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

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Abstract (400/400 words)

Purpose 75 words

Advancing a circular economy requires direct, system-wide quantification of the waste and material flows attributable to human activity. Yet Waste and Material Footprints (WMFs) remain under-reported in standard LCA and sparsely integrated into prospective assessments. We quantify WMFs across the ecoinvent database and examine their evolution under contrasting socio-economic pathways to: (i) reveal sectoral and supply-chain hotspots; (ii) position WMFs alongside conventional LCIA endpoints; and (iii) assess how scenario-aligned backgrounds modify footprint magnitudes and interpretation.

Methods 125 words

We constructed prospective LCI databases with *premise* (based on ecoinvent 3.9.1), aligned to two divergent *REMIND* Integrated Assessment Model (IAM) pathways—SSP1-PkBudg500 and SSP5-PkBudg500—for 2020–2050. We then applied *T-reX* to enable tracking of 70+ categories of waste and material flows and computed WMFs for 1593 market activities. In parallel, we calculated ReCiPe 2016 endpoint indicators to compare WMFs against established damage metrics. Activities were grouped into sectors to identify hotspots and explore temporal and scenario contrasts. Because the underlying inventories use economic allocation, we explicitly discuss interpretive limits for mass-based inference in the context of allocation-driven effects.

Results and discussion 125 words

Sectorally, mining, metals, and chemicals dominate both total and hazardous waste footprints, mirroring patterns in ReCiPe endpoints and reinforcing WMFs' decision relevance for risk, circularity, and prevention strategies. WMFs show statistically meaningful correlations with human-health and ecosystem damage indicators at

activity and sector aggregation. Across 2020–2050, we observe modest WMF reductions in both pathways, however, the magnitude of change is smaller than expected given policy narratives on waste prevention, improved collection/sorting, higher recycling yields and qualities, and expanded secondary-material markets. This gap likely reflects limited representation of waste-system transformations in IAM-linked pLCIs and highlights where circularity dynamics are under-specified. Interpretation of absolute WMF levels is also allocation-sensitive: price-based allocation can amplify high-value co-products and attenuate low-value by-products, decoupling WMFs from physical mass balances.

Conclusions and recommendations – 150 words

WMFs complement LCIA endpoints in prospective LCA by making material throughput and waste generation explicit, revealing hotspots that standard impact profiles can obscure. To approach mass-consistent interpretation, future work should test physical/flow-based allocation and explore consequential databases. Most critically, signigicant effort will need to be made to embed explicit waste-sector trajectories in prospective LCA databases in the way that sectors such as energy and transport are already included. Our results indicate a methodological gap: without scenario-dependent circularity modules, IAM-aligned databases understate WMF dynamics over time. Integrating these transformations will improve the fidelity and policy usefulness of pLCAs intended to guide circular-economy strategies.

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 Assessment
ProcBio	Processed biobased products
PVC	Polyvinyl chloride
RCP	Representative Concentration Pathway
ReCiPe	A standard LCIA method set

REE	Rare Earth Element
REO	Rare Earth Oxide
REMIND	REgional Model of Investment and Development
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 (1200 words)

Environmental context: why circularity and waste matter

Human activities continue to exceed key planetary boundaries, intensifying climate change, biodiversity loss, and resource depletion. In response, 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—refuse, rethink, repair, remanufacturing, and recycling (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 and system resilience (Carrara et al., 2023; Hartley et al., 2024).

Waste and material footprints in LCA

Footprints provide compact indicators of environmental pressure. 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, including hazardous fractions—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 (treatment), 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.

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—assesses 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).

premise, REMIND, and sectoral transformations

The premise workflow connects IAM projections to ecoinvent, producing pLCIs that regionalise markets and update process and supply-chain parameters for selected sectors (Sacchi et al., 2022; Sacchi et al., 2023). 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 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 cobalt (Van Der Meide et al., 2022), hydrogen (Wei et al., 2024) and cement (Müller 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).

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 tool 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. 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. 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 energy and transport transitions.

2 Methodology (1700 words)

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 (Bauer et al., 2017; Kriegler et al., 2017; Van Vuuren et al., 2017).

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 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: contrasts in waste and material footprints 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, CCS, hydrogen, 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 (Sacchi et al., 2022; IPCC, 2018).

