Young Scientists Summer Program

TRIANGULATION OF STOCK-FLOW INDICATORS OF MATERIAL CYCLES FROM MESSAGEix AND INDUSTRIAL ECOLOGY

Jan Streeck
jan.streeck@boku.ac.at

Approved by:

Supervisor: Volker Krey, Gamze Ünlü
Program: Energy, Climate, and Environment (ECE)
Date: September 30th 2022

This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

It was finished by September 30th 2022 and has not been altered or revised since.

Supervisor signature: Volker Krey

Table of contents

ZVR 524808900

The authors gratefully acknowledge funding from the Austrian Academy of Sciences (ÖAW) for the Young Scientists Summer Programme 2022.

Abstract

Climate change mitigation requires radical reductions of GHG emissions. The potential of different strategies to reduce GHGs is subject to fierce debate and investigation, the assessment of strategies requiring a technology-rich scenario approach. Technology-rich Integrated Assessment Models (IAMs) contribute to prominent science-policy interfaces such as the IPCC but have an important shortcoming: although material production accounts for ~1/4th of global GHG emissions, most IAMs ignore potential interventions in material life cycles as GHG mitigation option, which makes these assessments incomplete and neglects the contribution materials can make to reduce impacts. Recent advances in integrating major material flows into IAMs try to tackle this gap. However, the accurate quantification of material cycles is a challenge even in the scientific field primarily occupied with this task, Industrial Ecology, which merits the validation of indicators across methods.

Here we compared the material stock-flow indicators used in the IAM MESSAGEix, with recent results from Industrial Ecology and explained emerging differences by examining underlying data, for example activity (e.g., m² floor area) and material intensity (e.g., kg cement / m² floor area). For the comparison we obtained semi-independent data from (a) top-down, economy-wide Material Flow Analysis, as well as bottom-up, stock-driven data from (b) spatially explicit material stock, and (c) sectoral statistics-based stock-flow modelling. The target scope was the data-rich case study North America (USA & Canada) for the base year ~2015 and the sectors residential buildings, non-residential buildings and power (including preliminary data on roads and motor vehicles).

For overlapping system definitions, total material stocks varied by a factor of up to three among studies, stocks by material by up to fourteen, over the three sectors power, residential and non-residential buildings. For stock-driven studies, the varying stock levels could be explained by differing activity levels (up to factor 2) and/or material intensities (up to factor 33). For the top-down, inflow-driven study, the cumulative consumption of bricks for 1870-2017 and estimated from statistics was <60% of a bottom-up material stock estimate, potentially indicating underestimation in respective statistics.

The large differences of material stock estimates call for improved data and data reconciliation of activity levels, material intensities, material consumption and its end-use allocation, as well deeper cross-methods analysis. Data differences might emerge from: using activity data assembled for purposes other than material cycle modelling and resulting system boundary differences among studies; few available case studies on building material intensities which through intransparent documentation, heterogenous data processing and selectivity can lead to variation of applied intensities; the challenge to represent heterogeneity of technologies while being comprehensive in scope; and non-market material extraction not finding its way into statistics (e.g. for bricks).

For the momentary modelling of climate change mitigation through material efficiency, our results stress the need to explicitly address uncertainty through scenario and sensitivity analysis in order to ensure robustness of conclusions.

About the authors

Jan Streeck is a PhD student and researcher at the University of Natural Resources and Life Sciences, Vienna, Department for Economics and Social Sciences, Institute of Social Ecology.
(Contact: jan.streeck@boku.ac.at)

Acknowledgments

Many thanks to my supervisors Volker Krey and Gamze Ünlü, as well as to the whole Energy, Climate, and Environment (ECE) program, and all IIASA scientists who participated in YSSP activities, for their efforts in making the summer 2022 a memorable experience and providing me with new perspectives on known challenges. Additional thanks to all contributors who provided data and counsel for this work, in particular Alessio Mastrucci, Peter Berrill, David Frantz and André Baumgart. I also thank the Austrian Academy of Sciences (ÖAW) for funding and thereby enabling my research stay, the preliminary product of which is this report.

Introduction

Material production is responsible for ~1/4th of global GHG emissions with likely rising importance in the future (Hertwich 2019; Krausmann et al. 2020; Lamb et al. 2021). When modelling prospective decarbonization scenarios, it is thus key to include comprehensive material cycles, to adequately assess the potential of more efficient material management (Pauliuk 2017; Pauliuk et al. 2021). Recent advances in integrating material flows into technology-rich Integrated Assessment Models (IAMs) try to address this challenge (e.g. Kermeli et al. 2021). However, the accurate and robust quantification of material cycles is challenging even in the scientific field primarily occupied with this task, Industrial Ecology, which merits the validation of indicators across methods (Chen 2017; Tanikawa et al. 2021).

Material cycles are commonly described via stock and flow indicators which are investigated with the methods of dynamic Material Flow Analysis (dMFA). dMFA is a rapidly evolving scientific field for which methods can be sub-divided into stock-driven (bottom-up) and inflow-driven (top-down) approaches (Lanau et al. 2019; Müller et al. 2014; Wiedenhofer et al. 2019): Both sub-methods can compute material stocks, inflows and outflows, the choice of modelling approach often at as much about data availability, as it is about study scope. Stock-driven models use exogenous data on product stock units and material intensities to calculate material stocks, and can endogenously derive material flows via data on vintages, lifetimes and stock changes. Inflow-driven models, in contrast, start from exogenous data on annual inflows to stocks and then endogenously model the accumulation of material stocks as cohorts, as well as resulting outflows, via lifetime functions.

The difference between what is exogenous data and what is endogenously modelled is helpful in understanding the methods' strengths and limitations (Chen and Graedel 2015; Lanau et al. 2019; Wiedenhofer et al. 2019): starting from detailed data, stock-driven dMFA can provide high-resolution assessments of product stocks and related flows, while achieving a comprehensive material and time scope is highly challenging. In contrast, inflow-driven dMFA can build on long-term data on production, trade and consumption for a comprehensive material scope – is however less detailed and sensitive to lifetime assumptions when calculating stocks.

The reliance on different exogenous data of the sub-methods above can be exploited for triangulating estimates of material cycles to approximate their 'true value'. Here, we compare stocks and flows of bulk materials (e.g. cement, wood, iron & steel), as represented in the IAM MESSAGEix, with independent estimates from literature and own modelling. We focus on the data-rich case study of North America (USA & Canada) and the base year ~2015 and formulate the following research questions:

- How well do the estimates of bulk material stocks and flows of three semi-independent[1] material flow analysis approaches agree for the case study USA and Canada ~2015?
- Which differences in methods and data sources explain differences in stock-flow results?
- What do above results imply for modelling of material cycles and their integration into IAMs?

---

[1] The two stock-driven approaches might partially rely on material intensities from the same sources.

Methods

To answer our research questions, we collected U.S. material stock-flow and underlying input data from seven literature studies through data available in pertinent repositories and direct contact to lead authors (for some studies including Canada). In addition, we modelled U.S. economy-wide material stocks and flows, using a top-down, inflow-driven material flow model (see below). Subsequently, we compared the level of material stocks, their age structure and end-of-life outflows among studies. Additionally, we attempted to explain differences among studies, through focusing on model computations that were equivalent but used different data inputs (for instance, by comparing utilized statistics on activity and material intensity for bottom-up studies).

The collected studies represented three different methodological approaches of modelling material stocks and flows, which we describe below, together with surveyed studies.

Material Flow Analysis (MFA) methods and data sources

Top-down, inflow-driven, economy-wide MFA

The economy-wide variation of inflow-driven material flow analysis/accounting, draws on top-down statistics on production, trade and consumption of material flows and endogenously derives material stocks via lifetime functions (Wiedenhofer et al. 2019). Because respective statistics are compiled in an aggregate manner, they usually do not distinguish the end-use applications that materials are used in (Streeck et al. in revision_a). However, end-use can be differentiated by introducing end-use shares to split aggregate material consumption to end-use sectors or products. These end-use shares are based on industry shipments in physical or monetary units, like for instance applied in Pauliuk et al. (2013) and Cao et al. (2017).

Streeck (in preparation) applied end-use shares derived with the methodologies described in Streeck et al. (in revision_a, in revision_b) to long-term material flow data for the USA, compiled in Streeck et al. (2021). For modelling material stocks from flows, the authors drew on an advanced model version of Wiedenhofer et al. (2019), which is currently being prepared with involvement of study author and based on the ODYM framework (Wiedenhofer et al. in preparation; Pauliuk and Heeren 2020). Results showed long-term material stock and flow dynamics of 12 materials in 12 broad end-use sectors for the years 1870-2017, amongst others in residential and non-residential buildings, roads and other infrastructure as well as motor vehicles (see section results & SI.3/4)

Bottom-up, stock-driven, sectoral MFA

All of the studies grouped under bottom-up, stock driven models estimate material stocks by multiplying some kind of activity level (e.g. generation capacity of power technologies, floor area of buildings) by normalized material intensities to calculate material stocks; flows in turn can be derived from applying lifetime functions to the stock’s age structure (Müller et al. 2014; Lanau et al. 2019).

Kalt et al. (2021b) estimated the global material stocks of concrete, aluminum, copper and steel in power plants and grid infrastructure at regional resolution for 1980-2017. Activity levels were quantified as generation capacity of power technologies, primarily drawing on the U.S. Energy Information Administration for 1980-2017, IRENA for renewable energy 2000-2017 and the UNSD Energy Statistics Database; as well as length of transmission and distribution grids estimated with Open Street Map for 2017, GIS data from ESRI ArcGIS Hub, and (inter)national statistics; and as transformer capacity (see Kalt et al. (2021a) for details).[2] Material intensities for the respective activity levels were derived from >40 studies and applied as a low, medium and high estimate.

Deetman et al. (2021) estimated the global material stocks of concrete, aluminum, copper, cobalt, glass, lead, neodymium and plastics in power plants and related infrastructure for 1990-2050. Authors combined capacity data provided by the IAM IMAGE (Stehfest et al. 2014; van Vuuren et al. 2017) with material intensities gathered from 27 literature studies. Additionally, materials in grid infrastructure were calculated by multiplying estimated grid length from own work - primarily based on Open Street Map 2016 and a dataset by Arderne et al. (2020), as well as national statistics - with material intensities. Additionally, authors estimated materials in electricity storage technologies (required capacity from IMAGE) using material intensities based on 15 studies.

