



## IMAGE-materials 3.5.1.0: Dynamic material flow modelling in the IMAGE Integrated Assessment Model

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### Abstract

We present the IMAGE-materials model, a stock-driven dynamic material flow analysis model, part of the IMAGE integrated assessment model (IAM) framework. By combining modelling principles from the IAM and Industrial Ecology (IE) communities, the model quantifies material inflows, stocks, and outflows affected by climate and resource policy scenarios. IMAGE-materials is a recursive yearly simulation model that projects global material demand until 2100 for 26 world regions on a sectoral level for a wide variety of bulk and critical materials. The model includes buildings, vehicles, electricity, rail & road infrastructure, and a residual sector capturing the remaining demand, including different types and modes (e.g., housing types and transport modes). It is written using a modular, object-oriented Python architecture, enabling the easy addition of new sectors and data. Key assumptions include product lifetimes, material intensities, and technology mixes. The model is driven by service demand scenarios produced by the IMAGE framework, based on socio-economic and climate policy assumptions. IMAGE-materials can flexibly simulate the adoption of numerous circular economy measures, such as service demand reductions, lifetime extension, lightweighting, and recycling. Therefore, IMAGE-materials enables scientists and policymakers to explore mitigation pathways with a detailed additional dimension of material flows. It can thus assess the synergies and trade-offs between climate and circularity policies by explicitly accounting for their material implications. As such, IMAGE-materials integrates the fields of IAMs and IE, building on the strengths of each.



## 30 **1 Introduction**

IMAGE-materials 3.5.1.0 (von Köckritz et al., 2026) is a stock-driven dynamic material flow analysis model (dmFA) developed as part of the integrated assessment modelling framework (IAM) IMAGE. The model is designed to couple tightly to the energy system simulation model IMAGE-energy (De Boer & Van Vuuren, 2017), through service demand, enabling a joint energy and material analysis. This article introduces the overall structure of IMAGE-materials, outlining the design principles of the model, followed by a more detailed description of the sectors represented. Illustrative scenario results are presented to show the model's capabilities.

IAMs have been widely applied in global environmental change research and policy assessments (D. P. Van Vuuren et al., 2025). Historically, IAMs were primarily developed to assess climate change mitigation pathways, representing future energy and land system development and associated greenhouse gas emissions, reflecting the central role of energy, land, and agriculture in climate change mitigation. More recently, however, the models have been used to assess a broader range of sustainability challenges, including pollution, water and energy access, and food security. In parallel, increasing attention has been given to the resource dimension of sustainability (Pauliuk et al., 2017; UNEP, 2025; D. P. Van Vuuren et al., 2019). However, IAMs currently still have limited capacity to assess future resource use, as they have generally not represented material stocks and flows explicitly in mass terms. The explicit representation of material flows helps i) to assess associated greenhouse gas emissions and environmental impacts to evaluate the feasibility of mitigation scenarios, ii) to represent strategies to reduce material use, and iii) to evaluate human well-being through the provisioning of decent living standards (UNEP, 2024a; Vélez-Henao & Pauliuk, 2023; Wei et al., 2025). Several efforts have been made to extend IAMs with an explicit material dimension (Deetman et al., 2020; Ekholm et al., 2025, 2026; Marinova et al., 2020; Stegmann et al., 2022; Ünlü et al., 2024).

IMAGE-materials advances the field by offering the first systematic modelling framework that couples a mass-based material flow analysis (MFA) model to the well-established IAM IMAGE. This unites classical IAMs with MFA approaches from industrial ecology, creating a tightly coupled, cross-disciplinary modelling effort. At its core, IMAGE-materials is a dynamic stock-driven material flow model that explicitly tracks material inflows, stocks, outflows, and maintenance requirements over time.

IMAGE-materials covers the following material demand sectors: buildings, vehicles, electricity generation, grid, transmission and storage, road and rail infrastructure, and a residual sector, aggregating the remaining material use. Additionally, the model has an end-of-life sector. The framework is designed in a modular way, which allows for the continuous integration of more sectors and future extensions. The model is directly coupled to service demand calculated in IMAGE-energy, enabling a consistent linkage between energy and material use. This design allows IMAGE-materials to capture global resource dynamics,



including vintage tracking and the material consequences of shifts in service provision and technological change. By linking  
service demand with its associated material use, the model provides a tool for assessing energy-material interactions in global  
65 sustainability pathways.

The remainder of this article is structured as follows. Section 2 presents the overall model design, including the implementation  
of material flow analysis. Section 3 describes the sectoral modules currently implemented, namely vehicles, buildings,  
electricity, road and rail infrastructure, residual demand, and end-of-life. Section 4 provides demonstrative scenario results,  
70 and Section 5 concludes with a discussion of model applications and future developments.



## 2 Model structure

The following section describes the general model structure of IMAGE-materials. Fig. 1 presents the overall structure of the coupling between the energy and materials modules of IMAGE. IMAGE-materials is closely linked to IMAGE-energy; therefore, the simulation timeline and regional coverage are aligned. The model differentiates 26 regions, covering the globe. All regions can be treated as separate entities (linked via trade of energy carriers and inter-regional technological learning), allowing the representation of regional differences.

As shown, projected service demands (e.g. floorspace or passenger km) from IMAGE-energy act as input to the stock modelling in IMAGE-materials. The service demand data contains different subtypes, such as modes and vehicle technologies in the transport sector and building types in the residential sector. Additionally, exogenous input on product properties, such as lifetimes and material composition, is required, which are specified in the sectoral description in Section 3. Key outputs of IMAGE-materials, such as material demand and available scrap, can be fed back to IMAGE-energy to determine the associated industrial energy demand of material production.

Throughout this paper, we use the following subscripts when describing the model: R: Region; A: Area, S: Sector, T: Type, t: time.

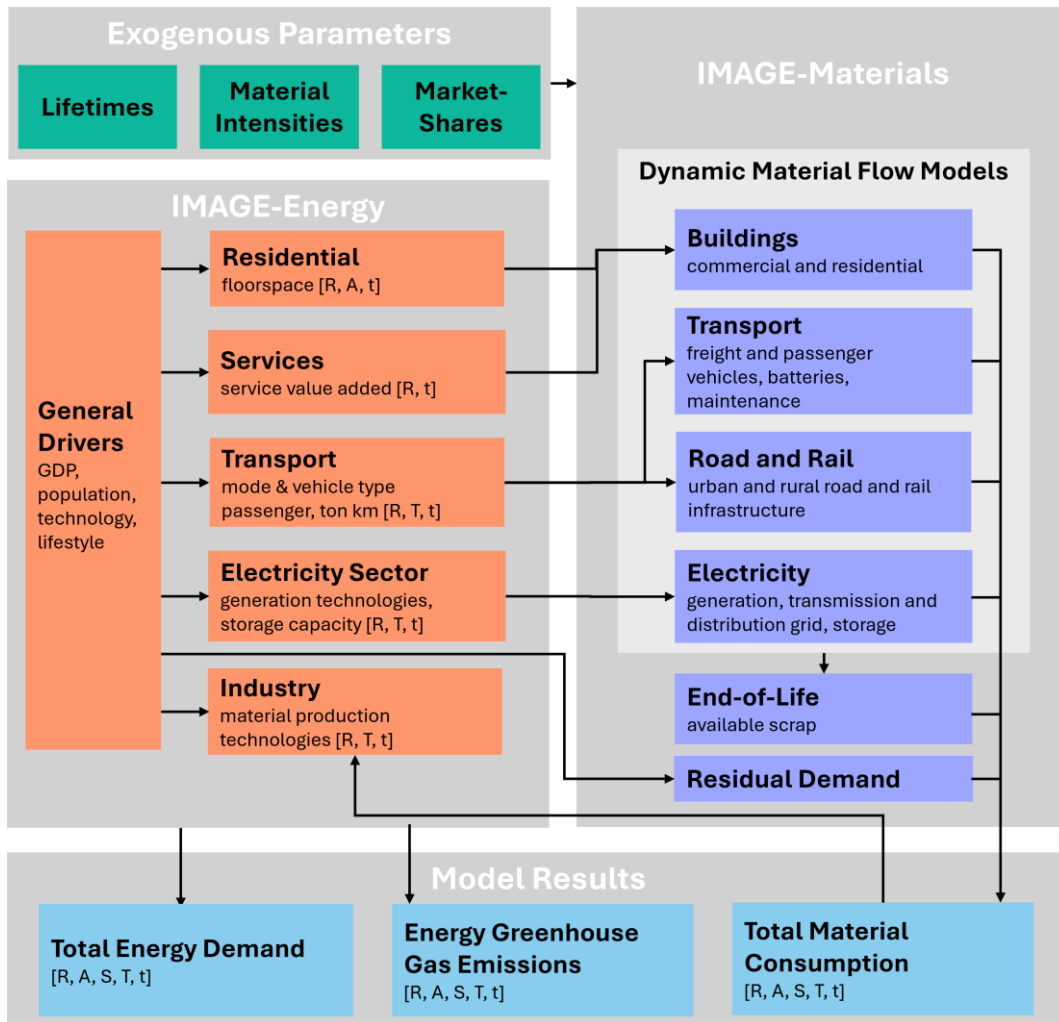


Figure 1: Model structure overview with IMAGE-energy and Exogenous driver to the material model on the left. The right side shows modules within IMAGE Materials. R: Region, T: Type or mode, A: Area (urban/rural), S: Sector, t: time.

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## 2.1 Service demand calculation in IMAGE

IMAGE is a global IAM that links demographic and economic drivers to energy, land, biogeochemical cycles, and climate to assess global environmental change and policy implications. IMAGE runs from 1971 to 2100 and covers 26 regions. It was developed to quantify long-term emissions, climate outcomes, and system feedbacks to inform policy and scenarios (Stehfest et al., 2014; D. Van Vuuren et al., 2021). Its energy module, referred to in this paper as IMAGE-energy, simulates the total energy system including supply, conversion, demand, and associated greenhouse gas emissions. It includes key dynamics such as technological substitution, learning-by-doing, resource depletion, and demand and efficiency responses to price changes. The model is regionally disaggregated, and separates final energy demand into the main end-use sectors, and treats energy transformation (power, refineries) separately (Stehfest et al., 2014; D. Van Vuuren et al., 2021). The principal end-use sectors

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100 modelled, listed in Table 1, are industry, transport, residential (households), and services, plus other non-energy and productive uses where relevant. One key element of IMAGE-energy is that energy demand is simulated via the demand of specific energy services, and thus explicitly includes projections of building floorspace, transport vehicles, etc.

Table 1: Relevant sectors for materials in IMAGE-energy

Sector	Service demand	Units and measurement	Main drivers and model decisions	Links to IMAGE-materials sector
<b>Transport</b>	Passenger and freight travel levels	Passenger-km (pkm) and tonne-km (tkm) as activity metrics; energy demand derived via energy per pkm/tkm (PJ)	Population, GDP, travel time, modal split, vehicle cost and efficiency, fuel prices, vehicle lifetimes, travel behaviour; modal and vehicle technology development	Vehicles, Road and Rail infrastructure
<b>Residential</b>	Floorspace, heating, cooling, cooking, and appliance service indicators	Floor area (m <sup>2</sup> per capita), appliance stocks and service demand for heating/cooling; energy reported as useful or final energy (PJ)	population and urbanization, private consumption, climate (heating/cooling degree days), fuel prices, technology development, electrification and appliance efficiencies	Buildings
<b>Services</b>	Commercial service activity	Energy demand for cooling, heating, appliances, cooking and information technology in PJ	Value added of service sector, service intensity changes, fuel prices	Buildings (IMAGE-materials projects commercial and public floorspace linked to service value added)
<b>Energy Production</b>	Electricity production	GW of installed capacity across 27 generation technologies covering fossils and renewables. Distribution and storage networks.	Overall electricity demand, electrification rate of energy system, fuel and technology prices, efficiencies	Electricity generation capacity, transmission and distribution networks, electricity storage
<b>Industry</b>	Energy demand for specific industrial outputs, such as steel, cement, etc.	Final energy in PJ; production capacity; industrial outputs in physical units (e.g., Mt steel) and activity indicators	Economic output, sectoral structure, fuel prices, energy intensity and process-level technology; differentiated by energy-intensive subsectors and process heat requirements	Bottom-up material demands calculated in IMAGE-materials drive energy demand for material production in the industry



				energy demand calculations in IMAGE Energy
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## 2.2 Material coverage

IMAGE-materials covers a broad variety of sectors with mode types, materials (Table 2), and regional differences. The sectors represented in IMAGE-materials are buildings, vehicles (and vehicle maintenance), electricity (grid, transmission, generation, and storage), road and rail infrastructure, and a residual sector, covering remaining demand for selected bulk materials beyond the sectors explicitly represented. Within each of these sectors, a wide variety of types and modes are represented, such as different types of vehicles and housing, which will be introduced in detail in Chapter 3.

