Waste and Material Footprints in prospective LCA: a macro study of 1593 activities from 2020-2050

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Abstract

Purpose

Advancing a circular economy requires system-wide quantification of waste and material flows. Yet waste and material footprints (WMFs) remain under-reported in LCA and sparsely integrated into prospective LCA (pLCA). Moreover, waste treatment is poorly represented in prospective databases, limiting decision relevance. We quantify WMFs using inventory data from *ecoinvent* and examine their evolution under contrasting temporal pathways to (i) reveal sectoral and supply-chain hotspots, (ii) position WMFs alongside LCIA endpoints, and (iii) assess how scenario-aligned backgrounds modify footprint magnitudes and circularity.

Methods

We built prospective LCI databases with *premise* (using *ecoinvent* v3.9.1) aligned to two REMIND pathways (SSP1-PkBudg500 and SSP5-PkBudg500) for 2020–2050. Using the *T-reX* program, we tracked over 70 waste and material categories and computed WMFs for 1593 market activities. In parallel, we calculated ReCiPe 2016 endpoints. We grouped activities into sectors to identify hotspots and explore temporal/scenario contrasts. We also calculated a waste hazardousness ratio as well as a waste circularity ratio (the share of each activity’s waste footprint routed to material recovery).

Results and discussion

Metals and alloys, chemicals, and ores–minerals–fuels dominate total and hazardous waste footprints and shape the upper tails of their distributions, with pronounced outliers in rare-earth production, precious-metal supply chains, and nuclear-fuel routes. From 2020 to 2050, median total waste generation and landfilling increase in both pathways, whereas recycling and composting expand more modestly, implying gradual shifts in end-of-life routing. Over the same period, the circularity ratio declines slightly, while the share of hazardous waste in total waste falls modestly, indicating some decoupling between waste quantity and hazard profile. Scenario contrasts are subtle: SSP1 shows higher 2050 medians for total waste and landfilling but a larger reduction in hazardousness, while SSP5 preserves slightly better circularity. Across indicators, activity-level heterogeneity dominates pathway effects overall.

Conclusions and recommendations

WMFs complement LCIA endpoints in prospective LCA by making material throughput and waste generation explicit and revealing hotspots that impact profiles can obscure. Temporal signals in current IAM-linked pLCIs are modest: recovery routes expand, but not fast enough to offset rising disposal and declining circularity. A key constraint is the limited representation of waste systems in LCI/pLCI datasets. Typically evident are: coarse treatment typologies, sparse regionalisation, inconsistent hazardous labelling, static collection yields, quality losses, and minimal secondary-market uptake. We recommend scenario-dependent circularity modules in future pLCIs and reporting WMFs with the circularity ratio to track whether recovery keeps pace with total waste growth.

Keywords

Circular economy, Waste footprints, Material footprints, Prospective life cycle assessment, Scenario-based life cycle modelling, Integrated assessment models, Critical raw materials, Integrated assessment models

List of abbreviations

AgriForeAnim	Agriculture, forestry, live animals & their products
CE	Circular Economy
Chemical	Chemical products
CPC	Cooperative Patent Classification
CRM	Critical Raw Material
CRT	Cathode Ray Tube
EF	Ecological Footprint
EoL	End-of-Life
GlasNonMetal	Glass and other non-metallic products
GLO	Global (*ecoinvent* location designation)
IAM	Integrated Assessment Model
IMAGE	Integrated Model to Assess the Global Environment
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LLDPE	Linear low-density polyethylene
MachElecTrans	Machinery, metal/electronic, transport equipment
MetalAlloy	Basic metals & alloys, incl. semi-finished products
MF	Material Footprint
MFA	Material Flow Analysis
OreMinFuel	Ores, minerals & fuels
PlastRub	Plastics & rubber products
pLCA	Prospective Life Cycle Inventory
pLCA	Prospective Life Cycle Assessment
ProcBio	Processed bio-based products
PVC	Polyvinyl chloride
RCP	Representative Concentration Pathway

ReCiPe	A standard LCIA method set
REE	Rare Earth Element
REMIND	REgional Model of Investment and Development
REO	Rare Earth Oxide
re-X	A broad set of circular economy strategies (“reduce”, “reuse”, “repair”, “recycle” etc.)
RoW	Rest of World (*ecoinvent* location designation)
SDG	Sustainable Development Goal
SSP	Shared Socioeconomic Pathway
T-reX	The Tool for analysing re-X in LCA
UNFC	United Nations Framework Classification for Resources
WF	Waste Footprint
WMF	Waste and Material Footprint

1 Introduction

The transition to a circular economy has become a central pillar of sustainability policy (Ellen MacArthur Foundation, 2015; European Commission, 2020; Pardo & Schweitzer, 2018). Circular strategies seek to decouple well-being from primary material extraction by reducing material demand and preventing waste across value chains through ‘re-X’ measures such as refuse, rethink, repair, remanufacture, and recycle (Kirchherr et al., 2017; Reike et al., 2018). Recent geopolitical tensions further underscore the vulnerability of globalised supply chains and the need for material efficiency, strategic autonomy, and system resilience (Carrara et al., 2023; Hartley et al., 2024).

1.1 Waste and material footprints in LCA

Footprints provide compact indicators of environmental pressure that can support decision-making for sustainability. The Ecological and Carbon Footprints initiated this “footprint family” (Čuček et al., 2015; Wackernagel, 1994), which has since expanded without fully converging on a coherent framework (Giampietro & Saltelli, 2014; B. G. Ridoutt & Pfister, 2013; Vanham et al., 2019). The Material Footprint (MF) (the total supply-chain material use attributable to products, sectors, or economies) correlates strongly with human-health and biodiversity damage and is recognised by the United Nations for SDG monitoring (Lenzen et al., 2021; Wiedmann et al., 2013). By contrast, the Waste Footprint (WF) (the mass or volume of waste generated along value chains) remains less developed and is often overlooked, despite evidence linking waste burdens to environmental damage and social inequity (Akese & Little, 2018; Laurenti et al., 2023; Steinmann et al., 2017). Considering WF alongside MF highlights where material use translates into waste generation, where hazardous waste arises, and where interventions may yield the greatest returns for circularity.

Life Cycle Assessment (LCA) is the prevailing method to quantify environmental impacts across product and service life cycles (Guinée et al., 2010). In standard practice, Life Cycle Impact Assessment (LCIA) methods (e.g., ReCiPe, CML) convert inventory flows (elementary exchanges between technosphere and biosphere) into impact scores (Guinée et al., 2002; Huijbregts et al., 2016). Several LCIA frameworks incorporate aspects of waste and material use (e.g., Swiss Eco-Factors, EDIP, EN15804, Crustal Scarcity Indicator) (Arvidsson et al., 2020; CEN (European Committee for Standardization), 2019; Hauschild & Potting, 2004; Swiss Federal Office for the Environment (FOEN), 2021), yet few provide transparent, mass-consistent accounting of MF and WF. Some also rely on abstract units (e.g., Umweltbelastungspünkte in the Swiss Eco-Factors) that can complicate interpretation. Moreover, because waste is commonly modelled as a service (i.e., as a waste treatment process), the magnitude and distribution of waste generation along supply chains can remain obscured, making upstream waste effectively “invisible” (Beylot et al., 2018; Guinée & Heijungs, 2021).

In practice, waste is often defined as material with negative economic value, but its significance extends far beyond treatment emissions (Bisinella et al., 2024; Guinée et al., 2004; Laurenti et al., 2023). Empirical studies confirm associations between waste burdens, environmental damage, and disproportionate impacts on vulnerable communities (Akese & Little, 2018; Pellow, 2023; B. Ridoutt et al., 2010). Reporting WF and MF alongside conventional LCIA indicators can therefore make material throughput and waste generation explicit, reveal hidden hotspots, and improve prioritisation of circular economy strategies.

1.2 Future-oriented LCA and prospective background databases

Emerging technologies required for deep decarbonisation will scale over coming decades, often after substantial learning and capital investment (International Energy Agency (IEA), 2021, 2022). Prospective LCA (pLCA) (also called ex-ante or anticipatory LCA) aims to predict likely environmental implications early enough to inform design and policy (Cucurachi et al., 2018; Van Der Giesen et al., 2020). Robust pLCAs require background data that reflect plausible future economic, technological, and policy conditions. Prospective life cycle inventory (pLCI) databases therefore combine current LCI data (e.g., *ecoinvent*) with scenario information from integrated assessment models (IAMs) and other sources (Sacchi et al., 2022; Steubing et al., 2023).

IAM scenario frameworks typically pair a shared socio-economic pathway (SSP)—a narrative of societal development from sustainability-oriented (SSP1) to fossil-intensive (SSP5)—with a representative concentration pathway (RCP) that specifies a climate outcome via radiative forcing, corresponding to temperature goals such as 1.5–2 °C (Aboumahboub et al., 2020; Meinshausen et al., 2020; Stehfest et al., 2014; Van Vuuren et al., 2017). Implemented in IAMs, SSP×RCP pairings generate region- and sector-specific trajectories for technology deployment and emissions (Sacchi et al., 2022). These scenarios are bounded by resource availability, infrastructure lock-in, and policy constraints such as carbon pricing, which shape feasible transitions (Pauliuk et al., 2017).