Unlu et al. (in preparation) estimated the global material stocks of cement, aluminum and steel in power plants for the IAM MESSAGEix regions and the base year 2015 by multiplying generation capacity of 21 power technologies by vintage from MESSAGEix (Krey et al. 2020) with material intensities from Arvesen et al. (2018). MESSAGEix optimizes fit to electricity generation and capacity factors, in the course of which original power technology capacities might be altered (slightly for most technologies, a little more for hydropower).

Berrill and Hertwich (2021) provided data on the material stocks of 10 materials in residential buildings for the USA 2019, potentially available by county and age cohort (via personal communication). The material stocks were obtained by multiplying floor area of 51 building archetypes with the respective material intensities. The authors calculated residential floor area by housing archetype via multiplying housing units per type with average floorspace per type-cohort-county.[3] For obtaining material intensities, Berrill & Hertwich used the Athena Impact Estimator (Athena Sustainable Materials Institute 2020) for all building archetypes (except one), from which the average intensity per aggregate building type (single family, multi family, mobile home) was calculated based on archetype mix in counties. Floor area for activity and material intensity estimates referred to 'useful floor area' (*excluding basements and garages*), in the paper supplementary information also termed 'gross living area'.

Pauliuk et al. (2021) presented data for material stocks of seven materials in residential buildings and five materials in passenger vehicles for 20 global regions, two of which are the USA and Canada, for the year 2015. The stock was obtained by multiplying activity per end-use archetypes (for historic data

[2] several steps of data cleaning and reconciliation were applied. For all countries where no data were available: linear regression on available data points to estimate grid infrastructure activity levels.
[3] units per type from ACS Table B25127 (US Census Bureau 2021); average floor space per house type are based on a representative sample by NREL (2020).

USA: four residential building types, five passenger vehicle drive trains) with respective material intensities. For U.S. residential buildings, the floor area estimate was based on Moura et al. (2015) who assembled time series of housing units by three types (single family, multi family, manufactured homes) by reconciling several national statistical sources and estimated related floor area based on average floor space data per vintage from the American Housing Survey (AHS). Floor area adhered to the following definitions (*including basements and attics*). Historical floor area stock was distinguished by three archetypes (single family, multi family, informal) for which material intensities were based on data compiled in Heeren and Fishman (2019), additional literature sources and floor area from above source.

Mastrucci et al. (2021) shared data on material stocks of seven materials in residential and commercial buildings for the USA and Canada 2020 (via personal communication). Residential building floor area was calculated by multiplying housing units with household size and average per capita floor area from IEA (exact definition of floor area unclear; including occupied dwellings only) distinguishing four building archetypes, cohorts and urban/rural regions. Data on commercial buildings was preliminary and based on a simpler representation compared to residential buildings (contact study authors for further information). Material intensities were derived and adapted from Deetman et al. (2020) and Marinova et al. (2020) by aggregating different building types and matching to MESSAGEix regions.

Bottom-up, stock-driven, remote sensing MFA

Frantz et al. (in preparation) presented material stock data for 16 materials in seven different types of (non-)residential buildings and road, rail, and other infrastructure for the USA (ca. 2018)[4] at high spatial resolution (10 m). Quantification of activity was based on raster data from Earth Observation satellites and vector data from Open Street Map that allow for calculation of above ground building volume (*agbv*) and building footprint. Building types were classified according to information on reflectance, spatial context and building height and based on training sites with known types. Activity was then combined with material intensities to estimate material stocks. For buildings, material intensities were compiled from 23 case studies and re-calculated from intensities per building unit or floor area to *agbv* using case study data or assumptions on number of building stories, floor height, useful per gross building area and roof volume. For road, rail and other infrastructure, material intensities were based on construction manuals and literature studies. For foundational methodological work, please see Haberl et al. (2021). In order to compare activity and material intensity to other bottom-up studies, we here estimated the gross floor area contained in *abgv* building stock (see SI.2).

[4] data for quantification partially for deviating years

Results

Herein, we compare the obtained stock-flow results among studies and analyze underlying data to explain differences. We focus on the sectors power, residential and non-residential buildings (results for additional end-uses in SI.3/4). Stock-flow results might refer to a year other than 2015 when data for the respective year was unavailable. Compared to overall uncertainty, this slight difference in time is expected to only marginally bias stock results which are the outcome of accumulation over many years (for an estimate of bias see subsection 'Limitations').

Overview: economy-wide vs. sectoral material stocks

For overview, we present an estimate of economy-wide material use of 12 materials (Streeck in preparation) and its relation to estimates for the three focus sectors power, residential and non-residential buildings in Figure 1. Economy-wide material stocks in 2017 were estimated at ~100 Gt, aggregates (36 Gt), concrete (29 Gt) and asphalt (26 Gt) constituting 91% of total stocks. Regarding stocks in the respective end-uses, the minimum and maximum among surveyed studies were 0.2-0.4% of total stocks for power, 12.4-42.8% for residential buildings and 6.4-20.1% for non-residential buildings. Please note: the economy-wide estimate is a result of inflow-driven modelling and itself attached with substantial uncertainty; material scope of studies is not overlapping (see SI.1 for details).

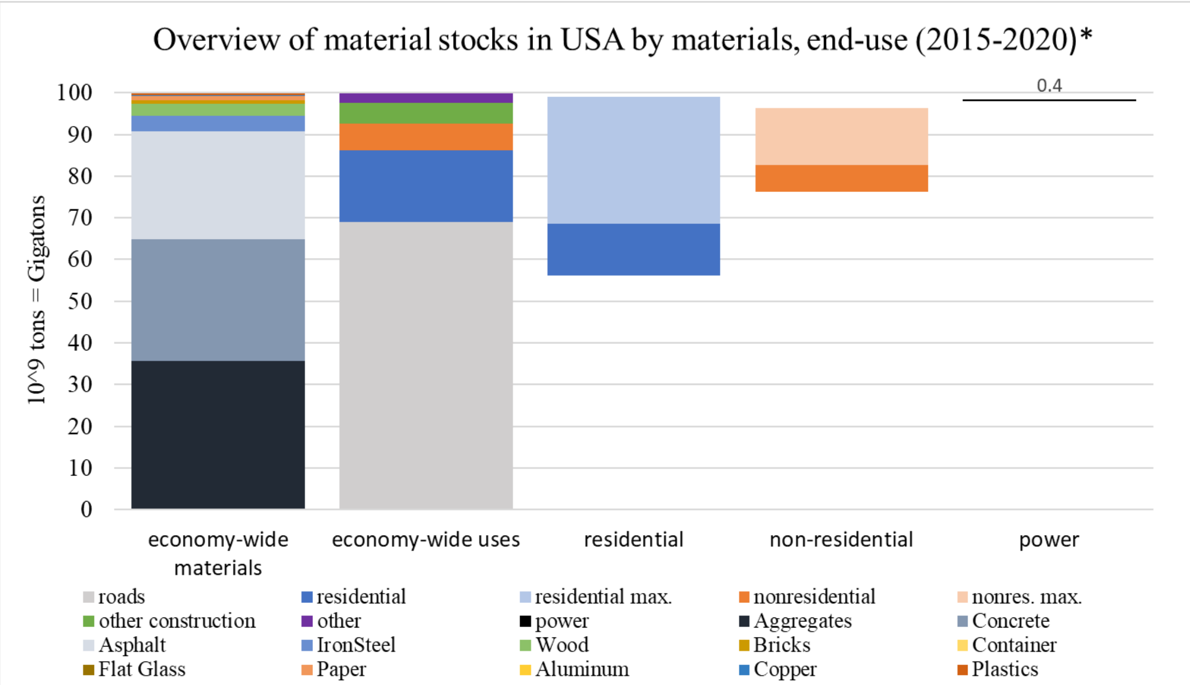

*Figure 1: Estimated economy-wide material use of 12 materials (Streeck, in preparation) and its relation to minimum (e.g. 'residential') and maximum (e.g. 'residential' + 'residential max.') estimates for the sectors power, residential and non-residential buildings among the studies described in the methods section. For study references please see methods section. *studies' time scope differs slightly, see subsection 'Limitations' below for an estimate of bias; material scope of studies is not overlapping (see SI.1 for details).*

Material stocks of power plants and grid infrastructure

For power plants and grids we gathered data from MESSAGEix and two other data sources for the USA and Canada (Deetman et al. 2021; Kalt et al. 2021b; Unlu et al. in preparation). MESSAGEix only assessed materials in power plants (2015), while Kalt et al. in addition estimated materials in grid infrastructure, and Deetman et al. in turn also in storage technologies. Sources referred to 2015, except for Kalt et al. who presented data for 2017. For Deetman et al., material stock results varied slightly for the year 2015 (0-2.2% per material) in different scenarios, indicating slight deviations of base data. Due to the small differences we did not follow up on these but instead used the baseline scenario ('BL' + 'default'; see resp. study for details).

Here, we only compare results for power plants, as these are the only overlap between the three sources. Unlu et al. power plant material stocks for steel (~equal Kalt et al. high) and aluminum (~equal Kalt et al. medium) were within the range of the two other studies, while cement stocks with 68% of the value of Kalt et al. (low) were comparatively low (see Figure 2). While Unlu et al. did not calculate material stocks of grid infrastructure, the latter constituted a substantial share of total stocks, especially for metals for other sources. Grid infrastructure made up 39-54% of the total for steel, 7-16% for cement, 84-98% for aluminum, 73-93% for copper (low-high values from Kalt et al.). Deetman et al. (2021) presented additional data for cobalt, glass, neodymium and plastics not shown here.

