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Quantifying the relationship between the waste footprint and environmental impact of products

DENIZ DEMIRER DEMIR

KTH ROYAL INSTITUTE OF TECHNOLOGY
SCHOOL OF ARCHITECTURE AND THE BUILT ENVIRONMENT

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Kvantifierat förhållande mellan avfallsfotavtryck och miljöpåverkan av produkter

Keywords: Product waste footprint, life cycle assessment, circular economy, environmental decision making, environmental sustainability

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Author: Deniz Demirer Demir

Supervisor: Rafael Laurenti

Examiner: Göran Finnveden

Department of Sustainable Development, Environmental Science and Engineering

School of Architecture and the Built Environment

KTH Royal Institute of Technology

Abstract

Despite the increasing public awareness about the waste that is created while consuming and disposing of products, the waste created by the raw material extraction and production phases is usually invisible to the consumers. In this respect, a product waste footprint indicator based on the life cycle perspective was recently proposed to address this knowledge gap, offering a better understanding of the environmental consequences of human consumption behaviour.

Using product waste footprint as an environmental indicator would be limited in capturing the full suite of life cycle environmental damages associated with a product. On the other hand, the strict interpretation of life cycle assessment is quite technical, costly and ineffective for communicating with broader audiences. Therefore, there is still a need for simpler and less costly options, such as the product waste footprint, for environmental decision making and communication.

The aim of this study is to find out if product waste footprint is a good proxy for the life cycle environmental impacts for different products. Data for 1400+ products from different product categories (agricultural, forestry, animal products; basic metal and alloys; chemicals; glass and other non-metallic products; machinery; ores, minerals and fuels; processed biobased products) were collected from the Ecoinvent 3.5 cut-off database using Brightway2 LCA framework. The results from linear regression analyses suggest that there is indeed a statistically significant and positive relationship between the product waste footprint and environmental damages to ecosystem diversity, human health, and resource availability. The regression models can explain up to more than 90% of the variance in environmental damages and they predict around 0.8% increase in environmental damages for each 1.0% increase in the waste footprints.

The strong association between the waste footprints and environmental damage indicators suggest that the waste footprint is a strong candidate to be part of the environmental sustainability communication between product companies, customers and other decision makers in the product supply chains. While the waste footprint does not aim to replace other environmental indicators, it can be used to increase customer awareness on the invisible waste, influence consumption behaviour and to promote circular economy.

Sammanfattning

Trots allmänt ökad medvetenhet om avfallet vid konsumtion och bortskaffande av produkter, är avfall från råmaterialutvinning och produktionsfaser vanligtvis osynligt för konsumenterna. I detta avseende föreslogs nyligen en avfallsindikator för produktavfall baserat på livscykeltänkande för att hantera detta kunskapsgap, vilket ger en bättre förståelse för miljökonsekvenserna av människors konsumtionsbeteende.

Att använda avfallsfotavtryck som en miljöindikator skulle vara begränsande för att fånga upp en produkts totala miljöpåverkan. Å andra sidan är den strikta tolkningen av livscykelbedömningen ganska teknisk, kostsam och ineffektiv för att kommunicera med bredare publik. Därför kvarstår behovet av enklare och billigare alternativ som PWF-indikatorn för miljöbeslut och kommunikation.

Syftet med denna studie är att ta reda på om avfallsfotavtryck är en bra proxy för livscykelns miljöpåverkan för olika produkter. Data för 1400+ produkter från olika produktkategorier (jordbruk, skogsbruk, animaliska produkter, basmetall och legeringar, kemikalier, glas och andra icke-metalliska produkter; maskiner; malmer, mineraler och bränslen; bearbetade biobaserade produkter) samlades in från Ecoinvent 3.5 cut-off databas med Brightway2 LCA-ramverk. Resultaten från linjära regressionsanalyser tyder på att det finns ett statistiskt signifikant och positivt samband mellan avfallsfotavtryck och miljöskador på ekosystemets mångfald, människors hälsa och resurstillgänglighet. Regressionsmodellerna kan förklara upp till 90% av variansen i miljöskador och de förutsäger upp till runt 0,8% ökning av miljöskadorna för varje 1,0% ökning av avfallets fotavtryck.

Den starka kopplingen mellan avfallsfotavtryck och miljöskadeangivare tyder på att avfallets fotavtryck är en stark kandidat för att vara en del av miljöhållbarhetskommunikationen mellan produktföretag, kunder och andra beslutsfattare i produktförsörjningskedjorna. Även om avfallets fotavtryck inte syftar till att ersätta andra miljöindikatorer, kan det användas för att öka kundernas medvetenhet om det osynliga avfallet, påverka konsumtionsbeteendet och för att främja cirkulär ekonomi.

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1. Introduction

1.1. Background

Although there is an increasing public awareness about the waste that is created by using and disposing products, the waste that is associated with the raw material extraction and production phases is usually invisible to the consumers. To account for the waste from those earlier phases of the product life cycle, the concept of pre-consumer waste footprint was previously studied at regional and sectoral levels, and a recent study has proposed the pre-consumer waste footprint as an environmental indicator on product level (Laurenti, Moberg and Stenmarck, 2017). Accounting for such a pre-consumer waste footprint can be a simple yet powerful tool to communicate the total waste associated with each product that we use or consume. In fact, a popular science report published by IVL Swedish Environmental Research Institute revealed how much waste is generated to produce some of the everyday items, and this report has received great media attention and public engagement in Sweden (Laurenti and Stenmarck, 2015).

In addition to several existing emission or resource based footprints, such as carbon footprint or water footprint, a pre-consumer waste footprint offers a new perspective on the environmental consequences of human consumption behaviour. However, like these other footprint based indicators, it is also limited in fully capturing the environmental damages associated with a given product by itself. Laurenti, Martin, and Stenmarck (2018) have conducted a stakeholder consultation to develop the communication of the waste footprint in the context of circular economy, during which some life cycle assessment (LCA) practitioners have expressed concerns about the sufficiency of the indicator in conveying the complex environmental impacts of a product. These concerns were, for example, favouring quantity over quality (a smaller amount of hazardous waste might cause a larger damage than a larger amount of non-hazardous waste), and that what happens with the waste (rather than the waste itself) is important to determine the actual environmental damage pathways and resulting impacts, and that the industries might misuse such an indicator to greenwash their products.

The potential limitations of waste footprint in capturing the total environmental impact is understandable and similar greenwashing attempts are certainly not unprecedented. However, the strict interpretation of life cycle assessment is quite technical and costly to do for many products, and ineffective for communicating the results with a broad audience. Therefore, the need for simpler and less costly metrics for decision making remains. In this regard, the concerns of life cycle assessment experts can be addressed by examining the relationship between the product waste footprint and the life cycle environmental impacts for different products and processes, and hence show the extent to which this indicator might serve as a proxy. The results would identify the potential of using product waste footprint as an indicator for common decision making scenarios that consumers, policy makers, product designers and engineers face every day.

1.2. Aim, objectives and research questions

The overarching aim of this project is to assess whether the life cycle product waste footprint is a good proxy for the life cycle environmental impacts for different products.

The objectives of this study are:

- to develop and apply a computational method to calculate the life cycle product waste footprint and life cycle environmental impact for a large number of products
- to build linear regression models to quantify the relationship between product waste footprint and the life cycle environmental impacts
- to discover the potential of product waste footprint in predicting a product's life cycle environmental damage to ecosystem diversity, human health and resource availability for different waste types (e.g. hazardous versus non-hazardous) and waste treatment processes (e.g. waste to material recovery, incineration etc.)

2. Methodology

The study is carried out in three phases to achieve the aim and objectives, going from qualitative assessments to quantitative assessments. These three phases are literature review, data collection and analysis. Figure 1 lists the main activities associated with each of the three phases.

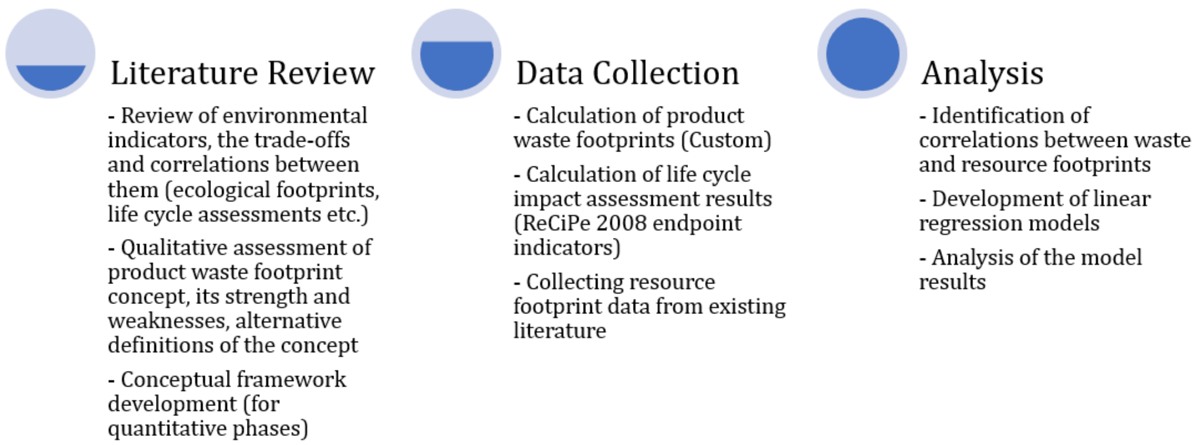

Figure 1. Three phase approach

The main activities and methodological choices for the above three phases are further detailed in the corresponding sections below.

2.1. Literature review methodology

The literature review is conducted to provide an overview of the types of indicators that are used for environmental decision making (e.g. ecological footprints, life cycle assessments), the trade-offs to consider while choosing the indicators to use, and the correlations between indicators that are already identified by the previous research. For these purposes, scientific literature was searched mainly through the online databases provided by KTH Library, and course books and notes were used. Furthermore, life cycle assessment practitioner blogs were used as another reference point to understand the benefits and challenges of common life cycle assessment practices from the industry. In this phase, the product waste footprint concept is studied in detail along with its strengths and weaknesses for different scenarios or users, which are identified by the previous studies. Similarities/differences of product waste footprints with the common resource footprints are assessed to derive alternative definitions of the concept. The learnings from the literature findings are later synthesized and used to develop a conceptual framework which would be the basis for the subsequent quantitative phases.

2.2. Data collection methodology

Following the literature review, the data collection phase addresses the compilation of necessary quantitative data which is defined in the conceptual framework. The data include the waste footprints, life cycle impact assessment results, and other supplementary data and characteristics associated with each product in the scope of this study. This phase relies on secondary data sources, in particular the Ecoinvent 3.5 cut-off database documented by Wernet et al. (2016), as well as the product resource footprints calculated and used by the study of Steinmann et al. (2017).

The products which are included in the scope of this study are chosen from product datasets available within the Ecoinvent 3.5 cut-off database, which is also the basis for the calculations of waste footprint and life cycle impact assessment results. Since the statistical analyses in the subsequent phase would require data for a large number of products, the data from this database was processed using Python 3.6 programming language on the open source LCA framework Brightway2 (Mutel, 2017). In comparison to traditional LCA software like SimaPro or openLCA, this has allowed for a larger degree of freedom in accessing and manipulating the data, as well as carrying out the calculations in bulk, i.e. iterating through many products in the database at once.

In order to collect the waste footprint information for the products in scope, custom computational methods were developed. A cradle-to-grave approach is followed in these calculations, i.e. considering all waste that is generated from the raw material extraction to the disposal of the product. Ecoinvent 3.5 cut-off database exclusively classifies all products and materials as either an allocatable, recyclable or waste product (Ecoinvent, n.d.); and therefore, allows for easy identification of waste generated at each step of the production processes. The waste footprint calculations in this study uses this classification and only accounts for the products/materials which are classified as waste by Ecoinvent. More details about the data structure of Ecoinvent datasets, choices regarding the product and waste classifications, and the custom computational methods for waste footprint calculation are further presented under the data collection section.

When it comes to calculating the total environmental damage of a product, on the other hand, there are several established life cycle impact assessment methods. While these different impact assessment methods can give different results, there is still a level of standardization, particularly for the *process* of the life cycle assessment. According to Curran (2015), the process for conducting a life cycle assessment starts with goal and scope definition which sets the purpose and boundaries for the study. This is followed by an inventory analysis phase during which material and energy input and outputs are collected for each step of the product's life cycle. Next, life cycle impact assessment phase aims to translate this *inventory* (e.g. 0.3 kg of methane emissions) to *impacts* on a certain category (e.g. global warming potential) via chosen characterization factors (e.g., 25 CO_2-equivalents per each kg of methane; hence, a total of 0.75 CO_2-equivalents contribution to global warming potential would be calculated). The impact assessment is complete once all inputs/outputs are characterized for the impact categories chosen. Finally, and throughout all these steps, the results are analysed and interpreted.

Certain key elements can differ for each life cycle assessment and require methodological decisions already while setting the goal and scope of the study. The main decisions impacting the environmental damage calculations of this study are the following:

1. Functional unit: LCA calculations are done on the basis of specific functions that a product or service satisfies. This can be challenging when considering the secondary utilities of products, and some practitioners consider the economic values of them (Horne, Grant and Verghese, 2009). In this study, the variety of products certainly would not allow for establishing a common ground across all products on the basis of product functionalities; however, there is still a need to normalize the results to a common unit to avoid arbitrary distortions in the statistical analysis. The alternatives considered were establishing the functional unit based on mass (e.g. environmental impact per kg of products) or price (e.g. environmental impact per € of products' price). For this study, the convention set by the previous research, e.g. Huijbregts et al. (2010) and Steinmann et al. (2017), was followed which is to set the functional unit as 1 kg of product. This also allowed to collect supplementary data on product resource footprints from the previous research.

2. System boundaries: The boundaries of an LCA, in broad terms, addresses the life cycle stages included in or excluded from the study as well as geographical boundaries (Curran, 2015). This study favours the cradle-to-grave approach including equipment, infrastructure or service (e.g. electricity, transportation etc.) requirements for manufacturing and supplying a product to the market. In terms of geographical boundaries, the data which represents the global average best is preferred over local alternatives.

3. Impact assessment methods: There are several established impact assessment methods (e.g. IMPACT2002+, TRACI, CML-IA, ReCiPe, ILCD etc.), all of which come with a set of recommended impact categories and characterization factors (Curran, 2015). There is no single answer about which of them must be used in a study and researchers need to choose the method that fits best with the goals of their study. This study uses ReCiPe 2008 method as implemented in Brightway2 considering both the

fit-for-purpose and the availability within the timeframe of this work. In particular, the following aspects contributed to this choice:

a. ReCiPe provides various indicators as opposed to more specific methods such as IPCC which focuses on climate change. Furthermore, it includes harmonized categories, in other words, offers not only several midpoint indicators, but also endpoint indicators (RIVM, n.d.).

b. According to a survey among LCA practitioners, ReCiPe was found to be the mostly used LCIA method (iPoint, 2018). Such popularity has the potential to allow future comparison of results beyond the scope of this thesis. In fact, this thesis provides an opportunity to compare the results with the study of Steinmann et al. (2017), which influenced the design of this study and used as a secondary data source.

c. ReCiPe is one of the most recently developed methods and considered to be an improvement over earlier methods such as CML 2000 and Eco-indicator 99. (PRé, n.d.)

d. ReCiPe is updated with a newer method in 2016, however, this was not implemented in the Ecoinvent database (and hence neither in Brightway2) during the thesis period. Since the timeframe of this thesis did not allow for implementing these updates on Brightway2, the ReCiPe 2008 method was chosen instead.