1.3 premise, REMIND, and sectoral transformations

The *premise* tool is a Python-based framework that takes life cycle inventory databases (like *ecoinvent*) and systematically modifies them with scenarios from integrated assessment/energy models to generate consistent, future-oriented LCA databases for prospective analysis (Sacchi et al., 2022; Sacchi et al., 2023). The *premise* workflow connects IAM projections to *ecoinvent*, producing pLCIs that regionalise markets and update process and supply-chain parameters for selected sectors. The most widely used IAMs are the REgional Model of Investment and Development (REMIND) (Aboumahboub et al., 2020) and the Integrated Model to Assess the Global Environment (IMAGE) (Stehfest et al., 2014). Neither IAM scenarios nor LCI databases currently provide full, high-resolution coverage across all sectors and regions. IAMs are detailed for electricity but sparser for agriculture, chemicals, and material cycles; standard LCIs prioritise current technologies, leaving emerging options under-represented (Pauliuk et al., 2017; Sacchi et al., 2023). The current default transformation domains include electricity generation and markets (with storage), cement (clinker ratio, kiln efficiency, optional carbon capture and storage (CCS)), iron and steel (process efficiency and CCS), fuels (refining, synthetic and biofuels, hydrogen), road freight (powertrain shares and fleet relinking), batteries (mass/energy-density scaling and market composition), heat supply (CO_2 factors), air-pollutant factors, and biomass markets distinguishing purpose-grown from residual feedstocks (Sacchi et al., 2023). Additional research has produced additional scenarios that can be integrated into pLCA databases with *premise* for sectors such as cement and steel (Müller et al., 2024), cobalt (Van Der Meide et al., 2022) and hydrogen (Wei et al., 2024).

While the aforementioned sectoral transformations can result in indirect changes to future waste flows (McDowall et al., 2025), waste management is not yet a dedicated transformation domain and other waste-sector inventories remain largely as they appear in the base database (Bisinella et al., 2024).

1.4 Aim and contribution of this study

Prospective analyses in LCA rely on the completeness and consistency of pLCIs, though, currently, they insufficiently represent waste-sector dynamics, creating a 'waste gap' that limits interpretation of future scenarios. Addressing this gap requires first clarifying how waste and material flows are represented in existing LCA and pLCA databases at both macro and activity levels.

This study applies a purpose built *python*-based WMF method named *T-reX* (McDowall et al., 2025)—integrated within Brightway and compatible with *premise*-based pLCIs—to explore and quantify waste generation (including hazardous waste) and material consumption (especially CRMs) across activities and sectors. Expanding on the standard *T-reX* approach, our objectives are to: (i) compute waste and material footprints at multiple levels of aggregation, (ii) identify hotspots along supply chains under present and prospective background conditions, and (iii) illustrate how results support circular-economy strategies and supply-chain risk management.

Rather than developing a new LCIA method or prospective database, we demonstrate how targeted footprint accounting complements existing indicators. The Waste and Material Footprint (WMF) approach developed in this study offers a product- and process-level lens that complements established approaches such as Material Flow Analysis (MFA) and Environmentally Extended Input–Output (EEIO) analysis. While MFA frameworks (e.g. Torres de Matos et al., 2020) provide system-wide flow quantification and EEIO models capture embodied impacts via monetary linkages (Wiedmann et al., 2013), both typically operate at an aggregate scale and are not designed to resolve prospective, scenario-aligned changes in supply chain configurations or end-of-life routes. WMFs, by contrast, can embed temporal, spatial, and technological detail consistent with LCA foreground models, enabling disaggregated tracking of circularity indicators and technosphere material burdens (Laurenti et al., 2023; Maçin et al., 2024).

In this study, comparison was made with the standard ReCiPe impact assessment method set (Huijbregts et al., 2016) with the aim of investigating the relationship between WMFs and the standard damage indicators of human health, ecosystems and resource availability. By reporting total waste, hazardous waste, and material consumption, and highlighting sectoral hotspots, our analysis shows how footprint accounting makes hidden burdens visible, clarifies interpretive limits, and delivers actionable insights for circular-economy policies and resource-risk management. Importantly, this work also provides a step toward embedding explicit waste-sector dynamics in future pLCA databases, where dedicated transformation modules could capture prevention, recycling, and secondary-material pathways alongside the extant energy and transport transitions.

2 Methodology

2.1 Selection and creation of pLCA databases

Using the LCI database *ecoinvent* (version 3.9.1) (Wernet et al., 2016) as a basis, we constructed pLCI databases using *premise* (Sacchi et al., 2022) over ten-year intervals from 2020 to 2050. *premise* links IAM outputs to background LCI data by regionalising markets and updating technology efficiencies, fuel mixes, and emissions profiles. In our case, REMIND outputs drove these updates. REMIND is a global energy–economy–climate model that produces internally consistent projections of energy demand, technology portfolios, and greenhouse-gas emissions under alternative socio-economic narratives (Aboumahboub et al., 2020). We selected two contrasting REMIND pathways: SSP1-PkBudg500 and SSP5-PkBudg500. SSP1 ("sustainability") represents low challenges to mitigation, rapid diffusion of clean technologies, and lower energy and material intensities. SSP5 ("fossil-fuelled development") represents high economic growth coupled with high energy demand and a strong reliance on fossil fuels, thereby raising mitigation challenges (see, e.g. Bauer et al., 2017; Kriegler et al., 2017; Van Vuuren et al., 2017 on SSPs standard practice).

Within the SSP–RCP framework, the "PkBudg500" constraint imposes a stringent cumulative CO_2 budget consistent with 1.5 °C-class mitigation (often associated with RCP1.9 in the literature), which forces both "scenario-worlds" to meet a comparable climate target (Van Vuuren et al., 2011). We deliberately use the same PkBudg500 constraint for SSP1 and SSP5 to enhance interpretability of pLCI comparisons. Using the same carbon budget (PkBudg500) for SSP1 and SSP5 holds climate ambition constant, so differences in the resulting pLCIs reflect socio-economic and technological structure rather than target stringency. This improves attribution in that the contrasts in waste and material footprints will stem from patterns of demand, fuel mixes, and infrastructure, not from divergent radiative-forcing goals. An approximately 500 Gt CO_2 century-scale budget is a 1.5 °C–class constraint (often associated with RCP1.9), ensuring major energy transitions with material implications (electrification, hydrogen, CO_2 storage) appear in both pathways, though to different extents. Thus, SSP1-PkBudg500 and SSP5-PkBudg500 share a common climate constraint but diverge structurally, providing a controlled basis for comparing footprints in prospective LCA (Intergovernmental Panel on Climate Change (IPCC), 2023).

2.2 Waste and material footprinting with *T-reX*

T-reX is a WMF method developed in *python* that operates directly on the technosphere to generate inventory-based waste and material footprints that can be computed like LCIA indicators while preserving exchange-level traceability (McDowall et al., 2025). After prospective databases are created (Section 2.1), the background is deconstructed to a flat, exchange-level list (via *Brightway/wurst*), which makes every technosphere flow addressable by name, unit, location, and metadata (Mutel, 2017b, 2017a). Pattern-based rules are then applied in two passes. First, waste detection targets exchanges whose names/units and treatment-chain context denote wastes, including routings to recycling, composting, anaerobic digestion, incineration, hazardous treatment, and landfill; "hidden" wastes that would otherwise be consumed inside treatment chains are surfaced at the point of generation, and hazardousness is taken only from explicit flags in the source inventories to avoid over-tagging from process names. Second, material demand is inferred from purchases of "market for …" activities corresponding to single materials or grouped families (e.g., rare earths, critical raw materials), so that footprints reflect supply-chain demand (including primary and secondary supply, co-production and substitution) rather than extraction events.

For each footprint category, the matched technosphere exchanges are mirrored one-to-one into an auxiliary "pseudo-biosphere" with unit-consistent characterisation factors. This preserves *Brightway's* calculation mechanics while yielding inventory totals (mass or volume) rather than impact-characterised scores; mirrored flows retain pointers to their source exchanges, enabling decomposition by sector, activity, or individual flow with full auditability. The same mirroring logic is applied to all database variants (current and *premise*-aligned), so temporal and scenario differences arise solely from underlying inventories. In the default configuration, *T-reX* provides ten waste categories (duplicated across mass and volume units) and a configurable panel of material-demand categories (with defaults aligned to the EU CRM list (European Commission, 2023)); both sets are easily extended by user rules. Together, these design choices allow footprint computation at activity, sector, or whole-database levels under current or prospective backgrounds while remaining faithful to the system model and allocation choices embedded in *ecoinvent*.

Operationally, *T-reX*'s workflow is automated and comprises: (i) optional configuration of waste/material categories; (ii) optional generation of *premise*-aligned prospective databases; (iii) database expansion to an exchange list; (iv) identification and categorisation of target exchanges; (v) construction of a *T-reX* "pseudo-biosphere" database; (vi) creation of pseudo-LCIA methods; (vii) exchange editing to mirror technosphere flows; and (viii) verification. The result is a *Brightway* project containing both the original biosphere and the *T-reX* pseudo-biosphere alongside one or more manipulated technosphere databases, ready for footprint calculation using standard LCA methodology.

2.3 Selection of activities in the LCA/pLCA databases

We restricted the analysis to a transparent, comparable set of background "market" activities from each LCI database (baseline *ecoinvent* and its prospective variants), then harmonised, classified, and merged them.

