





# Regional differences in pesticide use and footprints of Brazilian soybeans

A study of pressure and impact indicators in Paraná, Mato Grosso and Tocantins Master's thesis in Industrial Ecology

### AMANDA LUNDBERG

MASTER'S THESIS 2021:NN

#### Regional differences in pesticide use and footprints of Brazilian soybeans

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Department of Space, Earth and Environment Division of Physical Resource Theory The Land Use Research Group CHALMERS UNIVERSITY OF TECHNOLOGY Gothenburg, Sweden 2021 Regional differences in pesticide use and footprints of Brazilian soybeans A study of pressure and impact indicators in Paraná, Mato Grosso and Tocantins AMANDA LUNDBERG

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Cover: Pesticide application to a Brazilian soy field. Photo credit: Christel Cederberg

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#### Abstract

Brazil is the worldwide largest producer and exporter of soybeans and also among the nations with the largest pesticide use. This thesis investigate if it is possible to quantify pesticide footprints of soy in the Brazilian soybean states Paraná, Mato Grosso and Tocantins. This is done with two types of indicators; pressure indicators that quantify volume of pesticide active ingredients (AI) used on total cropland and cropland dedicated to soy; and impact indicators that quantify the potential ecotoxic impact on freshwater ecosystems caused by individual AI. The footprints are calculated for the three largest product classes herbicides, fungicides and insecticides. Different pesticide data sources are compared at the Brazilian national level and at the state level for Paraná. It was found that the Food and Agriculture Organization of the United Nations (FAOSTAT) underestimate the Brazilian pesticide AI sales when comparing with data from the Brazilian Environmental Institute (IBAMA), and that IBAMA has data gaps as a consequence of Brazilian competition laws regarding publication of individual AI especially for fungicides and insecticides when set against comprehensive state level data from Paraná Agriculture Defense Agency (ADAPAR). ADAPAR data was found difficult to use for calculations as it is based on sales of commercial products (CP), which can include multiple AI in different concentrations.

The pressure indicators for soy showed a small increase of AI volume per hectare cropland, the use in the investigated states and the whole nation is similar. The exceptions are larger total pesticide use for average Brazil, larger herbicide use in Tocantins and larger insecticide use in Mato Grosso. It was also found that Paraná and Mato Grosso have intensive agricultural systems with soy double-cropped with maize (safrinha) that influence the pressure indicators to become smaller when investigating harvested land compared to physical cropland. Because of large uncertainties with pesticide data, impact indicators were not calculated but instead a trend assessment of pesticide sales and their corresponding potential impacts was conducted. That showed large increase in application trends for the AI with highest potential impacts based on characterization factors (CF) for emissions to freshwater retrieved from the life cycle assessment (LCA) model USEtox. In order to assess potential impacts of pesticides applied to soy in Brazil with higher precision there is need for more accurate allocation methods of pesticide AI to soy as well as LCA models adapted to tropical climate.

Keywords: pesticides, active ingredients, herbicides, fungicides, insecticides, Brazilian soybean, Paraná, Mato Grosso, Tocantins, pressure indicator, impact indicator, USEtox.

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## 1 Introduction

Soybeans have been produced on a global scale in Brazil since the 1970-1980s [1] and the production and export has increased to such extent that Brazil is currently the top producer and exporter in the world [2]. Brazil is also in the world top when it comes to amount of pesticides used [3], and a large share is allocated to the soybean cultivation [4]. The trend shows increased use of pesticides in soy production [5], which is alarming due to many reasons e.g. adverse effects on other organisms than what is targeted as well as toxicity to the environment, wildlife and humans [6]. Except for increased pesticide use being a threat, the expansion of soy producing land by large-scale farmers and corporations is cause of a growing maldevelopment in terms of poverty and violated land owning rights [7].

The worldwide pesticide use has from 1990 to 2015 increased from 1,5 to 2,6 kg active ingredient (AI), which is the substance that executes the pesticide's effect [8], per hectare of cropland. Pesticides are determined to be one of the major drivers of biodiversity loss as well as an impact to humans in terms of diseases such as cancer, and especially in developing countries they are a cause of acute poisoning and death [9].

This thesis will investigate regional differences in Brazil by mapping the pesticide use in three states that have cultivated soy for different periods of time; one state that has cultivated soy for a long time in the South; one state in the Centre-West that has cultivated soy for some decades; and one newer soybean state in the frontier region of North/North-East (called "Matopiba" from the abbreviations in the states Maranhaõ, Tocantins, Piauí and Bahia). The states investigated are Paraná, Mato Grosso and Tocantins, which have different climate conditions because of their different geographical locations where the more recent soybean production expansions have occurred in tropical conditions. The different locations of the states as well as time lengths that soybeans have been cultivated for could affect the pesticide use pattern and effect on the environment and are expected to be important for the investigation.

#### 1.1 Aim

The aim of the thesis is to investigate if it is possible to quantify pesticide footprints of soy for three important soybean producing states at different states of development in terms of soybean cultivation and production (Paraná, Mato Grosso and Tocantins). If it is possible to calculate the footprints, the further aim is to analyze and compare them between the states in question. This is done in order to increase knowledge on pesticide use patterns and pesticide toxicity in Brazilian soy.

#### 1.2 Limitations

The thesis will focus on the Brazilian states Paraná, Mato Grosso and Tocantins. Other countries and states are excluded from the deeper analysis. The investigation of pesticides will include not include any compounds outside of the product classes herbicides, fungicides and insecticides.

#### 1.3 Research questions

The thesis will address the following topics:

- Which are the data sources for pesticide use at national and state level in Brazil, and which are the challenges when using them in environmental assessments?
- How large share of the total applied pesticides are used in the soybean production in Brazil?
- Which are the pesticide use trends in Brazil regarding the soybean production?
  - Are there any differences in the use between the Brazilian states Paraná, Mato Grosso and Tocantins?
- Can available data on pesticide use in Brazil be used to quantify impact indicators, so called pesticide footprints?

The questions are investigated with the working procedure of obtaining pesticide footprints of pesticides in soybean production in Paraná, Mato Grosso and Tocantins.

## Background

This chapter is laid out to first give insight about pesticides in general and the largest pesticide product classes in particular, thereafter some history on how soy was introduced in Brazil, how it has come to be the important crop of today and the Brazilian agricultural system. To finish the chapter off, a deep-dive in evaluation of pesticide impacts is presented.

#### 2.1 Pesticides

A pesticide is a compound that is used to kill pests, weeds or other hazards that threaten agricultural activities such as production of crops [6]. The active ingredient (AI) in a pesticide is the chemical compound that delivers the effect [8], for example what kills the targeted weed in the weed-killing pesticide type called herbicide. Except for the AI, a pesticide product contains different types of additives that gives the product its desired properties. There are different classifications of pesticides depending on the targeted organism, and this thesis will investigate the largest classes; herbicides, fungicides and insecticides that target weeds, fungi and insects respectively.

Some plants have been modified genetically in order for them to resist being affected by the toxic effects of certain pesticides. Crops with these modifications are key in agricultural practices where no-tillage is applied [10] (meaning that the soil is not stirred by ploughing or harrowing) such as in Brazil where no-tillage has been used since the 1970s in order to prevent soil erosion and water- and nutrient losses. One important crop that has been genetically engineered (GE) is the soybean, which is modified in order to resist the herbicide glyphosate. The extensive cultivation of the GE soybean and other GE crops leads to heavy reliance of glyphosate in order to control weeds [4].

Mode of action (MoA) is the train of events that occurs from the application of a pesticide to when the pest is controlled or killed [11], meaning the interaction of the pesticide AI and the targeted pest. A phenomenon that may arise when pesticides are largely used is resistance. Resistance can occur when using pesticides with the same MoA that kills pests with similar actions. Understanding how resistance occurs can help to prevent it emerge [12] with proper use of the knowledge applied in methods such as integrated pest management (IPM) [13]. IPM includes low inputs of pesticides and is recommended by e.g. the EU [14].

Global food production has more than doubled in the last century with the help of pesticide and fertilizer use, and the human population that continues to grow is dependent on the current intensive agricultural system to be fed [15]. The use of pesticides can be considered controversial because they cause severe environmental pollution but is needed to maintain high yields and food security [6]. This section will describe the largest pesticide classes in order to understand how they are used in Brazilian agriculture.

#### 2.1.1 Herbicides

Herbicides are weed controllers that consist of substances that kill or prevent the growth of weeds, and the use of them has the advantage that labour cost can be lowered compared to mechanical weed control because of the simpler application [10]. The herbicide application can occur before planting of the crop (pre-planting), before the crop growth (preemergence) and after the emergence of crops through the soil surface (post-emergence) [10, 16]. Correct application timing is important and leads to sufficient control of the weeds, while an incorrect timing could result in no control at all [16]. Applying a preplanting herbicide after emergence of the crop can be considered incorrect timing and the herbicide might harm the crop.

The herbicides used today can be categorized into selective and non-selective, where the selective are targeting specific weed species and the non-selective targets any species [10, 16]. Examples of selective herbicides are 2,4-D and atrazine, and compounds such as glyphosate and paraquate are examples of non-selective herbicides [17].

#### 2.1.2 Fungicides

Fungicides are toxic substances controlling the growth of parasitic fungi that threatens to damage plants, and are usually applied as sprays or dusts [18]. Different kinds of fungicides to control diseases in crop production have been used since the 1800s. Nonsystemic fungicides are well established as protectants against fungi before any fungal attack has occurred, and do not treat already infected plants. Systemic fungicides are taken up by the plants, thereafter being distributed in the tissue and can control and protect from growth of new infections [19].

Several non-systemic fungicides that are used in modern days have in some cases been used since the 1950s because of the benefit that their multi-site MoAs prevent resistance. Resistance in some fungal species has been developed as an effect of overuse of fungicides and the resistance can occur rapidly [18]. By using integrated management of fungicides, there is an opportunity to delay or avoid resistance. But the strategies to prevent resistance must be used over large areas in order to be successful [19]. It is not very effective to apply anti-resistance strategies at one farm if the neighbour does not apply any strategy at all, and this is because fungi can have millions of spores each and spread rapidly [18].

#### 2.1.3 Insecticides

Insecticides are defined as toxic substances used for killing insects, for the topic in this thesis the most important application is to protect crops but insecticides can also be used to kill insects carrying disease in order to protect humans or animals [20]. One way to classify insecticides is by its mode of penetration, where the toxic substance can have effect on the insect by ingestion, inhalation or penetration of the body covering. Synthetic

insecticides are commonly effective in all these three ways, it is therefore better to tell them apart by their chemical classification. The dominating category is the synthetic contact insecticides, which easily penetrates insects and are toxic to many species [20].

The MoA of insecticides vary, just as with MoA for herbicides and fungicides, and can be classified by how the insects are controlled so as to not destroy crops. The insecticides affecting the insects' nerve- and muscle-systems dominate the sales with 85 % of the sales value, in this category neonicotinoids have the largest sales share with 27 % of the market. Examples of neonicotinoid AI are acetamiprid and imidacloprid [21]. The MoA effect that these insecticides have on the nerve system is very attractive for pest control since the effect is high even with a small dose [5]. Another insecticide AI that is considered a low-dose pesticide is lambda-cyhalothrin, belonging in the group of pyrethroids, which has a recommended application dose in soy production of 3,75-7,5 g per hectare land [22]. This can be compared with a high-dose insecticide in the organophosphate group called acephate that has the recommended application of 0,75-1 kg per hectare soy in order to fight the same pest (soyworm) [23]. The application trend over the last ten years (2009-2019) shows that some high-dose insecticides decrease and are replaced with the use of low-dose insecticides that are far more toxic per unit of AI [5].

Overuse of insecticides risk resistance development among target insect populations. When the insects that survive insecticide spraying multiplies they can form a significant share of the population and in this way the resistance is increasing. Another risk with insecticides is that naturally occurring enemies to the targeted insects are also killed due to the insecticide application, and therefore the natural protection against insect attacks on the crops disappear [20]. Integrated management is essential as to not mis- or over-use insecticides [21].

#### 2.2 Soybean cultivation and expansion in Brazil

Soy is primarily crushed and the extracted oil is used as food or biofuel while the extracted protein rich soymeal is used as animal food. Soymeal is currently the most used protein-feed stock in the animal industry [24]. Brazilian soybean is to a very large extent exported to China, which is a shift from the EU being the most important importer of Brazilian soy at the start of the 21st century [4, 24, 25]. In 2016, China received a share of around 75 % of Brazilian soybean export [25]. This section will describe how the soybean was introduced in Brazil, the cultivation system where double-cropping with maize has gained large importance and how the expansion of agricultural land dedicated to soy affects the Brazilian savannah called Cerrado.

#### 2.2.1 Crop introduction in Brazil

The soybean was introduced in Brazil after American researchers adapted the crop to lower latitudes in order to produce high-quality protein meal to poultry farmers in the southern United States. This qualified the low latitude variety of soybean to be cultivated in southern Brazil that has a similar climate. Farmers therefore began to farm it in the late 1960s in the states of Rio Grande do Sul, Santa Catarina and Paraná [1]. In the 1980s, a new variety of the soybean crop that was adapted to even lower latitudes and therefore suited for tropical climate, was developed by the federal research institute in Brazil (Emprasa Brasileira de Pesquisa Agropecuaria, EMBRAPA). This meant opportunity to expand the production in the Cerrado region in the North-Western Brazil, where over 200 million hectares of land was considered available for the purpose [1] in the states of Mato Grosso, Mato Grosso do Sul and Goiás [25]. Since the lands for possible soybean cultivation were so grand it became an area with massive economic potential, and Brazil came to have the lowest production cost per hectare in the world because of rapid machinery development that lead to high efficiency [1].

The recent development in the expansion of soybean production shows an increase in the border areas of the Matopiba states (Maranhaõ, Tocantins, Piauí and Bahia) in North-Eastern Brazil [25]. This thesis will focus on three states that have different stages of development in terms of soybean cultivation and production, and they are shown in Figure 2.1 below. Paraná in yellow has cultivated soy since the crop came to Brazil in the 1960s; Mato Grosso in blue was object for the grand soybean expansion during the 1980s and forward; and Tocantins in red is part of what is called the new agricultural frontier where the expansion is most intensive today.



Figure 2.1: Map of Brazil, with the state of Paraná in yellow, Mato Grosso in blue, and Tocantins in red. From [26], adapted with permission, CC BY.

The current intensive soy production in Brazil relies on the use of pesticides [4] that is applied at multiple occasions each time the crop is cultivated. In Figure 2.2, examples of typical pesticides that are applied to soy during a year are shown.

INPUT	STAGE TIME	(DESICCATION)				REPRODUCTIVE STAGE		HARVEST/POST PLANTING (DESICCATION)		
		SEP	ост	NOV	DEC	JAN		FEB	MAR	APR
	В		Glyph	osate					1	L
MAJOR HERBICIDES (A.I) USED	MO-GM	2,4 D, 2,4 D + Glyphosate, Paraquat, Diuron + Paraquat	Metribuzin, cletodin, trifluralin		fome Imaz lacto feno: p-eth clorin	xaprope- iyl, muron, muron-		Paraquat, Diuron + Paraquat, Diquat		
MAJOR	GM		•			*, methami am+ciproco				
INSECTICIDES (A.I) USED	MD-NON				loprio	trina+thiar I + betacyfl , flube				
	GM					Pyraclostr epoxicona	zol,			
MAJOR FUNGICIDES (A.I) USED	NON-GM					azoxystrol cyprocona pyraclostr picoxystro trifloxystro cyprocona	azol, obin, obi, obin +			

\* Sales of endosulfan will be prohibited from 2013. \*\*Sales of methamidophosis were forbidden in 2012

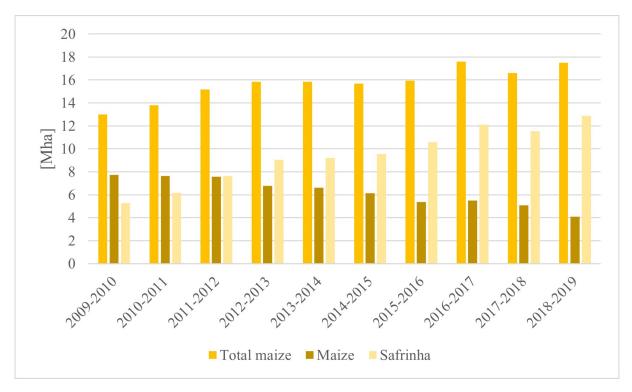
Figure 2.2: Examples of common pesticides in Brazilian soy production during the growing season [4].

#### 2.2.2 Double-cropping with maize

An important transition occurring due to the introduction of soybeans in Brazil was that many small-scale farms were replaced by medium- and large-scale farms. These farms in the Southern Brazil, for example Paraná, set up their farming system with a second crop of wheat or maize following the soybean [4]. A second-season corn is known as safrinha [4] and this type of crop system where two crops are cultivated the same crop year is called double-cropping [27].

The double-cropping with maize in Brazil has an increasing trend, in Figure 2.3 it is illustrated how much land is dedicated to maize production. The first maize is cultivated as the main crop, while the second maize (safrinha) is following another main crop in a yearly growing cycle, usually soy. The increase in double-cropping soy and maize has two main drivers. One reason is the use of no-tillage practice in soybean cultivation that has decreased the time between the soybean harvest and the planting of maize. The second

reason is that development of herbicide resistant maize, high quality inputs and technical improvements has made it easier to plant the crop close after the soybean harvest. Increase in double-cropping area is a response to higher agricultural prices and farmers increase their production without increase in land use or land use conversion [27].



**Figure 2.3:** Area for cultivation of maize in Brazil over the last decade [28]. The area for cultivation of total maize consists of area for maize production (first crop) and area for safrinha production (second crop).

The area for cultivation of maize can be compared with the area for cultivation of soybean, shown in Figure 2.4. The area for cultivation of soybean in the growing season 2018-2019 was 153 % of the area in 2009-2010. The expansion of safrinha production area was 244 % in the same period, while the land for the first crop of maize decreased with 47 %. Note that the safrinha area expansion has occurred on the land already holding soybean cultivations. The increase in double-cropping has the effect that more pesticides are used per unit of land since the land must be treated to kill off pests for two crop cycles per year compared to only one.