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**Table 2: Materials covered by sector by material group in IMAGE-materials.**

Material Group	Material	Buildings	Vehicles <sup>1</sup>	Electricity <sup>1</sup>	Road & Rail	Residual <sup>2</sup>
<b>Metals</b>	Steel	✓	✓	✓	✓	✓
	Aluminium	✓	✓	✓	✓	✓
	Copper	✓	✓	✓	✓	✓
	Cobalt		✓	✓		
	Lithium		✓	✓		
	Manganese		✓	✓		
	Neodymium		✓	✓		
	Nickel		✓	✓		
	Lead		✓	✓		
	Tantalum			✓		
<b>Non-metallic minerals</b>	Cement					✓
	Concrete	✓		✓	✓	
	Brick	✓			✓	
	Glass	✓	✓	✓		
	Sand				✓ <sup>3</sup>	✓
	Limestone				✓ <sup>3</sup>	✓
	Clay				✓ <sup>3</sup>	✓
<b>Biomass</b>	<b>Wood</b>	✓	✓		✓	
<b>Fossils</b>	<b>Plastics</b>		✓	✓		
	<b>Rubber</b>		✓			
	<b>Asphalt</b>				✓	

<sup>1</sup> All critical materials in these sectors are part of motor-engine batteries

115 <sup>2</sup> If checked material is covered by 100%, if not materials are not fully covered

<sup>3</sup> Sand, Limestone and Clay covered in the combined category of aggregates



### 2.3 Material Flow Analysis

- MFA is a well-established methodology for analyzing and tracking how materials are used, accumulated, and disposed of within society. Material flows can be seen as driven by a demand for a service, such as passenger-kilometers travelled, ton-kilometers transported, or floor area provided (m<sup>2</sup>) (Fu et al., 2022). Two broad approaches are commonly distinguished: inflow-driven and stock-driven modelling. In inflow-driven modelling, material stocks emerge because of assumed inflows of new products. In contrast, stock-driven modelling starts from a required level of service and determines the stock of products needed to deliver that service, from which inflows and outflows are derived endogenously.
- In IMAGE-materials, a stock-driven dynamic Material Flow Analysis (dMFA) is adopted as this drives the model to fulfil service demand via appropriate inflows and also aligns with the yearly service demand provided by IMAGE-energy. In other words, energy and materials demand share the same drivers, which make energy, emissions and materials trajectories internally consistent across these models. Furthermore, a stock-driven model is particularly suited to sectors with long-lived stocks, which are represented in IMAGE-materials. Long lifetimes create strong temporal inertia; therefore, stocks built decades ago still dominate current and future physical conditions. Additionally, a stock-based approach is also less affected by short-term market fluctuations, improving the ability to project into the future (Fu et al., 2022; E. Müller et al., 2014). A stock-driven DSM is thus a critical method to capture path dependence and, therefore, implications for resource use and emissions over decades (Bergsdal et al., 2007; Cao et al., 2018; Hu et al., 2010).
- A key feature of stock-driven DSM is vintage tracking, which explicitly represents cohorts of products entering the stock in different years. Vintage tracking is required because products of different ages can have different material compositions and lifetimes. These age-dependent dynamics cannot be captured with aggregate stock representations; therefore, the model includes survival rates, which determine what share of a stock from any given year remains in use for each subsequent year. The associated survival function specifies the fraction of a cohort that remains in use as a function of age. Survival functions are implemented through a survival matrix, which links yearly inflows to the remaining stock of that cohort in all subsequent years. Each element of the matrix represents the probability that a product entering the stock in year  $t$  is still in use in year  $t + n$ . Lifetimes are represented by both Weibull and Folded Normal distributions, depending on which distribution is empirically supported.
- Generally, the process of stock-driven DSM has the following steps:
1. Identify the required service level (e.g. amount of vehicle-kilometers or floor area).
  2. Translate the service demand into the product stock required, based on assumptions about the intensity of use (e.g. occupancy rates, m<sup>2</sup> per capita).



- 150
3. Based on the survival matrix of previous cohorts (historical inflows), calculate the outflows and remaining stocks in the current year. By comparing the remaining stock to the required product stock, the required inflow is derived.
  4. Using technology and potentially time and region-specific material compositions, translate product inflow, outflow, and stock to material inflow, outflow, and stock.

155 An additional modelling assumption is the allowance for surplus stock, such as temporarily unoccupied buildings or unused vehicles. This avoids unrealistic stock dynamics in response to short-term demand fluctuations. For example, sharp demand reductions, such as those observed during the COVID-19 pandemic, would otherwise lead to large and immediate outflows of vehicles, followed by unrealistically high inflows when demand recovers. Allowing surplus stock dampens these effects and yields more plausible stock and flow trajectories, consistent with previous dynamic stock modelling studies, and also allows  
160 for the use of the model to project very ambitious and transformative scenarios.

### Equations:

The following equations translate this descriptive method into the calculation methods used within the model. For further details on how this is implemented, refer to the published code<sup>1</sup>.

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$$inflow_t = \frac{\max(demand_t - \sum_c stock\_by\_cohort_{t,c}, 0)}{S_{t,c}}$$

With

t: current time step

c: cohort

170 S: survival function

### Equation 1 Inflow

Inflow is set to zero when existing stock exceeds demand, thus allowing a surplus. It is also divided by the survival in case there is a loss of inflow in the first year i.e.  $S_{t=0} < 1$ .

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$$stock\_by\_cohort_{t,c} = inflow_c * S_{t,c}$$

With  $t \geq c$

t: current time step

c: cohort

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<sup>1</sup> <https://github.com/imagepbl/IMAGE-materials>



180 S: survival function

**Equation 2 Stock**

Survival is  $survival = 1 - cumulative\ density\ function$  which is imported from scipy as follows.

185 With their respective distribution equation depending on empirical data:

$$S_{t,c} = \exp\left(-\left(\frac{t}{\lambda}\right)^s\right)$$

With

t: current time step

c: cohort

190 S: survival function

$\lambda$  = scale parameter

s = shape parameter

**Equation 3 Weibull distribution**

$$S_{t,c} = 1 - \left(\Phi\left(\frac{t - \mu}{\sigma}\right) + \Phi\left(\frac{-t - \mu}{\sigma}\right) - 1\right)$$

195 With

t: current time step

c: cohort

S: survival function

$\mu$  = mean

200  $\sigma$  = standard deviation

**Equation 4 Folded normal distribution**

Subsequently, the outflow is then defined as

$$\text{For } c < t: outflow_{t,c} = stock_{t-1,c} - stock_{t,c}$$

205 For  $c = t: outflow_{t,c} = inflow_t * S_{t,c}$

With

t: current time step

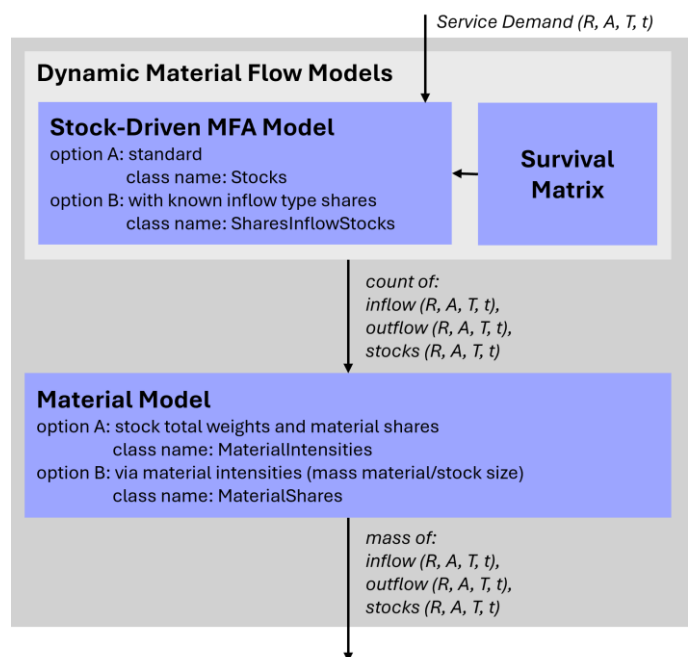
c: cohort

S: survival function

210 **Equation 5 Outflow**



## 2.4 Simulation Workflow



**Figure 2: Simulation Process of explicitly covered sectors. R = Region, T = Type or mode, A = Area (urban/rural), S = Sector, t = time.**

215 In general, the model is split into two phases: data pre-processing and simulation. The simulation timeline runs from 1971 – 2100 on a yearly increment and can be adapted flexibly. The preprocessing has two functions: prepare data for the simulation, and calculate historic inflows, outflows and stocks before 1970, to avoid a massive artificial product inflow in year one of the simulation phase. The simulation workflow shown in Fig. 2 is similar for all explicitly covered sectors. All included sectors with an explicit modelling (thus representing stocks, such as vehicles and buildings) of activity receive service demand from

220 IMAGE-energy and apply the stock-driven dMFA, which gets the survival matrix from the survival matrix model. All sectors, apart from electricity storage, apply option A (see Fig. 2), which is a standard stock-driven DSM. Option B is applied to the storage sector, which requires the exogenous market shares of inflow of storage types. The output of the stock-driven DSM is then fed into the Materials model, which multiplies the stock with the respective material intensities to calculate the mass of inflows, outflows, and stocks. Here, two routes can be selected: Option A, used by all sectors apart from the vehicles sector,

225 applies direct material intensities (mass of material/product). The vehicle model applies Option B, where, together with total stock weights and material shares, the masses are calculated.

## 2.5 Material scenario implementation

The scenario definition of IMAGE-materials builds on inputs from IMAGE-energy, as described above. These inputs follow established socioeconomic and policy narratives (e.g., Moss et al., 2010; Riahi et al., 2022). Thus, demand changes, such as



230 choice for different energy sources, floorspace, or transport demand, are generally driven by IMAGE-energy; however, they  
 can also partially further be adapted in IMAGE-materials. In addition, IMAGE-materials allows for the specification of  
 material-specific scenarios, such as Circular Economy (CE) strategies. CE-scenarios can be flexibly constructed by combining  
 measures from the broad set listed in Table 3. Both an implementation and a target year need to be set; the implementation  
 rates can be set in multiple ways: linear, immediate, or s-curve. It is possible to distinguish regional differences. For the  
 235 implementation of the CE scenario, a configuration is used to flexibly select and adjust measures. These measures are then  
 automatically implemented during the preprocessing stage of each module and subsequently integrated into the simulation  
 workflow. If no CE-scenario is specified, IMAGE-materials defaults to baseline values representing current material policies  
 - effectively constituting a material baseline scenario. The runtime of the model depends on scenario settings and sectors  
 included, and lies between 1 and 5 minutes per scenario defined.

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**Table 3: Scenario parameters in IMAGE-materials**

<b>Circular Economy Measure</b>	<b>Buildings</b>	<b>Vehicles</b>	<b>Electricity</b>	<b>Road &amp; Rail</b>	<b>Residual</b>
<b>Lifetime Extension</b>	- Lifetime increase in %	- Lifetime increase in % - Mileage increase in %	- Lifetime increase in %	- Lifetime increase in %	Can be assumed by adapting the alpha Gompertz coefficient
<b>Service demand Reduction</b>	- Driven by IMAGE-energy - Optional further decrease possible	- Driven by IMAGE-energy	- Driven by IMAGE-energy	- Driven by IMAGE-energy and increased urbanization	
<b>Lightweighting</b>	- Material intensity change in %	- Reduction total weight in %	- Reduction total weight in %	- Reduction total weight in %	
<b>Material Substitution</b>	- Selection of building structure types				
<b>Recycling</b>	Reuse rate of specific material in %, recycling rate of specific material in % Managed by the End of Life Module (Section 3.6)				



## 2.6 Code principles

IMAGE-materials 3.5.1.0 (von Köckritz et al., 2026) extends upon the specific materials modules (buildings, vehicles and  
245 electricity) developed by Deetman (Deetman, 2021; Deetman et al., 2018, 2020, 2021a), applying the ODYM packages by  
Pauliuk & Heeren (2020). From this basis, a modular framework, written in Python, was developed with object-oriented design  
principles, using the *prism* package<sup>2</sup>, based on *x-arrays* as the foundation for the models.

