Global Material Stocks of Agricultural Field Machinery

Quantification of the Current In-Use Stock and Exploration of Future Pathways through a Material Stock Scenario Analysis

by
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1 Introduction

The growing demand for food production and global developments concerning the intensification and mechanization of agriculture are likely to affect the material requirements of agriculture in some way in the future. However, there is a large gap in the scientific literature regarding both the current and future material requirements of the agricultural sector, particularly in relation to the materials embedded in agricultural machinery. To date, the size of the material stock of agricultural machinery has not been quantified on a global scale in the existing scientific literature.

Material flow assessment and its extensions are a set of analytical tools used in the interdisciplinary field of industrial ecology to study the flows and stocks of materials and their environmental impacts within different socioeconomic and natural systems. Recent research in the field has started to link material use to Integrated Assessment Models (IAMs), assessing the developments of material use in different Shared Socioeconomic Pathway (SSP) scenarios. While the potential future developments of the material stocks and flows of many different sectors and applications have already been investigated in this way, the agricultural sector is yet to be included in such analyses.

The main research question addressed by the reported study is as follows: *What are the global material stocks currently embedded in agricultural field machinery and how might these stocks develop in the future based on different Shared Socioeconomic Pathway scenarios?* This study represents a first attempt to estimate the size and composition of the current global material stock embedded in agricultural field machinery. The possible future developments of the material stock were modeled using scenario data on five SSPs generated by an integrated assessment model IMAGE.

1.1 Material Composition and Global Material Stocks of Agricultural Machinery

The global demand for agricultural products is expected to rise significantly in the coming decades due to population growth and changes in dietary patterns taking place in different parts of the world. In order to meet this increasing demand, agricultural production must grow by 50 percent from the level of 2012 by the year 2050 (Food and Agriculture Organization of the United Nations [FAO], 2017). Even though agricultural production is one of the major contributors to global warming, the sector itself is heavily affected by climate change (Wiebe et al. 2015). Natural degradation has decelerated the yield growth of agricultural production, which is mainly driven by productivity improvements brought by technological innovations and investments to agriculture (FAO, 2017). Agricultural mechanization plays an important role in the productivity growth of agriculture and it can improve food-security around the world (Böttinger et al. 2013).

While modern, mechanized agricultural practices can increase productivity and profitability of farming, they also increase the demand for different inputs to agriculture, including energy and materials, which are associated with different environmental impacts (Mantoam et al. 2020). The impacts of agricultural production related to the use-phase of agricultural machinery, particularly in relation to their energy consumption and GHG emissions, have been addressed quite comprehensively in the scientific literature. However, relatively little attention has been devoted to the environmental impacts of the materials used in the production of agricultural machinery. In fact, very little is known about the materials embedded in agricultural machinery in general, both in terms of the material compositions of individual machines and the material stocks they represent in different spatial and temporal scales.

When it comes to the material composition of agricultural machinery, the life-cycle inventory (LCI) and life-cycle assessment (LCA) literature contain some, albeit limited, information regarding material contents of agricultural machinery. One of the only LCA studies focusing specifically on tractors is reported by Lee et al. (2000); this study includes rough estimates of the inputs of five materials in different stages of the tractor lifecycle, but the material composition of the tractor is not reported explicitly. LCAs of agricultural products, which are more abundant than those focusing on agricultural machinery specifically, contain hardly any information on the material contents of farm machinery. There are two reasons for this; first of all, the impacts of raw materials used for the production of agricultural machinery are often left outside of the system boundary in life-cycle assessments of agricultural products altogether. This can be due to the general difficulty of defining a system boundary of agricultural production (Caffrey & Veal, 2013), and even the different LCA standards provide varying recommendations regarding the inclusion of machinery production within the system boundaries of LCAs of agricultural products (Kan et al. 2020). Another reason for the exclusion might be the general notion that the impacts of machinery production are negligible in comparison to the impacts of the use phase of machinery (Sievering et al. 2020), even though this idea is contested (Roer et al. 2012). Secondly, as noted by Lovarelli et al. (2016), information on the machinery material composition is extremely scarce in the literature, and machine manufacturers are often reluctant to publish such data. Consequently, even LCI databases such as ecoinvent (Wernet et al. 2016; Nemecek & Kägi, 2017) and Agro-footprint 5.0 (van Paassen et al. 2019) often rely on proxy data on trucks, and express the material composition of agricultural machinery in a few broad material categories. There are a few studies with a specific focus on the material embodiment of different agricultural products, which include the material use related to machinery depreciation, expressed in mass (Romanelli & Milan, 2010; Romanelli & Milan, 2012). However, no distinction is made between the different materials amounting to the total mass of the machinery.

Over the past few years, a series of studies have quantified the energy, water and carbon footprints of different types of agricultural machinery based on the material flows directly associated with their assembly and maintenance phases (Mantoam et al., 2014; Mantoam et al., 2016; Mantoam et al., 2018). A recently published article by Mantoam et al. (2020), which compiles and adds to the results of this research, provides detailed descriptions of the material contents of six different types of agricultural machinery. It is therefore the best currently available source concerning the material composition of agricultural machinery, and the data from this article was also used in this study.

Information regarding the total quantity of materials embedded in agricultural machinery currently in use is also limited in the scientific literature. Agricultural machinery is sometimes included in large-scale material flow assessments of specific materials (Passarini et al., 2018; Schipper et al., 2018). However, these studies treat agricultural machinery as one of many material applications included for the estimation of the *total* stocks and flows of the specific materials, and the results of these studies do not provide any information on the material stocks embedded within individual material applications. The material stock of agriculture is addressed more directly in an article by Dombi (2018), which proposes a model based on an economic production function to estimate the capital stocks of different sectors in both monetary and physical terms. This model was used to evaluate the mass of the fixed capital of the transportation and agricultural sectors in Hungary. However, the study does not consider the composition of the capital stock; no distinctions are made between different machinery types nor materials embedded in the machinery stock. The size and composition of the material stock of agricultural machinery are yet to be quantified on a global scale.

In order to assess the size of the global material stock embedded in agricultural machinery, it is important to gain an understanding of the scale of the agricultural machinery market and to estimate the number of machinery in use. A great variety of different types of agricultural machinery is used in the production of agricultural goods around the world today. In their overview of the global market of agricultural machinery and equipment, Mehta and Gross (2007) list major categories of agricultural equipment, which include tractors; harvesters; planting, seeding, and fertilizing machinery; haying machinery; plowing and cultivating machinery; 'other agricultural equipment', including different kinds of sprayers, dairy-related equipment, livestock-related equipment, feed grinders, crushers, and irrigation equipment; and finally, the parts and attachments for all aforementioned machinery. This article by Mehta and Gross, along with many other sources describing the global market of agricultural machinery and equipment, expresses the global demand and the market shares of these machinery categories in monetary terms, which are hard to translate into physical quantities of the different kinds of equipment. Furthermore, articles focusing on the sales of machinery do not reveal any information regarding the number of machines that are already in use, sold second-hand, or disposed of.

The best currently available source of quantitative data regarding the global numbers of agricultural machinery in use is the dataset published by Food and Agriculture Organization of the United Nations (FAOSTAT, 2018), which contains country-level data on the imports and exports (in monetary terms and physical numbers), and the number of agricultural machinery in use in each country. Due to large gaps in the data, this dataset alone is an insufficient inventory of the total numbers of different agricultural machinery in use globally, but it provides a good starting point for further estimates.

1.2 Material Stock Research and Material Scenario Modeling

The total material requirements of the global economy are expected to rise considerably in the coming decades (Schandl et al. 2020). This growing demand for materials is likely to have significant negative environmental impacts due to the often energy-intensive and polluting production methods of primary materials (OECD, 2019). That is why increasing efforts are devoted to the exploration of more sustainable sources or materials to satisfy the current and future material requirements of humanity (Krook & Baas, 2013). Such a potential alternative to primary material resources can be found in the societal stocks of materials that are already in use in various applications. The term 'urban mining', which is closely connected to concepts such as circular economy (Ghissellini et al. 2016) and material recycling, describes activities related to the exploration, recovery, and reprocessing of materials embedded in these in-use stocks for new uses (Baccini & Brunner, 2012). According to Graedel (2011), in order to assess the feasibility of urban mining activities, the three most important issues to be investigated are the amount of materials in use, the time frame for them to become available for recovery, and the form in which they can be found in society. This study mainly focuses on the first issue, as it attempted to quantify the global materials stocks embedded in agricultural machinery. Even though the term 'urban mining' (quite correctly) suggests that cities and other densely built areas have the most potential as sources of secondary materials, material stocks outside of these hubs should not be ignored.

In the interdisciplinary scientific field of industrial ecology, which “examines the flow of materials and energy at various scales as part of the study and pursuit of sustainable production and consumption” (Lifset and Graedel, 2015, p. 843), the main tool used in the study of material use in society is called material flow analysis (MFA). MFA can be used to map and quantify whole systems of material flows within different spatial and temporal scales, in order to gain a better understanding of the ‘metabolism’ of socioeconomic systems (Graedel, 2019). An extension of MFA, the dynamic material flow analysis, can be used to study the accumulation of materials within in-use stocks over time. In dynamic MFA, data on the lifetimes of different material applications is integrated into a top-down (often) flow-driven model or a bottom-up stock-driven model depending on the available data on material flows or stocks (Müller et al. 2014). The lifetime of a material stock represents a delay in the time in which material inflows to the stock become outflows again. According to Graedel (2019), data availability is currently one of the main challenges of MFA, and the determination of the lifetimes of different in-use stocks is still often based on rough estimates. Material stock accounting, which attempts to quantify the material stocks without the use of a dynamic flow model, is also often complicated by poor availability of data on the in-use stocks (Wiedenhofer et al., 2019).

This study does not fit in the definition of MFA entirely, as its focus is on the quantification of the in-use stocks of materials only. Admittedly, studying material flows moving in and out of societal stocks is essential from sustainability and urban mining perspectives, as these flows represent both the demand for new (or recycled) materials and the availability of secondary materials. The flows are also the source of most of the environmental impacts related to material use (Fritsche, 2013); material inflows are usually associated with the impacts of material production and manufacturing, whereas the material outflows are connected to the impacts of different waste management or recycling processes, or in the worst case, pollution and littering.

However, the in-use stocks of materials also merit special consideration, as they can provide quite a different perspective to the study of material use. The global material stocks have grown 23-fold during the 20th century (Krausmann et al., 2017). According to Baynes and Müller (2016), these in-use material stocks “record the cumulative resource flows—materials and energy— embedded in the infrastructure and artefacts of the socio-economic system” (p. 124). They argue that while material flows can potentially fluctuate significantly over a short time period for various reasons, the developments of the in-use stocks of materials are usually related to “deeper structural changes” in society. The material stocks are influenced by long term developments in the socioeconomic system, and at the same time, many of these stocks with long lifetimes also create the circumstances for said long term changes; they can be the source of lock-ins and path dependency. Baynes and Müller suggest that material flows are ultimately driven by demand for the services provided by the material stocks, instead of a demand for the flows as such. Furthermore, the size, efficiency, and quality of the in-use stocks is connected to both the wealth and the environmental performance of socioeconomic systems. Therefore, only studying the material flows without considering the stocks can lead to an inadequate understanding of economic and sustainable development of these systems (Baynes & Müller, 2016). This means that devoting particular attention to the in-use material stocks can be an appropriate approach for the investigation of large-scale changes in material use on a global scale over a long period of time.

However, long-term future developments of global material stocks are hard to predict. Even though the utilization of integrated assessment models (IAMs) in material research is a relatively new approach within the field of industrial ecology, they can be rather useful tools for the exploration of possible long-term developments in material use. Pauliuk et al. (2017) define integrated assessment models in the following way:

> Technology-rich IAMs are computer models that exhibit a comprehensive coverage of the global socio-ecological system: they cover environmental mechanisms, in particular the climate system and natural vegetation; the biophysical basis of society, including industries, households, and infrastructure; the economic, political, and behavioural superstructure that governs human decisions; and major coupling mechanisms between these elements. (p. 13)

Many IAMs base their assumptions regarding the future developments of the model-drivers on the framework of Shared Socioeconomic Pathways (SSPs), which represent five different potential narratives of the future (Riahi et al. 2017). Most IAMs contain hardly any explicit information on the physical material cycles in their assessment of environmental impacts of different scenarios (Pauliuk et al. 2017). However, recent research has started to connect material use models to existing IAMs. For instance, Schandl et al. (2020) have integrated different material-use narratives (that were based on, and consistent with the five SSP scenarios) to an IAM in order to quantify the total material requirements of the global economy in all SSP scenarios. They analysed the demand of four large material categories (biomass, fossil fuels, metals, and non-metallic minerals) within 21 economic sectors until 2060.

The integrated assessment model IMAGE has been developed to "analyse large-scale and long-term interactions between human development and the natural environment to gain better insight into the processes of global environmental change" (Stehfest et al. 2014, p. 14). In recent years, scenario data from IMAGE and its extensions have been used in models exploring the possible future developments of global stocks and flows of materials in many different sectors and applications. One of the first attempts of implementing IMAGE data in the development of material scenarios has been reported by Deetman et al. (2018). Their study incorporated IMAGE data into a scenario model that assessed the flows and stocks of five metals in different electricity generation technologies, cars, and electronic appliances towards 2050. Since the publication of this study, a similar approach has been adopted in the assessment of material usage in many other sectors. Marinova et al. (2020) used scenario data from IMAGE in their quantification of the global material stock of residential buildings between 1970 and 2050. A companion paper by Deetman et al. (2020) builds on this article; service sector buildings were added in the assessment of the global material stock of buildings, and a dynamic stock model including lifetime data of different buildings was created to quantify the material flows of construction and demolition. In another recent study, Deetman et al. (2021) analysed the stocks and flows of the global electricity sector in relation to the generation, transmission and storage of electricity. The study utilizes IMAGE data on the SSP2 scenario (both the baseline and the 2-degree policy scenario) to model the developments of the stocks and flows of different bulk and critical materials embedded in the global electricity sector towards 2050. Even though these studies have covered many of the major material stocks, various interesting societal stocks of materials remain to be analysed in the future within the SSP framework, as implemented by IMAGE. One of them is found in the agricultural sector, embedded in agricultural field machinery.

1.3 Research Gap, Research Questions and Report Structure

As discussed in the previous sections, there is a relatively large gap in the scientific literature regarding the material use in the global agricultural system, particularly in relation to the materials embedded in agricultural machinery. This applies to both the size and composition of the current material stock of the in-use machinery, as well as the potential development of this stock in the future. In order to address this research gap, this study made the first attempt to quantify the material stock embedded in agricultural field machinery currently in use globally, after which these results were incorporated into a material scenario analysis to answer the following main research question:

What are the global material stocks currently embedded in agricultural field machinery and how might these stocks develop in the future based on different shared socioeconomic pathway scenarios?

In order to answer the main research question, the following sub-questions are addressed:

- *What are the numbers of different types of agricultural machinery currently in use in the global agricultural system and what are their material compositions and average masses?*
- *How can data on agricultural production quantities be used to estimate the number of agricultural machinery in use in different parts of the world?*
- *What is the relative size of the material stock of agricultural machinery compared to other societal stocks of materials?*
- *How can the IMAGE model results on agricultural production patterns be used to explore the development of the number of agricultural machinery in use and the size of the material stock in different SSP scenarios?*
- *How can other variables available in IMAGE be used to model changes in agricultural mechanization levels around the world, and how do these changes affect the number of machinery in use and the size of the material stock in different SSP scenarios?*
- *What kinds of technological developments are currently taking place in the global agricultural system, and what could be their implications to the composition and size of agricultural machinery and the material stock embedded in them?*

The following Chapter 2 describes the data and methods used in the quantification of the current material stock of agricultural field machinery, as well as the methodology of the material scenario analysis, which utilizes data from an integrated assessment model IMAGE. Chapter 3 presents the results concerning the number of field machinery currently in use around the world and the size and composition of the material stock embedded in them. After this, the chapter describes the results of the scenario analysis, which explored the possible changes in both the number and the material stock of agricultural machinery in different SSP scenarios. Chapter 4 addresses some of the limitations of the study, and provides recommendations for future research on the topic. It also discusses some of the current developments taking place in the global agricultural system and the ways they might influence the material stock of agricultural machinery. Chapter 5 presents the final conclusions of the study.

2 Methods and Data

The study was divided into two stages. The first research objective was the quantification of the current material stock embedded in agricultural machinery in use globally. These results were then used in a scenario model in combination with data generated by IMAGE in order to explore the potential future developments of the material stocks of agricultural machinery in five SSP scenarios. In order to do this, the methodologies of the two research steps were harmonized, and the first research step of current stock quantification was designed to complement the scenario model.[1] The methods and data used for the quantification of the current material stock are described in the following section 2.1. Section 2.2 explains the methodology of the material stock scenario analysis, and the ways in which scenario data from IMAGE is used to explore the developments of the material stocks in five Shared Socioeconomic Pathways.

2.1 Quantification of the Current Material Stock

The global material stocks embedded in agricultural machinery can be calculated based on the number of different kinds of agricultural machinery currently in use, their material composition factors, and their average masses.

However, comprehensive global data on the numbers of different types of agricultural machinery currently in use in the world is not readily available in the literature. The best currently available source of information is a dataset published by FAO (FAOSTAT, 2018), which contains country-level data on ten different types of agricultural machinery between the years 1961 and 2009. While the dataset provides relatively comprehensive information on the number of tractors in use, the data on other types of machinery is rather sparse. Therefore, the global total numbers of different types of agricultural machinery in use need to be estimated in another way. The main approach adopted by this study was to link the existing FAO machinery data to agricultural production quantities (for which the FAO data is remarkably complete) by calculating *mechanization factors*, which represent the number of machinery used for the production of a particular quantity of agricultural products. More specifically, they describe the relationship of the size of the in-use machinery stock and the annual production quantities per country. The country-specific mechanization factors were aggregated into regional mechanization factors. Subsequently, these regional mechanization factors were multiplied by regionally aggregated production data to get an estimate of the number of agricultural machinery in use within each region.

Section 2.1.1 provides a more detailed description of the FAO data on agricultural machinery and agricultural production used in the first research step. Section 2.1.2 explains the calculation of the country-level and regional mechanization factors, which were used in the calculation of the current number of agricultural machinery in use. In order to assess the size of the material stock embedded in the agricultural machinery, the material compositions and the average masses of the different kinds of machinery needed to be estimated as well. Section 2.1.3 discusses the data sources and assumptions behind the values used in this study. The research

[1] The same model variables were used in both research steps, and the available data was aggregated, when necessary, based on standardized categories. For instance, the quantification of the current global material stock followed the regional categorization of 26 world regions used in the IMAGE model (Appendix C). The crop categories used in IMAGE were also used in both research steps, and the FAO production data used in the first research step was aggregated based on these categories.

process and required data inputs for the global material stock quantification are visualized in Figure 2.1.

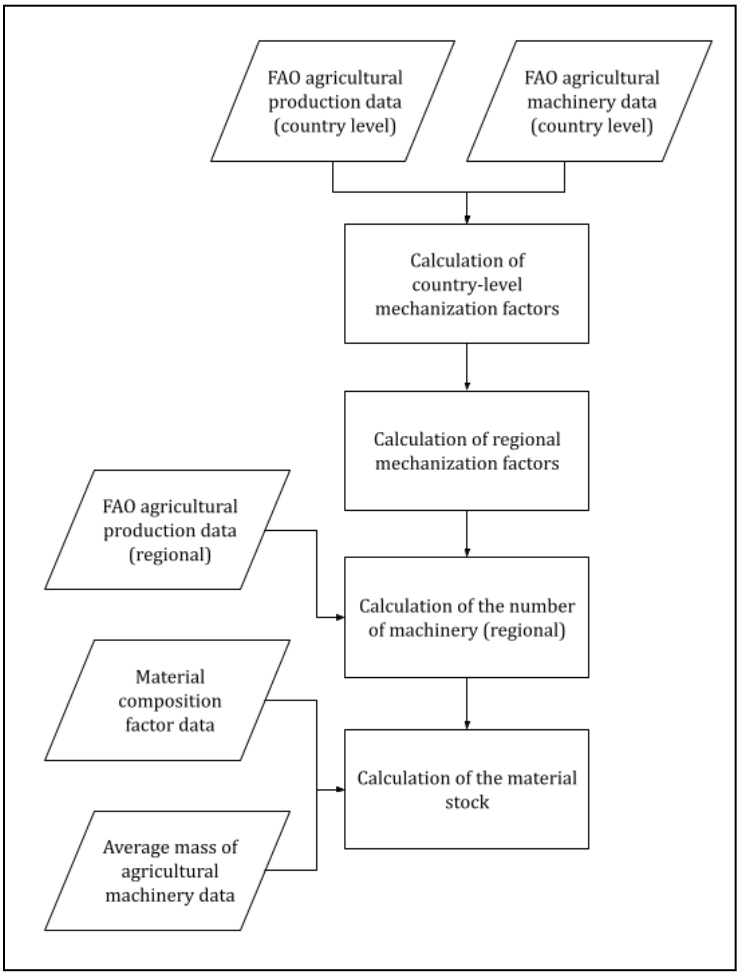


Figure 2.1: The research processes and data inputs of the material stock quantification step

2.1.1 Data on the Number Machinery and Agricultural Production Quantities

A dataset compiled by FAO (FAOSTAT, 2018) is currently the best available source of quantitative data on the number of different agricultural equipment in use in countries around the world. The dataset covers ten different types of agricultural machinery including tractors; combine harvester-threshers; manure spreaders and fertilizer distributors; ploughs; root and tuber harvesting machinery; seeders, planters and transplanters; straw and fodder balers; and milking machines.[2] The dataset contains country-specific annual data between the years 1961 and 2009

[2] Data on tractors is available for three subtypes, which include small one-axle pedestrian-controlled tractors, track-laying tractors, and 'regular' two-axle wheel tractors, which are called "other agricultural tractors" in the dataset. The dataset contains two higher-level categorizations of tractors; the category of "agricultural tractors, total" contains all three tractor subtypes, whereas the category "agricultural tractors" includes only two-axle wheel tractors and track-laying tractors, excluding the smaller pedestrian controlled tractors. This study divides tractors into two categories based on size, using a higher-level category of "agricultural tractors" available in the dataset, which includes both wheeled and track-laying two-axle tractors. Pedestrian controlled tractors were kept in their own separate category, as they are considerably smaller in size in comparison with the two-axle tractors, which is relevant for the calculation of material stocks.

on the imports and exports of agricultural machinery (both in terms of the monetary value and the number of traded machinery), as well as the number of machinery in use within each country. The trade data was disregarded as it did not fit the purposes of this study[3], but the available country-level data on the number of machinery in use was a valuable starting point for the inventorization of the current stock of in-use machinery.

The FAO dataset is highly variable when it comes to the completeness of data on the different types of agricultural machinery, in terms of both the countries and years covered. The data on tractors is rather comprehensive, as it covers the number of in-use machinery from 1961 until 2009 in over 200 countries. Data on the number of combine harvesters in use in each country is also available for the years between 1961 and 2009, whereas the data on other types of agricultural machinery only covers the years between 2000 and 2009. The dataset is described in more detail in a table in Appendix A. Figure 2.2 summarizes the data on the number of tractors available in the FAO dataset. The bars represent the number of countries for which tractor data is available per year, and the line (secondary vertical axis) represents the global sum of the available values of the number of tractors per year. As the graph shows, the number of countries with available tractor data decreases over time, which is the reason why the global sum value also plummets towards the end of the timeline. From the 1960s until the 1990s, where the number of countries covered remains relatively stable, the global sum of the number of tractors in use seems to be rising steadily. In reality, this trend might continue towards the more recent years as well, even though the available data for the 2000s is too scarce to confirm this. In order to get a better idea of the potential scale of the current global number of tractors, the most recent values available for each country were added together.[4] The result, around 30 million tractors, is also plotted on the chart in Figure 2.2 with a yellow data marker.

[3] Even though data on exports and imports can tell something about the flows of materials between different countries, it only covers a part of the agricultural machinery market, as the number of new manufactured machinery remaining in the production countries is not expressed by this data. If country-specific data (that was reasonably compatible with the FAO dataset) on the number of produced machinery was available, it could be combined with the trade data to calculate the net in-flows of new machinery per country. These flow results could then be combined with lifetime data in a dynamic stock model, which could estimate the accumulation of in-use stocks. Unfortunately, such annual data on the number of different agricultural machinery manufactured in each country seems to be rather scarce.