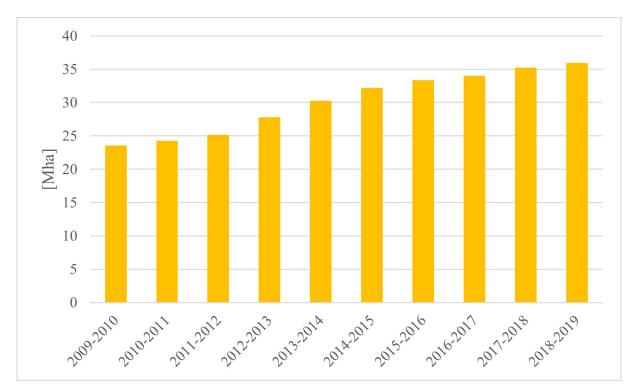
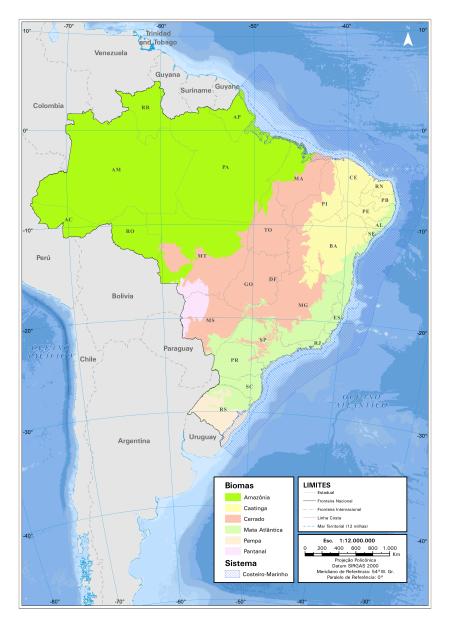


Figure 2.4: Area for cultivation of soybean in Brazil over the last decade in million hectares [28].

#### 2.2.3 Land use change in the Cerrado

The area used for cultivation of soy in Brazil has increased almost forty times [29] in the last 50 years (1969-2019), which has led to environmental effects such as deforestation, biodiversity loss, and water contamination and -eutrophication caused by pesticide use. Land conversion for cultivation of soy has amplified in the Brazilian Savannah called Cerrado [4]. The Cerrado is a biotope holding 5 % of the biodiversity on Earth and storing large amounts of carbon [30]. The Cerrado is located South-East of the Amazon and both Mato Grosso and the Matopiba region have the biotope within their state territories, which is illustrated in Figure 2.5 on the next page.

The Cerrado contains multiple forest and vegetation types, both dense forest areas and treeless grassland areas and everything in between [4]. It has similar characteristics to pasture, which can make it difficult to separate from the native ecosystem on for example satellite analyses. Therefore it can also be difficult to detect when Cerrado is transformed to pasture, and also the difference between Cerrado, pasture and cropland [31]. Deforestation is likely happening due to indirect land use change, for example land can be occupied by movement of cattle from former pasture areas [4]. According to a Brazilian study by the Ministry of Environment (MMA) and the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) municipalities with high deforestation rates also have large increases in new soy plantations [4]. This implies that the movement of cattle paves the way for expansion of area for soybean production.



**Figure 2.5:** Map of different biomes in Brazil 2019 where the red is the Cerrado. Tocantins (TO) is completely covered by the biome and Mato Grosso (MT) consists of a large share. From IBGE [32].

#### 2.3 Evaluating pesticide use and impacts

To assess pesticide use and its impacts due to soybean production, different indicators can be quantified, so-called pesticide footprints. That is what this project is ultimately working towards and it is based on the theory and method developed by Pollak 2020 [5] where the focus lay on obtaining a pesticide footprint for the entire country of Brazil. The following sections will present backgrounds to two types of indicators, pressure- and impact indicators, and address issues regarding evaluation of impacts in life cycle assessment (LCA).

#### 2.3.1 DPSIR

DPSIR is an acronym for Driving forces, Pressure, State, Impact and Response and it is a framework for structuring and analyzing indicators used by for example the European Environment Agency (EEA). Indicators are used in order to communicate information regarding an addressed subject. They are always simplifications of a complicated reality and focus on specific aspects, and these simplifications make them comparable and applicable in e.g. policy-making [33].

The DPSIR framework has systems perspective where development in social and economic areas causes *pressure* on the environment, which affects the environmental *state* to change. The change leads to *impacts* on humans and the environment, that can produce a *response* by society, leading back to the *driving forces* or directly affecting pressure, state or impacts [33].

In the DPSIR model there is room for analysis of dynamic situations and various feedbacks within the investigated systems. The assessed systems let the indicators be included in a broader picture than the "snapshot" of the reality that they represent without the societal and environmental inter-connectivity analysis [33].

For the thesis theme with pesticide use in soybean production in focus, the DPSIR framework is applied in order to understand the larger system. In Table 2.1 the relation of DPSIR to soy production in Brazil is shown.

DPSIR	Relation to soy production in Brazil					
Driving forces	<ul> <li>Need for cheap food to feed a growing global population.</li> <li>Need to combat pests in the cultivations by using pesticides in order to produce soybeans</li> </ul>					
Pressure	Use and emissions of pesticides through applications on fields					
State	Polluted freshwaters, soils, air etc.					
Impact	E.g. death of x % freshwater living organism due to exposure to a pesticide residual from a nearby pesticide application					
Response	By different actors e.g. by the government that can forbid certain pesticides					

Table 2.1: The DPSIR framework in relation to soy production in Brazil.

#### 2.3.2 Pesticide pressure indicators

The pressure indicators are representing *pressure* in the DPSIR model and in the specific case of pesticide use it refers to the volume of active ingredients (AI) required to cultivate one hectare or to produce one tonne of an agricultural goods. The applied AI volume dedicated to the total agricultural production or to the soy production are changing the environmental *state* leading to different *impacts*.

#### 2.3.3 Pesticide impact indicators in LCA

Similar to the pressure indicators representing *pressure* in DPSIR, the impact indicators are related to the term *impact* in the framework. Environmental impacts from applied pesticides must be evaluated according to the properties of the specific AI. Determining impacts per hectare of agricultural land or tonne product can be performed through Life Cycle Impact Assessment (LCIA in the LCA methodology) where individual chemicals, e.g. AI, have been assigned characterization factors (CF). The CF help to quantify the emitted chemical's potential ecotoxicity in a given media, e.g. in freshwater. This is parallel to the more well-known Global Warming Potentials (GWPs) that are used when calculating carbon footprints that includes multiple greenhouse gases. One important difference is that the total number of AI that are emitted to e.g. freshwater are very large, have many pathways in the environment and that the toxicity on aquatic organisms are far from fully known, especially under tropical conditions.

LCA is commonly used to evaluate these environmental impacts of e.g. agricultural production [9, 34, 35]. It is a method that the European Union (EU), among others,

applies in calculations of environmental footprints of products (PEF) including several food products [9]. Pesticide use is usually one of the factors that has the largest toxicity impact to both ecosystems and humans [34], and even though pesticides are widely used in the global food system their impacts are rarely included in LCA [35].

Gentil et al [34] describes three characterization models in LCA that are currently the most updated on pesticide emissions and toxicity;

- PestLCI as life cycle inventory (LCI) emission model,
- USEtox 2.1 as life cycle impact assessment (LCIA) (eco-)toxicity characterization model, and
- DynamiCROP 3.1 as model characterizing human exposure

Since the main focus of this thesis lay on environmental effects of pesticides the details of dynamiCROP will be excluded, and the following sections will describe PestLCI and USEtox.

#### 2.3.3.1 PestLCI

In order to make estimations of pesticide emissions caused by pesticide application in agricultural production, the model PestLCI can be used. From applications of pesticides in open fields the model estimates emissions to air, groundwater and soil. The model is developed for temperate climate such as in Western Europe, and it covers two distribution sets; primary distribution (up to a few minutes after application) and secondary distribution (when the pesticides have reached the crops, soils and surfaces outside the fields, and have been emitted to air through wind). The secondary distribution takes environmental processes into account, such as degradation and volatilization both on crop leaves and soil, uptake in plants, leaching and runoff [34].

The result from the modelling is distribution of pesticide emissions in the environment. The included processes can be modelled until the first rainfall following the application, which is decided by data on frequency of rainfalls by month. Estimates of the emissions are obtained by functions of [34]:

- Crop
- Location
- Growing season
- Active ingredient
- Farming practice
- Application method

The recommended time frame in PestLCI is one day, which has the effect that processes occurring later than one day after application will not be accounted for in the current model. This affects the modelling of processes such as leaching and runoff that are important in tropical regions as is further discussed in Section 2.3.5. The drift curves that are used to calculate emission fractions are adapted from temperate climates (in Europe) and research is needed in order to explore new drift curves for field application of pesticides in tropical conditions [34].

#### 2.3.3.2 USEtox

The USEtox steady-state model can calculate three indicators in two impact categories; human cancer toxicity, human non-cancer toxicity and freshwater aquatic ecotoxicity of chemical emissions. It characterizes the impacts in LCA with six environmental compartments [34]:

- Urban air
- Rural air
- Agricultural soil
- Natural soil
- Freshwater
- Coastal marine waters

USEtox is a mechanistic model that is based on all continents' conditions on average and gives results for an average continent, with continental and sub-continental parameterizations available but only recommended for sensitivity analysis. The model does not mirror tropical conditions and therefore more information about the effects of pesticides on ecosystems in tropical climate is required. In the current version there is a likely underestimation of the ecotoxic effects of pesticides on tropical ecosystems because of missing information [34].

Compared to PestLCI (described in Section 2.3.3.1), USEtox (and dynamiCROP) takes into account the more long-term processes that PestLCI disregards, but it does not have the possibility to spatially divide the emission model in order to allow for variations of factors in soil and climate. That means that processes influencing soil and climate are not considered properly [34].

#### 2.3.4 Challenges with impact indicators in LCA

LCA studies on agricultural products rarely takes into account pesticide impacts on humans and the environment, despite their known negative effects. It is known from experience that the discovery of hazardous effects from new pesticides can take up to 30 years and that we tend to underestimate them. For example neonicotinoids (a type of insecticide) were considered to cause less harm than the replaced insecticides because of the smaller volumes applied but it was later discovered that they accumulate in soils and have sublethal effects on pollinators [9].

To assess the impacts of pesticide use there is need for detailed data on volume and type of AI, application methods, crop types and crop development stages, soil properties and climate conditions, and many of these parameters are not available, especially in developing countries [9].

#### 2.3.5 Pesticide impact indicators in tropical climate

Tropical conditions are considered appropriate for a magnitude of crops with production all year around. In a tropical climate, there is no interruption in the agricultural production for a cold season. These conditions are not only favorable for production of crops, but also for occurrence of pests, which require farmers to use pesticides in large varieties and amounts [34].

There are large differences between crop production and pesticide use in temperate systems compared to tropical production systems. The impacts from pesticide emissions in tropical regions are specific and depending on regional differences in soil, climate, agricultural practices and crops. The models that are available and described here are the most up-to-date but they are not sufficient to assess effects on humans and ecosystems because of the model design that is not adapted to evaluate regional toxicity characterization [34]. This section will describe some of the characteristics of tropical climates that makes it difficult to use the models that are developed for temperate regions, which are explained by Gentil et al [34].

In a tropical climate the kinetic rates of processes are higher than in temperate climates and that leads to e.g. faster degradation. Another process that is faster due to higher temperatures often found in tropical climates, is volatilization of pesticides, which is explained by the higher vapour pressure that enhances the ability of the compound to vaporize into the air. Because of the sunlight radiation that usually is higher in tropical regions, the photodegradation of pesticides on plant surfaces is increased adjacent to pesticide application. Similarly, photolysis of pesticides on soil surfaces, especially in the beginning of plant growth, is important for the degradation processes [34].

The emissions of pesticides are highly dependent on how often and how much it rains, and in tropical regions this is especially important since the climate consists of periods of cloudburst and/or drought. The runoff increases with heavy rainfalls, which leads to peak emissions of pesticides in surface waters and toward groundwaters. Agricultural practices can also influence the runoff and leaching of pesticide residues; cover plants between crop rows can reduce runoff and crop residues can increase herbicide sorption and thereby reduce leaching. Factors such as these are therefore important to take into account when modelling pesticide emissions. The application method of pesticides on crops can vary a lot since there are large differences in the cropping systems depending on farm size and what is cultivated, and that is another reason to why the emissions can vary [34].

The soil characteristics in tropical regions vary greatly in for example organic carbon content, pH and anion exchange capacity, the decomposition rate of organic matter is higher and organic carbon content can be lower. In most areas in Brazil, the soil pH is low and that affects acidic herbicide residues to be more available for leaching. Some parameters depending on characteristics have strong effect on the results, such as [34]:

- Fraction of continuous micropores in the soil
- Volume fraction of water in the soil
- Fraction intercepted by leaves
- Leaf area index

The leaf area index and the related fraction intercepted by leaves should be investigated and implemented in the models for the crops under evaluation [34].

The accuracy of the assessment of toxicity impact decreases if there is need to use average values of applied pesticides or a similar compound as substitute to the investigated pesticide. Some compounds such as metal-based pesticides are not included in the current models, the same goes for metabolites of active ingredients that might have different (larger) toxic effects than the "parent compounds". Gentil et al urge that there should be possibilities to add sets of data with information about specific climate and soil since the factors are crucial for correct results [34].

There is a need for more research on how to account for effects in soil, which could be seen to belong to both the ecosphere and the technosphere in environmental system analysis. In what compartment the soil belongs affects how the emissions and impacts are modelled. PestLCI and USEtox do not have the same boundaries in terms of space and time and it is important to know which output from PestLCI can be used as input in USEtox in order to not double count mass transport processes [34].

## Methods

The procedure of obtaining pesticide use indicators will be explained in this chapter. In order to understand the challenges when calculating the indicators, the most important data sources will also be accounted for. This includes what data is provided by the different sources and how it is reported. The required data to calculate the indicators includes both pesticide sales and information about land use and production.

#### 3.1 Data sources

The required information to calculate the pesticide footprints is retrieved from various organizations, most part from Brazilian agencies. This section will describe the main data sources and what their provided data is used for in this thesis.

#### 3.1.1 Pesticide use data sources

The data sources related specifically to pesticide sales are accounted for first. Starting at the international level and finishing at the Brazilian state level.

#### 3.1.1.1 Food and Agriculture Organization of the United Nations (FAO-STAT)

The Food and Agriculture Organization of the United Nations, FAOSTAT, provides data on all kinds of agricultural production on a yearly basis for all states and regions in the world. Inputs to agriculture, emissions, produced goods, land use, different indicators are examples of available categories [29].

Through FAOSTAT is possible to retrieve data on yearly pesticide use for different nations, with sub-categories such as herbicides, fungicides and insecticides. The organization gathers data on pesticide use by sending out questionnaires to all countries worldwide [29]. The pesticide statistics published by FAOSTAT are used as comparison with what is reported at national level in Brazil. Furthermore numbers on land use for Brazil, for example amount of cropland and pasture, are compared to Brazilian statistics in order to verify the data.

#### 3.1.1.2 Brazilian Environmental Institute (IBAMA)

Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis, abbreviated IBAMA [36], is the Brazilian Environmental Institute. IBAMA provides data on the total sold amount of active ingredients (AI) at national level in total, and divided at

state level. They also report the sold amount of AI divided in product classes such as herbicides, fungicides and insecticides, among several others. The data that IBAMA provides are retrieved from actors in the pesticide industry, such as manufacturers, that are obliged to report their numbers on production, import, export and sales of pesticides every six months. Due to competition laws IBAMA only reveals AI registered by at least three different companies, which has the effect that many individual AI and their sold volumes are not available.

In 2017, 88 out of 329 sold AI were published with AI names and related volumes [36], which covers the majority of the sold volume [5].

#### 3.1.1.3 National Union of Plant Protection Products Industry (Sindiveg)

Sindicato Nacional da Indústria de Produtos para Defesa Vegetal (Sindiveg) is the national trade union for the pesticide industry in Brazil. They represent around 40 % of the Brazilian pesticide market that includes 26 companies in the business [37].

Sindiveg also publishes statistics related to pesticide sales and use at national level in Brazil. Included in the statistics are indexes over pesticide treated areas according to a number of applications of different pesticide products, which is presented as the total area for all cropland and as percentages for the largest crops. Figures on economic value and volume of the used products are also presented. The available data on Sindiveg's website is published for 2018 and 2019 [37].

Other data that is available to use in the analysis is a document called "Vendas de defensivos agrícolas por culturas de destinação e classes", translated to "Sales of crop protection products by destination crops and classes", that was retrieved from Sindiveg for the years 2012-2014 and is not currently available online. In this document the pesticide sales are divided into product classes and subcategories to the classes, according to the most important crops in Brazil. It was used by Pollak [5] to estimate pesticide allocation to soy and attempts to retrieve more current data from Sindiveg was made without success.

#### 3.1.1.4 Paraná Agriculture Defense Agency (ADAPAR)

Paraná is one of few - maybe the only - Brazilian state that shares detailed data on pesticide sales and uses. The organization that is gathering and publishing pesticide information from retailers is Paraná Agriculture Defense Agency, ADAPAR [38], called Agência de Defensa Agropecuária do Paraná in Portuguese. The pesticide data is published in a document named Dados do SIAGRO, which is an abbreviation in portugese translated to "Monitoring System for Trade and Use of Pesticides in the State of Paraná".

Dados do SIAGRO contains detailed data of pesticide sales in Paraná presented in percentages of total sold volume of commercial products. Shares of product classes, shares of individual AI and shares of the sales that are used in individual crops are published. The volume of commercial products is gathered by ADAPAR through a reporting system that retailers are required to fill in at least once a week in order to keep their sales license. Data is collected and published at municipality level [38].

#### 3.1.2 Other data sources

Data sources related to classification and calculations of pesticide indicators are presented here. They are all at the national level in Brazil.

#### 3.1.2.1 National Health Surveillance Agency (ANVISA)

The National Health Surveillance Agency is called Agência Nacional de Vigilância Sanitária (ANVISA) in portugese and it has the responsibility to regulate the food industry, among other duties. This means that ANVISA regulates the types of pesticide AI that are approved for use in agricultural production [39].