The steps required to process and prepare the raw input data for usage in the models have been separated from the models  
themselves and implemented in sector-specific preprocessing modules. Model parameters and scenario settings are fully  
250 configurable using configuration files that are co-located with raw data. Their presence is presumed at the root of the provided  
data path.

To aid with the conversion of coordinates present in the input, IMAGE-materials utilizes knowledge graphs (Fensel et al.,  
2020). It contains relations between different concepts. For example: a “car” is a “vehicle” and “automobile” is a synonym for  
“car”. Knowledge graphs offer convenient functionality for data manipulation, such as aggregating categories (e.g., from  
255 internal combustion engine and battery electric vehicle to cars) and disaggregating by splitting up categories (like cars into  
drive trains). Columns can be aggregated into a higher category (e.g. different types of cars can be aggregated into a new  
column called “car”), columns can be automatically renamed to other synonyms (e.g. “automobile” to “car”), and a column  
can be scattered to multiple columns (e.g. the lifetimes of cars can be used to create new columns with subtypes (the lifetimes  
of battery-electric engine cars, internal combustion engine cars, etc.) if this more specific data is otherwise not available).

260 Models are implemented as instances of a *prism* model and follow the modelling principles laid out by the *prism* framework.  
This means that they implement functions to set up an initial state and update the state iteratively according to a provided  
timeline. For the current implementation, the time increment between each step is assumed to always be  $\Delta t = 1$ . Recognizing  
that the models of different sectors share common elements, models such as a generic stock model (Stocks) and a material  
model (MaterialIntensities, MaterialShares) can be used for different sectors. These can be instantiated with the relevant data  
265 for one or multiple sectors and extended with other model components (e.g. EndOfLife, Maintenance, RestOf,  
SharesInflowStocks) to obtain a model to run simulations with. Finally, functionality for reporting the model output is  
implemented in its own 'reporting' module. Examples of visualizations of the model outputs are provided in Jupyter Notebooks  
(Granger & Perez, 2021) in the 'examples'.

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<sup>2</sup> As the *prism* package is not yet published, we shortly describe the package here. *Prism* is a package allowing recursive  
simulation over a predefined configurable timeline, providing functionality for multidimensional arrays that describe their  
dimensionality using named dimensions and coordinates, where coordinates can be categorized or represent an axis of a  
coordinate system represented by discrete coordinate steps. Multidimensional arrays conserve their (physical) units, and they  
are checked and retained in calculations. This is implemented using well-known packages in the Python scientific ecosystem,  
such as *xarray* (Hoyer & Hamman, 2017), *pint* (Grecco, Hernan, 2026), *scipy* (Virtanen et al., 2020), and *numpy* (Harris et al.,  
2020).



### 3 Modules

270 This section will describe all modules of the IMAGE-materials model. There are different types of modules: First, modules that represent sectors explicitly (buildings, vehicles, electricity and road & rail infrastructure) and apply the stock-based DSM (Sections 2.3 and 2.4). Some of these sectors have direct linkages, such as the vehicles and electricity sector, for the calculation of batteries. Second, the residual sector, while dependent on the other sectors, only covers the inflow of materials. And third, the end-of-life module calculates the recycling potential of the explicitly modeled sectors.

275 The sectors currently represented were chosen based on their large share of stock in the economy, long lifetimes, and relevant materials used.

The following abbreviations for data file dimensions are used:

- A: Area (Urban and Rural)
- C: Cohort
- 280 R: Region
- S: Sector (e.g. buildings or vehicles)
- T: Type (e.g. housing types or transportation modes)
- ST: Subtype (e.g. battery electric vehicle)
- BT: Battery Type (different battery chemistry)
- 285 M: Materials
- t: time

#### 3.1 Buildings

The buildings sector module is based upon Deetman et al. (2020) and Marinova et al. (2020). It represents four different types of residential housing, urban and rural respectively: i) high-rise, ii) apartment, iii) semi-detached, and iv) detached, and four  
290 types of commercial buildings: i) retail +, ii) offices, iii) hotels +, and iv) governmental +. The plus indicates that a broader range of housing is included (Deetman et al., 2020). Materials that are modelled in this sector are dominantly bulk materials: steel, aluminum, copper, cement, concrete, bricks, glass, and wood. Important assumptions that apply to all regions are that detached and semi-detached houses have a 25% share of cement, masonry, steel, and timber construction types, respectively, while it is assumed that apartment buildings have a share of 50% of the construction types steel and cement, respectively.  
295 High-rise buildings are 100% steel constructed. Furthermore, the share of housing types is assumed to be the same over all regions. The model, however, is capable to differentiate these assumptions over time and regions.

#### Data requirements

The following input data is retrieved from the IMAGE-energy model: Residential floorspace ( $\text{m}^2/\text{capita}$ ) [R, A, t], population (number of people) [R, A, t], service value added [R, t] (Million USD/capita). Furthermore the following exogenous data is  
300 required to run the model: average size of housing types ( $\text{m}^2/\text{capita}$ ) [R, A, T], historic population (number of people) [R, A, t],



housing type dynamics (%) [R, A, T, t], material intensities (metric ton/m<sup>2</sup>) [R, T] from the RASMI database (Fishman et al., 2024), and lifetime parameters for a Gompertz curve [R, A, T].

### Data processing

305 The main task of the preprocessing is to calculate the m<sup>2</sup> demand of future stock of commercial and residential building types per region. For residential housing, this is also provided in an urban and rural split, ensuring to cover urbanization dynamics. The preprocessing also provides the material intensities and product lifetimes in the right format to the stock modelling.

### Key challenges

310 Modelling material demand in the buildings sector comes with a few challenges. First, commercial buildings are not explicitly covered in IMAGE-energy. This means that there is no direct indication of service building floor space and instead service value added needs to be used as a proxy for economic activities. Furthermore, specifically for the residential sector, IMAGE-energy determines floorspace to calculate heating, cooling and lighting energy demand (Daioglou et al., 2012), therefore empty houses, garages, etc. are not included. That is, IMAGE-energy calculated “useful floorspace”, while for the purposes of determining material demand “gross floorspace” is what is required. The available material intensity data mainly stems from studies carried out in Europe and North America, limiting the validity of results in other world regions. Additionally, the share of housing and construction types is assumed to be the same in all regions and areas, which is a weak point but necessary due to limitations of available data. In terms of materials covered, the buildings sector is relatively complete, apart from sand, which is used to prepare and level the landscape (Watari et al., 2025).

### 3.2 Vehicles

320 The vehicle model is built on Deetman (2021) and represents both passenger and freight transport. For passenger transport, the model covers individual transport: i) cars, ii) bikes, and collective transport: iii) buses (regular and midi), iv) trains (regular and high-speed), and v) planes. For freight transport, the model covers: i) trucks (heavy and medium, light commercial vehicles), ii) freight rail, iii) freight planes, iv) inland ships, and v) international ships (small, medium, large, and very large). For cars, buses, and trucks, modes are additionally tracked with various engine subtypes: internal combustion engine, battery electric vehicles, hybrid electric vehicle, plug-in hybrid electric vehicle, as well as trolley buses.

325 Regarding materials, the model includes steel, aluminium, copper, plastics, rubber, glass, and wood. A key assumption is that vehicle weight and material composition remain constant across regions and time, while the model is capable of including these parameters varied by time and region. Also, a share of medium freight transport (from IMAGE-energy) is allocated to light commercial vehicles, and a share of regular buses (IMAGE-energy) is allocated to midi buses to reflect the large difference in weight and material composition.

330 The vehicles module incorporates a linked submodule for the maintenance of land-based vehicles (see 3.2.1 Maintenance). Also, the batteries of electric vehicles are modelled separately in a dedicated EV battery module (see 3.2.2 EV Batteries).

### Data requirements



The following input data are endogenous to the modelling framework of IMAGE: freight transport demand in tonne-kilometres (tkm) [R, T, ST, t], passenger transport demand in passenger-kilometres (pkm) [R, T, ST, t], vehicle technology shares for  
335 buses, cars, trucks and planes [R, T, ST, t]. Furthermore, the following data is exogenous. Scenario-independent data include additional load-factor assumptions for passengers and freight [T], the first year of operation for each vehicle type, battery-share data for vehicle inflow [T], and international shipping data such as the number of vessels [ST, t], capacity [ST, t], load factors [ST, t], mileage [ST, t], and vessel weight [ST, t]. Scenario-dependent data comprise vehicle lifetimes [T, t] and their associated lifetime-distribution parameters [T, ST, t], kilometrage estimates [R, T, ST, t], vehicle weights [R, T, ST, t], and  
340 material-fraction data [T, ST, M, t].

### **Data processing**

The main task of the data preprocessing is to translate, based on load factor and kilometres per year, transport service demand (pkm and tkm) from IMAGE-energy to the number of vehicles defined in IMAGE-materials, needed to fulfil the service. Additionally, exogenous data is harmonized in the required format for the stock modelling framework.

### **345 Key challenges**

Key challenges include the currently uniform application of vehicle weight and materials composition by region and time. This likely does not reflect reality, as these parameters vary over time and space, but it is a consequence of data limitations. Another key challenge for this sector is the difference in which vehicle modes are represented in IMAGE-energy and IMAGE-materials. Some vehicles are relevant from an energy perspective, and therefore included in IMAGE-energy, versus those modes where  
350 the material composition or weight varies so substantially that they need to be split into different modes in IMAGE-materials. For instance, we differentiate light commercial vehicles and midi buses, which are not tracked separately in IMAGE-energy. Whereas the energy model includes a much higher disaggregation of engine types compared to the material model.

### **3.2.1 Maintenance**

The maintenance module is built on von Köckritz et al. (2026). It represents scheduled maintenance material flows for road  
355 and rail transport modes and provides annual replacement material inflows to the vehicle model. Passenger modes covered are cars, regular buses, midi buses, trains, and high-speed trains; freight modes include light commercial vehicles, heavy, and medium freight trucks. The module focuses on planned component replacements and is designed to reflect the trade-off between lifetime extension and associated additional maintenance material demand. Maintenance is modelled per vehicle type, expressed as material demand per vehicle per year. Materials included are aluminium, steel, copper, glass, wood, plastics, and  
360 rubber.

### **Data requirements**

Required data includes maintenance material compositions per vehicle type, material fractions [T, M], vehicle weights [R, T, ST, t], and assumed lifetimes [T, t] that define the maintenance period. Scenario settings include the distribution of maintenance material over the lifetime and how maintenance material demand develops beyond the expected lifetime of the vehicle.



## 365 **Data processing**

The preprocessing prepares maintenance material fractions for integration with vehicle stocks. Total lifetime maintenance is normalised by vehicle lifetime to obtain annual fractions. A standard and a linear age-dependent model are available, with the latter redistributing maintenance intensity linearly over the vehicle lifetime while preserving total lifetime demand.

### **Simulation workflow**

370 Age-dependent maintenance flows are calculated using a linear formulation with a configurable end-of-life multiplier, with optional capping if lifetimes are extended (Von Kockritz et al., 2026). Maintenance flows are then computed by combining age-adjusted annual fractions with cohort-level stocks and vehicle weights, producing total scheduled maintenance inflows and corresponding, identical, outflows per time step for material accounting.

### **Key challenges**

375 While the model currently includes the best available data, this data largely originates from OECD countries. Also, only scheduled maintenance is included, meaning total maintenance material demand is likely underestimated. In addition, maintenance practices, repair behaviour, and replacement cycles have changed over time and vary by region, but are not yet regionally differentiated. For vehicle types lacking complete maintenance material data, missing fractions are filled using consistent proxies from similar modes.

## 380 **3.2.2 Electric Vehicle Batteries**

The Electric vehicle (EV) battery model represents the batteries in cars, trucks and buses, namely Battery Electric Vehicles (BEV), Plug-in Hybrid Electric Vehicles (PHEV), and Hybrid Electric Vehicles (HEV). It assumes that the lifetime of the battery is identical to its host vehicle, therefore no separate stocks are calculated. A subset of eight battery technologies listed for the dedicated storage batteries are assumed and the same (relative) market shares for these battery chemistries are derived as in the electricity storage module. The main outputs of the model are the inflow, stock, and outflow of EV battery capacity in MWh per battery and vehicle type, and the associated material stocks and flows. Further, given assumptions on the penetration of vehicle-to-grid technology and the share of capacity per vehicle available for vehicle-to-grid storage, the total storage capacity from EV vehicles available to the grid is being calculated.