[4] In the calculation of the sum of the most recent available values for each country, some countries that have ceased to exist were excluded from the calculation. This was done in order to avoid double counting, when more recent data for countries that currently exist in these same territories were available.

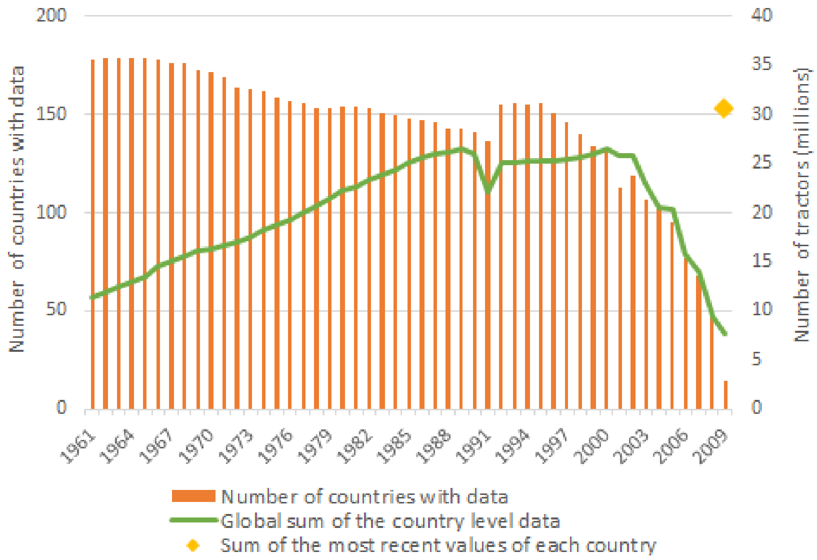


Figure 2.2: Summary of the available FAO data for tractors

This study focused on quantifying the stocks of agricultural tractors, combine harvesters, pedestrian-controlled tractors, and four types of tractor-drawn implements, including ploughs, root and tuber harvesting machinery, manure spreaders and fertilizer distributors, and seeders, planters and transplanters. It must be stressed that this selection of agricultural field machinery types, which is strongly influenced by data availability, does not cover all of the machinery used in the global agricultural system.[5] However, since the tractor is the "main technological paradigm in agriculture" (Cavallo, Ferrari & Coccia, 2015), and the most common and important type of agricultural machine around the world, it is a good starting point for the quantification of the material stock of agricultural machinery. Thanks to the good quality data available for tractors, the results for the current number of tractors in use are also likely to be more reliable than the results for some of the other types of machinery.

Due to the data gaps in the FAO dataset and the fact that it only contains data until the year 2009, the number of machinery that are currently in use were calculated by linking the machinery in-use stock data to data on annual production quantities. FAO has published very extensive datasets on the yearly production quantities of different agricultural products, for virtually all countries in the world, from the year 1961 onwards (FAOSTAT, 2021). This data was used for the calculation of the country-specific mechanization factors, which are explained in more detail in section 2.1.2. Furthermore, this FAO country-level production data was grouped

[5] The FAO dataset contains data on three additional machinery types: straw and fodder balers, milking machines and threshing machines. The reasons why these machinery types were excluded from the study vary. When it comes to threshers, the data is extremely scarce, and seems to contain multiple outliers. Furthermore, as the threshing machines have been steadily replaced by combine harvesters (De Lucia & Assennato, 1994), the underlying assumption of this study, which ties the number of machinery to the production quantities, might not fully apply to threshing machines. In the case of balers, they were excluded due to lack of country-level data on the production quantities of straw and hay. This makes it impossible to calculate the mechanization factors, which are the cornerstone of the methodology used in this study. As the main focus of the study was on agricultural field machinery used in crop production, milking machines (which, alone, would have given an incomplete picture of all specialized machinery used in animal husbandry) were excluded from the analysis.

and summed into regional production quantities, which were, in turn, used along with the regional mechanization factors for the calculation of the regional numbers of machinery in use.

The IMAGE model includes eight categories of food and feed crops, five categories of animal products, and three categories of biofuel crops; this grouping of agricultural products was also adopted in this study. The high level of detail in the FAO dataset, which reports the production quantities of different crops separately, is rather excessive for the purposes of this study. Using the IMAGE crop categorization simplified the calculations of the mechanization factors while preserving a slightly higher level of detail compared to using sum total production quantities of all crops. Furthermore, using the IMAGE categorization enabled the mechanization factors calculated in this first research step to be used as a starting point for the material stock scenario analysis.

The grouping of the FAO crop data according to the IMAGE categorization was performed manually based on a document provided by the contact person for the IMAGE model (J. Doelman, personal communication, September 28, 2020). It contains a list of crop types (as reported by FAO) that have been grouped into eight larger categories used in IMAGE, which include temperate cereals, tropical cereals, maize, rice, roots and tubers, pulses, oil crops, and other crops. A copy of this list can be found in Appendix B. The production quantities of all crops in each IMAGE crop group were summed for each year, for each of the countries.

2.1.2 Calculation of Mechanization Factors and the Number of Machinery

In order to estimate the total number of agricultural machinery in use based on the limited FAO machinery data, the data was linked to agricultural production data by calculating *mechanization factors*, which describe the number of machinery in use per agricultural production quantity. This approach was chosen, as the IMAGE data, which is used for the material stock scenario analysis in the second research stage, presents the agricultural sector mainly in terms of production quantities. Furthermore, the available FAO data on agricultural production likely gives the most comprehensive picture of the overall magnitude of global agriculture, which is useful when estimating the number of agricultural machinery on a global scale.

The term 'mechanization factor' is used in this report to refer to the relationship between the in-use machinery stock as an input and the products as an output of agricultural production. In other words, it describes the amount of machinery used for the production of a specific amount of agricultural products each year. The value of the mechanization factor also describes the level of mechanization in a particular country or region. The equation for the calculation of mechanization factors used in this study is simple:

$$mechanization\ factor = \frac{number\ of\ machinery\ in\ use}{mass\ of\ agricultural\ products\ produced\ annually}$$

The data on the number of machinery in use in a particular country, in a particular year, was divided by the corresponding data on the quantity of agricultural products produced in the same country, in the same year. The unit of the mechanization factors used throughout this study is *the number* (of machinery)*/kilotonne* (of agricultural products).

In order to preserve and utilize the level of detail both in the FAO data and the IMAGE scenario data to some extent, the machinery types were allocated to different agricultural product categories for the calculation of the mechanization factors. This means that the mechanization factors were calculated by dividing the number of machinery in each machinery category by the sum total mass of all agricultural products that are produced using said machinery. Agricultural tractors; pedestrian controlled tractors; manure spreaders and fertilizer distributors; ploughs; and seeders, planters, and transplanters are relatively 'general-purpose' machinery in crop production, and they were assumed to be used in the production of all crop types. Root and tuber harvesting machines were, for rather obvious reasons, only allocated to the crop category of "roots and tubers". Finally, the crop types that are generally harvested using combine harvesters were determined based on information from the book by Miu (2016). Table 2.1 illustrates the relationships between different machinery types and agricultural product categories assumed in this study.

Table 2.1: Allocation of the machinery types to IMAGE crop categories

Machinery/crop type	Temperate cereals	Tropical cereals	Roots and tubers	Pulses	Oil crops	Maize	Rice	Other crops
Agricultural tractors	X	X	X	X	X	X	X	X
Combine harvesters [a]	X	X			X	X	X	
Manure spreaders and fertiliser distributors	X	X	X	X	X	X	X	X
Pedestrian controlled tractors	X	X	X	X	X	X	X	X
Ploughs	X	X	X	X	X	X	X	X
Root and tuber harvesting machines			X					
Seeders, planters and transplanters	X	X	X	X	X	X	X	X

Sources: [a] Miu (2016)

Even though the usage patterns of different kinds of machinery are likely to vary between different agricultural products and regions in reality, this study makes three simplifying assumptions in the allocation of machinery to products. The first assumption is that if a type of machinery is used for the cultivation of a particular crop anywhere in the world, this is (at least potentially) the case everywhere else in the world as well. In reality, the usage patterns of different types of machinery in the cultivation of different crops might vary around the world, but such regional variations are not accounted for per crop type. The second assumption is that when a particular type of machinery is (or can be) used in the production of different kinds of crops, this machinery is used equally intensively for the production of all crop types it has been allocated to. The mechanization factors for each machinery type are calculated based on the sum of the produced mass of all applicable crop types, and no weighing is made based on variations in cultivation methods or mechanization intensities in the production of different crop types. These two assumptions can be noticed in the format of Table 2.3; it does not contain a geographical third dimension, and the machinery types are allocated to different crop types without any weighing. The third (and likely the most radical) assumption is that agricultural tractors are only used in the production of crops, although in reality, they are also used in animal husbandry as well as grass and hay production. This assumption was made for two main reasons. The first one is the lack of country-level data on grass and hay production quantities, which makes the inclusion of grass and hay production in the calculation of country-level mechanization factors impossible. The second reason is the difficulty to compare the production quantities of animal husbandry and crop cultivation.[6] These assumptions and their potential impacts on the results of the study are discussed in more detail in Chapter 4.

The country-level mechanization factors of each machinery type were calculated by first dividing all of the available values on the number of a particular type of machinery in use in a specific country in a specific year by the corresponding production data (in the same country in the same year). These production values were the sum of the production quantities of all crops to which the particular machinery type had been allocated. The yearly mechanization factors between 2000 and 2009 were averaged per country to form general mechanization factors of the 2000s. The large gaps in the FAO machinery data were mitigated by using the countries with available machinery data as a proxy for countries with similar production patterns and levels of agricultural mechanization. This study adopted the IMAGE categorization of 26 world regions, and the available country-level mechanization factors were aggregated into regional values based on this categorization.[7] It is important to note that this choice entails an assumption of a relative uniformity of agricultural practices and mechanization levels within each IMAGE region, which might not reflect the reality entirely.

The approach for the calculation of regional mechanization factors from the country-level values varied somewhat between the different machinery types. For most machinery types, the regional mechanization factors were determined by grouping the country-level values based on the IMAGE regional categorization, and calculating simple averages of the available mechanization factors for each region. This approach makes it easy for data anomalies or outliers to affect the results unproportionately. That is why the country-level mechanization factors that were clearly inconsistent with the values of other countries within the same region were excluded from the calculation of regional mechanization factors. When it comes to tractors, it was possible to calculate regional average mechanization factors that were weighted based on the relative production quantities of the countries within each IMAGE region. The weights for each country were calculated based on the average annual production quantities of the 2000s in relation to the total average production quantities of their respective IMAGE regions.[8]

If no country-level mechanization factor values were available for a particular IMAGE region due to gaps in the FAO machinery data, a broader categorization of five world regions was used instead. The IMAGE regions with no data were assigned the average value of a corresponding larger region. Appendix D contains a table where the IMAGE regions have been divided into these five larger regions; this categorization is largely based on the article by

[6] As mentioned earlier, the current material stock quantification step has been designed keeping its compatibility with the IMAGE model in mind; the FAO production data used for the calculation of the mechanization factors corresponds with the IMAGE production indicators. FAO data on animal husbandry that most reliably matches the IMAGE data concerns the number of live animals. As the background information on the animal husbandry indicators on IMAGE is limited, the number of live animals leaves the least amount of room for interpretation. However, comparing the number of live animals to the mass of crops produced is very difficult, if not impossible. Therefore, combining such data for the calculation of the mechanization factors was considered infeasible for this study.

[7] A table in Appendix C illustrates the categorization of countries in 26 IMAGE regions.

[8] In order to calculate the regional mechanization factors by applying weights for each country (based on their annual production quantities as fractions of the total production within their region), the number of countries included in the calculation needed to be maximized. Therefore, missing data for the mechanization factors of the 2000s was substituted by the average mechanization factor values from the most recent decades with available machinery data for the countries in question.

Doelman et al. (2018), where IMAGE regions have been divided into six world regions based on similarities in their land use dynamics and economics.[9] Table in Appendix A indicates whether the mechanization factors of different machinery types have been determined for each region based on the mechanization factors of countries within said IMAGE regions, or if they are based on the values of the larger regions.

After the calculation of the regional mechanization factors, the country-level FAO production data for the year 2018 (the sum of the production mass of relevant crop groups for each machinery type) were summed for each IMAGE region to form regional production values. The number of machinery in use in each IMAGE region was then calculated by multiplying the regional mechanization factors with regionalized production data. The equation for the calculation of number of machinery per region is the following:

$$number\ of\ machinery\ in\ use\ in\ a\ region\ =\ regional\ mechanization\ factor\ \times\ regional\ annual\ productio$$

2.1.3 Data on Material Composition and Average Mass

When the number of machinery in use is available, the material stock embedded in agricultural machinery can be calculated when the material composition factors and average masses of the machinery have been determined. This is rather challenging, however, because the literature does not provide any information regarding the characteristics of 'the global average tractor', or indeed the global average of any type of agricultural machinery. The material composition and average mass of this rather mythical 'global average farm machine' are quite impossible to determine with any certainty.

When it comes to the material composition of agricultural field machinery, a recent study by Mantoam et al. (2020) is the best source of information currently available. Their article provides detailed data on the material contents of four different tractors, a combine harvester, two sugarcane harvesters, a coffee harvester, a self-propelled sprayer, and a planter. This material composition data includes more than twenty different materials, expressed in kilograms of each material per machine. For the purposes of this study, the masses of the different materials in each machinery type were divided by the total masses of the machinery in order to obtain the material composition factors. The materials reported by Mantoam et al. were grouped into ten categories, including ductile iron, steel, aluminium, copper, lead, rubber, plastics, lubricants and fluids, plate glass, and other materials. The categorization of all of the individual materials and their material composition factors calculated based on the data by Mantoam et al. (2020) can be found in Appendix E. The tractor material composition factors used in this study are based on the average material compositions of the four tractors reported in the article. The same values were used for the pedestrian controlled one-axle tractors, which are assumed to differ from their larger two-axle counterparts only in terms of size. The material compositions of the combine harvester and the planter were taken at face value based on the information provided in the article. The planter, which is a tractor-drawn implement, was used as proxy for the other agricultural implements addressed in this study; the material compositions of ploughs, fertilizer distributors, and root and tuber harvesting machinery were determined based on the material composition of the planter.

[9] Doelman et al. (2018) article defines China as its own region, but in the five-region categorization used in this study China is included in the region South and East Asia. The five-region categorization is only used when no values are available for a particular IMAGE region. As the region of China is the same in both the IMAGE categorization and the broader regional categorization, including it in the broader categorization as its own region would be redundant.

The global average values for the mass of agricultural machinery might be even harder to determine. Agricultural machinery can vary in size enormously, and the average sizes of different machinery types are likely to differ between world regions to some extent. However, no data supporting the use of a regional differentiation regarding the average masses of machinery in the analysis could be found in the literature. Therefore, the average masses of the different machinery types were assumed to remain constant across all IMAGE regions. The assumptions on the average mass of different agricultural machinery have been mainly made based on the values found in a background report for ecoinvent 3.0 (Nemecek and Kägi, 2007). When the mass was reported for two or more variations of the same machinery type, the values were averaged. The value for pedestrian controlled tractors was found in an article by Velazquez-Miranda et al. (2018). The values used for the material composition factors and average masses are reported in Chapter 3.

The masses of the global stocks of different materials embedded in agricultural machinery were then calculated separately for each of the machinery types by simply multiplying the results on the number of in-use machinery by the material composition factors and assumed average masses of the machinery. The equation used for the calculation of the mass of the global stock of a particular material embedded in a specific machinery type is the following:

$$mass\ of\ material\ stock\ =\ number\ of\ machinery\ \times\ material\ composition\ factor\ \times\ average\ mass\ of\ mach$$

2.2 Material Stock Scenario Analysis

In order to gain some insight on the ways the material stock of agricultural machinery might develop in the future, a scenario analysis was conducted by integrating the results of the first research step with scenario data from an integrated assessment model IMAGE 3.0. IMAGE can be used to assess the interactions between the human socioeconomic system and the biophysical earth system on a large scale over time (Stehfest et al. 2014). The IMAGE framework consists of multiple submodels addressing different components of these two main systems, such as climate (MAGICC), land-use (IMAGE-LandManagement), the energy-system (TIMER), agricultural economy (MAGNET), and natural vegetation and hydrological cycles (LPJmL). The scenario data used in this study are the results of the implementation of different sets of scenario driver values based on the framework of Shared Socioeconomic Pathways (SSPs) in the IMAGE model (Van Vuuren et al. 2017). The SSPs, which have been created through extensive collaborative efforts to facilitate climate research, are a set of storylines that contain assumptions of alternative socioeconomic developments in the future (Riahi et al. 2017). The SSPs are based on five “qualitative descriptions of future changes in demographics, human development, economy and lifestyle, policies and institutions, technology, and environment and natural resources” (O’Neill et al., 2017, pp. 169), which have then been “translated into quantitative projections for main socioeconomic drivers” (Riahi et al. 2017, pp. 154). The five SSP scenario narratives are described in broad terms in table 2.2; a more elaborated outline of the assumptions in each scenario can be found in Appendix F.

The following sections provide a more detailed explanation on the ways in which IMAGE model data was used for the calculation of the in-use number and material stock of agricultural machinery in different SSP scenarios from 2000 until 2100. The base model, which is presented in section 2.2.1 largely resembles the structure of the current stock quantification step and keeps the regional mechanization factors constant over time. An alternative model, which attempts to account for the changes in mechanization levels over time is described in section 2.2.2.

Table 2.2: General descriptions of the five Shared Socioeconomic Pathways

Shared Socioeconomic Pathway	General description based on O'Neill et al. (2017)
SSP1: Sustainability *Taking the green road*	Commitment to sustainable development, equity, green growth and less resource-intensive economy.
SSP2: Middle of the road	Business as usual, development consistent with historical patterns.
SSP3: Regional rivalry *A rocky road*	International fragmentation, regional conflict and protectionism, weakened international cooperation towards sustainable development.
SSP4: Inequality *A road divided*	Inequalities within and across countries, weak and unequal investments to education, strengthened elites, declining social cohesion.
SSP5: Fossil-fueled development *Taking the highway*	Rapid economic growth and technological development, globalization, strong institutions, reliance on fossil fuels, resource- and energy-intensive lifestyles.

2.2.1 Base Model

The calculation steps of the 'base model' of the scenario analysis are largely similar to the ones used in the quantification of the current material stock; the only difference is the source of the production data. In order to calculate the number of agricultural machinery in use over time in different SSP scenarios, the regionalised FAO production data was replaced by IMAGE scenario data on crop production quantities from 2000 until 2100. This annual crop production data (appropriately allocated to each machinery type) was multiplied by the regional mechanization factors to calculate the number of different types of machinery in use each year. In the base model, the values of the mechanization factors calculated in the current stock quantification step were kept constant at their average levels of the 2000s. The annual masses of the material stocks were then calculated using the scenario results on the number of machinery in combination with the material composition factor and weight data that was also used in the quantification of the current material stock. In the base model, the changes in the sizes of material stocks are therefore only driven by changes in the production quantities of crops, as all other variables are kept constant. Figure 2.3, which is nearly identical to the figure describing the current stock quantification process, illustrates the structure of the base scenario model.

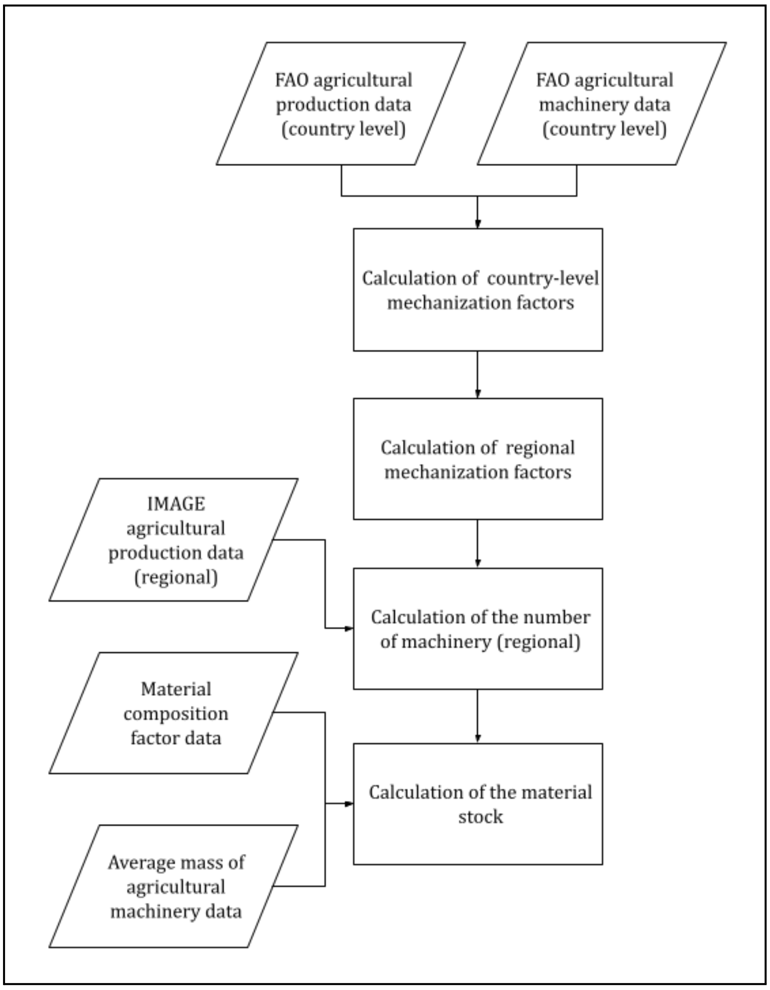


Figure 2.3: Structure of the base scenario model

There were a couple of issues that needed to be addressed in order to harmonize the data from IMAGE with the methodology and the results of the first research step. The first one was related to biofuels, as the IMAGE biofuel crop categories of maize, sugarcane and "non-woody biofuels" are assumed to be agricultural products. For the calculation of the mechanization factors in the first research phase, the FAO production data was categorized according to the IMAGE food and feed crop categories only, as it was not possible to split the production data of crops such as maize based on their end use (food and feed, or biofuel). The mechanization factors of most of the machinery types were calculated using the sum of all crops produced, which is likely to include the production quantities of crops cultivated for biofuel production as well. Therefore, in the scenario analysis, the numbers of the all-purpose machinery types (such as tractors) were calculated by multiplying the regional mechanization factors with the sum of all produced food and feed crops as well as biofuel crops.

There is one exception, however. As pedestrian controlled tractors are likely not used in the large-scale production of biofuel crops, the biofuel crop data from IMAGE was not assigned to them. The mechanization factors of pedestrian controlled tractors were calculated using FAO production data that likely includes some biofuel crop production. However, the biofuel crops potentially 'embedded' in the mechanization factors of pedestrian controlled tractors are unlikely to affect the results of the scenario analysis significantly, if at all, because the share of biofuel crops of the total agricultural production is currently very small. Many of the SSP scenarios assume a considerable increase in the biofuel crop production over time. Therefore, assigning biofuel crops to pedestrian controlled tractors, when, in fact, they are likely not used in their production at all, would probably have affected the results even more.

When it comes to the two machinery types that were allocated to only a part of the crop categories in the calculation of the mechanization factors, the combine harvesters are assumed to be used in the production of biofuel crops, whereas the roots and tubers machinery are not. Table 2.3 is an extension of the allocation table 2.1, illustrating the allocation of biofuel crops to different machinery types.

Table 2.3: Allocation of the machinery types to crop categories in the scenario analysis

Machinery/crop type	Food and feed crops	Biofuel crops
Agricultural tractors	Same allocations as in the first research step (Figure 2.1)	X
Combine harvesters		X
Manure spreaders and fertiliser distributors		X
Pedestrian controlled tractors		
Ploughs		X
Root and tuber harvesting machines		
Seeders, planters and transplanters		X

The second harmonization issue between IMAGE and FAO data is related to the crop category 'other crops', as the IMAGE scenario results for the production quantities of the crops in this category are only available in dry weight. This is problematic, as the mechanization factors were calculated using the production data from FAO (including 'other crops'), which were expressed in fresh weight. In order to include 'other crops' in the calculation of the number of agricultural machines in different scenarios, the IMAGE production data had to be converted from dry weight to fresh weight. The conversion factor was estimated by calculating the ratios of the yearly fresh weight production quantities (based on FAO data), and the dry weight production quantities (based on the IMAGE data for SSP2) of the 'other crops' in all IMAGE regions between 2000 and 2018.[10] As these ratios of fresh weight per dry weight of the produced 'other crops' were found to fall most frequently between 4,5 and 5,5, a conversion factor of 5 was assumed for all IMAGE regions. The IMAGE dry weight production data of 'other crops' was then converted to fresh weight by multiplying all values by the conversion factor. The total production quantities of all food and feed crops were therefore calculated by adding the converted data of 'other crops' to the (fresh weight) data of all other food and feed crop types.