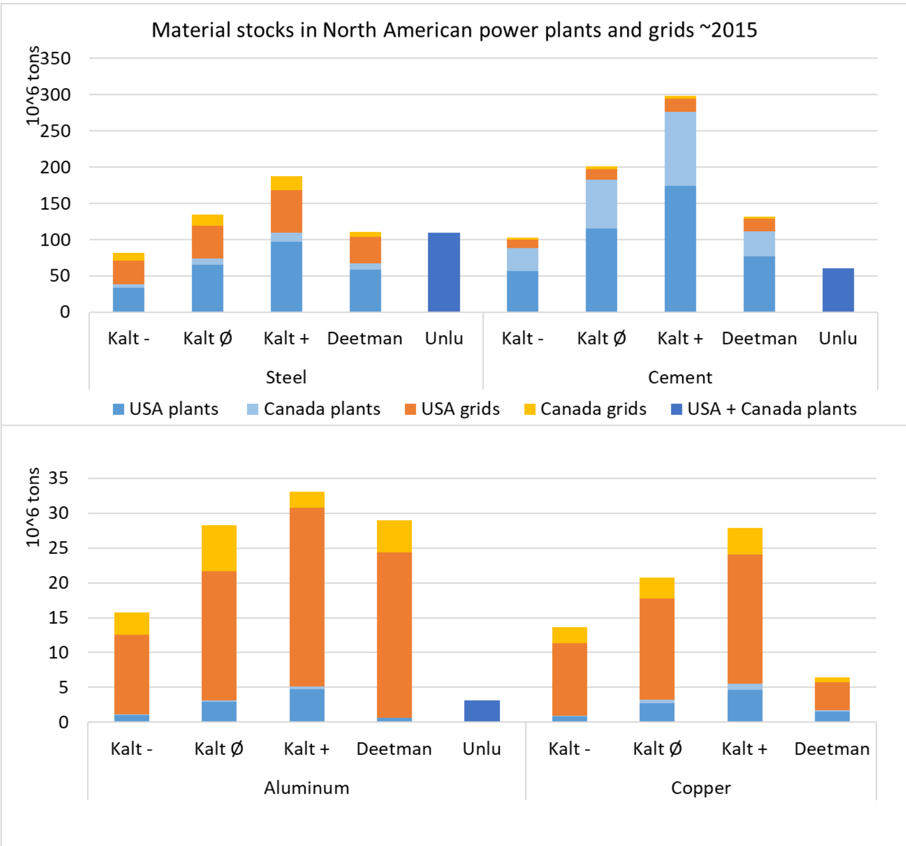

Figure 2: Material stocks of steel, cement, aluminum, copper in power plants and grid infrastructure in the USA and Canada in ~2015 (Deetman et al. (2021): 2015, Kalt et al. (2021): 2017, Unlu et al. (in preparation): 2015). Three values for Kalt et al. indicate low (-), medium (Ø) and high (+) estimates.

Material stock levels of power plants for the three studies on the level of individual technologies differed more than results with aggregated technologies. The by far largest differences emerged for hydro power, for which material stocks in Unlu et al. (in preparation) represented >770% of Kalt et al. (2021_high) stocks for aluminum, >450% of Deetman (2021) stocks for steel, and 55% of Kalt et al. (2021_low) stocks for cement. Large differences among sources also showed for nuclear (aluminum), coal (aluminum, cement), wind offshore (cement), gas (aluminum), solar and bioenergy (all three materials). For material stock figures per technology please see Table S3.

Differences in material stock levels could be explained by different assumed generation capacities and different material intensities. For hydro power, capacity in Unlu et al. (in preparation) was 24-27% lower than that of other sources, which might be a result of model calibration to electricity generation instead of capacity for hydropower. However, differences primarily emerged from varying material intensities: for steel, the intensity used by Unlu et al. (in preparation) was 6-23 times and for aluminum 10-35 times the value of other sources, while for cement, the material intensity used by Unlu et al. (in preparation) was only 23-76% of other sources. For values of capacities and material intensities please see tables Table S4 and Table S5.

Material stocks of residential buildings

For residential buildings, we gathered information for the USA from five sources (Berrill and Hertwich 2021; Pauliuk et al. 2021; Mastrucci et al. 2021; Frantz et al. in preparation; Streeck in preparation), representing all three modelling approaches described in the methods section and reporting for 7-16 materials. Mastrucci et al. (2021) and Pauliuk et al. (2021) also present data for Canada.

Here, we focus on results for the USA at resolution of 'all residential buildings' to include all sources. Berrill and Hertwich (2021), Mastrucci et al. (2021) and Frantz et al. (in preparation) reported results for sub-types of at least single and multi-family buildings (Pauliuk et al. (2021) calculated these types too, but did not report in repository results). For these studies, single family buildings made up the lions share of reported floor area (77-89 % of total among studies) and material stocks among all residential building types (79-89% of total; see Table S6 & Data SI).

The overlapping material scope among studies was only the four materials cement, sand and gravel to make concrete, iron and steel, and wood, constituting 61-99% of studies' total stocks. For this overlapping scope, cumulative minimum and maximum estimates of material stocks (9-26 Gt) differed by a factor of up to three (Figure 3; Table S7). On the level of individual materials the maximum factor difference was five (for iron and steel).

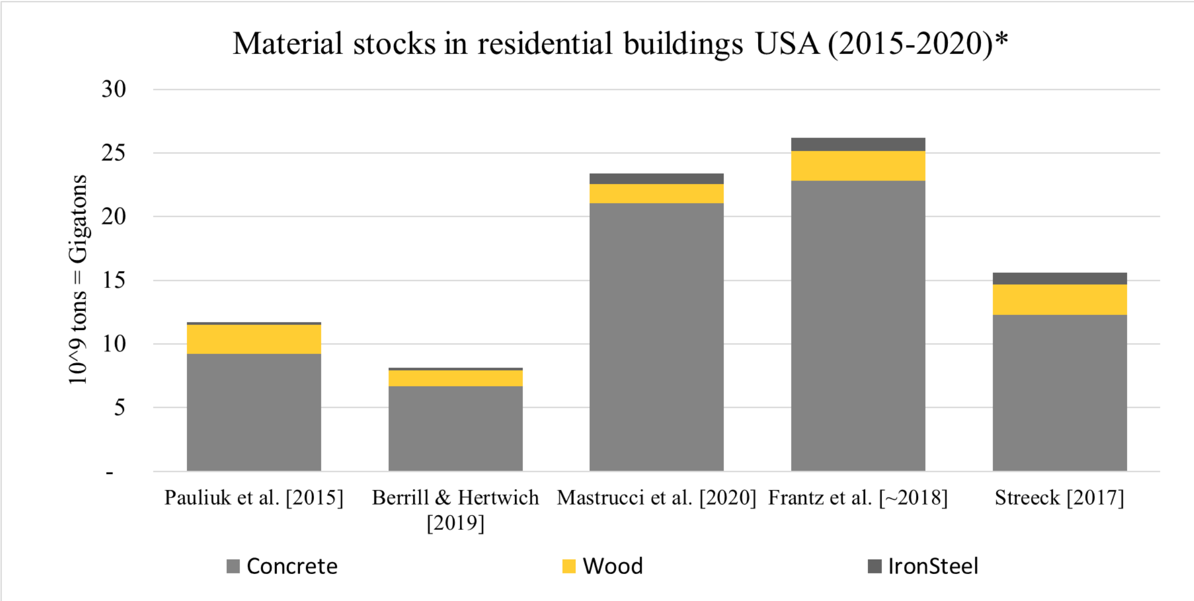

*Figure 3: Material stocks for five surveyed studies and overlapping materials scope (concrete, wood, iron and steel). *please mind that the year differs slightly between studies, indicated by [year]. For study references please see methods section.*

For the four stock-driven studies, the differences in material stocks could be explained by comparing activity levels (floor area) and material intensity. When comparing activity data, readers should keep in mind that the definition of floor area, i.e. whether gross or net and which building elements are included, differed among sources and was often times not transparently reported (more on this in discussion section). Pauliuk et al. (2021) and Berrill and Hertwich (2021) both reported close to 22 billion m² floor area, which was almost identical to the level of official statistics (U.S. Energy Information Administration 2018). Mastrucci et al. (2021) in turn calculated 27 billion m² floor area. For Frantz et al., who derived data on above ground building volume and building gross footprint (area) from remote-sensing data, we re-calculated to an estimate of *gross* floor area between 45-51 billion m² (see Table S6 & Data SI for floor area by building type). Our estimate of floor area for Frantz et al. was dependent on either floor height or floor number (see SI.2). Assuming only a single floor to receive a minimum estimate, would result in 24.1 billion m² gross floor area (GFA) for residential buildings in ~2018.

Average material intensities for all residential buildings (material stocks divided by floor area) for the overlapping materials scope differed by factors of up to three (see Table S8 for average material intensities). For partial study overlaps, factor differences were up to a factor of 10 (for copper).

For the inflow-driven material flow method in Streeck (in preparation), material stocks were estimated without relying on activity or material intensity and could thus not be adequately compared beyond material stock levels (see methods). However, one observation in comparison to other studies was, that the material stocks of bricks in residential buildings was only <30% of the values estimated in Frantz et al. (in preparation; Table S7); even the reported cumulative apparent consumption of bricks for all end-uses from 1870-2017 (Streeck et al. 2021) was <60% of the mentioned bottom-up material stock estimate.

Material flows, stock age structure and lifetimes

In addition to material stock levels, we compared the stocks' age structure and selected material flows. The modelled age structure, together with assumed lifetime distributions, substantially influences prospective end-of-life (EoL) outflows from stock, i.e. the demolition outflows at the end of a stock's lifetime. For products with a long lifetime, such as buildings, the EoL outflows roughly equal the material inflows required to maintain stable stock levels. Here, we compare whether the variation in material stock levels translates into proportional differences in material flows through vintage and lifetime assumptions. We focus on EoL outflows, as material inflows are biased by different assumed demand trajectories (i.e. floor area) for prospective studies. The studies for which flow data was available were mostly prospective not allowing for detailed comparison of the historical period.