2.2 Waste and material footprinting with T-reX

T-reX 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. 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. 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 CPC 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); 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 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 tooling.

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 global aggregates: GLO (global) and RoW (rest-of-world). We excluded activities that are waste or service oriented (name, CPC, or ISIC containing "recovery", "treatment", "disposal", "waste", "services", "scrap", "site preparation", "construction", "maintenance") to avoid conflating technosphere waste management with product supply. Finally, we limited reference units to mass and volume commodities (kilogram, cubic meter) 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.

This approach intentionally prioritises (i) market-level representativeness over plant-level specificity; (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. We note that name-based grouping can collide where names are reused across contexts; unique identifiers (activity code + database) mitigate this risk in downstream steps.

2.4 Categorisation of activities

To enable robust benchmarking—across sectors, and within sectors and sub-sectors—we grouped activities using the Central Product Classification (CPC) codes stored in the ecoinvent metadata. CPC is the United Nations' product taxonomy that organises goods and services by their material/functional characteristics; in LCA databases it provides a stable, method-agnostic key for harmonising heterogeneous activity names (and thus facilitates comparisons that are otherwise noise-prone at the activity level). We follow prior large-N 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 brightway2 and a python script written by the authors. 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 and Waste and Resource Footprint methods

For every activity–year–scenario combination, we computed a panel of T-reX footprints together with benchmark LCIA endpoints. The T-reX panel comprised ten waste footprints (total, hazardous, and route-specific recovery/disposal categories, each in mass and volume units) and sixty material-demand footprints (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. 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 juxtaposition with inventory-level signals (waste/material footprints) when examining whether waste- or material-intensive sectors are also damage-intensive. The endpoint framework, areas of protection, units, and midpoint-to-endpoint conversion are documented in Huijbregts et al. (2016), which we follow without modification.

All calculations were executed in Brightway on ecoinvent v3.9.1 and on premise-generated prospective backgrounds 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 (2500 words)

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 boxplot highlight the extreme skewness of waste generation within the technosphere: while most activities produce relatively modest quantities of waste, a small subset of heavy-industrial 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 (6.04×10^8; 1.61×10^8; 1.57×10^8, 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. In metals and alloys, gold–silver ingots (5.90×10^8 kg/kg), unrefined silver (5.37×10^8 kg/kg), and platinum (2.42×10^8 kg/kg; €20,600/kg) likewise exhibit extreme intensities aligned with very low ore grades and residue-rich pyrometallurgical–hydrometallurgical chains; these few activities materially shape the category's long upper tail. Machinery–electronics–transport is led by integrated circuits (logic and memory types: $1.75–1.76 \times 10^7$ kg/kg) and active electronic components (1.53×10^7 kg/kg; high unit prices), a pattern compatible with clean-room manufacturing that relies on ultra-pure inputs, high consumable use, and yield losses across many steps.

Other categories show the same mechanism—outlier processes dominate within otherwise modest distributions. In ores–minerals–fuels, enriched uranium products ($\sim 1.05–1.09 \times 10^7$ kg/kg; €586/kg) top the list, reflecting enrichment tails and extensive upstream processing. In processed bio-based products, silk items—reeled raw silk hank (2.79×10^6 kg/kg; €18.88/kg) and silk yarn (7.75×10^5 kg/kg; €31.01/kg)—and large-fish canning (1.02×10^6 kg/kg; €0.65/kg) point to high volumes of aqueous effluents and organic residues per kilogram of high-value output. 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 (€1.29/kg), indicating that large absolute waste burdens can arise even where unit values are low, particularly when polymerisation, compounding, and off-spec management are considered together. Non-metallic minerals are led by legacy and specialised glass products—CRT panel glass (8.03×10^4 kg/kg), solar collector glass tubes with silver mirrors (4.79×10^4 kg/kg), and glass fibre (2.91×10^4 kg/kg), where coating, forming, and cullet management contribute disproportionately relative to unit mass. Agriculture, forestry, and animal products show a similar outlier structure: cocoons (2.66×10^5 kg/kg; €8.26/kg), swine for slaughter (1.34×10^5 kg/kg; €5.48/kg), and greasy sheep fleece (5.88×10^4 kg/kg; €2.82/kg) concentrate aqueous and organic by-product streams in a handful of items, while most agricultural commodities remain near the 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 (for example: agriculture/forestry/animal products 2.48%, processed bio-based products 1.11%, chemicals 0.862%, glass/non-metallics 0.843%, ores/minerals/fuels 0.613%, plastics/rubber 0.421%, metals/alloys 0.492%, and machinery–electronics–transport 0.286%). This confirms that (as modelled by ecoinvent 3.9.1) only a small share of waste is presently routed to recovery via recycling, composting, or anaerobic digestion, and that the floor of the distributions lies close to zero.