The IMAGE results for the five SSPs regarding the global production quantities of food and feed crops (excluding 'other crops'), 'other crops' (in dry weight), and biofuel crops (maize, sugarcane and 'non-woody biofuels') are shown in Figure 2.4. The figure also contains a graph with the totals of all crops produced in different SSP scenarios, where the production of all food and feed crops (including 'other crops' converted to fresh weight) and biofuel crops have been added together.

[10] A figure showing the distribution of the ratios of fresh weight and dry weight of other crops produced in 26 IMAGE regions between 2000 and 2018 can be found in Appendix G.

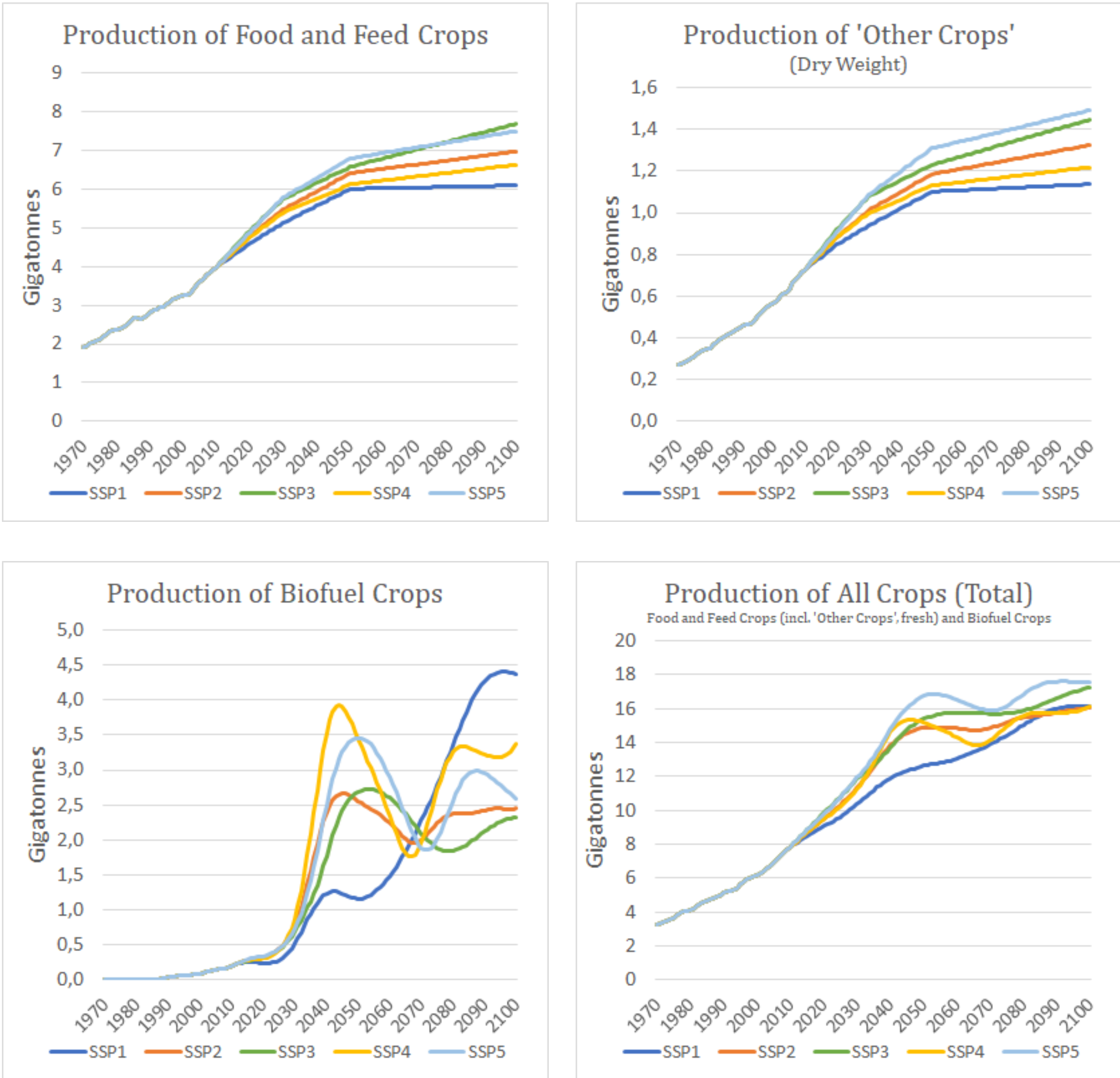


Figure 2.4: IMAGE data on crop production in five SSP scenarios

2.2.2 Dynamic Mechanization Model

In reality, the mechanization levels of different countries and regions are very unlikely to remain constant for decades to come. That is why a scenario model, in which the regional mechanization factors develop over time, was designed to complement the base model.[11] The IMAGE model was searched for variables possibly connected to agricultural mechanization levels, so that the changes in the mechanization factors could be modeled based on their relationship to these variables. As shown by Li et al. (2018), mechanization levels of particular countries and regions are influenced by various demographic, socio-economic, technological, biophysical, and policy-related factors. Therefore, finding a useful set of explanatory variables in the IMAGE results for a model that would accurately predict the development of mechanization

[11] A trend analysis of the historical mechanization factors of tractors is reported in Appendix M. No historical trends, which could be assumed to continue in the future, were found.

levels within different regions was considered a task too complex to be undertaken in the context of this study.

A potential response variable, which is possibly affected by (or, at least, correlated with) changes in agricultural mechanization levels, was considered instead. The IMAGE variable 'harvested yield' describes the mass of produced crops per area of agricultural land. According to the IMAGE 3.0 model description (Stehfest et al., 2014), the regional yield values are affected by both technological and biophysical circumstances of each region. In this study, the changes in harvested yield scenario data were used to model the changes in the mechanization factors. This approach entails an assumption that all of the developments in the harvested yield values are driven by changes in the mechanization levels. The limitations of this (rather bold) assumption are discussed in Chapter 3. The harvested yield data of different SSP scenarios was normalized by dividing the harvested yield values of each IMAGE region (from 2000 until 2100) with the regional average values of the harvested yield in the 2000s. These normalized harvested yield values were then multiplied by the 2000s regional mechanization factors of each machinery type, in order to obtain their yearly mechanization factor values from 2000 until 2100 for all five SSP scenarios. This way, the regional mechanization factors would change at the same rate as the harvested yield values of each region in different scenarios.

The dynamic mechanization factors were then multiplied by the IMAGE scenario data on production quantities in order to, again, estimate the development of the number of in-use machinery in different regions over time. Finally, the annual sizes of the different material stocks embedded in agricultural machinery were calculated by multiplying the number of machinery by the material composition factors and the average machinery masses, which were, again, kept constant. The calculation steps for the scenario model including dynamic mechanization factors are illustrated in Figure 2.5.

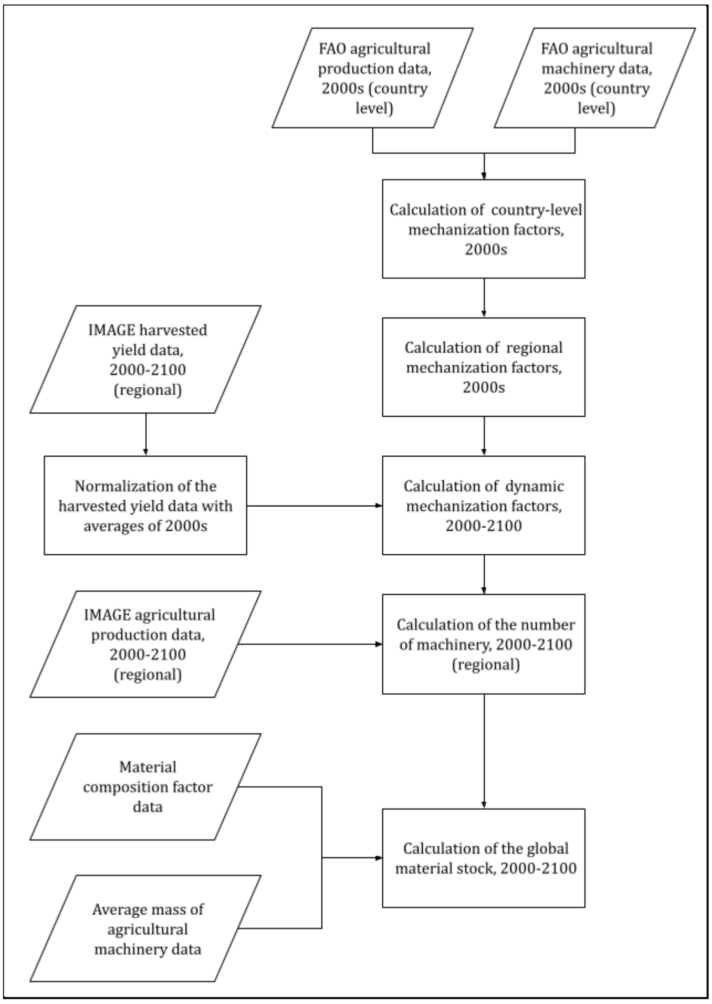


Figure 2.5: Structure of the dynamic mechanization scenario model

3 Results

This chapter presents the results of the quantification of the current material stock of agricultural field machinery, as well as the results of the scenario analysis, which modeled the development of the material stock in different SSP scenarios. In this chapter, the results concerning tractors—the true workhorses of agricultural production today—are highlighted in particular. The other machinery types are included in the results regarding the total material stocks embedded in agricultural field machinery. More detailed results for each of the individual machinery types can be found in the Appendices.

3.1 Current In-Use Stock Quantification Results

The first objective of this study was the quantification of the global material stock embedded in agricultural field machinery currently in use. The following sections present the results for the regional mechanization factors, as well as the material composition factors and assumed global average masses of the different machinery types, which were used for the estimation of the material stock of agricultural field machinery. After this, the estimated numbers of different types of agricultural machinery currently in use in the 26 IMAGE regions, as well as the approximate size and composition of the global material stock currently embedded in agricultural field machinery are presented. These results are then compared to global estimates of total stocks of specific materials and material stocks of specific sectors found in the literature.

3.1.1 Mechanization Factors

The regional mechanization factors are intermediate results that were used in the calculation of the number of in-use machinery in the current stock quantification step as well as the scenario analysis. They represent the number of machinery in use per annual agricultural product output, as well as the general level of mechanization within different world regions. Mechanization factors of tractors calculated based on FAO machinery and production data are shown in Figure 3.1, and the mechanization factors results of other machinery types can be found in Appendix H. Most of the regions with the highest mechanization factors are some of the wealthiest and most industrialized regions in the world. This is unsurprising, as the level of farm mechanization in different countries and regions is often positively correlated with different economic indicators (Böttinger et al. 2013).

The results regarding the mechanization factors of tractors do not necessarily reveal the whole picture of the true mechanization levels of different regions. For instance, the surprisingly low mechanization factor value of tractors in China could be explained by the high number of pedestrian controlled tractors, which are often used for similar field operations. Indeed, the perceived mechanization levels of different countries can vary significantly based on the selection of machinery used for the evaluation of mechanization levels. According to Justice and Biggs (2020), this notion is particularly accurate in the case of South Asia, where the relatively low number of larger tractors often leads to an assumption of a generally low level of mechanization in the region. However, this assumption is hardly accurate, as the spread of small-scale machinery has significantly increased agricultural productivity in South Asia.

While mechanization significantly increases agricultural productivity in general, the efficiency of machinery usage can vary, even among regions with the highest mechanization levels. The mechanization factor of tractors in Japan is significantly higher than the values of other regions, which might actually be a sign of inefficiencies, as more machinery is used per unit of crops produced. The agricultural sector of Japan is indeed highly mechanized, and the apparent inefficiency of machinery usage could be explained by the average farm sizes, which have remained small over time, and the prevalence of agricultural land fragmentation (Otsuka et al. 2016; Kawasaki, 2010). The mechanization level of the USA represents the other side of the coin; the lower value of the mechanization factor is likely due to the larger average size of farms, which can be managed efficiently using a smaller number of (larger) tractors (Key, 2019).

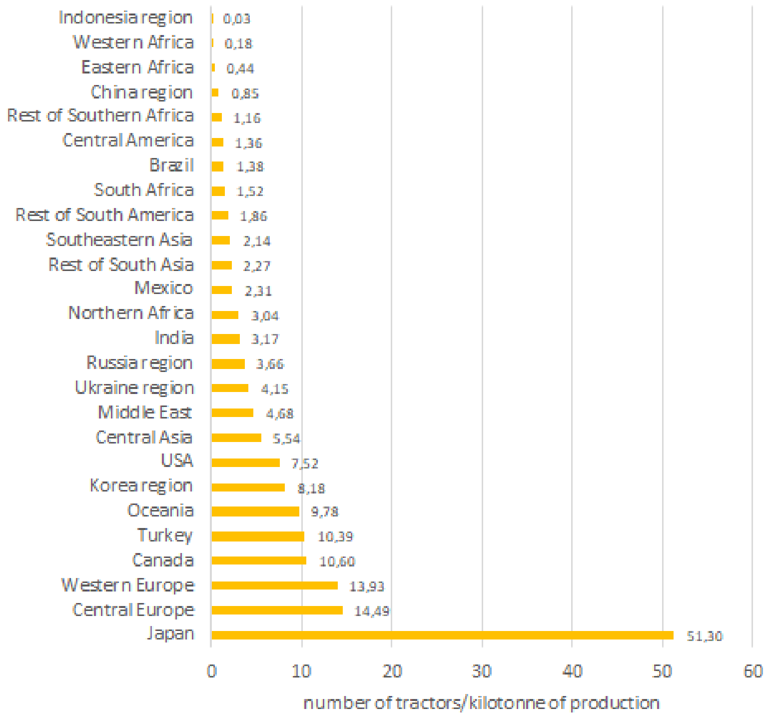


Figure 3.1: Regional mechanization factors of tractors in the 2000s

3.1.2 Current Number of Agricultural Field Machinery in Use

The estimated numbers of tractors in use within different 26 IMAGE regions are illustrated in Figure 3.2. Similar graphs containing the regional results for the number of other types of machinery in use can be found in Appendix I. The global total number of tractors is estimated to be around 33 million. This result is remarkably similar to the number of tractors presented in section 2.1.1 (around 30 million), which was calculated by summing the most recent values available for each country in the FAO dataset. The value for 2018 is predictably slightly higher, as the production quantities have grown over time, but it seems to fit the trend suggested by the initial exploration of the FAO dataset. Overall, the results for the number of in-use tractors can be considered relatively reliable, as their mechanization factors were calculated based on a large amount of data, which covers most of the countries in the world. The production-based weighting of the country-level data also minimized the influence of (usually very small) countries with atypical production patterns on the calculation of the regional mechanization factors.

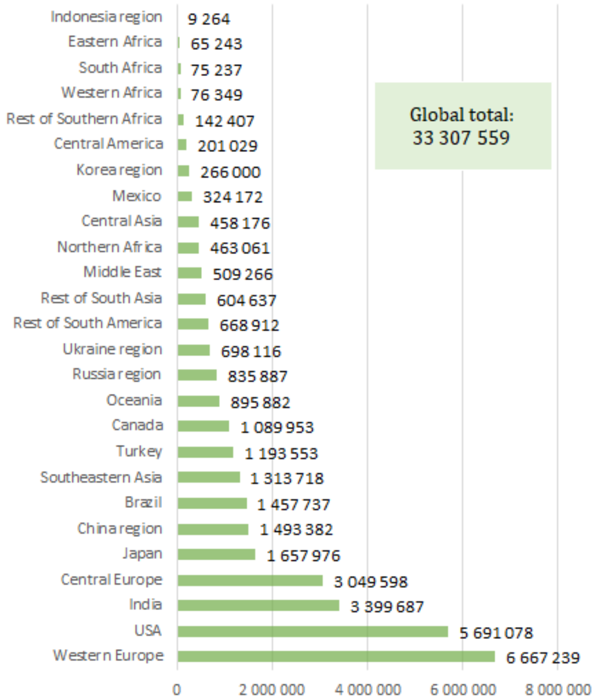


Figure 3.2: Estimated numbers of tractors currently in use per IMAGE region

The results for the estimated in-use numbers of all of the studied machinery types are presented in Figure 3.3. The total number of combine harvesters in use around the world was estimated to be around 9 million. This number of combine harvesters was, as expected, lower than the number of tractors. Despite being widely used for the harvesting of various crop types, combine harvesters are a more specialized type of field machinery in comparison to tractors, which are the ultimate generalists of agriculture. Due to good availability of data on the number of combine harvesters, these results can also be considered relatively reliable, although no weighting was used for the calculation of the regional average mechanization factors of combines.

The results for the other machinery types must be approached with more caution, as they are based on significantly smaller amounts of data. The number of root and tuber harvesting machinery (around 1 million) is significantly lower than the numbers of other machinery types. This was expected, as they are a highly specialized category of agricultural machinery, only linked to the production of roots and tubers. The estimated number of pedestrian controlled tractors is rather high, nearly 50 million, which could be due to the vast number of such small tractors being used in China and Southeast Asian countries. Similarly, the numbers of some of the tractor-drawn implements, especially ploughs (around 52 million) and manure spreaders and fertilizer distributors (around 38 million), as well as seeders, planters and transplanters (26 million) are rather high. If these implements are assumed to be drawn only by larger tractors, these results can seem rather suspicious, as the number of implements is unlikely to exceed the number of their power sources. However, pedestrian controlled tractors are also commonly used for pulling different implements, which makes the high numbers of implements seem more feasible. The implements pulled by pedestrian controlled tractors are likely significantly smaller than the ones pulled by larger tractors. This might become an issue when it comes to the results on the material stocks of implements, which were calculated using assumed average masses that are likely too heavy to be pulled by pedestrian controlled tractors.

When interpreting these numbers, it must be remembered that they were calculated using the average mechanization factors of the 2000s, which can be slightly outdated in relation to the production data of 2018 used for the calculation of the current number of in-use machinery. The real mechanization factors of 2018 might differ from the 2000s values used throughout this study to some extent. Nevertheless, these results (especially in the case of tractors and combine harvesters) can, at the very least, give some kind of an idea of the magnitude of the true number of machinery currently in use.

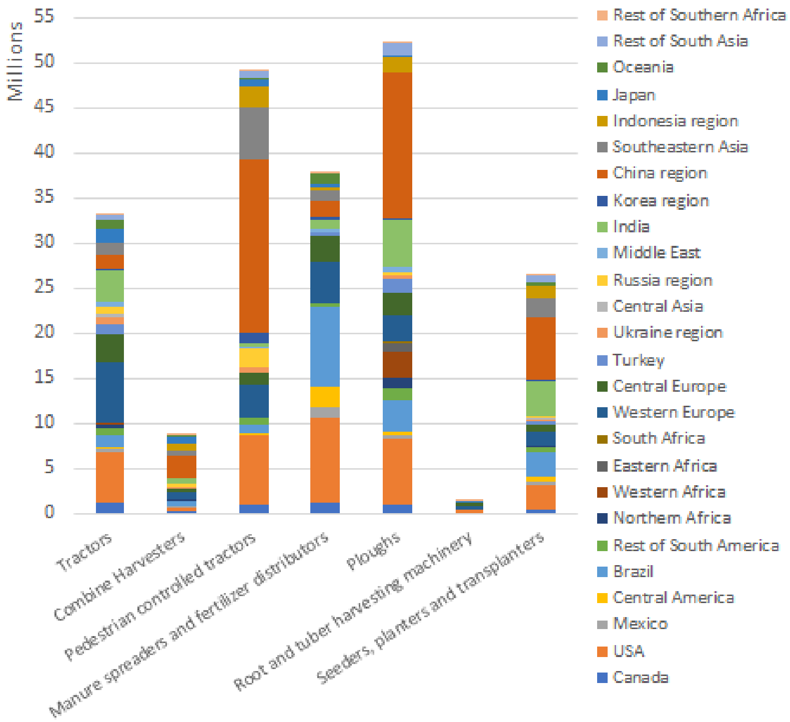


Figure 3.3: Estimated numbers of all machinery types currently in use per IMAGE region

3.1.3 Material Compositions and Average Masses of Field Machinery

The material composition factors calculated based on data found in an article by Mantoam et al. (2020) are reported in Table 3.1. The most important materials in the studied field machinery are iron and steel, which together make up more than 80 percent of the weight of all machinery types, as well as rubber, which accounts for around 5 to 10 percent of the total weight, depending on the type of machinery. These material composition factors of tractors, combine harvesters, and tractor-drawn implements were assumed for all IMAGE regions for the calculation of the material stocks embedded within different machinery types.

The average machinery masses assumed in this study are presented in Table 3.2, and they were based on data found in the literature (Nemecek & Kägi, 2007; Velazquez-Miranda et al., 2018). As no data could be found on regional variations in the average machinery sizes, these masses were also assumed for all IMAGE regions in the calculation of the mass of the material stocks.

Table 3.1: Material composition factors of agricultural field machinery
Calculated based on data in Mantoam et al. (2020)

Material	Tractors	Combine harvesters	Tractor-drawn implements
Ductile iron	54 %	18 %	22 %
Steel	29 %	65 %	66 %
Aluminium	0,83 %	2,0 %	1,0 %
Copper	0,20 %	0,31 %	0,01 %
Lead	0,24 %	0,21 %	-
Rubber	10,7 %	8,3 %	4,7 %
Plastics	2,0 %	3,2 %	5,5 %
Fluids and lubricants	2,2 %	1,8 %	0,31 %
Plate glass	0,28 %	0,08 %	-
Other materials	0,49 %	0,25 %	0,20 %

Table 3.2: Assumed global average masses of different agricultural machinery types

Machinery type	Assumed mass (kg)
Agricultural tractors [a]	3000
Combine harvesters [a]	8250
Manure spreaders and fertiliser distributors [a]	200
Pedestrian controlled tractors [b]	160
Ploughs [a]	775
Root or tuber harvesting machines [a]	3200
Seeders, planters and transplanters [a]	500

Sources: [a] Nemecek & Kägi (2007), [b] Velazquez-Miranda et al. (2018)

3.1.4 Current Material Stock of Agricultural Field Machinery

The size of the current material stock was calculated based on the results on the number of in-use machinery, and the material composition factors and assumed global average masses of the different machinery types presented above. The results concerning the sizes of the material stocks are presented as global sums, instead of regional values. The results regarding the number of machinery show the relative distribution of machinery between different regions already, making the reporting of the regional material stock results slightly redundant.

Furthermore, the material composition factors and the average mass of machinery, in particular, are likely to vary between regions in reality. As the values used for the calculation of the material stocks were assumed to be global averages, only reporting the global results seems warranted.

The results of the quantification of the current material stocks of agricultural machinery are presented in Figure 3.4. The most significant material stocks embedded in the studied agricultural machinery include steel (121 Mt), ductile iron (86 Mt), and rubber (21 Mt); and agricultural tractors and combine harvesters dominate as the machinery types with the largest embedded material stocks.