Pesticide information that is owned by ANVISA includes documents with information about specific AI that is used in the agricultural production in Brazil. The documents are part of a database of all AI regulated by ANVISA, and have information such as chemical class, product class (e.g. herbicide), human toxicity class and crops in which the AI has registered use, including application method. The documents with AI classification details are used in order to classify the data on AI that IBAMA and ADAPAR provide, and are the basis for the classification of pesticide products into the main groups herbicides, fungicides and insecticides.

#### 3.1.2.2 Brazilian Institute of Geography and Statistics (IBGE)

Instituto Brasileiro de Geografia e Estatística (IBGE) is the Brazilian Institute of Geography and Statistics and it collects data on all sorts of topics related to Brazil. Examples of statistics are numbers on populations in cities and states, and agricultural production volumes.

An important piece of statistics that IBGE provides is the official agricultural counting 2017 [40]. This provides information on areas of land dedicated to different purposes, e.g. cropland and pastures. The cropland data is divided by temporary and permanent crops where temporary crops include annual harvests of for example soybeans, and permanent crops refers to perennial varieties of different kinds of trees that are not harvested and replanted each growing season. Total cropland area is the physical area where crops are cultivated. The specific crop data also include production volumes. Since the agricultural counting is a very time consuming project where IBGE gathers data by door knocking it includes detailed data down to municipal level but is only performed once every ten years.

Apart from the official agricultural counting, IBGE also publishes data on agricultural production at municipal level each year [41]. The difference from the counting is that the information about land dedicated to different crops is referring to the harvested land instead of the physical land.

#### 3.1.2.3 National Supply Company (CONAB)

CONAB (Companhia Nacional de Abastecimento) is the National Supply Company in Brazil [28], referring to the supply of agricultural products. One interesting type of data provided by CONAB is historical data at state level on the most important crops cultivated in Brazil in terms of area dedicated to production and production volume. This information is used to investigate historical trends of soybean and maize production in the states of Paraná, Mato Grosso and Tocantins.

## 3.2 Pesticide use indicators

The indicators for investigations of pesticide use are, as explained in the Background chapter, separated into pressure- and impact indicators. By using data and statistics from the previously mentioned data sources calculations of both types of indicators are performed. The following sections will describe what needs to be done in order to obtain the indicators.

#### 3.2.1 Comparisons of pesticide data at national and state level

To be able to calculate the pressure indicators, knowledge about how the available data on pesticide sales can be used must be obtained. This is explored at the national and state levels by comparisons of the data that is provided by the organizations presented in Section 3.1.1.

At Brazilian national level, FAOSTAT [29] and IBAMA [36] publish data on volumes of pesticide AI sales that is comparable to each other. Information about total pesticide AI sales volumes as well as sales volumes of the product classes herbicides, fungicides and insecticides are collected and compared quantitatively.

At state level in Brazil, Paraná is used as comparison basis with data from IBAMA [36] and ADAPAR [38]. Since the available ADAPAR data on individual AI is presented as percentages of CP, it does not match the desired indicator format which is kg AI per hectare and tonne soy. The ADAPAR data is therefore examined through an analysis of what information is missing when attempting to calculate volumes of AI from the initial position containing percentages of AI. Since the IBAMA data has unknown gaps because of competition laws that prohibit publishing of some AI while the ADAPAR data does not suffer from the same losses, it is possible to compare the two data sets in order to gain understanding about what is missing. The procedure leading up to the comparison is accounted for below.

- 1. All sold AI are classified according to their associated product class (e.g. herbicide), based on product sheets published at the ANVISA website [39].
- 2. The largest product classes herbicides, fungicides and insecticides are sorted out.
- 3. For each individual AI in the relevant product classes, averages of the sold volume (IBAMA) or percentage (ADAPAR) for the years 2016-2018 are calculated.
- 4. The lists are sorted from largest to smallest according to the calculated average values.
- 5. For each product class the ten averagely largest AI are picked out.
- 6. The IBAMA and ADAPAR lists can now be compared in order to visualize reporting differences.

## **3.2.2** Determination of pressure indicators

The pressure indicators can be used to compare pesticide consumption in agricultural production as well as soy production at the national and state levels. The indicators that are attempted to be obtained are:

- kg AI per hectare cropland,
- kg AI per hectare land dedicated to soy production, and
- kg AI per tonne produced soybean.

The IBAMA data on volumes of sold pesticide AI is used as basis for all indicator calculations, in that way the pressures can be compared over time and among Brazil and the three investigated states. IBAMA reports the additive classes adjuvants and spreaders as AI, the volumes of these classes are substracted from the total pesticide AI volume before calculating footprints. Except for the total volumes of sold pesticide AI, the volumes of the largest product classes herbicides, fungicides and insecticides are included. The fungicide class is a summarization of the reported classes "fungicides" and "fungicide, acaricides", and equally for the insecticide class consisting of "insecticides" and "insecticide, acaricides".

The pesticide data includes total sold volumes applied to all agricultural land that consits of both cropland, grassland and pastures. Pesticide use on grassland and pastures is generally very low, which is why the focus lay on cropland. ADAPAR reports that 2,3 % of all pesticide CP is applied to pastures in 2017 [38], and Sindiveg reports 6 % in 2018 [37]. The ADAPAR figure is used for calculations regarding Paraná while the Sindiveg number is used for calculations including total Brazil, Mato Grosso and Tocantins.

The pressure indicator that describes volume of AI for all cropland is the starting point for the calculations. Pesticide data is already chosen, the next step is to choose land data. The IBGE agricultural counting from 2017 [40] includes information about cropland, meaning the physical land area dedicated to crops. It is also of interest to investigate the pesticide use on all harvested land since the area can be larger than the cropland area because of double-cropping, which is why the agricultural counting is compared with IBGE official yearly statistics (PAM) for the year 2017 [41].

For the calculations of pressure indicators specific for the soy cultivation and production, the same pesticide data used in the indicators for all cropland is chosen. Allocation of amounts of pesticide AI that are applied to soy must be performed, which is desribed in Section 3.2.3. It is of interest that the volumes of AI per hectare soy and volumes of AI per tonne soy for the nation and the included states should be comparable over a time period of five years (2015-2019) in order for trends to be shown. The yearly statistics on land use and production of crops provided by IBAMA is chosen to fulfill this purpose. Calculations of pressure indicators will therefore show volumes of pesticide AI per hectare of harvested land, as opposed to (physical) cropland.

#### 3.2.3 Allocation of pesticides to soybeans

The greatest challenge to obtain pressure indicators for soybeans is to allocate the volumes of pesticides AI that are applied in the soybean production. The total volume of pesticide AI as well as volumes of AI in the included product classes are known but the sizes of the proportions used specifically in soy are unknown and vary among product classes and among individual AI. Since the variations are unfamiliar, it is necessary to assume average allocations at the national and state levels.

The IBAMA sales volumes of pesticide AI, delimited to cropland according to the procedure in Section 3.2.2, are used as basis for the allocations. As a baseline it is assumed that 55 % of total pesticide use is allocated to soybean, which is a rough estimate from Sindiveg [37], and supposed the same for Brazil and the investigated states. However, this share is probably higher in states which are specialized in soybean production, as the three studied states here. Sensitivity scenarios with higher shares of pesticides allocated to soy are therefore explored.

Because of access to ADAPAR data providing information on share of pesticides used in soy [38], Paraná is chosen as a starting point when determining allocations in the sensitivity scenarios. The amount of pesticides used in soy according to ADAPAR was 60 % in Paraná 2018, which is the share that is used as basis for the adjustments in Mato Grosso and Tocantins. The adjustments are also based on the average intensity of the soybean producing area in relation to the total harvested cropland during the time period 2015-2019 for the three states (with data from IBGE [41]). For example the average share of land dedicated to soy in Paraná was 50 %. The average shares of land dedicated to soy in Mato Grosso and Tocantins are compared with the Paraná share, yielding in two ratios. These ratios are used to calculate shares of pesticides used in soy for the two states based on the known share in Paraná. Details on the allocation process are presented in Appendix F.2.

The percentages from Sindiveg [37] and ADAPAR [38] used in the allocations are based on volumes of pesticide CP. This is important to keep in mind since the indicators that are calculated give information about pesticide AI. The relations between different pesticide CP and pesticide AI are varying, which is why the allocation factors have inherent errors of unknown sizes.

#### 3.2.4 Freshwater ecotoxicity impact assessment

When it is estimated how much pesticides are used in the soy production, following the methodology in Sections 3.2.2-3.2.3, a quantification of individual AI can be done. Data on specific AI and their corresponding volumes are required in order to calculate impact indicators in the pesticide application, which are estimated with the LCA tool USEtox described in Section 2.3.3.2.

Not all applied pesticide will be released to the surrounding environment and cause impacts and therefore a factor of how much AI are leaked to freshwater can be used. In the methodology used by Pollak [5], an estimation of 1 % of the applied AI is assumed to be released to freshwater. By utilizing this same factor, estimations of emissions to freshwater can be made by multiplying the factor with the volumes of the applied individual AI to one hectare of soy producing land.

The estimations of AI emissions can thereafter be multiplied with compound specific characterization factors (CF). The CF are estimates of the potentially affected fractions (PAF) of freshwater species in a determined space and time per unit of emission, expressed as comparative toxic unit ecotoxicity (CTUe) per kg emitted substance (1 CTUe = PAF)

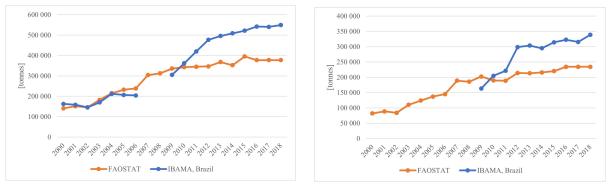
 $m^{3}$  \*day) [42]. The results are the indicators that show quantitative estimations of the potential impacts from pesticide AI application to freshwater ecosystems.

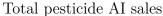
# Results

The results that will be presented in this chapter start at the larger scale and move toward a more detailed and specific scale. The first sections include comparisons between different sources providing data on pesticide sales in Brazil. Following the comparisons are results of pressure and impact indicators of pesticide use.

## 4.1 Pesticide use at national level

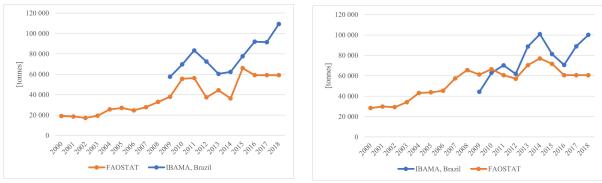
The sales of active ingredients (AI) at national level reported by IBAMA [36] was compared with statistics published by FAOSTAT [29] in Figures 4.1-4.2. Detailed data of which the figures are based on is presented in Appendix A for FAOSTAT and Appendix B for IBAMA.





Herbicide AI sales

**Figure 4.1:** Comparison of reported pesticide and herbicide sales in Brazil by FAOSTAT [29] and IBAMA [36].



Fungicide AI sales

Insecticide AI sales

Figure 4.2: Comparison of reported fungicide and insecticide sales in Brazil by FAO-STAT [29] and IBAMA [36].

FAOSTAT data on pesticide sales is gathered by questionnaires to nations worldwide [29]. As can be seen in the figures above, the published data from FAOSTAT has not changed since 2016, which could mean that Brazil has not answered the questionnaire in 2017 and 2018. The IBAMA data shows a larger increase in pesticide sales in all investigated categories than what is reported by FAOSTAT.

## 4.2 Pesticide data chosen for indicators at state level

Paraná is at present the only state in Brazil known to provide detailed data on pesticide sales, which is described in Section 3.1.1.4. The available data on sold amounts of AI from ADAPAR is presented as percentages of the total sold commercial product (CP) volume. The challenge with this is that the percentage of one individual AI is the sum of the volume of all sold CP containing that AI divided by the total volume sold CP. Different CP have differentiating formulations of one or more AI in combination with other compounds, meaning that they have different concentrations of AI. In order to be able to calculate impacts of pesticides the amounts of individual AI that are applied must be known. This is impossible to achieve with the current information since there are a large variety of product formulations for each used AI. For example a brief investigation of different glyphosate products yielded three separate concentrations of the AI; 43,8 % [43], 50 % [44] and 72 % [45]. In order to conduct the calculations leading up to the volumes of individual AI per hectare and tonne soy it was therefore not possible to use the ADAPAR data, which is illustrated in Figure 4.3.

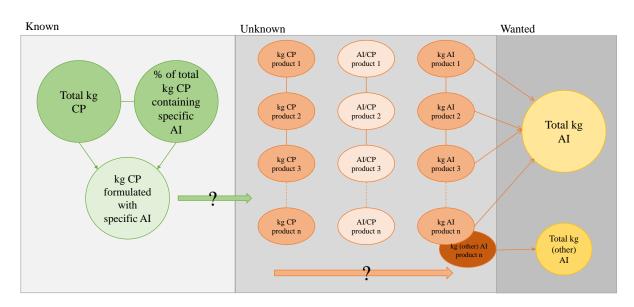


Figure 4.3: Illustration of the challenges with the available data on commercial products (CP) and active ingredients (AI) published by ADAPAR [38]. The filled green circles are known and when combined the volume of kg CP formulated with one present individual AI can be calculated. The filled orange circles represent what the green circles contain but are unknown, and the concentrations (AI/CP) is possible to traced when/if the CP are known. One CP might have more than one AI. What is searched for is the total kg of AI, illustrated by the yellow circles.

The pesticide data from ADAPAR [38] could instead be used for qualitative comparisons with data published at state level by IBAMA [36]. As it was known that the published IBAMA data reported on individual AI is not complete because of competition laws, information on sold AI from ADAPAR was used to investigate the knowledge gaps. The ten most sold AI in the product classes herbicides, fungicides and insecticides was selected for the investigation and are presented in Tables 4.1-4.3.

Table 4.1 shows that the types of herbicide AI that are sold in largest volumes on average 2016-2018 does not differ much between the two data sources. There are eight compounds in the lists that are identical according to both IBAMA and ADAPAR but fall in different order. That could be caused by differences between the two organizations' reporting systems.

The content and order of the AI in the IBAMA column in Table 4.1 would differ if the investigation would refer to one year at a time. For example there is missing data for diuron and clethodim 2016 and for diquat dibromide 2017, probably caused by the competition laws, and other compounds naturally replace their gaping top placements for the affected years. The averagely most sold herbicide AI for the three years says more about the trends in reported sales and therefore more about the potential differences between the data sources than doing the investigation for separate years. Overall the included AI of herbicides are similar over the time period 2016-2018 regarding both IBAMA and ADAPAR data.

IBAMA	ADAPAR
Glyphosate	Glyphosate
2,4-D	Paraquat
Atrazine	Atrazine
Paraquat dichloride	2,4 <b>-</b> D
Diuron (DCMU)	Diuron (DCMU)
Clethodim	Clethodim
Clomazone	Diquat
Tebuthiuron*	Haloxyfop-P-methyl*
Ametryn*	Picloram*
Diquat dibromide	Clomazone

**Table 4.1:** Comparison of the ten herbicide AI with largest sales in Paraná according toIBAMA and ADAPAR. Based on average sales for the years 2016-2018.

\*Differentiating between the data sources

The result of the comparison of the published average top ten fungicide AI is shown in Table 4.2. There are three compounds that are included in both the IBAMA and ADAPAR data, which means that seven AI are differentiating. The IBAMA as well as the ADAPAR data on individual AI are consistent over the time period 2016-2018.

**Table 4.2:** Comparison of the ten fungicide AI with largest sales in Paraná according to IBAMA and ADAPAR. Based on average sales for the years 2016-2018.

IBAMA	ADAPAR
Mancozeb	Mancozeb
Chlorothalonil*	Trifloxystrobin*
Carbendazim	Pyraclostrobin*
Thiophanate-methyl*	Cyproconazole
Sulfur*	Prothioconazole*
Tebuconazole*	Azoxystrobin*
Azoxystrobin*	Tebuconazole*
Fluazinam*	Epoxiconazol*
Cyproconazole	Carbendazim
Propiconazole*	Picoxistrobin*

\*Differentiating between the data sources

Table 4.3 shows the comparison of the published average top ten insecticide AI according to IBAMA and ADAPAR. In this comparison, five AI are coherent and five are differentiating. Both the data from IBAMA and ADAPAR on the most sold individual AI are consistent with a few exceptions over the time period 2016-2018.

IBAMA	ADAPAR
Acephate	Imidacloprid
Imidacloprid	Acephate
Methomyl	Beta-cyfluthrin*
Thiodicarb	Lambda-cyhalothrin
Lambda-cyhalothrin	$Thiamethoxam^*$
Diatomaceous $earth^*$	Methomyl
Diflubenzuron*	Lufenuron <sup>*</sup>
Acetamiprid*	Teflubenzuron*
Dimethoate*	Thidiocarb
$Chlorantraniliprole^*$	Chlorfenapyr*
*Differentiating betwee	en the data sources

**Table 4.3:** Comparison of the ten insecticide AI with largest sales in Paraná accordingto IBAMA and ADAPAR. Based on average sales for the years 2016-2018.

The result from the comparisons of published IBAMA and ADAPAR data at state level in Paraná is that the data sources' information differ regarding the averagely most sold pesticide AI. There are small differences for the herbicide AI, and more severe deviations for the fungicide and insecticide AI. A major explanation for the differences is most likely the fact that IBAMA does not report all AI due to the competition laws.

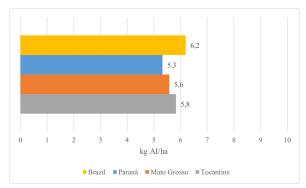
Using IBAMA data for indicator calculations would have the effect that all impacts from used AI are not accounted for. This issue is most urgent for fungicides and insecticides. While the data from ADAPAR is comprehensive at the qualitative level it is not possible to use for numerical operations, which is a problem when aiming to conduct indicator calculations. Because of this reason and that there are no state level pesticide data available for the other included states, IBAMA data was chosen for the calculations, with the knowledge of the present data gaps. The gaps have only been identified for Paraná, but it can be assumed that there are similar trends in other Brazilian states as well.