The wide spreads in a few categories reflect identifiable outliers. In agriculture/forestry/animal products, several biogenic commodities exceed 10%—notably vanilla (14.58%), green coffee (14.01%), and processing tomatoes (13.76%). Processed bio-based products show the highest maxima overall—cottonseed oil (16.16%) and cottonseed meal (15.99%), 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 6.26%), ores/minerals/fuels (tungsten concentrate 5.01%; steatite 6.01%), and a handful of machinery/electronics items (electron gun for CRT displays 4.26%). Chemicals are mostly near zero but include a few recovery-rich lines (helium, crude stockpiling 9.65%). By contrast, metals/alloys and plastics/rubber rarely exceed 2–3%, with isolated cases such as molybdenum trioxide (2.25%) and phenolic resin (2.17%) 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%, for example: plastics/rubber 0.198%, chemicals 0.081%, machinery–electronics–transport 0.105%, metals/alloys 0.033%, ores/minerals/fuels 0.226%, glass/non-metallics 0.085%, processed bio-based products 0.086%, and agriculture/forestry/animal products 0.109%. Distributions are nevertheless fat-tailed. Plastics and rubber has the highest central tendency (mean 3.85%) 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 6.09%; carbon-fibre reinforced plastic 5.74%; LCD polariser stacks 1.39%), while metals/alloys remains tightly centred but includes forming/drawing steps with elevated shares (aluminium sheet rolling 5.20%; steel pipe drawing 5.04%; copper wire drawing 2.63%). Glass/non-metallics is low-centred yet contains bituminous adhesive compounds among its highest values (3.61% hot; 3.61% cold) alongside ceramic tiles (0.84%). Agriculture and processed bio-products cluster near zero but still present isolated cases—marine fish (0.97%), tropical hardwood sawlogs (0.93%), reeled raw silk (1.26%), 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 focus here on 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 S1a 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 (4.95×10^3 kg gas per kg product), then metals and alloys (1.14×10^3), chemicals (6.43×10^{2}), plastics and rubber (3.77×10^{2}), processed bio-based products (7.85×10^{1}), ores–minerals–fuels (5.56×10^{1}), glass/non-metallics (3.30×10^{1}), and agriculture/forestry/animal products (3.18×10^{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 1.15×10^{7}, 7.65×10^{6}, and 3.85×10^{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 3.00×10^{5}, 2.32×10^{5}, and 2.41×10^{5} kg/kg—consistent with multi-step, yield-sensitive thermal processing. In ores–minerals–fuels, enriched-uranium products cluster around 4.01×10^{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 9.20×10^{5}, 5.04×10^{5}, and 4.39×10^{5} kg/kg. Categories with lower central tendencies still present specialised high-gas outliers, such as glass tubes with silver mirrors (1.67×10^{3} kg/kg), sanitary ceramics and basic refractories (1.0–1.03×10^{3}), PVF films and dispersions (5.6–5.0×10^{3}), and silk products (1.25×10^{4} and 3.35×10^{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 1.47×10^{3}, 1.02×10^{3}, and 7.32×10^{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 S1b shows that rare-earth element (REE) demand is highly concentrated and strongly right-skewed. Medians reveal the underlying pattern: machinery–electronics–transport sits highest (3.24×10^{-1} kg REE per kg product), followed by metals and alloys (7.14×10^{-2}), chemicals (2.79×10^{-2}), and plastics/rubber (2.01×10^{-2}); all other categories cluster near the floor (processed bio-products 3.65×10^{-3}; agriculture/forestry/animal products 3.12×10^{-3}; ores–minerals–fuels 2.22×10^{-3}; glass/non-metallics 