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Analyzing the relationship between product waste footprints and environmental damage – A life cycle analysis of 1,400+ products

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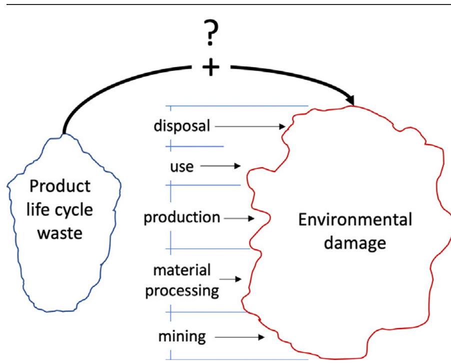
HIGHLIGHTS

- Reducing life cycle waste is an essential objective of the circular economy.
- Knowledge gaps on relationship between life cycle waste and environmental damage
- The waste footprint and environmental damage of 1487 products are computed.
- Significant correlations between waste footprint and environmental damage are found.
- For each 1 % increase in total waste, potential impacts increase by 0.75–0.84 %.

GRAPHICAL ABSTRACT



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ABSTRACT

A major problem for the circular economy is monitoring improvements in environmental sustainability. Measuring how much waste reduction efforts contribute to the decrease of environmental impact is difficult, because knowledge on whether life cycle waste amounts correlate with environmental damage is limited. In this article, product waste footprints are used to explore structural similarities and differences in associations with environmental damage. Using the waste flows linked to the production system of 1487 reference products from the Ecoinvent database, we found significant regression equations with R^2 of 0.75–0.89 between product waste footprints and potential impact on ecosystem diversity, human health and resource availability using log-transformed variables. For each 1 % increase in solid waste, potential impact on the environment increased by 0.75–0.84 %. This strong association between pre-consumer waste and environmental damage is particularly important for advocating for circular economy efforts at the point of consumption, where life cycle waste is invisible to consumers.

1. Introduction

Large parts of the total waste associated with a product can be generated even before the product reaches the hands of the consumers, e.g. during resource extraction, transportation, fuel and electricity production, and manufacturing processes (Laurenti et al., 2017). Taking a life cycle perspective, measuring this 'invisible' waste and communicating a cradle-to-grave product waste footprint (PWF) has been overlooked by the indicators of the circular economy (Harris et al., 2020). Accordingly, in traditional life cycle assessment (LCA) practice, the waste associated with a product would not be regarded as having environmental significance by itself. Instead, emissions and resource uses caused by waste treatment are included in the inventory analysis like other emissions and resource uses (Wernet et al., 2016).

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A family of footprint indicators were suggested in the debate on the environmental significance of footprints (Vanham et al., 2019). Ridoutt and Pfister (2013) argued that single-issue footprints are easier to communicate but they cannot capture the full complexity of environmental impact. Environmental impact results from life cycle impact assessment methods, however, may carry uncertainties inherent in the method (Chen et al., 2021). With the abundance of indicators with different merits and costs, a growing literature explores the relationships among them to re-simplify environmental decision-making. For example, several standard methodologies for life cycle impact assessment were shown to provide converging results pointing to fossil energy use as a dominating driver of environmental burdens (Huijbregts et al., 2010). Through a principal component analysis of 135 impact indicators, 92 % of the variance among products was found to be covered by a minimal set of six indicators (Steinmann et al., 2016).

In another study, popular resource footprints of fossil energy, freshwater, land and raw material use together accounted for 84 % of the variance in product rankings (Steinmann et al., 2017). Nevertheless, although these examples show significant correlations between various environmental indicators, this is not necessarily the case for all. For example, the widely used carbon footprint is often found not to be correlated with other impact assessment scores (Laurent et al., 2012), and a set of four headline indicators (carbon, land, water and materials) may not cover significant aspects of environmental impact (Steinmann et al., 2018).

In a stakeholder opinion survey, LCA experts pointed out potential risks in aggregating waste amounts in PWF to compare the environmental performance of products (Laurenti et al., 2018). The concern was that such aggregation could allow for an "unfair" advantage to those with low amounts of toxic waste in comparison to others with higher amounts of benign waste. The survey, nonetheless, was based on the stated responses of the LCA experts.

The state of the knowledge has been taken further in the present article. We explored the relationship between five types of ways to aggregate waste and three environmental damage indicators associated with the production of 1487 products. The ways to aggregate waste relate to total waste, solid waste, wastewater, hazardous waste, and recovered waste. The originality of the article pertains to demonstrating whether PWFs have a significant association with environmental damage using a computational method to work with a large number of life cycle inventories from the Ecoinvent database. The study contributes to a better understanding of life cycle waste inventories and their respective association with potential environmental damage.

After introducing the context of the study, the remainder of this article is divided into five sections. Section two explains the methodological path followed and the data used. The third describes the processed data and presents the findings of the regression analysis. The fourth section positions the results concerning previous related research and highlights the limitations of the study. The final section concludes by suggesting some opportunities for future research and the implications of our findings.

Table 1 shows the abbreviations used in the article.

Table 1
List of abbreviations.

AgriForeAnim	Agriculture, forestry, live animals & their products: Agricultural and forestry products Live animal, fish and their products
APOS	Allocation at the point of substitution
CC	Circularity
Chemical	Chemical products
FED	Fossil energy demand
FWC	Freshwater consumption
GlasNonMetal	Glass and other non-metallic products
HZ	Hazardousness
LCA	Life cycle assessment
LCIA	Life cycle impact assessment
LU	Land use
MachElecTrans	Machinery, metal/electronic, transport equipment: Machinery (general or special purpose) Metal/electronic equipment and parts Transport vehicles
MAE	Mean absolute error
MetalAlloy	Basic metals & alloys, incl. semi-finished products
MLR	Multilinear regression
MRSE	Mean root square error
MSW	Municipal solid waste
OreMinFuel	Ores, minerals & fuels
PlastRub	Plastics & rubber products
ProcBio	Processed biobased products: Food & beverages, animal feed Wood, straw & cork Pulp & paper Textile
PWF	Product waste footprint
RMU	Raw material use
SW	Solid waste
TW	Total waste
WW	Wastewater

2. Material and methods

There were four main stages to carrying out the study: (1) goal and scope definition, (2) selection of datasets, (3) data collection, and (4) data analysis. The first stage defined the functional unit, system boundaries and the life cycle impact assessment method to be used. In the second stage, the Ecoinvent v3.5 database was imported into the LCA framework, Brightway2. Then, by applying a set of exclusion criteria, 1487 reference products were selected from 16,002 datasets of Ecoinvent. The properties and classifications of all the waste flows that are linked into the product system (foreground and background), as well as the life cycle impact assessment results of the reference products, were collected using Brightway2 functions. Finally, all the data collected were imported into RStudio. The waste data were grouped into different fractions according to the Ecoinvent classification, and multilinear regression models were built to test a set of formulated hypotheses. Fig. 1 illustrates the main activities and elements of the methodological phases.