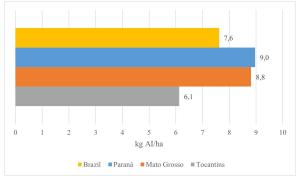
## 4.3 National and state pressure indicators – all cropland

The results from the calculations of the pressure indicators at national and state level for cropland and harvested land are accounted for in Figures 4.4-4.7. The difference between cropland and harvested land is that cropland refers to the physical area of land dedicated to cultivation, while harvested land can include larger amounts of land than what is physically available through double-cropping, as is explained in Section 2.2.2. The double-cropping is visualized in Figures 4.4-4.7 by the difference in kg AI per hectare on cropland compared to harvested land. The value is typically higher per ha cropland than per ha harvested land, since much of the cropland (especially the soy) are being double-cropped, and thus two harvests per year are applied with pesticides.

The calculated pressure indicators are presented with numbers in Appendix F.1 and published AI volumes related to each product class are accounted for in Appendix B. Over 90~% of the total volume of sold AI was accounted for when summarizing the product classes included in these indicators.

The graphs in Figure 4.4 show pressure indicators for total volume of pesticide AI used on harvested land and cropland. The numbers on applied kg per hectare were larger for the cropland compared to harvested land both at national and state level, Paraná and Mato Grosso have the largest differences because of the widespread double-cropping practice in these states.



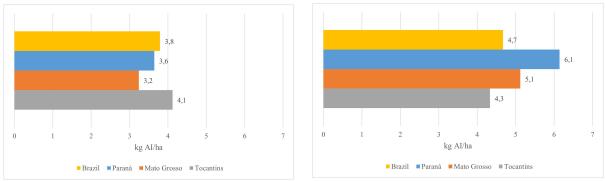


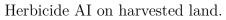
Pesticide AI on harvested land.

Pesticide AI on cropland.

Figure 4.4: Pressure indicators for kg of total pesticide AI per hectare of harvested land and cropland in 2017, for Brazil, Paraná, Mato Grosso and Tocantins.

Figure 4.5 illustrates pressure indicators for sold herbicides. There are trends with differences between AI volume applied to cropland and to harvested land, especially for Paraná and Mato Grosso.

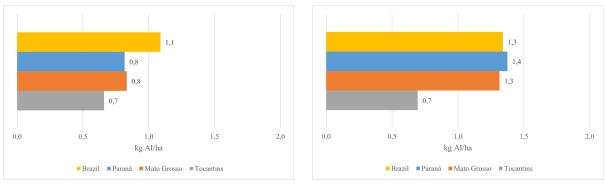


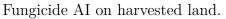


Herbicide AI on cropland.

**Figure 4.5:** Pressure indicators for kg of herbicide AI per hectare of harvested land and cropland in 2017, for Brazil, Paraná, Mato Grosso and Tocantins.

The pressures per hectare from fungicide AI application are similar in Brazil, Paraná and Mato Grosso as can be viewed in Figure 4.6. Tocantins stands out with a comparably small pressure indicator value on cropland that is close to the state's value on harvested land.

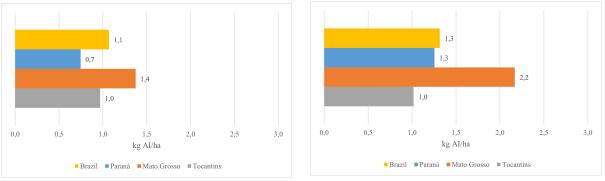




Fungicide AI on cropland.

Figure 4.6: Pressure indicators for kg of fungicide AI per hectare of harvested land and cropland in 2017, for Brazil, Paraná, Mato Grosso and Tocantins.

Figure 4.7 shows that Mato Grosso has large insecticide use per hectare compared to the other investigated areas. That is significant especially for the pressure indicator on cropland.



Insecticide AI on harvested land.

Insecticide AI on cropland.

Figure 4.7: Pressure indicators for kg of insecticide AI per hectare of harvested land and cropland in 2017, for Brazil, Paraná, Mato Grosso and Tocantins.

Table 4.4 shows the relationships between amount of harvested land compared to amount of cropland. That is a measurement of how much of the land that is cultivated multiple times a year. This is an explanation to why the Paraná pressure indicators differ much on cropland compared to harvested land, while they are similar for Tocantins.

**Table 4.4:** Comparisons of hectare harvested land and hectare cropland in Brazil, Paraná, Mato Grosso and Tocantins 2017. Data from IBGE [40, 41].

	Harvested land [ha] /cropland [ha]
Brazil	1,23
Paraná	1,68
Mato Grosso	1,58
Tocantins	1,05

## 4.4 National and state pressure indicators – soybeans

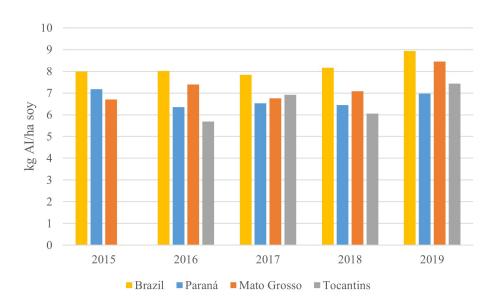
For the calculations of the pressure indicators specific for the soybean production, allocations of pesticide volumes used in soy were determined. The allocation factors are presented in Table 4.5. The factors were not adjusted over the investigated time period because of the uncertainties regarding the data that was used for assumption basis in the calculations. Adjusting the percentages would not cancel out the uncertainties since the allocation error sizes were unknown.

**Table 4.5:** Allocation factors determined for pesticide use in soybean production at the national and state levels. Based on data from Sindiveg [37] and ADAPAR [38], details can be found in Appendix F.2.

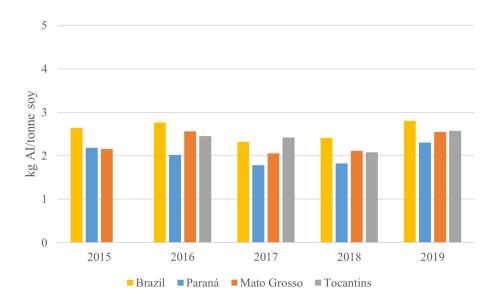
	Baseline	Sensitivity scenario
Brazil	55 %	55 %
Paraná	55 %	60 %
Mato Grosso	55 %	72 %
Tocantins	55 %	78 %

Illustrations of the calculated pressure indicators according to the sensitivity scenarios are shown in Figures 4.8-4.15 below. Detailed results from the calculations of both the baseline and sensitivity scenarios are available in Appendix F.3. No pressures could be calculated for Tocantins for the year 2015 because of missing data from IBGE regarding land use.

Figures 4.8-4.9 show the total calculated pressure indicators for the pesticide use in soy production. Figure 4.8 presents the volume of pesticide AI per hectare of harvested land where soybeans are cultivated, and Figure 4.9 show pesticide AI volume per produced tonne of soy. The pressures from pesticide AI use are higher for average Brazil than for the investigated soybean specialized states.



**Figure 4.8:** Illustration of calculated pressure indicators for total pesticide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold pesticide active ingredients (AI) per ha harvested land dedicated to soybeans in Brazil, Paraná, Mato Grosso and Tocantins.



**Figure 4.9:** Illustration of calculated pressure indicators for total pesticide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold pesticide active ingredients (AI) per produced tonne of soybeans in Brazil, Paraná, Mato Grosso and Tocantins.

In figures 4.10-4.11 the calculated pressure indicators for the herbicide use in soybean cultivation and production can be viewed. The pressures are relatively largest for average Brazil and Tocantins.

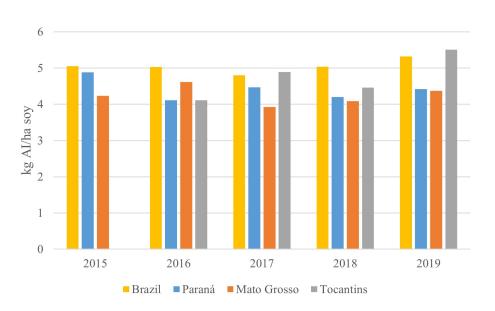
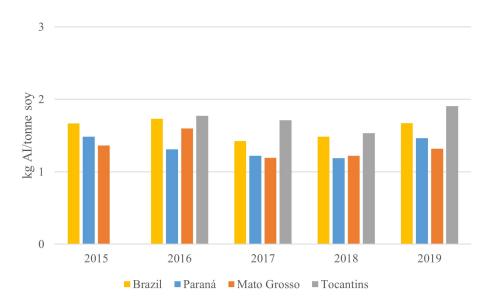
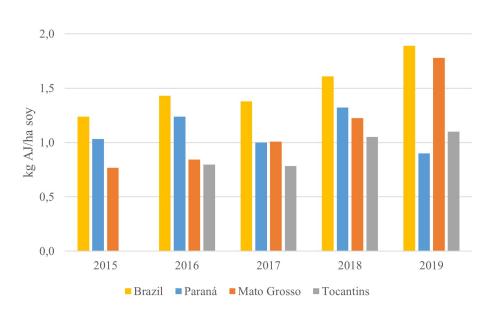


Figure 4.10: Illustration of calculated pressure indicators for herbicide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold herbicide active ingredients (AI) per ha harvested land dedicated to soybeans in Brazil, Paraná, Mato Grosso and Tocantins.



**Figure 4.11:** Illustration of calculated pressure indicators for herbicide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold herbicide active ingredients (AI) per produced tonne of soybeans in Brazil, Paraná, Mato Grosso and Tocantins.

Figures 4.12-4.13 show the calculated pressure indicators for the fungicide use in soybean cultivation and production. It is shown that the use is more intensive in average Brazil than the other included regions. The fungicide use in Mato Grosso 2019 is also standing out.



**Figure 4.12:** Illustration of calculated pressure indicators for fungicide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold fungicide active ingredients (AI) per ha harvested land dedicated to soybeans in Brazil, Paraná, Mato Grosso and Tocantins.

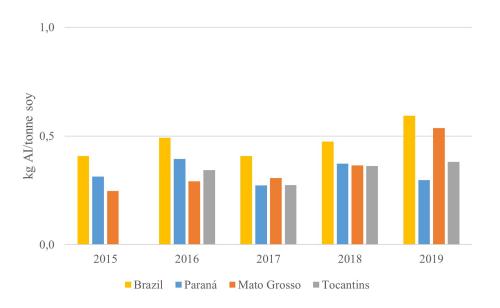
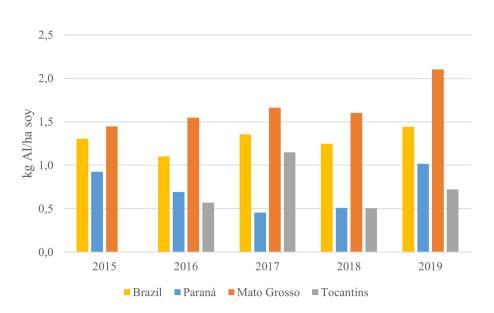
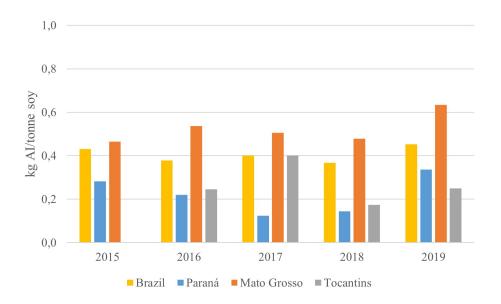


Figure 4.13: Illustration of calculated pressure indicators for fungicide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold fungicide active ingredients (AI) per produced tonne of soybeans in Brazil, Paraná, Mato Grosso and Tocantins.

The calculated pressure indicators for the insecticide use in soybean cultivation and production are shown in Figures 4.14-4.15. The use is comparatively high with an increasing trend in Mato Grosso, and also high for average Brazil.



**Figure 4.14:** Illustration of calculated pressure indicators for insecticide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold insecticide active ingredients (AI) per ha harvested land dedicated to soybeans in Brazil, Paraná, Mato Grosso and Tocantins.



**Figure 4.15:** Illustration of calculated pressure indicators for insecticide use 2015-2019 with sensitivity scenarios described in Table 4.5. Presented as kg sold insecticide active ingredients (AI) per produced tonne of soybeans in Brazil, Paraná, Mato Grosso and Tocantins.

## 4.5 Trends in national and state freshwater ecotoxicity impact indicators – soybeans

As has been shown in the results there are some problems regarding the data needed to calculate freshwater ecotoxicity impact indicators for use of pesticide AI in soybean production. The main issue is that there are large gaps in the published data from IBAMA [36] regarding which individual AI are revealed, and thereby which AI are possible to make quantifications of impacts on. As was shown in Section 4.2 the issue is most pressing for the product classes fungicides and insecticides. There are also problems with the errors associated to the allocations of pesticide AI to soy, as was discussed in Section 4.4. Additionally, there are uncertainties regarding the CF gathered from USEtox which are adapted for temperate conditions as large areas that are investigated in this thesis have tropical climate, described in Section 2.3.3.2. Instead of calculating numerical impacts for the most used AI in the included product classes that would lead to results with large undefined errors, an assessment of application trends regarding application of AI was conducted.

Average IBAMA data for reported pesticide AI volumes in the product classes herbicides, fungicides and insecticides 2016-2018 were sorted according to size. For all three states, the largest ten AI in each class were picked out and compared. Thereafter the AI which all three states had in common among the largest ten were picked out for the application trend assessment. Relative and absolute trends of all individual AI were calculated for the years 2015-2019, based on data shown in Appendix B.2. The absolute trends were based on yearly share of each AI compared to the total volume in the product class to whom the specific AI belongs. The basis for the relative trends were the sales volume of the investigated AI in 2015 in relation to the sales volume for each year 2015-2019. Both trends resulted in change in percentages which are illustrated according the direction of the application trend, shown in Figure 4.16. The application trends based on AI sales statistics were combined with the CF showing toxicity levels for the included individual AI, and visualizations of these factors are replacing the potentially calculated quantitative impact indicators.

Potential impact	CF (CTUe/kg)	Trends in use of AI	
Low	0-100	Very high increase $\uparrow$	
Moderate	100-10000	Increase 🏼	
High	10000-100000	Stable $\rightarrow$	
Very high	100000->	Decrease 🛛	

Figure 4.16: Categorization and color coding of potential impacts from application of one kg active ingredient with characterization factors (CF) in chemical toxic unit ecotoxicity (CTUe) per kg released AI, meaning how large potential ecotoxic impact one unit of AI will have in space and time expressed as potentially affected fraction of freshwater species (PAF) \*  $m^3$  \* day. The right part of the figure shows how the AI application trends are illustrated. Trends are based on relative and absolute change of sales volumes for the years 2015-2019 with 2015 as base. "Very high increase" represent over 150 % change from base value, "Increase" 100-150 %, "Stable" around 100 %, and "Decrease" lower than 100 % from the baseline. Support to the qualitative impact indicators in Figures 4.17-4.19.

Figure 4.17 shows the impact indicators for the five most commonly used herbicide AI in Paraná, Mato Grosso and Tocantins. The glyphosate use lay on a stable level in all of the states while the use of the other AI are increasing, except for 2,4-D use in Paraná. Trends on paraquat and clethodim show very high increases, and additionally the CF for paraquat is large meaning high potential toxicity to freshwater species. The other herbicides have relatively low CF. The marked AI in Figures 4.17-4.19 are in the Pesticide Action Network's (PAN) list of highly hazardous pesticides (HHP) [46].

	CF for emissions to	Application trend		
AI	freshwater (CTUe/kg)	PR	MT	то
Glyphosate*	321	$\rightarrow$	$\rightarrow$	$\rightarrow$
2,4-D	861	Ы	7	7
Paraquat dichloride*	119 000	$\uparrow$	$\uparrow$	$\uparrow$
Clethodim	1 832	$\uparrow$	$\uparrow$	$\uparrow$
Clomazone	7 780	7	7	7

\*In the PAN list of HHP

Figure 4.17: Qualitative impact indicators of the most sold herbicide active ingredients (AI). AI included in the Pesticide Action Network's (PAN) list of highly hazardous pesticides (HHP) are highlighted. Characterization factors (CF) for emissions of AI to freshwater at the continental scale presented in chemical toxic unit ecotoxicity (CTUe) per kg released AI, meaning how large potential ecotoxic impact one unit of AI will have in space and time expressed as potentially affected fraction of freshwater species (PAF) \*  $m^3$  \* day. Application trends for sold AI that are used in the soy production, based on absolute and relative sales changes during the time period 2015-2019, in Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

In Figure 4.18 the qualitative impact indicators for the most commonly used fungicides

are shown. The top three fungicides in the list are showing trends with very high increases in the use, and are also included in the list of HHP [46]. Especially chlorothalonil should be highlighted here because of its very high CF.

	CF for emissions to	Application trend		rend
AI	freshwater (CTUe/kg)	PR	MT	то
Mancozeb*	52 600	7	$\uparrow$	$\uparrow$
Chlorothalonil*	1 140 000	$\uparrow$	$\uparrow$	$\uparrow$
Carbendazim*	740 000	7	$\uparrow$	$\uparrow$
Thiophanate-methyl	7 410	7	7	Ы
Azoxystrobin	770 000	Ы	И	Ы
Tebuconazole	68 600	И	$\rightarrow$	И

\*In the PAN list of HHP

**Figure 4.18:** Qualitative impact indicators of the most sold fungicide active ingredients (AI). AI included in the Pesticide Action Network's (PAN) list of highly hazardous pesticides (HHP) are highlighted. Characterization factors (CF) for emissions of AI to freshwater at the continental scale presented in chemical toxic unit ecotoxicity (CTUe) per kg released AI, meaning how large potential ecotoxic impact one unit of AI will have in space and time expressed as potentially affected fraction of freshwater species (PAF) \* m<sup>3</sup> \* day. Application trends for sold AI that are used in the soy production, based on absolute and relative sales changes during the time period 2015-2019, in Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

The qualitative impact indicators in Figure 4.19 shows the most commonly used insecticide AI in Paraná, Mato Grosso and Tocantins and their use trends and toxicity. Lambdacyhalothrin stands out in both the CF and the increasing use in all investigated trends. Acetamiprid is not included in USEtox, which makes the impacts of the use impossible to analyze with this tool. It is not included in the HHP list either, but that does not have to mean that it is non-hazardous since the list is based on "widely accepted classifications" [46].

