**Waste and Material Footprints in prospective LCA: a study of 1600+ 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 **50+ categories** of waste and material flows and computed WMFs for **>1,600 market activities**. In parallel, we calculated **ReCiPe 2016 endpoint** indicators to benchmark 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

CE Circular Economy

CRM Critical Raw Material

CPC Cooperative Patent Classification

EF Ecological Footprint

EoL End-of-Life

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

MF Material Footprint

MFA Material Flow Analysis

pLCA Prospective Life Cycle Assessment

REMIND REgional Model of Investment and Development

RCP Representative Concentration Pathway

ReCiPe A standard LCIA method set

re-X A broad set of circular economy strategies (“reduce”, “reuse”, “repair”, “recycle” etc.)

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

# 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; Doka, 2024; 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; 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 (CO₂ factors), air-pollutant factors, and biomass markets distinguishing purpose-grown from residual feedstocks (Sacchi et al., 2023). Additional research has produced so called “community scenarios” which 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 changes to result in indirect changes to future waste flows (McDowall et al., 2025) and waste-to-energy appears indirectly via electricity markets, 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.

# Methodology (1500 words)

### Product Selection and Life Cycle Scope

### Prospective database selection and creation

### T-reX

### Waste and Resource Footprints

### Damage Footprints

### Regression Modeling

We used multiple linear regression (least-squares fitting) to relate the damage footprints to the resource footprints.

# Results (2500 words)

# Discussion (1500 words)

#### What this study adds

#### Strengths of the approach

#### Limitations and caveats

#### Outlook and use

# Conclusions (500 words)

# Supplementary Material

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

# Data availability

All publicly available data related to the development of the scenarios and the composition of 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.

Figure 1: 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.

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**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.

# References

Tables

# Supplementary material