1.16×10^{-3}). Means, however, are dominated by a small number of REE-specific markets, most starkly in chemicals, where the mean rises to 1.78×10^{4} kg/kg despite a near-zero median. This tail is anchored by scandium oxide (1.16×10^{7} kg/kg), lutetium oxide (2.52×10^{5}), and thulium oxide (6.74×10^{4}). Metals and alloys show similar tail behaviour (mean 1.36×10^{2}; max 8.80×10^{3}), driven by alloying and catalyst lines such as ferroniobium 66% (8.80×10^{3}), platinum (1.30×10^{3}), and metal catalysts for catalytic converters (9.52×10^{2}). Machinery–electronics–transport combines the highest central tendency with long upper tails (mean 3.99×10^{1}; max 2.64×10^{3}), reflecting magnet and battery supply chains (e.g., LaNi5 positive electrodes (2.64×10^{3}), NiMH prismatic batteries (8.85×10^{2}), and permanent magnets for electric motors (7.42×10^{2})). Ores–minerals–fuels exhibit sporadic but high-intensity purchases (mean 7.47×10^{1}; max 5.68×10^{3}), led by pyrochlore concentrate (5.68×10^{3}) and enriched-uranium fuel elements (3.87×10^{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 (7.29×10^{1}), LCD glass (1.30), and reeled raw silk hank (1.01). Agriculture/forestry/animal products remain close to the floor overall, though seed and cocoon markets register small but non-negligible purchases (cocoons 1.21×10^{-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 S1c), medians indicate the broad centre of pressure sits in machinery–electronics–transport (2.52×10^{3}), followed by plastics/rubber (7.20×10^{2}) and metals/alloys (7.27×10^{2}), with chemicals (5.39×10^{2}) close behind; ores–minerals–fuels (1.88×10^{2}), processed bio-products (5.25×10^{1}), glass/non-metallics (4.03×10^{1}), and agriculture/forestry/animal products (3.35×10^{1}) form a lower tier. Means, however, reveal extreme right tails, most pronounced in metals/alloys (mean 2.30×10^{5}; max 6.49×10^{6}) and chemicals (mean 2.83×10^{4}; max 4.65×10^{6}), driven by a narrow set of activities. In metals/alloys the tail is anchored by platinum and gold (6.49×10^{6}, 4.17×10^{6}, 3.99×10^{6}), while in chemicals it is rare-earth oxides (samarium–europium–gadolinium, praseodymium–neodymium, and REO concentrates at 4.65×10^{6}, 1.53×10^{6}, 1.48×10^{6}). Machinery–electronics–transport combines a high median with notable outliers tied to magnet and battery chains (LaNi electrodes 1.14×10^{6}; permanent magnets 4.02×10^{5}; NiMH batteries 3.83×10^{5}). Ores–minerals–fuels show sporadic but sizeable points (enriched uranium products 2.49×10^{5}). Plastics/rubber's relatively high median is shaped by fluoropolymer lines (tetrafluoroethylene film/monomer and polyvinylfluoride dispersion at 4.84×10^{3}–4.54×10^{3}). In glass/non-metallics, LCD glass and hard materials (silicon carbide, battery-grade synthetic graphite) sit atop the distribution (1.06×10^{3}; 600). Processed bio-products and agriculture feature much lower medians but still contain expensive, high-scarcity items (reeled raw silk 8.46×10^{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 S1d), medians place machinery–electronics–transport highest (1.04×10^{-1}), followed by metals/alloys (5.52×10^{-2}), with plastics/rubber (8.12×10^{-3}) and chemicals (9.33×10^{-3}) forming a middle tier; ores–minerals–fuels (1.68×10^{-3}), processed bio-products (2.73×10^{-3}), glass/non-metallics (1.31×10^{3}) and agriculture/forestry/animal products (2.39×10^{3}) cluster lower. Means, however, expose extreme right tails, most striking in metals/alloys (mean 3.43×10^{1}; max 1.09×10^{3}), reflecting precious metal chains that dominate category totals (platinum 1.09×10^{3}; metal catalyst for catalytic converters 6.55×10^{2}; gold $5.09 \times$