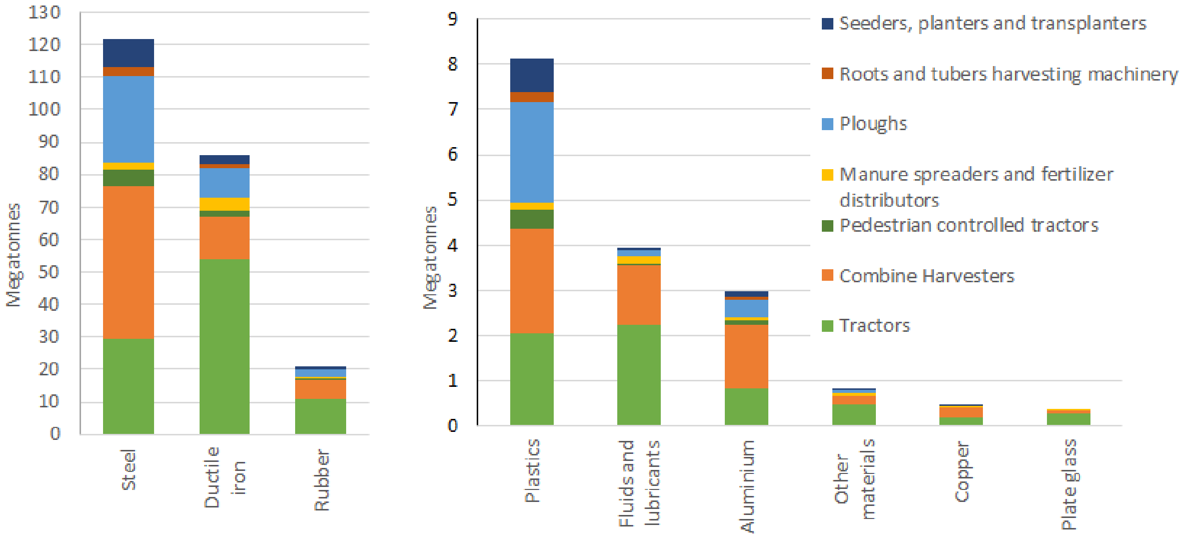


Figure 3.4: Global material stocks embedded in agricultural field machinery (Mt)

3.1.5 Comparison of Agricultural Machinery Stocks to Other Stocks of Materials

In order to put the material stock results in proportion, they were compared to other material stocks that have already been quantified and reported in the scientific literature. The comparison of the material stock of agricultural machinery to literature estimates of the total global stocks of specific materials can be found in table 3.3. As illustrated by the table, the 2018 in-use tractors, and the total of all machinery types contain very small fractions of the global total in-use stocks of specific materials. In most cases, the estimated stock of a particular material in agricultural machinery is less than one percent of the total stocks of these materials. However, as the studied machinery types represent only a part of all machinery used in global agriculture today, the agricultural sector is likely to embed a larger proportion of the total in-use stocks of materials than suggested here.

Table 3.3: Material stock of agricultural machinery in comparison with total global stocks of specific materials as reported in literature

Study	This study			Wieden-hofer et al. (2019)	IRP (2010)	Raunch (2009)	Geyer et. al (2017)	Mao & Graedel (2009)	Hatayama et al. (2010)	Liu et al. (2013)	Glöser et al. (2013)
Ref. year	2018			2014	2005	2000	2015	2000	2005	2009	2010
Stock	Tractors (Mt)	All machinery types (Mt and % of total)		Total global stock in all applications (Mt)							
Steel	29	122	1,0 %						12 700		
Iron	54	86	0,6 %		14 300	14 800					
Steel & Iron	83	208	0,9 %	24 245							
Aluminium	0.8	3.0	0,4-0,6 %	825	520	504				636	
Copper	0.2	0.4	0,1-0,2 %	401	227-358	311					350
Plastics	2.0	8.1	0,3 %	3 200			2 500				
Glass	0.3	0.4	0,03 %	1 449							
Lead	0.2	0.4	0,8-1,6 %		53			25			

The estimated material stocks of the studied field machinery were also compared to the global stocks of other sectors and applications, and this comparison can be found in table 3.4. The material stock estimate of residential and service sector buildings (Deetman et al. 2020) is, unsurprisingly, pronouncedly larger than the stock of agricultural machinery. The machinery stock is also significantly smaller than the stocks of materials estimated for the electricity infrastructure (Deetman et al. 2021). However, the comparison of the agricultural field machinery stock to the global stock of passenger vehicles estimated by Moradesi et al. (2014) is rather interesting. While the material stock of passenger cars is still clearly larger than the stock of agricultural machinery, the differences are less pronounced. The steel stock of the studied agricultural field machinery appears to be around 20 % of the size of the steel stock in cars, whereas the sizes of the iron stocks embedded in these two very different types of vehicles are actually rather comparable (86 Mt in agricultural machinery and 100 Mt in passenger cars). Again, it must be noted that the uncertainties of the results regarding the size of the material stock in all studied agricultural machinery are significant. Therefore, the estimated iron stocks cannot be automatically declared to nearly match the iron stock of passenger cars. However, when considering the (likely more reliable) results regarding the material stock of tractors alone, it seems that the iron stock of tractors is still more than half the size of the iron stock of cars whereas the steel stock is around 5 % of the size of the corresponding stock in passenger vehicles. The sum of the stocks of steel and iron in tractors (83 Mt) is slightly more than 10% of the total steel and iron stock of cars estimated in the study of Moradesi et al.

Table 3.4: Material stock of agricultural machinery in comparison with total global stocks of different sectors and applications as reported in literature

Study	This study		Deetman et al. (2021)	Moradesi et al. (2014)	Deetman et al. (2020)[a]
Reference year	2018		2015	2010	2018
Stock	Tractors (Mt)	All machinery (Mt)	Electricity infrastructure (Mt)	Passenger cars (Mt)	Residential and service sector buildings (Mt)
Steel	29	122	521	600	15 943
Iron	54	86		100	
Aluminium	0.8	3.0	132	70	1 358
Copper	0.2	0.4	38		325
Glass	0.3	0.4	3		2 197
Lead	0.2	0.4	2.5		

Note: [a] These values have been acquired by summing the 2018 material stock results of all building types found in the the Supplementary Data file of the article by Deetman et al. (2020)

3.2 Material Stock Scenario Results

The following sections present the dynamic mechanization factors modeled based on the harvested yield variable of IMAGE, after which the results for the projected changes in the number of in-use machinery and the size of the material stock in different SSP scenarios are reported. The results are presented for the base model, which uses constant mechanization factors of the 2000s, as well as the alternative scenario model that uses the dynamic mechanization factors for the calculation of the number of machinery until 2100.

3.2.1 Dynamic Mechanization Factors

The dynamic mechanization factors of the different types of agricultural machinery were calculated by applying the rate of change of the harvested yield values from IMAGE (normalized with the average values of the 2000s) to the constant mechanization factors presented in section 3.1.1. This approach was based on an assumption that all yield increases can be attributed to increasing mechanization and machinery use. The dynamic mechanization factors of tractors in SSP2 are shown in Figure 3.5.[12] In most of the regions with a lower initial mechanization level, the mechanization factors are rising steadily, even multiplying. However, in many cases they do not catch up with even the initial mechanization factors of wealthier regions. This is likely due to the significant differences with the initial values of mechanization factors. The mechanization factor's rates of change are based on regionally normalized changes in the harvested yield, and even significant relative increases in the values are not enough to raise the extremely low initial values fast enough.

The model for the dynamic mechanization factors appears to produce quite reasonable outcomes, although not necessarily for the right reasons. The mechanization factors of many of

[12] The dynamic mechanization factor values for tractors in all SSPs are reported in Appendix J.

the regions with initially high mechanization factors are either decreasing or stabilizing over time. Based on the historical trend analysis of tractor mechanization factors presented in Appendix M, this eventual stabilization of mechanization factors is to be expected to some extent. This stabilization, or decreasing, of mechanization values could be explained by the adoption of a smaller number of more efficient machinery, or generally increasing productivity of agriculture. However, such changes are not usually related to decreasing yields. Yet this is, in fact, what the model would suggest, if all of the yield changes were indeed attributed to mechanization. In reality, these decreasing harvested yields are likely related to factors other than the mechanization levels. Thich makes the basic assumption behind the modeling of dynamic mechanization factors lose some of its credibility.

Although farm mechanization is, indeed, often correlated with higher agricultural yields (Verma, 2006), the direct impacts of agricultural mechanization on the agricultural yields have been found to be limited (Binswanger, 1986). Mechanization has been shown to directly increase crop yields only in contexts where the soil is too heavy to be tilled by hand. However, there are a few ways in which mechanization can improve yields indirectly. Agricultural mechanization is often correlated with the adoption of many other yield-increasing practises such as fertilizer application, as it can support the (efficient and timely) utilization of such practices (Doie et al., 2016). In any case, this model of dynamic mechanization factors should be used with caution, as technological development and mechanization are, in fact, not the only driving forces behind the IMAGE scenario results on the harvested yield.

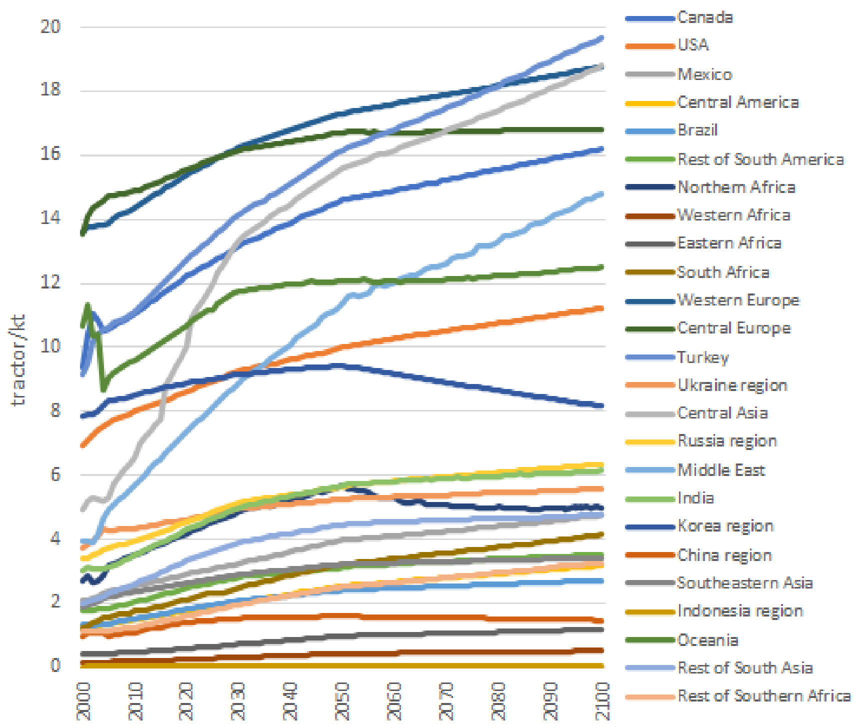


Figure 3.5: Dynamic mechanization factors of tractors in SSP2 (Japan excluded)

3.2.2 Number of Machinery in Five SSP Scenarios

The development of the number of machinery over time in different SSP scenarios was calculated by multiplying the scenario data on agricultural production by the constant mechanization factors (in the case of the base model) and the dynamic mechanization factors derived from the harvested yield changes (in the dynamic mechanization model). The scenario model results for the number of tractors in different scenarios are depicted in figure 3.6. The results of the dynamic mechanization model are plotted with a dashed line, whereas the base model results are plotted with continuous lines. The scenario results for the other machinery types can be found in Appendix K. As can be seen in the graph depicting the scenario results for the number of tractors over time, the results vary significantly between the different scenarios. By the year 2100, the number of tractors in the SSP5 with dynamic mechanization factors is more than twice the number of tractors in the base model SSP1.

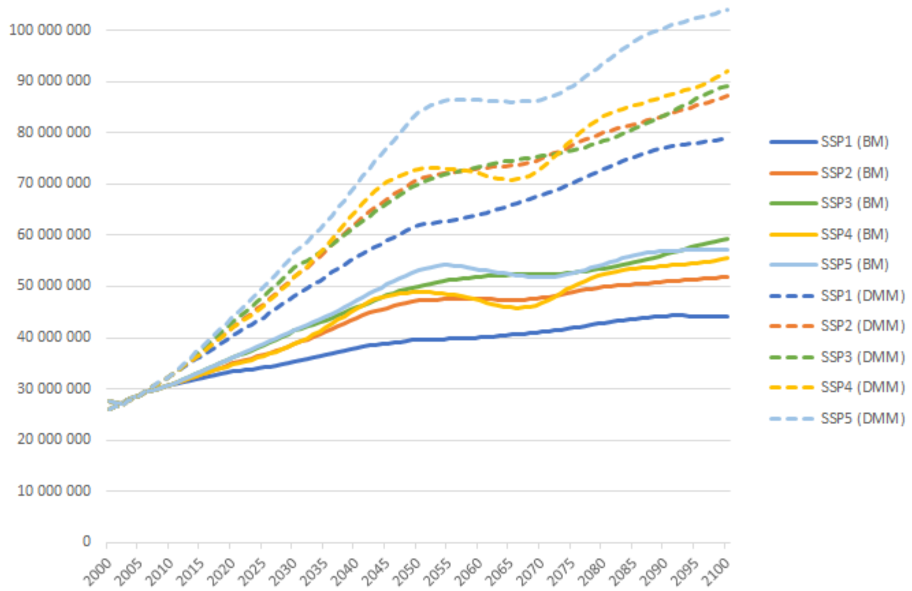


Figure 3.6: Global number of tractors in five SSPs, base model (BM) and dynamic mechanization model (DMM)

3.2.3 Material Stock of Agricultural Machinery in Five SSP Scenarios

The material scenario results resemble the results of the number of machinery in use. Figure 3.7 contains the results for the total material stock embedded in tractors, whereas the results for the total material stock of all studied machinery are depicted in figure 3.8.[13] Even in the most moderate scenario in terms of the stock growth, the base model SSP1, the material stocks grow by more than 50% from 2000 until 2100, whereas the results for the dynamic mechanization version of SSP5 more than triple in the same time frame. However, even this higher growth rate seems rather modest in comparison to the 23-fold growth of the global total material stock during the 20th century observed by Krausmann et al. (2017).

[13] The developments of the total steel and iron stock as well as the rubber stock in the five SSP scenarios are reported in Appendix L.

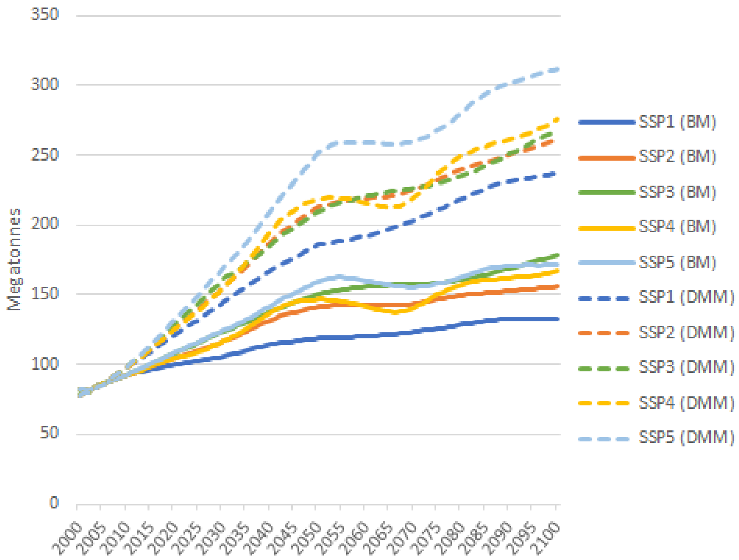


Figure 3.7: Total material stock of agricultural tractors in five SSPs, base model (BM) and dynamic mechanization model (DMM)

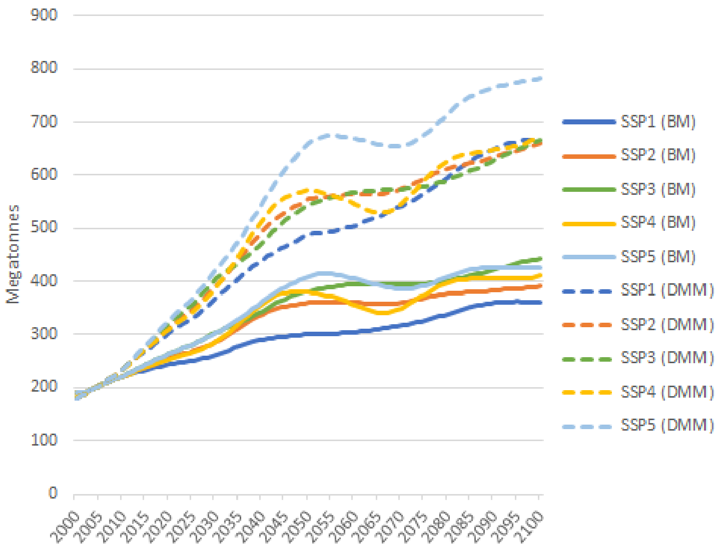


Figure 3.8: Total material stock of all studied agricultural machinery types in five SSPs, base model (BM) and dynamic mechanization model (DMM)

4 Discussion

This chapter explores some of the recent technological developments taking place in the global agricultural system, and their potential to affect the size and composition of the material stocks embedded within agricultural machinery in the future. The chapter also discusses some of the limitations of the study, and provides a few suggestions for the improvement of the scenario model, as well as some general recommendations for future research on the topic of material stocks of agricultural machinery.

4.1 Uncertainty and Potential Future Developments of Agriculture

Scenario models are always associated with a certain level of uncertainty, as future events and developments are impossible to predict with full accuracy. The scenario model developed for this study is rather conservative in nature, as it only assumes a further adoption and expansion of the already well-established agricultural technologies. However, the global agricultural system is undergoing various technological developments that might, in some way, affect the material stock embedded in agricultural machinery. Some of these developments in agricultural production technologies are expected to become widely adopted in the coming decades. As one of the main objectives of this study was to assess the future developments of the material stocks of agricultural machinery, it is important to discuss the potential impacts of these rising technologies on the numbers, material compositions, and sizes of agricultural machinery used in the global agricultural system.

One of the most prominent technological developments in agriculture is related to the adoption of different "Agriculture 4.0" technologies. The term refers to recent developments concerning the adoption of new digital technologies in agricultural production, which can facilitate precision farming and sustainable agricultural practices. These technologies include different kinds of sensors and robotics, big data and artificial intelligence-based data analysis methods, the Internet of Things, cloud computing, and decision support systems (dos Reis et al. 2020; Araujo et al. 2021). The physical layer of the architecture of Agriculture 4.0 is the most relevant aspect of these new technologies when it comes to agricultural machinery and equipment. This physical layer entails different sensing technologies, which are used to collect data on relevant field parameters and to monitor vegetation, soil, water, weather etc. (Araujo et al. 2021). Remote and proximal sensing can be performed by satellites, unmanned aerial and ground vehicles (UAVs and UGVs), conventional agricultural machinery such as tractors, or even hand held devices. The second component of the physical layer of Agriculture 4.0 includes the actuators/controllers, which perform agricultural tasks in the field. Agricultural robots, such as UAVs and UGVs, can perform various farm operations, such as precision spraying of agro-chemicals, crop harvesting, field cultivation, weed control, and irrigation (Araujo et al. 2021).

The introduction of different types of agricultural robots could influence the material stock of agricultural machinery in different ways. These types of autonomous "smart" machines are often significantly more complex in their material composition compared to conventional machinery. They can contain a range of materials commonly found in various electronic devices, some of which include different hazardous, scarce, and critical materials (Williams, 2011; Wäger et al. 2018). Such materials are often rather interesting from the material flow and stock research perspectives, even if they form only small fractions of the total material compositions of agricultural machinery. According to Blackmore (in King, 2020), current large manufacturers of agricultural machinery are not particularly interested in the development of agricultural robots, due to potential conflicts with their established business models. However, even the conventional agricultural machinery, such as tractors, already contain very modern technologies where all elements of the machine are connected to one central control and information system (Jørgensen, 2012). Conventional agricultural machines are also undergoing a transition toward becoming fully autonomous. Such developments are likely to lead to somewhat similar outcomes in terms of the increasing variety of the materials contained in the stocks of agricultural machinery, as would the introduction of entirely new types of autonomous equipment.

The trend towards autonomous machines might affect the material stock of agricultural machinery also in another way. According to van Henten (in King, 2020), "as soon as you remove the human component, size is irrelevant" as the working time on the field and its associated costs become a lesser concern. The conventional large machinery could therefore be replaced by smaller machinery, or even cooperating 'swarms' or small robots (dos Reis et al, 2020; Jørgensen, 2012). Despite these recent trends concerning the miniaturization of agricultural machinery, historically, the size and power of agricultural machinery have been increasing continuously, along with the productivity levels, and these trends seem to be still ongoing in many parts of the world (Jørgensen, 2012; Day, 2011). The steady increase in sizes has especially applied to tractors (Keller et al., 2019) and combine harvesters (Hanna & Quick, 2019). However, while these trends have mainly facilitated growing farm sizes in the developed world, they do not necessarily apply to all parts of the world, as farms in many low-income countries are, in fact, getting smaller (Valle & Kienzle, 2020). According to Valle and Kienzle (2020) "mechanization is not synonymous with tractorization", and the mechanization processes within these low-income regions could potentially involve 'leapfrogging' straight to smaller autonomous agricultural robots. The past trends of growing machinery occurring in many parts of the world have raised concerns over soil damage due to increasing pressure (Day, 2011; Valle & Kienzle, 2020). Introduction of smaller autonomous machinery has been suggested as a solution to these soil compaction issues, although other prevention measures, such as controlled traffic systems, can also alleviate the negative impacts of conventional heavy machinery (Day, 2011).

Apart from the integration of electronics (and thereby more complex combinations of materials) inside agricultural machinery, it is also possible that the bulk-materials used in agricultural machinery change over time. Some light and strong materials, which are already used by the automotive industry, might also spread to the agricultural sector (Joutsenvaara & Vierelä, 2013; Day, 2011). According to Joutsenvaara and Vierelä (2013), the general trends in the materials used in the agricultural sector move towards stronger and harder steels, as well as corrosion-resistant steel types such as stainless steel. The focus of the material selection for agricultural machinery is shifting towards reducing the environmental impacts of materials and increasing the wear-resistance, in order to extend the lifetimes of machinery (Martensen, 2006; Joutsenvaara & Vierelä, 2013).

Another current development that might have a significant influence on the material composition of agricultural machinery is the electrification of the field machinery fleet. Even though electric powertrains are a relatively new feature in field machinery, and not yet widely adopted, recent technological advances have shown that agricultural machinery might benefit from electrification (Lajunen et al., 2018). The benefits of electrification include increased efficiency, improved controllability and dynamic response, the opportunity to add new functionalities to the machinery, as well as decreased maintenance requirements (Moreda et al.

2016). The global efforts towards the reduction of GHG emissions are the main driver for the electrification of non-road mobile machines, including agricultural machinery (Lajunen et al. 2018). Electrification of agriculture will likely change the material compositions of machinery to some extent. The electric road vehicles require higher amounts of copper, aluminium, lithium, and rare earth elements compared to cars with internal combustion engines (Helmers, 2015). Agricultural electrification might cause a similar shift in the material contents of agricultural machinery.

4.2 Limitations of the Study and Recommendations for Future Research

The reported study has various limitations, and the scenario model can be improved in many ways in the future research. One of the most significant limitations of the methodology is related to the treatment of animal husbandry and the extent to which its effects on the material stock of agricultural field machinery are captured. Tractors are the only type of agricultural machinery addressed in this study, which are, at least to some extent, used directly in activities related to animal husbandry. However, due to the reasons presented in Chapter 2, they were assumed to be only used in the production of crops. The mechanization factors were therefore calculated using only data on crop production, and animal products were left out of this calculation entirely. Since both FAO and IMAGE production data used in the study include food crops produced also for animal feed, the effects of future developments in animal husbandry on the field machinery stock are captured to some degree through changes in the demand for these feed crops. However, the extent to which tractors are used in the activities directly related to animal husbandry and the production of non-food crops (such as hay and grass) for animal feed was not included in any way in the calculation of their mechanization factors. Therefore, the scenario model is somewhat limited in its ability to detect the full effect of animal husbandry on the number and the material stock of in-use tractors.

In general, the field machinery assessed in this study are mainly related to crop production, and specialized machinery related to animal husbandry and grass and hay production were not included in this study due to data scarcity or compatibility issues. The FAO machinery dataset does include data on balers, which are certainly used in the animal fodder production. However, in the absence of country-level data on the production quantities of grass and hay, it was impossible to calculate mechanization factors that could connect the number of balers to the scenario data of IMAGE. Milking machines—the only other machinery type included in the FAO dataset directly related to animal products—form only a small part of all machinery used in animal husbandry. Therefore, the research scope of this study was ultimately restricted to field machinery used in crop production only. In order to gain a better understanding of the material impacts of the different global diet patterns incorporated in the SSP narratives, future research should attempt to expand the assessment of agricultural material stocks to include the equipment and infrastructures directly related to animal husbandry as well.