2.1. Goal and scope definition

The calculations of the waste footprints and the potential environmental impact were based on the LCA methodology (ISO, 2006). The goal of the study was to account for the total waste generated in producing products and investigate the relationship with environmental damage indicators. The main decisions regarding the calculations of this study were:

1. Functional unit: LCA calculations were performed based on specific functions that a product or service satisfies. The wide variety of products in this study did not allow for establishing common ground based on product functionalities; however, there was still a need to use a reference flow for the results to a common unit to avoid arbitrary distortions in our assessment. The alternatives considered were establishing the functional unit based on mass (environmental impact per kg of products) and price (environmental impact per monetary unit of product price). Ultimately, the convention set by previous research (e.g. Huijbregts et al., 2010; Steinmann et al., 2017), was followed, which was to set the functional unit as 1 kg of product. This also allowed us to collect supplementary data on product resource footprints from Steinmann et al. (2017).
2. System boundaries: This study used 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 best represent the global average were preferred over local alternatives.
3. Impact assessment methods: There are several established life cycle environmental 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 (Finnveden et al., 2009).

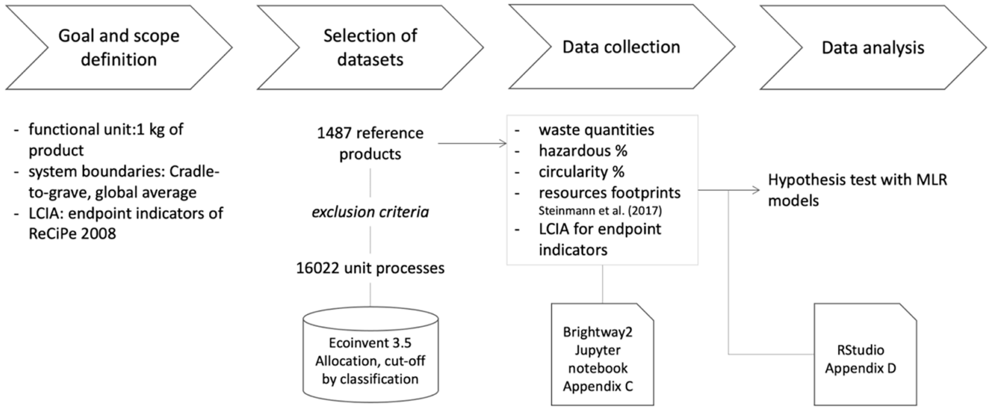

Fig. 1. Overview of the methodological path of the study.

This study used the ReCiPe 2008 method (Goedkoop et al., 2009) as implemented in Brightway2, considering both the fit-for-purpose and the availability within the timeframe of this work. It should be noted that ReCiPe has been updated with a newer method in 2016 (Huijbregts et al., 2017); however, this was not implemented in the Ecoinvent database (and not in Brightway2, either) when this work was done.

The ReCiPe 2008 method measures the environmental performance in 18 midpoint categories and three endpoint categories (Goedkoop et al., 2009). The midpoint indicators carry fewer assumptions and uncertainty, but the endpoint indicators can provide more intuitive metrics (Chen et al., 2021); therefore, the endpoint indicators were used. These are:

1. Damage to ecosystem diversity: This endpoint indicator is measured as the loss of species during a year, indicated with the unit *species.yr*.
2. Damage to human health: This endpoint indicator is measured as a disability-adjusted loss of life years, indicated with the unit *DALY*.
3. Damage to resource availability: This endpoint indicator is measured as increased cost due to resource depletion, indicated in the monetary unit *$*.

The life cycle environmental damage indicators were calculated using Brightway2. This did not require a custom algorithm to be developed; instead, the methods provided by the Brightway2 framework allowed for convenient access to endpoint results by iterating through the products in the database. However, these results were the normalized and weighted impact scores, and their units were *points*, one point being the damage of one "person/year" (Wernet et al., 2016). Therefore, the species.yr, DALY and $ results for the respective indicators were reverse-calculated from these results using "European Hierarchist" values for normalization and "Average" values for weighting. The formulas used for calculating the environmental damage indicators are found in section 2 of Appendix A.

2.1.1. Definition of waste

The EU Waste Framework Directive defines waste as any substance or object that the holder discards or intends or is required to discard (the European Parliament the Council of the European Union, 2008). It excludes some waste types, such as wastewater and radioactive waste, from its scope. Likewise, the definition and scope of waste can vary between different studies, and it is important to clarify what goes into the scope of each. In previous studies (Laurenti et al., 2018, 2017), the focus was on the pre-consumer waste footprint with a cradle-to-gate approach, i.e. the waste that is created from the raw material extraction up until the product leaves the downstream factory gate. Furthermore, wastewater was included to account for the total pre-consumer waste footprint for selected products.

In the present study, we took a cradle-to-grave approach to account for the product waste footprint. This allowed us to include the disposal process in the scope, which also contributes to the environmental damage associated with a product. Fig. 2 shows a representation of the alternative life cycle stages included in waste footprint definitions.