For prospective EoL outflows, the difference in material stocks by a factor of two between Mastrucci et al. (2021) and Pauliuk et al. (2021) did not translate into a proportional difference in EoL outflows, which only deviated by factor 0.9 in 2020 to 1.4 in 2060 (Figure 4). The lower differences can primarily be explained by longer lifetimes assumed by Mastrucci et al. (2021), leading to proportionate lower EoL outflows from stocks until 2060.[5]

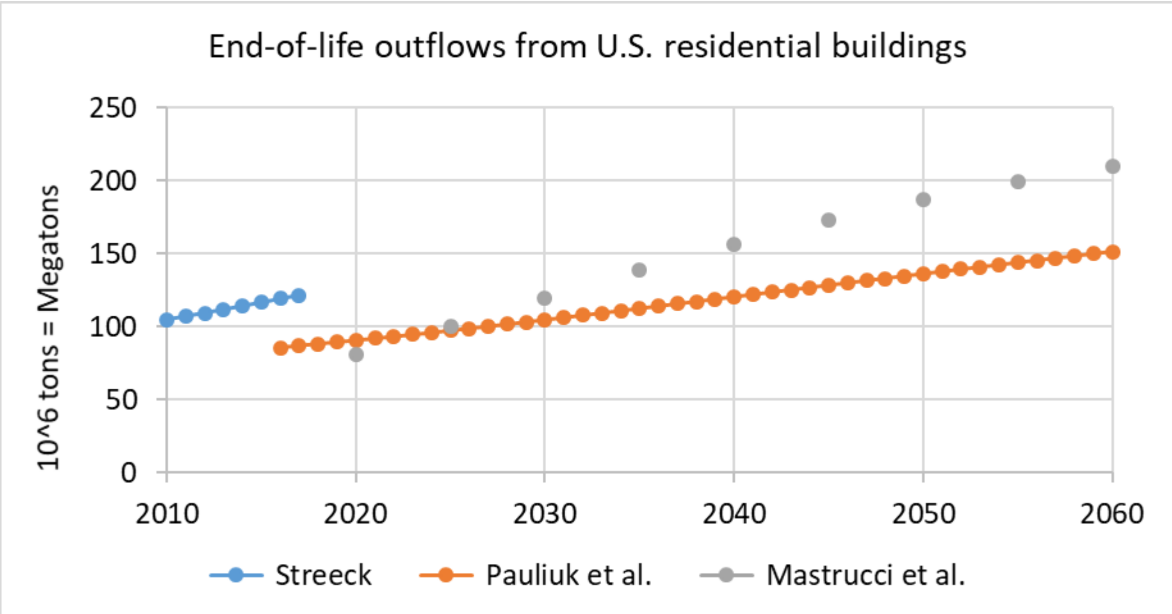

Figure 4: Estimated end-of-life outflows from stocks for overlapping material scope (aluminum, concrete, copper, glass, iron and steel, wood) for Mastrucci et al. (2021), Pauliuk et al. (2021) and Streeck (in preparation).

The observed age structure, in turn, would rather lead to an overall higher difference in EoL outflows compared to stocks, as Mastrucci et al. (2021) showed substantially higher share of material stocks in

[5] Mastrucci et al.: Weibull, mean 136 years, standard deviation 37 years; Pauliuk et al.: Normal, mean 90 years, standard deviation 27 years; Streeck: mean 75 years, standard deviation 23 years. To determine the exact contribution of age structure, lifetime values and lifetime distribution shape, we would need to run sensitivity analysis on the two models. Here, our description remains on a qualitative level.

cohorts <1945 compared to Pauliuk et al. (Table 1); here and for the time frame until 2060 this is reversed and trumped by the dominating effect of higher lifetimes.[6]

Regarding age structure for all studies, Streeck (in preparation) showed a substantially lower share of material stocks in early cohorts before 1940/45 compared to both Berrill and Hertwich (2021) and Mastrucci et al. (2021) (lower by ~8.8-20.9%-points). For remaining cohorts, Streeck (in preparation) and Berrill and Hertwich (2021) showed smaller deviations (0.9-5.7%-points). Given that Berrill and Hertwich (2021) derived age structure from a large representative sample of the U.S. housing stock (see methods section; NREL (2020)), while other studies included simplifications to different degrees, their results appear to best reflect the real-world status.

*Table 1: Age distribution of material stocks/floor space in residential buildings for four surveyed studies and overlapping material scope. Berrill and Hertwich (2021) – data to 2019, Streeck (in preparation) – to 2017, Mastrucci et al. (2021) – to 2020, Pauliuk et al. (2021) – to 2015. * here only accounting for results up to 2015; **only referring to the age structure of floor area (material stock data n.a.)*

Cohorts 1	**<1940**	**1940-1959**	**1960-1979**	**1980-1999**	**2000-2009**	**2010-17/19**
Berrill & Hertwich	12.5%	13.5%	22.6%	26.5%	16.6%	8.3%
Streeck	3.7%	10.8%	24.8%	32.2%	19.0%	9.4%
Cohorts 2	**<1945**	**1946-1990**	**1991-2015**	**2016-17/20**		
Mastrucci et al.	26.1%	32.0%	30.2%	11.7%		
Streeck	5.2%	50.9%	41.2%	2.7%		
Pauliuk et al. (floor area)**	16.2%	49.0%	34.8%			
Mastrucci et al.*	29.6%	36.2%	34.2%			
Streeck*	5.8%	52.2%	41.7%			

Material stocks of non-residential buildings

For non-residential buildings, we only received data for material stock levels and activity until the completion of this report. Please note that results related to Mastrucci et al. (2021) are preliminary, unpublished, not included in the citation, and include Canada (results would thus be lower when only referring to USA). Additionally, studies used different terms, referring to 'non-residential' and 'commercial' buildings. So far we could not settle whether this also implies different system boundaries (ongoing investigation).

The material stocks for non-residential buildings and the overlapping seven materials (see Figure 5) differed by a factor of up to 2.4 (6-14 Gt; Table S9) and made up 70-100% of total material stock mass. Per material, stocks differed by a factor of five on average and up to factor of 13.5 (for flat glass). Regarding activity (i.e. floor area), official statistics reported 9 billion m² floor area for

[6] For Pauliuk et al. 2021 only data on the age structure of floor area was available; as U.S. buildings are 85% single family buildings, to which a uniform set of material intensities was applied, floor area and stocks were roughly comparable.

commercial buildings in 2018 (U.S. Energy Information Administration 2021), our estimate from building volume data from Frantz et al. (in preparation) was 9.4-15.7 billion m² gross floor area in ~2018, and data associated to Mastrucci et al. (2021) reported 9.3 billion m². For Frantz et al., assuming only a single floor to receive a minimum estimate, would result in 7.6 billion m² gross floor area in ~2018 (see SI.2 and sub-section on residential buildings).

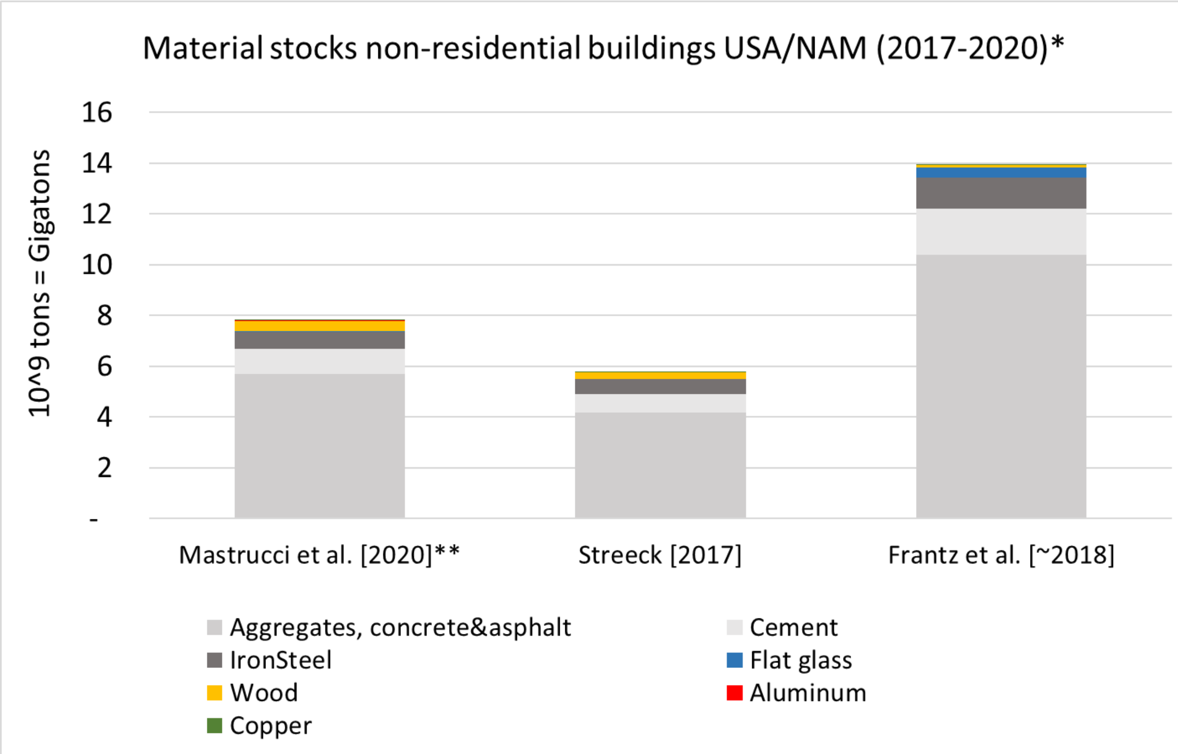

*Figure 5: Material stocks in non-residential / commercial buildings for three surveyed studies for an overlapping materials scope. *mind that the year differs slightly among studies, indicated by [year], **mind that the geographical reference differs: Mastrucci et al. (2021) refer to USA and Canada.*

Limitations

The material stock data presented herein exhibit slightly varying time scopes (see methods section). In order to approach the introduced bias through time variation, we here compare data from Streeck (in preparation), who presented annual data up to 2017, for 2015 and 2017, as the only source that showed data for multiple historical years. For residential buildings, stocks of the 12 materials in 2015 were 17.1 Gt, in comparison to 17.3 Gt in 2017, depicting an increase by 1.1% over two years. While data was not available for other studies, we expect time variation to similarly influence results only by few percentage points for long-lived end-uses, thus being trumped by variation in activity and material intensities (see sub-sections above). However, when assessing end-uses with low lifetimes, e.g. packaging, the introduced bias might be more pronounced and should receive closer attention.

Discussion

Above results illustrate the substantial uncertainties attached to estimating material stocks, varying by factors of up to fourteen for individual materials. For stock-driven studies, these results can be explained by diverging data on activity levels and material intensity used for modelling, as well as the difficulty to adequately represent heterogeneity while being comprehensive. Also for the single inflow-driven study, potential underestimation in semi-official data on production and consumption might partially explain observed differences. Below, we further elaborate on potential explanations for the deviation of results for material stocks, focusing on variance in activity and material intensity for modelling buildings.

Variance in activity

Variance in activity might result from potential underestimation of individual data sources, as well as non-matching system definitions with respect to floor area indicators.