385

### **Data requirements**

390 The following exogenous data is required. Scenario-independent data include cost per storage technology (\$ct/kWh) [C, BT], storage cost correction [C, BT], assumptions on the long-term price decline of storage technologies after 2050 [BT], energy density of storage technologies (kg/kWh) [C, BT], battery weights (kg) [C, T], fraction of EVs available for vehicle-to-grid (V2G) [t, T, R] and usable capacity of EV batteries for V2G applications [T]. Scenario-dependent data include material intensities [C, BT, M].

395



### Data processing

The first step is to convert all processed data into xarray structures with harmonized dimensions for time, region, vehicle type, battery type, and material. Battery market shares in annual battery inflows (purchases) are calculated using a multinomial logit model based on battery prices, consistent with the approach used in the storage sector. The data is interpolated where necessary and transformed into the correct format for the simulation.

### Simulation Workflow

The ElectricVehicleBatteries module is used to calculate both the battery capacity stocks and flows (in Wh power capacity) and the associated material stocks and flows (in kg). To infer the battery capacity stocks, no dynamic stock modelling is carried out. Instead, one battery per electric vehicle is assumed, and the resulting battery capacity per vehicle type and battery type is calculated based on the vehicle type-specific battery weights, energy densities, and battery market shares by simple multiplication.

### Key challenges

Regional differences are currently not represented. For example, lithium iron phosphate (LFP) batteries dominate passenger car sales in China, while they account for only a small share in the US and EU; however, the model assumes identical battery market shares globally. A key challenge is the limited availability of reliable regional price data and the difficulty of capturing non-price preferences that influence technology adoption. Beyond accurately representing the current state, projecting future technology developments remains uncertain and constitutes a major challenge.

### 3.3 Electricity

The electricity model is based on Deetman et al. (2018, 2021b) and covers i) electricity generation, ii) transmission and distribution grid, and iii) grid energy storage. Multiple generation technologies are covered, both conventional (with and without carbon capture and storage and heat production) and renewable. Grid is split up into high (aboveground and below ground), medium, and low voltage lines and grid additions (transformers and substations). The storage includes hydropower and stationary storage in the form of grid-scale batteries, mechanical storage technologies, and fuel-cells. The dedicated storage demand can be altered depending on availability assumptions of electric vehicle batteries using the vehicle-to-grid technology.

### Data requirements

The following input data are endogenous to IMAGE: electricity generation capacity per technology (onshore wind, coal etc.) (MW peak capacity) [t, T, R], electricity grid storage energy reservoir (MWh) [t, R], electricity grid, storage power capacity (MW) [t, R], and GDP per capita (US-Dollar/person) [t, R]. Furthermore, the following exogenous data is needed. Scenario-independent data include length of high-voltage (HV) grid lines per region in 2016 (km) [T, R], ratio between the length of HV to medium-voltage (MV) and low-voltage (LV) lines [R], regression constants describing the relation between GDP per



capita and the percentage of underground power-lines [R], number of transformers and substations per km of grid (units/km) cost per storage technology (\$ct/kWh) [C, T], storage cost correction [C, T], assumptions on the long-term price decline of storage technologies after 2050 [T], energy density of storage technologies (kg/kWh) [C, T] and hydro-dam power capacity data (MW) [R]. Scenario-dependent data include technology lifetimes and material intensities.

### Data processing

The following data preprocessing steps are taken. The electricity grid stock is based on a dataset on global HV grid length, which is scaled in time relative to the power generation capacity developments and then translated to MV and LV line lengths and transformer and substation stocks via empirical ratios. The dedicated storage stock is calculated based on a three-tier approach, where the storage demand is satisfied by 1. pumped hydropower, 2. electric vehicle batteries via vehicle-to-grid technology (passenger car BEV and PHEV), and 3. dedicated grid storage. The market shares of the specific storage technologies are calculated based on prices using a multinomial logit model.

### Key challenges

Key challenges include data availability and uncertainty regarding future technology trajectories. In many cases, regional differentiation of empirical ratios such as the lengths of medium- and low-voltage lines per high-voltage line cannot be implemented due to insufficient data. Future developments in technology, including photovoltaic sub-technologies (e.g. crystalline silicon, copper indium gallium selenide) and battery chemistries (e.g. lithium iron phosphate, lithium nickel cobalt manganese oxides), are also difficult to anticipate, yet they have a substantial influence on material intensities, particularly for critical minerals.

### 3.4 Transport Infrastructure

The transportation infrastructure model is built on Deetman (2021), Van Engelenburg et al. (2024), and Van Engelenburg et al. (in preperation) and represents the i) road and ii) rail infrastructure, combining travelled passenger and freight kilometres to determine the physical infrastructure required to support transport demand. Road infrastructure is subdivided into eight road types: motorway, primary, secondary, tertiary, local, informal, pedestrian, and cycling, which are also the types for bridges and tunnels. Furthermore, parking infrastructure is represented. Furthermore, obsolete or stranded infrastructure stocks is covered mostly present in rural areas and standard rail. All roads and parking are modeled in paved and unpaved areas. For urban and rural it is assumed that the sub-surface layer remains in stock. The lifetimes of roads thus represent the maintenance and repaving of in-use stocks. For rail infrastructure, three types are included: standard rail (intercity rail used by regular trains and freight trains), high-speed rail, and urban rail (subways, metro, and light rail). Additionally, obsolete stocks are modelled, which are primarily present in depopulating areas. The model covers: aggregates, asphalt, steel, concrete, aluminium, copper, wood, bricks, and stone. Material intensities and lifetimes are assumed to stay constant for transportation infrastructure over the simulation period.

### Data requirements



460 The following input data are endogenous to the modelling framework of IMAGE: freight transport demand in tkm, passenger  
transport demand in pkm, load factors for passenger vehicles, and load factors for freight transport to calculate total road and  
rail vehicle kilometers (vkm) usage. In addition, urban and rural population and GDP are used endogenously. The model is  
supplemented with exogenous data: urban areas (Li et al.), human development index (HDI) (Lui et al.), and material  
intensities (Van Engelenburg et al., 2024).

#### 465 **Data processing**

For the product stock calculation, we use the variables mentioned above to calculate urban and rural GDP per capita, urban  
and rural population density, urban, rail, and high-speed vkm. The paving share is determined by GDP per capita. Urban areas  
are used to calculate urban and rural population density, and HDI is used to model urban rail development, as there are no  
projected pkm available for urban rail specifically. Using the population and regional ratios, we calculate the ratio of road  
470 types, bridges, tunnels, and urban rail, standard rail, and high-speed rail length stocks and flows. Lifetimes range from 10.5  
years for urban motorways to 119 years for most rural bridges and tunnels. For road infrastructure we use Weibull distributions  
(roads, bridges, tunnels, parkings areas), for rail infrastructure we use a folded mean lifetime distribution due to limited data  
availability. For the product stock calculation, we use the variables mentioned above to calculate urban and rural GDP per  
capita, urban and rural population density, urban, rail, and high-speed vkm. We use these variables to calculate the urban rail  
475 per capita, urban and rural road per capita, rail per capita, and high-speed rail per capita.

#### **Key challenges**

Although regional material intensities are applied to road types, for rail, bridges, and tunnels these are currently not  
regionalized, better data could help to more accurately reflect regional diversity in infrastructure construction. A further  
challenge is the missing representation of auxiliary transportation infrastructure types such as streetlights, barriers, rail  
480 crossings, and embankments. It is likely that a significant amount of materials is present in these types, but currently there is  
no method to quantify this. Similar with bridges and tunnels, as there is no method available to establish a relationship between  
the growth of IMAGE input variables and the ratios of bridges and tunnels compared to the road areas in a network the  
modelling is limited to current known ratios.

#### **3.5 Residual Sectors**

485 The Rest module (Arp et al., under review) covers the residual material demand, thus inflow, not explicitly covered in all other  
sectors. It covers bulk materials of metals: steel, aluminium, copper and non-metallic minerals: sand, cement, limestone and  
clay. The most important assumption is that due to lack of data availability, for some materials, the projection of some regions  
are combined. They can be presented as single region results, however.

#### **Data requirements**



490 The following input data is endogenous to the modelling framework of IMAGE: sum of total inflow of all explicitly covered sectors (tons) [R, M, t], GDP per capita (Million USD/capita) [R, t] and population (people) [R, t]. Furthermore the following data is required and exogenous: historic apparent consumption (tons) [R, M, t] and material extraction data [R, M, t].

### Data processing workflow

The main task of the preparatory data manipulation is to first calculate the residual historic material consumption. This is done  
495 by summing the total consumption of all explicit sectors (vehicles, buildings, electricity, etc.) and subtract these from the total historic demand. Second, the per capita demand for these residual sectors is calculated, which is then used to be fitted to a Gompertz model:

$$cons_{cap}(t) (gdp_{cap}(t)) = re(t) * ae^{-be^{-c * gdp_{cap}(t)}}$$

Where

- 500 -  $a, b, c$  = Gompertz parameters
- $cons_{cap}$  = consumption per capita in the residual sectors
- $gdp_{cap}$  = gdp per capita
- $t$  = year
- $re$  = optional resource efficiency factor

505 The parameters  $a, b,$  and  $c$  are returned to the simulation workflow, as well as the population and GDP per capita. The optional resource efficiency factor of the residual demand reflects the cumulative selected measures of all explicit sectors, compared to a baseline scenario.

### Simulation workflow

This module does not follow an MFA approach, but calculates the inflow of materials in a yearly iteration using the Gompertz  
510 model.

$$Total\ consumption(t) = re(t) * ae^{-be^{-c * gdp_{cap}(t)}} * population(t)$$

### Key challenges

Key challenges are that for few regions-material combinations, the calculated historic material consumption of IMAGE-materials is higher than reported data on actual consumption. Reasons could be that data is not well reported and lacking, as  
515 well as that IMAGE-materials overestimates material intensities. Furthermore, data on apparent consumption of non-metallic minerals is scarce. Therefore, extraction data is assumed to be equal to apparent consumption for sand, limestone and clay.

### 3.6 End-of-Life

The End-of-Life (EoL) module quantifies annual material flows that are collected, reusable, and recyclable across end-use sectors and regions. It builds on the IMAGE work developed for UNEP (2024). Once products reach retirement following  
520 lifetime distributions, explicit sector modules generate annual material outflows, which the EoL module tracks and processes by applying region-, sector-, and material-specific collection, reuse, and recycling rates. Furthermore, material losses occurring between these stages are accounted for. Materials covered are steel, concrete, copper, glass, wood, and aluminum.



### Data requirements

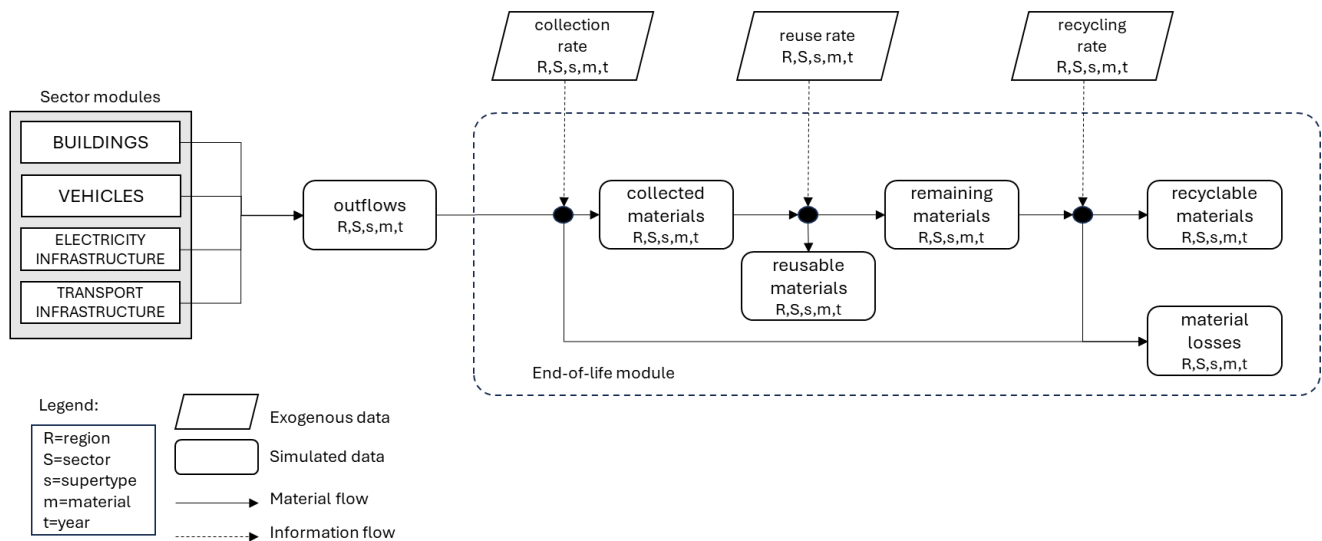
525 Required data include the following rates: collection (%) [R, S, M, t], reuse (%) [R, S, M, t], and recycling (%) [R, S, M, t] rates.