2.2. Selection of datasets

We used the Ecoinvent 3.5 database as a source of data for calculating the product waste footprint and life cycle environmental impact (Wernet et al., 2016). "Allocation, cut-off by classification" was the system model we used, which allocates the burdens of the virgin materials to the primary producer

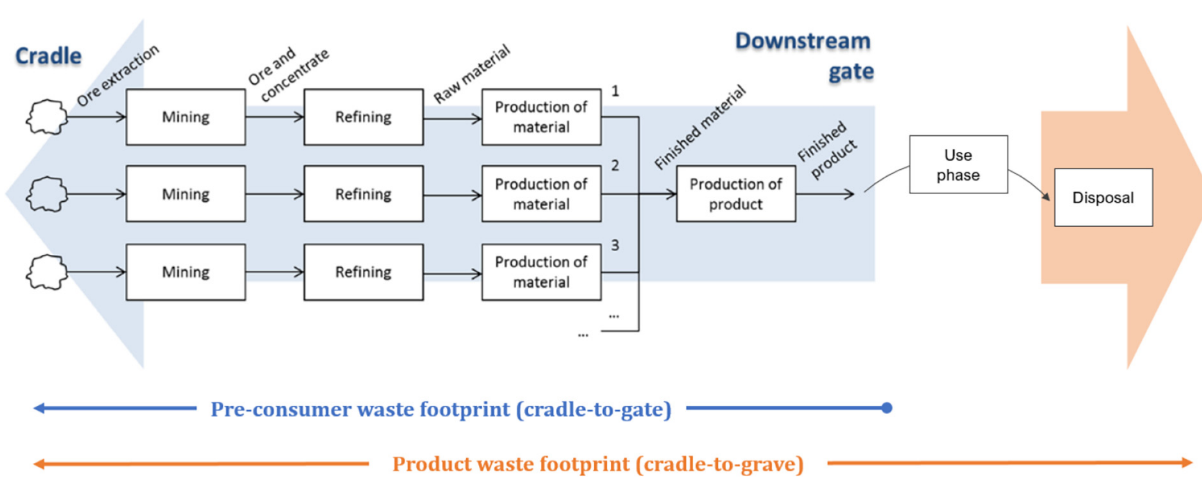

Fig. 2. Representation of the cradle-to-gate and cradle-to-grave approaches involved in measuring the waste footprint.

and provides the secondary materials as burden-free inputs to recycling processes (Steubing et al., 2016). In other words, the provision of recyclable materials for recycling or reuse does not give credit to the primary producer.

The Ecoinvent 3.5 cut-off database (Wernet et al., 2016) has 16,022 unit processes carrying inputs and outputs linked to each other, forming product supply chains. Not all of these processes produce the end products that fit the purpose of this study. Hence, to find relevant final production steps and the available products associated with them, we excluded the following datasets from the analysis of this study (a more detailed explanation of each choice is found in Appendix A):

i) Waste treatment and recyclable production processes
ii) Non-market processes
iii) Limited geographical coverage
iv) Infrastructure/facilities
v) Processes with non-product output

After these exclusions, 1487 datasets remained; these were present in 14 Ecoinvent product categories. To simplify our analysis, we further grouped the datasets according to their position on the supply chain (primary materials vs manufactured products, and biotic vs abiotic products). We finally ended up with eight groups. Table 2 shows the categories and 14 subcategories of products in scope.

Appendix E presents the data of the 16,022 unit processes' basic attributes, categorization and in/out of scope indicators and their category.

2.3. Data collection

This section describes the explanatory variables that composed the regression models, i.e. product waste footprints, hazardous percentage, circularity percentage, and resources footprints. The Ecoinvent database was processed using Python 3.6 on the open-source LCA framework Brightway2 (Mutel, 2017, 2015). Appendix C of the supplementary information provides the Python code developed for extracting the life cycle waste inventory data and the environmental damage calculations for the 1487 products analyzed in the study. The life cycle waste inventory data were used for calculating the product waste footprint, hazardous percentage, and circularity percentage. An R script was developed for performing these calculations; this script can be found in Appendix D.

2.3.1. Waste quantities

The Ecoinvent 3.5 cut-off database classifies all technosphere exchanges of a unit process as an allocatable, recyclable or waste product (Steubing et al., 2016). This classification was used to identify the waste generated at each step of a product's life cycle. The model of production processes in the Ecoinvent database usually has multiple unit processes linked as inputs, which in turn are composed of several other input processes. In these models, the supply chains grow upstream towards raw material extraction, and waste flows are modeled as part of the unit processes of the supply chain.

One can use more than one computational method to calculate the waste footprints. One method is to follow each branch of the supply chain upstream and account for the waste at each step. Another is to find out how much each waste treatment process is involved within the production system, because all waste outputs are further linked to waste treatment processes which would 'balance' the system by consuming this waste. In this study, the second method is used. This is achieved in two steps. The first step is to ascertain the total contribution of each unit process in producing the final product, for example, all "process contributions" including raw materials, electricity, manufacturing, assembly, and waste treatment to produce 1 kg of tomatoes or 1 kg of gold. These process contributions are represented in the form of a "supply vector" (16,022 × 1), where each index corresponds to a specific unit process. The second step is to sum the contributions of the waste treatment processes in kilograms, which corresponds to the total waste generated within that system.

However, it is important to only count the *relevant* waste treatment processes. For example, the waste treatment processes are present as "ordinary transformation" activities as well as in an aggregated form as the "market" processes in the Ecoinvent database. When one waste treatment process is linked to another in the form of such aggregation, the same waste would seem to be "consumed" by both, and therefore one of them needs to be chosen to avoid double counting. The ordinary transformation processes include more details about the type and subsequent treatment path of the waste; therefore, market values are omitted in waste footprint calculations. Considering this double counting potential as well as the inconsistent modeling among the products, the waste collection processes were also omitted.

The calculations were initially performed for each product's original unit, for example, a kilogram of apples, a liter of beverage, a meter of cable or an m^2 of a door. However, to reconcile the product waste footprint as a "per kg" indicator comparable across different products, the results were recalculated using each product's mass. When a product lacked mass information it was, if possible, approximated by another comparable product in the Ecoinvent database. For example, one unit of "used bicycle" is registered as 17 kg, and therefore the product "bicycle" was assumed to be the same. When no comparable product was found, it was excluded from the scope. Wastewater, originally represented in m^3, is approximated as 1000 kg when there was no alternative information.