The ReCiPe 2008 method measures the environmental performance in 18 midpoint categories and 3 endpoint categories (RIVM, n.d.). The midpoint indicators carry less assumptions and uncertainty, but the endpoint indicators can provide more intuitive metrics (Curran, 2015). With their more intuitive representation of environmental damages, the endpoint indicators can be more suitable for communicating with broader audiences. In this respect, endpoint indicators are found more consistent with the primary motivation of the emergence of product waste footprint as an environmental indicator. Consequently, ReCiPe 2008 endpoint indicators are chosen to calculate the environmental damages of products in this study:

1. Damage to ecosystem diversity: This endpoint indicator is measured as the loss of species during a year, indicated with the unit *species.yr*. The midpoint indicators contributing to the calculation of damage to ecosystem diversity are climate change, terrestrial acidification, freshwater eutrophication, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, agricultural land occupation, urban land occupation and natural land transformation.

2. Damage to human health: This endpoint indicator is measured as disability-adjusted loss of life years, indicated with the unit *DALY*. The midpoint indicators contributing to the calculation of damage to human health are climate change, ozone depletion, human toxicity, photochemical oxidant formation, particulate matter formation and ionising radiation.

3. Damage to resource availability: This endpoint indicator is measured as increased cost due to resource depletion, indicated in the monetary unit *$*. The midpoint indicators contributing to the calculation of damage to resource availability are mineral resource depletion and fossil fuel depletion.

When it comes to resource footprint data, the calculations made by Steinmann et al. (2017) were collected and used as-is in this study. The matching of products in the scope of this thesis and the list from Steinmann et al. (2017) was done based on the product names with exact matching. However, it should be noted that the database used by Steinmann et al. (2017) was a slightly earlier version of the Ecoinvent database (version 3.1), and therefore some differences might be present in the life cycle inventory of products.

2.3. Analysis methodology

In the last phase, the collected data is reviewed in more depth and analysed using statistical methods. This includes identifying the correlation between the variables, developing linear regression models and interpreting the model results. During this phase, the collected data was analysed using R programming language with RStudio software (RStudio Team, 2015).

Studying the joint behaviour of two variables to see whether they are related is possible with the correlation analysis. Correlation coefficient of a set of numerical pairs denote the degree of linear relationship between the two variables. It takes a value between -1 and 1, where the largest degree of positive relationship leads to a correlation coefficient of 1 and the most negative relationship leads to a correlation coefficient -1. If the correlation coefficient is near 0, it shows a lack of linear relationship. (Devore, 2009) This correlation analysis is done for each pair of explanatory variables in this study.

Linear regression analysis, on the other hand, aims to investigate the relationship between two or more variables in a way that we can know about one of the variables through the knowledge of the others. In other words, the objective is to build a probabilistic model that tells us about an independent variable (response variable) in relation to one or more dependent variables (predictor or explanatory variables). A general additive multiple linear regression model can be expressed with the following equation:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon$$

where Y is the response variable, $x_1, \ldots, x_k$ are the explanatory variables, and ϵ is a random variable assumed to be normally distributed with $E(\epsilon) = 0$ and $V(\epsilon) = \sigma^2$. Linear regression results estimate β_i values which can be interpreted as the expected change in Y associated with the change in the corresponding x_i value, all else being equal. (Devore, 2009)

In the regression analyses of this study, the environmental damages calculated based on the ReCiPe 2008 impact assessment method (damage to ecosystem diversity, damage to human health, and damage to resource availability) are the response variables (Y). For each of the environmental damage indicators, a different set of regression models with selected explanatory variables ($x_1, \ldots, x_k$) are built. These explanatory variables include, for example, the product waste footprints and resource footprints.

2.4. Limitations

The validity of the results of this study relies on the availability and quality of the life cycle inventory data used. While there is a large number of data points available for statistical analysis in the main data source of this study (Ecoinvent 3.5 cut-off database), any gaps or methodological inconsistencies in the life cycle inventories modelled in this database might skew the results. Overall, it can be expected to have a certain level of data quality as Ecoinvent provides detailed data quality guidelines for data submitters and the new datasets go through an independent editorial process (Ecoinvent, n.d.). However, it would be hard to verify and/or correct each dataset without independently carrying out detailed process analyses for each of them, which is not possible within the timeframe of this thesis.

The results of this study are expected to be generalizable to several types of products that exist in the Ecoinvent database. However, depending on the previous academic studies and perhaps the varying levels of industry interest in life cycle assessment studies, some product categories have a smaller number of products with available data, and therefore are represented to a lesser extent in this study.

The data collection methods, calculation algorithms and decisions made for handling missing data are documented in detail within the data collection section. This detailed documentation aims to allow reproducibility of the results in future studies.

3. Results

3.1 Literature review

3.1.1. Trade-offs and correlations between environmental indicators

We are developing our understanding of the unintended consequences of our production and consumption behaviour every day, and through this understanding, our management toolbox of environmental sustainability indicators is evolving to handle the complexities that we are facing. The environmental challenges that we are facing usually cannot be explained by a singular cause, but rather comes from complex cause-effect relationships. These relationships can be explained by the DPSIR framework (UNFAO, n.d., Kristensen, 2004), which depicts a chain of causal links:

1. (D)riving forces (economic sectors, human activities) are derived from a human need, for example the need for shelter, food, transportation.

↓

2. (P)ressures (emissions, waste) are exerted on the environment due to the activities fulfilling the needs, or in other words, driving forces.

↓

3. (S)tates (physical, chemical and biological) are the result of pressures which affect the quality of the environmental compartments, e.g. air, water or soil.

↓

4. (I)mpacts (on ecosystems, human health) are determined by the changes in the state of the environment and affect the welfare of humans.

↓

5. (R)esponses (prioritisation, target setting) by the society and policy makers can address one of the previous links of this chain to alleviate or minimize the problems, e.g. public transportation instead of private cars would be a response to the driving forces and regulating the emissions of cars would be a response to pressures.

Different environmental indicators can take place in the spectrum of DPSIR framework. For example, water consumption or raw material footprint would be indicators corresponding to the pressures. Cucek (2012) lists a family of similar footprints such as energy footprint, water footprint, carbon footprint, nitrogen footprint. On the other hand, the indicators from one of the prominent integrated environmental assessment approaches, the life cycle assessment, would be represented under impacts.

Steinmann et al. (2017) highlight the trade-off between using indicators situated early in the DPSIR framework versus later. Figure 2 shows the DPSIR chain and presents the considerations regarding the common trade-offs. For effective identification, prevention and remediation of environmental damages, the impacts on ecosystems and human health (which is situated later in the DPSIR chain) need to be quantified. These indicators are advantageous as they consider many relevant resource extractions or emissions, and therefore representing cause-effect pathways using a wider set of data points. However, such measures are usually associated with high cost due to the large amount of input data required and the results are largely uncertain due to the assumptions made in modelling complex processes. On the other hand, this is where the simpler footprint-based indicators (which are situated earlier in the DPSIR chain) are more advantageous; however, they might be overly simplistic to represent the full suite of environmental damages and fail to represent the quality of intuitive metrics offered by impact assessments. Therefore, it can be said that both sets of environmental indicators are useful for different decision making situations.

With the abundance of indicators both for measuring the pressures (e.g. footprint-based metrics) and more complex environmental performance assessment methods (e.g. midpoint and endpoint factors in the traditional life cycle assessment practice), it has become increasingly harder to choose the right set of indicators to use for environmental decision making. Researchers have started looking for ways to reduce this complexity and a new area of literature emerged which tries to explain the relationships between different indicators. For example, Berger and Finkbeiner (2011) examined how resource use is defined and measured. They have found strong linear relationships between several resource-oriented indicators; and therefore, called for reducing the number of indicators defining resource use. Huijbregts et al. (2010) reviewed six common life cycle impact assessment methodologies and showed that these impact assessment methods provide converging results and point to fossil energy use as a dominating driver of environmental burdens. Steinmann et al. (2016) conducted a principal component analysis to come up with an optimal set of indicators out

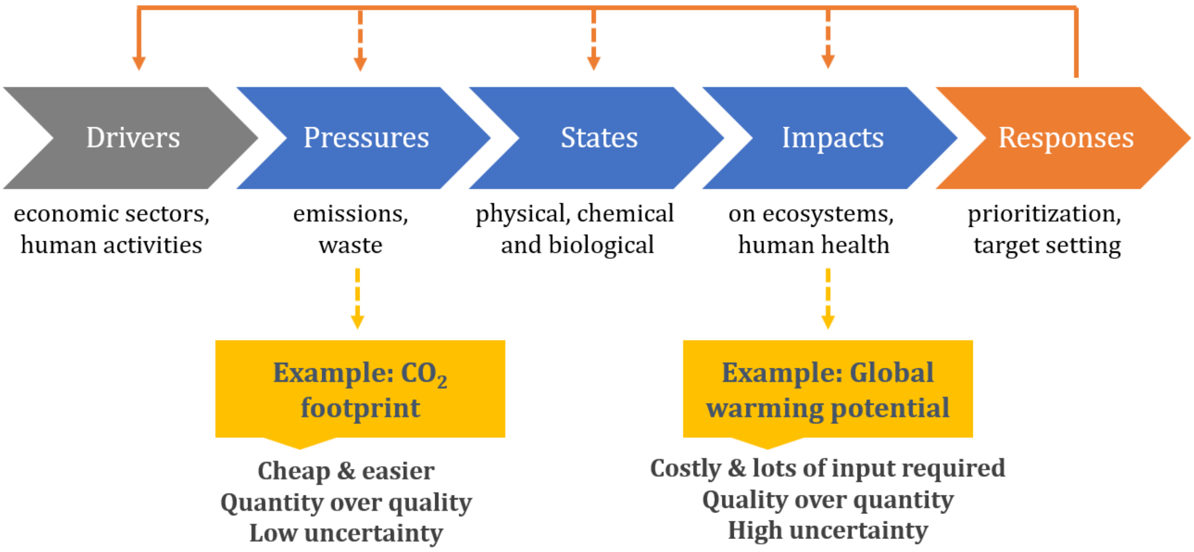

Figure 2. Trade-offs between the environmental indicators on DPSIR chain

of 135 impact indicators, and their results suggested that 92% of the variance among products could be covered by a minimal set of six indicators. Soon after, Steinmann et al. (2017) showed that common resource points regarding fossil energy, freshwater, land and raw material use together accounted for 84% of the variance in product rankings. On the other hand, the findings did not always indicate a positive relationship between the studied indicators. Laurent, Olsen and Hauschild (2012) have studied the widely used carbon footprint indicator and found that it is often not correlated with other impact assessment scores, suggesting that our focus on reducing the carbon footprint can lead to shifting the burdens from one domain to another. These examples from the literature show that a simplified and leaner set of impact assessment methodologies can be useful to communicate more easily and used for practical decision making, but we still need to be informed well about what out metrics represent in order to avoid shifting environmental burdens.

3.1.2. Product waste footprint as an environmental indicator

In order to address the knowledge gap regarding the "invisible" waste that is produced before a product reaches the consumers, the concept of a *pre-consumer* waste footprint indicator on the product level was previously developed. This pre-consumer waste footprint was recently calculated for around 10 selected consumer products that are frequently used in the everyday life, and the findings were published in a popular science report (Laurenti and Stenmarck, 2015) and as a journal article (Laurenti, Moberg and Stenmarck, 2017). These earlier work on the waste footprint indicator showed that the waste generated at the pre-consumer stages are not only highly variable among different products but also can be several orders of magnitude larger than the mass of the product itself.

Laurenti, Martin, and Stenmarck (2018) have conducted a stakeholder consultation to develop the communication of the waste footprint indicator in the context of circular economy. Based on their survey, the usefulness of the metric was found to be highest for consumers and the government, with opportunities recognized in increasing environmental awareness of the public, environmental policy making and visualizing waste flows. The metric was considered as less useful for industry and research institutions. Furthermore, during an open consultation, the risks of the waste footprint becoming misused was also raised by LCA experts. For example, in the traditional LCA methodology, it would not be the total waste quantity that represents the environmental damage, but the characteristics of the waste and its treatment path would be causing the pressuring factors (emissions/exchanges) on the environment. The concern is therefore the opportunity that is created for the companies to greenwash their products, for example, by giving an unfair advantage to those with low amounts of toxic waste in comparison to others with higher amounts of benign waste. Therefore, it can be said that the trade-offs between using simpler versus complex indicators was represented in the perspectives of the LCA experts during the stakeholder consultation of the pre-consumer waste footprint concept.

Within the pre-consumer waste footprint studies, the definition of waste primarily follows the EU Waste Framework Directive, which defines waste as "any substance or object which the holder discards or intends or is required to discard". (The European Parliament the Council of the European Union, 2008). However, different than this directive, the pre-consumer waste footprint studies have accounted for the wastewater as well. Nevertheless, for different cases, what product/material goes into the waste category can be different, and the waste footprint concept was developed as a customizable indicator for specific goal and scope definitions (Laurenti, Martin, and Stenmarck, 2018).

Circular economy approach considers what used to be waste as a potential resource, and the categorization of waste products might change in the future considering the active efforts and ambitious circularity goals set at international levels (European Environment Agency, 2016). Therefore, from a circular economy perspective, the waste footprint can be considered analogous with resource footprints. In fact, among the resource footprints, the material footprint would be a close match – while waste footprint accounts for the output side of the processes, material footprint accounts for the input side with the raw materials. Ritthoff, Holger, and Liedtke (2002) explains the "material input per service" concept as a product or service's use of resources from their extraction from nature, i.e. "the number of tons moved in nature". Water and air inputs are also included in this concept; however, they are recommended to be reported separately. When the material input is adjusted/ normalized based on the products' characteristics such as mass (kg) or energy (MJ), this footprint takes a new name as "material intensity".

3.1.3. Summary of key points and conceptual framework development

There are several environmental indicators – from simple to complex – in our environmental sustainability management toolbox, and new indicators continue to emerge or develop as we understand our contemporary environmental challenges better. Pre-consumer waste footprint is one of the recently developed environmental indicators which aims to increase awareness on the waste generated already before a product reaches the customer. As we are facing a waste crisis, but have ambitious goals on tackling this problem, a waste footprint indicator seems to be a relevant measure to support circular economy goals. However, with the increasing calls for reducing the number of environmental indicators, the waste footprint concept should "earn" its position among the other footprints with regard to its representativeness of environmental performance. Showing whether this is the case or not is the underlying motivation of this thesis.