Underestimation of activity

For stock-driven studies of buildings, activity corresponds to floor area. In our results, we found that the floor area estimates of remote-sensing studies (Frantz et al. in preparation; Arehart et al. 2021) were more than two times higher compared to data reported by official statistics and other MFA studies (U.S. Energy Information Administration 2018; Berrill and Hertwich 2021; Pauliuk et al. 2021).[7] As suggested by Arehart et al. (2021), this might point towards a potential underestimation of (total) floor area, when using data from official statistics that were assembled for a purpose other than material cycle modelling (e.g. for estimating heating and cooling energy demand instead of building mass).

Indeed, some floor area statistics themselves report exclusions of certain elements of the built environment, reflecting incompleteness with regards to material cycle modelling. For example, the U.S. Energy Information Administration (2018) notes that *'[u]nconditioned and unfinished areas in attics and attached garages are excluded'*. Additionally, survey based methods such as the latter can miss vacant houses. Above source excludes *'[v]acant housing units, seasonal units, second homes, military houses, and group quarters'*, further supporting the suggestion by Arehart et al. (2021).

However, also remote-sensing based floor area estimates are uncertain and highly sensitive to assumptions on the number of floors or floor height (see SI.2 & Arehart et al. (2021)). As minimum estimate, floor area would equal gross building footprint, thus supposing that all buildings only had one floor. Following this argument, results from Frantz et al. (in preparation) would yield a gross floor area estimate just ca. 9% higher for residential and 15% lower for non-residential buildings, compared to the mentioned U.S. statistics. While these values are quite close to official figures, we know real world floor area to be higher because buildings with more than one floor do exist. Overall, these observations support the conclusion, that official floor area statistics (at least for the USA residential buildings) might be at least slightly underestimating total floor area.

---

[7] Data derived from remote sensing is a result of modelling and may be biased itself.

For the inflow-driven study in our sample, activity corresponds to use of material mass. These data might be underestimating material use for materials that are not traded via the market (e.g. bricks from local clay, illegal logging, extraction of sand & gravel, etc.). The statistics on brick use compiled in Streeck (in preparation) were substantially lower compared to brick estimates in Frantz et al. (in preparation), which might point towards such an underestimation and partially explain the strong divergence of brick stocks.

Differing definitions of floor area

In addition to potential underestimation, the variance in activity might also result from differing definitions of floor area. There seems to be no universal definition of floor area indicators and several organizations seem to exhibit slightly varying definitions, i.e. see following text. Two aspects are primarily important when defining floor area: first, whether gross or net area is reported; and second, which building elements are included in the definition (for example, whether basements or garages are included in area indicators). Heeren and Fishman (2019), who compiled material intensity data from 33 studies, state that some studies do not even report whether referring to gross or net area, and that studies include different building elements. In our study sample, for example, activity in Berrill and Hertwich (2021) excludes basements and garages, while activity data used in Pauliuk et al. (2021) includes basements and attics but excludes garages. In their supplementary information, Berrill and Hertwich refer to floor area definitions of Fannie Mae (2021), while data used in Pauliuk et al. (2021) relies on definitions from the United States Census Bureau (2022). Overall, the use of particular definitions of floor area indicators is often implicit and tedious to follow.

Variance in material intensities

Variance in material intensities emerges from shortcomings in the data itself, such as intransparency and non-representativeness, as well as differences in how these data are used in modelling, such as selectivity, handling heterogeneity, and general matching of system boundaries.

Reporting material intensity data

Data on material intensities are spread throughout individual literature studies. For buildings, studies are primarily based on case-studies of individual or few buildings, referring to the context of a particular city, or on construction manuals (Heeren and Fishman 2019). Observed large deviations of intensities for one assigned building type illustrate building heterogeneity, making it difficult to choose representative data for the entire building stock of a type such as 'detached houses' (Marinova et al. 2020). Recent efforts towards combining and harmonizing material intensity data in databases try to tackle these problems (Heeren and Fishman 2019; Marinova et al. 2020). Concluding from their efforts, study authors describe current data points as limited, based on few sources, biased towards global north countries, based on methods specific to original studies, potentially using ambiguous material labels, and not exhibiting estimates of uncertainty. Additionally, system boundaries with regards to floor area definitions (gross or net) and included items might differ among studies. All of these limitations complicate the accurate use of material intensity data for practitioners.

We found that even between the two databases, the material intensity reportedly derived from a single case study differed substantially (Table 2). Further understanding the reasons for these differences requires additional detailed investigation and contact to study authors which is out of scope for this report.

Table 2: Material intensities of single family buildings (SF) derived from Reyna and Chester (2015) and as reported in Heeren and Fishman (2019) and Marinova et al. (2020). Please note that the first database mentioned refers to gross while the latter refers to net floor area (difference net-gross in Marinova et al. reported as factor 1.1 does not explain divergence)

	Concrete		Steel	
Cohort / material & source	Heeren & Fishman	Marinova et al.	Heeren & Fishman	Marinova et al.
SF <1950	360.6	-	8.6	5.2
SF 1950-1990/1	373.5	270.6	10.8	3.8
SF >1990	510.2	270.6	7.5	2.9

The discussed limitations complicate accurate and transparent data use which in practice can lead to large variance (see next sub-section); and emphasize the efforts still required towards well-documented and representative material intensity datasets. A main challenge will be to cater for the heterogeneity of buildings by types, construction period and geography while working from case studies on individual buildings or buildings groups towards data representative of the total building stock.

Using material intensity data

As for data documentation, also the application of material intensities in modelling studies is often times intransparent, making it difficult to trace the exact origin of used material intensities. For many studies, intensities are calculated ad-hoc, often without providing detailed documentation (Heeren and Fishman 2019). In our sample, some studies referred to the mentioned database sources but did not report subsequent data manipulation (e.g. averaging, (dis)aggregation per building type) in a way that would allow for reproducing results. Comparatively good documentation was achieved in Pauliuk et al. (2021) who exhibit detailed documentation for each country by material group. However, also for this study it was challenging to track to individual studies within intensity databases. Making used data entirely traceable and results reproducible remains as a major challenge in assessments of material cycles. Particularly important points which can lead to different results and require accurate documentation are:

First, the choice on how to combine multiple datapoints for the *same building type*: Marinova et al. (2020)[8], for instance, came up with a concrete intensity of 472 kg/m² for U.S. detached houses by averaging the available four datapoints assigned to this building type in different time periods in their

[8] Marinova et al. (2020) report intensities per net floor area

database. Due to the wide range of intensities among datapoints (271-795 kg/m²), selective choice, e.g. according to time period, can have major influence on derived (average) material intensities.

Second, the representation of heterogeneity of building types along the dimensions construction type, end-use, time and geography:

- Regarding construction type, the studies in our sample represented 3-51 archetypes (see methods). Some studies aggregated material intensity data for *different building types* into average intensities, which can lead to bias in comparison to studies that use disaggregated intensities. To obtain fitting categories for material intensities, Mastrucci et al. (2021) aggregated detached and row houses from Marinova et al. (2020) into one type category by weighting intensities via reported type shares. However, shares for building types in Marinova et al. (2020) are time-static and largely based on global averages. A study that represents intensities more disaggregated and has regional and dynamic (time) data on activity of building types, such as Berrill and Hertwich (2021),[9] can come to very different results.
- Regarding end-use type, the categorization of buildings towards different end-uses (e.g., residential vs. non-residential use of buildings) might on the one hand lead to assignment of ill-fitting material intensities and on the other hand shift material stocks into the wrong end-use categorization (especially when mixed uses are present). This might apply to different degrees for studies using different data and methods and partially explain result variation.[10]
- Regarding time and geography, studies might use average material intensities referring to other years/vintages and regions when fitting material intensities are not available, which might lead to differences compared to time-dynamic/regional studies (e.g. Marinova et al. (2020)).

In addition, the system boundaries for material intensities have to be matched to those of activity data (e.g. the same definition of floor area). To enable this and for general transparency we need to get better in facilitating traceability of model data, and in reproducing workflows that enable other researchers to repeat original analyses.

[9] Berrill & Hertwich (2021) do not use data from Marinova et al. (2020)

[10] For our results, the aggregate category 'all buildings' showed divergence of material stock results for an overlapping materials scope and amongst the three analyzed studies by factor ~1.9 (Figure S6). Compared to the divergence of the three studies for residential (factor ~1.7) and non-residential buildings (factor ~2.4), divergence was thus not substantially reduced via avoiding end-use allocation. Info regarding end-use allocation in studies: Frantz et al (in preparation) reported that for remote-sensing, the identification of building type from satellite images was challenging. However, authors stated that the distinction of broad categories such as residential vs. commercial/non-residential buildings, which were identified by textural context, worked rather well. Similar categorization problems can occur for statistics-based methods too (e.g. for mixed use).

Conclusions

The illustrated divergence of U.S. material stock estimates - amongst others caused by scarce and non-representative data sources and their heterogenous data processing, and non-matching system boundaries - showcases the need for continued and intensified community efforts towards harmonizing available and obtaining additional data for modelling material cycles. In particular, improved documentation and publication of entire study workflows will be crucial for enabling comprehension of study differences, hopefully enabling simplified reproducibility and convergence of results in the mid-term.

Special efforts seem to be warranted to extend available database seeds for material intensities, in order to achieve a better overview of heterogeneity, data uncertainty and to work from data derived for individual or groups of buildings/technologies towards datasets ~representative of the total technology stock in the long-term.[11] Improved documentation for reproducibility in that regard is urgently required. An easy but powerful example for this might be the explicit description or functional linking of the derivation of material intensities from original studies like partially done in Marinova et al. (2020). Regarding activity data, closer attention to adjusting and harmonizing data system boundaries towards the purpose of material cycle modelling or even collecting data in new surveys (e.g. away from a purely energy modelling perspective), as well as better understanding (non-market) material production, trade, consumption and end-use would be major goals.

The large uncertainty attached to current accounts of material cycles warrants scenario approaches and sensitivity analysis to manage this uncertainty. These approaches can help to evaluate the robustness of results with regards to the observed range of material stock-flow estimates, in order to conclude on the contribution that material management can make to decarbonization. If improved upon, the independent data sources and methods evaluated herein can make further contributions towards triangulating the 'real world quantity' of material stocks and flows.