10^{2}). Machinery–electronics–transport combines a high centre with large outliers tied to semiconductor and component manufacture (integrated circuits and active components at 8.23, 5.69, and 3.31). 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 0.161; LCD glass 0.024; reeled raw silk 0.635). Agriculture's top entries are ruminant liveweight markets (weaned calves/heifers and cattle 0.46–0.71), but most activities sit near the lower tail.

Relative to the inventory footprints, human-health damage overlaps strongly with the waste and material hotspots for metals/alloys and parts of machinery–electronics–transport, where precious metals, REEs, and complex processing co-locate. Divergences are also evident: categories with diffuse natural-gas dependence do not necessarily translate into high DALY medians, and some high-waste lines (bulk polymers, glass) contribute less to endpoint damage than precious-metal and REE chains. This suggests 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 governed by related but distinct mechanisms.

3.5.3 Damage to ecosystems

For damage to ecosystems (Figure S1e), on median values, machinery–electronics–transport sits highest (1.54 × 10^{-4}), followed by metals/alloys (6.15 × 10^{-5}). A lower tier clusters around 1–2 × 10^{-5}—agriculture/forestry/animal products (1.79 × 10^{-5}), chemicals (1.82 × 10^{-5}), plastics/rubber (1.62 × 10^{-5}) and processed bio-products (1.50 × 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 3.74 × 10^{-2}; max 1.20), with notable but much smaller tails in ores–minerals–fuels (mean 9.36 × 10^{-4}) and machinery–electronics–transport (mean 5.23 × 10^{-4}).

The upper tails are anchored by a narrow set of activities. In metals/alloys, platinum (1.20), metal catalysts for catalytic converters (0.729), and gold (0.474) 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 (0.0098, 0.0072, 0.0053), reflecting semiconductor fabrication's energy- and chemical-intensive steps. Chemicals show REE oxides as clear hotspots (lutetium 0.041, thulium 0.011, scandium 0.010), while ores–minerals–fuels register enrichment and fuel-element steps (0.011–0.0113). Categories with low centres still feature identifiable outliers: fluoropolymer lines in plastics/rubber (4.24 × 10^{-4} and 4.02 × 10^{-4}), LCD glass and hard materials in glass/non-metallics (3.82 × 10^{-5} to 3.11 × 10-^{5}), and silk products in processed bio-products (0.00193). Agriculture's tail is led by ruminant liveweight and fleece markets (6.99 × 10^{-4} to 4.56 × 10^{-4}), though the median remains low.

Relative to our waste and material footprints, ecosystem damage concentrates where precious metals, REEs, and advanced components co-locate, overlapping with REE demand and parts of the waste tails, yet it diverges from diffuse natural-gas dependence (which raises energy use broadly but does not uniformly translate into high species-year damage). This implies pairing tail-targeted measures in REE, precious metal, and semiconductor routes 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 3.55×10^3 in 2020 to 4.89×10^3 kg/kg (SSP1) and 4.51×10^3 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 0.094% to 0.076% in SSP1 and to 0.089% 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 0.880 to 0.819 (−6.9%), while SSP5 shifts from 0.879% to 0.844%. 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 ~1.95 to ~1.48–1.59), 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 ~9.6–9.7×10^6 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 6.93×10^{-3} kg/kg to 1.14×10^{-2} kg/kg in SSP1 and to 9.01×10^{-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 ~4.53×10^4 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 (0.888 kg/kg to 0.982 kg/kg in SSP1; 0.888 kg/kg to 0.975 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 (1500 words)

What this study adds

Total waste footprints across sectors

Waste circularity and hazardousness across sectors

Material demand footprints across sectors

ReCipe LCIA results across sectors

Temporal and scenario trends in waste footprints

Strengths of the approach

Limitations and caveats

Outlook and use

5 Conclusions and recommendations (500 words)

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.