Concerning the practical implementation of the selected algorithm, the methods provided by Brightway2 were used to import the datasets for the 1487 products, build the technosphere matrix, and solve for the supply vector for a given functional demand (Mutel, 2015). It should be noted that we calculate the waste generated cumulatively from all steps involved in the life cycle of a product – 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. The computational details of the calculations can be found in section 4 of the Python script provided in Appendix C (Calculating process contributions for products: the PWF basis through product system balance).

Table 2
Product categories and number of products.

Ecoinvent product category	Shorthand name (used in figures)	# of products
Agriculture, forestry, live animals & their products:	AgriForeAnim	190
Agricultural and forestry products		
Live animal, fish and their products		
Basic metals & alloys, incl. Semi-finished products	MetalAlloy	69
Chemical products	Chemical	549
Glass and other non-metallic products	GlasNonMetal	108
Machinery, metal/electronic, transport equipment:	MachElecTrans	197
Machinery (general or special purpose)		
Metal/electronic equipment and parts		
Transport vehicles		
Ores, minerals & fuels	OreMinFuel	126
Plastics & rubber products	PlastRub	83
Processed biobased products:	ProcBio	165
Food & beverages, animal feed		
Wood, straw & cork		
Pulp & paper		
Textile		

2.3.2. Hazardousness and circularity

First, the total waste was separated into two fractions: solid waste or wastewater; then the solid waste fraction was further classified based on its hazardousness and recoverability for subsequent treatment. The computational details of these calculations can be found in the chunk "3. Waste type calculations" of the R script provided in Appendix D.

The hazardousness of a material may depend on both the waste contents and their concentrations. For this study, simplified criteria (based on the activity/product classifications offered by the Ecoinvent database) were followed:

- Solid waste flows were considered either hazardous or non-hazardous, regardless of where they were produced or treated. Accordingly, if a flow was considered hazardous in one instance, it was computed as hazardous in all other instances.

- A solid waste flow was regarded as hazardous when the hazardousness was clearly stated in its subsequent waste treatment activity (e.g. activity name "treatmeent 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").
- Solid waste flows were classified as non-hazardous when no indication was found for them to be hazardous. This rule was also applied with composite waste, e.g. "used electric bicycle", considering that the concentration of hazardous materials could be a tiny percentage of the total mass of the product waste.

It should be noted that the high hazardousness ratios for many products might indicate a weakness in the validity of this measure. For example, hazardous waste might be included in the life cycle inventories more completely than non-hazardous waste, with the expectation that they have a more significant impact on the environment. The approach used in this study might also be overestimating the hazardous waste amounts since a waste categorized as hazardous is never categorized as non-hazardous in another process.

The circularity percentage was given by the fraction of solid waste that is treated with material recovery or biological treatment operations as the immediate next process in the value chain. For all product categories, the circularity percentage was not higher than 40 % and concentrated on the lower end. The information provided in the activity name and the ISIC code registered in Ecoinvent was considered for this classification. The initial categorization included the following four categories, of which materials recovery and biological treatment were considered "circular" approaches.

- Materials recovery: Activities 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.

2.3.3. Resource footprints

Four resource footprints were intended to be used as control variables in the regression models. Information on resource footprints was collected from Steinmann et al. (2017) and used as-is in this study. The exact matching of products was done based on the product names. However, it should be noted that the database used in calculating these resource footprints 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. The resource footprints used were:

1. Fossil 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 (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 use over time, excluding land transformation.
4. Freshwater consumption (m^3): Amount of evaporated water plus the amount of water incorporated into the products. Calculated as the difference between freshwater extracted from nature and the amount of water returned.

2.4. Data analysis

A set of nine hypotheses were formulated for each of the endpoint indicators of the ReCiPe method (see Fig. 3). The model included the three forms of accounting waste quantities, the two waste category indicators, and the four resource footprints described above. This model for the hypotheses was the base for relating the waste types to the damage indicators.

Both waste quantities and environmental damage indicators were log-transformed for the development of the multilinear regression models because they varied by several orders of magnitude across products. Due to much of the data being clustered near 0, a natural logarithm was chosen for the transformation. The variables included in regression analysis are summarized in Table 3, with their unit of measure and data transformation used.

Section 3 of Appendix A presents basic descriptive statistics for all numeric variables. Appendix B contains the processed data for the 1487 products used in the regression analysis. Appendix D has the R code written for the regression analysis – chunk "4. Explanatory variables" contains the calculation of the PWFs and waste category indicators.

3. Results

Table 4 presents the top three products regarding the largest amount of waste per kilogram of product and what the largest waste flow in the respective product is. The mean, standard deviation, lowest and maximum waste values of the eight categories analyzed are also highlighted. Gold showed the highest waste density (produced waste per kg of product) of the 1487 products analyzed, followed by wafer fabricated for integrated circuit, platinum, and rhodium and palladium. Sulfidic tailing was a prominent waste flow among metals and machinery products; the presence of relatively large flows of spoil from lignite mining was seen in the product system where lignite was modeled as a fuel for steam-electric power generation such as uranium and plastics; wastewater was a common flow among biobased products such as cotton textile and vegetable oils. A 10^4 fold

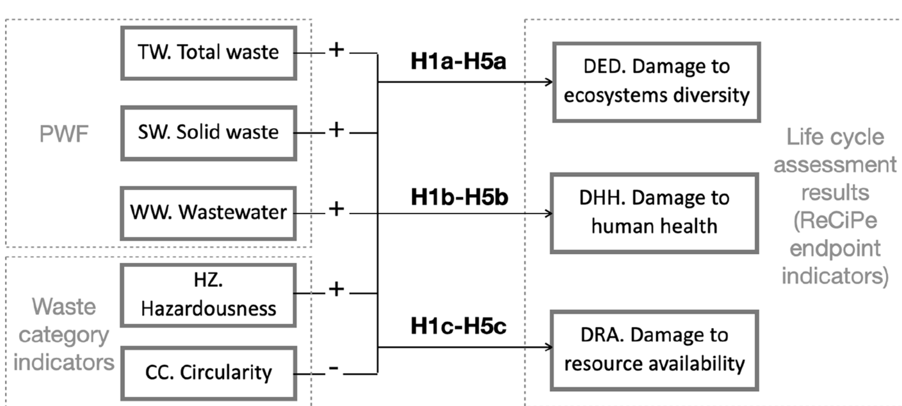

Fig. 3. Initial hypotheses formulated for the study.

