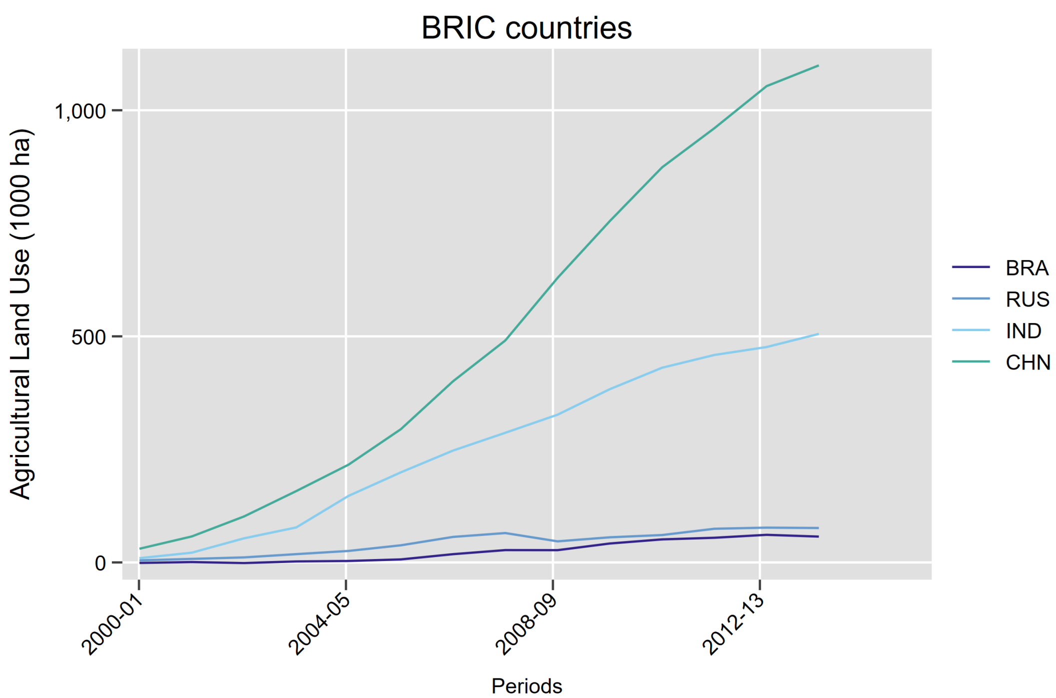
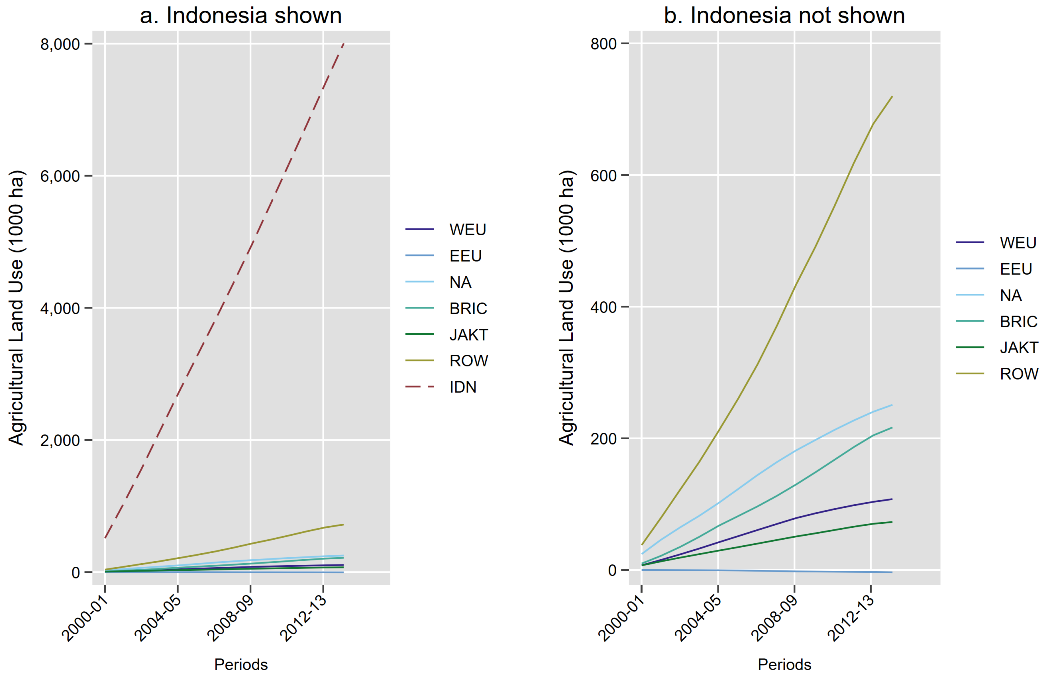


Figure 13: Changes in Final Demand of population by Region



5.3 Robustness Check - Comparison of Physical vs. MRIO Trade Model

Using the deforestation emission trade data linked by the physical trade model brings the potential risk that the results are biased through missing intermediate trade flows. Advantages and disadvantages of using this data are already discussed in Section 2.4 and 3.

To see how much the results from section 5.1 are biased, I compare the total deforestation emissions estimates in the results of Section 5.1 with the data linked to an MRIO model from Stadler et al. (2018).[18] Since the categories of crops differ significantly (56 vs. 9), only the total emissions embodied in production, domestic use, measured with CBA and per leading importers are compared. This comparison will give an idea of the potential bias and can set incentives for further research on how the bias is within different crop categories.

[18]The two trade data sets were both linked to deforestation emission data from Pendrill et al. (2019) and made publicly available under https://zenodo.org/record/4250532.

Figure 14: Deforestation Emissions embodied Indonesia's Agricultural Production and in its Domestic Use between 2005 - 2018: Comparison of two models