Filters were applied to isolate the activities of interest. By default, we selected only activities whose names begin with "market for …" and whose activity type equals "market activity", thereby focusing on market supply nodes rather than transformation or site-specific producer datasets. To avoid duplication we further restricted locations to *ecoinvent's* (mutually exclusive) global aggregates: GLO (global) and RoW (rest-of-world). We excluded activities that are waste or service oriented (name or classification containing "recovery", "treatment", "disposal", "waste", "services", "scrap", "site preparation", "construction", "maintenance") to avoid conflating technosphere waste management with product supply. Finally, we limited activities to those with mass or volume units, with volumes subsequently converted to masses so that material and waste footprints could be interpreted consistently across the activity set. After filtering, a total of 1593 activities remained in the selection, the complete data pertaining to these is provided in the supplementary information (section S2).

This approach intentionally prioritises (i) market-level representativeness; (ii) globally comparable inventories over regional differentiation; and (iii) physically interpretable commodities over service or energy-only flows. Limitations include potential omission of region-specific markets, energy carriers with non-mass units (e.g., kWh), and any product supplied exclusively via non-market datasets.

2.4 Categorisation of activities

To enable robust benchmarking across sectors, and within sectors and sub-sectors, we grouped activities using the Cooperative Patent Classification (CPC) codes stored in the *ecoinvent* metadata. CPC is the international standard for product taxonomy that organises goods and services by their material/functional characteristics (European Patent Office (EPO), 2025). In LCA databases it provides a stable, key for harmonising heterogeneous activity names (and thus facilitates comparisons that are otherwise noise-prone at the activity level). We follow prior macro-scale LCA work that aggregates products to analyse cross-category patterns (e.g., (Laurenti et al., 2023)), and rely on the CPC fields available in *ecoinvent* v3.x (Wernet et al., 2016). Table 1 lists the number of activities for each category.

Each activity was assigned a category and sub-category from CPC ranges, with explicit overrides for edge cases. Where CPC ranges overlap, later rules supersede earlier ones (e.g., plastics/rubber overrides chemicals). The resulting alignment used in the study is:

- **AgriForeAnim**
  - Agricultural & forestry products: CPC 00000–01999, 03000–03999, 39000–39999
  - Live animals, fish & their products: CPC 02000–02999, 04000–04999
- **ProcBio**
  - Food & beverages, animal feed: CPC 21000–23999, 42000–42999
  - Textile: CPC 26000–28199
  - Wood, straw & cork: CPC 31000–31999 (plus CPC 38100)
  - Pulp & paper: CPC 32000–32999 (plus CPC 38450→Textile)
- **OreMinFuel**
  - Ores, minerals & fuels: CPC 11000–17999, 33000–33999, 60000–69999
- **Chemical**
  - Chemical products: CPC 18000–18999, 34000–34699, 34800–35499
- **PlastRub**
  - Plastics & rubber products: CPC 34700–34799, 35500–36999
- **GlasNonMetal**
  - Glass & other non-metallic products: CPC 37000–37999
- **MetalAlloy**
  - Basic metals & alloys (incl. semi-finished): CPC 40000–41999

- **MachElecTrans**
  - • Metal/electronic equipment & parts: CPC 43000–48999, 49941–49999 (plus CPC 38150→Furniture)
  - • Transport vehicles: CPC 49000–49940

2.5 Extraction of activity price data

Market price data was obtained from the *ecoinvent* database using *Brightway* and a *python* script written by the authors (included in the supplementary information, section S3). The first step was to partially import the 'ecospold2' files in the uncompressed database, each of which represents a single activity. Our *python* script then scanned the metadata for each activity to extract the price attribute, saving it in a csv file along with the name and unique identifying code. This data is available in the supplementary information, section S2.

2.6 Calculations with LCIA methods and Waste and Resource Footprint methods

For every activity–year–scenario combination, we computed a panel of *T-reX* WMFs together with benchmark LCIA endpoints. The *T-reX* panel comprised ten waste footprints (including total, hazardous, and route-specific recovery/disposal categories, each in mass and volume units) and sixty material-demand footprints (both single materials and aggregated classes). Each method was instantiated by creating the corresponding pseudo-biosphere flows and characterisation tables and then running Brightway calculations on the filtered "market" activity set (Section 2.3). Scores are returned in the physical units of the mirrored exchanges. Negative material scores (arising where co-product supply offsets purchases) were retained to reflect the database's allocation/substitution logic rather than truncated, and were handled explicitly in interpretation. Quality-assurance checks covered unit consistency, exclusivity of hazardous tagging to explicitly flagged exchanges, and routing partitions (recovery vs disposal) summing to total waste within numerical tolerances.

In parallel, we calculated ReCiPe 2016 (H) endpoints (human health (DALY), ecosystems (species·year), and resource scarcity (USD2013)) for the same activity set and all background years/scenarios (Huijbregts et al., 2016). ReCiPe 2016 was chosen because it is widely adopted, methodologically harmonised, provides a compact set of interpretable endpoints, and offers a well-documented mapping from midpoints to endpoints at a global scale. Using endpoints, rather than a large basket of midpoints, supports concise comparison with inventory-level signals (waste/material footprints) when examining whether waste- or material-intensive sectors are also damage-intensive.

All calculations were executed in *Brightway* with the database *ecoinvent* v3.9.1 and on *premise*-generated prospective background databases (also based on *ecoinvent* v3.9.1) aligned to REMIND scenarios, ensuring that regionalised markets, technology efficiencies, fuel mixes, and emissions profiles propagate identically into both sets of indicators. This design enables like-for-like comparisons across activities, sectors, years, and scenarios, and allows interrogation of divergences between LCIA damage and inventory-based footprints—for example, those driven by allocation effects in *ecoinvent* or by the current under-specification of future waste-system transformations in prospective databases.

2.7 Calculation of waste circularity ratio

Waste circularity (C_w) was calculated as the proportion of total waste that is routed to recovery-oriented treatment rather than final disposal. For each activity, total waste generation (W_{total}) was compared against the summed quantities of waste that are recycled, composted, or anaerobically digested. The indicator was defined as:

$$C_w = \frac{\sum(W_{recycled} + W_{composted} + W_{digested})}{W_{total}} * 100$$

This formulation captures the share of waste that remains circulating within the technosphere, providing a simple mass-balance measure of material recovery. $W_{recycled}$ includes both mechanical and chemical recycling processes; $W_{composted}$ represents organic fractions entering aerobic composting; and $W_{digested}$ covers biogenic waste treated through anaerobic digestion. All three components were identified from *T-reX* waste exchange data based on process names and CPC classifications. Activities with C_w=0 correspond to fully linear waste pathways, whereas higher percentages indicate greater reintegration of materials into productive use and thus higher degrees of circularity.

2.8 Calculation of waste hazardousness ratio

The waste hazardousness ratio (H_w) was calculated to indicate the share of total waste that is classified as hazardous within each activity. It expresses the proportion of all outgoing waste flows identified as hazardous (e.g., toxic, corrosive, flammable, or otherwise regulated) relative to the total waste generated. The indicator was defined as:

$$H_w = \frac{W_{hazardous}}{W_{total}} * 100$$

where $W_{hazardous}$ represents the mass of all waste exchanges labelled as hazardous in the database metadata, and W_{total} is the sum of all waste outputs from the activity, irrespective of classification. This metric provides a normalised measure of waste toxicity potential at the inventory level, allowing comparisons across sectors independent of total waste magnitude. A higher H_w value denotes a larger fraction of hazardous waste within an activity's total waste profile, while lower values indicate predominantly non-hazardous material streams.

3 Results

3.1 Total waste footprints across sectors

Table 2 and Figure 1 together depict the distribution of total waste footprints across the main industrial categories. Both the descriptive statistics and the box plot highlight the extreme skewness of waste generation within the technosphere: while most activities produce relatively modest quantities of waste, a small subset of processes contributes disproportionately large amounts. Metals and alloys dominate, exhibiting median values two to three orders of magnitude higher than most other sectors and an extended upper tail driven by mining, smelting, and refining processes. The chemical and machinery–electronics–transport categories also display broad interquartile ranges and numerous outliers, underscoring their structural complexity and diversity of production scales. In contrast, agriculture, forestry, and animal products and non-metallic minerals cluster tightly around low median values, indicating generally limited waste generation per functional unit. The log-scaled spread observed in Figure 1 emphasises that even within individual categories, waste intensity can vary by up to six orders of magnitude, reflecting differences in process technology, regional supply-chain composition, and allocation effects. Overall, these patterns confirm that waste formation is highly concentrated in material- and energy-intensive industries, reinforcing the need for targeted circularity interventions in metallurgical and chemical value chains rather than diffuse, economy-wide measures.

The activity-level maxima reported in Table 3 identify the processes that anchor these upper tails and clarify why sectoral aggregates skew so strongly. In chemicals, the top entries are lutetium oxide, thulium oxide, and heavy water, each with extraordinary waste intensities—on the order of 10^8 kg waste per kg product (6.0×10^8; 1.6×10^8; 1.6×10^8, respectively)—and high prices (€165–620 in 2005 euros per kg). These values are consistent with ultra-selective separations from dilute feeds (e.g., multi-stage solvent extraction for rare earths; isotope separation for D_2O), where low yields, extensive reagent use, and large raffinate streams dominate the footprint (Zapp and Schreiber, 2022). In metals and alloys, gold–silver ingots (5.9×10^8 kg/kg), unrefined silver (5.4×10^8 kg/kg), and platinum (2.4×10^8 kg/kg; €20,600/kg) likewise exhibit extreme intensities aligned with very low ore grades and residue-rich pyrometallurgical–hydrometallurgical chains (Calvo et al., 2016); these few activities materially shape the category's long upper tail. Machinery–electronics–transport is led by integrated circuits (1.8×10^7 kg/kg) and active electronic components (1.5×10^7 kg/kg), a pattern compatible with clean-room manufacturing that relies on ultra-pure inputs, high consumable use, and yield losses across many steps (Williams et al., 2002).