### Data processing

The main goal of data preprocessing is to prepare the EoL parameters for simulation by compiling the collection, reuse, and recycling rates. When applicable, scenario-dependent measures, e.g., increased reuse or recycling, are implemented at this stage, overwriting values for the target year.

### 530 Simulation workflow

At each simulation time step, the EoL module aggregates product-level material outflows from each sector module into a smaller set of “supertypes” (e.g., passenger vs. freight transport, urban vs. rural buildings, electricity generation, grid, and storage) across regions and materials. For each supertype, it breaks down total outflows into collected material, reused material (a share of collected), and recyclable material (a share of the collected-but-not-reused remainder), and explicitly accounts for 535 losses from non-collection and from collected material that is neither reused nor recycled. Figure 2 illustrates the simulation workflow of the EoL module.



**Figure 3: Overview of End-of-Life module structure.**

### Key challenges

540 One key limitation in the EoL module concerns the assumption of uniform collection, reuse, and recycling rates across regions. While EoL rates are expected to be relatively similar for certain materials and sectors in some regions (e.g., recycling rates for steel from vehicles in OECD countries with mature waste management systems and relatively similar scrap prices), this assumption does not hold universally. For instance, EoL handling can vary depending on scrap prices, collection and recycling infrastructure, informal dismantling, and regulatory infrastructure, among other factors. As collection, reuse, and recycling



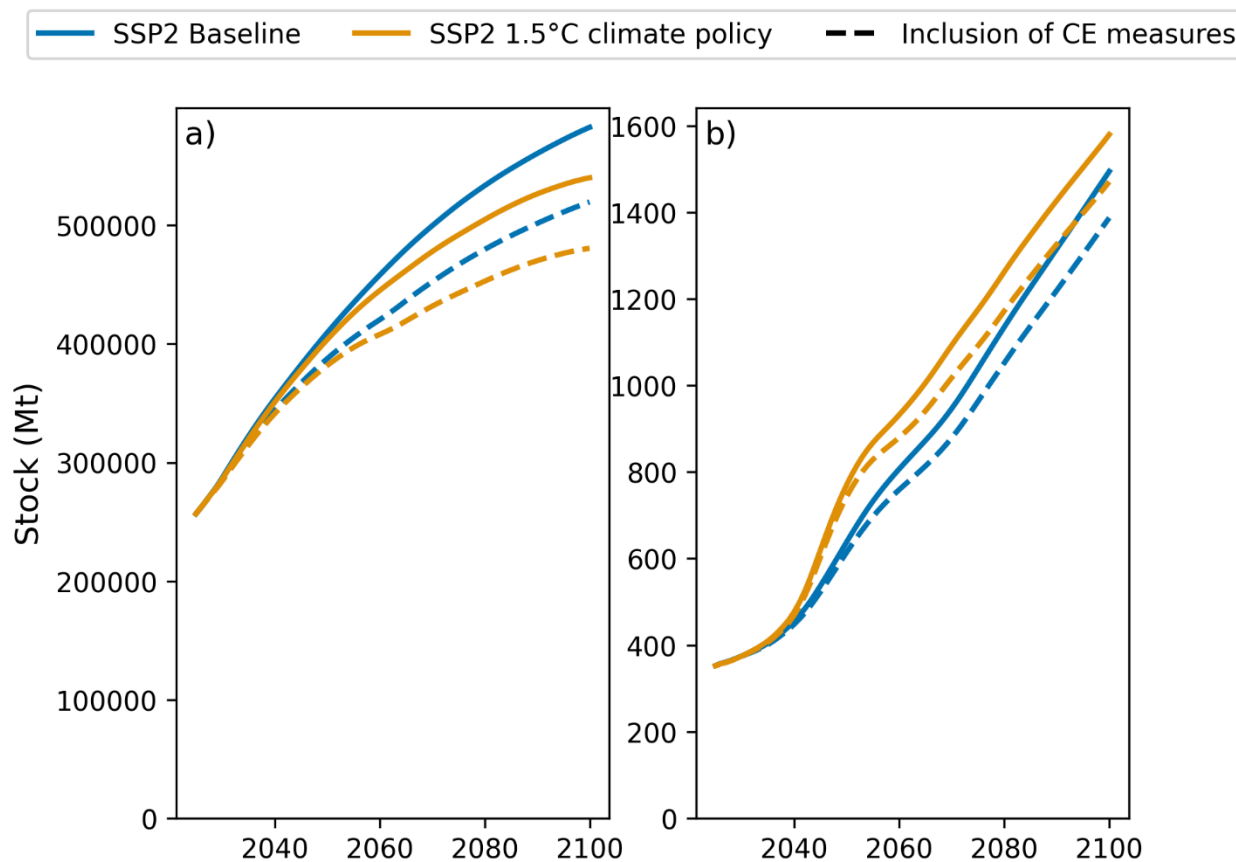
545 rates data is scarce and often not harmonized across sources, this limitation reflects current data constraints and should be interpreted as an average end-of-life performance (De Sa & Korinek, 2021; Wilson et al., 2009). Moreover, currently only regional recycling is considered, i.e. scrap flows are not traded between regions, which is a key limitation. Therefore, improving the regional granularity of data and including recycling between regions are areas for future development.

#### 4 Illustrative results

550 As a demonstration of IMAGE-materials we ran four SSP2 scenario: with and without climate policy (1.5C), and with and without CE measures. We mostly discuss the SSP2 results. The Figures 4 - 7 aim to showcase the overall capability and behavior of the model. It is not our intention here to analyze the results here in the context of a specific research goal.

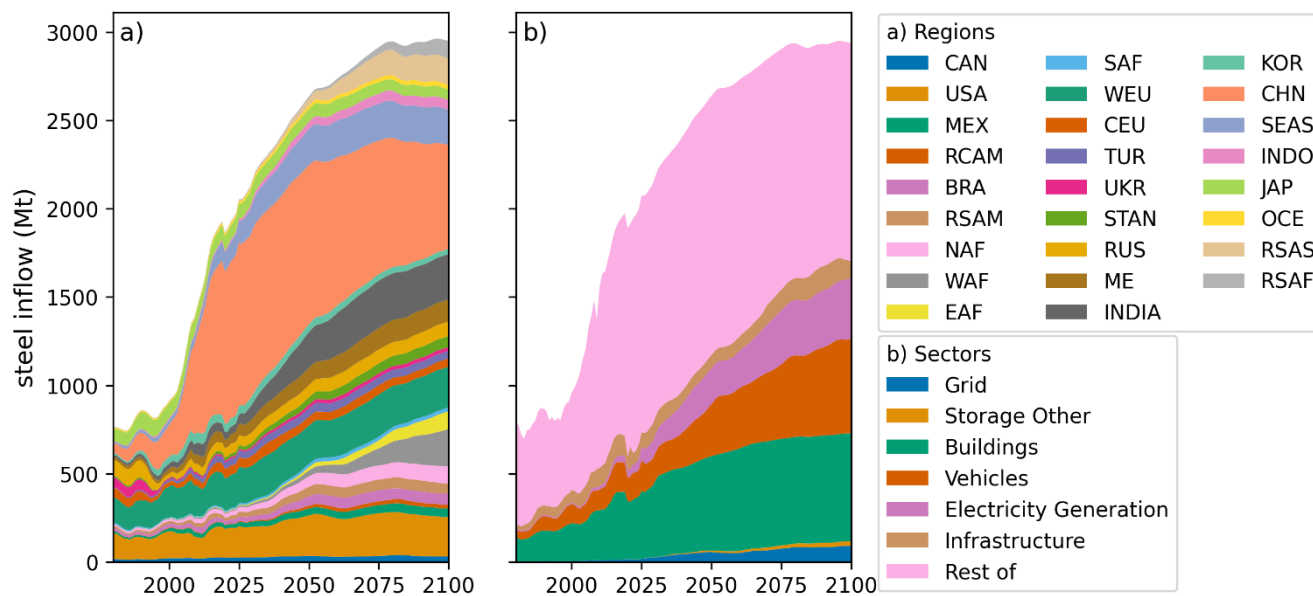
##### 4.1 Showcasing model results

555 Figure 4 shows the development of a) global concrete stocks and b) plastic stocks across the four defined scenarios. These results demonstrate that IMAGE-materials is capable of capturing the distinct material-side effects of different climate and circular economy (CE) policies.



**Figure 4: a) concrete stock and b) plastic stock over 4 scenarios: SSP2 baseline and SSP2 1.5C climate policy, with and without additional circular economy measures**

560 Figure 5 shows the SSP2 baseline scenario (without CE measures) in more detail. It shows the global steel consumption, illustrating how IMAGE-materials tracks multiple dimensions. Panel (a) displays the distribution across the 26 IMAGE regions (full names can be found in the SI), while panel (b) shows the sectoral breakdown. This breakdown illustrates the model's ability to capture regional and sectoral heterogeneity in material demand, which is essential for understanding the structural drivers of global steel inflows.



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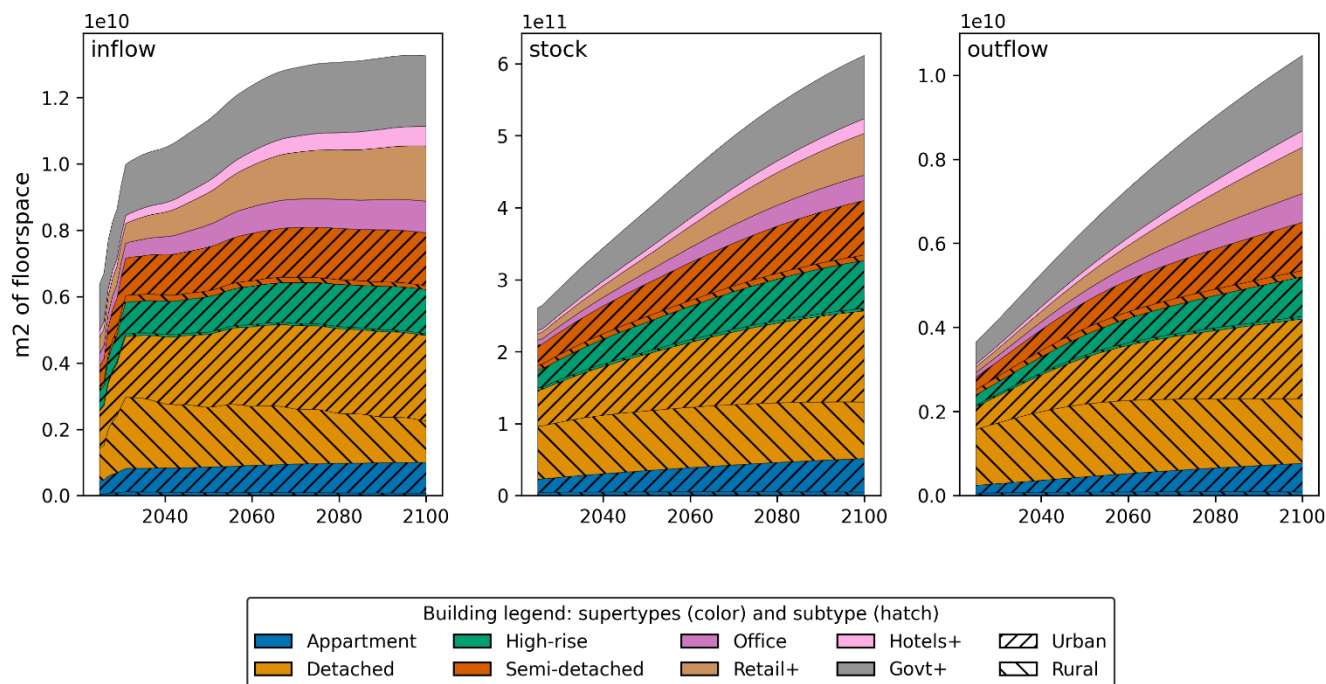
**Figure 5: SSP2 baseline (without climate or circular economy measures) results for global steel consumption in Mt. a) shows regional split up, b) shows sectoral split up**

While the primary focus of IMAGE-materials lies at the material level, the model also represents the product level, as illustrated in Fig. 6. This figure highlights furthermore an additional dimension of detail in the model. Within each sector, different product types can be specified; for example, in the buildings sector distinctions can be made between rural and urban buildings, as well as between high-rise buildings, apartments, semi-detached houses, and detached houses. As a result, the model can track not only the inflows, stocks, and outflows of materials, but also those of the corresponding products. This product-level representation links material demand to specific technologies and services, enabling more realistic modelling of stock dynamics and CE strategies.