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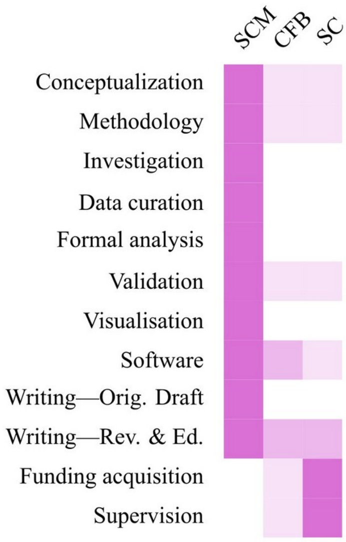
CRediT authorship visualisation



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 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

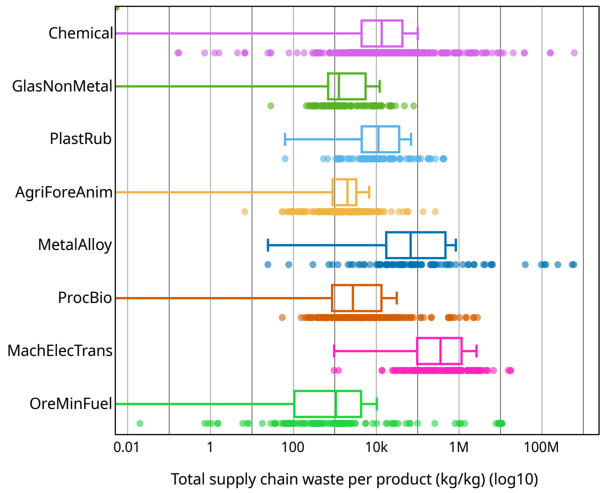
Figure 1. Distribution of total supply-chain waste per product (kg waste per kg product, $\log_{10}$ scale) across major industrial categories for a total of 1593 activities in ecoinvent 3.9.1 . Boxes show interquartile ranges with median lines; whiskers indicate 1.5× IQR, and dots denote the individual activities.

Figure 2. Waste circularity and hazardousness ratios across industrial categories for a total of 1593 activities in ecoinvent 3.9.1. 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 – Carbon dioxide (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).

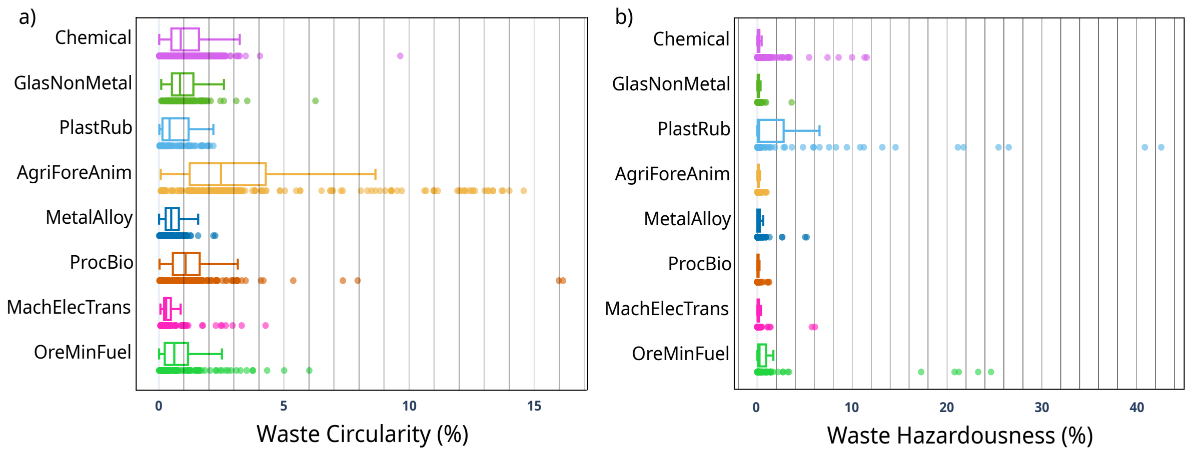
Figures

1.