The use of waste footprint concept in this study has a few differences compared to the previous studies. First, the pre-consumer waste footprint studies have so far taken the life-cycle perspective using a cradle-to-gate approach, in other words, accounted for the waste that is created from the raw material extraction up until the product leaves the downstream factory gate (Laurenti, Moberg and Stenmarck, 2017). However, the product life cycle stages included in this study will use the cradle-to-grave approach. Many products modelled in the Ecoinvent 3.5 cut-off database includes product disposal within their system boundaries, and these processes contribute to the environmental damages associated for those products. By including the same life cycle stages, the scope of processes used for waste footprint calculations become consistent with those used for environmental damage calculations. Figure 3 shows a representation of the alternatives in terms of the life cycle stages included in waste footprints. It should be noted that the use phase inventory is frequently omitted from the default linked system models in Ecoinvent database.

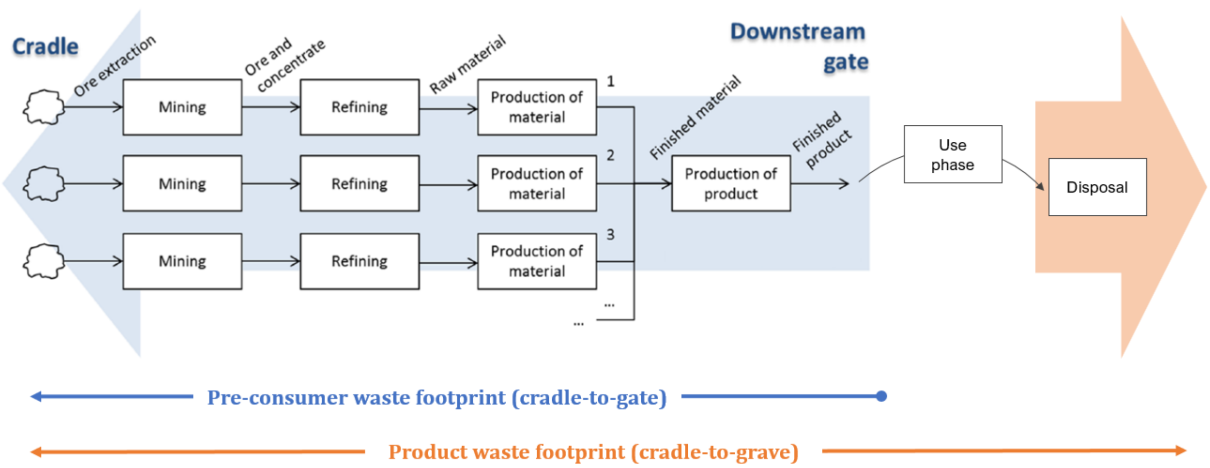

Figure 3. Representation of the cradle-to-gate and cradle-to-grave approaches involved in measuring the waste footprint (modified from Laurenti, Moberg and Stenmarck, 2017)

Secondly, the waste definitions in the earlier studies included wastewater as part of the waste footprint. This was different than the EU Waste Framework Directive as well as how a similar resource footprint – material intensity – approaches to water consumption on the input side of the life cycle inventory. Since the waste footprint is the key explanatory variable which this research focuses on, it was decided that different versions of the waste definitions will be tested via regression analyses, leading to three separate variables:

1. Total waste (kg): This is in line with the primary waste footprint definition suggested and used in the earlier waste footprint studies, e.g. Laurenti, Moberg and Stenmarck (2017). This amount is the sum of solid waste and wastewater.
2. Solid waste (kg): Using only solid waste is more consistent with the EU Waste Framework Directive and more similar to the way material intensity indicator separates water consumption from the raw material inputs, e.g. in Ritthoff, Holger and Liedtke (2002).
3. Wastewater (kg): Wastewater itself is not of primary interest, though it is included to compare with the other definitions.

Lastly, instead of drawing similarities, a difference between the waste footprint and the material intensity should also be noted. Considering the material balance of each unit process, under ideal conditions, the material inputs should mainly translate into outputs in the form of waste and emissions. Therefore, it could be expected for the waste footprint and material intensity to be associated, i.e. in terms of the balance between the materials extracted and ultimately returned back to nature. However, even if a raw material is extracted once from the nature within the life cycle of a product, a waste can be processed in multiple steps. This study calculates the waste cumulatively from those steps – for example, if 1.0 kg of municipal solid waste is treated by incineration, which leads to 0.1 kg of incineration residue to be landfilled, these steps are assumed to create a total of 1.1 kg of waste footprint.

Besides the main response variables (environmental damage indicators) and the main explanatory variables (different versions of waste footprint indicators), there are three sets of control variables that are chosen for further investigation during the analysis phase:

1. Waste type & treatment path indicators: In order to address the concerns of LCA practitioners regarding the quality of information offered by the waste footprint indicator, one measurement to represent the waste type (the hazardousness ratio) and one measurement to represent the subsequent waste treatment path (the circularity ratio) is included in the regression models.
2. Product category: The products in the scope of this study are divided into categories and sub-categories. The sub-categories are used as a categorical control variable in the regression models.
3. Resource footprints: The resource footprints calculated by Steinmann et al. (2017) are used as supplementary control variables in the regression models.

Figure 4 summarizes all variables that are addressed in the quantitative phases of this thesis, and the following section details how each of these variables are calculated in more detail.

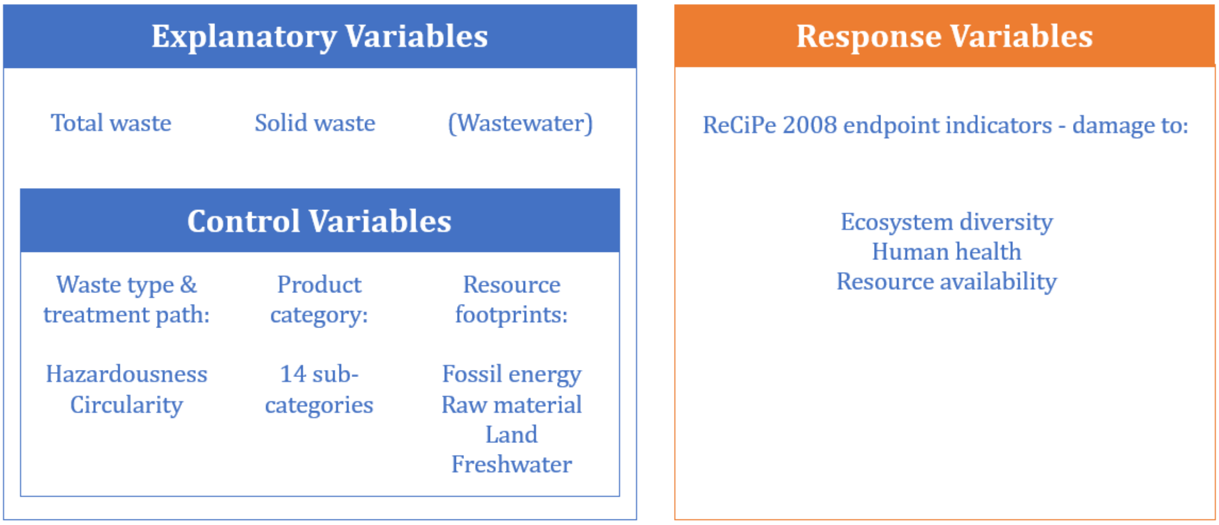

Figure 4. Conceptual framework for multiple linear regression models

3.2. Data collection

The product waste footprint and environmental impacts of several products were calculated based on Ecoinvent 3.5 database which was released in August 2018. The system model used was "Allocation, cut-off by classification", which allocates the burdens of the production of virgin materials to the primary producer whereas providing the secondary materials as burden free inputs to recycling processes. In other words, provision of recyclable materials for recycling or reuse do not give credit to the primary producer. All product exchanges within the technosphere are categorized as either allocatable, recyclable or waste. Allocatable products are the reference flows of regular production processes. The main difference between recyclables and waste products are their economic value: unlike waste products, recyclables carry some value as input materials and therefore there is an incentive for their collection. (Ecoinvent, n.d.)

3.2.1. Setting the product scope

3.2.1.1. Product selection

Selection of the products from the Ecoinvent database was carried out in two steps. First, the products were shortlisted based on their easy-to-access characteristics which were already available as coded information in the database. Most of the products were eliminated during this step. The resulting shortlist of products are reviewed in more detail during the second step, which determined the final scope of products. Figure 5 represents the gradual product scoping procedure.

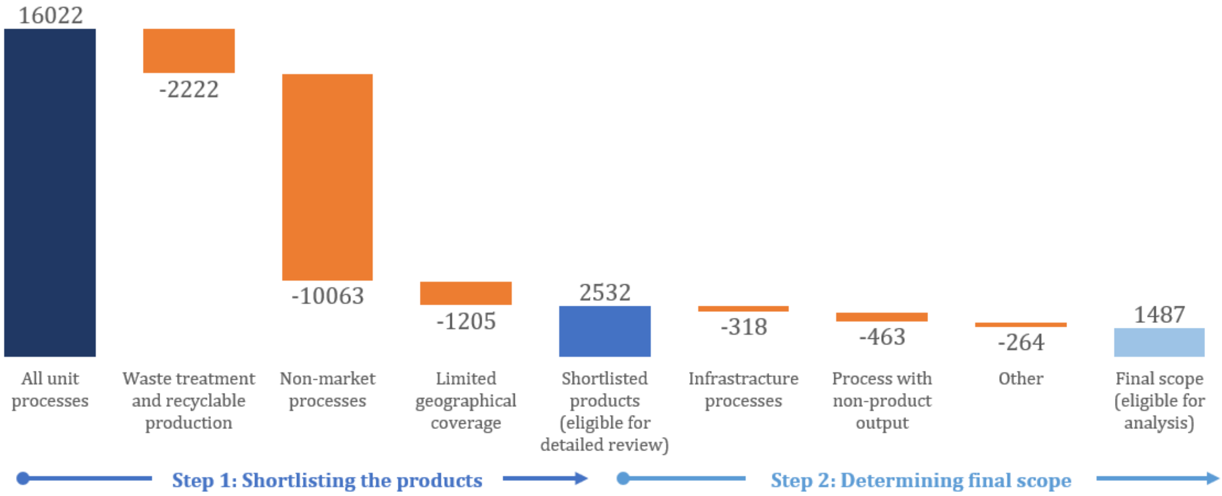

Figure 5. Product selection out of all single output unit processes that produce/consume allocatable, recyclable or waste products

Step 1. Shortlisting the products

This step aims to identify and eliminate the processes that are not supposed to be analysed; and hence, create a shortlist of those that are eligible for a more detailed review. The following processes were eliminated in this step:

a) Waste treatment and recyclable production processes: 2038 out of 16022 unit processes in the Ecoinvent 3.5 cut-off database are waste treatment processes, i.e. activities which are consuming waste products. An additional 184 processes are producing recyclables, which are supporting the recycling process chains, or just included as special datasets to provide burden free recycled content to the users. Both these groups of processes are not interesting to calculate the product waste footprint for since they are not intentionally built products.

b) Non-market processes: The production processes can either be "transformation" or "market" processes, and both types can exist in the database for one product. The transformation processes take input materials and energy to produce a product or service as an output. The resource extractions, waste and emissions related to a transformation process is included in its inventory. Market processes, on the other hand, aggregates the transformation processes from several markets (countries, suppliers, etc.), and include the inputs related to transportation from the supplier to the consumer as well. (Ecoinvent, n.d.)

Market processes are chosen over transformation processes in this study, because:

- market processes are consolidating several suppliers, which is favourable in order to reach results that are representative on a larger scale
- the cradle-to-grave life cycle waste footprint perspective is better represented with the inclusion of transportation between the supplier and customer

- choosing market processes is in line with the approach of similar studies in the literature, e.g. Steinmann et al. (2017).

c) Limited geographical coverage: Some products have market processes for a number of different locations, i.e. specific states, countries or regions. Of these market activities, for each product, only the product with the largest geographical coverage was chosen. This meant that the Global ("GLO") values were selected over all other options, and Rest of World ("RoW") values were selected over specific geographies where "GLO" option was lacking.[1]

After going through these steps, a total of 2532 processes remained in scope and were eligible for a more detailed review and categorization.

Step 2. Determining the final scope

This step aims to identify products that are eligible for the footprint calculation and analysis, hence remain in the final scope. During this more detailed review of the shortlisted products, more criteria were considered to see if the product fits well enough for the subsequent analyses, such as the activity and product names, the International Standard Industrial Classification (ISIC) code of the activity (UNSD, 2008), and the Central Product Classification (CPC) code of the reference product (UNSD, 2015). Where further clarification was needed, comments and documentation from the data submitters were also reviewed.

a) Infrastructure / facilities: In order to focus more on consumer-relevant products and considering the unreliability of the full life cycle data as the scale grows, production and services related to infrastructural products are excluded from the scope. Some examples in this group are:

- Construction: Airport, anaerobic digestion plant, gas power plant, cement factory, mine infrastructure, paper mill, petroleum pipeline, road, residual material landfill, sugar refinery, electricity transmission network, sewer grid, greenhouse glass walls / roof.
- Construction services: Blasting, machine operations, storage, excavation, wood preservation processes, road maintenance.

b) Processes with non-product output: Some processes can be used as building blocks to contribute to other life cycle models, but they are not linked to their own supply chain and therefore cannot produce a standalone product by themselves. Some examples in this group are:

- Processing / manufacturing support services (mostly lacking material inputs), e.g. sewage and waste collection, publishing, blow moulding, wood chipping, locomotive maintenance, photovoltaic facade installation, support services to agriculture, hunting, forestry, fishing, irrigation, planting tree.

[1] While "RoW" should be a good proxy for the largest geographical coverage in most cases, this may not always be true. For example, a process specialized for locations such as China, Europe or US might cover the largest producers, leaving the "RoW" option less representative of the product's most common production chains.

- Services, e.g. electricity, transportation, internet connection.
- Process-specific burdens (not "processes" in the conventional sense, but accounting for specific burdens or requirements), e.g. sanitary landfill process-specific burdens, polar fleece production energy use.

c) Other: Individual products are favoured over aggregation where both options exist; for example, specific chemicals are preferred instead of the "inorganic chemicals" as a product. Some waste/scrap treatment processes, albeit having an "allocatable" output, are not included. Additional products were dropped from the final list due to lacking information about product mass, because a waste footprint calculation "per kg" of these products were not possible. Lastly, some products were eliminated due to duplication or high similarity with other products based on their waste footprint, environmental damage indicators and/or biosphere flows.

3.2.1.2. Product categorization

The remaining processes with single allocatable outputs are classified into the following eight groups shown in Table 1. Example products in each group, together with their CPC numbers, are provided in the Appendix.