Table 3
List of variables of the multilinear regression analysis.

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		
PWF (Product waste footprint)	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 waste to total solid waste per kilogram product (in % points)	–
	Circularity: The ratio of circular to total solid waste treatment per kilogram product (in % points)	–
Resource footprints (for $n = 950$)	Fossil 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	–

difference was observed between the category with the lowest and the largest mean; metalalloy was the category with the largest mean – accounting for five of the top six products – and standard deviation; agriforeanim had the lowest mean and standard deviation. Appendix F presents the complete list of waste flows and amounts generated by the production of the products analyzed.

Fig. 4 shows a histogram of the hazardous ratio (left-hand side) and circularity ratio (right-hand side) for the product categories analyzed. “Basic metals & alloys, incl. semi-finished products” followed by “machinery, metal/electronic, transport equipment” and “chemical products” had the largest mean with regard to hazardous waste as a percentage of total waste. Not surprisingly, “agricultural forestry, live animal & their products” and “processed biobased products” showed both the lowest mean for hazardous ratio and the largest mean for circularity ratio of all product categories.

High correlations were found between solid waste and environmental damage indicators (Fig. 5a), and between different PWF definitions, as well as between most of the other pairs of explanatory and response variables (Fig. 5b). This is because the explanatory variables are likely to be confounding variables, i.e. the more raw materials/energy/water/land used per kilogram of product, the more waste can be expected to emanate from these processes. Resource footprints can also be directly involved in environmental damage calculations, creating a potential multicollinearity issue.

To address the multicollinearity problem, the variance inflation factor (VIF) was checked for each explanatory variable. VIF shows the increase in the variance of a coefficient due to the variable's linear relationship with other predictors in a regression model (Akinwande et al., 2015). Numerical variables having a VIF >5 were excluded from the hypothesis model – land use change was excluded from all models. The multicollinearity analysis indicated six regression models for each environmental damage indicator.

3.1. Regression models

Significant regression equations were found with R^2 of 64–88 % for damage to ecosystem diversity, 72–92 % for damage to human health, and 74–91 % for damage to resource availability, based on total waste (TW), solid waste (SW), wastewater (WW), hazardousness (HZ), circularity (CC), raw material use (RMU), freshwater consumption (FWC), and fossil energy demand (FED); where TW, SW, WW and RMU were measured in the natural logarithm of kg, HZ and CC in percentage, FWC in the natural logarithm of m^3, and FED in the natural logarithm of MJ. The results of

Table 4
Products with the largest waste generation per category, largest waste flow of each product, and waste statistics of categories.

Product			Category (kg)				
Name	Kg of waste per kg	Largest waste flow	Product category	Mean	std	Min	Max
Swine for slaughtering, live weight	2.10E+01	Inert waste, for final disposal	Agriforeanim	1.50E+00	2.70E+00	3.50E-03	2.10E+01
Radish	1.50E+01	Spoil from hard coal mining					
Coffee, green bean	1.30E+01	Spoil from hard coal mining					
Heavy water	1.10E+04	Wastewater, unpolluted	Chemical	7.70E+01	6.80E+02	2.50E-02	1.10E+04
Tantalum, powder, capacitor-grade	9.80E+03	Non-sulfidic tailing, off-site					
Metallization paste, front side	3.20E+03	Sulfidic tailing, off-site					
Solar collector glass tube, with silver mirror	2.40E+01	Spoil from lignite mining	Glasnonmetal	2.00E+00	3.70E+00	5.90E-02	2.40E+01
Insulation spiral-seam duct, rockwool, dn 400, 30 mm	1.70E+01	Spoil from hard coal mining					
Silicon carbide	1.70E+01	Spoil from lignite mining					
Wafer, fabricated, for integrated circuit	2.60E+05	Wastewater from wafer fabrication	Machelectrans	1.80E+03	1.80E+04	5.80E-01	2.60E+05
Integrated circuit, logic type	1.60E+04	Sulfidic tailing, off-site					
Electronic component, active, unspecified	9.80E+03	sulfidic tailing, off-site					
Gold	1.00E+06	Sulfidic tailing, off-site	Metalalloy	2.20E+04	1.30E+05	9.40E-02	1.00E+06
Platinum	2.20E+05	Sulfidic tailing, off-site					
Rhodium	1.90E+05	Sulfidic tailing, off-site					
Uranium, enriched 4.2 %, in fuel element for light water reactor	1.80E+04	Spoil from lignite mining	Oreminfuel	1.60E+03	4.70E+03	1.70E-03	1.80E+04
Enriched uranium, 4.2 %	1.80E+04	Spoil from lignite mining					
Uranium, enriched 4 %, in Fuel element for light water reactor	1.70E+04	Spoil from lignite mining					
Polyvinylfluoride, film	5.20E+01	Spoil from lignite mining	Plastrub	6.30E+00	1.00E+01	2.00E-02	5.20E+01
Polysulfone	4.40E+01	Wastewater, average					
Polyvinylfluoride, dispersion	4.20E+01	Spoil from lignite mining					
Textile, knit cotton	1.30E+02	Wastewater, average	Procbio	6.60E+00	2.10E+01	1.90E-02	1.30E+02
Soybean oil, refined	1.20E+02	Wastewater from vegetable oil refinery					
Vegetable oil, refined	1.10E+02	Wastewater from vegetable oil refinery					