575

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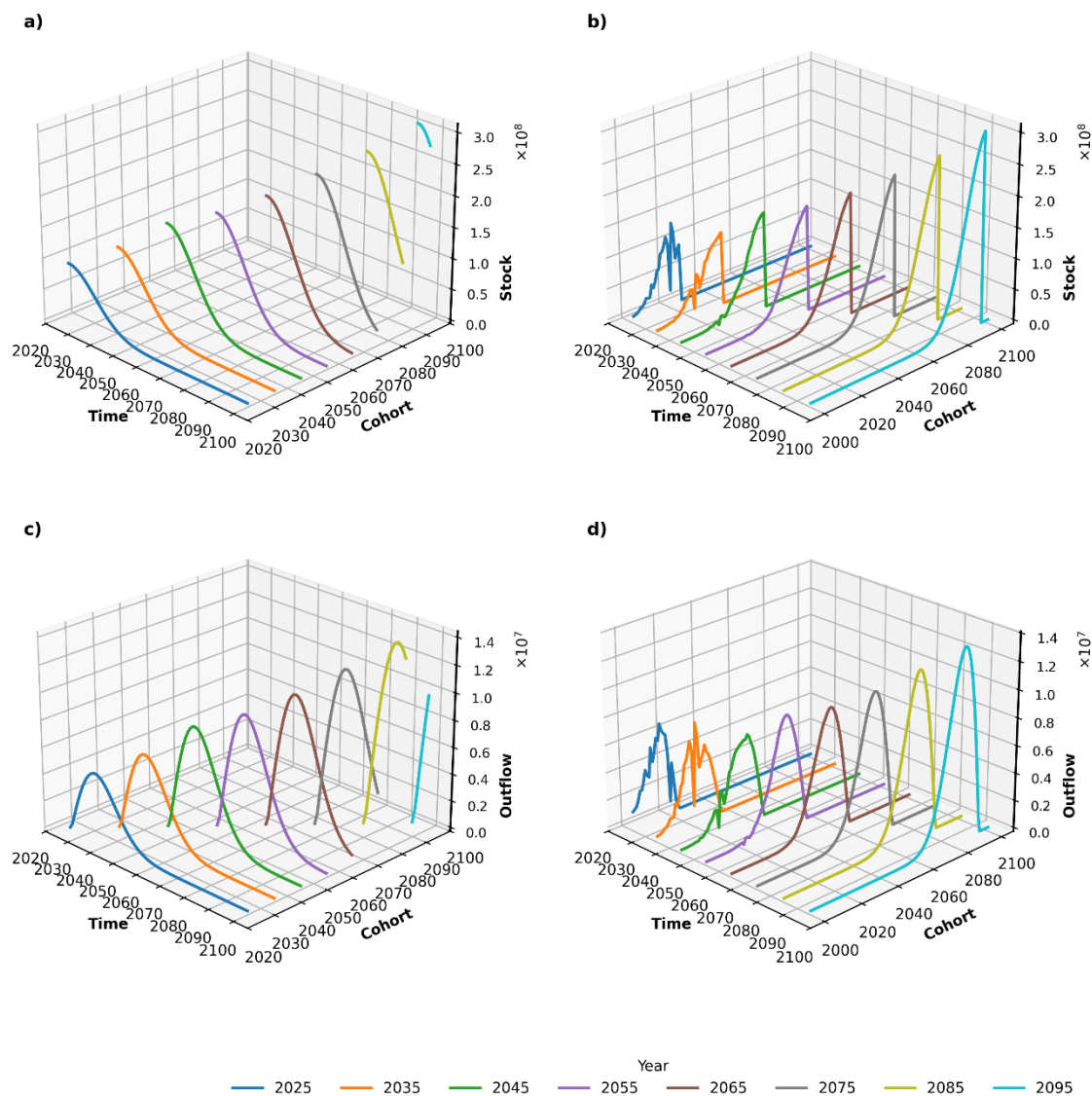
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**Figure 6: SSP2 baseline product inflow, stock and outflow of building types**

Zooming in further, IMAGE-materials tracks every mode and time as cohorts over time, as illustrated for cars in Fig. 7. The figure depicts the stock–flow dynamics of passenger cars in the model. The left panels show stocks (a) and outflows (c) over calendar time for specific age cohorts. Each line thus only displays a fraction of the total stock/outflow, that is the fraction contributed by this cohort. The right panels (b and d) present the same dynamics from a total stocks perspective. Each line illustrates a snapshot of the total product stock/outflow in a given year, displaying its composition as a distribution over the different age cohorts.

Over time, each cohort gradually depreciates and exits the stock, generating outflows as vehicles reach the end of their lifetime. While the calendar-time plots capture the aggregate evolution of stocks and outflows, the cohort perspective highlights the lifecycle of individual inflow cohorts. This dual approach allows the model to track time along two dimensions - calendar time and cohort time - providing a consistent representation of stock accumulation, product lifetimes, and the timing of future outflows.



600 **Figure 7: Cohort tracking of all car modes in the vehicle module, shown here in 10 year steps; a) shows the development of in-stock products over time of a defined cohort, b) shows also the stock, however as distribution over different cohorts at one point in time, c) shows outflows over time of defined cohorts, d) shows also outflow, however directly indicates the specific cohorts the outflow is originating from in a given year.**

#### 4.2 Model validation

605 The inflow calculated in IMAGE-materials of bulk materials: (steel, aluminum, copper, cement, sand, limestone, clay) is calibrated to total historic demand on a material and regional level (Arp et al, under review). Here, the residual sector module plays an important role, as it creates the buffer-zone between the explicitly covered demand, and total demand, which is then projected to the future. Product service demand itself is calibrated to historical values within IMAGE-energy, while total



material demand is aligned with regional apparent consumption data for bulk materials such as steel (Van Ruijven et al., 2016),  
 610 aluminum (International Aluminium, 2024; United Nations, 2025), copper (Matos et al., 2015; United Nations, 2025), and  
 cement (Van Ruijven et al., 2016), and with regional extraction data for sand, limestone, and clay (IRP, n.d.). Global totals  
 reported in the UNEP Global Resources Outlook 2024 are used as an additional validation reference. Overall, the resulting  
 future projections for bulk materials are broadly consistent with estimates from other studies (Bonnet et al., 2019; IEA, 2024b;  
 Keramidas et al., 2024; Klose & Pauliuk, 2023; Schipper et al., 2018; UNEP, 2024b, 2025; Van Ruijven et al., 2016; World  
 615 Cement Association, 2024). However, it is important to emphasize that the model produces projections rather than predictions,  
 meaning that strict validation of future outcomes is not possible.

### Sector specific validation

#### Buildings

620 For buildings, Deetman et al. (2020) compared old model results per capita stock of cement, steel and aluminum values to  
 other studies (Cao et al., 2017; Hatayama et al., 2010; Liu et al., 2013; D. B. Müller et al., 2011) with different regional foci,  
 which were in line. In a recent comparative study (Streeck et al., 2025), the old version of IMAGE-materials was found to be  
 in the upper range compared to other models. With recent model improvements, results have decreased and are now within the  
 low to mid-range compared to other models. Table 4 shows these and further comparisons with more recent studies.

625

**Table 4: Comparing building model outcomes of material stock**

Material group	Material	Year	Region	IMAGE-materials (baseline)	Other studies	Comment / Reference
Non-metallic minerals	Concrete	2020	Europe (IMAGE regions West and Central Europe combined)	32 ton/capita	50 – 60 ton/capita (depending on cold to warm regions)	(Lotz et al., 2024)
	Concrete	2020	USA	18 Gt	10 Gt - 35 Gt	(Streeck et al., 2025) Values depending on different models compared, years ranging from 2015 - 2020
	Concrete	2020	China	102 Gt	43Gt – 146 Gt	
	Bricks	2020	USA	7 Gt	1.2 Gt – 3.3 Gt	
	Bricks	2020	China	14 Gt	15 Gt – 57 Gt	
	Glass	2020	USA	92 Mt	146 Mt – 672 Mt	
Glass	2020	China	111 Mt	155 Mt – 755 Mt		



Metals	Steel	2020	Europe (IMAGE West- and Central Europe combined)	2.8 ton/capita	2.8-3.1 ton/capita (depending on cold to warm regions)	(Lotz et al., 2024)
	Steel	2005	Europe (IMAGE West- and Central Europe combined)	2.5 ton/capita	1.3 – 3.5 ton/capita	(Deetman et al., 2020; Hatayama et al., 2010; D. B. Müller et al., 2011)
	Steel	2005	USA	4.1 ton/capita	2 – 4 ton/capita	Values depending on different models compared, years ranging from 2015 - 2020
	Steel	2020	USA	1517 Mt	288 Mt – 2248 Mt	
	Steel	2020	China	2448 Mt	1,306 – 20,000 Mt	
	Aluminum	2020	USA	40 Mt	40 Mt – 179 Mt	
	Aluminum	2020	China	48 Mt	12 Mt – 613 Mt	
	Copper	2020	USA	5 Mt	7 Mt – 33 Mt	
Copper	2020	China	10 Mt	2 Mt – 83 Mt		
Biomass	Wood	2020	USA	1 Gt	0.9 Gt – 2.4 Gt	
	Wood	2020	China	1.6 Gt	0.5 Gt – 6 Gt	

Lower concrete per capita values in Europe in comparison to Lotz et al. (2024) may result from several factors. First, commercial building floor space is derived from the service value added relationship, which may lead to an underestimation. Second, Lotz et al. (2024) implement material intensities based on building cohorts, where earlier cohorts have higher concrete material intensities. This could explain the higher concrete stock reported in their results. Additionally to the validation of material stocks, Deetman (2021) compared the relative development of residential and commercial floorspace in chapter 5, where for example globally, service related stock grows faster than residential stock which is confirmed by other studies.

### 635 Vehicles

Not much data is available on global material flows for vehicles. While the regions are not fully identical, Table 5 below compared European values from IMAGE materials with the Urban Mine Platform (2025). The comparison shows alignment in terms of steel and aluminum stock and inflow in terms of magnitude with some fluctuations in exact comparison. Generally, IMAGE-materials has rather higher inflows with lower stocks compared to the reference.

640 **Table 5: Comparing vehicle model outcomes of material inflow and stock for passenger cars and light commercial vehicles summed \* region is EU27 + 4**

Material	Year	Region	IMAGE-materials (BL)	Other studies	Reference
Steel inflow	2010	Europe (IMAGE regions West and	$1.9 * 10^7$ ton	$1.2 * 10^7$ ton*	
Steel inflow	2025		$1.6 * 10^7$ ton	$7.7 * 10^6$ ton*	



Steel stock	2010	Central Europe combined)	$2.3 * 10^8$ ton	$3.0 * 10^8$ ton*	(Urban Mine Platform, 2025)
Steel stock	2025		$2.8 * 10^8$ ton	$3.1 * 10^8$ ton*	
Aluminum inflow	2010		$3.0 * 10^6$ ton	$2.0 * 10^6$ ton*	
Aluminum inflow	2025		$4.0 * 10^6$ ton	$2.6 * 10^6$ ton*	
Aluminum stock	2010		$3.2 * 10^7$ ton	$4.0 * 10^7$ ton*	
Aluminum stock	2025		$5.4 * 10^7$ ton	$8.0 * 10^7$ ton*	

645 For vehicles data availability for the product level is better compared to material data. Therefore, Table 6 compares global product values per vehicle type with literature estimates as developed by (Deetman, 2021). These values are compared to the most recent model output for historical data. Generally, the values align in terms of magnitude with some vehicle types under- and some overestimated. However, the literature estimate calculated is still highly uncertain due to a lack of data.