Table 1. Product categories in scope

No	Product category (and subcategories)	Shorthand name	# of products
1	Agriculture, forestry, live animal & their products a. Agricultural and forestry products b. Live animal, fish and their products	AgriForeAnim	190
2	Basic metals & alloys, incl. semi-finished products	MetalAlloy	69
3	Chemical products	Chemical	549
4	Glass and other non-metallic products	GlasNonMetal	108
5	Machinery, metal/electronic, transport equipment a. Machinery (general or special purpose) b. Metal/electronic equipment and parts c. Transport vehicles	MachElecTrans	197
6	Ores, minerals & fuels	OreMinFuel	126
7	Plastics & rubber products	PlastRub	83
8	Processed biobased products a. Food & beverages, animal feed b. Wood, straw & cork c. Pulp & paper d. Textile	ProcBio	165

3.2.2. Calculating product waste footprints

3.2.2.1. Computational methods for waste footprint calculation

To find out the product waste footprint indicators for several products, manual calculations are not a viable alternative and a computational method is needed. For this purpose, two alternative algorithms were considered during this study with their respective strengths and weaknesses. A mixed method would give the most detailed data for the waste footprints. However, for this initial study, the second alternative was chosen. The following sections describe both alternatives and their strengths and weaknesses.

Option 1: Waste accounting by travelling through supply chain graph

The first option reflects the way we commonly visualize a product's supply chain graph. The main idea is counting the waste generated at each step (unit process), starting from a product's downstream gate (its final production step) and moving towards the cradle of the product to do the same. In other words, each step should collect the waste generated within a unit process (with their respective amounts), plus register the inputs that the unit process requires (with their respective amounts) to "process them" in the same way. With the pre-sorting or classification of each input/output as either a waste, recyclable or allocatable product, this becomes a straightforward task. In fact, this was the algorithm which was described in the pre-consumer waste footprint screening by Laurenti, Moberg and Stenmarck (2017), albeit performed in a manual fashion. With the computational power and the full database at hand, the same computation can be done with a lot more ease.

In terms of the algorithm design, repeated measures of the same calculations moving through the branches of a tree, i.e. considering the supply chain as a tree structure with branches extending towards the cradle of various material inputs and the root being the final production process, suggests the possibility of a recursive algorithm rather than an iterative one, although an iterative algorithm may also be used. However, in either way, the important thing is to find a base case scenario - a condition which no further recursive calls (or new iterations) will be called. This base case scenario should then return without accounting for any waste or register any further inputs to process on the same branch of the tree. This is an appropriate place to implement a cut-off point, such as some kg of mass inputs, km of required transportation or a unit of infrastructure/machinery etc. However, subjective choices need to be made here, as no precedence was found for setting a cut-off for all possible inputs contributing to the production of a product.[2] In theory, with high computational power, the accuracy of waste calculations can be improved substantially by choosing a cut-off point that is much smaller than what would be preferred in a manual case. However, the trade-off between the cut-off point and run time of the algorithm must also be considered.

Option 2: Waste accounting using the computational structure of LCA

The second option does not require travelling through the supply chain to be able to collect the waste outputs at each step. Instead, the aim is to initially find out how much contribution

[2] 10% cut-off point was chosen for material inputs in the manual calculations of Laurenti, Moberg and Stenmarck (2017).

is required from several different processes to produce a product and derive the waste footprint based from the contributions from the specific waste treatment processes. In fact, the concept of “process contributions” are at the core of the basic models of life cycle inventory analysis and this computational structure is the working principle behind the conventional life cycle assessment software (Heijungs and Suh, 2002).

Figure 6 shows the general model of relationships between unit processes that can be described by a linear space, i.e. the technosphere matrix, which is represented by A. The A matrix represents the products in each row, and processes (activities that produce the products) in each column. Each element a_{ij} in this matrix contains the amount of input or output flows of product i from activity j. When a_{ij} is positive, the process j *produces* a_{ij} amount of product i; whereas when a_{ij} is negative, the process j *consumes* a_{ij} amount of product i. One special case is when i=j (meaning that a_{ij} is in the diagonal of the matrix A), this flow depicts the reference production flow for the activity j. In Ecoinvent database, the reference flows usually have $a_{ij} = 1$ as it depicts the reference production at the unitary level, with few exceptions of $0 < a_{ij} < 1$ (in case of, for example, production losses). Similarly, a_{ij} is always negative for waste treatment activities, and takes the value $a_{ij} = -1$.

Given the data required to build a technosphere matrix, the required process contributions, shown by supply vector (s), can be calculated for any functional unit placed in the final demand vector (f). To be more specific, the supply vector provides how much of each activity needs to contribute to produce the demanded product as well as to consume the excess outputs (such as waste). To put in mathematical terms, the supply vector can be calculated with the formula $s = A^{-1} f$.

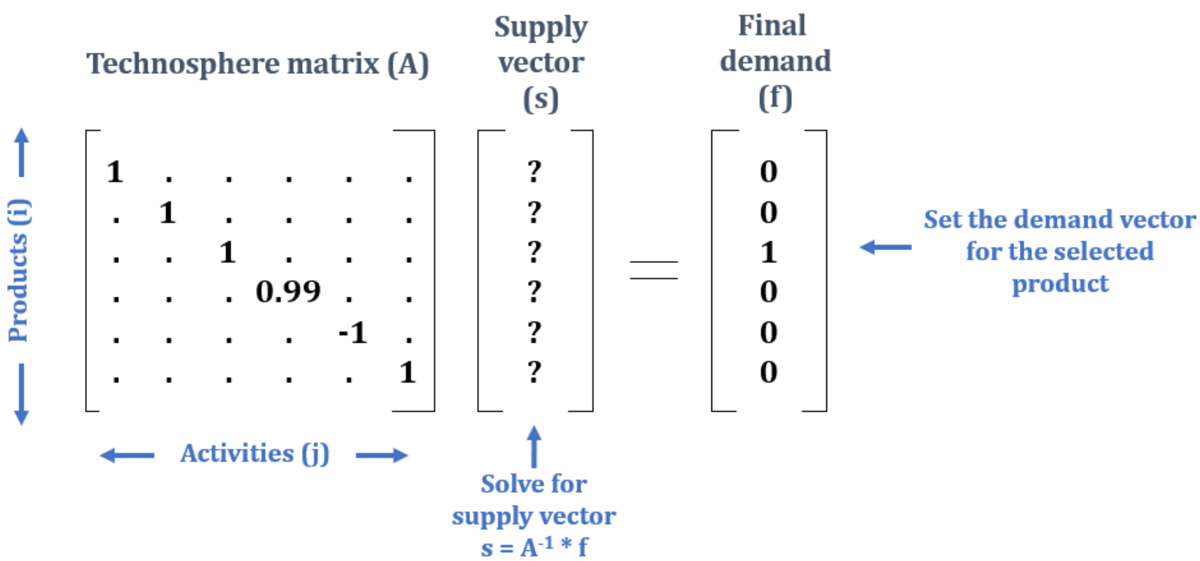

Figure 6. Representation of the basic inventory problem and its solution[3]. The values on technosphere matrix and the final demand vector are examples.

[3] This is a generalized example model. Using real life data, the systems might be over- or under-determined and give way to different solution methods.

All products categorized as waste in the Ecoinvent database have a corresponding waste treatment process (2038 unit processes) with a_{ij}= -1 on the diagonal of the technosphere matrix. Therefore, the amount of waste that these processes consume (the supply vector value at the same row index) will indicate how much of that waste is generated to satisfy the final demand in the model. At this step, only the relevant[4] waste treatment processes should be considered, and it must be ensured that the units of waste products are consistent (e.g. in kilograms) when adding them to calculate the total waste footprint.

Comparison of the calculation methods

The first algorithm, travelling through the supply chain graph, is more advantageous in having control over the data collection process and for collecting more detailed process information. For example, at each step, the waste amounts can be associated with the process type which they originated from, e.g. waste from final production, waste from fuel/electricity or transportation, waste from input materials, etc. Such details are not accessible using the second algorithm, since it only provides the final solution without the possibility for such classification. On the other hand, the first algorithm requires having a cut-off point, which might be arbitrary or inconsistent between material-intensive or energy-intensive products. The usage of cut-off point for the waste footprint calculation could also create a discrepancy with the environmental damage calculations, because the environmental damages would be calculated based on the full life cycle modelled on Ecoinvent, i.e. without the cut-off involvement. In this respect, the second algorithm would perform better to ensure both the waste footprint and the environmental damages are calculated on a consistent ground.

For the aim and objectives of this thesis, the second approach was found to be more suitable. As an initial attempt on quantifying the relationship between the product waste footprint and environmental damage indicators, the level of detail regarding the process origins of the waste was not considered as crucial at this time. Additionally, the second algorithm showed the benefits of avoiding an arbitrary cut-off point and running the algorithm faster. Nevertheless, for future studies, both approaches could be considered.

3.2.2.2. Waste footprint calculation

When it comes to the practical implementation of the selected algorithm, the methods provided by Brightway2 was used. The Ecoinvent 3.5 datasets were exported in the form of 16022 separate files, each containing the details of one unit process in a single-output process format.[5] Brightway2 provides the methods to import these datasets and build the technosphere matrix of size 16022 x 16022 to start with. Furthermore, it provides the methods to solve for the supply vector for a given functional demand, including the ability to solve overdetermined systems (Mutel, 2014). The implementation of this algorithm has therefore relied on several methods provided by Brightway2.

[4] Note that some of the waste treatment processes are skipped in the waste accounting to avoid double counting, such as market processes and market groups. These are detailed later in this report.

[5] An economic allocation has been applied to multi-output processes to form the single-output processes in the cut-off system model.

While the "process contributions" from the waste treatment processes can be used to calculate the waste generated in a product system, it is important to only count the relevant waste treatment processes. For example, the waste treatment activities which are ordinary transformation processes are also present in an aggregated form as the market processes in the Ecoinvent database, with the addition of inputs for transportation. When one waste treatment activity links to another in the form of such aggregation, a waste would be "consumed" by both the market process and the transformation process. Therefore, only one of them should be counted to avoid double counting. The market processes provide less detail whereas the ordinary transforming activities include more explanation on the type and subsequent treatment path of the waste. Therefore, it was decided that only the ordinary waste treatment activities would be counted, and market values are skipped. Besides the market activities, the waste collection processes were also found to be a source of potential double counting – mathematically speaking on the technosphere matrix, these processes *consume* the waste that they collect; but in practice, they only hand the waste over to a waste treatment process, e.g. landfilling. Considering this double counting potential as well as the inconsistent modelling of waste collection among the products, the waste collection processes were also skipped.

The calculations were initially performed for each product's original unit, e.g. a kilogram of apples, a litre of beverage, a meter of cable or a m^2 of door. However, in order to reconcile the product waste footprint as a "per kg" indicator comparable across different products, the results were divided by each product's mass. When a product lacked mass information, if possible, it was approximated by another comparable product in the Ecoinvent database. For example, 1 unit of "used bicycle" is registered as 17 kg, and therefore the product "bicycle" was assumed to be the same. Nevertheless, some products (and mostly services) neither have mass-relevant information, nor have an easily estimable relationship with mass, i.e. when the original units are km, hectares, hour, m^2.year, person.km, km.year, meter.year, KWH, MJ, ton.km or kg.day. Such products were excluded from the scope. The mass information was necessary on the waste side as well. Wastewater, originally represented in m^3, is approximated as 1000 kg when there was no alternative information.

The calculated product waste footprints had high variances among different product categories. Figure 7 shows the distribution of the total and solid waste footprints for 8 product categories. Since the waste footprints vary several orders of magnitude, the figure represents the waste footprints on a natural logarithmic scale and therefore the "0" point on the x-axis represents 1 kg of waste and the negative values represent the interval between 0-1 kg of waste. The median total waste footprint was less than 1 kg for the product categories of "agriculture, forestry, live animal & their products" and "glass and other non-metallic products". The highest median waste footprint was found in the product category "Machinery, metal/electronic, transport equipment", which might be explained by the complexity of these products, and hence, their potential of longer supply chains along which waste can be generated. The highest footprints were found in the "basic metals & alloys, including their semi-finished products", with gold and platinum at the top with high amounts of waste modelled in Ecoinvent for their mining operations.

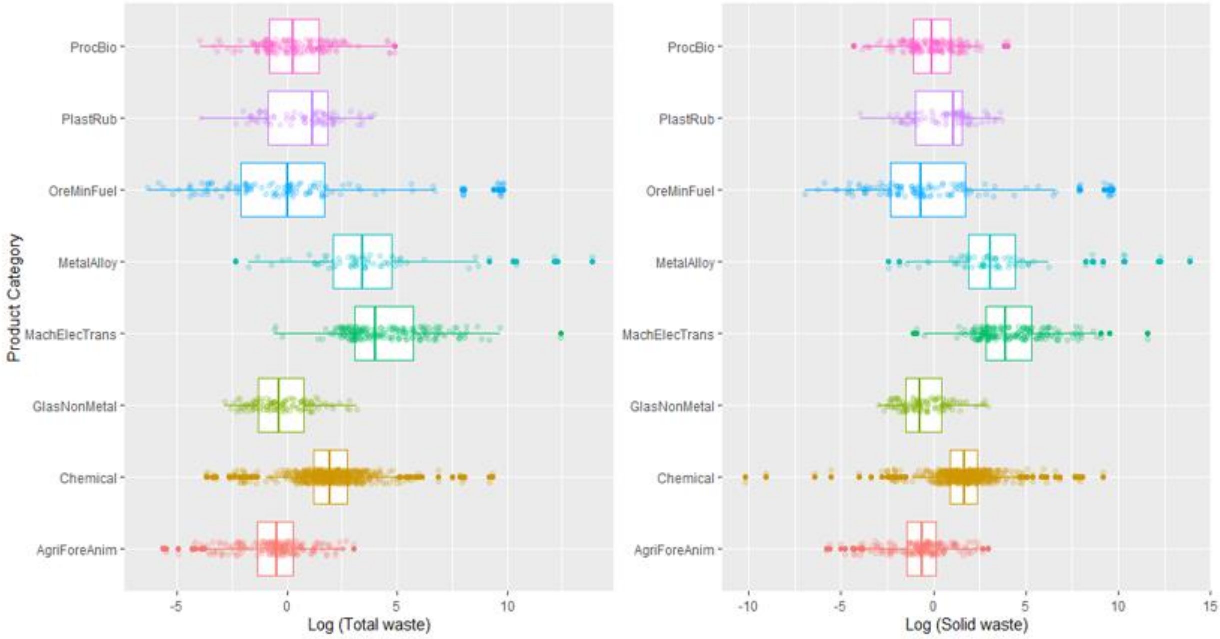

Figure 7. Total and solid waste footprints of different product categories

3.3.2.3. Waste type and treatment path categorization

While it is easy to distinguish waste from allocatable and recyclable products, it needs more review to be classified based on its characteristics and subsequent treatment paths. In this regard, the waste products are first classified as solid waste and wastewater, and later only the solid waste is further classified in this study. This is because the wastewater treatment activities do not have classifiable coded information in the database.

In terms of waste characteristics, a categorization of hazardous and non-hazardous waste is used in this study. It is not always straightforward to do this classification as hazardousness can depend on both the contents and their concentration; however, such a detailed review of the chemical and physical properties of the waste is beyond the scope of this thesis. In order to reduce the complexity of this categorization task, the following simplified criteria (based on the activity/product classifications offered by Ecoinvent database) were chosen:

- The hazardousness of a waste can be identified when it is clearly stated as "hazardous" given the waste treatment activity (e.g. activity name "treatment of bilge oil, hazardous waste incineration") or its ISIC code (e.g. ISIC code 3822: "Treatment and disposal of hazardous waste") or CPC code (e.g. CPC 34666: "Hazardous pesticides").
- A waste product, regardless of where it is produced or treated, can either be a hazardous or non-hazardous waste, it cannot be classified as both. For example, if a waste is treated with both hazardous and non-hazardous waste treatment scenarios in different places, the waste is classified as hazardous at all cases.