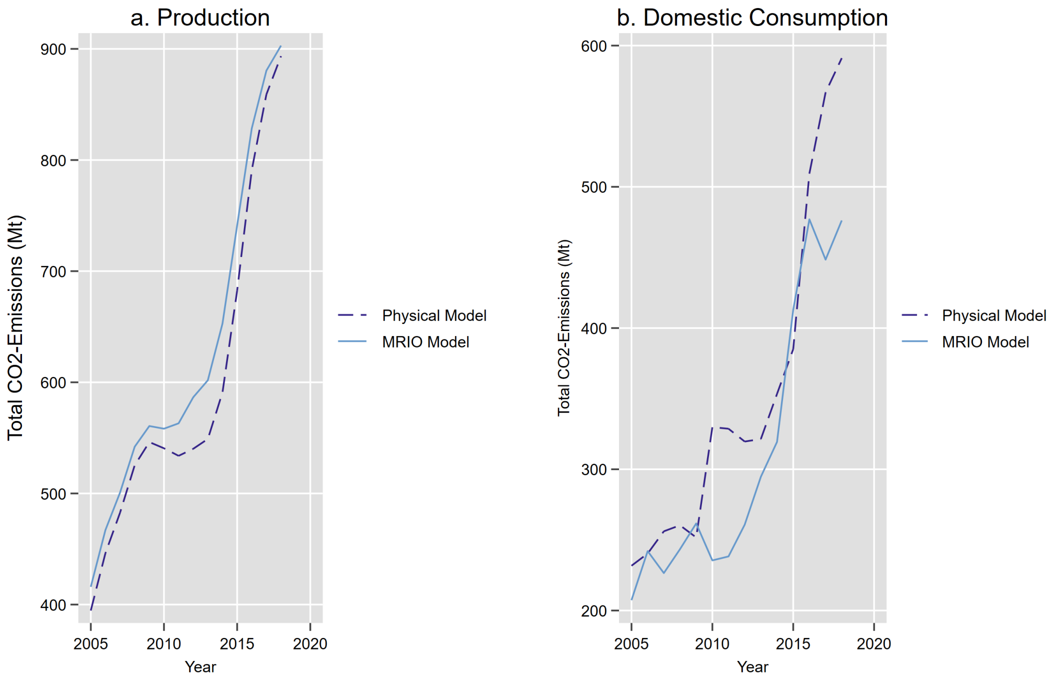


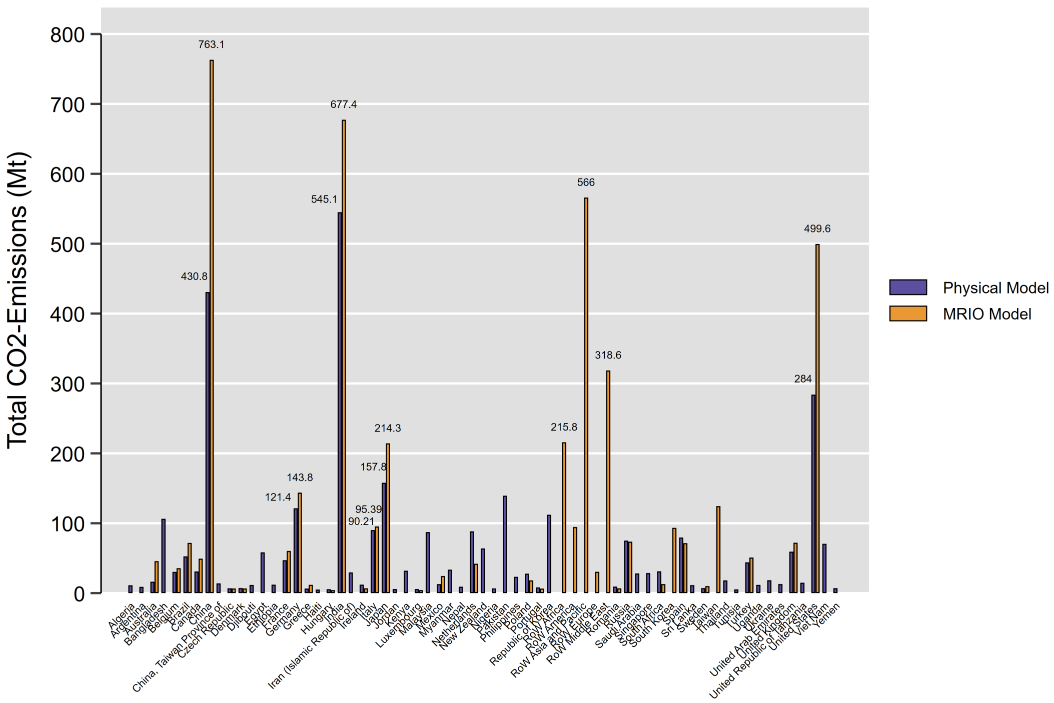
Figure 14 indeed shows differences in the calculated deforestation emissions. A tiny difference is found in the emissions embodied in production (Figure 14a), where the physical model is slightly below the MRIO model, especially between 2010 and 2015. This should ideally not be the case, as the emissions from agricultural production in Indonesia are not yet biased by intermediate trade flows and may indicate differences in the data composition, which could be related to the number of crops considered. A closer analysis of both data sets reveals that the small difference in emissions embodied in production could be due to forestry crops in the MRIO model, which is not included in the physical model.

Figure 14b shows the emissions embodied in Indonesia's domestic consumption. There are noticeable differences between the two models. The physical model overestimates Indonesia's 'consumed' deforestation emissions in most years. One possible explanation is that agricultural deforestation emissions from Indonesia are further 'processed' in other sectors in Indonesia and then exported. The emissions, which are then embodied in intermediate trade flows between sectors and consumed by a nation other than Indonesia, are not included in the physical model. Hence, Indonesia's consumption is overestimated. This means that the results of the first part of this thesis regarding how much Indonesia consumes are overestimated. Consequently, the results should be treated carefully. To understand if the total BEET of crops from Indonesia has changed, I also compare emissions measured with CBA (see Figure A.3 in the Appendix). Again, the physical model overestimates the emissions in most of the years. The total PBA arrived from using the Stadler et al. (2018) model is 8,802 Mt of CO_2, which is slightly above the PBA calculated with the physical model (see Table 2). The CBA measured with the MRIO model is 4,344 Mt and thus lower than the CBA from the physical model. Thus, the BEET arrived when using the MRIO model is 4,457 Mt, which is higher and still positive than the BEET (3,359 Mt) shown in Table 2. Nevertheless, Indonesia remains a net exporter of deforestation emissions due to agricultural production.

Figure 15 shows the major importing nations of deforestation emissions and their amount of embodied emissions of their overall imports (including all products over the whole period) calculated by the physical and MRIO model.

The MRIO model of the EXIOBASE3 database covers fewer countries than the physical model does (Stadler et al., 2018). For that reason, the MRIO model includes sum aggregated regions, which also depict the graph. However, they will not be interpreted as I do not aggregate the same regions of the physical trade model, and therefore, a direct comparison is not possible. More important is the difference in estimated emissions for the leading importers such as China, India, the United States, Germany and Japan. In all cases, the physical trade model underestimates the embodied emissions in their import. For China and the United States, over 200 Mt of carbon emissions due to deforestation are not accounted in the physical trade model (Figure 15).

Figure 15: Top Importer of Deforestation Emissions including all Products between 2005 - 2018: Comparison of two Models



6 Discussion

In this section, the results of this thesis are linked to the discussed literature. Moreover, due to the high relevance of deforestation and CO_2 emissions on political agendas, political implications are addressed. The section concludes with limitations and future research suggestions.

6.1 Discussion of the Results

6.1.1 Linkages between the First and Second Research Question

Regarding the answer to the first research question of whose consumption drives Indonesia's deforestation emissions, the results show that Indonesia's domestic consumption is overall larger than the consumption of other importing countries. Nevertheless, the BEET is positive, supporting the 2. Hypothesis.

China as a leading importer of agricultural deforestation emissions is in line with the findings of Kastner et al. (2021) who argue that China has become a significant importer of agricultural products due to a shift in tariffs after 1980. Moreover, Pendrill et al. (2019) also emphasize the role of Western Europe, of which Germany, Italy and the Netherlands are identified among the top ten importers of deforestation emissions. Pendrill et al. (2019) find that countries of the Middle East were also significant importers of palm oil from the tropics of Asia. Nevertheless, my results do not show the role of the Middle East region. The findings of the first part's results support the argument that emissions outsourcing to tropical countries is a possible risk in the agricultural sector due to the risk of deforestation in the case of Indonesia (Kastner et al., 2021; Streck, 2021).

The comparison of the physical trade model versus the MRIO model shows that it is crucial to take intermediate trade flows between sectors and nations into account, as otherwise, the emissions embodied in imports for some nations are underestimated. In contrast, emissions embodied in Indonesia's consumption are overestimated. Estimating the bias between the two models regarding the traded crops remains open for future research and requires the aggregation of the 56 crops from the physical model into nine larger categories.