Other categories show the same mechanism—outlier processes dominate within otherwise modest distributions. In ores–minerals–fuels, enriched uranium products (around 1.1×10^7 kg/kg; €586/kg) top the list, reflecting enrichment tails and extensive upstream processing (Gibon et al., 2023). In processed bio-based products, silk items—reeled raw silk hank (2.8×10^6 kg/kg; €19/kg) and silk yarn (7.8×10^5 kg/kg; €31.0/kg)—and large-fish canning (1.0×10^6 kg/kg; €0.65/kg) point to high volumes of aqueous effluents and organic residues per kilogram of output (Gutiérrez et al., 2019). For plastics and rubber, high-volume commodities such as PVC (emulsion and bulk polymerisation) and LLDPE occupy the top three ($\sim 4.1–4.4 \times 10^5$ kg/kg) despite low prices

(€1.3/kg), indicating that large absolute waste burdens can arise even where unit values are low. Non-metallic minerals are led by legacy and specialised glass products—CRT panel glass (8.0×10^4 kg/kg), solar collector glass tubes with silver mirrors (4.8×10^4 kg/kg), and glass fibre (2.9×10^4 kg/kg), where coating, forming, and cullet management contribute disproportionately relative to unit mass (European Commission, 2013). Agriculture, forestry, and animal products show a similar outlier structure: cocoons (2.7×10^5 kg/kg; €8.3/kg), swine for slaughter (1.3×10^5 kg/kg; €5.5/kg), and greasy sheep fleece (5.9×10^4 kg/kg; €2.8/kg) concentrate aqueous and organic by-product streams in a handful of items, while most agricultural commodities remain near the low category median.

Two cross-cutting implications follow from Table 3. First, the sectoral tails are shaped by processes characterised by either extreme selectivity (rare-earth oxides, heavy water, semiconductor devices) or very low natural concentrations (precious metals, platinum-group metals, nuclear fuels), where large material throughputs and auxiliary inputs are intrinsic to achieving specification, hence high waste per kilogram of final product. Second, price and waste intensity are only loosely coupled: some of the highest waste intensities coincide with very high prices (platinum, integrated circuits), but others occur in low-price, high-volume goods (PVC, LLDPE), implying that prioritisation should consider both mass-based contributions and economic leverage. These observations reinforce the case for targeted interventions: improving yields and reagent recovery in separation-intensive chains (rare earths, precious metals, nuclear fuels), and scaling process-control and scrap-looping strategies in polymers, glass, and electronics, where small fractional improvements at very large scales can meaningfully suppress the long-tail contribution to the technosphere's aggregate waste footprint.

3.2 Waste circularity across sectors

Figure 2a illustrates the distribution of waste circularity (C_w) across the eight aggregated industrial categories. Overall, circularity remains low, with medians below 5% in every category (agriculture/forestry/animal products 2.5%, processed bio-based products 1.1%, chemicals 0.86%, glass/non-metallics 0.84%, ores/minerals/fuels 0.61%, plastics/rubber 0.42%, metals/alloys 0.49%, and machinery–electronics–transport 0.29%). This confirms that (as modelled by *ecoinvent* v3.9.1) only a small share of waste is presently routed to recovery via recycling, composting, or anaerobic digestion.

The wide spreads in a few categories reflect identifiable outliers. In agriculture/forestry/animal products, several biogenic commodities exceed 10%—notably vanilla (14.6%), green coffee (14.0%), and processing tomatoes (13.8%). Processed bio-based products show the highest maxima overall—cottonseed oil (16.2%) and cottonseed meal (16.0%), which is consistent with well-established by-product recovery chains in the industry. More modest but still notable recoveries occur in glass/non-metallics (borosilicate glass tubes 6.3%), ores/minerals/fuels (tungsten concentrate 5%; steatite 6%), and a handful of machinery/electronics items (electron gun for CRT displays 4.3%). Chemicals are mostly near zero but include a few recovery-rich lines (e.g., helium, crude stockpiling 9.7%). By contrast, metals/alloys and plastics/rubber rarely exceed 2–3%, with isolated cases such as molybdenum trioxide (2.3%) and phenolic resin (2.2%) marking the upper tails.

Taken together, these statistics reinforce a predominantly linear metabolism: even where outliers exist, most activities in metals, chemicals, and high-volume manufacturing sit near zero circularity. Improving representation of future waste-management transformations in prospective LCA databases (and targeting the specific hotspots identified above) will be essential if circularity gains are to be credibly reflected in scenario analyses.

3.3 Waste hazardousness across sectors

Figure 2b shows the share of each activity's total waste that is classified as hazardous (H_w). Across the technosphere, hazardous fractions are generally small. Most categories cluster close to zero with medians around 0–2% (plastics/rubber 0.20%, chemicals 0.08%, machinery–electronics–transport 0.11%, metals/alloys 0.03%, ores/minerals/fuels 0.23%, glass/non-metallics 0.09%, processed bio-based products 0.09%, and agriculture/forestry/animal products 0.11%). Distributions are nevertheless fat-tailed. Plastics and rubber has the highest central tendency (mean 3.9%) and the broadest spread, with a long upper tail reaching into the tens of percent; the top activities include styrene–acrylonitrile (42.6%), ABS (40.9%), and PVDC granulate (26.5%), consistent with solvent- and additive-rich streams. Chemicals retain a low median but show persistent double-digit outliers, e.g., tebuconazole (11.5%), semiconductor-grade gallium (11.3%), and carbon tetrachloride (10.0%). Ores/minerals/fuels also exhibit high outliers despite a low median, led by pipeline olefins such as ethylene (24.6%) and propylene (23.3%).

Machinery–electronics–transport features sporadic peaks (aluminium collector foil for Li-ion cells 6.1%; carbon-fibre reinforced plastic 5.7%; LCD polariser stacks 1.4%), while metals/alloys remains tightly centred but includes forming/drawing steps with elevated shares (aluminium sheet rolling 5.2%; steel pipe drawing 5.0%; copper wire drawing 2.6%). Glass/non-metallics is low-centred yet contains bituminous adhesive compounds among its highest values (3.6% hot; 3.6% cold) alongside ceramic tiles (0.8%). Agriculture and processed bio-products cluster near zero but still present isolated cases—marine fish (1.0%), tropical hardwood sawlogs (0.9%), reeled raw silk (1.3%), and certain fish products (1.1%)—that should not be overlooked.

Taken together, these results indicate that hazardousness is weakly coupled to total waste magnitude: material-intensive sectors dominate in tonnes, but hazardous fractions are concentrated in specific sub-processes within plastics/rubber, chemicals, selected ore/fuel supply chains, and niche manufacturing steps. Prioritisation should therefore consider both dimensions—volume and Hw—to avoid overlooking small but risk-relevant streams.

3.4 Material demand footprints across sectors

While sixty material-demand footprints were computed (full results in Supplementary Information S2), we restrict our focus here to two policy-salient indicators with contrasting patterns of concentration and pervasiveness: natural gas and rare-earth elements (REEs).

3.4.1 Natural gas demand

Figure 4 indicates that natural-gas demand is pervasive across the technosphere yet strongly right-skewed, with a handful of activity types anchoring the upper tail. Medians reveal the broadly distributed baseline—machinery–electronics–transport highest (5.0×10^3 kg gas per kg product), then metals and alloys (1.1×10^3), chemicals (6.4

× 10^2), plastics and rubber (3.8 × 10^2), processed bio-based products (7.9 × 10^1), ores–minerals–fuels (5.6 × 10^1), glass/non-metallics (3.3 × 10^1), and agriculture/forestry/animal products (3.2 × 10^1) but means are pulled upward by extreme outliers. In metals and alloys the tail is dominated by precious-metal refining, with gas intensities of 1.2 × 10^7, 7.7 × 10^6, and 3.9 × 10^6 kg/kg for unrefined gold, gold, and platinum, respectively; these alone explain the large mean–median separation in that category. Electronics exhibits similarly elevated hotspots—integrated circuits (logic and memory) and active components at 3.0 × 10^5, 2.3 × 10^5, and 2.4 × 10^5 kg/kg—consistent with multi-step, yield-sensitive thermal processing. In ores–minerals–fuels, enriched-uranium products cluster around 4.0 × 10^5 kg/kg, reflecting enrichment and fuel-element fabrication. Chemicals show a modest median but wide spread due to gas's dual role as heat and feedstock, with lutetium oxide, scandium oxide, and heavy water at 9.2 × 10^5, 5.0 × 10^5, and 4.3 × 10^5 kg/kg. Categories with lower central tendencies still present specialised high-gas outliers, such as glass tubes with silver mirrors (1.7 × 10^3 kg/kg), sanitary ceramics and basic refractories (1.0–1.0 × 10^3), PVF films and dispersions (5.6–5.0 × 10^3), and silk products (1.3 × 10^4 and 3.4 × 10^3). The agricultural category, while more clustered and having the lowest median value, still presents high demand outliers such as cocoons, cashew, and tilapia which reach 1.5 × 10^3, 1.0 × 10^3, and 7.3 × 10^2 kg/kg. Occasional small negative minima are numerically negligible and reflect allocation/crediting artefacts rather than genuine net production. Overall, natural-gas use is diffuse at baseline but aggregate burdens are dominated by a narrow set of thermal-intensive hotspots in metallurgical, electronic, nuclear-fuel, and selected specialty lines, implying that targeted efficiency upgrades and fuel switching in these tails will deliver the largest system-wide reductions.