- If no indication is found for the waste to be hazardous, it is classified as non-hazardous. This approach also works well with composite waste, e.g. "used electric bicycle", considering the concentration of hazardous materials would be a small percentage of the overall mass of the waste product.

The hazardousness percentage was calculated based on the solid waste footprint of each product and its distribution is presented in Figure 8. The hazardousness can be up to 100% and distributed with a concentration towards the higher end. This might indicate a weakness on the validity of this measure, and it can possibly be explained by several factors. For example, hazardous waste might be inventoried more accurately than the non-hazardous waste by the data submitters, with the expectation that they matter more for environmental damage. Another explanation might be based on the hazardousness categorization approach used in this study, which might be overestimating the hazardous waste amount while underestimating the non-hazardous waste (since a waste categorized as hazardous cannot be categorized as non-hazardous in another process).

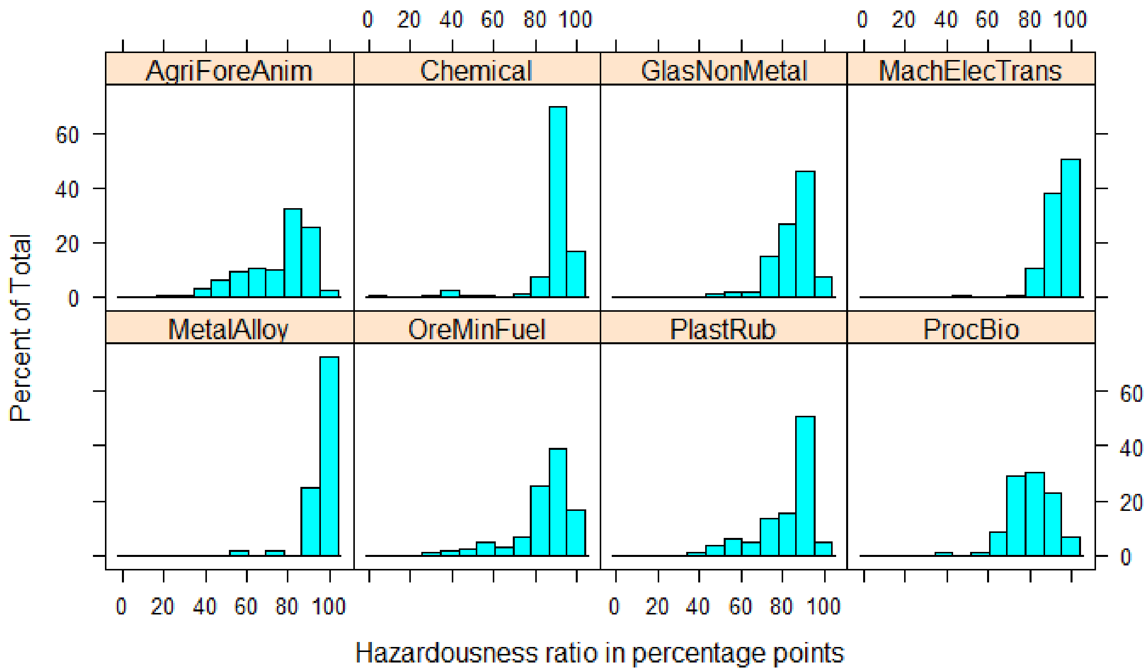

Figure 8. Distribution of hazardousness ratio in different product categories

When it comes to the treatment path of the waste, solid waste is categorized based on the activity treating the waste. The information provided in the activity name and the ISIC code was considered for this classification. The initial categorization included the following four categories.

- Materials recovery[6]: Activities that are aimed at recovering materials, which may include manual dismantling, mechanical treatment (shredding/separation), sorting and recycling.
- Biological treatment: Anaerobic digestion, industrial composting, landfarming.
- Incineration/burning: Municipal or hazardous waste incineration, open burning.
- Landfill/deposit: Deposits in different landfill types, open dumping, impoundment, opencast refill, surface or underground deposits. This category also includes wear/tear emissions from infrastructure.

To account for the treatment path of the waste footprint of products, a circularity percentage was calculated based on the solid waste footprint, i.e. the amount of material recovery or biological treatment operations within the calculated solid waste footprint. Figure 9 is a histogram that shows the distribution of products falling into different percentage brackets in each category. For all product groups, the circularity percentage was not higher than 40% and concentrated on the lower end.

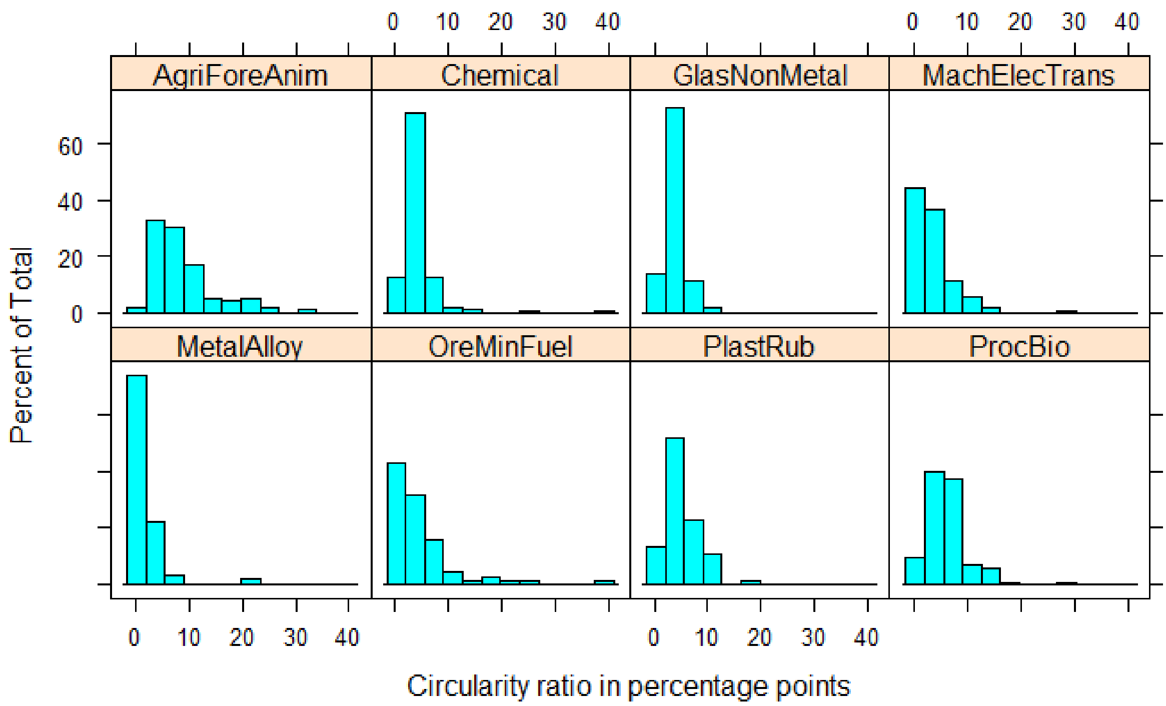

Figure 9. Distribution of circularity ratio in different product categories

[6] The ISIC code for these processes are mostly "3830 - Materials recovery". According to UNSD (2008), the processing of waste into secondary raw materials is categorized in this class. This may involve physical or chemical transformations and not considered to be a part of manufacturing.

3.2.3. Calculating environmental damages

The life cycle environmental damage indicators were also calculated using Brightway2 and this did not require a custom algorithm to be developed. The characterization factors for ReCiPe 2008 endpoint indicators were present in the Brightway2 implementation, and the methods provided by the Brightway2 framework allowed for convenient access to endpoint results by iterating through the products in the database.

However, it should be noted that the endpoint results extracted using Brightway2 were normalized and weighted impact scores, and their units were *points*, one point being the damage of one "person/year" (Hischier and Weidema, 2010). The scores were determined based on ReCiPe 2008 methodology, using "European Hierarchist" values for normalization and "Average" values for weighting (RIVM, 2014). Therefore, the species.yr, DALY and $ results for the respective indicators were reverse-calculated from these scores. The normalization and weighting factors of ReCiPe 2008 are presented in Table 2 and Table 3.

Table 2. Normalization factors (RIVM, 2014)

Impact category	Unit	Individualist	***Hierarchist***	Egalitarian
Ecosystems	species.yr/ p/yr	0.00018584477	***0.00018082254***	0.00027455178
Human health	DALY/ p/yr	0.020999191	***0.020187184***	0.041095714
Resources	$/ p/yr	131.4033	***308.23606***	308.23606

Table 3. Weighting factors (RIVM, 2014)

Perspective	Ecosystems	Human health	Resources	Total
Average	***400***	***400***	***200***	***1000***
Individualist	250	550	200	1000
Hierarchist	400	300	300	1000
Egalitarian	500	300	200	1000

Therefore, the following formula were used to calculate the damage indicators in their non-normalized and non-weighted form.

Damage to...

*Ecosystem Diversity [species.yr] = (X [points] / 400) * 0.00018082254 [species.yr/person/year]*

*Human Health [DALY] = (X [points] / 400) * 0.020187184 [DALY/person/year]*

Resource Availability [$] = (X [points] / 200) * 308.23606 [$/person/year]

where X was the original result obtained from Brightway2 for the respective endpoint indicator.

3.2.4. Collecting resource footprints

The resource footprints that are used as a control variable were taken from a previous study by Steinmann et al. (2017) - these calculations were accepted as is and the calculation principles explained by the authors are summarized below:

1. Non-renewable energy demand (MJ): This energy demand is calculated based on the total amount of fossil energy required, including energy from oil, coal, gas, and peat.
2. Raw material use (kg): Total amount of all raw materials extracted from the earth, excluding fossil fuels (but covered by the non-renewable energy demand) and biotic resources. Metal extractions were converted to ore extractions based on metal-specific ore grades.
3. Land use (m^2.yr): Total area of land used over time, excluding land transformation.
4. Freshwater consumption (m^3): Amount of evaporated water plus the amount of water that is incorporated in the products. Calculated as the difference between freshwater extracted from nature and the amount of water returned.

3.3. Analysis

3.3.1. Review of variables and data transformation

All variables that are included in the quantitative analyses are collected in Table 4, which is a summary reference for their definition and unit of measure. The response variables included are the endpoint indicators from ReCiPe 2008 method (3 variables, numeric). The explanatory variables are waste footprints (3 variables, numeric), waste type indicators (2 variables, numeric), resource footprints (4 variables, numeric), and product groups (1 variable, categorical). The Appendix presents basic descriptive statistics for all numeric variables.

Table 4. List of variables

Group	Definition	Transformation
Response variables		
Life cycle assessment results, ReCiPe 2008 endpoint indicators	Damage to ecosystems diversity (species.yr) per kilogram product	Natural log.
	Damage to human health (DALY) per kilogram product	Natural log.
	Damage to resource availability (surplus cost $) per kilogram product	Natural log.
Explanatory variables		
Waste footprints	Total waste (kg) per kilogram product	Natural log.
	Solid waste (kg) per kilogram product	Natural log.
	Wastewater (kg) per kilogram product	Natural log.
Waste category indicators	Hazardousness: The ratio of hazardous to solid waste (in percentage points between 0-100)	NA
	Circularity: The ratio of circular to solid waste (in percentage points between 0-100) Circular waste includes material recovery & biological treatment, excludes incineration/burning & landfill/deposit.	NA
Resource footprints, from Steinmann (2017)	Non-renewable energy demand (MJ) per kilogram product	Natural log.
	Raw material use (kg) per kilogram product	Natural log.
	Land use (m^2.yr) per kilogram product	Natural log.
	Freshwater consumption (m^3) per kilogram product	Natural log.
Product Group	Indicates one of the 14 product sub-categories	NA

Since the environmental damage indicators, product waste footprints as well as the resource footprints varied several orders of magnitude, they were log-transformed prior to model fitting. Due to much of the data being clustered near 0, natural logarithm was chosen for the transformation. This step has made the variables more linear and easier to model using linear regression. For example, Figure 10 shows three scatter plots for the visual relationship between the log-transformed environmental damage indicators and log-transformed solid waste footprints.

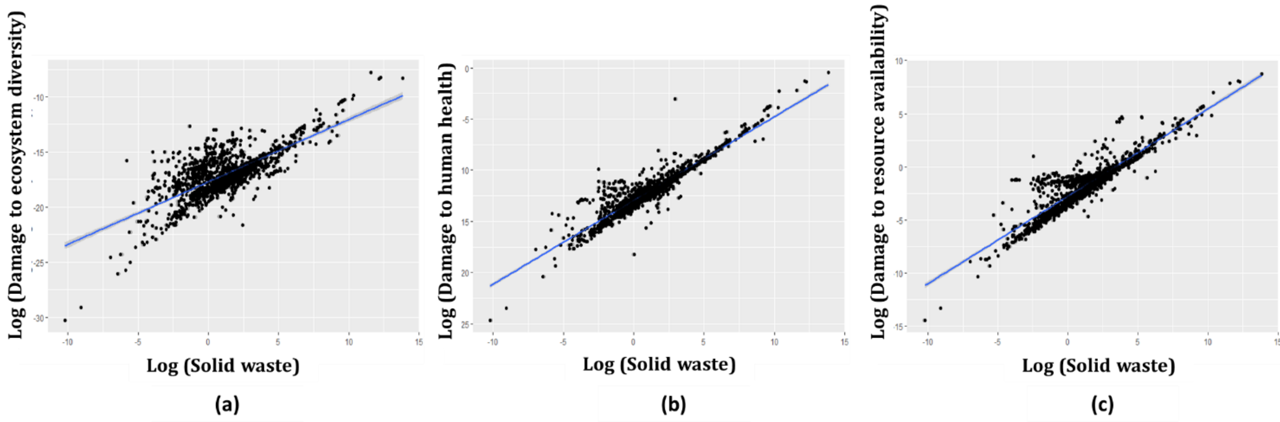

Figure 10. Environmental damage indicators and solid waste footprints visualized – after natural logarithm transformation.

3.3.2. Correlation between variables

Correlation coefficients (see Figure 11) measures the strength of the linear association between pairs of numerical variables. Correlation was checked among the explanatory variables, and high correlations were found among the different product waste footprint definitions as well as between most of the other pairs of waste and resource footprints. This is not counterintuitive, especially considering that the resource footprints are likely to be confounding variables, i.e. the more raw materials (or the energy/water/land) used per kilogram of product, the more waste can be expected to emanate from these processes as well as the environmental damages.

3.3.3. Multiple regression results

The regression results are presented in Tables 5-6-7, each table corresponding to the regression models developed for one of the response variables, i.e. the environmental damage indicators. The tables show the regression coefficient for each explanatory variable as well as its the confidence interval [in brackets below] at 95% confidence level.