Turning to my second research question, the SDA identifies final demand per capita and population as critical enhancing drivers for agricultural land use, while changes in Leontief decreased the land use in Indonesia. The final demand per capita and the population were strongest driven by Indonesia, which rejects the 3. Hypothesis. The significant positive effect of changes in Indonesia's final demand on its land use may be linked to the increasing deforestation emissions embodied in Indonesia's consumption. This is in line with the findings of the literature arguing that population growth and consumption per capita can enhance land expansion (DeFries et al., 2010; FAO, 2017). Unfortunately, the SDA cannot detect which crop cultivation is linked to land use changes. Nevertheless, it could be that crops such as palm oil, rubber, coconuts and rice, identified in the first analysis as primary crops, could be the crops cultivated on the increased land use. Nevertheless, further research is needed for accurate conclusions.

Two possible explanations may explain Indonesia's large impact of final demand per capita and population. First, Indonesia's population is in total growing with an average annual population growth rate of 1.5 % between 2008 to 2013 (Aji, 2015). Even if literature suggests that population growth is not a significant driver of deforestation in Asian countries when using regression models (Jha & Bawa, 2006; Leblois et al., 2017; T. K. Rudel et al., 2009), the SDA shows that changes in the population increase agricultural land use in Indonesia, which is one of the primary drivers of tropical deforestation.

Second, Indonesia's strong economic growth helped to reduce its poverty, lifting 11 million people from 2006 to 2014 above the poverty line (1.5 USD/day), which means the relative poverty as %-share of the population declined from 17.8 % in 2006 to 11 % in 2014 (Aji, 2015). Moreover, the income per capita experienced between 2000 and 2014 a positive annual growth rate (World Bank, 2014c). More people who live above the poverty line and the increase in income per capita may increase the consumption per capita for crops, resulting in increasing land use. Evidence for this assumed relationship has been found in other studies looking at different regions (Godfray et al., 2010; Tilman et al., 2011).

Moreover, final demand by population can be explained mainly by RoW (besides Indonesia). However, due to the structure of the WIOD tables, a further division of the RoW countries is not possible. The role of the population of RoW in Indonesia's agricultural land use may be driven by countries of the Middle East, as Pendrill et al. (2019) find that palm oil from Asia-Pacific regions, including Indonesia, is, besides China and Western Europe, primarily consumed countries of the Middle East. However, the descriptive analysis of the first part has not proven the role of the Middle East as an importer of agricultural products from Indonesia. In contrast, the analysis of importers of different crops shows that Pakistan and Bangladesh have a significant amount of deforestation emissions embodied in their imports of primarily palm oil. Hence, investigating the role of RoW might be an interesting starting point for further investigation and would require the use of MRIO tables, covering more countries.

Overall, the results from the SDA and the robustness check show the relevance of analyzing changes in Indonesia's agricultural land use from a global multi-regional perspective of trade. This supports the arguments of Pendrill et al. (2019), Kastner et al. (2021) and Franco-Solís and Montanía (2021) about the role of foreign demand and exports of agricultural products for the domestic land use footprint of tropical countries. Even if the conducted SDA does not allow to create a direct link to deforestation emissions of the first analysis due to the different data structure and variation in the period, literature agrees that most tropical deforestation (including Indonesia) is driven by agricultural production (Kastner et al., 2021; López & Galinato, 2005; Tsujino et al., 2016). Thus, it can be assumed that the investigated drivers of Indonesia's agricultural land use changes may also explain deforestation drivers in Indonesia. For example, the role of China's and India's consumption of embodied deforestation emissions may be linked to the results of the SDA analysis that China and India's final demand per capita are strongly driving increasing agricultural land use in Indonesia. Linking the deforestation emissions to changes in agricultural land use and the MRIO tables is an exciting starting point for further investigation.

6.1.2 Environmental Kuznets Curve

Section 2 already discusses the role of evidence supporting an EKC for deforestation. Suppose the findings of an increasing amount of deforestation emissions through agricultural production (Figure 3) are linked to Indonesia's positive growth of income per capita at the same time (World Bank, 2014b). In that case, an inverse U-shape is not visible as both have an increasing trend. This would not necessarily contradict the EKC if, in the future, with increasing income per capita, Indonesia's rate of deforestation emission decrease. But the current results support the literature arguing against the existence of an EKC for deforestation, at least in Indonesia. My findings contradict the results of Waluyo and Terawaki (2016), who found an EKC of deforestation in Indonesia and estimated a turning point of USD 990 between 1962 to 2007. This turning point is in my study period past, so the increase in deforestation emissions, at least through agricultural production, speaks against an EKC. As agricultural production is in Indonesia the strongest force behind deforestation (Austin et al., 2019), I assume that it is unlikely that the total deforestation also caused by other factors is decreasing and could lead to an EKC if the total deforestation rate has slowed down. However, the EKC for deforestation is not measured in this thesis. Thus, testing for it remains open. Moreover, the future development of deforestation in Indonesia is hard to predict due to the several different global and domestic drivers and also increasing priority of zero-deforestation measurements. If an EKC can be seen in the future or not is unclear. More important is that, regardless of economic growth, more substantial efforts are needed to slow down deforestation.

6.2 Policy Implications

The two-part analysis of this thesis has shown that global trade, foreign demand, and domestic consumption play a key role in Indonesia's deforestation and land use changes. Policies aiming to reduce deforestation emissions and land use expansion should therefore focus on local and global policy implications, targeting the supply and demand side simultaneously (Pendrill et al., 2019).[19]

[19] Afforestation as one of the most effective policies, which can offset deforestation emissions from deforested areas and is the only chance to extend forest area again (DeFries et al., 2010), is not accounted for in this thesis, which results in more considerable uncertainty about the net emission value of the first parts of results. Hence, I will not suggest direct policy implications able to offset deforestation in this section but rather discuss factors that

To prevent being a target country for emission leakages from deforestation, it is essential to be part of the UNFCC REDD+ program. This prevents agricultural importing countries from avoiding their responsibility for deforestation emissions (Streck, 2021). Moreover, considering telecoupling through international trade flows, I argue in favour of a CBA or shared responsibility approach when it comes to accounting for deforestation emissions in Indonesia regarding the evaluation of its NDCs, supporting the view of Pendrill et al. (2019) and others. Furthermore, in favour of a shared responsibility approach would speak that multinational corporate companies need to take responsibility as well, such as Unilever, who is responsible for 4 % of the global supply of palm oil (Pacheco et al., 2017).

In recent years, zero-deforestation commitments targeting commodity groups with the most significant impact, such as palm oil and rubber, have already been established to address the demand side. However, with the increasing pressure of changes in the final demand by population and consumption per capita, more substantial efforts need to be made by implementing further demand-side measures. Action needs to be taken from the importing countries such as China, Western Europe and India. Trade policies of importing zero-deforestation products can help take the pressure of deforestation risk in tropical countries like Indonesia. For example, in November 2021, the European Commission proposed a new regulation for deforestation-free products to minimize their consumption footprint elsewhere (European Commission, 2021).[20] The effectiveness of this regulation for Indonesia's tropical forests remains open for now.