	CF for emissions to	Application trend		rend
AI	freshwater (CTUe/kg)	PR	МТ	то
Acephate*	626	7	7	$\uparrow$
Imidacloprid*	3 200	$\rightarrow$	$\rightarrow$	7
Methomyl*	28 900		$\rightarrow$	Ы
Lambda-cyhalothrin*	139 000 000		$\uparrow$	$\uparrow$
Acetamiprid	n/a		7	$\uparrow$
*In the PAN list of HHP				

**Figure 4.19:** Qualitative impact indicators of the most sold insecticide active ingredients (AI). AI included in the Pesticide Action Network's (PAN) list of highly hazardous pesticides (HHP) are highlighted. Characterization factors (CF) for emissions of AI to freshwater at the continental scale presented in chemical toxic unit ecotoxicity (CTUe) per kg released AI, meaning how large potential ecotoxic impact one unit of AI will have in space and time expressed as potentially affected fraction of freshwater species (PAF) \* m<sup>3</sup> \* day. Application trends for sold AI that are used in the soy production, based on absolute and relative sales changes during the time period 2015-2019, in Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

#### 4. Results

# Discussion

This chapter includes discussions about the used pesticide data sources and the calculated pesticide pressure- and impact indicators. Reasons to why the indicators differ among Brazil and the three included states are analyzed.

## 5.1 Challenges with the reported pesticide data

One of the main challenges in conducting this thesis has been to deal with uncertainties regarding the available data. The variability in the data also lead to uncertainties regarding the results and therefore the results should be seen as trend pointers as opposed to definite answers.

First off, it was shown that the presented pesticide sales data at the national level differs between FAOSTAT and IBAMA and that FAOSTAT underestimates the total pesticide sales as well as the sales of the largest product classes. The underestimation in sales volumes arose around 2010 and has been systematic and increasing ever since, and the sales volumes have not been updated since 2016 which is why the last three reported years carry identical figures. The discrepancies could be an effect of that Brazilian authorities are not filling in the FAOSTAT questionnaires correctly, and the reason as to why there are errors compared to IBAMA numbers is unknown. That the data is not consistent with national statistics could lead to underestimations of pesticide use effect in global studies relying on FAOSTAT agricultural statistics. This might be a problem for other nations as well, where monitoring and enforcement of environmental laws are lacking. FAOSTAT data is basis for calculations and conclusions in many studies and it is of high importance that numbers are correct in order not to underestimate e.g. environmental effects.

Also, it was shown that pesticide sales data at the Paraná state level is challenging to use due to two main reasons; ADAPAR publish specific AI but not in which CP they are included or their corresponding sales volumes, and IBAMA publish sales volumes of individual AI but does not include all sold AI because of the national competition laws. The implication from the results regarding ADAPAR data is that it can be used to give hints, to verify credibility of other data sources and to conduct comparisons of data, but not to make any actual calculations since the concentrations of AI vary between different CP. That is unfortunate since the details about specific pesticide products that are used in cultivation of individual crops, as well as other valuable information, are available in a database owned by ADAPAR. Such information is essential when attempting to make calculations on the effects of pesticide use in the state of Paraná. The fact that ADAPAR is publishing such detailed information about the sales of pesticide AI should, despite the difficulties in using them, must be applauded as an excellent example of transparency and other Brazilian states should be encouraged to follow their example.

Since IBAMA does not publish all sold individual AI and their corresponding volumes, calculations and conclusions based solely on this data will include incomplete information. When comparing the ten most sold AI in Paraná in the largest pesticide product classes, the fungicides and insecticides turned out to be most uncertain since more than half of the top ten pesticide AI in the two categories differed between IBAMA and ADAPAR. The decision to not calculate quantitative impact indicators for individual AI was made partly because of the discovery of the width of this data gap in Paraná, among other factors such as uncertainties regarding effects of these AI in tropical climates. The question of which AI that are not reported due to the competition laws in e.g. Mato Grosso, that has high insecticide use per hectare in comparison with Brazil and the other states, is an important one to investigate, but requires different resources than the ones available for this thesis. It would for example be necessary to make field studies in soy producing regions to better understand the insecticide application methods and in order to investigate used compounds, the state of Mato Grosso would have to publish data on sold insecticide AI.

## 5.2 Pesticide use pressures

The pressure indicators for overall agriculture in average Brazil were determined to 6,2 kg AI/ha for harvested land and 7,6 kg AI/ha for cropland. The total footprint calculated with IBAMA numbers in this thesis for 2017 can be compared with the official statistics from FAOSTAT that presents a figure of 5,94 kg AI/ha including arable land and permanent crops [29]. The difference between the sources can be explained by the data gap that has already been discussed.

The agricultural system in Brazil includes widespread double-cropping, which has the result that the same land area is cultivated, and therefore treated with pesticides, twice a year meaning that the negative local ecological effects of pesticide use become larger. There are also larger health risks for the workers dealing with the often toxic substances. It was shown that in Paraná and Mato Grosso, a much larger share of cropland area is double-cropped than in Tocantins and the average of Brazil. Since the main crops in these states are soy and maize it is reasonable to assume that much of the double-cropping is related to soy and maize in rotation. The total pesticide use and the herbicide use showed these double-cropping trends for Paraná and Mato Grosso.

The allocation of pesticides to soy is applied to the harvested land and for soy only, the intensity of the pesticide application would be higher if considering the pressure per physical land as well as accounting for the double-cropping. But even though there are known uncertainties with the soy allocation due to missing or incomplete data, the results give indications of the current use. The baseline and sensitivity scenarios can be considered a span of application intensity where the baseline scenarios are the least intensive and the sensitivity scenarios are the most intensive. The total pesticide as well as the fungicide footprints are larger in average Brazil's baseline scenario than for the sensitivity scenarios that were applied on the different states. Tocantins' herbicide footprint is relatively large as well as the insecticide footprint in Mato Grosso. To understand the reason behind these results, more research is needed.

## 5.3 Assessment of potential pesticide effects on freshwater with impact indicators

For the most sold pesticide AI in the three largest product classes, the compounds with very high CF for emissions to freshwater had the largest increase in their application trends in all investigated states. A herbicide showing that trend is paraquat dichloride, which is a dessicant [39] and is used to control glyphosate-resistant weeds in soy production [47]. The substance has been issued with a ban in 2017 by ANVISA because of the high toxicity and human mortality associated with it [47], the prohibition was postponed to 2020 due to pressures from the pesticide lobby [47] and entered into force in September 2020. The second and third most used fungicides are chlorothalonil and carbendazim, which also showed very large increases in application trends. An insecticide showing similar trends is lambda-cyhalothrin that has exceptionally high CF compared to other AI. These AI are not experiencing any restrictions by ANVISA in the near future according to their product sheets [39].

The available data on pesticide use in Brazil could be used to quantify impact indicators for specific AI but because of the known errors from the data mapping and allocation, the results in a quantification of impacts with USEtox would contain these errors in the same or larger extent. One example is the insecticide AI lambda-cyhalothrin with very high CF where small errors in application volumes would cause extremely large errors in quantified potential impact. But even if the application volume errors of individual AI would be negligible there are other problems present when quantifying potential impacts; firstly there are knowledge gaps in which AI are applied, and secondly the methods of determining the impacts are developed for temperate climates in central Europe [34]. The knowledge gaps at the Paraná state level in applied individual AI that was found when comparing IBAMA and ADAPAR data was large, especially for the most used fungicides and insecticides. There are currently difficult or impossible to assess the gaps in other states. This is due to that Paraná is the only state that transparently publish data on sold pesticide products.

In order to make impact assessments more accurate in areas with tropical/subtropical climate such as Brazil [48], there is need for research on LCA tools such as PestLCI and USEtox in order for the models to fit tropical climates [34]. It is also required to know more about the application conditions and soil types in specific locations when applying the models [34], which have not been under investigation during this work. This is complex data that is needed at a local level in order to get more representative results from USEtox or other tools investigating the impact of pesticide application.

The visualization of the AI application trends in the results showed the importance of considering sales volume trends and toxicity of substances simultaneously in order to get a more comprehensive view of the potential impact without numerical estimations. An insecticide AI that has missing CF for emissions to freshwater is acetamiprid, which has the effect that a dimension of the results is missing as it is not possible to relate the high increase in application trend to a potential toxicity. Pietrzak et al 2019 [49] showed that the occurance of acetamiprid (and other AI) has increased in water bodies in the EU, and compound is included in watch lists where organic compounds that requires future monitoring are presented. The watch lists include compounds that are expected to pose

hazards to aquatic organisms and mammals and that do not have enough information to either assess the hazards and/or to model the exposure data. The results showed that the included compounds need specific regulations and monitoring [49]. That compounds are listed in such ways could lead to increased knowledge and possible regulations in the EU - including information that is needed in model development of e.g. USEtox.

## Conclusion

The most important data sources for pesticide use include IBAMA at the national level and ADAPAR at the Paraná state level. Pesticide data at state level for other Brazilian states has not been found. There are challenges associated with the available data on pesticide use in Brazil both at the national level and at state level. FAOSTAT data underestimate the Brazilian pesticide AI sales compared to IBAMA and have a systematic error in the reporting since 2010 and forward. Furthermore at the national level, IBAMA does not include sales volumes on all specific AI because of the national competition laws and consequently there are data gaps on individual AI. At state level in Paraná the data from ADAPAR is based on CP, which makes it impossible to use to determine volumes of sold specific AI and their potential impacts. The ADAPAR data could be used to show the IBAMA data gaps at Paraná state level for individual AI, which were especially large in the product classes fungicides and insecticides.

The trend of the pesticide use in Brazilian soy production shows a small increase of the overall use over the years 2015-2019. Among the most used AI in all three states, the AI with high potential impacts according to their CF are also experiencing high increase in use in all three product classes. The herbicide paraquat dichloride, the fungicides chlorothalonil and carbendazim, as well as the insecticide lambda-cyhalothrin have been facing this development. In order to make assessments of potential impacts of pesticide use in soybean production in Brazil with the LCA models investigated in this thesis, they must be updated to fit tropical conditions.

Future work is necessary in order to increase the knowledge about pesticide use and the associated effects. Topics that have come up during this thesis work and that can be assessed in other works include the following;

- The pressure from pesticide application to physical cropland in Brazilian soy specialized states are high, how does this affect the agricultural systems in these regions in terms of e.g. productivity and biodiversity?
- Further investigations around how the production of the second crop of maize (safrinha) and soy are related and what their connectivity means for the pesticide use and economics and health for e.g. farmers, farm workers and rural people.
- Try to answer the question on why the insecticide use in Mato Grosso is so high and which types of AI are applied that are not shown in the IBAMA statistics.
- Attempts to make general application scenarios of pesticides in soy production in Brazil starting with herbicides, which seem to be quite similar in volumes and types applied.

All attempts to increase knowledge in the field are important in order to highlight the

issue of increased pesticide use and force the topic up on the agenda for stakeholders to notice and take action on.

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# A FAOSTAT data

The table below present data on sales of pesticide active ingredients (AI) and the largest pesticide product classes in Brazil retrieved from the Food and Agriculture Organization of the United Nations (FAOSTAT). The product class fungicides was merged with bactericides in the statistics, which is the reason why bactericides are included in the table. All volumes have the unit tonnes.

Year	Pesticides	Herbicides	Fungicides and bactericides	Insecticides
2000	140 423	81 862	19 072	28 382
2001	151 523	88 359	18 607	29 799
2002	145 552	83 859	17 262	29 208
2003	182 446	110 215	19 363	34 049
2004	214 725	124 060	25 631	43 192
2005	232 232	136 853	26 999	43 763
2006	238 716	144 986	24 707	45 435
2007	304 031	189 101	27 734	57 421
2008	$312 \ 637$	$185 \ 665$	32 881	65 642
2009	335  742	202 554	37 934	61 180
2010	342 580	$189\ 537$	55 583	66 471
2011	$345 \ 026$	188 745	56 253	60 614
2012	346583	214 201	37 381	57 170
2013	367  778	213 244	44 310	70 424
2014	352 336	215 725	36 328	77 043
2015	395 646	220 186	66 051	71 663
2016	377 176	234 384	59 124	60 607
2017	377 176	234 384	59 124	60 607
2018	377 176	234 384	59 124	60 607

Table A.1: FAOSTAT data on sold pesticide AI in Brazil 2000-2018 [29].

# В

### IBAMA data

This Appendix will present the pesticide AI data used in the thesis, which has been retrieved from the Brazilian Environmental Institute (IBAMA, Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis). All volumes in the tables in this appendix have the unit tonnes.

#### B.1 Product classes

Table B.1 below shows the pesticide sales for the largest product classes in Brazil 2000-2018. These numbers are compared with the FAOSTAT data in Appendix Table A.1, which is why the category "Fungicide, bactericides" is included. The product classes "Fungicide, acaricides" and "Insecticide, acaricides" are added to "Fungicides" and "Insecticides" respectively in all the thesis work. In Table B.1, the unreported pesticide sales for 2007 and 2008 is due to that the data is not "systemized by IBAMA".

Year	Pesticides	Herbicides	Fungicides, Fungicide, acaricides and Fungicide, bactericides	Insecticides and Insecticide, acaricides
2000	162 462	-	-	-
2001	158 305	-	-	-
2002	145 985	-	-	-
2003	169 862	-	-	-
2004	211 828	-	-	-
2005	206 592	-	-	-
2006	204 124	-	-	-
2007	-	-	-	-
2008	-	-	-	-
2009	305 239	163 120	57 550	44 312
2010	361 662	204 957	69 646	62 957

Table B.1: IBAMA data on sold pesticide AI in Brazil 2000-2018 [36].

2011   419 529	221 330	83 439	70 302
2012   476 555	298 872	72 516	61 888
2013   495 773	303 573	60 396	88 720
2014   508 557	294 916	62 351	100 795
2015   521 525	314 453	77  665	81 216
2016   541 861	322 755	91 948	70 593
2017   539 945	315 573	91 567	88 913
2018   549 280	338 838	109 371	100 067

The following Tables B.2-B.5 show data on sold volumes of AI in Brazil, Paraná, Mato Grosso and Tocantins for the years 2015-2019. They include volumes of all reported product classes published by IBAMA. The last row in each table include the total sold AI volume where adjuvant and spreader are excluded, which is the numbers that the calculations in the thesis are based on. That is because it should be comparable with e.g. the European Union's system of pesticide reporting where adjuvant and spreader are not included product classes. IBAMA has excluded these two categories from their statistics from 2018 and forward.

Table B.2:	IBAMA	data o	on sold	pesticide	AI in	Brazil	in all	reported	$\operatorname{product}$	classes
[36].										

Product class		Solo	l AI in Br	azil	
	2015	2016	2017	2018	2019
1 - Herbicide	314 453	322 755	315 573	338 838	369 579
2 - Fungicide	61 917	66 222	65 115	73 315	94 435
3 - Insecticide	51 183	47 030	54 544	57 309	72 425
4 - Insecticide, acaricide	30 033	23 562	34 369	26 601	27 642
5 - Acaricide, fungicide	15 074	25 624	25 437	34 906	36 709
6 - Adjuvant	20 799	23 283	21 302	-	-
7 - Acaricide	7 404	6 744	7 932	6 779	7 188
8 - Spreader	3 100	3 746	3 800	-	-
9 - Insecticide, acaricide, fungicide	1 372	1 912	2 779	4 258	4 303

10 - Insecticide, acaricide, adjuvant	6 588	11 099	2 197	-	-
11 - Growth regulator	2345	2 163	2 112	2 709	3 742
12 - Insecticide, fungicide	1 336	1 180	1 301	1 532	1 147
13 - Fungicide, bactericide	674	102	1 014	1 150	1 246
14 - Insecticide, cupinicide	475	677	776	691	-
15 - Adjuvant, insecticide	2 654	4 160	579	-	-
16 - Insecticide, nematicide	1 590	837	547	605	484
17 - Fungicide, formicide, herbicide, insecticide, nematicide	_	_	392	_	-
18 - Seed protector	145	105	126	122	141
19 - Formicide	16	16	25	21	21
20 - Formicide, insecticide	21	25	24	25	24
21 - Mulloscicide	0,21	0,22	0,11	0,03	0,15
22 - Fungicide, formicide, herbicide, insecticide, acaricide, nematicide	346	615	_	403	439
23 - Insecticide, formicide, fungicide, nematicide	_	_	_	16	16
24 - Insecticide, cupinicide, formicide	-	-	-	-	939

25 - Insecticide, acaricide, cupinicide, formicide, fungicide	-	-	-	-	56
Total	521  525	541  861	539  945	$549\ 280$	620  538
Total (adjuvant, spreader excluded)	497 626	514 829	514 844	549 280	620 538

**Table B.3:** IBAMA data on sold pesticide AI in Paraná in all reported product classes[36].

Product classes		Sold	AI in Pa	raná	
	2015	2016	2017	2018	2019
1 - Herbicide	43 286	37 804	39 604	38 327	40 431
<b>2</b> - Fungicide	6 834	7 843	6 499	8 663	10 632
3 - Insecticide	4 366	3 644	4 026	4 638	5 686
4 - Insecticide, acaricide	3 848	2 716	4 069	2 933	3 620
5 - Acaricide, fungicide	2 306	3 552	2 364	3 385	2 460
6 - Adjuvant	3 311	3 991	2 363	-	-
7 - Acaricide	386	222	295	434	442
8 - Spreader	570	867	952	-	-
9 - Insecticide, acaricide, fungicide	9	15	31	-	29
10 - Insecticide, acaricide, adjuvant	1 706	1 923	493	73	-
11 - Growth regulator	72	56	49	43	57
12 - Insecticide, fungicide	193	154	144	130	142
13 - Fungicide, bactericide	80	1	77	53	72
14 - Insecticide, cupinicide	25	25	43	42	-

15 - Adjuvant, insecticide	419	419	72	-	-
16 - Insecticide, nematicide	97	70	35	35	50
17 - Fungicide, formicide, herbicide, insecticide, nematicide	-	-	11	-	-
18 - Seed protector	0	0	0	0	0
19 - Formicide	0	0	1	1	1
20 - Formicide, insecticide	0	0	1	1	1
21 - Mulloscicide	0	0	0	0	0
22 - Fungicide, formicide, herbicide, insecticide, acaricide, nematicide	8	6	-	14	23
23 - Insecticide, formicide, fungicide, nematicide	-	-	-	0	0
24 - Insecticide, cupinicide, formicide	-	-	-	_	71
25 - Insecticide, acaricide, cupinicide, formicide, fungicide	-	_	_	-	0
Total	67 516	63 310	61 130	58 770	63 715
Total (adjuvant, spreader excluded)	63 636	$58 \ 452$	57 815	58 770	63 715

Table B.4:	IBAMA	data d	on sold	pesticide	AI in	Mato	$\operatorname{Grosso}$	in all	reported	product
classes $[36]$ .										