Within each of the Tables 5-6-7, six models are included, and they represent the analysis from the use of two different datasets: without versus with the resource footprints. The first dataset including all products in the scope of this study (with n = 1487 observations) was used to build the Models 1-2-3 shown in each table[7]. The second dataset, used in Models 4-5-6, includes the resource footprint data as well. However, these models can only use a subset of the former observations (with n = 950 observations) since the resource footprint data from Steinmann et al. (2017) was not available for the whole scope of products in this

[7] One product was excluded from the regression models built for the response variable "damage to human health" due to having a negative value, which was not included in the natural logarithm transformations.

study. The control variables (waste category indicators and product group information) are included in the models using both datasets.

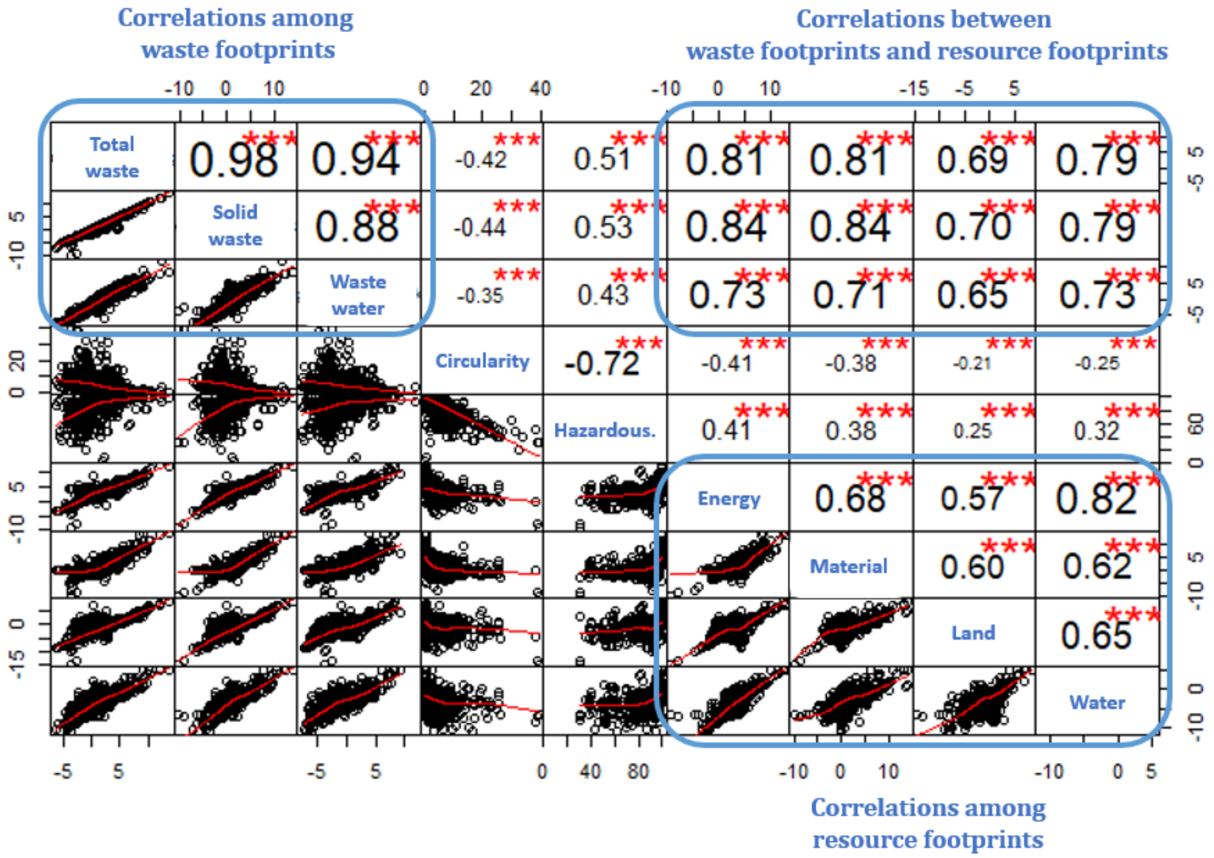

Figure 11. Correlation between explanatory variables (after data transformations)

In multiple regression using several explanatory variables, it is better to have less correlation between the explanatory values. This is because the aim is to explain the expected changes in Y that can be predicted based on different x_i values separately, but explanatory variables behaving in a similar way can distort the estimations of the regression models. In other words, it becomes harder to estimate the effect of any particular variable. This is called a multicollinearity problem (Wooldridge, 2012), and one solution is not adding highly correlated variables together in a model. As shown by Figure 11, multicollinearity was a potential issue which needed to be considered in building the regression models of this study. In order to avoid the multicollinearity problem, at first, the most comprehensive models were developed, which were later checked for *variance inflation factor* (VIF) which shows the extent of increase in a coefficient's variance due to the collinearity problem. Models with VIF > 5 for any of the numerical variables were not included in the final regression models. This meant that, due to high correlation between the waste footprints and resource footprints, only few resource footprints could be included in each model at once and it was not possible to add the land use in any of the models.

The final regression models can explain 64-88% of the variance in damage to ecosystem diversity, 72-92% of the variance in damage to human health and 74-91% of the variance in damage to resource availability. Furthermore, the results show a statistically significant (>99% confidence level) and positive relationship between the waste footprints (measured as both total and solid waste) and damage to ecosystem diversity, human health and resource availability. Since the models are log-transformed on both sides of the regression equation for these variables, the coefficients must be interpreted multiplicatively. In other words, the coefficients show the expected percentage of change in the response variable corresponding to each 1% change in the explanatory variables. For example, the Model 1 for each regression set predict that when the total waste is increased by 100% (doubled), there would be an expected 73% increase in damage to ecosystem diversity (Table 5), an expected 81% increase in damage to human health (Table 6), and an expected 74% increase in damage to resource availability (Table 7). Similarly, according to the Model 2 from the regression sets, doubling the solid waste means an expected 75%, 84% and 78% increase respectively for each of the environmental damage indicators. Therefore, the coefficients are not only statistically but also practically significant for both total waste and solid waste. Wastewater coefficients are smaller as shown in the Model 3 of the regression sets, but its association with the environmental damage indicators remains statistically significant in all models. When controlled for resource footprints (in the Models 4-5-6), the statistical significance of the coefficients for the total and solid waste footprints remain strong, although the coefficients can reduce for more than 20 percentage points. Nevertheless, when compared with the coefficients of resource footprints included in the models, the coefficients for the waste footprint are higher.

When it comes to the circularity percentage of the waste, the models suggest a statistically significant (albeit at somewhat varying levels) and negative relationship with the three environmental damage indicators. Since these percentage points are not log-transformed, but only the response variables are log-transformed, an additive change in this explanatory variable should be interpreted as a multiplicative change in the response variables. For example, one percentage point increase in the circularity of the waste footprint predicts a reduction in damage to ecosystem diversity, human health or resource availability between 0.02-0.08% across all regression models. Therefore, while the results show statistical significance, it can be argued that the coefficients are so small that they are not practically significant to support actual decision making scenarios. A plausible explanation for this effect might be the usage of cut-off system model as the data source. More circularity can come from the additional steps in the waste treatment process for material recovery chains and the burdens associated with the sorting, shredding, recovery operations remain with the primary product in the cut-off system model. In other words, the benefits of having more circular processes – if any – might be offset with the burdens of these additional steps in the cut-off dataset, all the while not receiving any credit for producing recyclables.

The relationship between the hazardousness ratio and the environmental damage indicators show a similar picture when used with total and solid waste footprints in different models. For example, one percentage point increase in hazardousness can predict changes between up to 0.03% decrease and up to 0.01% increase in the damage to ecosystem diversity, human health or resource availability across all regression models. The result suggesting a decrease in the environmental damage when hazardousness increases may sound counterintuitive. If this relationship is indeed correct, hazardous wastes might have been modelled with more "careful" waste handling scenarios to minimize environmental damage. Alternatively, there might be a different variable which is correlated with the hazardousness ratio but not accounted for in the models despite having an explanatory power on the environmental damage indicators. Nevertheless, as discussed in the data collection section, it might be a measurement error as it is hard to identify hazardous and non-hazardous waste types, and hence the models might just be quantifying a "noise" in the data.

All the models include the product sub-category as a control variable, and the sub-categories are chosen over the higher categories for this purpose to have a more accurate representation of different types of products. For example, the sub-categories regarding forestry and animal products might have different product characteristics although they are in the same higher-level product group. The only difference is that the Models 4-5-6 do not contain the products from sub-categories "machinery (general or special purpose)" and "transport vehicles" since these products were not within the scope of Steinmann et al. (2017). The detailed results for the coefficients of product types can be found in the Appendix.

Below the regression coefficients in the Tables 5-6-7, the intercept value is noted. This intercept shows the environmental damage levels predicted by the model for when the value of every explanatory variable is 0. However, this is not a practically relevant scenario according to the sample data collected from Ecoinvent database. Since there is no such practical case, the intercept lies beyond the area represented by the data; and therefore, omitted from the interpretation of the results.

Table 5. Linear regression results for damage to ecosystem diversity

Dependent variable:	Log (Damage to ecosystem diversity)					
Estimation:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log (Total waste)	0.73 ***			0.61 ***		
	[0.70, 0.75]			[0.55, 0.66]		
Log (Solid waste)		0.75 ***			0.48 ***	
		[0.72, 0.77]			[0.43, 0.53]	
Log (Wastewater)			0.58 ***			0.09 ***
			[0.55, 0.61]			[0.06, 0.12]
Hazardousness % point	-0.02 ***	-0.02 ***	0.00	-0.03 ***	-0.03 ***	-0.01 **
	[-0.03, -0.01]	[-0.03, -0.01]	[-0.01, 0.00]	[-0.04, -0.02]	[-0.04, -0.02]	[-0.02, -0.00]
Circularity % point	-0.04 ***	-0.02 *	-0.05 ***	-0.08 ***	-0.07 ***	-0.04 ***
	[-0.06, -0.02]	[-0.04, -0.00]	[-0.07, -0.03]	[-0.11, -0.06]	[-0.09, -0.05]	[-0.06, -0.02]
Log (Raw material use)				0.14 ***		0.12 ***
				[0.09, 0.19]		[0.09, 0.15]
Log (Freshwater consumption)					0.35 ***	0.16 ***
					[0.30, 0.40]	[0.12, 0.20]
Log (Non-renewable energy demand)						0.58 ***
						[0.53, 0.63]
(Intercept)	-14.49 ***	-14.33 ***	-14.23 ***	-13.18 ***	-12.16 ***	-15.32 ***
	[-15.15, -13.83]	[-14.96, -13.71]	[-15.00, -13.47]	[-14.07, -12.29]	[-12.92, -11.41]	[-16.00, -14.64]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1487	1487	1487	950	950	950
R2	0.72	0.75	0.64	0.75	0.82	0.88

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table 6. Linear regression results for damage to human health

Dependent variable:	Log (Damage to human health)					
Estimation:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log (Total waste)	0.81 ***			0.55 ***		
	[0.78, 0.83]			[0.50, 0.59]		
Log (Solid waste)		0.84 ***			0.66 ***	
		[0.82, 0.86]			[0.62, 0.70]	
Log (Wastewater)			0.62 ***			0.06 ***
			[0.59, 0.65]			[0.03, 0.08]
Hazardousness % point	-0.02 ***	-0.02 ***	0.00	-0.02 ***	-0.03 ***	0.00
	[-0.02, -0.01]	[-0.03, -0.02]	[-0.01, 0.01]	[-0.03, -0.02]	[-0.03, -0.02]	[-0.00, 0.01]
Circularity % point	-0.05 ***	-0.03 ***	-0.07 ***	-0.08 ***	-0.06 ***	-0.03 ***
	[-0.06, -0.03]	[-0.05, -0.02]	[-0.09, -0.05]	[-0.10, -0.06]	[-0.08, -0.04]	[-0.05, -0.02]
Log (Raw material use)						0.25 ***
						[0.22, 0.28]
Log (Freshwater consumption)				0.31 ***	0.23 ***	0.12 ***
				[0.27, 0.36]	[0.19, 0.27]	[0.08, 0.15]
Log (Non-renewable energy demand)						0.58 ***
						[0.54, 0.62]
(Intercept)	-11.28 ***	-11.09 ***	-11.18 ***	-9.42 ***	-9.50 ***	-13.21 ***
	[-11.83, -10.74]	[-11.56, -10.61]	[-11.92, -10.44]	[-10.14, -8.70]	[-10.12, -8.87]	[-13.80, -12.62]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1486	1486	1486	950	950	950
R2	0.86	0.89	0.74	0.86	0.90	0.92

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table 7. Linear regression results for damage to resource availability

Dependent variable:	Log (Damage to resource availability)					
Estimation:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log (Total waste)	0.74 ***			0.47 ***		
	[0.72, 0.77]			[0.42, 0.53]		
Log (Solid waste)		0.78 ***			0.60 ***	
		[0.75, 0.80]			[0.54, 0.65]	
Log (Wastewater)			0.56 ***			0.01
			[0.53, 0.59]			[-0.03, 0.04]
Hazardousness % point	-0.01 ***	-0.01 ***	0.01	-0.02 ***	-0.02 ***	0.00
	[-0.02, -0.00]	[-0.02, -0.01]	[-0.00, 0.01]	[-0.03, -0.01]	[-0.03, -0.02]	[-0.00, 0.01]
Circularity % point	-0.04 ***	-0.02 **	-0.06 ***	-0.08 ***	-0.06 ***	-0.02 *
	[-0.06, -0.02]	[-0.04, -0.01]	[-0.08, -0.04]	[-0.10, -0.05]	[-0.08, -0.03]	[-0.04, -0.00]
Log (Raw material use)						0.14 ***
						[0.11, 0.17]
Log (Freshwater consumption)				0.33 ***	0.24 ***	0.04
				[0.27, 0.38]	[0.19, 0.29]	[-0.00, 0.08]
Log (Non-renewable energy demand)						0.78 ***
						[0.74, 0.83]
(Intercept)	-2.35 ***	-2.15 ***	-2.27 ***	-0.14	-0.19	-4.69 ***
	[-2.96, -1.74]	[-2.70, -1.59]	[-3.04, -1.50]	[-1.01, 0.73]	[-0.98, 0.61]	[-5.35, -4.03]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1487	1487	1487	950	950	950
R2	0.83	0.86	0.74	0.81	0.84	0.91

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

4. Discussion

This study was the first attempt at quantification of the relationship between the product waste footprint and the life cycle environmental damage indicators. For this purpose, broad definitions of waste (e.g. total waste, solid waste) were used with simplified indicators for the type of waste and waste treatment path (e.g. the ratios for hazardousness and circularity). While this study highlights that a relationship exists using these broader terms, these definitions can be extended in future studies to pinpoint the higher and lower predictive powers of the different waste types (e.g. glass, plastic, radioactive, MSW, etc) or waste from different production stages (e.g. production of input materials, final production, fuel and electricity). The algorithms mentioned in the data section can be easily adapted to different waste categorizations by changing them as background parameters. Similarly, more detailed analyses can be done to explore other environmental impact categories. While endpoint indicators were chosen for this study, looking at midpoint indicators might reveal further insights into which damage paths the waste footprints are highly associated with.