The results also show the significant and increasing consumption of Indonesia. Hence, to address Indonesia's responsibility in the fight against deforestation, the supply side and local policies need to be implemented. In recent years, Indonesia's government has taken significant measures in its Low Carbon Development Initiative (LCDI) program to slow down deforestation, including bans on expansions of palm oil plantations into peatlands and forests (Mumbunan & Davey, 2019). The program includes five steps that are crucial for reaching the goals (Mumbunan & Davey, 2019). First, the Forest Moratoriums (discussed in Section 2) should be expended, while at the same time, bans on further land conversion for commercial agriculture should be implemented. Second, land use conflicts between communities need to be resolved to strengthen their relationship, which can increase their effort to reduce environmental degradation. Third, local communities need financial support to subsidize their production while preventing further agricultural expansion. The following two points are also in line with the four suggested strategies to reduce land use expansion by Foley et al. (2011) and Godfray et al. (2010). As the fourth step, agricultural supply chains need to be improved to reduce food waste as well as land use

should be addressed when discussing policy implications in the context of deforestation in Indonesia in general.

[20] The new regulation imposes binding due diligence rules for suppliers who want to sell certain agricultural and forestry goods on the European market that are linked with deforestation (European Commission, 2021). This demand-side measure should ensure that only deforestation-free commodities are allowed in the European Union. Suppliers are required to trace back the geographical coordinates of where the good was produced to identify deforestation linkages (European Commission, 2021).

efficiency must be increased. Therefore, the closing of so-called yield-gaps is crucial. Yield gaps refer to the under-performing of land use compared to the ideal, highest efficient use. Fifth, a more diverse diet for Indonesia's population with a system shift to agroforestry production should help secure food supply while reducing the stress on forests. In addition, a global diet shift will help to decrease the pressure on land systems further, but remains the responsibility of international actors. While the first four implications target the supply side, the fifth addresses the demand side. The combination of these five measurements highlights the importance of a twofold responsibility of producer and consumer again.

However, Indonesia's forest law enforcement, responsible for protecting its forests, experiences constraints in its budget and workers (Tacconi, Rodrigues, & Maryudi, 2019). Learnings about Brazil's forest management could help solve the financial constraints, as they are financing their forest management primarily due to international cooperation and the REDD+ program (Tacconi et al., 2019).

FAO (2017) predicts that the demand for agricultural products will increase unprecedented through population growth and changes in consumption per capita, putting high pressure on land systems and leading to deforestation. The impact of environmental consequences of the increasing demand for crops will depend on the development of global crop production and agricultural technologies (Tilman et al., 2011). Suppose the agricultural trade relationship between under-yielding nations, i.e. importers of agricultural products, and high-yielding nations (agricultural exports) will continue. In that case, the high-yielding nations will experience an extensive amount of environmental degradation without technological improvements (Tilman et al., 2011). Tilman et al. (2011) argue that technological and financial transfers should go from under-yielding countries to the high-yielding countries to reduce their pressure on land use and environmental degradation such as deforestation, which could solve Indonesia's financial constraints for a more protective forest management.

6.3 Limitations and Future Research

Using agricultural land use as a proxy for deforestation faces the limitation of not being able to interpret the changes in land use as an increase or decrease in deforestation. It cannot be determined whether expanding land use leads to deforestation through the clearing of forests or whether already cleared areas from other industrial uses have been converted. Moreover, indirect land use changes are not measured, such as agricultural land use displacing industrial land use. Industrial land could then be pushed and replaces forest areas elsewhere, causing deforestation (Cederberg, Persson, Schmidt, Hedenus, & Wood, 2019). High spatial resolution satellite data can be used to detect if land use changes induced deforestation and then be linked to MRIO tables to overcome this problem.

Furthermore, it could also be essential to consider carbon emissions from agricultural production to account for emissions from the deforestation of a crop and emissions from its production in trade flows. Nevertheless, comprehensive data accounting, e.g. for emissions from pesticides and agrochemicals, is significantly lacking in tropical countries (Cederberg et al., 2019).

Another limitation that should be addressed is grouping the countries into the rest of the world region (RoW) in the WIOD tables. The descriptive analysis has shown that countries such as Pakistan and Bangladesh, which are accounted for in the WIOD under RoW, have significant import shares of Indonesia's crops. Nevertheless, it is not possible to take a deeper look into their single role in land-use change in the SDA due to the grouping. The grouping is a required step for the WIOD tables as necessary data of several countries have not been collected or are not available. However, the trade flows of the whole economy should be considered in the input and output analysis (Timmer et al., 2015). To have a complete system and because of the reason that RoW's trade flows account for around 15 % of the global trade, the following crucial assumption is made that the countries of the RoW have a similar technology status as Brazil, China, India, Indonesia and Mexico (Timmer et al., 2015). Measuring which population of the RoW is driving the final demand of RoW, MRIO tables with higher coverage of countries is necessary, which requires first the step of deflating the MRIO tables from other databases such as EXIOBASE3, which remains open for future research. Using the EXIOBASE3 database brings the additional advantage of having a higher sector division (Stadler et al., 2018).

Moreover, the results of the SDA have shown that in the latest period, Indonesia's agricultural land use experienced a reducing effect through changes of the Leontief Inverse. Further research on the decomposition of the Leontief Inverse is necessary to see if the technology production effect or trade structure effect drives it.

7 Conclusions

Increasing demand for agricultural products is the primary driver of tropical deforestation in Indonesia. The predicted growth of population and economic development will further increase the demand for agricultural land and will continue to cost further forest conversion without appropriate forest protection measurements and agricultural efficiency gains. Policymakers need to know which agricultural production currently endangers forests the most for effective sustainable measurements. Moreover, they must also understand the overall economic role of crops linked to deforestation for their economy, their export share, and how dependent their population is on these products.

By answering the first research question of how much agricultural-induced deforestation emissions are embodied in Indonesia's domestic consumption versus the consumption of other countries, this thesis reveals the role of global agricultural trade for Indonesia's deforestation carbon emissions from several crops and is thereby contributing to the literature with more profound insides of in trade embodied deforestation emissions. This thesis illustrates that Indonesia was an overall net deforestation emissions exporter from 2005 to 2018, which is mostly driven by the large export share of palm oil. Four of Indonesia's crops (palm oil, rubber, rice and coconuts) cause most of its production-based emissions. Domestic consumption has strongly increased for these products, which makes Indonesia the most prominent consumer compared to the other countries since 2015. Nevertheless, countries like India, China, the United States and some Western European countries also play a significant role. Deforestation emissions could result from land use changes when Indonesia's forest is converted to agricultural land use. When determining drivers of land use changes by using MRIO tables and applying a SDA, the second research question is answered: What are the drivers of Indonesia's agricultural land use changes. The SDA shows that the most substantial factors of increasing agricultural land in Indonesia are the final demand per capita and population. Thereby, the impact of Indonesia's final demand is significantly larger than that of other nations. Between 2000 and 2014, 84 % of the total final demand impact on the increase in land use accounts for Indonesia's final demand per capita, while 14 % is explained by other regions of the world, where China and India play a primary role. The strong positive impact of changes from final demand on land use is to some extent balanced out with the land use decreasing effect of changes in the Leontief inverse and land use intensity. Moreover, the thesis's findings are in line with the argument of other researchers to account for intermediate trade flows when estimating deforestation to avoid a bias in the results by comparing the results of the bilateral trade model with a MRIO model. The SDA applied to Indonesia's land use has not been performed before. Its findings contribute to the literature with new evidence about land use drivers from a global perspective and can provide a foundation for further research in the debate about emission responsibility accounting and policy measurements. To slow down deforestation in Indonesia, demand- and supply-side measures are urgently necessary and current policies must be extended. Thereby the role of international actors is indispensable.