3.4.2 Rare earth element demand

Figure 5 shows that rare-earth element (REE) demand is highly concentrated and strongly right-skewed. Medians reveal the underlying pattern: machinery–electronics–transport sits highest (3.2 × 10^{-1} kg REE per kg product), followed by metals and alloys (7.1 × 10^{-2}), chemicals (2.7 × 10^{-2}), and plastics/rubber (2.0 × 10^{-2}); all other categories cluster near the floor (processed bio-products 3.6 × 10^{-3}; agriculture/forestry/animal products 3.1 × 10^{-3}; ores–minerals–fuels 2.2 × 10^{-3}; glass/non-metallics 1.1 × 10^{-3}). Means, however, are dominated by a small number of REE-specific markets, most starkly in chemicals, where the mean rises to 1.7 × 10^4 kg/kg despite a near-zero median. This tail is anchored by scandium oxide (1.1 × 10^7 kg/kg), lutetium oxide (2.5 × 10^5), and thulium oxide (6.7 × 10^4). Metals and alloys show similar tail behaviour (mean 1.3 × 10^2; max 8.8 × 10^3), driven by alloying and catalyst lines such as ferroniobium 66% (8.8 × 10^3), platinum (1.3 × 10^3), and metal catalysts for catalytic converters (9.5 × 10^2). Machinery–electronics–transport combines the highest central tendency with long upper tails (mean 3.9 × 10^1; max 2.6 × 10^3), reflecting magnet and battery supply chains (e.g., $LaNi_5$ positive electrodes (2.6 × 10^3), NiMH prismatic batteries (8.8 × 10^2), and permanent magnets for electric motors (7.4 × 10^2)). Ores–minerals–fuels exhibit sporadic but high-intensity demands (mean 7.4 × 10^1; max 5.6 × 10^3), led by pyrochlore concentrate (5.6 × 10^3) and enriched-uranium fuel elements (3.8 × 10^2). Plastics/rubber, glass/non-metallics, and processed bio-products have low medians and modest spreads but include identifiable outliers such as tetrafluoroethylene film on glass (7.2 × 10^1), LCD glass (1.3), and reeled raw silk hank (1.0). Agriculture/forestry/animal products remain close to the floor overall, though seed and cocoon markets register small but non-negligible purchases (cocoons 1.2 × 10^{-1}; fodder beet and sugar beet seed 9.5 × 10^{-2}). Occasional negative minima (down to about -3 × 10^{-4} kg/kg) are numerically negligible and reflect allocation or substitution credits rather than genuine negative demand. In sum, the REE footprint is tail-dominated: database-wide purchases are governed by a narrow set of specialised activities in REE processing, alloying, magnets, and advanced components, implying that targeted interventions in these chains will be far more effective than diffuse, economy-wide measures.

3.5 ReCiPe LCIA results across sectors

Values from ReCiPe's endpoint LCIA methods are not directly comparable in magnitude to inventory footprints; we therefore discuss rankings and trends only.

3.5.1 Damage to resource availability

For damage to resource availability (Figure 6), medians indicate the broad centre of pressure sits in machinery–electronics–transport (2.5 × 10^3), followed by plastics/rubber (7.2 × 10^2) and metals/alloys (7.2 × 10^2), with chemicals (5.3 × 10^2) close behind; ores–minerals–fuels (1.8 × 10^2), processed bio-products (5.2 × 10^1), glass/non-metallics (4.0 × 10^1), and agriculture/forestry/animal products (3.3 × 10^1) form a lower tier. Means, however, reveal extreme right tails, most pronounced in metals/alloys (mean 2.3 × 10^5; max 6.4 × 10^6) and chemicals (mean 2.8 × 10^4; max 4.6 × 10^6), driven by a narrow set of activities. In metals/alloys the tail is anchored by platinum and gold (6.4 × 10^6, 4.1 × 10^6, 4.0 × 10^6), while in chemicals it is rare-earth oxides (samarium–europium–gadolinium, praseodymium–neodymium, and REO concentrates at 4.6 × 10^6, 1.5 × 10^6, 1.4 × 10^6). Machinery–electronics–transport combines a high median with notable outliers tied to magnet and battery chains (LaNi electrodes 1.1 × 10^6; permanent magnets 4.0 × 10^5; NiMH batteries 3.8 × $10^{5)}$. Ores–minerals–fuels show sporadic but sizeable points (enriched uranium products 2.4 × 10^5). Plastics/rubber's relatively high median is shaped by fluoropolymer lines (tetrafluoroethylene film/monomer and polyvinylfluoride dispersion at 4.8 × 10^3–4.5 × 10^3). In glass/non-metallics, LCD glass and hard materials (silicon carbide, battery-grade synthetic graphite) sit atop the distribution (1.0 × 10^3; 600). Processed bio-products and agriculture feature much lower medians but still contain expensive, high-scarcity items (reeled raw silk 8.4 × 10^3; cocoons 996).

In relation to our inventory footprints, resource scarcity concentrates even more sharply in precious-metal, REE and magnet/battery chains, overlapping with REE demand tails and parts of the waste tails, but diverging from diffuse natural-gas dependence.

3.5.2 Damage to human health

For damage to human health (Figure 7), medians place machinery–electronics–transport highest (1.0 × 10^{-1}), followed by metals/alloys (5.5 × 10^{-2}), with plastics/rubber (8.1 × 10^{-3}) and chemicals (9.3 × 10^{-3}) forming a middle tier; ores–minerals–fuels (1.6 × 10^{-3}), processed bio-products (2.7 × 10^{-3}), glass/non-metallics (1.3 × 10^3) and agriculture/forestry/animal products (2.3 × 10^3) cluster lower. Means, however, expose extreme right tails, most striking in metals/alloys (mean 3.4 × 10^1; max 1.0 × 10^3), reflecting precious metal chains that dominate category totals (platinum 1.09 × 10^3; metal catalyst for catalytic converters 6.5 × 10^2; gold 5.0 × 10^2). Machinery–electronics–transport combines a high centre with large outliers tied to semiconductor and component manufacture (integrated circuits and active components at 8.2, 5.6, and 3.3). Ores–minerals–fuels show a modest median yet sizeable extremes from nuclear-fuel steps (enriched uranium fuel elements 20.4). Chemicals display a near-zero median but contain REE oxide hotspots (lutetium 17.9; scandium 11.7; thulium 4.77). Plastics/rubber, glass/non-metallics, and processed bio-products remain low-centred but include identifiable high lines (e.g., tetrafluoroethylene film 0.16; LCD glass 0.02; reeled raw silk 0.6). Agriculture's top entries are ruminant live-weight markets (weaned calves/heifers and cattle 0.4–0.7), but most activities sit near the lower tail.

Relative to the inventory footprints, human-health damage aligns closely with the waste and material hotspots in metals/alloys and in parts of machinery–electronics–transport, especially where precious metals, REEs, and complex processing are jointly required. Divergences are also evident: categories with diffuse dependence on natural gas do not systematically translate into high DALY medians, and some high-waste product lines (such as bulk polymers and glass) contribute less to endpoint damage than precious-metal- and REE-intensive chains. These patterns suggest pairing tail-targeted material strategies in precious-metal, REE, and semiconductor routes with cross-cutting energy and emissions controls, recognising that waste tonnage and health damage are related but governed by partially distinct mechanisms.

3.5.3 Damage to ecosystems

For damage to ecosystems (Figure 8), on median values, machinery–electronics–transport sits highest (1.5×10^{-4}), followed by metals/alloys (6.1×10^{-5}). A lower tier clusters around $1–2 \times 10^{-5}$—agriculture/forestry/animal products (1.7×10^{-5}), chemicals (1.8×10^{-5}), plastics/rubber (1.6×10^{-5}) and processed bio-products (1.5×10^{-5})—while glass/non-metallics and ores–minerals–fuels lie near the floor (3×10^{-6}). Means reveal a strongly right-skewed distribution dominated by metals/alloys (mean 3.7×10^{-2}; max 1.2), with notable but much smaller tails in ores–minerals–fuels (mean 9.3×10^{-4}) and machinery–electronics–transport (mean 5.2×10^{-4}).

The upper tails are anchored by a narrow set of activities. In metals/alloys, platinum (1.2), metal catalysts for catalytic converters (0.7), and gold (0.5) dominate category totals—consistent with precious/PGM supply chains driving ecosystem damage. In machinery–electronics–transport, integrated circuits and active components sit at the top (9.8×10^{-3}, 7.2×10^{-3}, 5.3×10^{-3}), reflecting semiconductor fabrication's energy- and chemical-intensive steps. Chemicals show REE oxides as clear hotspots (lutetium 0.04, thulium 0.01, scandium 0.01), while ores–minerals–fuels register enrichment and fuel-element steps (0.011). Categories with low centres still feature identifiable outliers: fluoropolymer lines in plastics/rubber (4.2×10^{-4} and 4.0×10^{-4}), LCD glass and hard materials in glass/non-metallics (3.8×10^{-5} to $3.1 \times 10\text{-}^{5}$), and silk products in processed bio-products (1.9×10^{-3}). Agriculture's tail is led by ruminant live-weight and fleece markets (6.9×10^{-4} to 4.5×10^{-4}), though the median remains low.