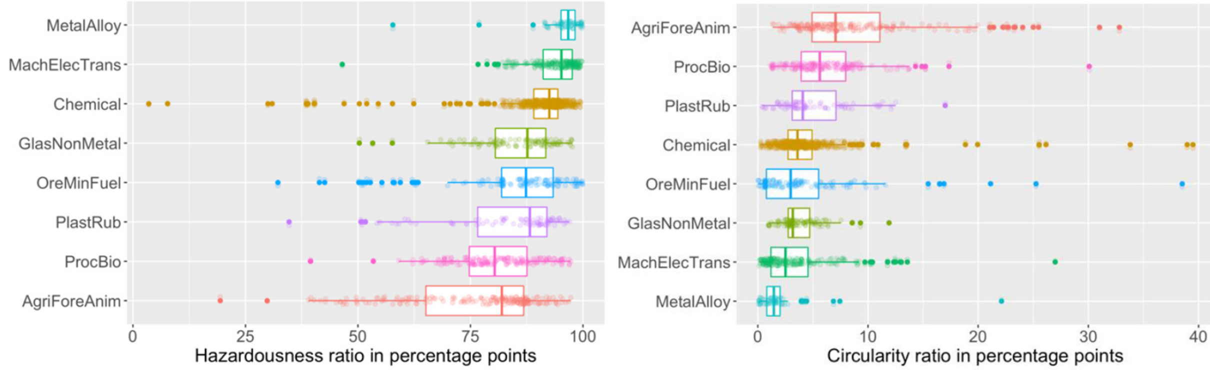

Fig. 4. Boxplot of hazardousness ratios (left-hand side) and circularity ratios (right-hand side) for analyzed product categories.

the multilinear regression analysis are presented in Tables 5-7, with each table corresponding to the regression models developed for one of the environmental damage indicators. The tables show the regression coefficients for each explanatory variable with its confidence interval [in brackets below] at a 95 % confidence level, mean absolute error (MAE), and root mean square error (RMSE). The regression equations can be seen in section 4 of Appendix A.

3.1.1. Waste quantities

The results showed a statistically significant and positive relationship between the PWF (measured as both total and solid waste) and environmental damage to ecosystem diversity, human health and resource availability. Since these variables were log-transformed on both sides of the regression equation, the coefficients need to be interpreted multiplicatively. For instance, model 1 in each regression set predicted that when the total waste increases 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 model 2 from the regression sets, doubling the solid waste means an expected 75 %, 84 % and 78 % increase respectively for each of the three environmental damage indicators. The regression coefficients for the wastewater were smaller, as shown in the third model of each regression set, but its association with the environmental damage indicators was also statistically significant. According to these results, the relationship was both statistically and practically significant for total and solid waste. When controlled for resource footprints in the fourth and fifth models, the statistical significance of both total and solid waste footprints remained strong. Although some coefficients decreased by >0.20, they remained higher than the coefficients of the respective resource footprints used in the model.

3.1.2. Hazardousness percentage

The relationship between the hazardousness ratio and the environmental damage indicators shows a similar picture when used with total and solid waste footprints in different models. Each percentage point increase in hazardousness can predict either a slight decrease or a slight increase in damage to ecosystem diversity, human health or resource availability across all regression models. The parts of the result suggesting a decrease in the environmental damage when hazardousness increases may be counterintuitive, rejecting the hypothesis of a positive relationship. However, treatment of waste that is classified as hazardous may be done in a more controlled way leading to lower environmental impact.

3.1.3. Circularity percentage

Regarding the variable circularity percentage, the models suggest a statistically significant (albeit at varying levels) and negative relationship with the three environmental damage indicators. Nevertheless, the coefficients are quite small and may not be practically significant. The small coefficients might partly be explained by the cut-off system model used as the data source. A high circularity percentage can be a result of the additional steps created in the waste treatment process, e.g. in material recovery chains, where the burdens associated with the sorting, shredding, and recovery operations remain with the primary product. In other words, the benefits of having more circular processes – if any before the cut-off – might be offset by the burdens of these additional steps, all the while not receiving any credit for producing recyclables.

4. Discussion

The findings of the present study are aligned with previous studies that highlight the prominence of environmental degradation caused by varied wastes generated from diverse industrial activities (Bhattacharya et al., 2006; Hatje et al., 2017; Noli and Tsamos, 2016; Norgate et al., 2007; Wang et al., 2022). Nonetheless, there are several limitations that need acknowledgement. The first limitation concerns the data. The validity of our results relies on the availability and quality of the life cycle inventory information. While there are many data points in the Ecoinvent 3.5 cut-off database, depending on the previous 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.

In addition, a life cycle assessment study such as the one in this article, looks at the current status quo situation (Finnveden, 2000). If society is changing to a new equilibrium, e.g. by changing the energy system from fossil-based to renewables, the correlation structure falls apart.

Moreover, any gaps or methodological inconsistencies in the life cycle inventories modeled in Ecoinvent might impact the results. The Ecoinvent datasets can have different system boundaries and/or approach to end-of-life modeling; some of the processes, for example, account for waste in detail where others do not; moreover, some production chains include machinery/infrastructure requirements as inputs while others exclude them. Even though some of these choices are present in the comment fields of the datasets, the lack thereof does not guarantee the completeness of the data. Further assessments and/or corrections of the life cycle inventories offered by Ecoinvent were beyond the scope of our study. Nevertheless, a certain level of data quality is guaranteed as there are detailed data quality guidelines for data submitters and the new datasets go through an independent editorial process (Wernet et al., 2016).

The second limitation that needs acknowledgement is that correlation does not imply causation. The fact that the waste footprints showed a strong correlation with environmental damage is not proof of structural causality. Causality is required in terms of societal relevance. In other words, are there reasons to believe that reducing waste is also reducing environmental damage? Steinmann et al. (2017) looked into the main underlying causes of environmental damage and argued that resource footprints are indeed