Product class		Sold Al	in Mato	Grosso	
	2015	2016	2017	2018	2019
1 - Herbicide	56 083	62 028	53 748	56 988	62 834
2 - Fungicide	7 366	7 904	8 935	11 343	18 314
3 - Insecticide	10 507	13 126	11 860	14 686	21 076
4 - Insecticide, acaricide	8 649	7 699	10 904	7 632	9 112
5 - Acaricide, fungicide	2 814	3 439	4 866	5 719	7 249
6 - Adjuvant	4 452	5 188	7 791	-	-
7 - Acaricide	268	295	424	321	483
8 - Spreader	202	224	318	-	-
9 - Insecticide, acaricide, fungicide	0	0	166	276	131
10 - Insecticide, acaricide, adjuvant	1 601	3 540	452		-
11 - Growth regulator	843	710	728	1 326	1 618
12 - Insecticide, fungicide	130	153	152	147	143
13 - Fungicide, bactericide	123	0	2	82	177
14 - Insecticide, cupinicide	62	119	110	125	-
15 - Adjuvant, insecticide	223	395	14		-
16 - Insecticide, nematicide	49	50	134	138	78
17 - Fungicide, formicide, herbicide, insecticide, nematicide	-	-	4	-	-
18 - Seed protector	28	29	30	20	12

19 - Formicide	0,02	0,03	0,10	0,10	0,09
20 - Formicide, insecticide	0,13	0,20	0,10	0,10	0,10
21 - Mulloscicide	0	0	0	0	0
22 - Fungicide, formicide, herbicide, insecticide, acaricide, nematicide	0,25	2	_	16	36
23 - Insecticide, formicide, fungicide, nematicide	-	_	-	0	0
24 - Insecticide, cupinicide, formicide	-	-	-	-	197
25 - Insecticide, acaricide, cupinicide, formicide, fungicide	-	_	_	-	13
Total	93 402	104 901	100 638	98 819	121 473
Total (adjuvant, spreader excluded)	88 749	99 490	92 529	98 819	121 473

**Table B.5:** IBAMA data on sold pesticide AI in Tocantins in all reported product classes[36].

Product class Sold AI in Tocantins								
	2015 2016 2017 2018 201							
1 - Herbicide	4 623	4 645	5 620	5 579	6 803			
2 - Fungicide	791	672	647	866	1 1 1 2 7			
3 - Insecticide	485	421	682	506	618			
4 - Insecticide, acaricide	221	223	638	128	273			
5 - Acaricide, fungicide	158	229	253	451	233			

6 - Adjuvant	275	189	183	-	-
7 - Acaricide	3	0	1	0	2
8 - Spreader	73	177	178	-	-
9 - Insecticide, acaricide, fungicide	7	4	2	5	42
10 - Insecticide, acaricide, adjuvant	79	171	66	-	-
11 - Growth regulator	3	15	15	28	17
12 - Insecticide, fungicide	5	9	9	8	8
13 - Fungicide, bactericide	0	0	0,29	3	44
14 - Insecticide, cupinicide	5	8	6	6	-
15 - Adjuvant, insecticide	19	38	10	-	-
16 - Insecticide, nematicide	3	1	-1	0	0
17 - Fungicide, formicide, herbicide, insecticide, nematicide	-	-	0	-	-
18 - Seed protector	1	0,22	1	0,02	0,06
19 - Formicide	0	0	0	0	0
20 - Formicide, insecticide	0,02	0,10	0,10	0,07	0,05
21 - Mulloscicide	0	0	0	0	0
22 - Fungicide, formicide, herbicide, insecticide, acaricide, nematicide	0	0,16	-	1	1

23 - Insecticide, formicide, fungicide, nematicide	-	-	-	0	0
24 - Insecticide, cupinicide, formicide	-	-	-	-	9
25 - Insecticide, acaricide, cupinicide, formicide, fungicide	-	-	-	-	0
Total	6  752	6 802	8 310	7 581	9 177
Total (adjuvant, spreader excluded)	6 403	6 436	7 949	7 581	9 177

#### **B.2** Active ingredients

In this section, the volumes of the most used AI registered in soy that the three states (Paraná, Mato Grosso and Tocantins) have in common will be presented. This is done for the three largest product classes that are investigated in this thesis. All volumes in Tables B.6-B.14 are presented in tonnes.

#### B.2.1 Herbicides

The five most sold herbicide AI and their corresponding sales volumes for 2015-2019 are presented in Tables B.6-B.8. Based on the five largest herbicide AI that the three states had in common out of the top most sold herbicides among the published volumes from IBAMA [36].

**Table B.6:** IBAMA data on the sales volumes of the five most sold herbicide AI inParaná 2015-2019 [36].

Active ingredient	Sold volume in Paraná									
	2015	2016	2017	2018	2019					
Glyphosate	27 713	22 210	24 122	25 059	24 633					
2,4-D	8 304	6 501	7 190	5 757	6 475					
Paraquat dichloride	1 426	2 041	1 828	1 248	2 126					

Clethodim	466	-	418	608	899	
Clomazone	230	217	356	418	354	

**Table B.7:** IBAMA data on the sales volumes of the five most sold herbicide AI in Mato Grosso 2015-2019 [36].

Active ingredient	Sold volume in Mato Grosso								
	2015	2016	2017	2018	2019				
Glyphosate	38 837	41 846	31 484	33 639	38 685				
2,4-D	7 989	8 507	9 845	8 336	9 380				
Paraquat dichloride	859	1 024	1 014	1 321	1 901				
Clethodim	189	-	460	750	952				
Clomazone	307	294	459	343	339				

**Table B.8:** IBAMA data on the sales volumes of the five most sold herbicide AI in Tocantins 2015-2019 [36].

Active ingredient	Sold volume in Tocantins								
	2015	2016	2017	2018	2019				
Glyphosate	3 205	2 691	2 869	3 071	4 019				
2,4-D	778	1 141	1 580	1 392	1 459				
Paraquat dichloride	40	130	123	140	254				
Clethodim	9	-	37	64	85				
Clomazone	27	24	61	24	44				

#### B.2.2 Fungicides

The six most sold fungicide AI and their corresponding sales volumes for 2015-2019 are presented in Tables B.9-B.11. Based on the six largest fungicide AI that the three states had in common out of the top most sold fungicides among the published volumes from IBAMA [36].

Active ingredient	Sold volume in Paraná					
	2015	2016	2017	2018	2019	
Mancozeb	2 861	4 486	2 710	4 774	3 820	
Chlorothalonil	171	537	730	866	2 152	
Carbendazim	580	594	554	812	772	
Thiophanate-methyl	437	400	479	574	503	
Azoxystrobin	466	398	547	161	255	
Tebuconazole	521	370	228	339	528	

**Table B.9:** IBAMA data on the sales volumes of the six most sold fungicide AI in Paraná2015-2019 [36].

**Table B.10:** IBAMA data on the sales volumes of the six most sold fungicide AI in MatoGrosso 2015-2019 [36].

Active ingredient	Sold volume in Mato Grosso							
	2015	2016	2017	2018	2019			
Mancozeb	3 343	4 472	5 155	7 268	11 917			
Chlorothalonil	7	145	511	1 044	2 711			
Carbendazim	410	525	769	1 260	1 952			
Thiophanate-methyl	231	264	352	305	424			
Azoxystrobin	694	503	977	456	683			
Tebuconazole	381	330	307	379	580			

**Table B.11:** IBAMA data on the sales volumes of the six most sold fungicide AI in Tocantins 2015-2019 [36].

Active ingredient	Sold volume in Tocantins							
	2015 2016 2017 2018 2019							
Mancozeb	183	284	296	545	398			
Chlorothalonil	3	14	36	49	279			
Carbendazim	19	31	36	43	43			
Thiophanate-methyl	99	89	46	35	23			

Azoxystrobin	83	25	40	128	46
Tebuconazole	102	66	46	44	70

#### B.2.3 Insecticides

The five most sold insecticide AI and their corresponding sales volumes for 2015-2019 are presented in Tables B.12-B.14. Based on the five largest insecticide AI that the three states had in common out of the top most sold fungicides among the published volumes from IBAMA [36].

**Table B.12:** IBAMA data on the sales volumes of the five most sold insecticide AI inParaná 2015-2019 [36].

Active ingredient	Sold volume in Paraná						
	2015	2016	2017	2018	2019		
Acephate	3 098	3 208	3 181	3 372	4 887		
Imidacloprid	1 116	887	809	926	935		
Methomyl	380	224	258	375	453		
Lambda-cyhalothrin	152	173	142	164	236		
Acetamiprid	38	21	21	73	41		

**Table B.13:** IBAMA data on the sales volumes of the five most sold insecticide AI in Mato Grosso 2015-2019 [36].

Active ingredient	Sold volume in Mato Grosso					
	2015	2016	2017	2018	2019	
Acephate	5 739	8 809	8 187	7 528	9 514	
Imidacloprid	1 495	1 714	1 502	1 885	1 687	
Methomyl	1 155	935	824	1 011	1 482	
Lambda-cyhalothrin	303	351	371	483	669	
Acetamiprid	297	512	558	379	419	

Active ingredient	Sold volume in Tocantins				
	2015	2016	2017	2018	2019
Acephate	93	260	234	165	264
Imidacloprid	72	85	102	108	123
Methomyl	89	52	100	81	83
Lambda-cyhalothrin	15	5	12	17	35
Acetamiprid	7	11	23	22	35

**Table B.14:** IBAMA data on the sales volumes of the five most sold insecticide AI inTocantins 2015-2019 [36].

# C ADAPAR data

This appendix present data that has been retrieved from the Paraná Agriculture Defense Agency (ADAPAR, Agência de Defensa Agropecuária do Paraná). All percentages in the upcoming tables are based on the total sold volume of commercial products (CP) shown in Table C.1. The CP volumes are presented in tonnes.

**Table C.1:** ADAPAR data on volumes of sold commercial products (CP) in Paraná 2015-2019 [38].

	2015	2016	2017	2018	2019
Sold CP	100 573	$92\ 161$	92  398	92  904	$95\ 287$

In Table C.2 the different soy and maize categories published by ADAPAR and their corresponding percentages of pesticide sales are presented.

**Table C.2:** ADAPAR data on the shares of total pesticide sales dedicated to soy and maize production in Paraná 2015-2019 [38].

	2015	2016	2017	2018	2019
Soy	$47,\!3\%$	50,7%	52,3%	56,9%	53,2%
Soy GMO	$1,\!5\%$	4,7%	4,7%	3,6%	6,7%
Soy OGM BPS-CV-127-9	$0,\!0\%$	$\mid 0,0\%$	$\mid$ 0,0%	0,0%	0,0%
Soy Liberty Link	$0,\!0\%$	0,0%	0,0%	0,0%	0,0%
Soy summarized	48,9%	$55,\!3\%$	56,9%	60,5%	59,9%
Maize	$16{,}7\%$	19,6%	18,4%	17,3%	17,4%
Maize GMO	$0,\!2\%$	$\mid 0,6\%$	0,9%	1,0%	1,0%
Maize Liberty Link	0,0%	0,0%	0,0%	0,0%	0,0%
Maize summarized	16,9%	20,2%	$19,\!3\%$	18,3%	18,4%

Tables C.3-C.5 show the most sold AI in the product classes herbicides, fungicides and insecticides. The fungicide class includes "fungicide, acaricides" and the insecticide class includes "insecticide, acaricides". The most sold in each product class is based on the

average percentages for the years 2016-2018, which have been sorted from largest to smallest and thereafter the largest ten was picked out.

**Table C.3:** ADAPAR data on shares of pesticide commerical products for the most soldherbicide AI in Paraná 2015-2019 [38].

Active ingredient	2015	2016	2017	2018	2019
Glyphosate acid equivalent	$4,\!2\%$	$13,\!6\%$	14,0%	14,7%	12,8%
Glyphosate + potassium	$0,\!0\%$	6,7%	6,9%	$6,\!2\%$	7,7%
Glyphosate	8,9%	8,1%	6,9%	6,7%	6,2%
Glyphosate + potassium salt $ $	0,9%	$2,\!2\%$	2,0%	2,6%	2,3%
Glyphosate / Glyphosate acid equivalent	1,5%				
Glyphosate summarized	$15,\!4\%$	30,5%	29,9%	30,2%	29,0%
Paraquat	$2,\!1\%$	5,1%	$7,\!4\%$	5,8%	6,9%
Atrazine	$2,\!0\%$	$5,\!1\%$	5,0%	4,7%	4,7%
2,4-D	$2,\!0\%$	$3,\!0\%$	3,3%	$3{,}5\%$	3,5%
2,4-D acid equivalent	0,3%	$1,\!3\%$	1,3%	$1,\!4\%$	1,6%
2,4-D amine (dimethylamine salt of 2,4-dichloro- phenoxyacetic acid)	0,7%	1,0%	0,9%	1,0%	1,3%
2,4-D dimethylamine salt		$0,\!0\%$	0,1%	0,0%	0,0%
2,4-D summarized	$3,\!0\%$	$5,\!4\%$	5,7%	6,0%	6,4%
Diuron (DCMU)	0,0%	1,7%	1,7%	$1,\!3\%$	1,5%
Clethodim	1,8%	0,8%	$1,\!1\%$	1,4%	2,5%
Haloxyfop-P-methyl	$0,\!4\%$	0,5%	$0,\!6\%$	0,6%	0,3%
Picloram	$0,\!3\%$	0,5%	0,5%	$0,\!6\%$	0,4%
Picloram acid equivalents	$0,\!0\%$	$0,\!1\%$	0,2%	$0,\!2\%$	0,1%
Picloram + potassium salt			0,0%	0,0%	0,0%
Picloram summarized	0,3%	$0,\!6\%$	0,7%	0,8%	0,6%
Diquat	$0,\!6\%$	0,5%	0,5%	0,7%	0,7%
Clomazone	0,5%	0,3%	0,4%	0,5%	$0,\!4\%$
Picloram + potassium salt         Picloram summarized         Diquat	0,3% 0,6%	0,6% 0,5%	0,0%   0,7% 0,5%	$\begin{array}{c c} 0,0\% \\ 0,8\% \\ 0,7\% \end{array}$	0,0 0,6 0,7

Active ingredient	2015	2016	2017	2018	2019
Mancozeb	0,7%	$3,\!1\%$	2,7%	$3{,}6\%$	3,5%
Trifloxystrobin	$0,\!0\%$	2,1%	2,0%	$2,\!3\%$	2,0%
Pyraclostrobin	$0,\!1\%$	1,5%	$1,\!4\%$	1,8%	1,6%
Cyproconazole	0,2%	$1,\!6\%$	$1,\!3\%$	1,8%	1,5%
Prothioconazole	$1,\!0\%$	$1,\!3\%$	$1,\!3\%$	$1,\!4\%$	$0,\!6\%$
Azoxystrobin	$0,\!1\%$	1,5%	$1,\!3\%$	$1,\!2\%$	$1,\!0\%$
Tebuconazole	$0,\!4\%$	$1,\!2\%$	$1,\!0\%$	$1,\!6\%$	2,0%
Epoxiconazol	$0,\!0\%$	$1,\!0\%$	$1,\!0\%$	1,5%	$1,\!3\%$
Carbendazim	0,9%	$1,\!2\%$	$1,\!0\%$	$1,\!1\%$	0,9%
Picoxistrobin	$0,\!0\%$	0,8%	0,7%	$1,\!4\%$	1,8%

**Table C.4:** ADAPAR data on shares of pesticide commerical products for the most soldfungicide AI in Paraná 2015-2019 [38].

**Table C.5:** ADAPAR data on shares of pesticide commerical products for the most soldinsecticide AI in Paraná 2015-2019 [38].

Active ingredient	2015	2016	2017	2018	2019
Imidacloprid	$1,\!9\%$	$2,\!4\%$	2,5%	2,7%	2,2%
Acephate	2,3%	2,5%	2,5%	2,5%	2,2%
Beta-cyfluthrin	$0,\!2\%$	$1,\!2\%$	$1,\!3\%$	$1,\!3\%$	1,0%
Lambda-cyhalothrin	$0,\!6\%$	$1,\!1\%$	$1,\!2\%$	$1,\!3\%$	1,1%
Thiamethoxam	$0,\!6\%$	$1,\!0\%$	$1,\!1\%$	$1,\!1\%$	0,8%
Methomyl	$1,\!4\%$	$1,\!2\%$	$1,\!0\%$	0,9%	0,8%
Lufenuron	0,7%	$0,\!3\%$	$0,\!2\%$	$0,\!2\%$	$0,\!3\%$
Teflubenzuron	1,8%	$0,\!2\%$	$0,\!2\%$	$0,\!2\%$	$0,\!2\%$
Thidiocarb	$0,\!3\%$	$0,\!2\%$	$0,\!2\%$	$0,\!2\%$	$0,\!1\%$
Chlorfenapyr	$0,\!2\%$	$0,\!2\%$	$0,\!2\%$	$0,\!2\%$	$0,\!1\%$

# D IBGE data

The data in this appendix present information on land use and soy production that is retrieved from the Brazilian Institute of Geography and Statistics (IBGE, Instituto Brasileiro de Geografia e Estatística). The first section regards the official agricultural counting and the second data from the municipal agricultural production.

#### D.1 Official agricultural counting 2017

Tables D.1-D.4 present data on land use in Brazil, Paraná, Mato Grosso and Tocantins, which is retrieved from the official agricultural counting made 2017 by IBGE. Specific information about the soy production is presented in Table D.5. All numbers in the tables have the unit hectares.