Future research is necessary to overcome limitations regarding the data of deforestation embodied in intermediate trade flows, the country coverage and the methodology by further decomposing the Leontief. More data on deforestation emissions linked to each stakeholder of the global supply chain of crops of Indonesia can provide further ground in the debate of full- or shared responsibility approaches regarding who should take responsibility for Indonesia's deforestation emissions. Moreover, research to evaluate the impact of Indonesia's policy strategies needs to be conducted to understand how land expansion and deforestation in Indonesia can be slowed down.

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A Appendix A

A.1 Additional Results

Figure A.1: Main Importer of Deforestation Emissions including all Products between 2005 - 2018

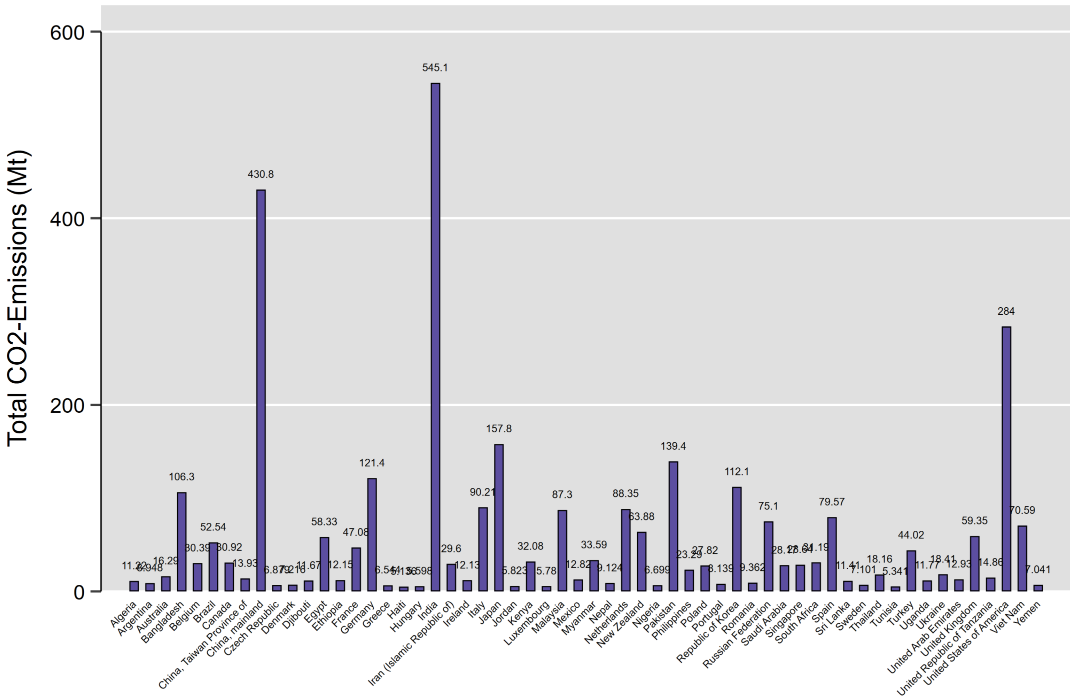

Figure A.2: Main Importer of Deforestation Emissions including all Products

Figure A.3: Deforestation Emissions of Indonesia measured with CBA Approach: Comparison of two Models

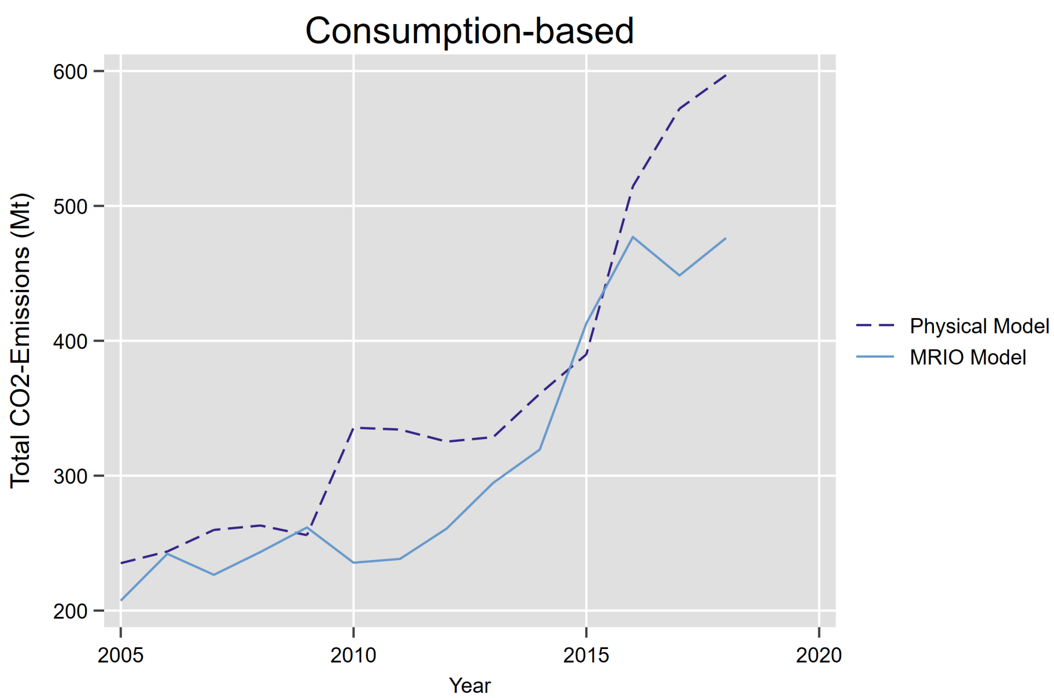

Table A.1: Results of SDA: Changes in 1,000 ha

Periods	Agricultural Land Use	Land-use Intensity	Leontief-Inverse	FD Mix Effect	FD per capita	Population Effect	Total FD
2000-2001	521.64	-1909	2233.4	-1678	1272.5	602.74	198.137
2001-2002	487.046	-709.735	3003.4	-2265.7	-148.907	607.987	-1806.7
2002-2003	2833.026	-1577	4471.6	-378.862	-313.407	630.695	-61.574
2003-2004	2357.952	1410	-2162.4	-539.026	2984.1	665.278	-3110.4
2004-2005	-1519.222	-2926.8	-1081.4	-1138.2	2959.2	667.978	2489
2005-2006	-347.565	-749.385	-1100.2	-73.214	922.795	652.439	1502
2006-2007	1496.314	873.353	-1173.8	-1005.4	2145.2	656.961	1796.8
2007-2008	998.773	-316.897	-1413.7	-1790	3844.2	675.169	2729.369
2008-2009	1608.862	743.364	683.682	657.205	-1168.6	693.210	181.857
2009-2010	-3.261	-1449	-1450.8	-695.865	2882.4	710.004	2896.5
2010-2011	902.834	-1215	-305.936	-967.525	2672.5	718.795	2423.77
2011-2012	-2.279	-2444.1	-1134.1	-9.068	2861	723.989	3576
2012-2013	499.186	-1586.4	-828.411	-109.955	2302.2	721.752	2914
2013-2014	-6339.074	-1968.1	-6240	53.982	1139.6	675.444	1869.1
Column Sum	3,494.232	-13824.699	-6498.665	-9939.628	24354.782	9402.442	17597.86

B Appendix B

B.1 Information regarding the Input-output Data

Figure B.1: World Input Output Table Explanation for three Regions: Author's construction based on Timmer et al. (2014)