Relative to the waste and material footprints, ecosystem damage is concentrated in activities where precious metals, REEs, and advanced components coincide, overlapping with REE demand and parts of the waste distribution tails, but diverging from the more diffuse reliance on natural gas (which raises energy use broadly but does not consistently translate into high species-year damage). This pattern suggests that tail-targeted interventions in REE, precious-metal, and semiconductor routes need to be coupled with cross-cutting controls on emissions and process chemicals to address ecosystem risks most effectively.

3.6 Temporal and scenario trends in waste footprints

Figure 3 synthesises temporal trends in nine inventory-based waste and material indicators, reported as distributions across the 1593 selected market activities for 2020–2050 under SSP1-PkBudg500 and SSP5-PkBudg500. We describe medians and dispersion (min–max, standard deviation) to emphasise central tendencies while acknowledging persistently fat-tailed behaviour.

Captured CO_2 routed to storage (a) grows from a near-zero median in 2020 to substantial magnitudes by 2050 in both pathways, reflecting widespread deployment of CCS under the shared carbon budget. The median rises to 472 kg/kg (SSP1) and 388 kg/kg (SSP5) by 2050, with very wide spreads that expand over time (maxima reach 5.5×10^7 kg/kg and 3.4×10^7 kg/kg, respectively), indicating a small set of CCS-intensive activities emerging as outliers.

Total waste generation (b) increases steadily in both scenarios. Median values move from 3.5×10^3 in 2020 to 4.9×10^3 kg/kg (SSP1) and 4.5×10^3 kg/kg (SSP5) by 2050, i.e., +38% and +27%. Distributions remain broad and heavy-tailed throughout (stable maxima around 3.0×10^8 kg/kg), suggesting that sectoral heterogeneity persists even as backgrounds evolve.

The hazardousness share (c) declines modestly over time, with a stronger reduction in SSP1. Medians fall from 0.09% to 0.08% in SSP1 and to 0.09% in SSP5. Despite lower medians, variability remains large (standard deviations around 2 across years) and maxima stay high (declining from 41% to 34–36%), consistent with a long tail of hazardous-waste-intensive processes that standard scenario updates do not remove.

The waste circularity ratio (d) slips slightly in both pathways. SSP1 medians move from 0.88 to 0.82 (−6.9%), while SSP5 shifts from 0.88% to 0.84%. This soft deterioration occurs alongside rising total waste and only modest gains in specific recovery routes, implying that disposal grows faster than recovery for the median activity. Spread narrows only marginally (standard deviation drops from 2.0 to 1.5–1.6), indicating limited convergence.

Route-specific categories confirm these patterns. Landfilling (e) increases at the median by 41% in SSP1 (301 to 424 kg/kg) and 28% in SSP5 (301 to 384), with maxima extending from 7.0×10^6 to 9.6–9.7 $\times 10^6$ kg/kg. Recycling (f) rises more gently (16% in SSP1 (40.1 to 46.7 kg/kg) and 13% in SSP5 (40.1 to 45.2 kg/kg), insufficient to offset the faster growth in total waste. Composting (g) exhibits the sharpest relative gain from a very low base: medians increase from 6.9×10^{-3} kg/kg to 1.1×10^{-2} kg/kg in SSP1 and to 9.0×10^{-3} kg/kg in SSP5; however, the absolute levels remain negligible for most activities, and dispersion is dominated by a small number of large organic streams (max 4.5×10^4 kg/kg throughout). Waste incineration (h) grows modestly (~15% in both SSPs), with medians rising from 11.4 kg/kg to 13.1 kg/kg and stable, wide ranges (max 3.5×10^5 kg/kg). Open burning (I) edges upward by 10% in both scenarios (0.89 kg/kg to 0.98 kg/kg in SSP1; 0.89 kg/kg to 0.98 kg/kg in SSP5). Its tail remains high: maxima hover around 2.9×10^4, pointing to persistent uncontrolled disposal hotspots.

Across indicators, SSP1 tends to show slightly higher 2050 medians for total waste and landfilling than SSP5, despite the sustainability narrative, while achieving a larger reduction in hazardousness share. SSP5 often shows slightly less deterioration in circularity. The shared CO_2 budget drives CCS growth in both cases, with the SSP1 median exceeding SSP5 by 2050, yet variability is so large that pathway differences are dwarfed by between-activity heterogeneity. Overall, the box-plot distributions indicate incremental change rather than step-changes: recovery routes expand, but not fast enough to prevent a gradual decline in circularity and rising disposal for the median activity; fat tails remain for nearly all categories, underscoring the importance of targeted interventions in the most waste-intensive and poorly managed nodes of the technosphere.

4 Discussion

4.1 What this study adds

This study provides a macro-level prospective quantification of waste and material footprints (WMFs) across 1593 market activities, offering system-wide benchmarks from 2020 to 2050. The analysis reveals strong sectoral contrasts. Mining, metals, and basic chemicals dominate both total and hazardous waste outputs, while services and light manufacturing generate lower footprints per unit output. These sectoral patterns align with ReCiPe endpoint results, indicating that WMFs serve as credible proxies for environmental damage, especially in human health and ecosystem quality categories. This reinforces conclusions from Laurenti et al. (2023), who found consistent correlations between waste intensity and endpoint damage scores.

In addition to total waste flows, our study differentiates waste circularity and hazardousness across sectors. Sectors with established recycling networks (e.g. ferrous metals) exhibit high circularity, while others (e.g. mixed municipal and construction waste) remain predominantly linear. Our results confirm that waste quality attributes such as circularity percentage and hazardousness meaningfully influence associated impact profiles. For example, high hazardous waste does not always translate to high damage scores, reflecting controlled treatment processes that limit environmental release—an insight consistent with Laurenti et al.'s (2023) findings.

We also quantify sectoral material demand footprints, which typically mirror waste outputs but provide additional insights—particularly for high-tech products that use critical materials in small volumes. These results capture potential raw material supply risks not evident from waste alone and offer a second, complementary lens on throughput.

Crucially, we assess for the first time WMF trajectories under IAM-aligned prospective scenarios. While absolute waste volumes tend to increase with economic activity, waste intensity shows only modest improvement over 2020–2050 in both SSP1 and SSP5-based pathways. Small scenario differences do emerge, however, many sectors remain static in their waste intensities, reflecting limited representation of circularity transformations in the *premise*-modified pLCIs. This underlines a methodological blind spot: unlike the energy system, the waste system remains largely "frozen" in today's conditions. Without explicit modelling of future waste system trajectories, pLCA may understate the dynamics of waste-related environmental burdens.

4.2 Strengths of the approach

This study advances methodological practice by integrating WMF accounting directly into LCA using a "pseudo-LCIA" approach via *T-reX*. Customisable *python* scripts are provided to allow easy reuse in future studies. By tracking waste and material flows from technosphere inventories in physical units, our method maintains full compatibility with standard LCA workflows while improving interpretability. Unlike damage-based footprints that rely on complex weighting or cause-effect chains, our results offer direct observables such as kilograms of waste produced or kilograms of natural gas consumed. This makes them more communicable, especially for circular economy audiences focused on mass flows and reuse potential.

Moreover, we align WMF tracking with scenario-aligned background databases using the *premise* framework.

This ensures that footprint results reflect upstream system decarbonisation and technological shifts from IAM outputs. While IAM-pLCA integration has typically focused on carbon and energy flows, our study broadens its scope by tracing non-emission material and waste flows across time and policy futures.

Interpretively, the *T-reX* method positions waste not as a background service flow (as in *ecoinvent's* disposal treatment convention) but as an observable technosphere output and a pseudo-biosphere exchange. This realigns LCA with a more physical and intuitive accounting structure—closer to mass-balance logic and consistent with recent critiques of the "waste-as-service" model (Guinée & Heijungs, 2021).

4.3 Limitations and caveats

Several limitations temper the interpretation of our results. First, the footprint calculations depend on how waste is classified and allocated in the underlying LCI. We inherit *ecoinvent's* economic allocation conventions, which can suppress mass-based waste signals in high-value co-product systems and exaggerate them in low-value processes. For example, by-products with minimal market value may appear heavily waste-intensive, even if physically minor. While such allocation rules are standard, they limit the physical interpretability of absolute WMF values. Future work should explore physical or consequential allocation to better align with material mass flows.

Second, the classification of what counts as "waste" is context- and time-dependent. Industrial residues reused in another process (e.g. blast furnace slag) are excluded from waste tallies, while functionally similar materials discarded in landfills are counted. As material markets evolve, these boundaries may shift, requiring adaptive definitions.

Third, our method does not yet differentiate between the environmental risk of different wastes. One tonne of inert mining waste and one tonne of toxic sludge carry very different impacts but contribute equally to the total WMF. Users must therefore interpret footprint magnitudes in the context of waste composition and fate. Incorporating fate-specific indicators or hazard-weighted metrics would increase the decision relevance of the method.

A further limitation is the limited coverage of sectoral transformation in the scenario-linked pLCIs. *Premise* currently modifies key sectors (energy, cement, steel, transport) but does not adjust many manufacturing or waste management processes. As a result, WMFs remain static across many sectors, despite plausible expectations of circularity gains. Bisinella et al. (2024) and van der Giesen et al. (2020) have flagged this same gap, arguing that pLCA models must evolve to capture circular economy dynamics explicitly, especially in waste recovery, substitution, and material efficiency.

Uncertainty also remains intrinsic to ex-ante LCA. While we use established SSP-based scenarios, actual developments could diverge significantly. Moreover, spatial differentiation is limited: our results are global averages, and local waste impacts or recycling potentials are not captured. A kilogram of waste in a region with landfill scarcity or weak regulation may cause much more harm than the same mass in a highly regulated context.