As mentioned before, many of the limitations of the study are related to data scarcity, which is also the reason why the reliability of the results varies considerably between the different machinery types. When it comes to tractors and combine harvesters, the amount of data available for the calculation of the regional mechanization factors was significantly higher in comparison with other machinery types. Sometimes the country-level data on the number of machinery was so scarce that the regional mechanization factors had to be based on the average values of larger regions. Agricultural tractors were the only machinery type for which the regional mechanization factors were calculated using a weighted average (based on the countries' relative shares of the total production in each region) of the country-level mechanization factors. For most of the machinery types, the regional mechanization factors were based on a simple average of the country-level mechanization factors, which could let the values of smaller countries influence the regional mechanization factors disproportionately. In this study, some of the clear outliers were excluded from the calculations of the averages, but other, more deliberate and customized methods for the generalization of scarce data could perhaps be considered in the future research.

Another limitation in both the material stock quantification and the scenario analysis steps is related to the data used for the average masses and material compositions of agricultural machinery. As explained in the methodology chapter, reliable data on the true global average masses and material compositions of machinery is not available in literature, and whether the values used in the analysis represent these global averages with sufficient accuracy is quite uncertain. Quantitative data on regional differences and historical developments of the characteristics of in-use machinery is equally scarce. That is why the values used in the current material stock quantification as well as the scenario analysis were assumed to apply to all world regions and to remain constant over time. However, these assumptions are unlikely to reflect reality very well. Both the sizes and technical properties (and thereby material contents) of agricultural machinery are likely to vary both regionally and over time, depending on the local circumstances and diverse socioeconomic factors, such as average farm sizes and level of wealth. Future research should seek to gain a better understanding of the weights of the machinery and their distribution in different geographical regions. Regional distribution and the changes of the average masses and material compositions could also be modeled based on some variables available in IMAGE. However, in order to do this, more data on the factors influencing the average machinery sizes as well as the complexity of the material compositions need to be found. Machinery manufacturers are likely to possess valuable data on the regional sales of different machinery models. This sales data could be combined with data on the weights or other technical specifications of these particular machines in order to learn about the regional differences in the typical sizes and types of machinery used.

There are also a few potential limitations related to the design of the models used in this study. For instance, the way in which the different types of agricultural machinery were allocated to the different crop categories for the calculation of the mechanization factors might have also influenced the results. The weighing was only based on the total masses of the different crop types produced, even though it is possible that in reality, some crop types require more intensive farming practices and a higher number of machinery per produced mass than others. Machinery usage intensities in the production of different crops might also vary regionally, yet the same allocations of machinery to crop types were applied to the whole world in the calculation of the mechanization factors.

Another model design decision, the utilization of harvested yield data for the modeling of the changes in mechanization factors (which assumes the changes in yields to be fully attributable to changes in mechanization levels), was discussed in more detail in Chapter 3. Harvested yield is not a perfect variable for its intended purpose in this study, as it is affected by various other factors in addition to mechanization and technological circumstances; agricultural yields have also not been found to be directly affected by mechanization alone. Nevertheless, there is a correlation between the yields and machinery usage, likely caused by the indirect yield impacts of agricultural mechanization through the facilitation of actually effective yield improving activities, such as fertilizer application. Harvested yield might well be the best variable for the dynamic mechanization model currently available in IMAGE. The modeled dynamic mechanization factors also seem relatively reasonable, even if not for the right reasons. The scenario results generated by the dynamic mechanization model should therefore not be discarded automatically. Nevertheless, the model for the dynamic mechanization factors should be improved in the future. As agricultural mechanization has been clearly shown to improve agricultural productivity, further research should perhaps try to link the mechanization factors to some agro-economic variables.

There are many ways in which the scenario model used in this study could be improved, given that the factors affecting the average weights, material compositions and mechanization levels are better understood. Figure 4.1 suggests an alternative structure for a scenario model, which includes dynamic models of material composition and machinery size in addition to an improved model for the dynamic mechanization factors. However, the data requirements of this alternative model are significantly harder to satisfy in comparison to the scenario models used in this study, as region-specific data for the material compositions and average masses of machinery are still extremely scarce in the literature.

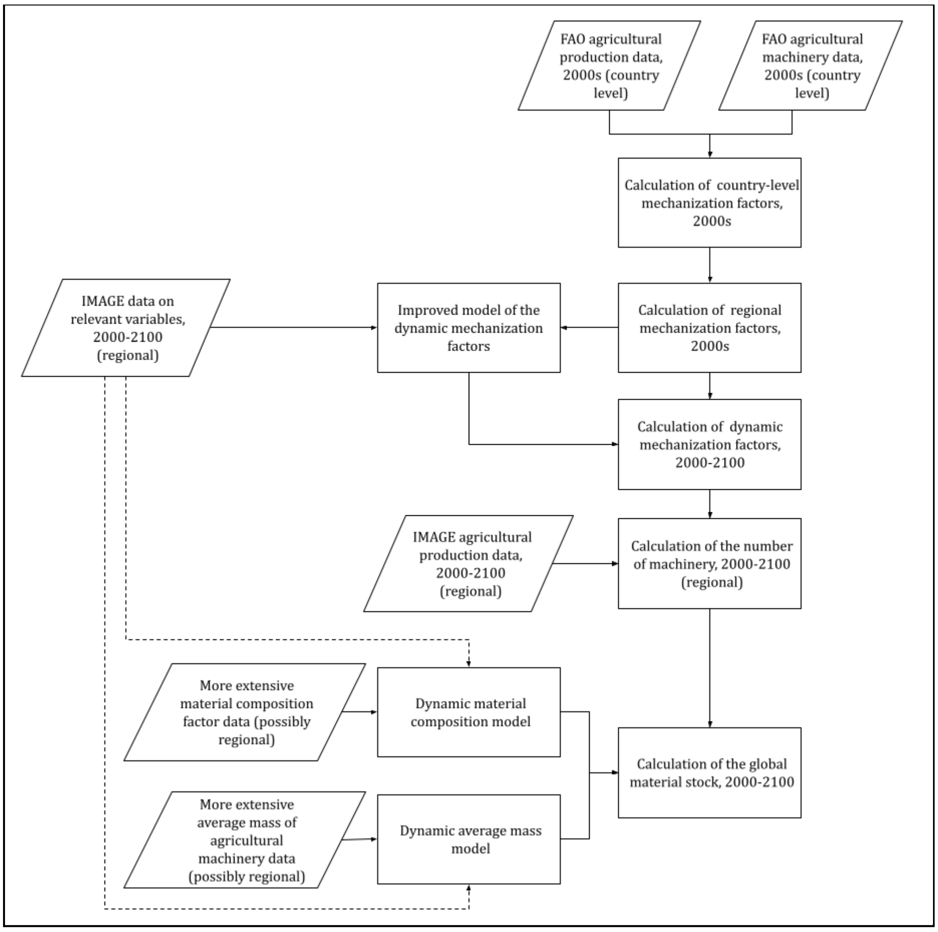


Figure 4.1: Structure of an improved and extended material stock scenario model

Section 4.1 outlined some of the technological developments that might have an impact on the material stock of agriculture in the future, and more research is required for a better understanding of the significance of these impacts. The changing material composition of machinery, particularly in relation to the electrification of agriculture, is an interesting topic for future research. While electric tractors are still mainly in an introduction phase, they might become a viable alternative to tractors with combustion engines relatively soon. The potential adoption rates of electric tractors in different parts of the world could be modelled based on some technological or economic variables from IMAGE. These adoption rates could also be modelled based on past experiences regarding the adoption of electric road-vehicles in different parts of the world. Data on the material compositions of these new electric tractors would also be needed for such a model. Assumptions regarding the material contents of the engine and the battery could be based on the material contents of large electric vehicles with similar power output ranges, if no data on electric tractors specifically was available. Another current technology development that might be interesting to assess from a material-use perspective is the introduction of field-work robots, which can differ from traditional machinery significantly in terms of both their sizes and material contents. Assumptions regarding their physical characteristics and adoption rates in different world regions or socio-economic contexts should be investigated further.

While this study focused solely on the stocks of materials embedded in agricultural machinery, the material flows related to these in-use stocks also require some attention in the future research. As mentioned in the first chapter, material flows are connected to most of the environmental impacts associated with material use, and the inflows and outflows of materials in and out of material stocks represent the demand for materials, and availability of secondary materials for recovery. In order to include material flows to the material stock model established in this study, the next important step is the acquisition of machinery lifetime data. The lifetimes of agricultural machinery can vary drastically, and a tractor might still lead a long 'second lifetime', sometimes on the other side of the world, after the initial owner has replaced it due to its depreciated value (ARN, 2019). The surprisingly short estimates and assumptions of tractor lifetimes found in literature might be based on the more easily determined 'primary lifetimes' spent with the original owners, which might not reflect the entire life cycles of tractors nor their time as a part of the material stock. The global trade of second-hand agricultural machinery can further complicate the establishment of a material flow model. Including the flows of second hand machinery in a model based on global aggregates might not be a very demanding task as long as the 'multiple lifetimes' of these machines are taken into account. However, modeling the primary, secondary, as well as waste flows of machinery between different world regions is a challenge of another magnitude. International trade data can be a useful source of information, but does not cover the machinery remaining within the production countries, nor the market of secondhand machinery.

An interesting material flow connected to agricultural machinery that might deserve some special attention is the rubber used in the tyres of agricultural machinery. This study only included the rubber contained in the initial set of tyres after the manufacturing of the machinery in the analysis of the material stocks. However, the actual rubber flows (and possibly stocks) are likely many times larger than what was assumed in this study, since the lifetimes of the rubber tyres are significantly shorter than the lifetimes of the machinery itself, and they get replaced more often.

This study only addressed a few types of agricultural field machinery, while many other agricultural material stocks, including different types of machinery and infrastructures, were left outside of the research scope. Therefore, the total material stock of the global agricultural system is likely significantly larger than what the results of this study suggest, and more research is required for the quantification of the whole material stock of the global agricultural system. Some of the agricultural stocks yet to be analysed include specialized machinery used in animal husbandry, irrigation systems, greenhouses, storage facilities, trailers and wagons, animal housing, fencing, and an endless number of other types of well-established and emerging agricultural equipment and infrastructures.

5 Conclusion

This study quantified the global material stock currently embedded within in-use agricultural field machinery, and explored the potential future developments of the material stock using IMAGE scenario data on five Shared Socioeconomic Pathways. The current numbers of the different types of machinery in use were calculated by linking available data on the number of in-use machinery to agricultural production data through the calculation of mechanization factors. Data on the material compositions and the average masses of agricultural machinery, which was found in the literature, was used in combination with the results for the number of machinery to estimate the sizes of the stocks of different materials embedded within agricultural field machinery. Steel (121 Mt), ductile iron (86 Mt), and rubber (21 Mt) were identified as the largest material stocks embedded in the field machinery in use globally. Most of the materials of the studied machinery were found in tractors and combine harvesters. The estimated material stocks of agricultural field machinery were also compared to other societal stocks of materials reported in the literature. In most cases, the agricultural stocks seem to be rather negligible in relation to the total stocks of particular materials, as well as the material stocks embedded in other sectors. An exception to this were the material stocks of passenger vehicles; the stock of steel in tractors appeared to be around 5 % of the steel stock of passenger cars, whereas the iron stocks of tractors are more than a half the size of the stocks in cars.

The mechanization factors calculated in the first research step were also used in combination with agricultural scenario data from IMAGE to explore potential future developments of the number of in-use machinery and the size of the material stock in different SSP scenarios. Two scenario models were developed; the base model assumed constant mechanization levels, whereas the dynamic mechanization model used the IMAGE variable of harvested yield to model changes in mechanization factors. The scenario results varied to some extent between the five SSPs, but the differences between the base model and the dynamic mechanization model scenarios were more pronounced. According to the SSP1 base model, the total material stock of the studied agricultural field machinery grows by 50 % during the 21st century, whereas the SSP5 dynamic mechanization model predicts a tripling of the material stock within the same timeframe.

This study has multiple limitations, some of which are related to data availability and some to the design of the models themselves. The limitations of the study and their potential impacts on the results were discussed, and ideas for further improvement of the models were presented. This study attempted to fill some of the research gap regarding the physical stock of the global agricultural system, yet significant gaps in the knowledge remain. Potential directions for further research on the topic of agricultural material stock were explored. Some of the most important questions to be addressed in future research concern the regional variations in the average machinery weight, the full material impacts of animal husbandry, and the material flows of agricultural machinery, including the rubber tyres. Some of the current and potential future developments in the global agricultural system, which might in some way affect the agricultural material stock, were also addressed briefly. This study adopted a rather conservative approach for the material scenario analysis by only focusing on already well-established agricultural technologies. However, in order to gain a more comprehensive picture of the potential futures of material use in global agriculture, the current technology developments should be eventually integrated into quantitative assessments of the material stocks and flows of agriculture as well.

This study represents a first attempt to quantify the global material stock embedded in agricultural machinery, and despite its limitations, it can give an idea of the scale of the stock, and provide a starting point for future research on the topic. Only time will tell how the global agricultural system and its material stock are affected by different technological innovations and developments in mechanization in the coming years and decades. In the meanwhile, one can continue the cultivation of the budding relationship between the fields of integrated assessment modeling and material flow analysis.

6 Bibliography

ARN. (2019, January 2). *A Tractor is never rubbish.* Greenlight. https://greenlight.nl/a-tractor-is-never-rubbish/?lang=en

Araújo, S. O., Peres, R. S., Barata, J., Lidon, F., & Ramalho, J. C. (2021). Characterising the Agriculture 4.0 Landscape—Emerging Trends, Challenges and Opportunities. *Agronomy, 11*(4), 667.

Baynes, T. M., & Müller, D. B. (2016). A socio-economic metabolism approach to sustainable development and climate change mitigation. In R. Clift & A. Druckman (Eds.), *Taking stock of industrial ecology* (pp. 117-135). Springer.

Baccini, P., & Brunner, P. H. (2012). *Metabolism of the anthroposphere: analysis, evaluation, design*. MIT Press.

Binswanger, H. (1986). Agricultural mechanization: a comparative historical perspective. *The World Bank Research Observer, 1*(1), 27-56.

Böttinger, S., Doluschitz, R., Klaus, J., Jenane, C., & Samarakoon, N. (2013). Agricultural Development and Mechanization in 2013: A Comparative Survey at a Global Level [Paper presentation]. CECE-CEMA Summit 2013: Towards a competitive industrial production for Europe. Brussels.

Caffrey, K. R., & Veal, M. W. (2013). Conducting an agricultural life cycle assessment: challenges and perspectives. *The Scientific World Journal, 2013*.

Cavallo, E., Ferrari, E., & Coccia, M. (2015). Likely technological trajectories in agricultural tractors by analysing innovative attitudes of farmers. *International Journal of Technology, Policy and Management, 15*(2), 158-177.

Day, W. (2011). Engineering advances for input reduction and systems management to meet the challenges of global food and farming futures. *The Journal of Agricultural Science, 149*(S1), 55-61.

De Lucia, M., & Assennato, D. (1994). *Agricultural engineering in development: post-harvest operations and management of foodgrains,* (FAO Agricultural Services Bulletin No. 96). Food and Agriculture Organization of the United Nations.

Deetman, S., Pauliuk, S., Van Vuuren, D. P., Van Der Voet, E., & Tukker, A. (2018). Scenarios for demand growth of metals in electricity generation technologies, cars, and electronic appliances. *Environmental science & technology, 52*(8), 4950-4959.

Deetman, S., Marinova, S., van der Voet, E., van Vuuren, D. P., Edelenbosch, O., & Heijungs, R. (2020). Modelling global material stocks and flows for residential and service sector buildings towards 2050. *Journal of Cleaner Production, 245*, 118658.

Deetman, S., de Boer, H. S., Van Engelenburg, M., van Der Voet, E., & van Vuuren, D. P. (2021). Projected material requirements for the global electricity infrastructure–generation, transmission and storage. *Resources, Conservation and Recycling*, *164*, 105200.

Diao, X., Silver, J., & Takeshima, H. (2016). Agricultural mechanization and agricultural transformation (No. 1527). International Food Policy Research Institute.

dos Reis, Â. V., Medeiros, F. A., Ferreira, M. F., Machado, R. L. T., Romano, L. N., Marini, V. K., ... & Machado, A. L. T. (2020). Technological trends in digital agriculture and their impact on agricultural machinery development practices. *Revista Ciência Agronômica, 51*, 1-12.

Food and Agriculture Organization of the United Nations. (2017). *The future of food and agriculture – Trends and challenges.*

FAOSTAT. (2018). Machinery. [Data set]. Food and Agriculture Organization of the United Nations. http://www.fao.org/faostat/en/#data/RM

FAOSTAT. (2021). Crops. [Data set]. Food and Agriculture Organization of the United Nations. http://www.fao.org/faostat/en/#data/QC

Fritsche, U. R. (2013). Global material flows and their environmental impacts: an overview. In M. Angrick, A. Burger & H. Lehmann (Eds.), *Factor X,* (pp. 3-17). Springer.

Geyer, R., Jambeck, J. R., & Law, K. L. (2017). Production, use, and fate of all plastics ever made. *Science advances, 3*(7), e1700782.

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner production, 114*, 11-32.

Glöser, S., Soulier, M., & Tercero Espinoza, L. A. (2013). Dynamic analysis of global copper flows. Global stocks, post consumer material flows, recycling indicators, and uncertainty evaluation. *Environmental Science & Technology, 47*(12), 6564-6572.

Graedel, T. E. (2011). The prospects for urban mining. *Bridge*, *41*(1), 43-50.

Graedel, T. E. (2019). Material flow analysis from origin to evolution. *Environmental science & technology*, *53*(21), 12188-12196.

Hanna, H. M., & Quick, G. R. (2019). Grain Harvesting Machinery. In M. Kutz (Ed.), *Handbook of Farm, Dairy and Food Machinery Engineering* (pp. 157-174). Academic Press.

Hatayama, H., Daigo, I., Matsuno, Y., & Adachi, Y. (2010). Outlook of the world steel cycle based on the stock and flow dynamics. *Environmental science & technology, 44*(16), 6457-6463.

Helmers, E. (2015). Possible resource restrictions for the future large-scale production of electric cars. In S. Hartard & W. Liebert (Eds.), *Competition and Conflicts on Resource Use* (pp. 121-131). Springer.

Hertwich, E., van der Voet, E., Suh, S., Tukker, A., Huijbregts M., Kazmierczyk, P., Lenzen, M., McNeely, J., & Moriguchi, Y. (2010). *Assessing the Environmental Impacts of Consumption and Production: Priority Products and Materials.* A Report of the Working Group on the

Environmental Impacts of Products and Materials to the International Panel for Sustainable Resource Management. United Nations Environment Programme.

International Resource Panel. (2010). *Metal stocks in society: Scientific synthesis*. United Nations Environment Programme.

Jørgensen, M. H. (2012). Agricultural field machinery for the future–From an engineering perspective. *Agronomy Research, 10*(1), 109-113.

Justice, S., & Biggs, S. (2020). The spread of smaller engines and markets in machinery services in rural areas of South Asia. *Journal of Rural Studies, 73*, 10-20.

Kan, D., Vieira, M., & Verweij-Novikova, I. (2020). *Life cycle analysis of horticultural products: Memo on capital goods modelling*. Wageningen University & Research.

Kawasaki, K. (2010). The costs and benefits of land fragmentation of rice farms in Japan. *Australian Journal of Agricultural and Resource Economics, 54*(4), 509-526.

Keller, T., Sandin, M., Colombi, T., Horn, R., & Or, D. (2019). Historical increase in agricultural machinery weights enhanced soil stress levels and adversely affected soil functioning. *Soil and Tillage Research, 194*, 104293.

Key, N. (2019). Farm size and productivity growth in the United States Corn Belt. *Food Policy, 84*, 186-195.

King, A. (2017). Technology: The future of agriculture. *Nature, 544*(7651), S21-S23.

Krausmann, F., Wiedenhofer, D., Lauk, C., Haas, W., Tanikawa, H., Fishman, T., Miatto, A., Schandl, H. & Haberl, H. (2017). Global socioeconomic material stocks rise 23-fold over the 20th century and require half of annual resource use. *Proceedings of the National Academy of Sciences, 114*(8), 1880-1885.

Krook, J., & Baas, L. (2013). Getting serious about mining the technosphere: a review of recent landfill mining and urban mining research. *Journal of Cleaner Production*, *55*, 1-9.

Lajunen, A., Sainio, P., Laurila, L., Pippuri-Mäkeläinen, J., & Tammi, K. (2018). Overview of powertrain electrification and future scenarios for non-road mobile machinery. *Energies, 11*(5), 1184.

Lee, J., Cho, H. J., Choi, B., Sung, J., Lee, S., & Shin, M. (2000). Life cycle assessment of tractors. *The International Journal of Life Cycle Assessment, 5*(4), 205-208.

Li, W., Wei, X., Zhu, R., & Guo, K. (2019). Study on factors affecting the agricultural mechanization level in China based on structural equation modeling. *Sustainability, 11*(1), 51.

Lifset, R., & Graedel, T. E. (2015). Industrial Ecology. In J. D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences: Second Edition* (2nd ed., Vol. 11, pp. 843–853). Elsevier Inc.

Liu, G., Bangs, C. E., & Müller, D. B. (2013). Stock dynamics and emission pathways of the global aluminium cycle. *Nature Climate Change, 3*(4), 338-342.

Lovarelli, D., Bacenetti, J., & Fiala, M. (2016). A new tool for life cycle inventories of agricultural machinery operations. *Journal of Agricultural Engineering, 47*(1), 40-53.

Mantoam, E. J., Milan, M., Gimenez, L. M., & Romanelli, T. L. (2014). Embodied energy of sugarcane harvesters. *Biosystems Engineering, 118*, 156-166.

Mantoam, E. J., Romanelli, T. L., & Gimenez, L. M. (2016). Energy demand and greenhouse gases emissions in the life cycle of tractors. *Biosystems Engineering, 151*, 158-170.

Mantoam, E. J., Mekonnen, M. M., & Romanelli, T. L. (2018). Energy, water and material footprints of agricultural machinery industry. *Agricultural Engineering International: CIGR Journal, 20*(3), 132-140.

Mantoam, E. J., Angnes, G., Mekonnen, M. M., & Romanelli, T. L. (2020). Energy, carbon and water footprints on agricultural machinery. *Biosystems Engineering, 198*, 304-322.

Mao, J., & Graedel, T. E. (2009). Lead in-use stock: A dynamic analysis. *Journal of Industrial Ecology, 13*(1), 112-126.

Marinova, S., Deetman, S., van der Voet, E., & Daioglou, V. (2020). Global construction materials database and stock analysis of residential buildings between 1970-2050. *Journal of Cleaner Production, 247*, 119146.

Martensen, K. (2006). Progress in typical materials for agricultural machinery. *Agricultural Engineering International: CIGR Journal, 8.*

Mehta, A., & Gross, A. C. (2007). The global market for agricultural machinery and equipment. *Business Economics*, *42*(4), 66-74.

Miu, P. (2015). *Combine harvesters: theory, modeling, and design*. CRC Press.

Modaresi, R., Pauliuk, S., Løvik, A. N., & Müller, D. B. (2014). Global carbon benefits of material substitution in passenger cars until 2050 and the impact on the steel and aluminum industries. *Environmental science & technology, 48*(18), 10776-10784.

Moreda, G. P., Muñoz-García, M. A., & Barreiro, P. J. E. C. (2016). High voltage electrification of tractor and agricultural machinery–A review. *Energy Conversion and Management, 115*, 117-131.

Müller, E., Hilty, L. M., Widmer, R., Schluep, M., & Faulstich, M. (2014). Modeling metal stocks and flows: a review of dynamic material flow analysis methods. *Environmental science & technology, 48*(4), 2102-2113.

Nemecek, T., Kägi, T., & Blaser, S. (2007). *Life cycle inventories of agricultural production systems: Data v2.0* (Report No. 15), ecoinvent.

OECD. (2019). *Global Material Resources Outlook to 2060: Economic Drivers and Environmental Consequences*, OECD Publishing.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., ... & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global environmental change, 42*, 169-180.