**Table D.1:** IBGE data on land use in Brazil based on the official agricultural counting 2017 [40].

Temporary crops	$55\ 642\ 060$	
Permanent crops	7 755 817	
Flowers	119 928	
Total cropland		$63 \ 517 \ 805$
Natural pastures	47 323 399	
Planted pastures, good conditions	$100 \ 311 \ 258$	
Planted pastures, degraded	11 862 890	
Total pasture		$159 \ 497 \ 547$
Total agricultural land		$223 \ 015 \ 352$

**Table D.2:** IBGE data on land use in Paraná based on the official agricultural counting2017 [40].

Temporary crops	6 087 812
Permanent crops	209 533
Flowers	5 317

Total cropland		$6 \ 302 \ 662$
Natural pastures	836 166	
Planted pastures, good conditions	3 098 967	
Planted pastures, degraded	81 503	
Total pasture		4 016 636
Total agricultural land		10 319 298

**Table D.3:** IBGE data on land use in Mato Grosso based on the official agricultural counting 2017 [40].

Planted pastures, degraded	1 562 264		
Planted pastures, good conditions	17 453 290		
Natural pastures	3 995 697		
Total cropland		9 865	599
Flowers	8 711		
Permanent crops	99 608		
Temporary crops	9 757 280		

**Table D.4:** IBGE data on land use in Tocantins based on the official agricultural counting2017 [40].

Total agricultural land		9	674	175
Total pasture		8	454	545
Planted pastures, degraded	787 634			
Planted pastures, good conditions	$5\ 285\ 579$			
Natural pastures	2 381 332			
Total cropland		1 :	219	630
Flowers	3 440			
Permanent crops	172 719			
Temporary crops	1 043 471			

	Area [ha]	Production [tonnes]
Paraná	4 271 463	15 252 347
Mato Grosso	8 862 732	29 778 544
Tocantins	728 150	2 017 693

**Table D.5:** IBGE data on soy production in Paraná, Mato Grosso and Tocantins based on the official agricultural counting 2017 [40].

### D.2 Municipal agricultural production

Tables D.6 and D.7 includes data on land use and production of soy that has been retrieved from the Municipal agricultural production provided by IBGE. The years 2016-2019 are easily available on the IBGE website. Data for 2015 is retrieved from an archive where data is published only for the states with the largest agricultural production, which is why the year 2015 is blank in Table D.6.

**Table D.6:** IBGE data on soy production areas and volumes in Brazil, Paraná, Mato Grosso and Tocantins 2015-2019 [40].

	Soy area [ha]	Soy production [tonnes]
Brazil		
2015	32 181 243	97 464 936
2016	33 183 119	96 394 820
2017	33 959 879	114 732 101
2018	34 771 690	117 887 672
2019	35 881 447	114 269 392
Paraná		
2015	5 240 402	17 229 378
2016	5 450 788	17 122 294
2017	5 236 903	19 181 853
2018	5 371 973	19 026 204
2019	5 400 517	16 322 933
Mato Gr	OSSO	
2015	8 966 679	27 850 954
2016	9 102 722	26 277 303
2017	9 264 356	30 479 870

2018	9 437 849	31 608 562
2019	9 724 149	32 242 463
Tocantins		
2015	-	-
2016	828 435	1 922 508
2017	842 160	2 410 207
2018	917 608	2 667 936
2019	905 044	2 615 178

**Table D.7:** IBGE data on harvested temporary and permanent crops in Brazil. Paraná, Mato Grosso and Tocantins, the areas dedicated to soy production, and the soy shares of the annual harvested land in each territory respectively [41].

	Harvested temporary crops [ha]	Harvested permanent crops [ha]	Harvested soy[ha]	Soy share of annual harvested land	Average soy share
Brazi	il				
2016	69  627  596	5 832 166	33 183 119	0,440	
2017	72 914 819	5 280 757	33 959 879	0,434	
2018	72 572 833	5 248 299	34 771 690	0,447	
2019	$75\ 295\ 614$	5 280 786	35 881 447	0,445	
					0,442
Para	ná				
2016	$10\ 571\ 759$	132 532	5 450 788	0,509	
2017	$10\ 485\ 008$	129 852	5 236 903	0,493	
2018	10 300 829	125 289	$5\ 371\ 973$	0,515	
2019	$10 \ 501 \ 729$	120 737	5 400 517	0,508	
					0,507
Mato	Grosso				
2016	$14 \ 249 \ 896$	47 192	9 102 722	0,637	
2017	15 540 733	45 448	9 264 356	0,594	
2018	$15\ 471\ 367$	44 509	9 437 849	0,608	
2019	16 592 915	39 127	9 724 149	0,585	

				0,606
Tocantins				
2016   1 195 553	4 572	828 435	0,690	
2017   1 278 379	4 083	842 160	0,657	
2018   1 353 589	5 496	917 608	0,675	
2019   1 413 202	13 704	905 044	0,634	
				0,664

### E CONAB data

This appendix provides historical data from the National Supply Company in Brazil, CONAB (Companhia Nacional de Abastecimento) [28]. Tables E.1 and E.2 provides data on soy and maize production in Brazil. The total production of maize is parted by time of harvest, where safrinha refers to the second crop of maize often cultivated after the soy harvest while maize is the first crop on the year.

	Soy production in Brazil							
Year	Area cultivated [ha]	Production [tonnes]	Yield [kg/ha]					
2009-2010	23 467 900	68 688 200	2 927					
2010-2011	24 181 000	75 324 300	3 115					
2011-2012	$  25 \ 042 \ 200$	66 383 000	2 651					
2012-2013	27 736 100	81 499 400	2 938					
2013-2014	30 173 100	86 120 800	2 854					
2014-2015	32 092 900	96 228 000	2 998					
2015-2016	33 251 900	95 434 600	2 870					
2016-2017	33 909 400	114 075 300	3 364					
2017-2018	35 149 200	119 281 700	3 394					
2018-2019	35 874 000	115 029 900	3 206					

Table E.1: CONAB data on soy production in Brazil from 2009 to 2019 [28].

Table E.2: CONAB data on maize production in Brazil from 2009 to 2019 [28].

Maize production in Brazil							
Area cultivated [ha]				Pro	duction [to	nnes]	
Year	Maize	Safrinha	Total	Maize	Safrinha	Total	
2009-2010	7 724 000	5 269 900	12 993 900	34 079 200	21 938 800	56 018 100	
2010-2011	7 637 700	6 168 400	13 806 100	34 946 700	22 460 300	57 406 900	
2011-2012	7 558 500	$7 \ 619 \ 600$	15 178 100	33 867 100	39 112 700	72 979 500	

$ \mid 2012\text{-}2013 \mid 6\ 783\ 100 \mid 9\ 046\ 200  \mid 15\ 829\ 300 \mid 34\ 576\ 700 \mid 46\ 928\ 900 \mid 81\ 505 $	700
2013-2014   6 617 700   9 211 200   15 828 900   31 652 610   48 399 100   80 051	700
2014-2015   6 142 300   9 550 600   15 692 900   30 082 012   54 590 500   84 672	400
2015-2016   5 356 600   10 565 900   15 922 500   25 758 103   40 772 700   66 530	600
2016-2017   5 482 500   12 109 200   17 591 700   30 462 015   67 380 900   97 842	800
2017-2018   5 082 100   11 534 300   16 616 400   26 810 696   53 898 900   80 709	500
2018-2019   4 103 900   12 878 000   17 492 900   25 646 701   73 177 700   100 04	2 700

H,

### **Indicator calculations**

Presented below are calculations and background data for the indicators in the thesis. First sections concern the pressure indicators and allocations of pesticides to soy, and thereafter the impact indicator follow.

#### **F.1** Pressure indicators - all cropland

Tables F.2-F.4 below show numbers related to the calculations of the pressure indicators for all cropland for Brazil, Paraná, Mato Grosso and Tocantins. They are based on land use data from the official agricultural counting 2017 [41], pesticide sales volumes from IBAMA [36] and assumptions of shares of pesticide use to pasture from ADAPAR [38] and Sindiveg [37]. Equations F.1 and F.2 show how the pressure indicators have been calculated, with Paraná numbers as examples.

$$\frac{kgAI}{haHarvestedLand} = \frac{57814.83tonnesAI * (1 - 0, 023)}{10614860ha} * 1000 = 4,95kgAI/ha$$
(F.1)

$$\frac{kgAI}{haCropland} = \frac{57814,83tonnesAI * (1 - 0,023)}{6302662ha} * 1000 = 8,97kgAI/ha$$
(F.2)

Share to AI [tonnes] pasture, Tonne AI Classification kg AI/ha Hectares **IBAMA** 2018to cropland Sindiveg Physical cropland area Herbicide 315 573 0,060 296 639 63 517 805 4,67Fungicide 90 552 0,060 85 119 63 517 805 1,34Insecticide 88 913 0,060 83 579 63 517 805 1,32

483 953

 $63 \ 517 \ 805$ 

0.060

**Table F.1:** Calculated pressure indicators for all cropland in Brazil.

Total Pesticide

514 844

7.62

Harvested cropland area					
Herbicide	315 573	0,060	296 639	78 195 576 3,79	
Fungicide	90 552	0,060	85 119	78 195 576   1,09	
Insecticide	88 913	0,060	83 579	78 195 576   1,07	
Total Pesticide	e   514 844	0,060	483 953	78 195 576 6,19	

 ${\bf Table \ F.2:} \ {\rm Calculated \ pressure \ indicators \ for \ all \ cropland \ in \ Paraná.}$ 

Classification	AI [tonnes], IBAMA	Share to pasture, ADAPAR	Tonne AI to cropland	Hectares	kg AI/ha
	Pl	nysical cropl	and area		
Herbicide	39 604	0,023	38 709	6 302 662	6,14
Fungicide	8 863	0,023	8 663	6 302 662	1,37
Insecticide	4 026	0,023	3 935	6 302 662	0,62
Total Pesticide	57 815	0,023	56 508	6 302 662	8,97
	Ha	rvested crop	land area		
Herbicide	39 604	0,023	38 709	10 614 860	3,65
Fungicide	8 863	0,023	8 663	10 614 860	0,82
Insecticide	4 026	0,023	3 935	10 614 860	0,37
Total Pesticide	57 815	0,023	56 508	10 614 860	5,32

Table F.3: Calculated pressure indicators for all cropland in Mato Grosso.

Classification	AI [tonnes], IBAMA	Share to pasture, 2018 Sindiveg	Tonne AI to cropland	Hectares	kg AI/ha			
	Physical cropland area							
Herbicide	53 748	0,060	50 523	9 865 599	$5,\!12$			
Fungicide	13 801	0,060	12 973	9 865 599	$  1,\!32  $			
Insecticide	22 764	0,060	21 398	9 865 599	2,17			
Total Pesticide	92 529	0,060	86 977	9 865 599	8,82			
Harvested cropland area								
Herbicide	53 748	0,060	50 523	15 586 181	3,24			

Fungicide   13 801	0,060	12 973	15 586 181   <b>0,83</b>
Insecticide   22 764	0,060	21 398	15 586 181   <b>1,37</b>
Total Pesticide   92 529	0,060	86 977	15 586 181   <b>5,58</b>

 Table F.4: Calculated pressure indicators for all cropland in Tocantins.

Classification	AI [tonnes], IBAMA	Share to pasture, 2018 Sindiveg	Tonne AI to cropland	Hectares	kg AI/ha		
Physical cropland area							
Herbicide	5 620	0,060	5 283	1 219 630	4,33		
Fungicide	900	0,060	846	1 219 630	0,69		
Insecticide	1 320	0,060	1 241	1 219 630	1,02		
Total Pesticide	7 949	0,060	7 472	1 219 630	6,13		
	Har	vested crop	pland area				
Herbicide	5 620	0,060	5 283	1 282 462	4,12		
Fungicide	900	0,060	846	1 282 462	0,66		
Insecticide	1 320	0,060	1 241	1 282 462	0,97		
Total Pesticide	7 949	0,060	7 472	1 282 462	5,83		

#### F.2 Allocation of pesticides to soy

Sindiveg has earlier provided detailed data on pesticide commercial product use that are dedicated to the most cultivated crops, according to product classes. This data was used in order to allocate AI to soy in Pollak's work [5] but was only available up until 2014 and the assumption that the pesticide application situation has remained unchanged since then had to be made. Attempts to obtain data from Sindiveg for more recent years were made with no answer from the organization. On the Sindiveg website data from 2018 and 2019 is available, which explains the gap in the data in Table F.5. The 2018 Sindiveg data is treated like a rough estimate since there are no indications on how the numbers have been calculated.

**Table F.5:** Share of pesticide commercial products (CP) used in soy production according to Sindiveg 2014 and 2018 [37], and ADAPAR 2018 [38].

Source of information	Details		Pesticide CP to soy
Sindiveg 2014, detailed pdf-file	Total tonnes CP	830 264	
	Tonnes CP to soy	458  103	
	Share to soy (Brazil)		0,552
Sindiveg 2018, website	Share to soy (Brazil)		0,550
ADAPAR 2018. dados do siagro (excel)	Soy	0,5693	
	Soy (GMO)	0,0358	
	Soy (liberty link)	0,0000	
	Share to soy (Paraná)		0,605

The 55 % reported by Sindiveg 2014 and 2018 roughly matches the area dedicated to soy out of the total annual cropland, shown in Table F.6. Since the data in Table F.6 is based on the official agricultural counting made by IBGE only every tenth year, data from the IBGE statistics on municipal agricultural production (PAM) had to be used in order to investigate if there were similar numbers on soy share of annual cropland over the last years. Average shares from 2016-2019 of harvested cropland where annual and perennial crops were included is shown in Table F.7. Details about the numbers presented in Table F.7 can be viewed in Appendix Table D.7.

**Table F.6:** Share of annual cropland dedicated to soy production. Data from the IBGEagricultural count 2017 [40].

	Temporary crops, physical cropland [ha]	Soy [ha]	Soy share of annual cropland
Brazil	55 642 060	30 722 657	0,552
Paraná	6 087 812	4 271 463	0,702
Mato Grosso	9 757 280	8 862 732	0,908
Tocantins	1 043 471	728 150	0,698

**Table F.7:** Average share of annual cropland that is dedicated to soy production for the years 2016-2019. Data from IBGE statistics on municipal agricultural production (PAM) [41].

	Soy share of harvested cropland
Brazil	0,442
Paraná	0,507
Mato Grosso	0,606
Tocantins	0,664

From the numbers in Table F.7 it was calculated that the soy share in Mato Grosso and Tocantins is around 20 % and 30 % higher than in Paraná respectively. Out of these numbers a sensitivity scenario was created, where the amounts of AI allocated to soy production were adjusted according to these percentages in Mato Grosso and Tocantins. The base for the calculations was the reported amount of pesticide CP that is dedicated to soy in Paraná according to ADAPAR 2018 [38], which is approximately 60 %. The sensitivity scenario is shown in Table F.8.

**Table F.8:** The baseline and sensitivity scenarios for allocation of pesticide AI to soybeanproduction in Paraná, Mato Grosso and Tocantins.

	Baseline	Sensitivity Scenario	)
	Based on average Sindiveg data	Adjusted higher share due to soybean specialisation in states	Comment
Parana	55%	60%	Parana state statistics of share to soybean in the state 2018 [38]
Mato Grosso	55%	72%	60% * 1,2 = 72%
Tocantins	55%	78%	60% * 1,3 = 78%

#### F.3 Pressure indicators for soy production

In this section, there will follow tables with calculations on pressure indicators for pesticide use in soy production in Brazil, Paraná, Mato Grosso and Tocantins. The indicators are based on land use data from the Municipal agricultural counting by IBGE [41], pesticide volumes from IBAMA [36] and assumptions of shares of pesticide use to pasture from

#### ADAPAR [38] and Sindiveg [37].

	Share to pasture	Ton AI to cropland	Share to soy	Ton AI to soy	kg AI/ ha soy	kg AI/ tonne soy			
Baseli	Baseline scenario - total pesticides								
2015	0,060	467 768	0,550	257 272	7,99	2,64			
2016	0,060	483 939	0,550	266 167	8,02	2,76			
2017	0,060	483 953	0,550	266 174	7,84	2,32			
2018	0,060	516 324	0,550	283 978	8,17	2,41			
2019	0,060	583 306	0,550	320 818	8,94	2,81			
Baseli	ine scenari	io - herbicid	es						
2015	0,060	295 586	0,550	162 572	5,05	1,67			
2016	0,060	303 390	0,550	166 864	5,03	1,73			
2017	0,060	296 639	0,550	163 151	4,80	1,42			
2018	0,060	318 508	0,550	175 179	5,04	1,49			
2019	0,060	347 404	0,550	191 072	5,33	1,67			
Baseli	ine scenari	io - fungicid	es						
2015	0,060	72 371	0,550	39 804	1,24	0,41			
2016	0,060	86 335	0,550	47 484	1,43	0,49			
2017	0,060	85 119	0,550	46 815	1,38	0,41			
2018	0,060	101 728	0,550	55  950	1,61	0,47			
2019	0,060	123 276	0,550	67 802	1,89	0,59			
Baseli	ine scenari	io - insectici	$\operatorname{des}$						
2015	0,060	76 343	0,550	41 989	1,30	0,43			
2016	0,060	66 357	0,550	36 496	1,10	0,38			
2017	0,060	83 579	0,550	45 968	1,35	0,40			
2018	0,060	78 875	0,550	43 382	1,25	0,37			
2019	0,060	94 063	0,550	51 735	1,44	0,45			

Table F.9:	Calculated	pressure	indicators	for	pesticide	use in	soy	production in Brazil.
Table 1.5.	Calculated	pressure	marcators	101	pesuciae	use m	sОу	production in Diazn

	Share to pasture	Ton AI to cropland	Share to soy	Ton AI to soy	kg AI/ ha soy	kg AI/ tonne soy	
Baseline scenario - total pesticides							
2015	0,023	62 197	0,550	34 208	6,53	1,99	
2016	0,021	57 232	0,550	31 478	5,77	1,84	
2017	0,023	56  508	0,550	31 079	5,93	1,62	
2018	0,026	57 257	0,550	31 492	5,86	1,66	
2019	0,023	62 239	0,550	34 231	6,34	2,10	
Basel	line scenar	io - herbicid	es				
2015	0,023	42 307	0,550	23 269	4,44	1,35	
2016	0,021	37 015	0,550	20 358	3,73	1,19	
2017	0,023	38 709	0,550	21 290	4,07	1,11	
2018	0,026	37 341	0,550	20 537	3,82	1,08	
2019	0,023	39 494	0,550	21 722	4,02	1,33	
Basel	line scenar	io - fungicid	es				
2015	0,023	8 933	0,550	4 913	0,94	0,29	
2016	0,021	11 157	0,550	6 136	1,13	0,36	
2017	0,023	8 663	0,550	4 765	0,91	0,25	
2018	0,026	11 738	0,550	6 456	1,20	0,34	
2019	0,023	8 024	0,550	4 413	0,82	0,27	
Basel	line scenar	io - insectici	$\operatorname{des}$				
2015	0,023	8 028,52	0,550	4 415,69	0,84	0,26	
2016	0,021	6 227,16	0,550	3 424,94	0,63	0,20	
2017	0,023	3 934,78	0,550	2 164,13	0,41	0,11	
2018	0,026	4 518,66	0,550	2 485,27	0,46	0,13	
2019	0,023	9 090,28	0,550	4 999,65	0,93	0,31	
Sensi	tivity scen	ario - total j	pesticides				
2015	0,023	62 197	0,605	37 632	7,18	2,18	
2016	0,021	57 232	0,605	34 628	6,35	2,02	
2017	0,023	56 508	0,605	34 190	6,53	1,78	
2018	0,026	57 257	0,605	34 644	6,45	1,82	

 Table F.10:
 Calculated pressure indicators for pesticide use in soy production in Paraná.