Together, these caveats point to key directions for future refinement: dynamic waste classification, hazard weighting, greater scenario coverage, and spatial resolution.

4.4 Outlook and use

Our findings highlight three areas for immediate uptake and future research.

First, WMFs offer a vital complement to standard impact categories in LCA, particularly for assessing alignment with circular economy strategies. As governments and corporations adopt CE targets (e.g. halving residual waste, increasing secondary material shares), they need metrics that connect supply chain performance with waste and material throughput. Our method provides such metrics, grounded in LCI and compatible with standard software. Policymakers can use WMFs to identify high-priority sectors, benchmark progress, and track improvements in circularity over time.

Second, scenario-modified WMFs enable policy foresight. Analysts can assess how different decarbonisation or material transition pathways might affect not just emissions but also resource and waste outcomes. This aligns LCA with broader sustainability goals, including resource security and pollution prevention, and supports whole-economy transition planning.

Third, our results point to the need for expanded scenario coverage in pLCA. This includes explicit modelling of waste collection, sorting, reuse, and recycling systems—modules that remain underdeveloped in current IAM-pLCA pipelines. Developing such modules, or linking with existing circular economy models (e.g. MFA or stock-flow models), would allow future LCI datasets to better reflect CE policy ambitions.

Used alongside economy-wide frameworks such as MFA or EEIO, WMFs can help reconcile product-level circularity assessments with system-level material and waste balances, supporting cross-scale consistency checks and hybrid analyses (Torres de Matos et al., 2020; Wiedmann et al., 2013). In practical terms, this enables, for example, using MFA or stock–flow models to set boundary conditions and targets, while WMFs in pLCA diagnose which technologies and value chains actually deliver the required reductions in primary material use and residual waste. In turn, institutional or city-scale MFA–LCA frameworks (e.g., Maçin et al., 2024) could adopt WMFs as core indicators, strengthening the link between operational waste-management plans and prospective supply-chain performance.

Overall, this study demonstrates that WMFs can be rigorously and transparently integrated into prospective LCA, revealing meaningful patterns across sectors and scenarios. While limitations remain—especially around allocation, waste characterisation, and scenario scope—the methodological advances offer a concrete foundation for embedding circularity into forward-looking environmental assessments.

5 Conclusions and recommendations

This study introduces a systematic framework for quantifying waste and material footprints (WMFs) in prospective life cycle assessment, integrating 1593 market activities and multiple scenario-aligned inventories to track flows from 2020 to 2050. The results demonstrate that WMFs vary widely across sectors, with mining, metals, and chemicals contributing disproportionately to total and hazardous waste generation. These patterns align closely with conventional LCIA damage profiles, reinforcing the interpretive and policy value of WMFs as complementary indicators in sustainability assessments.

By distinguishing waste quality attributes (such as circularity potential and hazardousness) and linking them to scenario-based changes in supply chains, the approach reveals important blind spots in current pLCA practices. While energy-related transformations are well captured in IAM-linked databases, circularity measures and waste system evolution remain under-represented. As a result, WMFs show only modest improvements over time, underscoring the need for targeted integration of waste-sector dynamics into future pLCI development.

Methodologically, the combination of transparent, physically grounded footprint indicators with scenario-aligned inventories represents a step forward for both LCA and circular economy modelling. The *T-reX* framework allows practitioners to extract and interpret resource throughput and waste burdens in a manner consistent with established LCA workflows but with far greater clarity on material cycling and discard.

Compared to MFA and EEIO approaches, the WMF method enables greater resolution of where and how waste and material burdens arise within specific supply chains, particularly under prospective, scenario-based conditions. While MFA excels at economy-wide stock-flow tracking (Torres de Matos et al., 2020) and EEIO links resource use to consumption patterns (Wiedmann et al., 2013), both often lack the granularity to capture process-level shifts or product-level circularity under future interventions. WMFs fill this gap but face limitations in coverage and interpretation, especially when used without parallel impact assessment (Laurenti et al., 2023). For comprehensive circularity assessments, hybridising or parallelising these methods could provide deeper insight by combining the systemic breadth of MFA and IO with the temporal and technological depth of LCA.

Looking ahead, further development is needed to incorporate fate-differentiated waste flows, refine allocation choices for mass-based inference, and extend scenario coverage beyond the currently modelled sectors. Nonetheless, the WMF framework presented here offers a robust platform for linking life cycle thinking to material efficiency, waste prevention, and critical raw material strategies—supporting informed decisions in the context of global sustainability transitions. As circular economy targets become increasingly central to policy, tools that trace waste and material flows through prospective supply chains will be evermore essential.

Supplementary Material

The supplementary material supplied in the appendices of this manuscript contain the following sections:

S1.Additional figures referenced in the text

S2.Complete tabulated data

S3.Python scripts used for the production of results

Data availability

All publicly available data related to this manuscript is available in online repositories hosted by Zenodo (https://doi.org/10.5281/zenodo.16995460) and Github (https://github.com/Stew-McD/T-reX_LCA-MacroStudy)

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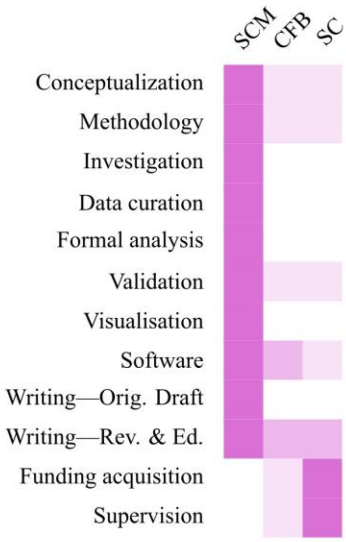
CRediT authorship contribution statement

Stewart Charles McDowall: Conceptualisation, Methodology, Investigation, Data curation, Formal analysis, Validation, Visualisation, Writing: original draft, Writing: review & editing, Visualisation.

Carlos Felipe Blanco: Conceptualisation, Methodology, Validation, Writing: review & editing, Funding acquisition, Supervision.

Stefano Cucurachi: Conceptualisation, Methodology, Validation, Writing: review & editing, Funding acquisition, Supervision.

CRediT authorship visualisation



Declarations

Competing interests

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.

Open access

Use of artificial intelligence

The authors declare that no generative artificial intelligence tools were used in the generation of the research data or results reported in this paper. Generative AI was used solely to assist in the editing and refinement of the manuscript text, with all content reviewed and approved by the authors.

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Tables

Table 1 Categorisation and count of the selected market activities

Category full name	Abbreviated name	Count
Agriculture, forestry, live animals & their products	AgriForeAnim	212
Chemical products	Chemical	669
Glass and other non-metallic products	GlasNonMetal	110
Machinery, metal/electronic, transport equipment	MachElecTrans	122
Basic metals & alloys, incl. semi-finished products	MetalAlloy	86
Ores, minerals & fuels	OreMinFuel	132
Plastics & rubber products	PlastRub	78
Processed biobased products	ProcBio	184

Table 2 Waste footprint statistics for each category (total waste)

Category	Mean	std	Min	Max
AgriForeAnim	5.32E+03	2.13E+04	-1.04E+02	2.66E+05
Chemical	1.70E+06	2.50E+07	0.00E+00	6.04E+08
GlasNonMetal	5.13E+03	1.02E+04	-2.89E+02	8.03E+04
MachElecTrans	1.27E+06	2.75E+06	9.62E+02	1.76E+07
MetalAlloy	2.08E+07	9.07E+07	2.43E+01	5.90E+08
OreMinFuel	9.35E+05	2.83E+06	0.00E+00	1.09E+07
PlastRub	5.14E+04	1.01E+05	6.28E+01	4.36E+05
ProcBio	9.35E+04	3.64E+05	0.00E+00	2.79E+06

Table 3 Top three activities for each product category with the “Waste - Total” footprint method

Category	Name	Waste – Total (kg/kg)	Price (EUR2005/kg)
AgriForeAnim	market for cocoons	2.66E+05	8.26
AgriForeAnim	market for swine for slaughtering, live weight	1.34E+05	5.48
AgriForeAnim	market for sheep fleece in the grease	5.88E+04	2.82
Chemical	market for lutetium oxide	6.04E+08	619.06
Chemical	market for thulium oxide	1.61E+08	165.4
Chemical	market for heavy water	1.57E+08	620
GlasNonMetal	market for panel glass, for cathode ray tube display	8.03E+04	0.8
GlasNonMetal	market for solar collector glass tube, with silver mirror	4.79E+04	3.78
GlasNonMetal	market for glass fibre	2.91E+04	0.8
MachElecTrans	market for integrated circuit, logic type	1.76E+07	1260.01
MachElecTrans	market for integrated circuit, memory type	1.75E+07	121.85
MachElecTrans	market for electronic component, active, unspecified	1.53E+07	745.98
MetalAlloy	market for gold-silver, ingot	5.90E+08	2337.81
MetalAlloy	market for silver, unrefined	5.37E+08	314.63
MetalAlloy	market for platinum	2.42E+08	20600
OreMinFuel	market for enriched uranium, 4.2%	1.09E+07	586
OreMinFuel	market for uranium, enriched 4.2%, in fuel element...	1.09E+07	586
OreMinFuel	market for uranium, enriched 4%, in fuel element...	1.05E+07	586
PlastRub	market for polyvinylchloride, emulsion polymerised	4.36E+05	1.29
PlastRub	market for polyethylene, linear low density, granulate	4.17E+05	1.29
PlastRub	market for polyvinylchloride, bulk polymerised	4.14E+05	1.29
ProcBio	market for reeled raw silk hank	2.79E+06	18.88