Otsuka, K., Liu, Y., & Yamauchi, F. (2016). The future of small farms in Asia. *Development Policy Review, 34*(3), 441-461.

Passarini, F., Ciacci, L., Nuss, P., & Manfredi, S. (2018). *Material Flow Analysis of Aluminium, Copper, and Iron in the EU-28* (Report No. EUR 29220 EN). European Union.

Pauliuk, S., Arvesen, A., Stadler, K., & Hertwich, E. G. (2017). Industrial ecology in integrated assessment models. *Nature Climate Change, 7*(1), 13-20.

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., ... & van Vuuren, D. P. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change, 42*, 331-345.

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., ... & Lutz, W. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Global Environmental Change*, *42*, 153-168.

Roer, A. G., Korsaeth, A., Henriksen, T. M., Michelsen, O., & Strømman, A. H. (2012). The influence of system boundaries on life cycle assessment of grain production in central southeast Norway. *Agricultural Systems, 111*, 75-84.

Romanelli, T. L., & Milan, M. (2010). Material flow determination through agricultural machinery management. *Scientia Agricola, 67*, 375-383.

Romanelli, T. L., & Milan, M. (2012). Machinery management as an environmental tool-material embodiment in agriculture. *Agricultural Engineering International: CIGR Journal, 14*(1), 63-73.

Schandl, H., Lu, Y., Che, N., Newth, D., West, J., Frank, S., ... & Hatfield-Dodds, S. (2020). Shared socio-economic pathways and their implications for global materials use. *Resources, Conservation and Recycling*, *160*, 104866.

Schipper, B. W., Lin, H. C., Meloni, M. A., Wansleeben, K., Heijungs, R., & van der Voet, E. (2018). Estimating global copper demand until 2100 with regression and stock dynamics. *Resources, Conservation and Recycling, 132*, 28-36.

Sieverding, H., Kebreab, E., Johnson, J. M., Xu, H., Wang, M., Grosso, S. J. D., ... & Stone, J. J. (2020). A life cycle analysis (LCA) primer for the agricultural community. *Agronomy Journal, 112*(5), 3788-3807.

Stehfest, E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Biemans, H., Bouwman, A., den Elzen, M., Janse, J., Lucas, P., van Minnen, J., Müller, C., & Prins, A. (2014). *Integrated Assessment of Global Environmental Change with IMAGE 3.0. Model description and policy applications*. PBL Netherlands Environmental Assessment Agency.

Valle, S. S., & Kienzle, J. (2020). *Agriculture 4.0: Agricultural robotics and automated equipment for sustainable crop production,* (Integrated Crop Management No. 24). Food and Agriculture Organization of the United Nations.

van Paassen, M., Braconi, N., Kuling, L., Durlinger, B., & Gual, P. (2019). *Agri-footprint 5.0: Part 2: Description of Data.* Agri-footprint.

Van Vuuren, D. P., Stehfest, E., Gernaat, D. E., Doelman, J. C., Van den Berg, M., Harmsen, M., ... & Tabeau, A. (2017). Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. *Global Environmental Change, 42*, 237-250.

Velazquez-Miranda, E., Bory-Reyes, J., Silva-Navarro, G., Garcia-Perez, O. A., & Trujillo-Franco, L. G. (2018, July 8-12). *On the dynamic analysis, evaluation and functional design of a two-wheel tractor*. [Paper presentation]. 25th International Congress on Sound and Vibration (ICSV25), Hiroshima, Japan.

Verma, S. R. (2006). Impact of agricultural mechanization on production, productivity, cropping intensity, income generation and employment of labour. *Status of farm mechanization in India,* 133-153. Indian Council of Agricultural Research.

Wäger, P. A., Hischier, R., & Widmer, R. (2015). The material basis of ICT. In L. Hilty & B. Aebischer (Eds.), *ICT Innovations for Sustainability,* (vol. 301, pp. 209-221). Springer, Cham.

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): overview and methodology. *The International Journal of Life Cycle Assessment, 21*(9), pp.1218–1230.

Wiebe, K., Lotze-Campen, H., Sands, R., Tabeau, A., van der Mensbrugghe, D., Biewald, A., ... & Willenbockel, D. (2015). Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios. *Environmental Research Letters, 10*(8), 085010.

Wiedenhofer, D., Fishman, T., Lauk, C., Haas, W., & Krausmann, F. (2019). Integrating material stock dynamics into economy-wide material flow accounting: concepts, modelling, and global application for 1900–2050. *Ecological economics, 156*, 121-133.

Williams, E. (2011). Environmental effects of information and communications technologies. *Nature, 479*(7373), 354-358.

7 Appendix

Appendix A

Number of countries with data for each of the machinery types per IMAGE region

IMAGE region	AT	CH	PCT	P	SPT	MSFD	RTHM
1	1	1	0	0	0	0	0
2	1	1	0	0	0	0	0
3	1	0	0	0	0	0	0
4	27	2	3	4	3	2	0
5	1	0	0	0	0	0	0
6	12	5	2	5	5	2	1
7	6	3	2	3	0	1	0
8	22	3	6	7	1	2	2
9	13	3	1	0	0	0	0
10	1	1	0	0	0	0	0
11	21	18	8	3	3	4	5
12	19	17	4	9	10	8	6
13	1	1	1	1	1	1	1
14	3	3	2	3	3	3	2
15	4	3	0	3	3	1	2
16	4	4	1	4	4	3	2
17	14	7	2	5	5	5	2
18	1	1	1	0	0	0	0
19	2	1	1	0	0	0	0
20	2	2	1	1	2	0	0
21	8	4	4	1	0	1	0
22	3	1	0	0	0	0	0
23	1	1	1	0	0	0	1
24	16	0	1	1	0	0	0
25	6	3	3	2	3	1	2
26	9	0	1	1	0	0	0
	203	85	45	53	43	34	26
Empty data in yellow cells has been substituted by the data of larger regions							
AT = Agricultural Tractors, CH = Combine harvesters, PCT = Pedestrian controlled tractors, P = Ploughs, SPT = Seeders, plarters and transplanters, MSFD = Manure spreaders and fertilizer distributors, RTHM = Root and tuber harvesting machinery							

Appendix B

Temperate cereals	Rice	Maize	Tropical cereals
Barley Oats Rye Wheat	Rice, paddy	Maize	Millet Sorghum
Pulses	**Roots and tubers**	**Oil crops**	
Bambara beans Beans, dry Broad beans, horse beans, dry Chickpeas Cow peas, dry Lentils Lupins Peas, dry Pigeon peas Pulses, nes Vetches	Cassava Potatoes Roots and tubers, nes Sweet potatoes Taro (cocoyam) Yams Yautia (cocoyam)	Castor oil seed Coconuts Groundnuts, with shell Hempseed Kapok fruit Karite nuts (shea nuts) Linseed Melonseed Mustard seed Oil, palm fruit Oilseeds nes Olives	Poppy seed Rapeseed Safflower seed Sesame seed Soybeans Sunflower seed Tung nuts
Other crops			
Agave fibres nes Almonds, with shell Anise, badian, fennel, coriander Apples Apricots Areca nuts Artichokes Asparagus Avocados Bananas Bast fibres, other Beans, green Berries nes Blueberries Brazil nuts, with shell Buckwheat Cabbages and other brassicas Canary seed Carobs Carrots and turnips Cashew nuts, with shell Cashew apple Cauliflowers and broccoli Cereals, nes Cherries Cherries, sour Chestnut Chicory roots	Chillies and peppers, dry Chillies and peppers, green Cinnamon (canella) Cloves Cocoa, beans Coffee, green Cranberries Cucumbers and gherkins Currants Dates Eggplants (aubergines) Fibre crops nes Figs Flax fibre and tow Fonio Fruit, citrus nes Fruit, fresh nes Fruit, stone nes Fruit, tropical fresh nes Garlic Ginger Gooseberries Grain, mixed Grapefruit (inc. pomelos) Grapes Hazelnuts, with shell Hemp tow waste Hops Jute Kiwi fruit	Kola nuts Lemons and limes Lettuce and chicory Maize, green Mangoes, mangosteens, guavas Manila fibre (abaca) Mate Melons, other (inc.cantaloupes) Mushrooms and truffles Mustard seed Nutmeg, mace and cardamoms Nuts, nes Okra Onions, dry Onions, shallots, green Oranges Papayas Peaches and nectarines Pears Peas, green Pepper (piper spp.) Peppermint Persimmons Pineapples Pistachios Plantains Plums and sloes	Pumpkins, squash and gourds Pyrethrum, dried Quinces Quinoa Ramie Raspberries Rubber, natural Seed cotton Sisal Spices, nes Spinach Strawberries String beans Sugar beet Sugar cane Sugar crops, nes Tangerines, mandarins, clementines, satsumas Tea Tobacco, unmanufactured Tomatoes Triticale Vanilla Vegetables, fresh nes Vegetables, leguminous nes Walnuts, with shell Watermelons

Appendix C

No.	IMAGE region	Countries
1	Canada	Canada
2	USA	United States of America, Saint Pierre and Miquelon
3	Mexico	Mexico
4	Central America	Anguilla, Antigua and Barbuda, Aruba, Bahamas, Barbados, Belize, Bermuda, Cayman Islands, Costa Rica, Cuba, Dominican Republic, El Salvador, Grenada, Guadeloupe, Guatemala, Haiti, Honduras, Jamaica, Martinique, Montserrat, Netherlands Antilles, Nicaragua, Panama, Puerto Rico, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Trinidad and Tobago, Turks and Caicos Islands, British Virgin Islands, United States Virgin Islands
5	Brazil	Brazil
6	Rest of South America	Argentina, Bolivia (Plurinational State of), Chile, Colombia, Ecuador, Falklands Islands, French Guiana, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela (Bolivarian Republic of)
7	Northern Africa	Algeria, Egypt, Libya, Morocco, Tunisia, Western Sahara
8	Western Africa	Benin, Burkina Faso, Cameroon, Cabo Verde, Central African Republic, Chad, Democratic Republic of the Congo, Congo, Côte d'Ivoire, Equatorial Guinea, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau. Liberia, Mali, Mauritania, Niger, Nigeria, Sao Tome and Principe, Senegal, Sierra Leone, Saint Helena, Ascension and Tristan da Cunha, Togo
9	Eastern Africa	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Mayotte, Mauritius, Réunion, Rwanda, Seychelles, Somalia, Sudan, South Sudan, Uganda
10	South Africa	South Africa
11	Western Europe	Andorra, Austria, Belgium, Denmark, Faroe Islands, Finland, France, Germany, Gibraltar, Greece, Iceland, Ireland, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Svalbard and Jan Mayen, Sweden, Switzerland, United Kingdom, Vatican City State
12	Central Europe	Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, North Macedonia, Poland, Romania, Serbia, Slovakia, Slovenia, Montenegro
13	Turkey	Turkey
14	Ukraine region	Belarus, Moldova, Ukraine
15	Central Asia	Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan
16	Russia region	Armenia, Azerbaijan, Georgia, Russian Federation
17	Middle East	Bahrain, Iran (Islamic Republic of), Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Palestine, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Yemen
18	India	India
19	Korea region	Democratic People's Republic of Korea, Republic of Korea
20	China region	China, mainland, China, Hong Kong SAR, China, Macao SAR, China, Taiwan Province of, Mongolia
21	Southeastern Asia	Brunei Darussalam, Cambodia, Lao People's Democratic Republic, Malaysia, Myanmar, Philippines, Singapore, Thailand, Viet Nam
22	Indonesia region	East Timor, Indonesia, Timor-Leste, Papua New Guinea
23	Japan	Japan
24	Oceania	American Samoa, Australia, Cook Islands, Fiji, French Polynesia, Guam, Kiribati, Marshall Islands, Micronesia (Federated States of), Nauru, New Caledonia, New Zealand, Niue, Northern Mariana Islands, Palau, Pitcairn, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna Islands
25	Rest of South Asia	Afghanistan, Bangladesh, Bhutan, Maldives, Nepal, Pakistan, Sri Lanka
26	Rest of Southern Africa	Angola, Botswana, Lesotho, Malawi, Mozambique, Namibia, Eswatini, Tanzania, Zambia, Zimbabwe

Appendix D

1 OECD	2 Latin America	3 Middle East & Mid-Asia	4 Sub-Saharan Africa	5 South & East Asia
1 Canada 2 USA 11 Western Europe 12 Central Europe 19 Korea region 23 Japan 24 Oceania	3 Mexico 4 Central America 5 Brazil 6 Rest of South America	7 Northern Africa 13 Turkey 14 Ukraine region 15 Central Asia 16 Russia region 17 Middle East	8 Western Africa 9 Eastern Africa 10 South Africa 26 Rest of Southern Africa	18 India 20 China region 21 Southeastern Asia 22 Indonesia region 25 Rest of South Asia

Appendix E

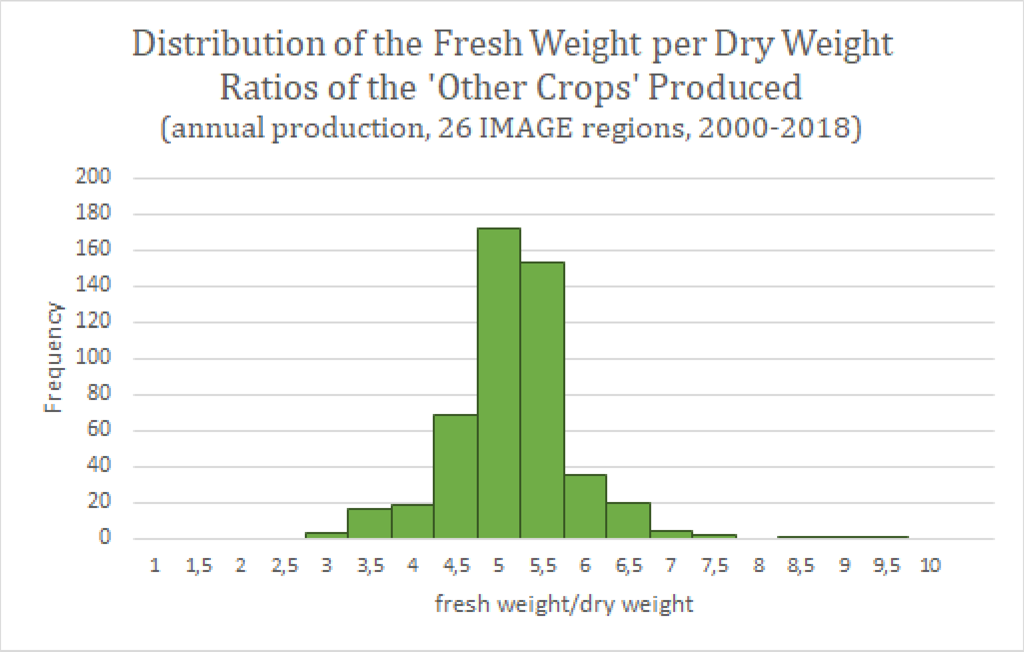
Table X: Material composition factors of tractors, combine harvesters and tractor drawn implements calculated based on Mantoam et al. (2020)

Material category in Mantoam et al. (2020)	Material category in this study	Material	Tractors	Combine harvesters	Tractor drawn implements
Metallic materials	Ductile iron	Ductile iron	53,87 %	18,29 %	22,46 %
	Steel	Carbon steel	29,30 %	64,90 %	65,44 %
		Steel wire	0,04 %	0,26 %	0,15 %
		Stainless steel	0,00 %		0,01 %
	Aluminium	Aluminium	0,83 %	1,97 %	1,00 %
	Copper	Copper	0,20 %	0,31 %	0,01 %
	Lead	Lead	0,24 %	0,21 %	
Non-Metallic materials	Rubber	Rubber	10,71 %	8,31 %	4,70 %
	Plate glass	Plate glass	0,28 %	0,08 %	
	Plastics	Polyethylene high density	0,55 %	1,13 %	5,21 %
		Polypropylene	0,55 %	0,32 %	0,14 %
		Recycled ABS	0,25 %	0,17 %	
		Polyurethane	0,23 %	0,11 %	
		Nylon 6.6	0,21 %	1,40 %	0,12 %
		Polyurethane foam	0,11 %	0,07 %	
		PVC (Poly vinyl chloride)	0,15 %		
	Other materials	Sulphuric acid (H2SO4)	0,04 %	0,04 %	
		Chemical powder ABC	0,06 %	0,03 %	
		Paper (printed news)	0,02 %	0,02 %	0,02 %
		Cellulose film	0,03 %	0,01 %	
		Fiberglass & polyester	0,09 %		
		Fibreglass & aluminium	0,01 %		
		Cotton synthetic fibre	0,09 %	0,03 %	
Lubricants and fluids	Lubricants and fluids	Hydraulic oil	1,21 %	1,03 %	0,27 %
		Diesel oil	0,22 %	0,19 %	
		Engine oil	0,30 %	0,15 %	
		Lubricating oil	0,41 %	0,42 %	
		Grease	0,07 %	0,03 %	0,04 %
		Anticorrosive fluid	0,02 %	0,01 %	
Paint and solvent	Other materials	Paint	0,11 %	0,11 %	0,14 %
		Solvent	0,03 %	0,03 %	0,04 %

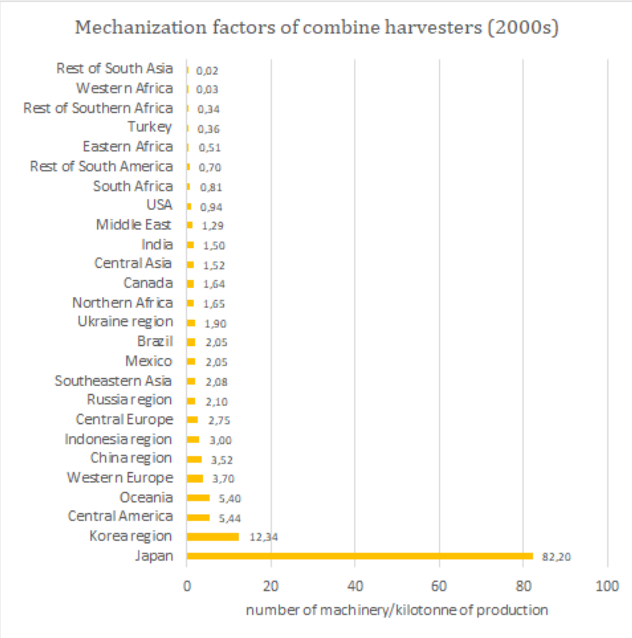
Appendix F

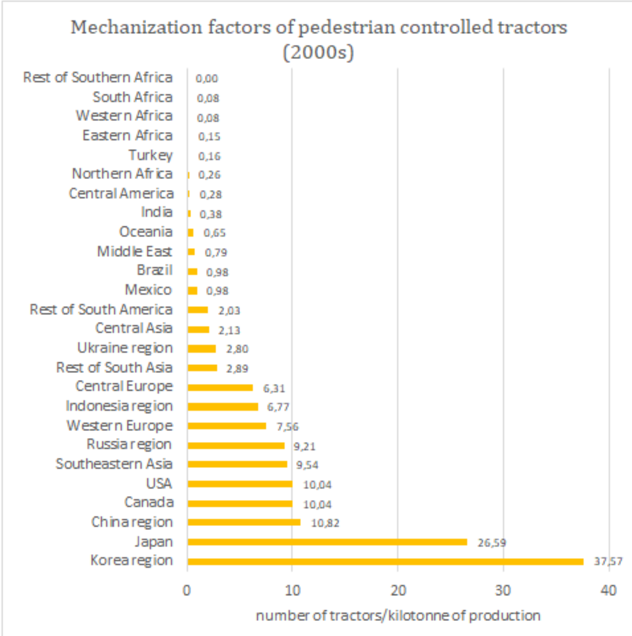
SSP	General assumptions based on O'Neill et al. (2017)	Assumptions related to agriculture and land-use based on Popp et al. (2017)
SSP1	- Relatively low population growth - Medium economic growth in high-income countries, high growth elsewhere - Reduced inequality across and within countries - Moderate international trade - Rapid technological development - Low carbon and energy intensity - Policies focused on sustainable development	- Strong land-use change regulation - High improvements in agricultural productivity - Low growth in food consumption, low meat consumption
SSP2	- Medium population growth - Medium, uneven economic growth - Uneven moderate reductions in inequality across and within countries - Moderate international trade - Medium, uneven technological development - Medium carbon intensity, uneven energy intensity - Weak policy-focus on sustainability	- Medium land-use change regulation - Medium-paced agricultural productivity growth - Material-intensive consumption, medium meat consumption
SSP3	- Low population growth in high-income countries, high growth elsewhere - Slow economic growth - High inequality, especially across countries - Strongly constrained international trade - Slow technological development - High carbon and energy intensity - Low priority for environmental issues	- Limited land-use change regulation - Low agricultural productivity growth - Resource-intensive consumption
SSP4	- Low population growth in high-income countries, relatively high growth elsewhere - Low economic growth in low-income countries, medium growth elsewhere - High inequality, especially within countries - Moderate international trade - Rapid technology development in some sectors, slow in others - Low/medium carbon and energy intensity - Locally-focused environmental policies in high and middle-income countries, little attention to global issues	Regional contrasts between high and low income countries: - High/low land-use change regulation - High/low agricultural productivity - High/low consumption
SSP5	- Relatively low population growth - High economic growth - Strongly reduced inequality, especially across countries - High international trade, regionally specialized production - Rapid technological development - High carbon and energy intensity - Environmental policies locally focused, little concern with global issues	- Medium land-use change regulation - Resource-intensive, rapid increase in agricultural productivity - Material-intensive consumption, high meat consumption

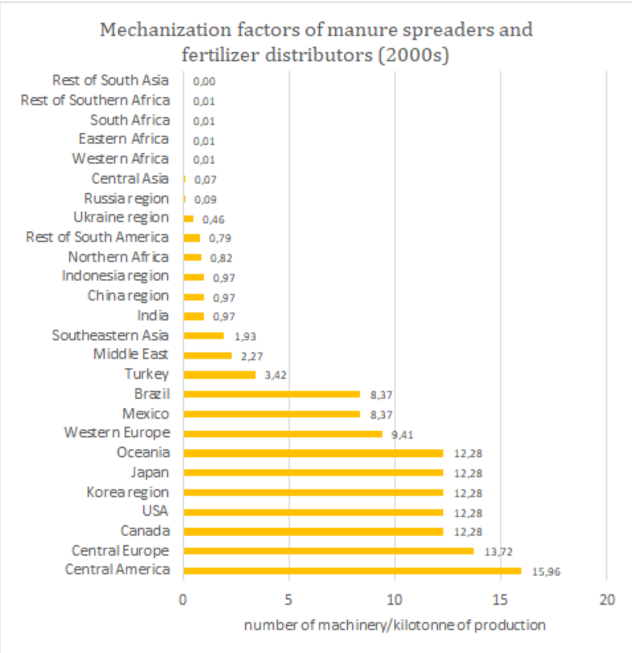
Appendix G

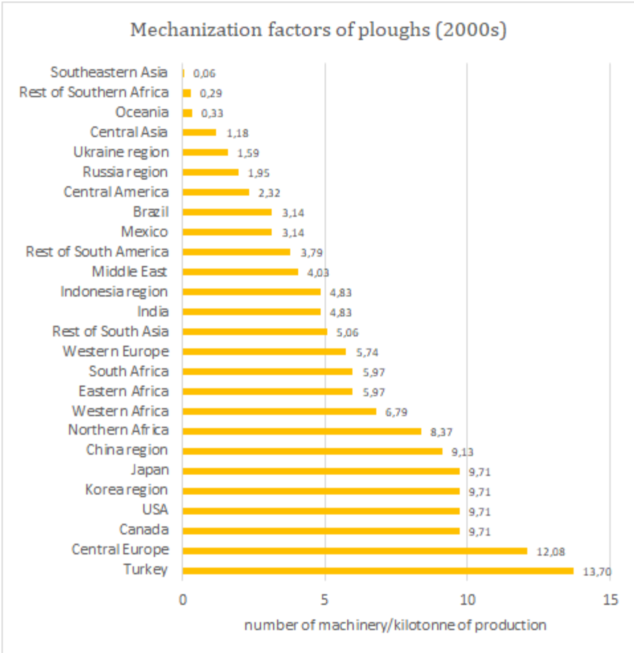

Distribution of the Fresh Weight per Dry Weight Ratios of the 'Other Crops' Produced
(annual production, 26 IMAGE regions, 2000-2018)
Frequency
200
180
160
140
120
100
80
60
40
20
0
1 1,5 2 2,5 3 3,5 4 4,5 5 5,5 6 6,5 7 7,5 8 8,5 9 9,5 10
fresh weight/dry weight