[11] At the moment, only the top-down, inflow-driven method calculates results representative for the whole building stock, but has its own limitations with regards to sensitivity to lifetimes and large uncertainty attached to end-use shares (data).

International Institute for Applied Systems Analysis
IIASA www.iiasa.ac.at

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria

Email: permissions@iiasa.ac.at

Supplementary information (SI)

SI.1 Tables and figures to support main text

*Table S3: MESSAGEix material stocks in power technologies, as well as Deetman et al. (2021), mapped to Kalt et al. categories (10^6 tons). * very small*

	Steel					Aluminum					Cement					Copper			
	MESSAGEix	Kalt_low	Kalt_med	Kalt_high	Deetman	MESSAGEix	Kalt_low	Kalt_med	Kalt_high	Deetman	MESSAGEix	Kalt_low	Kalt_med	Kalt_high	Deetman	Kalt_low	Kalt_med	Kalt_high	Deetman
Nuclear	8.7	7.9	10.2	12.5	5.1	0.113	0.023	0.068	0.113	0.009	7.2	6.8	11.1	15.3	4.1	0.2	0.9	1.7	0.1
Hydro total	61.1	3.7	8.3	12.8	13.4	1.242	0.049	0.105	0.161	-	38.1	69.1	145.1	221.1	80.8	0.1	0.7	1.3	0.3
Tidal, wave	-	*	*	*	-	-	*	*	*	-	-	*	*	*	-	*	*	*	-
Geothermal	-	*	0.3	0.5	-	-	0.009	0.013	0.017	-	-	*	*	*	-	*	*	*	-
Wind Onshore	14.0	10.0	14.2	18.4	9.0	0.188	0.078	0.268	0.457	0.065	4.4	3.8	7.5	11.3	4.9	0.1	0.4	0.6	0.2
Wind Offshore	0.01	0.01	0.01	0.02	-	0.00007	0.00002	0.00008	0.00013	-	0.001	-	0.003	0.007	-	*	*	*	-
Coal	11.8	8.6	18.6	28.6	24.6	0.626	0.057	0.458	0.859	0.147	5.1	4.3	11.9	19.4	15.5	0.2	0.6	0.9	0.4
Gas	9.2	4.5	13.5	22.5	5.5	0.588	0.045	0.383	0.720	0.174	4.0	3.1	4.1	5.1	2.7	0.3	0.5	0.7	0.5
Oil	1.2	0.7	1.5	2.3	4.7	0.076	0.030	0.047	0.063	0.039	0.5	0.4	0.4	0.5	2.1	*	*	0.1	0.1
Solar PV	1.0	0.9	2.4	4.0	3.0	0.315	0.815	1.734	2.653	0.203	0.4	0.2	0.8	1.5	-	0.1	0.1	0.2	0.1
Solar CSP	0.8	0.3	0.9	1.5	0.9	0.025	0.005	0.023	0.042	0.009	0.3	0.0	0.1	0.2	0.3	*	0.01	0.01	0.01
Bioenergy & MSW	1.2	1.4	3.8	6.3	0.1	0.008	0.019	0.044	0.068	0.001	0.4	1.1	1.6	2.0	0.4	0.03	0.05	0.07	0.03
Other	-	-	-	-	0.9	-	-	-	-	0.013	-	-	-	-	0.6	-	-	-	0.01
Total	109.1	37.9	73.7	109.5	67.2	3.2	1.1	3.1	5.2	0.7	60.2	88.8	182.7	276.5	111.5	1.0	3.3	5.5	1.7

*Table S4: MESSAGEix power technologies (Unlu et al., in preparation), as well as Deetman et al. (2021), material intensities mapped to Kalt et al. categories (10^6 tons/GW). Please mind the different units for steel, cement and aluminum, copper. * very small*

	Steel								Cement							
10^6 tons/GW	MESSAGEix_low	MESSAGEix_high	Kalt_low	Kalt_med	Kalt_high	Deetman_av	Deetman_low	Deetman_high	MESSAGEix_low	MESSAGEix_high	Kalt_low	Kalt_med	Kalt_high	Deetman_av	Deetman_low	Deetman_high
Nuclear	0.08	0.08	0.07	0.09	0.11	0.04	0.04	0.04	0.06	0.06	0.06	0.10	0.14	0.04	0.04	0.04
Hydro total	0.44	0.46	0.02	0.05	0.07	0.07	0.07	0.07	0.27	0.29	0.38	0.79	1.21	0.43	0.43	0.43
Tidal, wave	-	-	0.02	0.05	0.07	-	-	-	-	-	0.38	0.79	1.21	-	-	-
Geothermal	-	-	0.02	0.11	0.20	-	-	-	-	-	0.02	0.02	0.02	-	-	-
Wind Onshore	0.15	0.17	0.10	0.14	0.18	0.12	0.12	0.12	0.05	0.05	0.04	0.08	0.11	0.07	0.07	0.07
Wind Offshore	0.34	0.42	0.25	0.40	0.55	0.16	0.16	0.16	0.05	0.06	-	0.12	0.24	0.08	0.08	0.08
Coal	0.04	0.04	0.03	0.07	0.10	0.08	0.03	0.11	0.02	0.02	0.02	0.04	0.07	0.05	0.02	0.05
Gas	0.02	0.02	0.01	0.03	0.05	0.03	*	0.11	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.05
Oil	0.02	0.02	0.02	0.03	0.05	0.08	0.07	0.09	0.01	0.01	0.01	0.01	0.01	0.03	0.03	0.03
Solar PV	0.04	0.06	0.02	0.06	0.09	0.15	0.15	0.15	0.01	0.02	*	0.02	0.03	-	-	-
Solar CSP	0.48	0.49	0.17	0.51	0.85	0.58	0.58	0.58	0.16	0.17	0.02	0.07	0.13	0.20	0.20	0.20
Bioenergy & MSW	0.16	0.17	0.07	0.20	0.33	0.03	0.01	0.04	0.05	0.05	0.06	0.08	0.11	0.03	0.01	0.04

	Aluminum								Copper					
10^3 tons/GW	MESSAGEix_low	MESSAGEix_high	Kalt_low	Kalt_med	Kalt_high	Deetman_av	Deetman_low	Deetman_high	Kalt_low	Kalt_med	Kalt_high	Deetman_av	Deetman_low	Deetman_high
Nuclear	0.98	0.98	0.20	0.60	1.00	0.08	0.08	0.08	1.40	8.20	15.00	0.76	0.76	0.76
Hydro total	8.91	9.27	0.27	0.57	0.88	-	-	-	0.50	3.69	6.88	1.70	1.70	1.70
Tidal, wave	-	-	0.27	0.57	0.88	-	-	-	0.50	3.69	6.88	-	-	-
Geothermal	-	-	3.80	5.30	6.80	-	-	-	1.00	1.70	2.40	-	-	-
Wind Onshore	1.73	2.49	0.78	2.68	4.58	0.87	0.87	0.87	1.33	3.64	5.95	2.73	2.73	2.73
Wind Offshore	2.47	3.10	0.78	2.68	4.58	1.44	1.44	1.44	1.33	6.78	12.23	5.57	5.57	5.57
Coal	2.18	2.18	0.20	1.60	3.00	0.50	0.50	0.50	0.70	1.95	3.20	3.16	1.15	6.28
Gas	1.21	1.21	0.10	0.85	1.60	0.46	0.38	0.65	0.60	1.10	1.60	2.72	0.38	6.28
Oil	1.21	1.21	0.65	1.00	1.35	0.60	0.60	0.60	0.65	0.93	1.20	3.96	0.76	5.90
Solar PV	10.41	18.91	18.44	39.22	60.00	10.18	10.18	10.18	1.32	2.98	4.64	6.34	6.34	6.34
Solar CSP	13.47	15.46	2.60	13.30	24.00	5.50	5.50	5.50	0.80	3.90	7.00	3.15	3.15	3.15
Bioenergy & MSW	1.13	1.17	1.00	2.25	3.50	0.21	0.05	0.26	1.50	2.50	3.50	2.20	0.76	3.63

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria

Email: permissions@iiasa.ac.at

Table S5: MESSAGEix power technology capacities, as well as Deetman et al. (2021), mapped to Kalt et al. (GW)

Technology/year	2015	2017	2015
Model:	Unlu et al. (MESSAGEix)	Kalt et al.	Deetman et al.
Nuclear	115.4	113.2	116.8
Hydro - Run-of-river	-		
Hydro - Reservoir	-		
Hydro - Pumped storage	-		
Hydro total	139.2	183.4	189.5
Tidal, wave	-	0.02	-
Geothermal	-	2.5	-
Wind Onshore	89.2	99.8	74.4
Wind Offshore	0.03	0.03	-
Coal	287.7	286.4	291.1
Gas	485.4	450.2	339.5
Oil	62.8	46.6	64.3
Solar PV	28.1	44.2	20.0
Solar CSP	1.7	1.8	1.6
Bioenergy & MSW	6.9	19.3	11.3
Other	-	-	5.8
Total	1,216.4	1,247.5	1,114.3

*Table S6: Activity levels for floor area for stock-driven studies of residential buildings. Definitions of floor area might differ and are thus not always exactly comparable (see methods section). *floor area estimated from above ground building volume and building footprint (see SI.2)*

Building type [10^9 m²]	Berrill & Hertwich (2021)	Mastrucci et al. (2021)	Frantz et al. (in preparation)*	Pauliuk et al. (2021)	U.S. Energy Information Administration (2018)
Year	2019	2020	~2018	2015	2015
Single-family	18	24.5	35-40	18.7	18.7
Multi-family	1	3.1	4.4-4.5	2.6	2.6
Other residential	3.2	-	6.2	0.8	0.8

Table S7: Material stocks of residential buildings in the USA, estimated for the indicated year. For source studies please refer to the methods section in the main manuscript.

residential buildings (10^6 tons)	Pauliuk et al. [2015]	Berrill & Hertwich [2019]	Mastrucci et al. [2020]	Frantz et al. [~2018]	Streeck [2017]	Streeck [2017] all end-uses
Steel	232	208	825	1,024	917	3,653
Aluminum	88		114	113	20	125
Copper	33		30	8	20	80
Plastics	992				164	602
Cement	1,205	468	3,155			
Wood	2,263	1,273	1,533	2,341	2,378	2,961
Paper					47	859
Concrete aggregates	8,022		17,879			
Concrete		6,678		22,812	12,303	29,129
Fiberglass		998				
Glass		164	79	288	30	119
Gypsum		512				
Insulation		41		207		
Sand&Gravel		1,757		5,047	880	35,703
Other metals				5		
Bricks				2,835	528	783
Other minerals				5,001		
Bitumen				48		
Other fossil fuel based				791		
Other biomass				1,281		
Other		295		967		
Total	12,836	12,394	23,616	42,768	17,287	74,013

Table S8: Average material intensities for residential buildings and indicated studies/years.