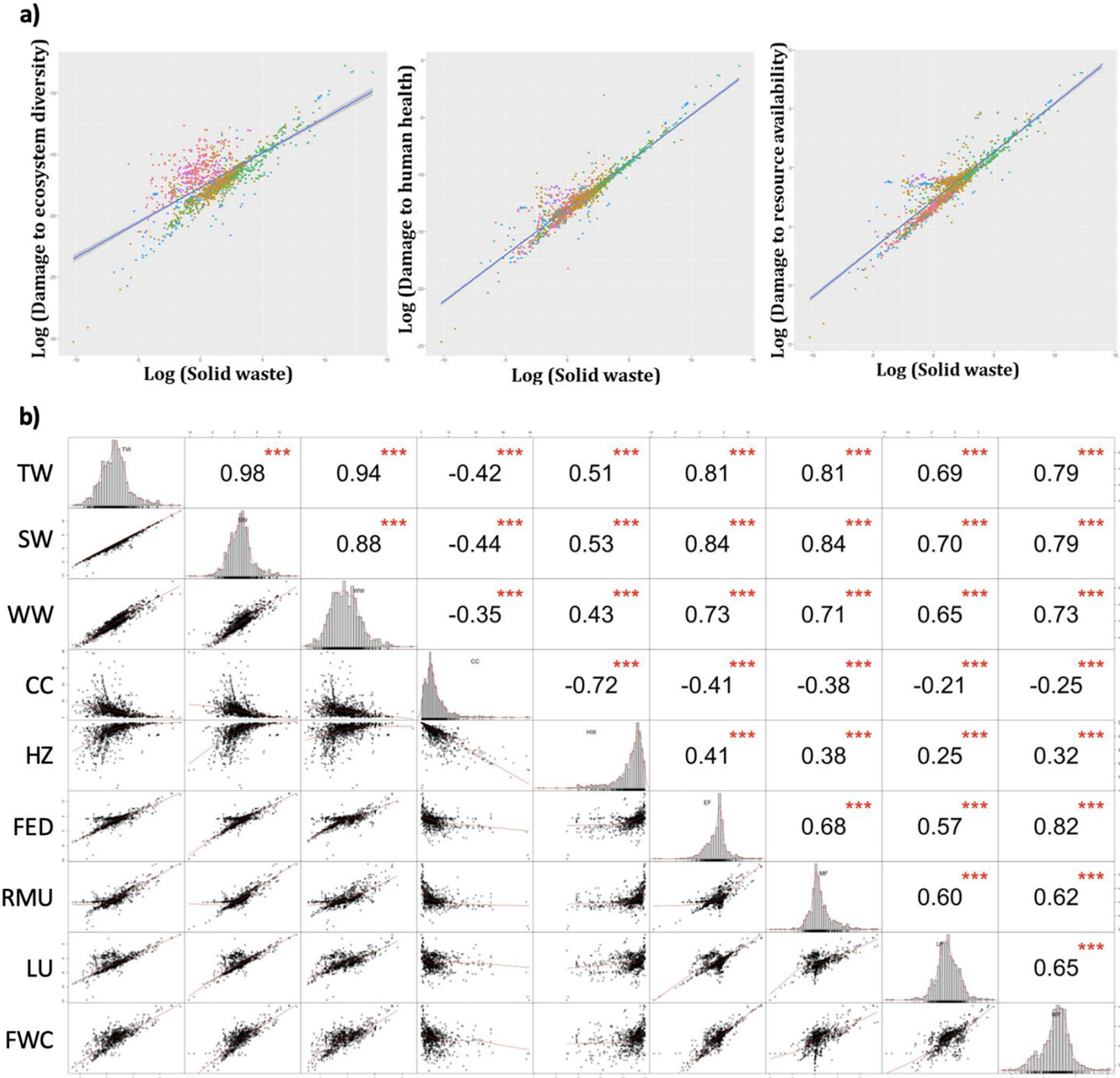

Fig. 5. a) Environmental damage indicators and solid waste footprints visualized – after natural logarithm transformation; b) Pearson correlation between explanatory variables – after natural logarithm transformation.

causally related to damage footprints. Such a causality may not hold for waste. Accordingly, the interpretation of the results must be performed with caution, as there is no underlying causality in the correlations found.

To check for such causation, the technical implementation of the regression analysis requires improvement in at least two ways. The first is to construct a linear mixed effect model with fixed and random factors and work with an information criterion, such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC), to avoid overfitting (Vrieze, 2012). For instance, the product groups could be used as a random effect, so the regression is executed in a balanced way. As we included some extra explanatory variables, the risk of overfitting might be present. AIC and/or BIC could help to find the optimal model structure.

5. Conclusions and future directions

This study explored the relationship between the life cycle product waste footprint and environmental damage. Using comprehensive life cycle waste inventories associated with a large number of products, we found that waste amounts accounted for the majority of the variation in environmental damage. Six regression models showed significant regression equations with R^2 of 0.64–0.88 for damage to ecosystem diversity, 0.74–0.92 for damage to human health, and 0.74–0.91 for damage to resource availability using log-transformed variables. Solid waste was the strongest predictor of the variation of environmental damage in all the regression models that did not have resource footprints as controlled variables (solid waste R^2 0.75–0.84; wastewater R^2 0.56–0.62; total waste

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*** [0.70, 0.75]			0.61*** [0.55, 0.66]		
Log (solid waste)		0.75*** [0.72, 0.77]			0.48*** [0.43, 0.53]	
Log (wastewater)			0.58*** [0.55, 0.61]			0.09*** [0.06, 0.12]
Hazardousness % point	−0.02*** [−0.03, −0.01]	−0.02*** [−0.03, −0.01]	0.00 [−0.01, 0.00]	−0.03*** [−0.04, −0.02]	−0.03*** [−0.04, −0.02]	−0.01** [−0.02, −0.00]
Circularity % point	−0.04*** [−0.06, −0.02]	−0.02* [−0.04, −0.00]	−0.05*** [−0.07, −0.03]	−0.08*** [−0.11, −0.06]	−0.07*** [−0.09, −0.05]	−0.04*** [−0.06, −0.02]
Log (raw material use)				0.14*** [0.09, 0.019]		0.12*** [0.09, 0.15]
Log (freshwater consumption)					0.35*** [0.30, 0.40]	0.16*** [0.12, 0.20]
Log (fossil energy demand)						0.58*** [0.53, 0.63]
(Intercept)	−14.49*** [−15.15, −13.83]	−14.33*** [−14.96, −13.71]	−14.23*** [−15.00, −13.47]	−13.18*** [−14.07, −12.29]	−12.16*** [−12.92, −11.41]	−15.32*** [−16.00, −14.64]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1487	1487	1487	950	950	950
R^2	0.72	0.75	0.64	0.75	0.82	0.88
MAE	0.72	0.88	0.70			
RMSE	0.77	1.22	0.87			

[ ]: confidence interval; MAE: mean absolute error; RMSE: root mean square error.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.005$.

R^2 0.73–0.81). Hazardousness percentage showed a negative relationship with environmental damage in all the models (R^2 between −0.01 and −0.03); this apparent contradiction could be explained by the fact that the treatment of waste classified as hazardous is generally carried out in a more controlled way, leading to lower environmental impact; this hypothesis, however, needs further investigation. Circularity percentage also showed a significant negative relationship with the three environmental damage indicators in all the regression models (R^2 between −0.02 and − 0.08), indicating that the environmental damage of products decreases with the increase of material reuse throughout the value chain.