650 **Table 6: Global vehicle stock estimate validation ). In case multiple sources are used, the year of comparison is an average. \* For some vehicles, the comparison is based only on selected regions (here, the numbers do not indicate global totals), e.g. inland shipping is compared only for the sum of Europe, China, the US and Russia. For regional assumptions regarding trains refer to appendix 7 in .**

Vehicle	year	Model result	Literature estimate	Reference
Passenger				
Airplanes	2017	15,004	23,000	(Capocitti et al., 2010; Howe et al., 2013; IATA, 2016, 2018; Lopes, 2010)
Trains*	2017	55,548	54,852	(Fava-Verde, 2018; Nahlik et al., 2016; Stripple & Uppenberg, 2010; Yue et al., 2015)
High Speed Trains	2019	2,465	4,959	
Buses	2016	12,353,574	10,400,000	(Daimler, 2020; Laver, R et al., 2007; Law et al., 2011; Nordelöf et al., 2019)
Bicycles	2014	296 Million	1 to 2 Billion	(Bonilla-Alicea et al., 2020; Luo et al., 2019)
Cars	2016	1,26 Billion	1.1 Billion	(Deetman et al., 2018)
Freight				
Airplanes	2017	3,059	1,920	See references of passenger airplanes
Trains*	2016	26,810	83,566	See references of passenger trains
Trucks	2015	93,279,035	186,000,000	(Daimler, 2021; Dun et al., 2015; Law et al., 2011; Sen et al., 2017; Yang et al., 2018)
International ships	2018	67,992	76,000	(Chatziniolaou & Ventikos, 2015; Dinu & Ilie, 2015; Fan et al., 2018; Messmer & Friscknecht, 2016; Woods, 2009)
Inland ships*	2015	339,571	222,000	



For EV battery material inflows, the model output for 2020 compares relatively well with estimates by (IEA, 2021g) for nickel, cobalt and manganese, while underestimating the copper and lithium inflows (see Table 7).

655

**Table 7: Comparing EV battery model outcomes of material inflows**

Variable	Material	Year	Region	IMAGE-materials (BL)	Other studies	Comment / Reference
inflow	Copper	2020	Global	52 kt	110 kt	(IEA, 2021g)
inflow	Lithium	2020	Global	5.7 kt	20 kt	
inflow	Nickel	2020	Global	87 kt	80 kt	
inflow	Cobalt	2020	Global	34 kt	21 kt	
inflow	Manganese	2020	Global	33 kt	25 kt	

### Electricity

Compared to IEA estimates of historic global total grid length, the grid length in IMAGE-materials is underestimated by around 10 million km up until 2010, where it matches the 60 million km reported by the IEA (IEA, 2023). The share of distribution grid of total grid length is 94-95% in IMAGE-materials which corresponds well to the 93% reported by the IEA (IEA, 2023). The pumped hydropower storage capacity stocks (GWh) are underestimated. While the International Renewable Energy Agency (IRENA) reports 4,508 GWh pumped hydropower storage capacity in 2017 (IRENA, 2017), IMAGE-materials models 80 GWh for that year. This will be updated in a future version. Global stationary, non-pumped hydropower storage for 2017 is estimated as 162 GWh by IRENA compared to 20 GWh in IMAGE-materials. In 2030 (2050), IMAGE-materials projects dedicated energy storage stocks to be 240 (10,630) GWh in the baseline and 300 (21,830) GWh in the climate policy case. This is an order of magnitude smaller than the estimated 5,821-8,426 GWh estimate in the REmap\_Doubling scenario by IRENA in 2030 (IRENA, 2017). The IEA projects in its STEPS scenario 760 GW of battery grid storage capacity in 2030 with an average discharge duration of 2.7 h, resulting in 2,050 GWh energy storage capacity (not considering efficiency losses) (IEA, 2024a). However, for 2050 the IEA projects in the STEPS scenario a grid scale battery deployment of 10,100 GWh (2970 GW by 3.4 h discharge duration), which is close to the baseline scenario estimate in IMAGE-materials. It must be noted though, that most often storage capacity is reported in terms of power capacity, while IMAGE-materials storage stock modelling takes place in terms of energy capacity.

The material inflow and stock for different electricity subsectors compare mostly well with IEA estimates or estimates by (Kalt et al., 2021), while some estimates deviate more strongly. For example, global lithium inflow for dedicated storage is underestimated by IMAGE-materials, while the copper inflow for power generation technologies is overestimated in 2020. The steel and copper stocks for power generation fall within the range given by (Kalt et al., 2021), while the aluminium stock



for this sector is underestimated. For grid lines, this is reversed and global stock estimates for steel and copper are underestimated, while aluminium falls within the range of (Kalt et al., 2021), though being in the lower side.

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**Table 8: Comparing electricity model outcomes of material stocks and inflows**

Sub-sector	Variable	Material	Year	Region	IMAGE-materials (BL)	Other studies	Comment / Reference
Dedicated storage	inflow	Copper	2020	Global	0.31 kt	8 kt	(IEA, 2021f)
	inflow	Lithium	2020	Global	0.02 kt	2 kt	Grid-scale battery storage (for the case of no vehicle-to-grid deployment)
Generation	inflow	Copper	2020	Global	1337 kt	261 kt	(IEA, 2021a, 2021b, 2021d, 2021e)
	inflow	Nickel	2020	Global	64 kt	103 kt	
	inflow	Manganese	2020	Global	9.8 kt	55 kt	
	inflow	Neodymium	2020	Global	3.4 kt	3.1 kt	
	stock	Steel	2017	Global	667 Mt	211–638 Mt	(Kalt et al., 2021)
	stock	Steel	2017	China	228 Mt	63–186 Mt	For technologies: CSP, solar PV (rooftop), solar PV (ground-mounted), wind onshore, wind offshore, geothermal, nuclear, bioenergy & waste, hydro, coal, gas, oil
	stock	Steel	2017	India	36 Mt	14–42 Mt	
	stock	Copper	2017	Global	21 Mt	5.3–30 Mt	
	stock	Copper	2017	China	7.1 Mt	1.4–8.0 Mt	
	stock	Copper	2017	India	0.7 Mt	0.3–1.6 Mt	
	stock	Aluminium	2017	Global	8.4 Mt	11–37 Mt	
stock	Aluminium	2017	China	2.6 Mt	3.5–12 Mt		
stock	Aluminium	2017	India	0.4 Mt	0.5–2.1 Mt		
Grid lines	inflow	Copper	2020	Global	3.1 Mt	4.6 Mt	(IEA, 2021c)
	inflow	Aluminium	2020	Global	4.4 Mt	9.1 Mt	
	stock	Steel	2017	Global	177 Mt	237–505 Mt	(Kalt et al., 2021)
	stock	Steel	2017	China	34 Mt	69–160Mt	Transmission and distribution grids
	stock	Copper	2017	Global	71 Mt	90–189 Mt	
	stock	Copper	2017	China	13 Mt	20–49 Mt	
	stock	Aluminium	2017	Global	94 Mt	85–221 Mt	
	stock	Aluminium	2017	China	17 Mt	21–61 Mt	



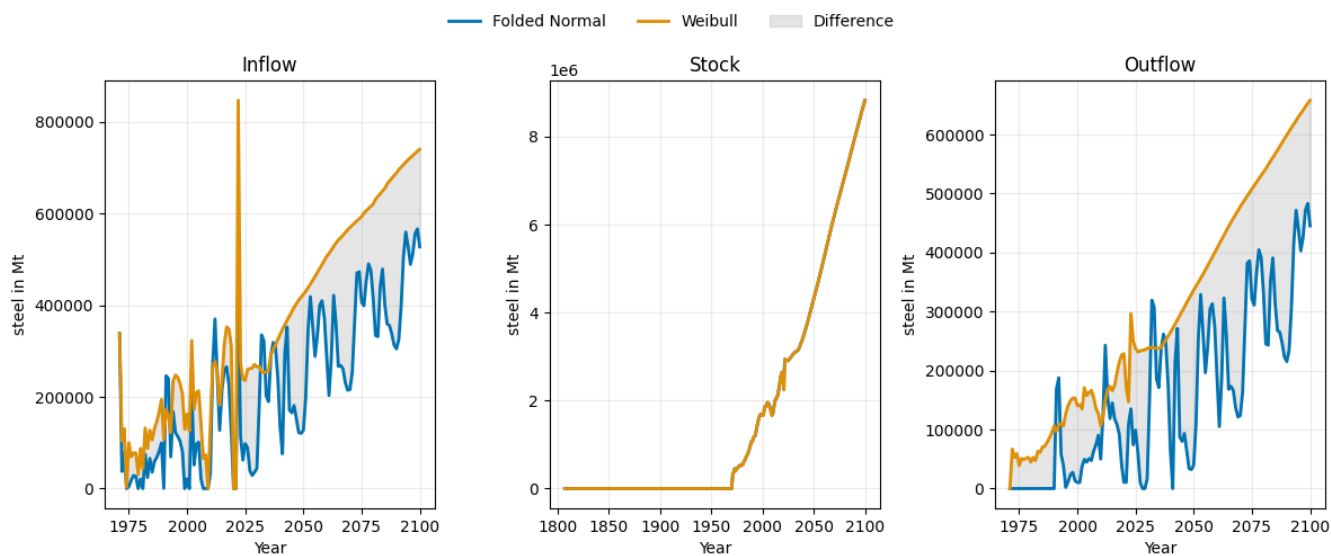
Grid transformer	inflow	Copper	2020	Global	1.1 Mt	0.4 Mt	(IEA, 2021c)
	stock	Steel	2017	Global	105 Mt	33–76 Mt	(Kalt et al., 2021)
	stock	Steel	2017	China	19.1 Mt	9.1–20 Mt	
	stock	Copper	2017	Global	23 Mt	4.7–11 Mt	
	stock	Copper	2017	China	4.1 Mt	1.3–2.8 Mt	
	stock	Aluminium	2017	Global	4.1 Mt	4.6–11 Mt	
	stock	Aluminium	2017	China	0.8 Mt	1.3–2.9 Mt	

### Road & Rail Infrastructure

685 For the current situation road & rail infrastructure results are based on the TRIPI database (Van Engelenburg et al., 2024). Within this study, the road length is compared to other studies (Wiedenhofer et al., 2024) and statistical sources stating that the road length is comparable to other studies, but higher than statistical and older studies (Meijer et al., 2018; Rousseau et al., 2022). The use of OpenStreetMap data allows for modelling the full networks, not only the reported road and rail networks. Additionally, the results have been compared on the physical infrastructure growth with Meijer et al. (2018), and Rothman et al. (2015). The projected physical growth from the road infrastructure within the IMAGE-materials is 23% compared to 19% for Meijer et al (2018). And 30% for Rothman et al. (2015) for the period 2015 - 2050. Additionally, our calculated material inflows (growing from 8.6 Gt/yr to 12.6 Gt/yr) and outflows (5.4 Gt/yr to 8.5 Gt/yr) are in a comparable range to the 4-12 Gt/yr estimated by Wiedenhofer et al. (2024).

### 4.3 Sensitivity

695 IMAGE-materials offers a broad range of capabilities to assess model sensitivity to input parameters, which is evaluated by varying key inputs. For instance, different lifetime distributions can be applied: as Fig. 8 shows, both Weibull and folded normal distributions are currently implemented and can be applied in the model, while additional distributions could be incorporated if required. Lifetime and lifetime distribution assumptions of the vehicles and buildings model were assessed by Deetman (2021) in chapter 3, and chapter 5 (including Appendix 5).