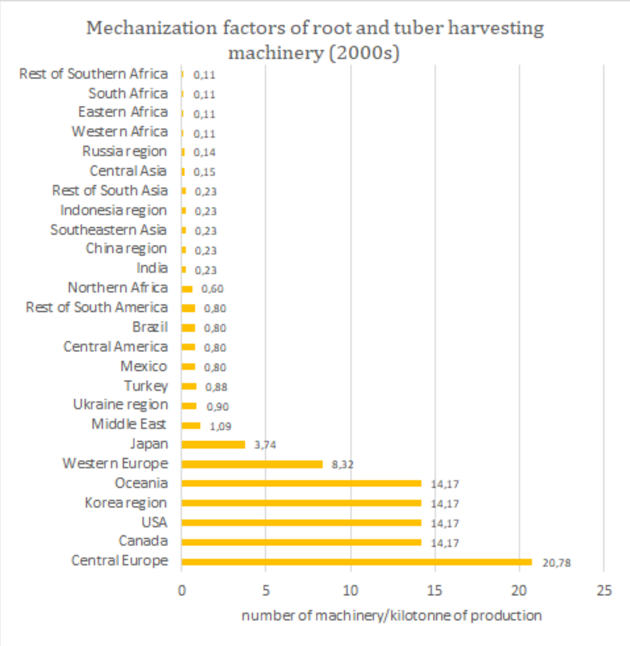
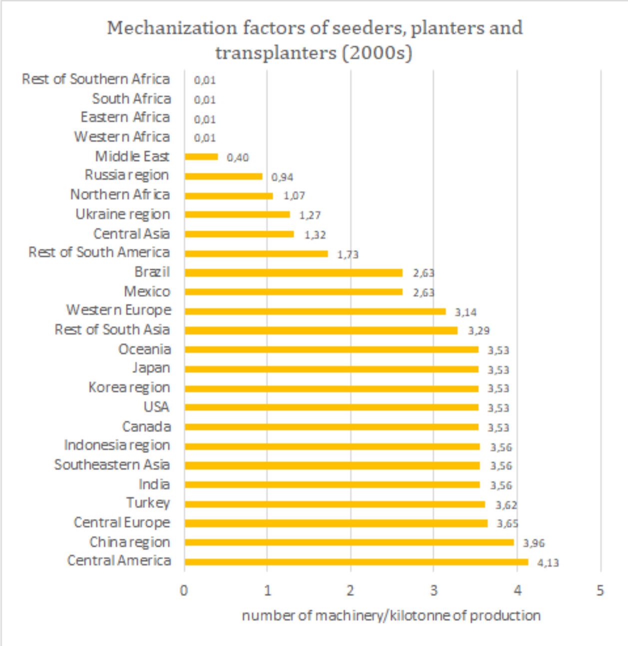
Appendix H


Mechanization factors of combine harvesters (2000s)
Rest of South Asia 0,02
Western Africa 0,03
Rest of Southern Africa 0,34
Turkey 0,36
Eastern Africa 0,51
Rest of South America 0,70
South Africa 0,81
USA 0,94
Middle East 1,29
India 1,50
Central Asia 1,52
Canada 1,64
Northern Africa 1,65
Ukraine region 1,90
Brazil 2,05
Mexico 2,05
Southeastern Asia 2,08
Russia region 2,10
Central Europe 2,75
Indonesia region 3,00
China region 3,52
Western Europe 3,70
Oceania 5,40
Central America 5,44
Korea region 12,34
Japan 82,20
0 20 40 60 80 100
number of machinery/kilotonne of production

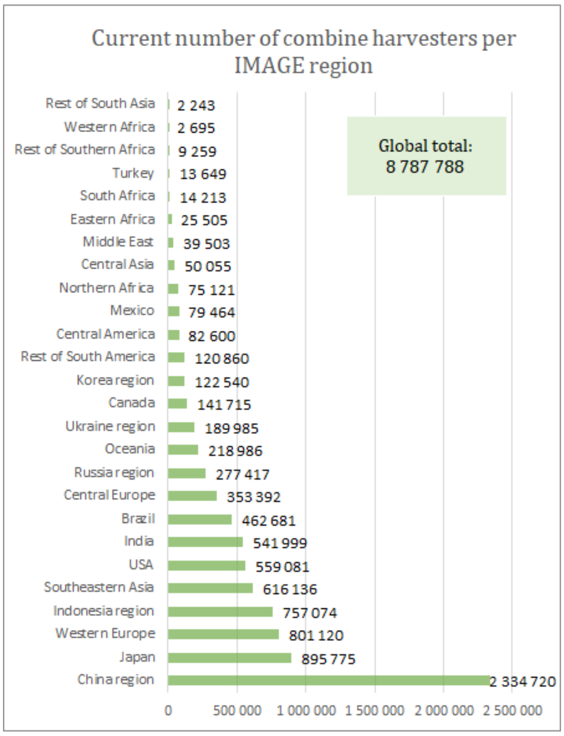

Mechanization factors of pedestrian controlled tractors (2000s)
Rest of Southern Africa 0,00
South Africa 0,08
Western Africa 0,08
Eastern Africa 0,15
Turkey 0,16
Northern Africa 0,26
Central America 0,28
India 0,38
Oceania 0,65
Middle East 0,79
Brazil 0,98
Mexico 0,98
Rest of South America 2,03
Central Asia 2,13
Ukraine region 2,80
Rest of South Asia 2,89
Central Europe 6,31
Indonesia region 6,77
Western Europe 7,56
Russia region 9,21
Southeastern Asia 9,54
USA 10,04
Canada 10,04
China region 10,82
Japan 26,59
Korea region 37,57
0 10 20 30 40
number of tractors/kilotonne of production

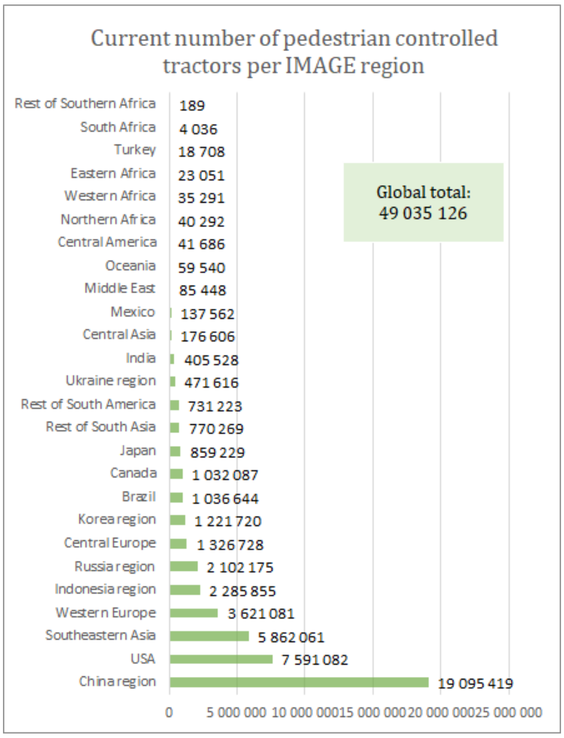

Mechanization factors of manure spreaders and fertilizer distributors (2000s)
Rest of South Asia 0,00
Rest of Southern Africa 0,01
South Africa 0,01
Eastern Africa 0,01
Western Africa 0,01
Central Asia 0,07
Russia region 0,09
Ukraine region 0,46
Rest of South America 0,79
Northern Africa 0,82
Indonesia region 0,97
China region 0,97
India 0,97
Southeastern Asia 1,93
Middle East 2,27
Turkey 3,42
Brazil 8,37
Mexico 8,37
Western Europe 9,41
Oceania 12,28
Japan 12,28
Korea region 12,28
USA 12,28
Canada 12,28
Central Europe 13,72
Central America 15,96
0 5 10 15 20
number of machinery/kilotonne of production

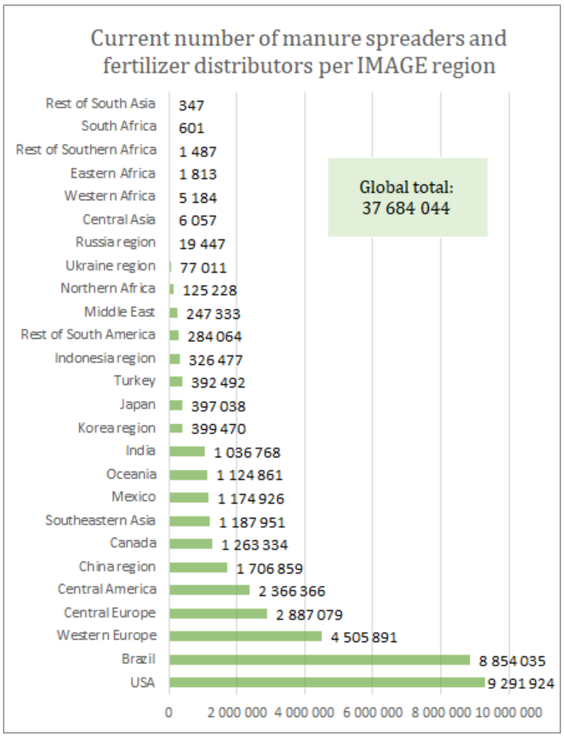

Mechanization factors of ploughs (2000s)
Southeastern Asia 0,06
Rest of Southern Africa 0,29
Oceania 0,33
Central Asia 1,18
Ukraine region 1,59
Russia region 1,95
Central America 2,32
Brazil 3,14
Mexico 3,14
Rest of South America 3,79
Middle East 4,03
Indonesia region 4,83
India 4,83
Rest of South Asia 5,06
Western Europe 5,74
South Africa 5,97
Eastern Africa 5,97
Western Africa 6,79
Northern Africa 8,37
China region 9,13
Japan 9,71
Korea region 9,71
USA 9,71
Canada 9,71
Central Europe 12,08
Turkey 13,70
0 5 10 15
number of machinery/kilotonne of production

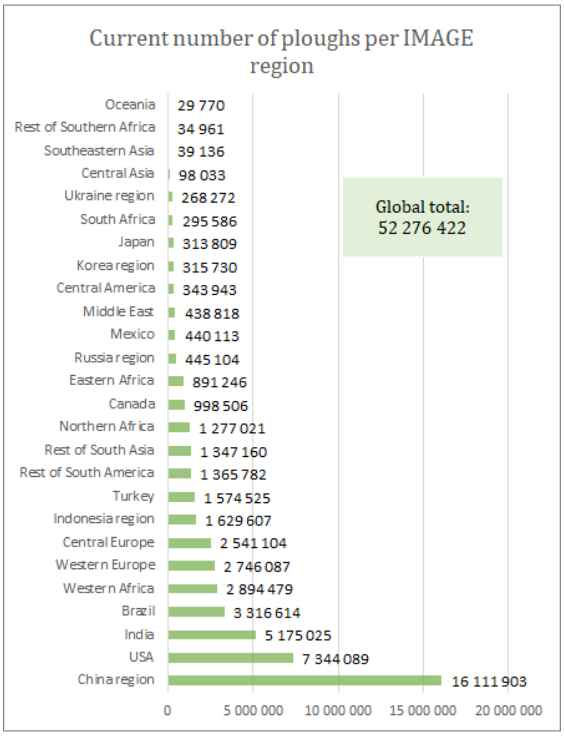

Mechanization factors of root and tuber harvesting machinery (2000s)
Rest of Southern Africa
South Africa
Eastern Africa
Western Africa
Russia region
Central Asia
Rest of South Asia
Indonesia region
Southeastern Asia
China region
India
Northern Africa
Rest of South America
Brazil
Central America
Mexico
Turkey
Ukraine region
Middle East
Japan
Western Europe
Oceania
Korea region
USA
Canada
Central Europe
0,11
0,11
0,11
0,11
0,14
0,15
0,23
0,23
0,23
0,23
0,23
0,60
0,80
0,80
0,80
0,80
0,88
0,90
1,09
3,74
8,32
14,17
14,17
14,17
14,17
20,78
0
5
10
15
20
25
number of machinery/kilotonne of production

Mechanization factors of seeders, planters and transplanters (2000s)
Rest of Southern Africa
South Africa
Eastern Africa
Western Africa
Middle East
Russia region
Northern Africa
Ukraine region
Central Asia
Rest of South America
Brazil
Mexico
Western Europe
Rest of South Asia
Oceania
Japan
Korea region
USA
Canada
Indonesia region
Southeastern Asia
India
Turkey
Central Europe
China region
Central America
0,01
0,01
0,01
0,01
0,40
0,94
1,07
1,27
1,32
1,73
2,63
2,63
3,14
3,29
3,53
3,53
3,53
3,53
3,53
3,56
3,56
3,56
3,62
3,65
3,96
4,13
0
1
2
3
4
5
number of machinery/kilotonne of production

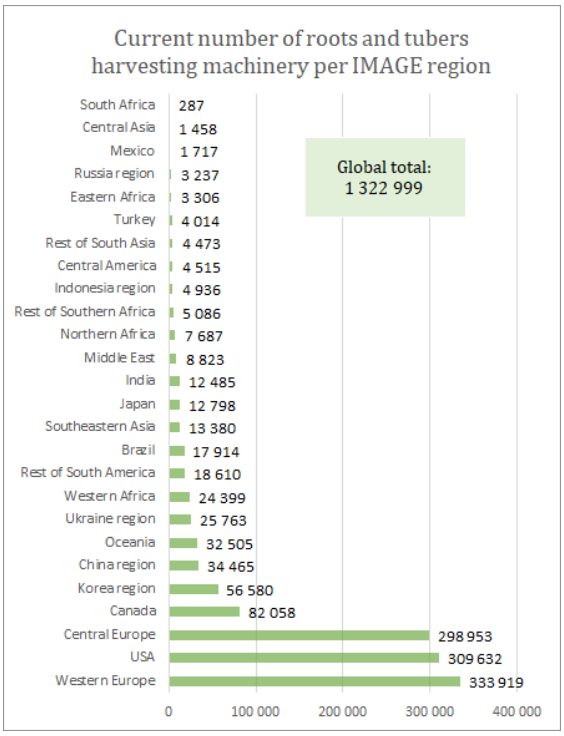
Appendix I


Current number of combine harvesters per IMAGE region
Global total: 8 787 788
Rest of South Asia 2 243
Western Africa 2 695
Rest of Southern Africa 9 259
Turkey 13 649
South Africa 14 213
Eastern Africa 25 505
Middle East 39 503
Central Asia 50 055
Northern Africa 75 121
Mexico 79 464
Central America 82 600
Rest of South America 120 860
Korea region 122 540
Canada 141 715
Ukraine region 189 985
Oceania 218 986
Russia region 277 417
Central Europe 353 392
Brazil 462 681
India 541 999
USA 559 081
Southeastern Asia 616 136
Indonesia region 757 074
Western Europe 801 120
Japan 895 775
China region 2 334 720
0 500 000 1 000 000 1 500 000 2 000 000 2 500 000

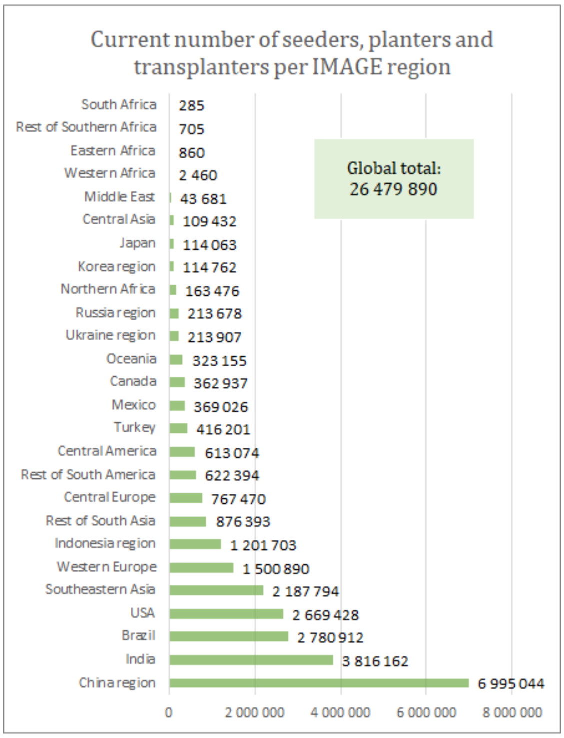

Current number of pedestrian controlled tractors per IMAGE region
Global total: 49 035 126
Rest of Southern Africa 189
South Africa 4 036
Turkey 18 708
Eastern Africa 23 051
Western Africa 35 291
Northern Africa 40 292
Central America 41 686
Oceania 59 540
Middle East 85 448
Mexico 137 562
Central Asia 176 606
India 405 528
Ukraine region 471 616
Rest of South America 731 223
Rest of South Asia 770 269
Japan 859 229
Canada 1 032 087
Brazil 1 036 644
Korea region 1 221 720
Central Europe 1 326 728
Russia region 2 102 175
Indonesia region 2 285 855
Western Europe 3 621 081
Southeastern Asia 5 862 061
USA 7 591 082
China region 19 095 419
0 5 000 000 10 000 000 15 000 000 20 000 000 25 000 000


Current number of manure spreaders and fertilizer distributors per IMAGE region
Global total: 37 684 044
Rest of South Asia 347
South Africa 601
Rest of Southern Africa 1 487
Eastern Africa 1 813
Western Africa 5 184
Central Asia 6 057
Russia region 19 447
Ukraine region 77 011
Northern Africa 125 228
Middle East 247 333
Rest of South America 284 064
Indonesia region 326 477
Turkey 392 492
Japan 397 038
Korea region 399 470
India 1 036 768
Oceania 1 124 861
Mexico 1 174 926
Southeastern Asia 1 187 951
Canada 1 263 334
China region 1 706 859
Central America 2 366 366
Central Europe 2 887 079
Western Europe 4 505 891
Brazil 8 854 035
USA 9 291 924
0 2 000 000 4 000 000 6 000 000 8 000 000 10 000 000


Current number of ploughs per IMAGE region
Global total: 52 276 422
Oceania 29 770
Rest of Southern Africa 34 961
Southeastern Asia 39 136
Central Asia 98 033
Ukraine region 268 272
South Africa 295 586
Japan 313 809
Korea region 315 730
Central America 343 943
Middle East 438 818
Mexico 440 113
Russia region 445 104
Eastern Africa 891 246
Canada 998 506
Northern Africa 1 277 021
Rest of South Asia 1 347 160
Rest of South America 1 365 782
Turkey 1 574 525
Indonesia region 1 629 607
Central Europe 2 541 104
Western Europe 2 746 087
Western Africa 2 894 479
Brazil 3 316 614
India 5 175 025
USA 7 344 089
China region 16 111 903
0 5 000 000 10 000 000 15 000 000 20 000 000



Current number of roots and tubers harvesting machinery per IMAGE region
Global total: 1 322 999
South Africa 287
Central Asia 1 458
Mexico 1 717
Russia region 3 237
Eastern Africa 3 306
Turkey 4 014
Rest of South Asia 4 473
Central America 4 515
Indonesia region 4 936
Rest of Southern Africa 5 086
Northern Africa 7 687
Middle East 8 823
India 12 485
Japan 12 798
Southeastern Asia 13 380
Brazil 17 914
Rest of South America 18 610
Western Africa 24 399
Ukraine region 25 763
Oceania 32 505
China region 34 465
Korea region 56 580
Canada 82 058
Central Europe 298 953
USA 309 632
Western Europe 333 919
0
100 000
200 000
300 000
400 000



Current number of seeders, planters and transplanters per IMAGE region
Global total: 26 479 890
South Africa 285
Rest of Southern Africa 705
Eastern Africa 860
Western Africa 2 460
Middle East 43 681
Central Asia 109 432
Japan 114 063
Korea region 114 762
Northern Africa 163 476
Russia region 213 678
Ukraine region 213 907
Oceania 323 155
Canada 362 937
Mexico 369 026
Turkey 416 201
Central America 613 074
Rest of South America 622 394
Central Europe 767 470
Rest of South Asia 876 393
Indonesia region 1 201 703
Western Europe 1 500 890
Southeastern Asia 2 187 794
USA 2 669 428
Brazil 2 780 912
India 3 816 162
China region 6 995 044
0
2 000 000
4 000 000
6 000 000
8 000 000