We see several opportunities for future research. First, this study adopted broad definitions of waste (i.e. total waste, solid waste, wastewater), with simplified indicators for the type of waste and waste treatment path (i.e. hazardousness and circularity), and endpoint indicators (i.e. environmental damage). Including more detailed categories of different waste types (e.g. tailings, glass, plastic, radioactive, MSW), midpoint indicators (e.g. global warming potential, acidification potential), and other broad areas of protection, such as biodiversity, could improve our understanding of the structural similarities and differences in determinants of environmental concerns related to life cycle waste generation.

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*** [0.78, 0.83]			0.55*** [0.50, 0.59]		
Log (solid waste)		0.84*** [0.82, 0.86]			0.66*** [0.62, 0.70]	
Log (wastewater)			0.62*** [0.59, 0.65]			0.06*** [0.03, 0.08]
Hazardousness % point	−0.02*** [−0.02, −0.01]	−0.02*** [−0.03, −0.02]	0.00 [−0.01, 0.01]	−0.02*** [−0.03, −0.02]	−0.03*** [−0.03, −0.02]	0.00 [−0.00, 0.01]
Circularity % point	−0.05*** [−0.06, −0.03]	−0.03*** [−0.05, −0.02]	−0.07*** [−0.09, −0.05]	−0.08*** [−0.10, −0.06]	−0.06*** [−0.08, −0.04]	−0.03*** [−0.05, −0.02]
Log (raw material use)						0.25*** [0.22, 0.28]
Log (freshwater consumption)				0.31*** [0.27, 0.036]	0.23*** [0.19, 0.27]	0.12*** [0.08, 0.15]
Log (fossil energy demand)						0.58*** [0.54, 0.62]
(Intercept)	−11.28*** [−11.83, −10.74]	−11.09*** [−11.56, −10.61]	−11.18*** [−11.92, −10.44]	−9.42*** [−10.14, −8.70]	−9.50*** [−10.12, −8.87]	−13.21*** [−13.80, −12.62]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1487	1487	1487	950	950	950
R^2	0.86	0.89	0.74	0.86	0.90	0.92
MAE	1.07	0.64	1.01			
RMSE	0.59	1.22	0.87			

[ ]: confidence interval; MAE: mean absolute error; RMSE: root mean square error.
*** $p < 0.001$.

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*** [0.72, 0.77]			0.47*** [0.42, 0.53]		
Log (solid waste)		0.78*** [0.75, 0.80]			0.60*** [0.54, 0.65]	
Log (wastewater)			0.56*** [0.53, 0.59]			0.01*** [−0.03, 0.04]
Hazardousness % point	−0.01*** [−0.02, −0.00]	−0.01*** [−0.02, −0.02]	0.01 [−0.00, 0.01]	−0.02*** [−0.03, −0.01]	−0.02*** [−0.03, −0.02]	0.00 [−0.00, 0.01]
Circularity % point	−0.04*** [−0.06, −0.02]	−0.02*** [−0.04, −0.01]	−0.06*** [−0.08, −0.04]	−0.08*** [−0.10, −0.05]	−0.06*** [−0.08, −0.03]	−0.02* [−0.04, −0.00]
Log (raw material use)						0.14** [0.11, 0.17]
Log (freshwater consumption)				0.33*** [0.27, 0.038]	0.24*** [0.19, 0.29]	0.04 [−0.00, 0.08]
Log (fossil energy demand)						0.78*** [0.74, 0.83]
(Intercept)	−2.35*** [−2.96, −1.74]	−2.15*** [−2.70, −1.59]	−2.27*** [−3.04, −1.50]	−0.14*** [−1.01, −0.73]	−0.19*** [−0.98, 0.61]	−4.69*** [−5.35, −4.03]
Product sub-category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1487	1487	1487	950	950	950
R^2	0.83	0.86	0.74	0.81	0.84	0.91
MAE	0.54	0.98	0.48			
RMSE	0.89	0.83	1.23			

[ ]: confidence interval; MAE: mean absolute error; RMSE: root mean square error.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.005$.

In addition, looking at alternative impact assessment methods could be of interest. Of special relevance could be other approaches for assessing resource depletion (Sonderegger et al., 2020), including assessments based on exergy analysis (Finnveden and Östlund, 1997) and exergoenvironmental analysis (Aghbashlo et al., 2021). This is relevant since it is known that different methods define resource depletion in different ways and produce different results (e.g. Berger et al., 2020; Finnveden et al., 2016).

Second, the data used were based on the cut-off system model, which does not give credit to the waste producer for recycling activities. Future research could use the datasets based on allocation at the point of substitution (APOS) and consequential system models to investigate how the results of the regression analysis would change.

Third, for consumers it may be easier to understand the product waste footprint – an indicator measured simply in kilograms – than environmental impacts measured in less common units such as species*year, DALY or CO_2-eq. However, it is not clear if consumers would change purchasing decisions with the disclosure of product life cycle waste quantities and, if so, how. Investigating the potential impact of waste footprints on consumer behavior may be another topic for future studies.

In summary, from the strict LCA, waste, in general, is considered to be an impact category by itself thus, in life cycle inventories, industrial waste flows are modeled until they reach final treatment (in an ideal real-life situation). Here, we demonstrated, for the first time, that waste flows do have a strong statistically significant relationship with environmental damage. Although causation was not proved, our findings provide an important conceptual advance in the understanding of products' environmental impact. Furthermore, we believe that this novel information will be of interest to researchers working on circular economy indicators, as well to consumers, communicators, policymakers and industry.

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CRediT authorship contribution statement

Rafael Laurenti: Conceptualization, Funding acquisition, Resources, Writing- Reviewing and Editing, Supervision. **Deniz Demirer Demir**: Methodology, Software, Data curation, Formal analysis, Writing- Original draft preparation, Visualization, Investigation. **Göran Finnveden**: Writing- Reviewing and Editing, Validation.

Data availability

Code and data have been shared as supplementary material.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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