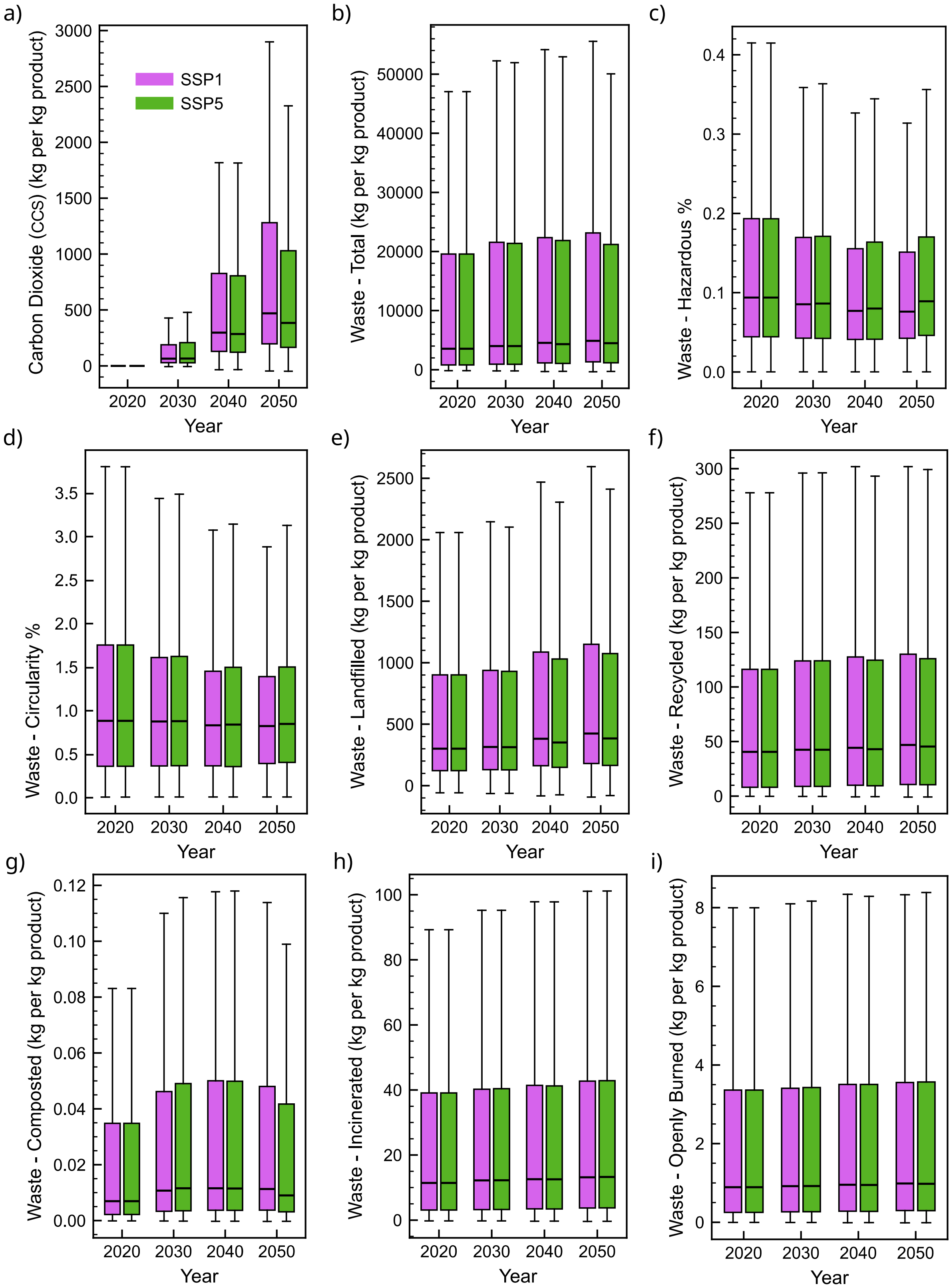
Chemical
GlasNonMetal
PlastRub
AgriForeAnim
MetalAlloy
ProcBio
MachElecTrans
OreMinFuel
0.01
1
100
10k
1M
100M
Total supply chain waste per product (kg/kg) (log10)

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 (%)

666 3.



a)
b)
c)
d)
e)
f)
g)
h)
i)
SSP1
SSP5
Carbon Dioxide (CCS) (kg per kg product)
Waste - Total (kg per kg product)
Waste - Hazardous %
Waste - Circularity %
Waste - Landfilled (kg per kg product)
Waste - Recycled (kg per kg product)
Waste - Composted (kg per kg product)
Waste - Incinerated (kg per kg product)
Waste - Openly Burned (kg per kg product)
2020
2030
2040
2050
Year