Material (intensities in kg/m²)	Berrill & Hertwich (2021)	Mastrucci et al. (2021)	Frantz et al. (in preparation)*	Pauliuk et al. (2021)
Year	2019	2020	ca. 2018	2015
Bricks			55.7-62.4	
Flat glass	7.4	2.9	5.7-6.4	
Cement	21.1			
Concrete	300.9	765.0	447.9-502.1	418.1
Bitumen			1.0-1.1	
Wood	57.4	55.8	46.0-51.5	102.6
Iron and steel	9.4	30.0	20.1-22.5	10.5
Aluminum		4.2	2.2-2.5	4.0
Copper		1.1	0.1-0.2	1.5
Plastics				
Aggregates (not for concrete, asphalt)	79.2		99.1-111.1	
Insulation	1.9			
Fiberglass	45.0			
Gypsum	23.1			
Plastics				45.0
Other metals			0.1	
Other minerals			98.2-110.1	
Other biomass			25.1-28.2	
Other fossil fuel based			15.5-17.4	
All other	13.3		19.0-21.3	

Table S9: Material stocks of non-residential/commercial buildings in the USA (Streeck and Frantz et al.) and USA + Canada (Mastrucci et al), estimated for the indicated year.

Materials / studies	Mastrucci et al. [2020]	Streeck [2017]	Frantz et al. [~2018]
Bricks		173	300
Container		-	
Flat glass	43	28	383
Cement	1,003	741	1,842
Concrete		-	
Bitumen		-	58
Asphalt		-	
Paper		20	
Wood	391	233	85
IronSteel	657	568	1,224
Aluminum	25	13	15
Copper	1	11	2
Other metals		-	1
Plastics		94	
Aggregates, concrete&asphalt	5,686	4,180	10,383
Aggregates other		351	4,842
All other minerals			743
Other biomass-based materials			21
All other fossil fuel based materials			3
Insulation			33
All other materials			166
Total	7,808	6,411	20,100

SI.2 Conversion of building volume and area to floor area

There are three ways to calculate gross floor area (gfa) from the data provided by Frantz et al. (in preparation). One draws on above ground building volume (agbv), one on gross (building) footprint, and the third combines information of both indicators:

$$gfa = \frac{agbv}{floor\ height\ * \left(1 + \frac{roof\ volume\ factor}{building\ height}\right)} \tag{1}$$

$$gfa = \ gross\ footprint * number\ of\ floors \tag{2}$$

$$gfa = \ gross\ footprint * \frac{agbv/_{gross\ footprint}}{floor\ height} \tag{3}$$

We used the third one (3), which instead of assuming number of floors per building type (2), derives average building height by dividing agbv by gross footprint, and then uses an estimate of average floor height to estimate average number of floors in (2). We assume that the floor height is a parameter that varies less than number of floors and thus results in a better estimate. In comparison to the first option, options (2-3) do not include roof volume, which can further bias the floor area estimate. For the parameters in above equations, we leaned on the data points collected by Frantz et al. (in preparation) to calculate material intensities (see SI.4).

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria

Email: permissions@iiasa.ac.at

SI.3 Additional results

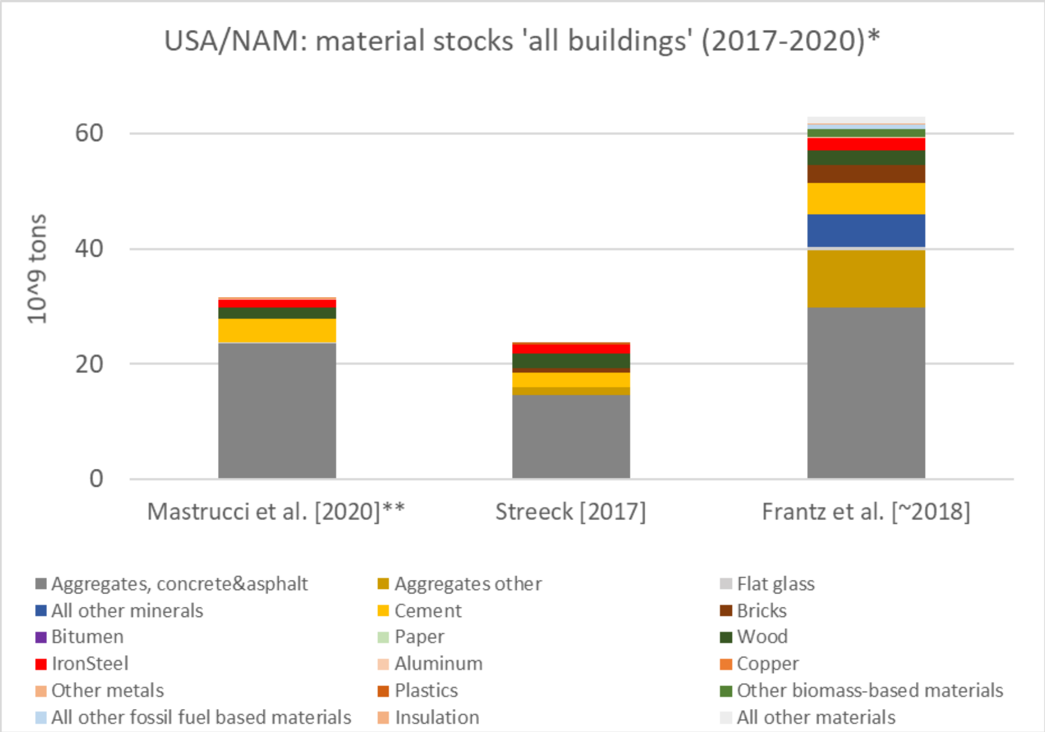

*Figure S6: Material stocks for all buildings in the USA (Streeck in preparation; Frantz et al. in preparation; Mastrucci et al. 2021) *please mind that the year differs slightly between studies, indicated by [year] **mind that the geographical reference differs - Mastrucci et al. (2021) referring to USA and Canada.*

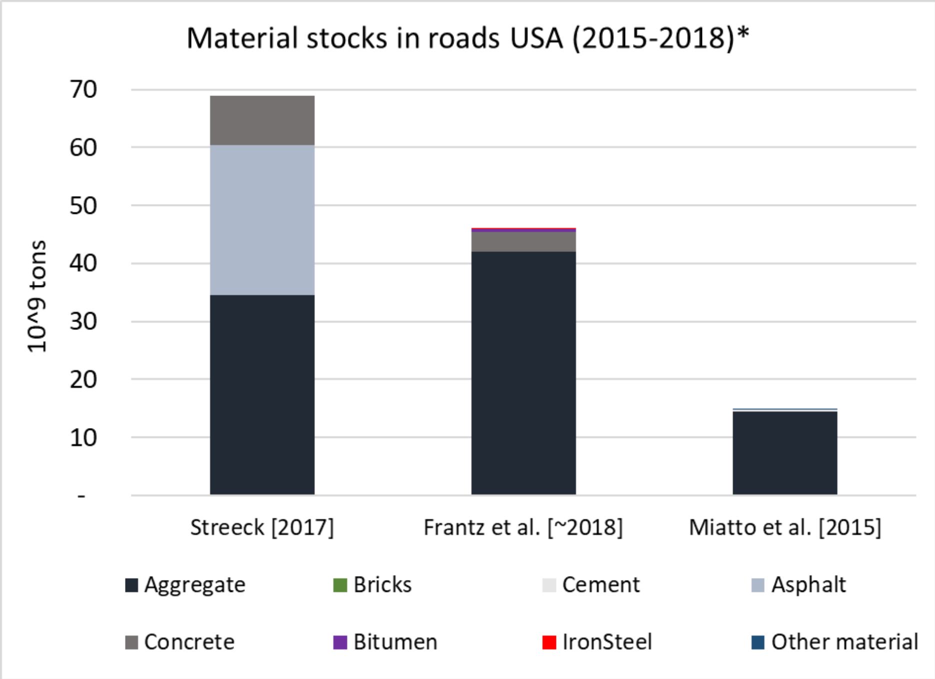

*Figure S7: Material stocks for roads in the USA (Streeck in preparation; Frantz et al. in preparation; Miatto et al. 2017). *please mind that the year differs slightly between studies, indicated by [year]*

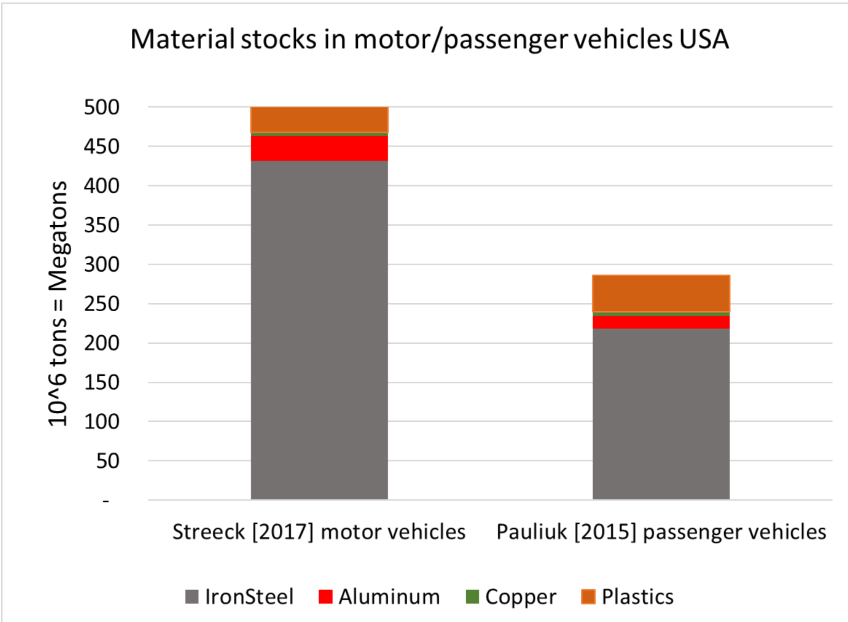

Figure S8: Material stocks for motor/passenger vehicles in the USA (Streeck in preparation; Pauliuk et al. 2021). Please mind that Pauliuk et al. only refers to passenger vehicles, while Streeck et al. include all motor vehicles; and the year differs slightly between studies, indicated by [year].