		Country A	**Country B**	**Rest of World (RoW)**	$\mathbf{f}_A$	$\mathbf{f}_B$	$\mathbf{f}_{RoW}$	**X**
		Intermediate Consumption	Intermediate Consumption	Intermediate Consumption	Final Domestic Demand	Final Domestic Demand	Final Domestic Demand	Total
		Industry (j)	Industry (j)	Industry (j)				
Country A	Industry (i)	Intermediate use of domestic output ($Z_{Ai,Aj}$)	Intermediate use by B of exports from A ($Z_{Ai,Bj}$)	Intermediate use by RoW of exports from A ($Z_{Ai,RoWj}$)	Final use of domestic output	Final use by B of exports from A	Final use by RoW of exports from A	Output in A
Country B	Industry (i)	Intermediate use by A of exports from B	Intermediate use of domestic output	Intermediate use by RoW of exports from B	Final use by A of exports from B	Final use of domestic output	Final use by RoW of exports from B	Output in B
Rest of World (RoW)	Industry (i)	Intermediate use by A of exports from RoW	Intermediate use by B of exports from RoW	Intermediate use of domestic output	Final use by A of exports from RoW	Final use by B of exports from RoW	Final use of domestic output	Output in RoW
		Value Added	Value Added	Value Added				
		Output in A (X_A)	Output in B (X_B)	Output in RoW (X_{RoW})				
Land Use		Land use embodied in A's output	Land use embodied in B's output	Land use embodied in RoW's output				

Note: **Z**, **f** and **x** are the in the Appendix C.1 defined matrices and vectors, which are further used to calculated the Leontief and other components of the SDA. Land use is resulting in the defined row vector **d**.

Table B.1: Matching land use change from EORA to WIOD Sector Classification

	WIOD ISIC 4.1 Industry Categories (56)	EORA Industry Classification (77)
A01	Crop and animal production, hunting and related service activities	Paddy, Other grains, Food Crops, Non-food crops, Livestock and poultry
A02	Forestry and logging	Forestry
A03	Fishing and aquaculture	Fishery
B	Mining and quarrying	Crude petroleum and natural gas, Iron ore, Other metallic ore, Non-metallic ore and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products	Milled grain and flour, Fish products, Slaughtering, meat products and dairy products, Other food products, Beverage, Tobacco
C13-C15	Manufacture of textiles, wearing apparel and leather products	Spinning, Weaving and dyeing Knitting, Wearing apparel, Other made-up textile products, Leather
C16	Manufacture of wood and of products of wood, straw and cork	Timber, Other wooden products
C17	Manufacture of paper and paper products	Pulp and paper
C18	Printing and reproduction of recorded media	Printing and publishing
C19	Manufacture of coke and refined petroleum products	Refined petroleum and its products
C20	Manufacture of chemicals and chemical products	Synthetic resins and fiber, Basic industrial chemicals, fertilizers, pesticides, Drugs, medicine, Other chemical products
C21	Manufacture of basic pharmaceutical products and preparations	
C22	Manufacture of rubber and plastic products	Plastic products, Tires and tubes, Other rubber products
C23	Manufacture of other non-metallic mineral products	Other non-metallic mineral products
C24	Manufacture of basic metals	Cement and cement products, Glass and glass products, Iron and steel, Non-ferrous metal, Metal products
C25	Manufacture of fabricated metal products, except machinery and equipment	
C26	Manufacture of computer, electronic and optical products Electronic computing equipment, Other electronics and electronic products, Household electrical equipment	Television sets, radios,audios and communication equipment,
C27	Manufacture of electrical equipment	Heavy Electrical equipment
C28	Manufacture of machinery and equipment n.e.c.	Boilers, Engines and turbines, General machinery, Metal working and specialized machinery, Precision machines
C29	Manufacture of motor vehicles, trailers and semi-trailers	Motor vehicles, Motor cycles
C30	Manufacture of other transport equipment	Shipbuilding, Other transport equipment
C31-C32	Manufacture of furniture; other manufacturing	Wooden furniture,Other manufacturing products

Table B.2: Continued Table of B.1: Matching land use change from EORA to WIOD Sector Classification

	WIOD ISIC 4.1 Industry Categories (56)	EORA Industry Classification (77)
C33	Repair and installation of machinery and equipment	
D35	Electricity, gas, steam and air conditioning supply	Electricity and gas
E36	Water collection, treatment and supply	Water supply
E37-E39	Sewerage; waste collection, treatment and disposal activities etc.	
F	Construction	Building construction, Other construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	
G46	Wholesale trade, except of motor vehicles and motorcycles	Wholesale and retail trade
G47	Retail trade, except of motor vehicles and motorcycles	
H49	Land transport and transport via pipelines	Transportation
H50	Water transport	
H51	Air transport	
H52	Warehousing and support activities for transportation	
H53	Postal and courier activities	
I	Accommodation and food service activities	
J58	Publishing activities	
J59-J60	Video, television production, sound recording and music activities	
J61	Telecommunications	Telephone and telecommunication
J62-J63	Computer programming, information service activities	
K64	Financial service activities, except insurance and pension funding	Finance and insurance
K65	Insurance, reinsurance and pension funding	
K66	Activities auxiliary to financial services and insurance activities	
L68	Real estate activities	Real estate
M69-M70	Legal, accounting, management consultancy activities	
M71	Architectural and engineering activities	
M72	Scientific research and development	Education and research
M73	Advertising and market research	
M74 - M75	Other professional, scientific and technical activities; veterinary activities	
N	Administrative and support service activities	
O84	Public administration and defence; compulsory social security	Public administration
P85	Education	
Q	Human health and social work activities	Medical and health service
R-S	Other service activities	Restaurants , Hotel, Other services
T	Activities of households as employers undifferentiated	
	goods- and services-producing activities of households for own use	Household
U	Activities of extraterritorial organizations and bodies	

C Appendix C

C.1 Technical Supporting Information for the Methodology

In this part of the Appendix, I show the technical details about the SDA technique that was used to decompose changes in Indonesia's agricultural land use. The following description of methodology is based on Dietzenbacher, Kulionis, and Capurro (2020) and Arto and Dietzenbacher (2014), but repeating citations of these in the following has been avoided. For the following explanation, an economy with three countries and three sectors is considered, nevertheless the same theory can be applied for any number of sectors and countries. Vectors and scalars are denoted in lower-case letters, while matrices are depict in upper-case letters.

The main component of the SDA is the MRIO table, which depicts all flows of goods and services (in monetary unit) between the three countries and sectors. A MRIO table (in this thesis a MRIO table of the WIOD) exists of main three components:

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z_{11}} & \mathbf{Z_{12}} & \mathbf{Z_{13}} \\ \mathbf{Z_{21}} & \mathbf{Z_{22}} & \mathbf{Z_{23}} \\ \mathbf{Z_{31}} & \mathbf{Z_{32}} & \mathbf{Z_{33}} \end{bmatrix} \mathbf{F} = \begin{bmatrix} \mathbf{f_{11}} & \mathbf{f_{12}} & \mathbf{f_{13}} \\ \mathbf{f_{21}} & \mathbf{f_{22}} & \mathbf{f_{23}} \\ \mathbf{f_{31}} & \mathbf{f_{32}} & \mathbf{f_{33}} \end{bmatrix} \mathrm{x} = \begin{bmatrix} \mathbf{x_1} \\ \mathbf{x_2} \\ \mathbf{x_3} \end{bmatrix}$$

where $\mathbf{Z}^{\mathrm{rs}}$ gives the matrix accounting for intermediate trading between country r to country s. An element of $\mathbf{Z}$ such $\mathbf{z}^{\mathrm{rs}}{}_{\mathrm{ij}}$ is the trade volume of country r's sector i to the sector j of sector s; $\mathbf{F}$ is a matrix exciting of different column vectors of final demand $\mathbf{f}^{\mathrm{rs}}$, and the element $\mathbf{f}^{\mathrm{rs}}{}_{\mathrm{i}}$ denotes the final demand of country s for the in country r produced good i; $\mathbf{x}^{\mathrm{r}}$ denotes a column vector of the total gross outputs in country r. In the next step, the MRIO table has been extended with the vector $\mathbf{d}^{\mathrm{r}}$, which gives for each sector i the related total agricultural land use (in 1000 ha) for crops and permanent pasture and the scalar $\mathbf{p}^{\mathrm{r}}$ that denotes total population in country r:

$$\mathbf{d} = \begin{bmatrix} \mathbf{d_1} \\ \mathbf{d_2} \\ \mathbf{d_3} \end{bmatrix} \mathbf{p} = \begin{bmatrix} \mathbf{p_1} \\ \mathbf{p_2} \\ \mathbf{p_3} \end{bmatrix}$$

As next step, the matrix $\mathbf{A}$ of input coefficients is calculated by dividing $\mathbf{Z}$ with the inverse diagonal matrix of $\mathbf{x}$: $\mathrm{A} = \mathrm{Z}\widehat{\mathrm{x}}^{-1}$. $\mathbf{x}$ equals to $\mathbf{Zi} + \mathbf{Fi}$ ($\mathbf{i}$ is a column summation vector with ones of appropriate length). $\mathbf{Zi}$ can be substitutes by $\mathbf{Ax}$, with the arbitrary final demand $\mathbf{F}$, the standard input-output model $\mathbf{x} = \mathbf{L}\ \mathbf{Fi}$ can be written as $\mathbf{x} = (\mathbf{I}\ \text{-}\mathbf{A})^{-1}\ \mathbf{F}$. With $(\mathbf{I}\ \text{-}\mathbf{A})^{-1}$ denoting the Leontief Inverse $\mathbf{L}$.

Similar are the land use coefficients defined as $\mathbf{e}^{\mathrm{r}} = \mathrm{d}^{\mathrm{r}}(\widehat{\mathrm{x}}^{\mathrm{r}})^{-1}$, resulting in the vector $\mathbf{e}$.

Land use change can be rewritten then as:

$$\mathbf{q} = \widehat{\mathbf{e}}\mathbf{x} = \widehat{\mathbf{e}}\mathbf{LFi} \tag{C.1}$$

With $\mathbf{f}^{\mathrm{t}} = (\mathbf{F^t i})$, C.1 can be also expressed with sectorial land use as

$$\mathbf{q_i^r} = \sum_{\mathbf{j}} \sum_{\mathbf{s}} \sum_{\mathbf{k}} \mathbf{e_i^r l_{ij}^{rk} f_j^{ks}} \tag{C.2}$$

As next level, the final demand matrix can be further decomposed into following different components:

$$\mathbf{f_j^{ks}} = \mathbf{G_j^s y^s p_j^s} \tag{C.3}$$

where $\mathrm{p^s}$ denotes the population size of country s, $\mathrm{y^s}$ is the final demand per capita in country and G is the mix of final demand, resulting from the final demand per good j ($\mathrm{f^{ts}}_\mathrm{j}$) divided by the total final demand of country s ($\mathrm{F^{ts}}$).

From expression C.2 and C.3, total land use can be expressed as the following:

$$\mathbf{q^r} = \sum_{\mathbf{i}} \sum_{\mathbf{j}} \sum_{\mathbf{s}} \sum_{\mathbf{k}} \mathbf{e_i^r l_{ij}^{rk} G_j^s y^s p^s} \tag{C.4}$$

Expression C.4 depicts the land use of country r as the product of a series of five factors.

In the SDA of this thesis, the land use of all other countries has been set to zero, which allows to only investigate how changes in one of these five factors of the whole economy is influence the land use change in Indonesia. The non-uniqueness problem of several ways to decompose has already been mentioned in Section 4. Dietzenbacher and Los (1998) have proposed to use the simple average of all possible k! decompositions, where k is the number of factors, in my case 5. Dietzenbacher and Los (1998) show that the average of all k! decompositions can be approximated by the simple average of the so-called two polar decompositions. This approach developed as the most standard approach for structural decomposition analysis. Thereby, the changes in land use between two years 0 and 1 are given by $\Delta \mathrm{q} = \mathrm{q}^1 - \mathrm{q}^0$. Thus, the two polar decompositions look $\Delta \mathrm{q_a^r} \mathrm{and} \Delta \mathrm{q_b^r}$ like the following, with the subscripts 0 and 1 indicating for time 0 and 1:

$$\begin{aligned}
\Delta \mathrm{q_a^r} = & \sum_{\mathrm{i}} \sum_{\mathrm{j}} \sum_{\mathrm{s}} \sum_{\mathrm{k}} (\Delta \mathrm{e_i^r}) \mathrm{l_{ij1}^{rk} G_{j1}^s y_1^s p_1^s} + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \sum_{\mathrm{s}} \sum_{\mathrm{k}} \mathrm{e_{i0}^r} (\Delta \mathrm{l_{ij}^{rk}}) \mathrm{G_{j1}^s y_1^s p_1^s} \\
& + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \sum_{\mathrm{s}} \sum_{\mathrm{k}} \mathrm{e_{i0}^r l_{ij0}^{rk}} (\Delta \mathrm{G_j^s}) \mathrm{y_1^s p_1^s} + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \sum_{\mathrm{s}} \sum_{\mathrm{k}} \mathrm{e_{i0}^r l_{ij0}^{rk} G_{j0}^s} (\Delta \mathrm{y^s}) \mathrm{p_1^s} \\
& + \sum_{\mathrm{i}} \sum_{\mathrm{j}} \sum_{\mathrm{s}} \sum_{\mathrm{k}} \mathrm{e_{i0}^r l_{ij0}^{rk} G_{j0}^s y_0^s} (\Delta \mathrm{p^s})
\end{aligned} \tag{C.5}$$

The next expression is the parallel expression to C.5 but 0 and 1 are reversed:

$$\begin{aligned}\Delta q_b^r = &\sum_i \sum_j \sum_s \sum_k (\Delta e_i^r) l_{ij0}^{rk} G_{j0}^s y_0^s p_0^s + \sum_i \sum_j \sum_s \sum_k e_{i1}^r (\Delta l_{ij}^{rk}) G_{j0}^s y_0^s p_0^s \\ &+ \sum_i \sum_j \sum_s \sum_k e_{i1}^r l_{ij1}^{rk} (\Delta G_j^s) y_0^s p_0^s + \sum_i \sum_j \sum_s \sum_k e_{i1}^r l_{ij1}^{rk} G_{j1}^s (\Delta y^s) p_0^s \\ &+ \sum_i \sum_j \sum_s \sum_k e_{i1}^r l_{ij1}^{rk} G_{j1}^s y_1^s (\Delta p^s)\end{aligned} \tag{C.6}$$