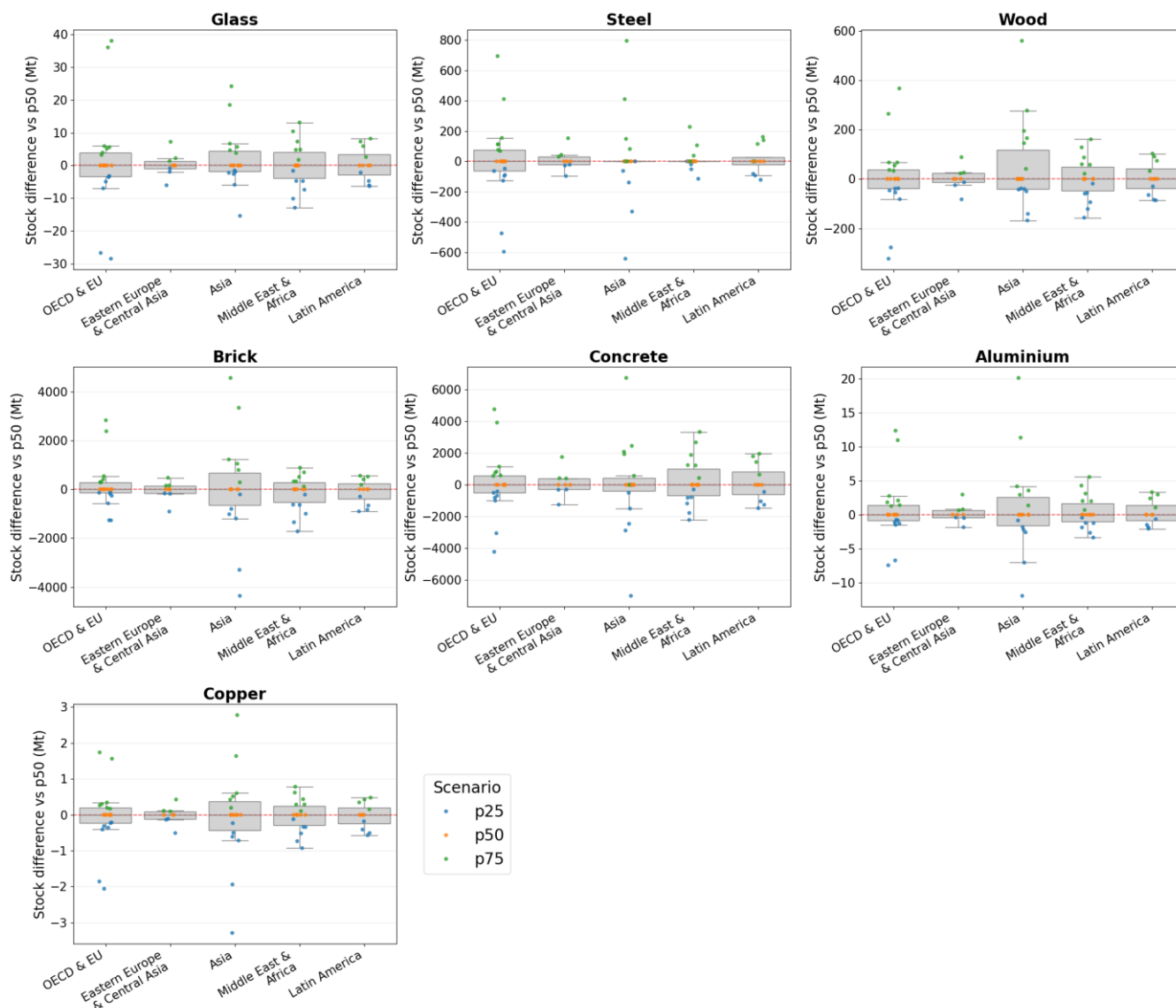
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**Figure 8: Illustrative Weibull distribution (shape: 0.65, scale: 10.3) (Nomura & Suga, 2013) vs. Folded normal distributions (mean: 20, standard deviation: 0.281) (Huisman, 2020) for passenger airplanes in Japan. The spike is caused by the covid pandemic. The standard model uses the Folded Normal distribution.**

Furthermore, material intensities can be adjusted, effectively serving as scaling factors within the model. Figure 9, for example, shows how variations in the p-values of the RASMI dataset (Fishman et al., 2024) affect the inflows of all materials for buildings. Similarly, the weights of product can be varied to assess their influence on model outcomes.

Additional sensitivity analyses are presented by Deetman (2021) in chapter 4 (material intensities of buildings), chapter 5 (the Gompertz curve parameter  $\alpha$ , representing the saturation level in the relationship between commercial floorspace and service value added), and chapter 6 (battery material composition and the deployment of storage capacity technologies).

710



**Figure 9: Deviation of material stock projections in 2025 from the median scenario of material intensities (RASMI p – 50 values) for residential buildings by material and R5 region. Single dots represent R26 regions, within the R5 region grouping.**

## 5 Conclusions

715 This paper documents IMAGE-materials, a global material flow model coupled to the IMAGE IAM framework. The computational novelty of the model presented is the modular framework, which forms a common basis for the sectors covered, as well as allowing easy extension of the model. The scientific novelty of the framework lies in connecting service demand with material stocks and flows. We present a closely linked materials model with a broad range of regions, sectors, and materials covered, which points to the closer integration with IMAGE-energy achieved.



720 IMAGE-materials enables detailed scenario analysis of future material demand associated with living standards and lifestyles,  
effects of climate policies, and circular economy strategies. Whereas most IAMs account for materials only indirectly, through  
associated energy use or economic development, IMAGE-materials stands out as it tracks material inflow, stocks, and outflows  
explicitly in terms of mass, driven by service demand. This, for instance, enables modelling the decoupling of material use  
from economic growth, a core aspect of circularity. Other IAMs are pursuing similar efforts, albeit with slightly differing  
725 approaches (e.g. Ünlü et al., 2024).

Compared to historical data, the model aligns well with observed material demand. The resulting future projections for bulk  
materials are broadly consistent with estimates from other studies, confirming the general reliability of results. Nevertheless,  
it is important to emphasize that the model produces projections rather than predictions, used for modelling trends in resource-  
730 use following socio-economic changes. Model performance varies by region: in regions with high data availability, the model  
reproduces historical patterns more accurately than in data-scarce regions.

IMAGE-materials shows important sectoral differences. In the buildings sector, long lifetimes of 50–100 years create  
considerable inertia in material cycles, making retrofit and refurbishment crucial strategies and potential for future model  
735 improvements. In the vehicles sector, medium-level lifetimes lead to faster stock turnover than in buildings. Because  
environmental impacts from vehicle use phases and material required to maintain older vehicles are substantial, lifetime  
extension is not always the optimal strategy from an overall sustainability perspective. These sectoral contrasts highlight the  
need for differentiated policy approaches to material use.

740 This paper documents a harmonized and efficiently coded improvement of the previous version of the model (Deetman et al.,  
2020) that is publicly accessible (<https://doi.org/10.5281/zenodo.19708090>). Recent model development focuses on  
improvements in the inclusion of material efficiency and circularity strategies, as well as covering the total material demand  
with the residual sector.

#### 745 **Limitations**

Several limitations should be acknowledged. First, the regional differentiation of material intensities remains limited. Material  
intensities per product can vary substantially across world regions, yet available data do not always support region-specific  
parameterization, potentially introducing bias in regional estimates. Relatedly, the temporal evolution of material intensities is  
only partially implemented; in reality, technological learning, material substitution, and changing design standards cause  
750 intensities to shift over time, affecting both historic and future projections.

Second, the coverage of materials differs across sectors. The residual sector currently includes steel, aluminum, copper,  
cement, sand, limestone, and clay, but does not cover materials such as wood, plastics, rubber, brick, glass, and rare minerals.  
As a result, total material demand is not fully represented for all material categories.



755 Third, while lifetime distributions are calibrated to the best available data, inherent uncertainty remains in these assumptions, particularly for long-lived product categories such as buildings and infrastructure, where empirical end-of-life data are scarce. Fourth, direct comparison of total demand or sectors is not always possible, and any validation necessarily involves weighing the reliability of the reference data against the model results.

760 After all, the model makes projections to potential futures, so validation of the future is inherently difficult. Finally, while IMAGE-materials aligns with IMAGE-energy, wood demand is also modelled in IMAGE-land, which is not aligned yet. Furthermore, the plastics and paper & pulp sector in IMAGE-energy, should be linked more closely.

Importantly, the regional and temporal parameter differentiation, residual sector granularity, lifetime data and validation limitations are also possible with the model as it is currently designed. The lack thereof is therefore a data, not a model design limitation.

765

### **Outlook**

770 Despite these limitations, IMAGE-materials provides a bridge between detailed dynamic bottom-up MFA from the field of Industrial Ecology and global IAMs. It supports policy analysis and planning for sustainable material management by enabling scenario-based exploration of material futures, depending on socio-economic development and (climate-) policies. It can be used to analyze the circular economy and other material interventions on the global and regional scale.

775 Future work aims to increase the scope and detail of the model by incorporating additional sectors, such as fossil fuel infrastructure, and by improving the regional granularity of parameters where data availability allows. Further model development will focus on including trade dynamics, implementation of systemic sensitivity and uncertainty analyses (such as Monte Carlo analysis), deeper integration of recycling dynamics and material substitution pathways, laying the groundwork for more comprehensive assessments, such as for the circular economy and decent living standards. Additionally, further integration of IMAGE-materials and IMAGE-energy is being pursued, enabling yearly data exchange and offering the potential to add and uncover dynamics in the material-energy nexus.

## **780 6 Appendix A: User Manual**

The IMAGE-materials model is documented online (<https://image-materials.readthedocs.io/>, last access: April 2026), where a quick-start guide can be found, and further detailed instructions for installation, preprocessing, and simulation are available. The workflow consists of three main stages: preprocessing of input data, configuration of the simulation, and execution of the simulation. The model is implemented in Python and relies on the prism and pym packages, which are not public yet, however



785 will become available in the future. All requirements are specified in the pyproject.toml file on GitHub. The readme contains  
an installation guide.

To run the model, users can execute the Jupyter Notebook scripts in the ‘examples’ folder. Here, all sectors are represented,  
and it is shown how sectors are combined, as well as how climate and CE-scenarios can be combined.

790

To create new modules, such as an additional sector, the user first needs to create the preprocessing. This step transforms raw  
input data into harmonized, model-ready datasets. The preprocessing scripts then generate intermediate data that serve as direct  
inputs to the material flow simulation. At a minimum, this data contains: stock demand, lifetime parameters, and material  
intensities or material shares. Then, the simulation can be set up by using the class structure described in Section 2.4 Simulation

795 Workflow. In the final step, the timeline needs to be defined, and the simulation can be executed.

## 7 Code and data availability

IMAGE-materials is publicly available on Zenodo: <https://doi.org/10.5281/zenodo.19708090>, can be cited as IMAGE-  
materials 3.5.1.0 (von Köckritz et al., 2026). The documentation is available at: [https://image-  
materials.readthedocs.io/en/stable/](https://image-materials.readthedocs.io/en/stable/)

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### 7.1 License

IMAGE-materials is currently under copyright by the IMAGE Materials team, Utrecht University 2026. This repository will  
be integrated into the IMAGE framework, and will be licensed open source under the license chosen by the framework.

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805 Updates to this copyright will be made available on GitHub.

Data necessary to run the model for an SSP2 baseline is stored on GitHub as well.

## 8 Interactive computing environment

As IMAGE-materials depends on packages not yet made public by the Dutch Environmental Agency (PBL), the model cannot  
yet be executed by others. PBL plans to publish these packages in the near future. Updates regarding this will be made public

810 on GitHub.



## 9 Author contributions

FA: Writing – original draft, Writing – review and editing, Visualization, Methodology, Formal analysis, Conceptualization, Software

815 LK: Writing – original draft, Writing – review and editing, Visualization, Methodology, Formal analysis, Conceptualization, Software

JT: Writing – original draft, Writing – review and editing, Methodology, Software

MZ: Writing – original draft, Writing – review and editing, Visualization, Methodology, Software

ME: Writing – original draft, Writing – review and editing, Methodology, Software

820 RB: Writing – original draft, Writing – review and editing, Software

SD: Conceptualization, Funding acquisition, Supervision, Methodology, Software

VD: Writing – original draft, Writing – review and editing, Funding acquisition, Supervision, Methodology

OE: Writing – review and editing, Funding acquisition, Supervision

RS: Software

825 MB: Writing – review and editing, Software

DV: Writing – review and editing, Funding acquisition, Supervision

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840



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#### **Declaration of generative AI and AI-assisted technologies in the writing process**

845 During the preparation of this work, the authors used ChatGPT and Claude in order to review the sections of text and provide assistance with readability. After using this tool, the authors reviewed and edited the content and take full responsibility for the content of the publication.



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