Appendix J

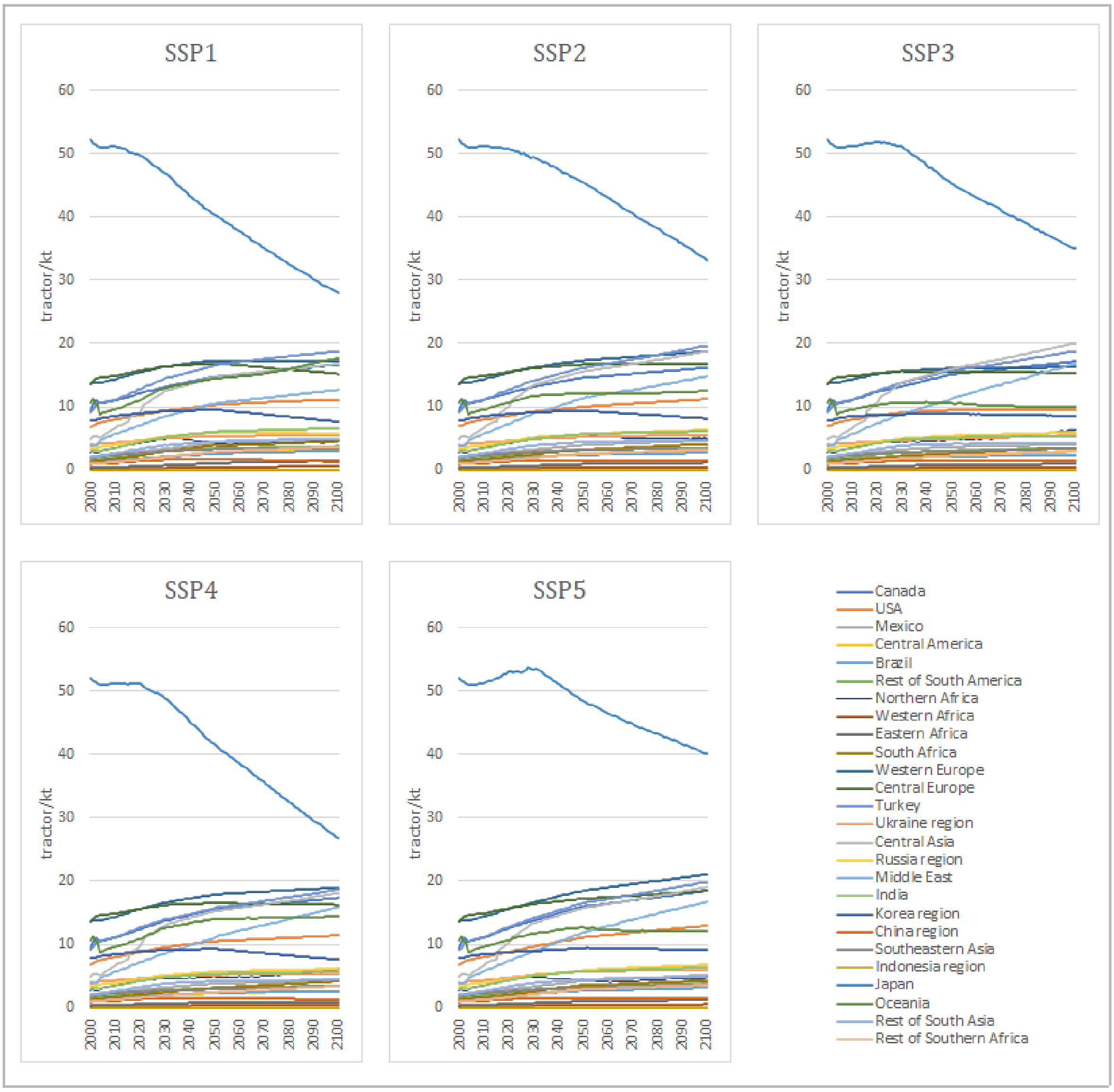
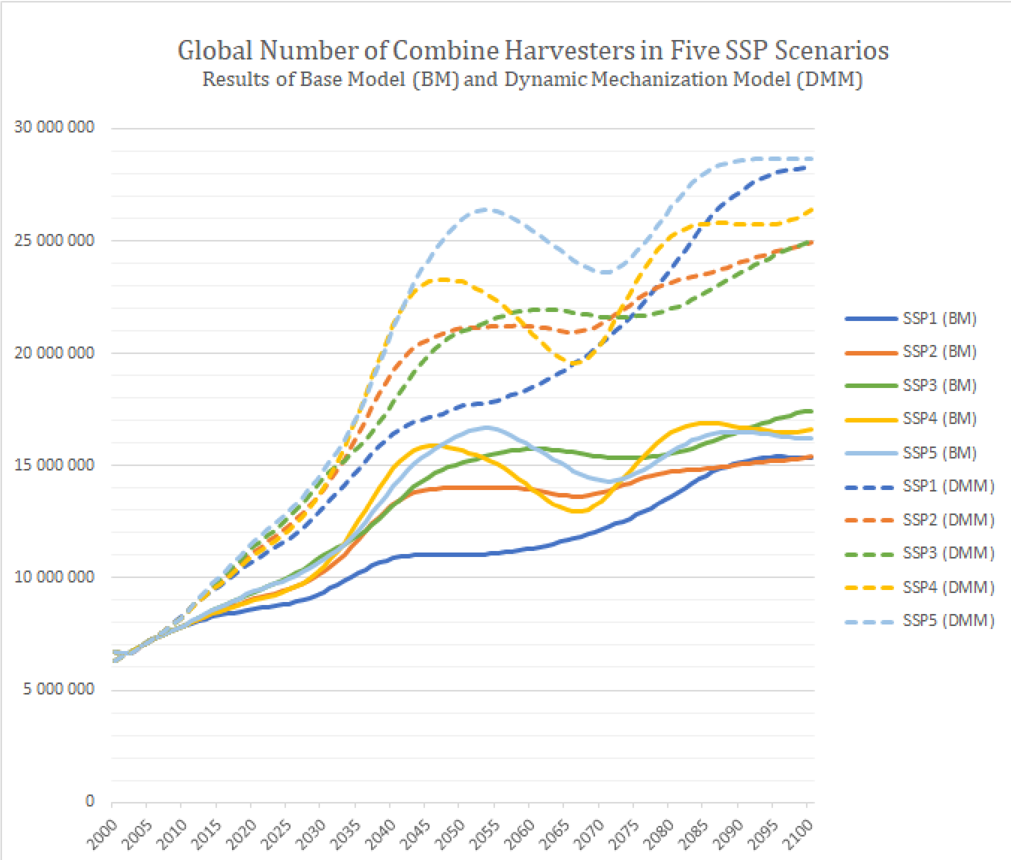
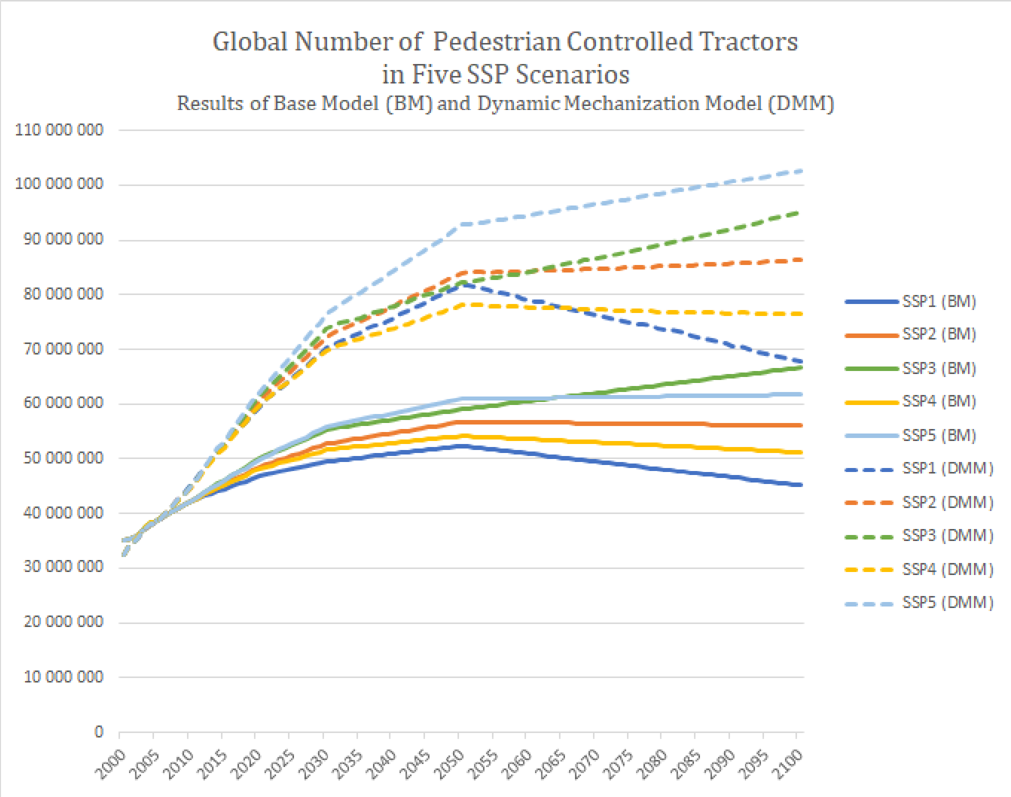


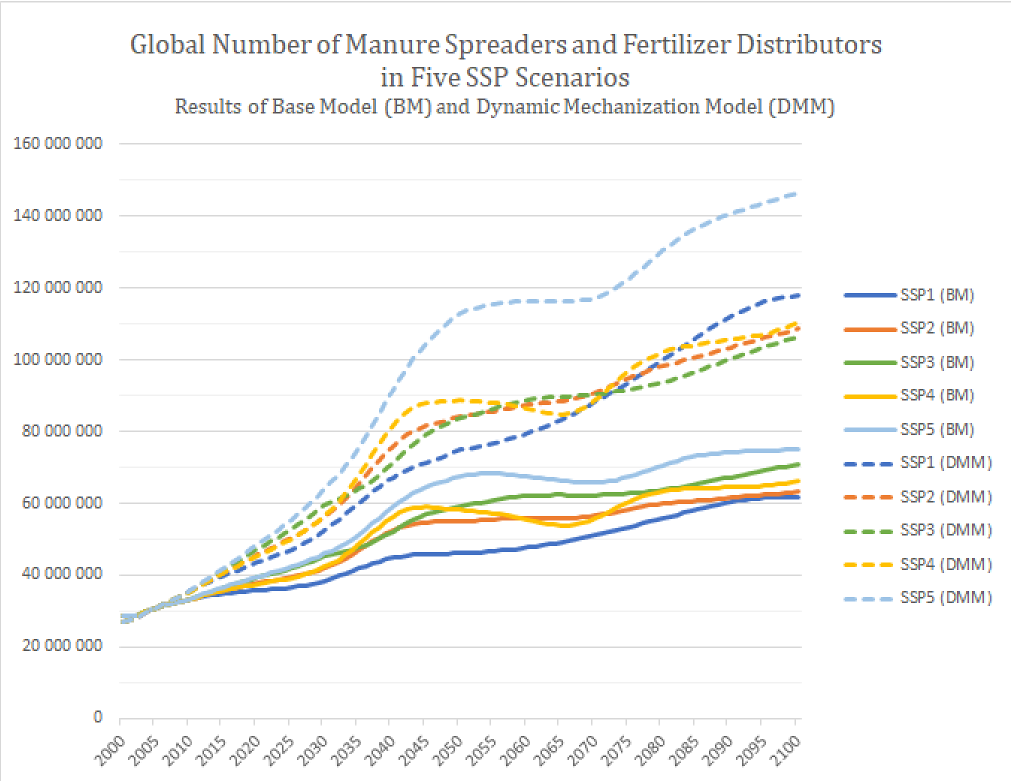
Figure: Dynamic mechanization factors of tractors (number/kt) in five SSP scenarios

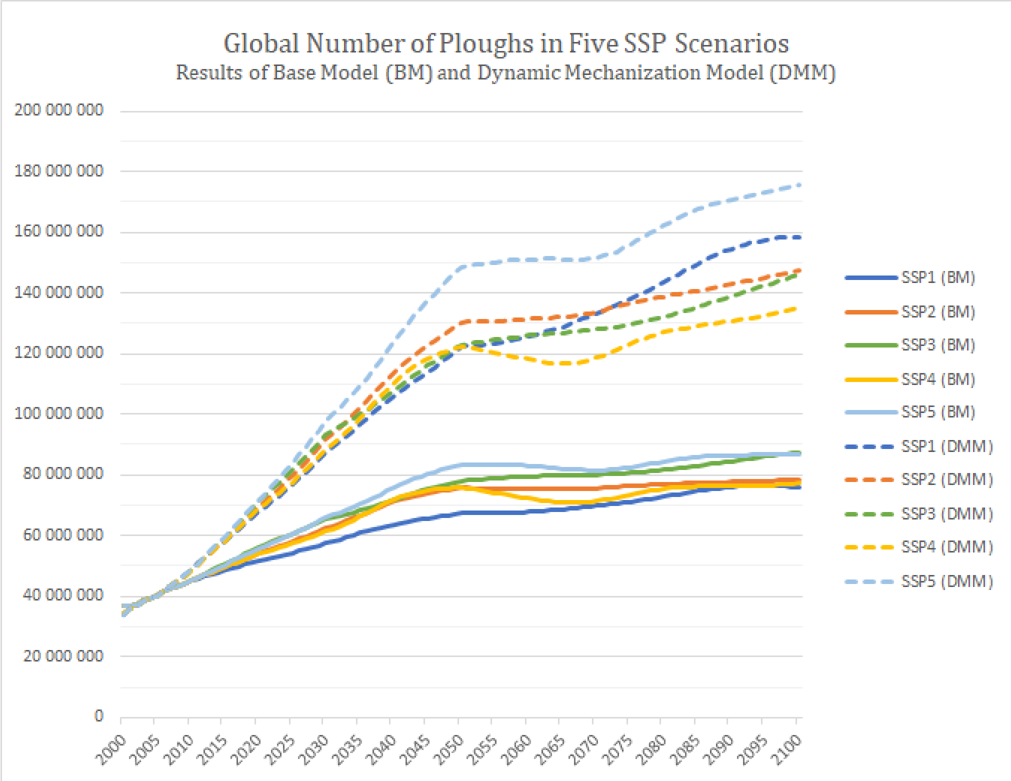
Appendix K

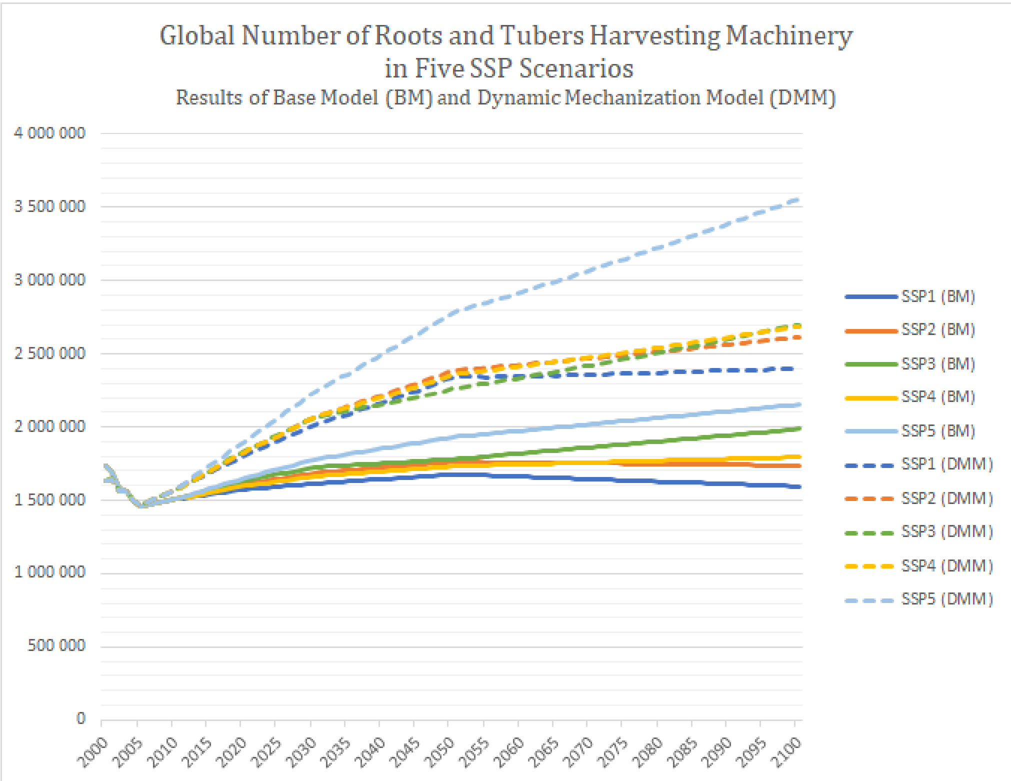


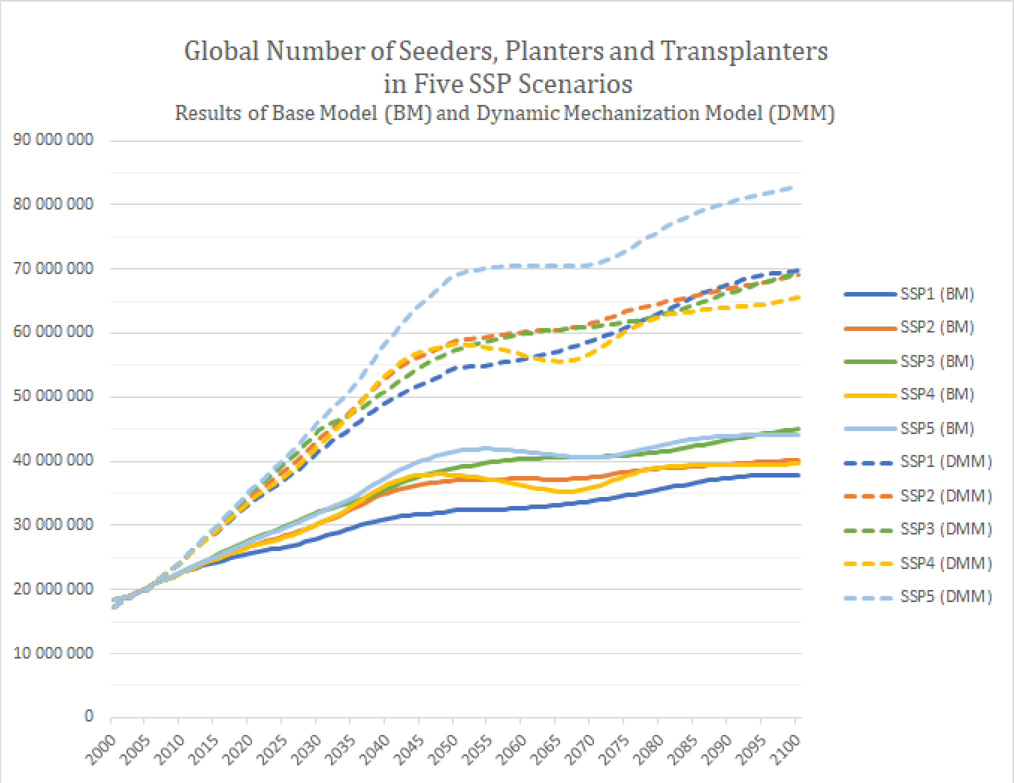
Global Number of Combine Harvesters in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
30 000 000
25 000 000
20 000 000
15 000 000
10 000 000
5 000 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)


Global Number of Pedestrian Controlled Tractors
in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
110 000 000
100 000 000
90 000 000
80 000 000
70 000 000
60 000 000
50 000 000
40 000 000
30 000 000
20 000 000
10 000 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)


Global Number of Manure Spreaders and Fertilizer Distributors
in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
160 000 000
140 000 000
120 000 000
100 000 000
80 000 000
60 000 000
40 000 000
20 000 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)

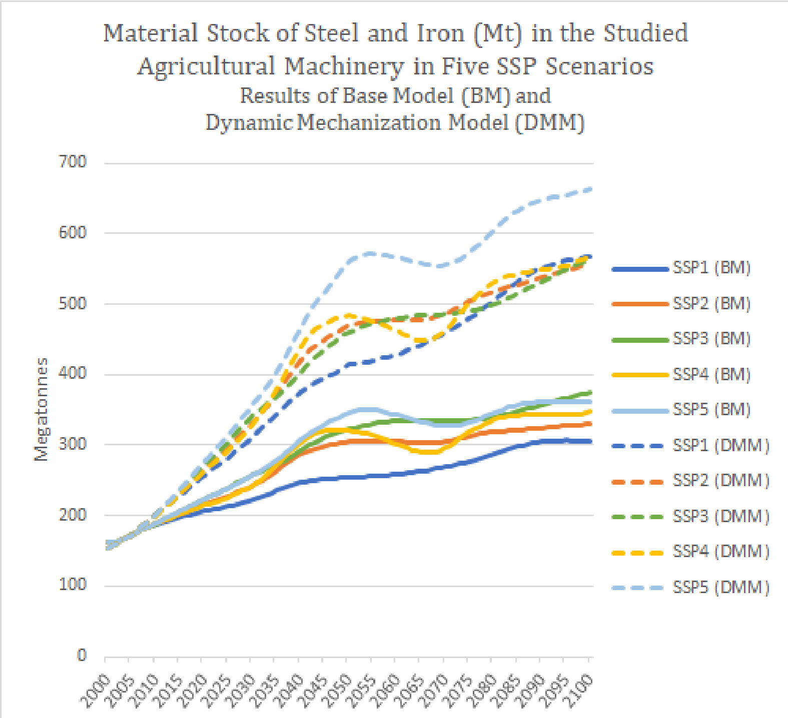

Global Number of Ploughs in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
200 000 000
180 000 000
160 000 000
140 000 000
120 000 000
100 000 000
80 000 000
60 000 000
40 000 000
20 000 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)


Global Number of Roots and Tubers Harvesting Machinery
in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
4 000 000
3 500 000
3 000 000
2 500 000
2 000 000
1 500 000
1 000 000
500 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)

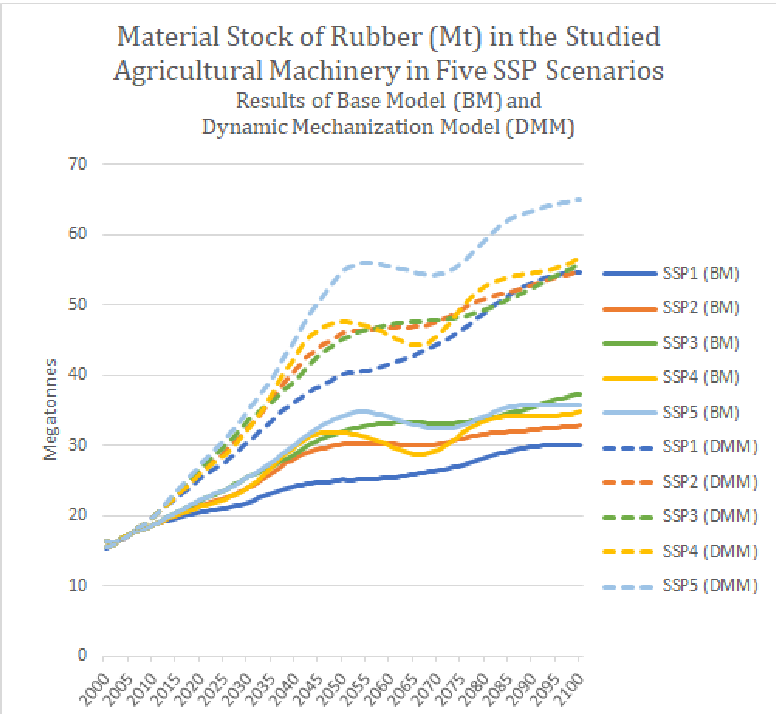


Global Number of Seeders, Planters and Transplanters
in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
90 000 000
80 000 000
70 000 000
60 000 000
50 000 000
40 000 000
30 000 000
20 000 000
10 000 000
0
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)

Appendix L



Material Stock of Steel and Iron (Mt) in the Studied Agricultural Machinery in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
Megatonnes
0
100
200
300
400
500
600
700
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)



Material Stock of Rubber (Mt) in the Studied Agricultural Machinery in Five SSP Scenarios
Results of Base Model (BM) and Dynamic Mechanization Model (DMM)
Megatonnes
0
10
20
30
40
50
60
70
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
2055
2060
2065
2070
2075
2080
2085
2090
2095
2100
SSP1 (BM)
SSP2 (BM)
SSP3 (BM)
SSP4 (BM)
SSP5 (BM)
SSP1 (DMM)
SSP2 (DMM)
SSP3 (DMM)
SSP4 (DMM)
SSP5 (DMM)

Appendix M

Trend analysis of historical mechanization factor values

The development of the 'dynamic mechanization model' started with checking the historical values of mechanization factors for any potential trends that could be extrapolated into the future. However, based on the past developments of the regional mechanization factors of tractors (as shown in the figure), it is difficult to detect any constant trends that could be assumed to continue in the future. In fact, when extrapolated into the future based on the historical trends (using the regional trendlines from 1960s to 2000s, or from 1990s to 2000s), the mechanization factors of some of the regions would eventually reach negative, or otherwise unreasonable, values.

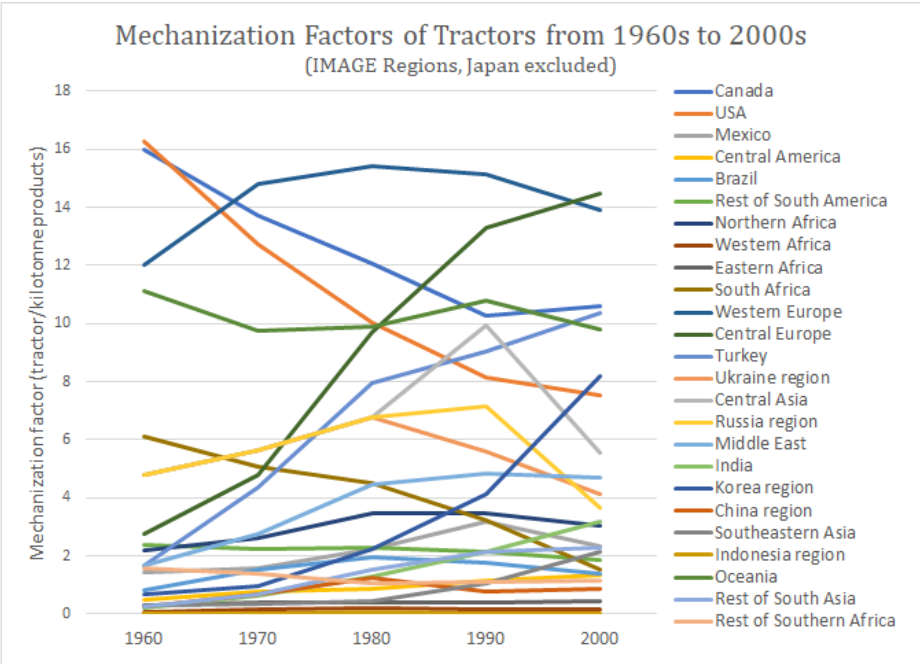


Figure: Regional mechanization factors from 1960s to 2000s

In many industrialized regions, the mechanization factor growth has stabilized over time, and sometimes started to decrease. This increasing production per machine could be explained by productivity and efficiency improvements. In many of the other regions, the mechanization factors have been growing at different rates in the past decades and started their acceleration at different times. It might be possible that all of the world regions are going through a similar trajectory of first increasing mechanization, then a stabilization of the growth, and finally decreasing mechanization levels. However, based on the historical data, the timing, speed of growth and possible stabilization levels of mechanization vary significantly between different regions, and are likely to vary in the future as well. Therefore, even if the regions were indeed following a somewhat similar development pattern of mechanization (which might not be the case), it would be extremely hard to extrapolate any of the past trends into the future as such.