Now the average of the two polar decompositions Δq_a^randΔq_b^r can be taken:

$$\Delta q^r = \frac{1}{2}(\Delta q_a^r + \Delta q_b^r) \tag{C.7}$$

It is possible to decompose the elements of expression C.5 and C.6 further by separating the components of the Leontief Inverse **L** into the two effects a) production technology effect and b) variations in the trading structure of intermediate consumption. This separation means in technical terms that the changes of the Leontief inverse matrix ΔL is decomposed into changes in the direct input matrix **A**. With $\mathbf{L}^1 = (\mathbf{I}\text{-}\mathbf{A}^1)^{-1}$ and $\mathbf{L}^0 = (\mathbf{I}\text{-}\mathbf{A}^0)^{-1}$, ΔL can be expressed as $=\mathbf{L}^1$ - $\mathbf{L}^0 = \mathbf{L}^0\mathbf{A}^1\mathbf{L}^1$ - $\mathbf{L}^0\mathbf{A}^0\mathbf{L}^1 = \mathbf{L}^0(\Delta\mathbf{A})\mathbf{L}^1$. As $\mathbf{L}^0(\Delta\mathbf{A})\mathbf{L}^1$ is equivalent to $\mathbf{L}^1(\Delta\mathbf{A})\mathbf{L}^{10}$, $\Delta\mathbf{L}$ does not need to be expressed as average of two equations (Miller & Blair, 2009). Furthermore, they are several different ways to further decompose $\Delta\mathbf{A}$. Miller and Blair (2009) (p.604) suggest the "straightforward disaggregation into column-specific changes". A column in **A** depicts the production recipe of a sector. Thus, identifying variations column by column can determine the impact of input changes per each sector in the whole economy. For n-sectors:

$$\mathbf{A^1 = A^0 + \Delta A} \begin{bmatrix} \mathbf{a_{11}^0 + \Delta a_{11}} & \cdots & \mathbf{a_{1n}^0 + \Delta a_{1n}} \\ \vdots & & \vdots \\ \mathbf{a_{n1}^0 + \Delta a_{n1}} & \cdots & \mathbf{a_{nn}^0 + \Delta a_{nn}} \end{bmatrix}$$

So far, shipment coefficients have not been considered in the MRIO tables and the decomposition approach, thereby they make an important contribution to MRIO tables compared to inter-regional IO framework (Miller & Blair, 2009). However, for a complete decomposition of the Leontief Inverse, shipment coefficients need to be considered, which leads to a transformation of the current IO matrices and vectors dimensions. The shipment coefficients reflect the trade costs, which are included in the **Z** matrix of intermediate trade flows from region r to s. Thereby, the sum of each column of **Z** equals the total shipment costs of good i going into the region of the column from all other regions. The total shipment costs for good i coming from several region r = 1,...p can be determined as following:

$$T_i^s = z_i^{1s} + z_i^{2s} + \cdots + z_i^{rs} + \cdots + z_i^{ps} \tag{C.8}$$

The shipment coefficients can then be arrived by diving each element z_{ij}^{rs} by its T_i^s:

$$c_i^{rs} = \frac{z_i^{rs}}{T_i^s}$$

This can be written as following vector and also diagonal matrix for each existing origin and destination pair of two countries:

$$\mathbf{c^{rs}} = \begin{bmatrix} \mathbf{c_1^{rs}} \\ \vdots \\ \mathbf{c_n^{rs}} \end{bmatrix} \quad \mathbf{\hat{c}^{rs}} = \begin{bmatrix} \mathbf{c_1^{rs}} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{c_2^{rs}} & \cdots & \mathbf{0} \\ \vdots & & & \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{c_n^{rs}} \end{bmatrix}$$

There are also intra-regional matrices of $\hat{c}^{ss}$.

The shipment coefficients matrices then extend the technical coefficient matrices **A**, that can also be written as pair-wise matrices of $\mathbf{A}^r$, $\mathbf{A}^s$ and so on (see p.91 of (Miller & Blair, 2009) for an overview of a two sector, two region example). As the shipment coefficients also account for trade to the final demand consumer and not only producing sectors, $\mathbf{f}^s$ can also be extended by $\hat{c}^{ss}\mathbf{f}^s$ as well as $\hat{c}^{rs}\mathbf{f}^s$. Therefore the standard IO-model equation of $\mathbf{x}$ = ($\mathbf{I}$ -$\mathbf{A}$)$^{-1}$ $\mathbf{F}$ can be rewritten:

$$\mathbf{(I - CA)x = CF} \tag{C.9}$$

converted to

$$\mathbf{x = (I - C_aA)^{-1}C_fF} \tag{C.10}$$

with following matrices and vectors in a p-region setting:

$$\mathbf{A} = \begin{bmatrix} \mathbf{A^r} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A^s} & \cdots & \mathbf{0} \\ \vdots & \vdots & & \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A^p} \end{bmatrix}, \mathbf{C} = \begin{bmatrix} \mathbf{\hat{c}^{11}} & \cdots & \mathbf{\hat{c}^{1p}} \\ \mathbf{\hat{c}^{21}} & \cdots & \mathbf{\hat{c}^{2p}} \\ \vdots & & \\ \mathbf{\hat{c}^{p1}} & \cdots & \mathbf{\hat{c}^{pp}} \end{bmatrix}, \mathbf{x} = \begin{bmatrix} \mathbf{x^r} \\ \mathbf{x^s} \\ \vdots \\ \mathbf{x^p} \end{bmatrix}, \mathbf{f} = \begin{bmatrix} \mathbf{f^r} \\ \mathbf{f^s} \\ \vdots \\ \mathbf{f^p} \end{bmatrix}$$

.

The above defined expression C.10 equals more simplified following:

$$\mathbf{x = \tilde{L}C_fF} \tag{C.11}$$

Coming back to the SDA model, the extension of the standard equation with the shipment coefficients to equation C.10 enables to decompose the Leontief in the technology effect as well as the intermediate trade effect. The land use intensity change equation C.1 is then extend with

$\mathrm{C_a}$ and $\mathrm{C_f}$, which needs to be considered separately when applying the decomposition analysis (Miller & Blair, 2009). For a shorter and more precise overview, the part of decomposition of the Leontief would look like following example and would be implemented in both of the polar-decomposition equations, replacing $\mathbf{\Delta L}$:

$$\Delta\tilde{\mathrm{L}} = \tilde{\mathrm{L}}^1(\Delta \mathrm{CA})\tilde{\mathrm{L}}^0$$

with

$$\Delta \mathrm{CA} = (1/2)(\Delta \mathrm{C})(\mathrm{A}^0 + \mathrm{A}^1) + (1/2)(\mathrm{C}^0 + \mathrm{C}^1)(\Delta \mathrm{A})$$

Moreover, $\mathrm{C_f}$ is decomposed in the same way as the other single factors of equation C.4 in the example of the two polar decompositions explained above.

In a simpler way, the land use change equation C.1 that should be decomposed with the decomposition of **A** is often written in the literature in the following manner, where **H** stands for the production structure, i.e. technology effect, and **T** stands for the trade structure effect that is element-wise multiplied, while $\mathrm{C_f}$ can be understood as trade sourcing effect **B** (Kulionis & Wood, 2020):

$$\mathbf{q} = \widehat{\mathbf{e}}\mathbf{x} = \widehat{\mathbf{e}}(\mathbf{I} - \mathbf{T} \otimes \mathbf{H})^{-1}(\mathbf{B} \otimes \mathbf{G})\widehat{\mathbf{y}}\widehat{\mathbf{p}} \tag{C.12}$$

Where **e**, **G**, **y** and **p** are the already above defined factors of land us intensity and final demand components.

Nevertheless, the applied decomposing of the Leontief inverse remains open for further research.