The study was conducted using the datasets based on the cut-off system model, which does not give credit to the waste producer for recycling activities. Therefore, another path for future research can involve repeating the study using the datasets based on allocation at the point of substitution (APOS) and consequential system models to verify or challenge the results presented here. However, the lack of pre-classification of allocatable, recyclable and waste products in those system models might require slight changes in the waste footprint calculation algorithms discussed in this study.

Regarding the data quality, datasets in Ecoinvent can have inconsistent system boundaries regarding the life cycle stages and/or the approach to end of life modelling. For example, some of the datasets accounted for waste in more detail where others did not; and some datasets included machinery/infrastructure requirements while others did not. Even though some of these choices of the data modeller are transparent in the comment fields of the datasets, the lack thereof does not guarantee the completeness of the data. This has been a limitation of this study which might have impacted the results. Further assessments on the life cycle inventory models offered by Ecoinvent was beyond the scope of this thesis.

Besides the additional detailed studies aiming to quantify the relationships discussed in this study on the product level, a new pathway for research could be studying the waste footprints on a broader scale, such as defining the waste footprints on household or socio-economic levels. In fact, the waste footprint indicator can be based on different units, e.g. waste footprint per Euro spent. Waste footprint calculations based on price points could reveal new results on how different purchasing decisions – for example, given a household budget - might lead to predicted changes in the environmental damage.

Lastly, while the results of this study have shown that there is indeed a strong association between the waste footprints and environmental damages, only the active decision to use this information in the intended way would make a positive difference for the environment. Therefore, another path for research would be to determine how customers would integrate the waste footprint information, if/when made visible to them, into their daily purchasing decisions.

5. Conclusion

In this study, the product waste footprints and life cycle environmental damages were calculated for a large number of products, and the predictive power of the waste footprints on the environmental damages were analysed. The results from linear regression analyses suggest a significant and positive relationship between these variables. These findings indicate that the waste footprint is a valuable indicator which can be used as a proxy for environmental damages, and it is a strong candidate to be a part of the environmental sustainability communication between product companies and customers as well as among the other stakeholders in the product supply chains.

Future research can seek to improve our understanding of the relationship between the waste footprint and environmental damage concepts, and design more detailed studies focusing on different product types, waste categories and environmental damage indicators. Additionally, studying the potential of product waste footprints in influencing consumer purchasing and consumption behaviours would be another interesting pathway for future research.

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Appendix

A. Product categories and example products

1a. Agricultural and forestry products

- CPC 01 - Products of agriculture, horticulture and market gardening: “almond”, “fava bean seed, for sowing”
- CPC 03 - Forestry and logging products: “bundle, energy wood, measured as dry mass”, “cleft timber, measured as dry mass”

1b. Live animal, fish and their products

- CPC 02 - Live animals and animal products (excluding meat): “sheep for slaughtering, live weight”, “cow milk”
- CPC 04 - Fish and other fishing products: “landed anchovy, fresh”, “trout, from aquaculture”

2. Basic metals & alloys, including their semi-finished products

- CPC 41 - Basic metals: “aluminium, cast alloy”, “spiral-seam duct, steel, DN 125”

3. Chemical products

- CPC 18 - Natural water: “tap water”, “water, decarbonised, at user”
- CPC 34 - Basic chemicals: “2,3-dimethylbutan”, “sulfuric acid”
- CPC 35 - Other chemical products; man-made fibres: “acrylic filler,” “printing ink, offset, without solvent, in 47.5% solution state”

4. Glass and other non-metallic products

- CPC 37 - Glass and glass products and other non-metallic products n.e.c.: “adhesive mortar”, “packaging glass, green”

5a. Machinery (general or special purpose)

- CPC 43 - General-purpose machinery: “air filter in exhaust air valve”, “flexible duct, aluminium/PET DN of 125”, “heat pump 30kW”
- CPC 44 - Special-purpose machinery: “non-ferrous metal smelter”, “hot water tank, 600l”

5b. Metal/electronic equipment and parts

- CPC 38 - Furniture; other transportable goods n.e.c.: “floating collar cage”, “floating hexagonal metal cage”
- CPC 42 - Fabricated metal products, except machinery and equipment: “anode, for metal electrolysis”, “door, outer, wood-aluminium”
- CPC 45 - Office, accounting and computing machinery: “computer, laptop”, “printer, laser, black/white”

- CPC 46 - Electrical machinery and apparatus: “battery cell, Li-ion”, “cathode, $LiMn_2O_4$, for lithium-ion battery”
- CPC 47 - Radio, television and communication equipment and apparatus: “cable, data cable in infrastructure”, “capacitor, electrolyte type, > 2cm height”
- CPC 48 - Medical appliances, precision and optical instruments, […]: “backlight, for liquid crystal display”, “electronics, for control units”
- CPC 49 - Transport equipment: “charger, for electric scooter”, “silencer, steel, DN 125”

5c. Transport vehicles

- CPC 49 - Transport equipment: “bicycle”, “tanker, transoceanic”

6. Ores, minerals & fuels

- CPC 11 - Coal and peat: “hard coal”, “peat moss”
- CPC 12 - Crude petroleum and natural gas: “petroleum”, “natural gas, liquefied”
- CPC 13 - Uranium and thorium ores and concentrates: “uranium ore, as U”, “uranium, in yellowcake”
- CPC 14 - Metal ores: “lead concentrate”, “magnesium oxide”
- CPC 15 - Stone, sand and clay: “anhydrite rock”, “shale”
- CPC 16 - Other minerals: “lime”, “pumice”
- CPC 33 - Coke oven products; refined petroleum products […]: “benzene”, “petrol, 15% ETBE additive by volume, with ethanol from biomass”
- CPC 17200 - Coal gas, water gas, producer gas and similar gases, […]: “biogas”, “methane, 96% by volume”

7. Plastics & rubber products

- CPC 36 - Rubber and plastics products: “polymethyl methacrylate, sheet”, “horticultural fleece”
- CPC 347 - Plastics in primary forms: “polyphenylene sulfide”, “polyethylene terephthalate, granulate, bottle grade, recycled”
- CPC 34800 - Synthetic rubber and factice derived from oils, […]: “silicone product”, “synthetic rubber”

8a. Food & beverages, animal feed

- CPC 21 - Meat, fish, fruits, vegetables, oils and fats: “red meat, live weight”, “coconut, dehusked”
- CPC 22 - Dairy products and egg products: “cream, from cow milk”, “whey”

- CPC 23 - Grain mill products, starches and starch products; […]: “sugar, from sugar beet”, “oat grain, feed”
- CPC 24 – Beverages: “soybean beverage”

8b. Wood, straw & cork

- CPC 31 - Products of wood, cork, straw and plaiting materials: “bark chips, wet, measured as dry mass”, “EUR-flat pallet”

8c. Pulp & paper

- CPC 32 - Pulp, paper and paper products; printed matter […]: “carton board box production, with offset printing”, “tissue paper”

8d. Textile

- CPC 26 - Yarn and thread; woven and tufted textile fabrics: “textile, jute”, “yarn, kenaf”
- CPC 27 - Textile articles other than apparel: “fleece, polyethylene”
- CPC 28 - Knitted or crocheted fabrics; wearing apparel: “textile, knit cotton”

B. Descriptive statistics for numerical variables

Table A1. Descriptive statistics - Primary response and explanatory variables

Statistic	Response variables (Environmental damage to...)			Explanatory variables (Product waste footprints)		
	... ecosystem diversity	... human health	... resource availability	Total waste	Solid waste	Wastewater
nbr.val	1487	1487	1487	1487	1487	1487
nbr.null	0	0	0	0	0	0
nbr.na	0	0	0	0	0	0
min	7.18E-14	-5.57E-06	5.51E-07	1.73E-03	3.69E-05	4.52E-04
max	4.13E-04	6.35E-01	6.32E+03	1.03E+06	1.03E+06	1.50E+05
range	4.13E-04	6.35E-01	6.32E+03	1.03E+06	1.03E+06	1.50E+05
sum	1.93E-03	1.82E+00	2.30E+04	2.14E+06	1.93E+06	2.12E+05
median	3.87E-08	6.02E-06	2.28E-01	4.38E+00	3.37E+00	5.12E-01
mean	1.30E-06	1.23E-03	1.54E+01	1.44E+03	1.30E+03	1.42E+02
SE.mean	4.07E-07	5.09E-04	5.54E+00	7.43E+02	7.23E+02	1.01E+02
CI.mean	7.99E-07	9.98E-04	1.09E+01	1.46E+03	1.42E+03	1.98E+02
var	2.47E-10	3.85E-04	4.56E+04	8.21E+08	7.78E+08	1.52E+07
std.dev	1.57E-05	1.96E-02	2.14E+02	2.87E+04	2.79E+04	3.90E+03
coef.var	1.21E+01	1.60E+01	1.38E+01	1.99E+01	2.15E+01	2.74E+01

Table A2. Descriptive statistics (contd.) - Control variables

	Control variables					
	Waste category indicators		(Resource footprints, from Steinmann et al., 2017)			
Statistic	Circularity percentage	Hazardousness percentage	Nonrenewable energy demand	Raw material use	Land use	Freshwater consumption
nbr.val	1487	1487	950	950	950	950
nbr.null	0	0	0	0	0	0
nbr.na	0	0	537	537	537	537
min	2.92E-02	3.52E+00	8.48E-05	4.88E-05	5.07E-07	1.19E-05
max	3.95E+01	1.00E+02	3.44E+05	1.10E+06	3.86E+03	2.18E+02
range	3.95E+01	9.64E+01	3.44E+05	1.10E+06	3.86E+03	2.18E+02
sum	7.30E+03	1.28E+05	1.38E+06	3.84E+06	1.15E+04	1.44E+03
median	3.79E+00	9.06E+01	5.43E+01	1.98E+00	2.34E-01	5.99E-02
mean	4.91E+00	8.64E+01	1.45E+03	4.05E+03	1.21E+01	1.51E+00
SE.mean	1.15E-01	3.33E-01	5.71E+02	1.78E+03	4.73E+00	4.38E-01
CI.mean	2.26E-01	6.53E-01	1.12E+03	3.50E+03	9.28E+00	8.60E-01
var	1.98E+01	1.65E+02	3.10E+08	3.02E+09	2.13E+04	1.82E+02
std.dev	4.45E+00	1.28E+01	1.76E+04	5.50E+04	1.46E+02	1.35E+01
coef.var	9.05E-01	1.49E-01	1.21E+01	1.36E+01	1.20E+01	8.92E+00

C. Detailed results for linear regression models

Table A3. Linear regression model results for damage to ecosystem diversity (without resource footprints)

Dependent variable:	Log (Damage to ecosystem diversity)		
Estimation:	Model 1	Model 2	Model 3
Log (Total waste)	0.73 ***		
	[0.70, 0.75]		
Log (Solid waste)		0.75 ***	
		[0.72, 0.77]	
Log (Wastewater)			0.58 ***
			[0.55, 0.61]
Hazardousness % point	-0.02 ***	-0.02 ***	0.00
	[-0.03, -0.01]	[-0.03, -0.01]	[-0.01, 0.00]
Circularity % point	-0.04 ***	-0.02 *	-0.05 ***
	[-0.06, -0.02]	[-0.04, -0.00]	[-0.07, -0.03]
Log (Raw material use)			
Log (Freshwater consumption)			
Log (Non-renewable energy demand)			
prod: Basic metals & alloys, semi-finished products	-2.66 ***	-2.60 ***	-2.16 ***
	[-2.98, -2.33]	[-2.91, -2.29]	[-2.54, -1.79]
prod: Chemical products	-2.19 ***	-2.02 ***	-2.29 ***
	[-2.39, -1.99]	[-2.21, -1.84]	[-2.53, -2.06]
prod: Food & beverages, animal feed	-0.52 **	0.01	-1.02 ***
	[-0.83, -0.21]	[-0.28, 0.31]	[-1.38, -0.66]
prod: Glass and other non-metallic products	-2.55 ***	-2.37 ***	-2.98 ***
	[-2.82, -2.28]	[-2.62, -2.11]	[-3.28, -2.67]
prod: Live animal, fish and their products	-0.54	-0.38	-0.73 *
	[-1.15, 0.07]	[-0.96, 0.19]	[-1.43, -0.04]
prod: Machinery (general or special purpose)	-2.32 ***	-2.24 ***	-2.27 ***
	[-2.70, -1.94]	[-2.60, -1.88]	[-2.71, -1.83]
prod: Metal/electronic equipments and parts	-2.40 ***	-2.32 ***	-2.02 ***
	[-2.70, -2.11]	[-2.60, -2.04]	[-2.36, -1.68]
prod: Ores, minerals & fuels	-2.59 ***	-2.44 ***	-2.55 ***
	[-2.85, -2.34]	[-2.68, -2.20]	[-2.84, -2.25]
prod: Plastics & rubber products	-1.47 ***	-1.41 ***	-1.43 ***
	[-1.75, -1.18]	[-1.68, -1.14]	[-1.76, -1.11]
prod: Pulp & paper	-1.24 ***	-1.14 ***	-1.38 ***
	[-1.67, -0.81]	[-1.55, -0.73]	[-1.87, -0.88]
prod: Textile	-0.95 *	-0.78	-0.71
	[-1.77, -0.13]	[-1.55, 0.00]	[-1.65, 0.23]
prod: Transport vehicles	-2.56 ***	-2.52 ***	-2.43 ***
	[-3.00, -2.11]	[-2.94, -2.10]	[-2.94, -1.93]
prod: Wood, straw & cork	0.05	0.21	-0.42 *
	[-0.25, 0.35]	[-0.08, 0.50]	[-0.77, -0.08]
(Intercept)	-14.49 ***	-14.33 ***	-14.23 ***
	[-15.15, -13.83]	[-14.96, -13.71]	[-15.00, -13.47]
N	1487	1487	1487
R2	0.72	0.75	0.64

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table A4. Linear regression model results for damage to ecosystem diversity (with resource footprints)