2019   0,023	62 239	0,605	37 657	6,97	2,31			
Sensitivity scenario - herbicides								
2015   0,023	42 307	0,605	25 598	4,88	1,49			
2016   0,021	37 015	0,605	22 396	4,11	1,31			
2017   0,023	38 709	0,605	23 421	4,47	1,22			
2018   0,026	37 341	0,605	22 593	4,21	1,19			
2019   0,023	39 494	0,605	23 896	4,42	1,46			
Sensitivity scen	nario - fungi	cides						
2015   0,023	8 933	0,605	5 405	1,03	0,31			
2016   0,021	11 157	0,605	6 750	1,24	0,39			
2017   0,023	8 663	0,605	5 241	1,00	0,27			
2018   0,026	11 738	0,605	7 102	1,32	0,37			
2019   0,023	8 024	0,605	4 855	0,90	0,30			
Sensitivity scen	nario - insect	ticides						
2015   0,023	8 028,52	0,605	4 858	0,93	0,28			
2016   0,021	6 227,16	0,605	3 768	0,69	0,22			
2017   0,023	3 934,78	0,605	2 381	0,45	0,12			
2018   0,026	4 518,66	0,605	2 734	0,51	0,14			
2019   0,023	9 090,28	0,605	5 500	1,02	0,34			

**Table F.11:** Calculated pressure indicators for pesticide use in soy production in MatoGrosso.

	Share to pasture	Ton AI to cropland	Share to soy	Ton AI to soy	kg AI/ ha soy	kg AI/ tonne soy		
Base	line scenar	io - total pe	sticides					
2015	0,060	83 424	0,550	45 883	5,12	1,65		
2016	0,060	93 520	0,550	51 436	5,65	1,96		
2017	0,060	86 977	0,550	47 838	5,16	1,57		
2018	0,060	92 890	0,550	51 089	5,41	1,62		
2019	0,060	114 185	0,550	62 802	6,46	1,95		
Base	Baseline scenario - herbicides							
2015	0,060	52 718	0,550	28 995	3,23	1,04		

2016   0,060	58 307	0,550	32 069	3,52	1,22
2017   0,060	50 523	0,550	27 788	3,00	0,91
2018 0,060	53 568	0,550	29 463	3,12	0,93
2019 0,060	59 064	0,550	32 485	3,34	1,01
Baseline scenar	rio - fungicid	les			·
2015 0,060	9 569	0,550	5 263	0,59	0,19
2016 0,060	10 663	0,550	5 864	0,64	0,22
2017 0,060	12 973	0,550	7 135	0,77	0,23
2018 0,060	16 038	0,550	8 821	0,93	0,28
2019 0,060	24 029	0,550	13 216	1,36	0,41
Baseline scenar	rio - insectic	ides			
2015   0,060	18 007	0,550	9 904	1,10	0,36
2016   0,060	19 576	0,550	10 767	1,18	0,41
2017   0,060	21 398	0,550	11 769	1,27	0,39
2018   0,060	20 979	0,550	11 538	1,22	0,37
2019 0,060	28 377	0,550	15 607	1,61	0.48
0,000	20 511	0,000	10 007	1,01	0,48
Sensitivity scer	1		10 007	1,01	
,	1		60 065	6,70	2,16
Sensitivity scer	nario - total	pesticides		1 ·	
Sensitivity scen           2015   0,060	nario - total   83 424	pesticides   0,720	60 065	6,70	2,16
Sensitivity scen           2015   0,060           2016   0,060	<b>ario - total</b>   83 424   93 520	<b>pesticides</b>   0,720   0,720	60 065   67 335	6,70   7,40	2,16   2,56
Sensitivity scen           2015   0,060           2016   0,060           2017   0,060	<b>ario - total</b>   83 424   93 520   86 977	pesticides         0,720         0,720         0,720         0,720	60 065   67 335   62 624	6,70   7,40   6,76	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$
Sensitivity scen           2015   0,060           2016   0,060           2017   0,060           2018   0,060	<b>ario - total</b>   83 424   93 520   86 977   92 890   114 185	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720	60 065   67 335   62 624   66 881	6,70   7,40   6,76   7,09	2,16     2,56     2,05     2,12
Sensitivity scen           2015   0,060           2016   0,060           2017   0,060           2018   0,060           2019   0,060	<b>ario - total</b>   83 424   93 520   86 977   92 890   114 185	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720	60 065   67 335   62 624   66 881	6,70   7,40   6,76   7,09	2,16     2,56     2,05     2,12
Sensitivity scer           2015   0,060           2016   0,060           2017   0,060           2018   0,060           2019   0,060           Sensitivity scer	hario - total   83 424   93 520   86 977   92 890   114 185 hario - herbio	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         cides	60 065   67 335   62 624   66 881   82 213	6,70   7,40   6,76   7,09   8,45	2,16   2,56   2,05   2,12   2,55
Sensitivity scer           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           Sensitivity scer         2015           2015         0,060	hario - total   83 424   93 520   86 977   92 890   114 185 hario - herbio   52 718	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720	60 065   67 335   62 624   66 881   82 213   37 957	6,70   7,40   6,76   7,09   8,45   4,23	2,16   2,56   2,05   2,12   2,55   1,36
Sensitivity scer           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           Sensitivity scer         2015           2015         0,060	ario - total         83 424         93 520         86 977         92 890         114 185         pario - herbio         52 718         58 307	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720	60 065   67 335   62 624   66 881   82 213   37 957   41 981	$ \begin{array}{c cccc} & 6,70 \\ & 7,40 \\ & 6,76 \\ & 7,09 \\ & 8,45 \\ \hline & 4,23 \\ & 4,61 \\ \end{array} $	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$
Sensitivity scer           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           2015         0,060           2016         0,060           2017         0,060	hario - total   83 424   93 520   86 977   92 890   114 185 hario - herbio   52 718   58 307   50 523	pesticides         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720         0,720	60 065   67 335   62 624   66 881   82 213   37 957   41 981   36 377	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$
Sensitivity scer           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2016         0,060           2017         0,060           2018         0,060	ario - total         83 424         93 520         86 977         92 890         114 185         ario - herbid         52 718         58 307         50 523         53 568         59 064	pesticides         0,720	60 065   67 335   62 624   66 881   82 213   37 957   41 981   36 377   38 569	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$
Sensitivity scer           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2019         0,060           2015         0,060           2016         0,060           2017         0,060           2018         0,060           2017         0,060           2018         0,060           2018         0,060           2019         0,060	ario - total         83 424         93 520         86 977         92 890         114 185         ario - herbid         52 718         58 307         50 523         53 568         59 064	pesticides         0,720	60 065   67 335   62 624   66 881   82 213   37 957   41 981   36 377   38 569	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$
Sensitivity scer         2015       0,060         2016       0,060         2017       0,060         2018       0,060         2019       0,060         2015       0,060         2016       0,060         2017       0,060         2018       0,060         2017       0,060         2018       0,060         2019       0,060         2019       0,060	ario - total         83 424         93 520         86 977         92 890         114 185         ario - herbid         52 718         58 307         50 523         53 568         59 064         ario - fungio	pesticides         0,720	60 065   67 335   62 624   66 881   82 213   37 957   41 981   36 377   38 569   42 526	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$

2018   0,060	16 038	0,720	11 547	1,22	0,37
2019   0,060	24 029	0,720	17 301	1,78	0,54
Sensitivity sc	enario - ins	ecticides			
2015   0,060	18 007	0,720	12 965	1,45	0,47
2016   0,060	19 576	0,720	14 094	1,55	0,54
2017   0,060	21 398	0,720	15 407	1,66	0,51
2018   0,060	20 979	0,720	15 105	1,60	0,48
2019   0,060	28 377	0,720	20 431	2,10	0,63

**Table F.12:** Calculated pressure indicators for pesticide use in soy production in To-<br/>cantins.

	Share to pasture	Ton AI to cropland	Share to soy	Ton AI to soy	kg AI/ ha soy	kg AI/ tonne soy
Base	line scenar	io - total pe	sticides			
2015	0,060	6 019	0,550	3 310	-	-
2016	0,060	6050	0,550	3 327	4,02	1,73
2017	0,060	7 472	0,550	4 110	4,88	1,71
2018	0,060	7 126	0,550	3 919	4,27	1,47
2019	0,060	8 627	0,550	4 745	5,24	1,81
Base	line scenar	io - herbicid	es			
2015	0,060	4 346	0,550	2 390	-	-
2016	0,060	4 366	0,550	2 401	2,90	1,25
2017	0,060	5 283	0,550	2 906	3,45	1,21
2018	0,060	5 244	0,550	2 884	3,14	1,08
2019	0,060	6 395	0,550	3 517	3,89	1,34
Base	line scenar	io - fungicid	es			
2015	0,060	892	0,550	491	-	-
2016	0,060	847	0,550	466	0,56	0,24
2017	0,060	846	0,550	465	0,55	0,19
2018	0,060	1 238	0,550	681	0,74	0,26
2019	0,060	1 278	0,550	703	0,78	0,27
Base	line scenar	io - insectici	des			

2015   0,060	664	0,550	365	-	-
2016 0,060	605	0,550	333	0,40	0,17
2017   0,060	1 241	0,550	683	0,81	0,28
2018 0,060	596	0,550	328	0,36	0,12
2019 0,060	838	0,550	461	0,51	0,18
Sensitivity sce	nario - tota	l pesticide	8		
2015   0,060	6 019	0,780	4 695	-	-
2016   0,060	6 050	0,780	4 719	5,70	2,45
2017   0,060	7 472	0,780	5 828	6,92	2,42
2018   0,060	7 126	0,780	5 558	6,06	2,08
2019   0,060	8 627	0,780	6 729	7,43	2,57
Sensitivity sce	nario - herb	oicides			
2015   0,060	4 346	0,780	3 390	-	-
2016   0,060	4 366	0,780	3 405	4,11	1,77
2017   0,060	5 283	0,780	4 121	4,89	1,71
2018   0,060	5 244	0,780	4 091	4,46	1,53
2019   0,060	6 395	0,780	4 988	5,51	1,91
Sensitivity sce	nario - fung	gicides			
2015   0,060	892	0,780	696	-	-
2016   0,060	847	0,780	661	0,80	0,34
2017   0,060	846	0,780	660	0,78	0,27
2018   0,060	1 238	0,780	966	1,05	0,36
2019   0,060	1 278	0,780	997	1,10	0,38
Sensitivity sce	nario - inse	cticides			
2015   0,060	664	0,780	518	-	-
2016   0,060	605	0,780	472	0,57	0,25
2017   0,060	1 241	0,780	968	1,15	0,40
2018   0,060	596	0,780	465	0,51	$  0,\!17$
2019   0,060	838	0,780	654	0,72	0,25

### F.4 Impact indicators

Tables F.13-F.15 show which the seven most sold AI in the product classes herbicides, fungicides and insecticides are according to IBAMA [36], in the respective state. They also show whether the specific AI is included in the Pesticide Action Network's (PAN) list of Highly Hazardous Pesticides (HHP) [46]. In the tables, the asterisk means: \*Included in the seven most sold AI reported by ADAPAR in the product class, deviating from the seven most sold AI reported by IBAMA.

**Table F.13:** The most sold herbicide AI in Paraná (PR), Mato Grosso (MT) and Tocantins (TO), their classifications and if they belong in the Pesticide Action Network's (PAN) list of Highly Hazardous Pesticides (HHP).

AI	States	Classification	In PANs HHP list
Glyphosate	PR, MT, TO	Non-selective	X
2,4-D	PR, MT, TO	Selective	
Paraquat dichloride	PR, MT, TO	Non-selective	X
Diuron	PR	Selective	X
Clethodim	PR, MT, TO	Selective	
Clomazone	PR, MT, TO	Selective	
Bantazon	PR, TO	Selective	
Haloxyfop-P-methyl*	PR	Selective	X
Trifluralin	MT	Selective	X
Diquat dibromide	MT	Non-selective	X
Triclopyr-butotyl	ТО	Selective	

**Table F.14:** The most sold fungicide AI in Paraná (PR), Mato Grosso (MT) and Tocantins (TO), their classifications and if they belong in the Pesticide Action Network's (PAN) list of Highly Hazardous Pesticides (HHP).

AI	States	Classification	In PANs HHP list
Mancozeb	PR, MT, TO	Carbamate	X
Chlorothalonil	PR, MT, TO	Chloronitrile	X
Carbendazim	PR, MT, TO	Benzimidazole	X
Thiophanate-methyl	PR, MT, TO	Benzimidazole	
Flauzinam	PR	Phenylpyridinamine	
Azoxystrobin	PR, MT, TO	Strobilurin	

Tebuconazole	PR, MT, TO	Triazole
Trifloxystrobin*	PR	Strobilurin
Pyraclostrobin*	PR	Strobilurin
Cyproconazole*	PR	Triazole
Prothioconazole*	PR	Triazolinthione
Defenoconazole	MT, TO	Triazole

**Table F.15:** The most sold insecticide AI in Paraná (PR), Mato Grosso (MT) and Tocantins (TO), their classifications and if they belong in the Pesticide Action Network's (PAN) list of Highly Hazardous Pesticides (HHP).

AI	States	Classification	In PANs HHP list
Acephate	PR, MT, TO	Organophosphate	X
Imidacloprid	PR, MT, TO	Neonicotinoid	X
Methomyl	PR, MT, TO	Carbamate	X
Thiodicarb	PR	Carbamate	X
Lambda-cyhalothrin	PR, MT, TO	Pyrethroid	X
Diflubenzuron	PR, TO	Benzoylurea	
Acetamiprid	PR, MT, TO	Neonicotinoid	
Beta-cyfluthrin*	PR	Pyrethroid	X
Thiamethoxam*	PR	Neonicotinoid	X
Lufenuron*	PR	Benzoylurea	X
Malathion	MT	Organophosphate	X
Diafenthiuron	MT	Thiourea	X
Chlorantraniliprole	ТО	Anthranilic diamide	X
Dimethoate	ТО	Organophosphate	X

In the tables shown above, the most sold AI that all three states have in common have been picked out. It is five herbicide and insecticide AI and six fungicide AI. In Tables F.16-F.18 the 2015-2019 sales volumes for these AI are shown since the impact indicators in Section 4.5 are based on this.

Table F.16: IBAMA data on 2015-2019 sales volumes [36] for the most sold herbicide
AI common for Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

	PR	MT	ТО
Glyp	hosate		
2015	27 713	38 837	3 205
2016	22 210	41 846	2 691
2017	24 122	31 484	2 869
2018	25  059	33 639	3 071
2019	24 633	38 685	4 019
<b>2,4-</b> D	)		
2015	8 304	7 989	778
2016	6501	8 507	1 141
2017	7  190	9 845	1 580
2018	5  757	8 336	1 392
2019	$6\ 475$	9 380	$1 \ 459$
Para	quat dic	hloride	
2015	1 426	859	40
2016	$2 \ 041$	1 024	130
2017	1 828	1 014	123
2018	$1\ 248$	1 321	140
2019	2 126	1 901	254
Cleth	nodim		
2015	466	189	9
2016	0	0	0
2017	418	460	37
2018	608	750	64
2019	899	952	85
Clom	azone		
2015	229	307	27
2016	217	294	24
2017	356	459	61
2018	418	343	24

2019 354	339	44
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**Table F.17:** IBAMA data on 2015-2019 sales volumes [36] for the most sold fungicide AI common for Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

	PR	MT	то
Mane	cozeb		
2015	2 861	3 343	183
2016	4 486	4 472	284
2017	2 710	5 155	296
2018	4 774	7 268	545
2019	3 820	11 917	398
Chlo	rothalo	nil	
2015	171	7	3
2016	537	145	14
2017	730	511	36
2018	866	1 044	49
2019	2 152	2 711	279
Carb	endazi	m	
2015	580	410	19
2016	594	525	31
2017	554	769	36
2018	812	1 260	43
2019	772	1 952	43
Thio	phanat	e-methy	rl
2015	437	231	99
2016	400	264	89
2017	479	352	46
2018	574	305	35
2019	503	424	23
Azox	ystrob	in	
2015	466	694	83
2016	398	503	25

2017 247	977	40
2018   161	456	128
2019 255	683	46
Tebuconaz	ole	
2015   521	381	102
2016 370	330	66
2017   228	307	46
2018 339	379	44
2019   528	580	70

**Table F.18:** IBAMA data on 2015-2019 sales volumes [36] for the most sold insecticide AI common for Paraná (PR), Mato Grosso (MT) and Tocantins (TO).

	$\mathbf{PR}$	MT	то
Acep	hate		
2015	3 098	5 739	93
2016	3 208	8 809	260
2017	3 181	8 187	234
2018	3 372	7 528	165
2019	4 887	9 514	264
Imid	aclopri	d	
2015	1 116	1 495	72
2016	887	1 714	85
2017	809	1 502	102
2018	926	1 885	108
2019	935	1 687	123
Meth	omyl		
2015	380	1 155	89
2016	224	935	52
2017	258	824	100
2018	374	1 011	81
2019	453	1 482	83
Lam	oda-cyl	nalothr	in

2015	152	302	15
2016	173	351	5
2017	142	371	12
2018	164	483	17
2019	236	669	35
Aceta	amiprie	d	
	-		
2015	38	297	7
2015 2016	38 21	297 512	7   11
		1	
2016	21	512	11