ProcBio	market for fish canning, large fish	1.02E+06	0.65
ProcBio	market for yarn, silk	7.75E+05	31.01

Figure Captions

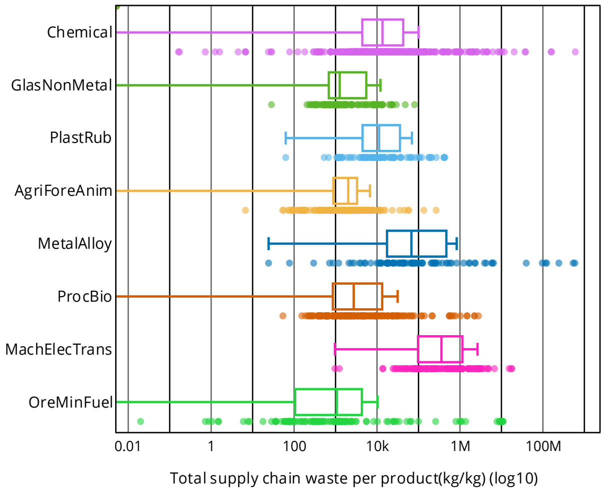
Figure 1. Distribution of total supply-chain waste per product (kg waste per kg product, $\log_{10}$ scale) across major industrial categories for a total of 1593 activities in *ecoinvent* v3.9.1 . Boxes show interquartile ranges with median lines; whiskers indicate 1.5× IQR, and dots denote the individual activities.

Figure 2. Waste circularity and hazardousness ratios across industrial categories for a total of 1593 activities in *ecoinvent* v3.9.1. The subfigures are: (a) Waste circularity—the share of total waste routed to recovery by recycling, composting, or anaerobic digestion, and (b) Waste hazardousness—the fraction of total waste classified as hazardous. Boxes show interquartile ranges with medians; whiskers denote 1.5×IQR; points are individual activities.

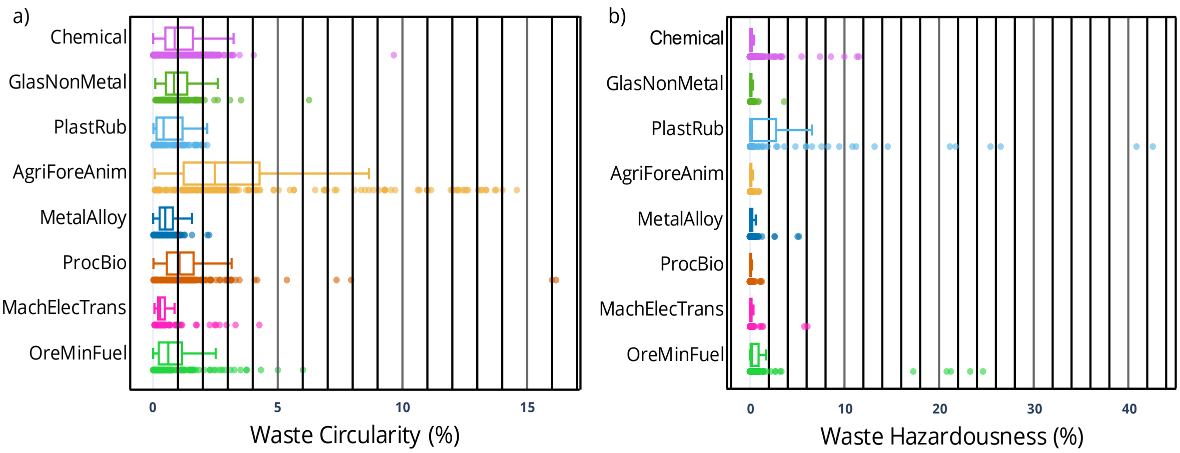
Figure 3. Scenario-based temporal trends in a selection of waste footprints, depecting the distribution of scores for 1593 activities in current and prospective LCA databases from 2020 to 2050 under the SSP1-PkBudg500 and SSP5-PkBudg500 scenario models. The subfigures are: (a) Waste – from carbon capture and storage (CCS) (kg/kg), (b) Waste – Total (kg/kg), (c) Waste – Hazardousness (%), (d) Waste – Circularity ratio (%), (e) Waste – Landfilled (kg/kg), (f) Waste – Recycled (kg/kg), (g) Waste – Composted (kg/kg), (h) Waste – Incinerated (kg/kg) and (i) Waste – Openly burned (kg/kg).

Figures

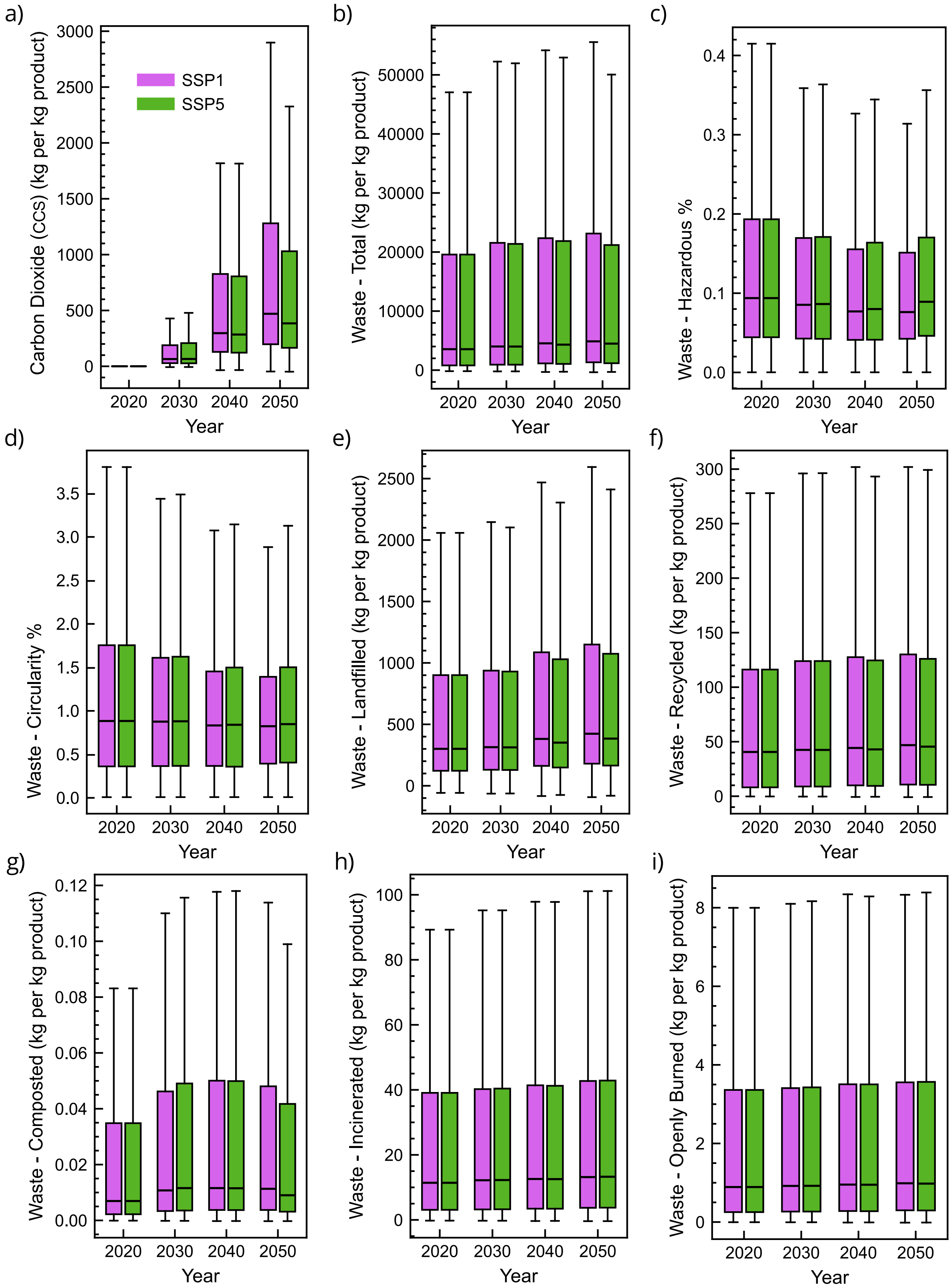
1.


Chemical
GlasNonMetal
PlastRub
AgriForeAnim
MetalAlloy
ProcBio
MachElecTrans
OreMinFuel
0.01
1
100
10k
1M
100M
Total supply chain waste per product(kg/kg) (log10)

2.


a)
Chemical
GlasNonMetal
PlastRub
AgriForeAnim
MetalAlloy
ProcBio
MachElecTrans
OreMinFuel
0
5
10
15
Waste Circularity (%)
b)
Chemical
GlasNonMetal
PlastRub
AgriForeAnim
MetalAlloy
ProcBio
MachElecTrans
OreMinFuel
0
10
20
30
40
Waste Hazardousness (%)

790 3.


a)
SSP1
SSP5
Carbon Dioxide (CCS) (kg per kg product)
b)
Waste - Total (kg per kg product)
c)
Waste - Hazardous %
d)
Waste - Circularity %
e)
Waste - Landfilled (kg per kg product)
f)
Waste - Recycled (kg per kg product)
g)
Waste - Composted (kg per kg product)
h)
Waste - Incinerated (kg per kg product)
i)
Waste - Openly Burned (kg per kg product)
Year

791