Dependent variable:	Log (Damage to ecosystem diversity)		
Estimation:	Model 4	Model 5	Model 6
Log (Total waste)	0.61 ***		
	[0.55, 0.66]		
Log (Solid waste)		0.48 ***	
		[0.43, 0.53]	
Log (Wastewater)			0.09 ***
			[0.06, 0.12]
Hazardousness % point	-0.03 ***	-0.03 ***	-0.01 **
	[-0.04, -0.02]	[-0.04, -0.02]	[-0.02, -0.00]
Circularity % point	-0.08 ***	-0.07 ***	-0.04 ***
	[-0.11, -0.06]	[-0.09, -0.05]	[-0.06, -0.02]
Log (Raw material use)	0.14 ***		0.12 ***
	[0.09, 0.19]		[0.09, 0.15]
Log (Freshwater consumption)		0.35 ***	0.16 ***
		[0.30, 0.40]	[0.12, 0.20]
Log (Non-renewable energy demand)			0.58 ***
			[0.53, 0.63]
prod: Basic metals & alloys, semi-finished products	-3.01 ***	-2.23 ***	-2.84 ***
	[-3.42, -2.60]	[-2.57, -1.90]	[-3.13, -2.54]
prod: Chemical products	-2.28 ***	-2.10 ***	-2.91 ***
	[-2.54, -2.02]	[-2.32, -1.88]	[-3.10, -2.72]
prod: Food & beverages, animal feed	-0.25	0.13	-0.14
	[-0.67, 0.17]	[-0.23, 0.48]	[-0.44, 0.16]
prod: Glass and other non-metallic products	-2.82 ***	-1.99 ***	-2.74 ***
	[-3.17, -2.48]	[-2.29, -1.70]	[-2.99, -2.48]
prod: Live animal, fish and their products	0.95 *	0.57	0.40
	[0.02, 1.89]	[-0.23, 1.37]	[-0.27, 1.06]
prod: Machinery (general or special purpose)			
prod: Metal/electronic equipments and parts	-2.75 ***	-2.14 ***	-2.94 ***
	[-3.15, -2.36]	[-2.45, -1.82]	[-3.23, -2.65]
prod: Ores, minerals & fuels	-3.09 ***	-2.22 ***	-3.19 ***
	[-3.41, -2.77]	[-2.50, -1.93]	[-3.43, -2.94]
prod: Plastics & rubber products	-1.29 ***	-1.52 ***	-2.72 ***
	[-1.62, -0.95]	[-1.81, -1.22]	[-2.97, -2.46]
prod: Pulp & paper	-1.18 ***	-1.01 ***	-1.23 ***
	[-1.67, -0.69]	[-1.43, -0.60]	[-1.58, -0.88]
prod: Textile	-0.85 *	-1.12 **	-1.39 ***
	[-1.66, -0.05]	[-1.80, -0.43]	[-1.96, -0.81]
prod: Transport vehicles			
prod: Wood, straw & cork	-0.50	0.07	-0.77 **
	[-1.29, 0.30]	[-0.61, 0.75]	[-1.33, -0.20]
(Intercept)	-13.18 ***	-12.16 ***	-15.32 ***
	[-14.07, -12.29]	[-12.92, -11.41]	[-16.00, -14.64]
N	950	950	950
R2	0.75	0.82	0.88

*** p < 0.001; ** p < 0.01; * p < 0.05; [ ]: confidence interval.

Table A5. Linear regression model results for damage to human health (without resource footprints)

Dependent variable:	Log (Damage to human health)		
Estimation:	Model 1	Model 2	Model 3
Log (Total waste)	0.81 ***		
	[0.78, 0.83]		
Log (Solid waste)		0.84 ***	
		[0.82, 0.86]	
Log (Wastewater)			0.62 ***
			[0.59, 0.65]
Hazardousness % point	-0.02 ***	-0.02 ***	0.00
	[-0.02, -0.01]	[-0.03, -0.02]	[-0.01, 0.01]
Circularity % point	-0.05 ***	-0.03 ***	-0.07 ***
	[-0.06, -0.03]	[-0.05, -0.02]	[-0.09, -0.05]
Log (Raw material use)			
Log (Freshwater consumption)			
Log (Non-renewable energy demand)			
prod: Basic metals & alloys, semi-finished products	0.09	0.14	0.75 ***
	[-0.18, 0.36]	[-0.10, 0.37]	[0.39, 1.12]
prod: Chemical products	-0.14	0.04	-0.17
	[-0.30, 0.03]	[-0.11, 0.18]	[-0.39, 0.06]
prod: Food & beverages, animal feed	-0.42 **	0.18	-0.89 ***
	[-0.67, -0.16]	[-0.05, 0.40]	[-1.24, -0.54]
prod: Glass and other non-metallic products	-0.37 ***	-0.16	-0.83 ***
	[-0.59, -0.15]	[-0.35, 0.03]	[-1.13, -0.53]
prod: Live animal, fish and their products	0.51 *	0.68 **	0.39
	[0.01, 1.01]	[0.24, 1.11]	[-0.29, 1.06]
prod: Machinery (general or special purpose)	0.01	0.08	0.17
	[-0.30, 0.33]	[-0.19, 0.36]	[-0.26, 0.60]
prod: Metal/electronic equipments and parts	0.00	0.06	0.60 ***
	[-0.24, 0.24]	[-0.15, 0.27]	[0.28, 0.93]
prod: Ores, minerals & fuels	-0.05	0.12	0.03
	[-0.26, 0.16]	[-0.07, 0.30]	[-0.25, 0.31]
prod: Plastics & rubber products	0.66 ***	0.71 ***	0.74 ***
	[0.42, 0.89]	[0.51, 0.92]	[0.42, 1.06]
prod: Pulp & paper	-0.39 *	-0.29	-0.49 *
	[-0.75, -0.04]	[-0.60, 0.03]	[-0.97, -0.01]
prod: Textile	-0.26	-0.08	0.09
	[-0.93, 0.41]	[-0.67, 0.51]	[-0.81, 1.00]
prod: Transport vehicles	-0.23	-0.20	0.05
	[-0.59, 0.14]	[-0.52, 0.11]	[-0.45, 0.54]
prod: Wood, straw & cork	-0.75 ***	-0.58 ***	-1.25 ***
	[-1.00, -0.51]	[-0.79, -0.36]	[-1.59, -0.91]
(Intercept)	-11.28 ***	-11.09 ***	-11.18 ***
	[-11.83, -10.74]	[-11.56, -10.61]	[-11.92, -10.44]
N	1486	1486	1486
R2	0.86	0.89	0.74

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table A6. Linear regression model results for damage to human health (with resource footprints)

Dependent variable:	Log (Damage to human health)		
Estimation:	Model 4	Model 5	Model 6
Log (Total waste)	0.55 ***		
	[0.50, 0.59]		
Log (Solid waste)		0.66 ***	
		[0.62, 0.70]	
Log (Wastewater)			0.06 ***
			[0.03, 0.08]
Hazardousness % point	-0.02 ***	-0.03 ***	0.00
	[-0.03, -0.02]	[-0.03, -0.02]	[-0.00, 0.01]
Circularity % point	-0.08 ***	-0.06 ***	-0.03 ***
	[-0.10, -0.06]	[-0.08, -0.04]	[-0.05, -0.02]
Log (Raw material use)			0.25 ***
			[0.22, 0.28]
Log (Freshwater consumption)	0.31 ***	0.23 ***	0.12 ***
	[0.27, 0.36]	[0.19, 0.27]	[0.08, 0.15]
Log (Non-renewable energy demand)			0.58 ***
			[0.54, 0.62]
prod: Basic metals & alloys, semi-finished products	0.73 ***	0.62 ***	-0.10
	[0.41, 1.05]	[0.34, 0.89]	[-0.36, 0.16]
prod: Chemical products	-0.01	0.14	-0.75 ***
	[-0.22, 0.20]	[-0.04, 0.32]	[-0.92, -0.58]
prod: Food & beverages, animal feed	-0.16	0.33 *	0.06
	[-0.50, 0.18]	[0.03, 0.62]	[-0.20, 0.32]
prod: Glass and other non-metallic products	0.08	0.20	-0.67 ***
	[-0.20, 0.36]	[-0.04, 0.45]	[-0.89, -0.45]
prod: Live animal, fish and their products	0.81 *	0.74 *	0.53
	[0.05, 1.57]	[0.08, 1.40]	[-0.05, 1.11]
prod: Machinery (general or special purpose)			
prod: Metal/electronic equipments and parts	0.45 **	0.38 **	-0.51 ***
	[0.15, 0.76]	[0.11, 0.64]	[-0.76, -0.26]
prod: Ores, minerals & fuels	0.19	0.30 *	-0.78 ***
	[-0.08, 0.46]	[0.07, 0.53]	[-0.99, -0.56]
prod: Plastics & rubber products	0.68 ***	0.82 ***	-0.48 ***
	[0.40, 0.96]	[0.58, 1.06]	[-0.71, -0.26]
prod: Pulp & paper	-0.20	-0.09	-0.25
	[-0.60, 0.20]	[-0.43, 0.26]	[-0.56, 0.05]
prod: Textile	-0.38	-0.17	-0.34
	[-1.03, 0.28]	[-0.74, 0.39]	[-0.84, 0.15]
prod: Transport vehicles			
prod: Wood, straw & cork	-0.70 *	-0.49	-1.43 ***
	[-1.35, -0.06]	[-1.05, 0.07]	[-1.92, -0.94]
(Intercept)	-9.42 ***	-9.50 ***	-13.21 ***
	[-10.14, -8.70]	[-10.12, -8.87]	[-13.80, -12.62]
N	950	950	950
R2	0.86	0.90	0.92

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table A7. Linear regression model results for damage to resource availability (without resource footprints)

Dependent variable:	Log (Damage to resource availability)		
Estimation:	Model 1	Model 2	Model 3
Log (Total waste)	0.74 ***		
	[0.72, 0.77]		
Log (Solid waste)		0.78 ***	
		[0.75, 0.80]	
Log (Wastewater)			0.56 ***
			[0.53, 0.59]
Hazardousness % point	-0.01 ***	-0.01 ***	0.01
	[-0.02, -0.00]	[-0.02, -0.01]	[-0.00, 0.01]
Circularity % point	-0.04 ***	-0.02 **	-0.06 ***
	[-0.06, -0.02]	[-0.04, -0.01]	[-0.08, -0.04]
Log (Raw material use)			
Log (Freshwater consumption)			
Log (Non-renewable energy demand)			
prod: Basic metals & alloys, semi-finished products	0.91 ***	0.94 ***	1.53 ***
	[0.61, 1.22]	[0.67, 1.21]	[1.16, 1.91]
prod: Chemical products	0.78 ***	0.94 ***	0.76 ***
	[0.60, 0.97]	[0.77, 1.11]	[0.53, 1.00]
prod: Food & beverages, animal feed	-0.48 **	0.07	-0.91 ***
	[-0.77, -0.19]	[-0.19, 0.33]	[-1.27, -0.54]
prod: Glass and other non-metallic products	0.03	0.22	-0.40 *
	[-0.22, 0.27]	[-0.00, 0.44]	[-0.71, -0.09]
prod: Live animal, fish and their products	0.49	0.63 *	0.38
	[-0.07, 1.05]	[0.13, 1.14]	[-0.32, 1.09]
prod: Machinery (general or special purpose)	0.62 ***	0.67 ***	0.78 ***
	[0.27, 0.97]	[0.35, 0.99]	[0.33, 1.22]
prod: Metal/electronic equipments and parts	0.95 ***	0.99 ***	1.53 ***
	[0.68, 1.22]	[0.74, 1.23]	[1.19, 1.87]
prod: Ores, minerals & fuels	0.89 ***	1.05 ***	0.97 ***
	[0.66, 1.13]	[0.84, 1.26]	[0.68, 1.26]
prod: Plastics & rubber products	1.77 ***	1.82 ***	1.85 ***
	[1.51, 2.04]	[1.58, 2.06]	[1.52, 2.18]
prod: Pulp & paper	0.07	0.16	-0.01
	[-0.33, 0.47]	[-0.20, 0.52]	[-0.51, 0.49]
prod: Textile	0.44	0.60	0.78
	[-0.31, 1.20]	[-0.08, 1.28]	[-0.17, 1.72]
prod: Transport vehicles	0.58 **	0.59 **	0.85 **
	[0.17, 0.99]	[0.22, 0.95]	[0.33, 1.36]
prod: Wood, straw & cork	-0.22	-0.06	-0.68 ***
	[-0.50, 0.05]	[-0.31, 0.19]	[-1.03, -0.33]
(Intercept)	-2.35 ***	-2.15 ***	-2.27 ***
	[-2.96, -1.74]	[-2.70, -1.59]	[-3.04, -1.50]
N	1487	1487	1487
R2	0.83	0.86	0.74

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; [ ]: confidence interval.

Table A8. Linear regression model results for damage to resource availability (with resource footprints)

Dependent variable:	Log (Damage to resource availability)		
Estimation:	Model 4	Model 5	Model 6
Log (Total waste)	0.47 ***		
	[0.42, 0.53]		
Log (Solid waste)		0.60 ***	
		[0.54, 0.65]	
Log (Wastewater)			0.01
			[-0.03, 0.04]
Hazardousness % point	-0.02 ***	-0.02 ***	0.00
	[-0.03, -0.01]	[-0.03, -0.02]	[-0.00, 0.01]
Circularity % point	-0.08 ***	-0.06 ***	-0.02 *
	[-0.10, -0.05]	[-0.08, -0.03]	[-0.04, -0.00]
Log (Raw material use)			0.14 ***
			[0.11, 0.17]
Log (Freshwater consumption)	0.33 ***	0.24 ***	0.04
	[0.27, 0.38]	[0.19, 0.29]	[-0.00, 0.08]
Log (Non-renewable energy demand)			0.78 ***
			[0.74, 0.83]
prod: Basic metals & alloys, semi-finished products	1.50 ***	1.35 ***	0.75 ***
	[1.12, 1.89]	[1.00, 1.70]	[0.46, 1.03]
prod: Chemical products	0.86 ***	0.99 ***	0.04
	[0.61, 1.11]	[0.76, 1.22]	[-0.15, 0.22]
prod: Food & beverages, animal feed	-0.38	0.04	-0.08
	[-0.79, 0.03]	[-0.33, 0.42]	[-0.37, 0.21]
prod: Glass and other non-metallic products	0.43 *	0.53 ***	-0.28 *
	[0.09, 0.78]	[0.22, 0.84]	[-0.53, -0.03]
prod: Live animal, fish and their products	-0.04	-0.11	-0.25
	[-0.96, 0.88]	[-0.96, 0.73]	[-0.89, 0.40]
prod: Machinery (general or special purpose)			
prod: Metal/electronic equipments and parts	1.50 ***	1.39 ***	0.60 ***
	[1.13, 1.87]	[1.05, 1.72]	[0.32, 0.88]
prod: Ores, minerals & fuels	1.25 ***	1.33 ***	0.18
	[0.92, 1.57]	[1.04, 1.63]	[-0.06, 0.42]
prod: Plastics & rubber products	1.70 ***	1.84 ***	0.21
	[1.37, 2.04]	[1.53, 2.15]	[-0.04, 0.46]
prod: Pulp & paper	0.18	0.28	0.10
	[-0.30, 0.66]	[-0.16, 0.72]	[-0.24, 0.44]
prod: Textile	0.23	0.40	0.09
	[-0.56, 1.02]	[-0.32, 1.13]	[-0.46, 0.65]
prod: Transport vehicles			
prod: Wood, straw & cork	-0.20	-0.01	-1.02 ***
	[-0.98, 0.58]	[-0.73, 0.70]	[-1.57, -0.47]
(Intercept)	-0.14	-0.19	-4.69 ***
	[-1.01, 0.73]	[-0.98, 0.61]	[-5.35, -4.03]
N	950	950	950
R2	0.81	0.84	0.91

*** p < 0.001; ** p < 0.01; * p < 0.05; [ ]: confidence interval.

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