International Institute for Applied Systems Analysis
IIASA www.iiasa.ac.at

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria

Email: permissions@iiasa.ac.at

SI.4 Data

For access to the data SI, please contact the author to receive permission for an associated private GitHub repository.

Address: IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria

Email: permissions@iiasa.ac.at

References

Arderne, C.; Zorn, C.; Nicolas, C.; Koks, E. E. (2020): Predictive mapping of the global power system using open data. In *Scientific data* 7 (1), p. 19. DOI: 10.1038/s41597-019-0347-4.

Arehart, Jay H.; Pomponi, Francesco; D'Amico, Bernardino; Srubar, Wil V. (2021): A New Estimate of Building Floor Space in North America. In *Environmental Science & Technology* 55 (8), pp. 5161–5170. DOI: 10.1021/acs.est.0c05081.

Arvesen, Anders; Luderer, Gunnar; Pehl, Michaja; Bodirsky, Benjamin Leon; Hertwich, Edgar G. (2018): Deriving life cycle assessment coefficients for application in integrated assessment modelling. In *Environmental Modelling & Software* 99, pp. 111–125. DOI: 10.1016/j.envsoft.2017.09.010.

Berrill, Peter; Hertwich, Edgar G. (2021): Material flows and GHG emissions from housing stock evolution in US counties, 2020–60. In *Buildings and Cities* 2 (1), pp. 599–617. DOI: 10.5334/bc.126.

Cao, Zhi; Shen, Lei; Liu, Litao; Zhao, Jianan; Zhong, Shuai; Kong, Hanxiao; Sun, Yanzhi (2017): Estimating the in-use cement stock in China: 1920–2013. In *Resources, Conservation and Recycling* 122, pp. 21–31. DOI: 10.1016/j.resconrec.2017.01.021.

Chen, Wei-Qiang; Graedel, T. E. (2015): Improved alternatives for estimating in-use material stocks. In *Environmental Science & Technology* 49 (5), pp. 3048–3055. DOI: 10.1021/es504353s.

Chen, Wei-Qiang (2017): Dynamic Product-Level Analysis of In-Use Aluminum Stocks in the United States. In *Journal of Industrial Ecology* 22 (6), pp. 1425–1435. DOI: 10.1111/jiec.12710.

Deetman, S.; Boer, H. S. de; van Engelenburg, M.; van der Voet, E.; van Vuuren, D. P. (2021): Projected material requirements for the global electricity infrastructure – generation, transmission and storage. In *Resources, Conservation and Recycling* 164, p. 105200. DOI: 10.1016/j.resconrec.2020.105200.

Deetman, Sebastiaan; Marinova, Sylvia; van der Voet, Ester; van Vuuren, Detlef P.; Edelenbosch, Oreane; Heijungs, Reinout (2020): Modelling global material stocks and flows for residential and service sector buildings towards 2050. In *Journal of Cleaner Production* 245, p. 118658. DOI: 10.1016/j.jclepro.2019.118658.

Fannie Mae (2021): Selling Guide, B4-1.3-05, Improvements Section of the Appraisal Report. Available online at https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B4-Underwriting-Property/Chapter-B4-1-Appraisal-Requirements/Section-B4-1-3-Appraisal-Report-Assessment/1032992541/B4-1-3-05-Improvements-Section-of-the-Appraisal-Report-09, checked on 9/28/2022.

Frantz, David; Wiedenhofer, Dominik; Baumgart, André; Haberl, Helmut; Hostert, Patrick (in preparation): High-resolution material stock maps for the USA.

Haberl, Helmut; Wiedenhofer, Dominik; Schug, Franz; Frantz, David; Virág, Doris; Plutzar, Christoph et al. (2021): High-Resolution Maps of Material Stocks in Buildings and Infrastructures in Austria and Germany. In *Environmental Science & Technology* 55 (5), pp. 3368–3379. DOI: 10.1021/acs.est.0c05642.

Heeren, Niko; Fishman, Tomer (2019): A database seed for a community-driven material intensity research platform. In *Scientific data* 6 (1), p. 23. DOI: 10.1038/s41597-019-0021-x.

Hertwich, Edgar (2019): The Carbon Footprint of Material Production Rises to 23% of Global Greenhouse Gas Emissions. DOI: 10.31235/osf.io/n9ecw.

Kalt, Gerald; Thunshirn, Philipp; Haberl, Helmut (2021a): A global inventory of electricity infrastructures from 1980 to 2017: Country-level data on power plants, grids and transformers. In *Data in brief* 38, p. 107351. DOI: 10.1016/j.dib.2021.107351.

Kalt, Gerald; Thunshirn, Philipp; Wiedenhofer, Dominik; Krausmann, Fridolin; Haas, Willi; Haberl, Helmut (2021b): Material stocks in global electricity infrastructures – An empirical analysis of the power sector's stock-flow-service nexus. In *Resources, Conservation and Recycling* 173 (4), p. 105723. DOI: 10.1016/j.resconrec.2021.105723.

Kermeli, Katerina; Edelenbosch, Oreane Y.; Crijns-Graus, Wina; van Ruijven, Bas J.; van Vuuren, Detlef P.; Worrell, Ernst (2021): Improving material projections in Integrated Assessment Models: The use of a stock-based versus a flow-based approach for the iron and steel industry. In *Energy* 122 (1), p. 122434. DOI: 10.1016/j.energy.2021.122434.

Krausmann, Fridolin; Wiedenhofer, Dominik; Haberl, Helmut (2020): Growing stocks of buildings, infrastructures and machinery as key challenge for compliance with climate targets. In *Global Environmental Change* 61, p. 102034. DOI: 10.1016/j.gloenvcha.2020.102034.

Krey, V.; Havlik, P.; Kishimoto, P. N.; Fricko, O.; Zilliacus, J.; Gidden, M. et al. (2020): MESSAGEix-GLOBIOM Documentation - 2020 release.

Lamb, William F.; Wiedmann, Thomas; Pongratz, Julia; Andrew, Robbie; Crippa, Monica; Olivier, Jos G. J. et al. (2021): A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. In *Environ. Res. Lett.* 16 (7), p. 73005. DOI: 10.1088/1748-9326/abee4e.

Lanau, Maud; Liu, Gang; Kral, Ulrich; Wiedenhofer, Dominik; Keijzer, Elisabeth E. E.; Yu, Chang; Ehlert, Christina (2019): Taking stock of built environment stock studies: Progress and prospects. In *Environmental Science & Technology*. DOI: 10.1021/acs.est.8b06652.

Marinova, Sylvia; Deetman, Sebastiaan; van der Voet, Ester; Daioglou, Vassilis (2020): Global construction materials database and stock analysis of residential buildings between 1970-2050. In *Journal of Cleaner Production* 247, p. 119146. DOI: 10.1016/j.jclepro.2019.119146.

Mastrucci, Alessio; van Ruijven, Bas; Byers, Edward; Poblete-Cazenave, Miguel; Pachauri, Shonali (2021): Global scenarios of residential heating and cooling energy demand and CO2 emissions. In *Climatic Change* 168 (3-4). DOI: 10.1007/s10584-021-03229-3.

Miatto, Alessio; Schandl, Heinz; Wiedenhofer, Dominik; Krausmann, Fridolin; Tanikawa, Hiroki (2017): Modeling material flows and stocks of the road network in the United States 1905–2015. In *Resources, Conservation and Recycling* 127, pp. 168–178. DOI: 10.1016/j.resconrec.2017.08.024.

Moura, Maria Cecilia P.; Smith, Steven J.; Belzer, David B. (2015): 120 Years of U.S. Residential Housing Stock and Floor Space. In *PloS one* 10 (8), e0134135. DOI: 10.1371/journal.pone.0134135.

Müller, Esther; Hilty, Lorenz M.; Widmer, Rolf; Schluep, Mathias; Faulstich, Martin (2014): Modeling Metal Stocks and Flows: A Review of Dynamic Material Flow Analysis Methods. In *Environmental Science & Technology* 48 (4), pp. 2102–2113. DOI: 10.1021/es403506a.

NREL (2020): ResStock Housing Characteristics. ResStock v2.3.0. Available online at https://github.com/NREL/OpenStudio-BuildStock/tree/master/project_national/housing_characteristics.

Pauliuk, Stefan (2017): Industrial Ecology Data Commons. Available online at http://www.database.industrialecology.uni-freiburg.de/.

Pauliuk, Stefan; Heeren, Niko (2020): ODYM—An open software framework for studying dynamic material systems: Principles, implementation, and data structures. In *Journal of Industrial Ecology* 24 (3), pp. 446–458. DOI: 10.1111/jiec.12952.

Pauliuk, Stefan; Heeren, Niko; Berrill, Peter; Fishman, Tomer; Nistad, Andrea; Tu, Qingshi et al. (2021): Global scenarios of resource and emission savings from material efficiency in residential buildings and cars. In *Nature communications* 12 (1), p. 5097. DOI: 10.1038/s41467-021-25300-4.

Pauliuk, Stefan; Wang, Tao; Müller, Daniel B. (2013): Steel all over the world: Estimating in-use stocks of iron for 200 countries. In *Resources, Conservation and Recycling* 71, pp. 22–30. DOI: 10.1016/j.resconrec.2012.11.008.

Reyna, Janet L.; Chester, Mikhail V. (2015): The Growth of Urban Building Stock: Unintended Lock-in and Embedded Environmental Effects. In *Journal of Industrial Ecology* 19 (4), pp. 524–537. DOI: 10.1111/jiec.12211.

Stehfest, Elke; van Vuuren, Detlef P.; Bouwman, Arno; Kram, Tom (2014): Integrated Assessment of Global Environmental Change with IMAGE 3.0. Model description and policy applications. Available online at https://www.pbl.nl/en/publications/integrated-assessment-of-global-environmental-change-with-IMAGE-3.0.

Streeck, Jan (in preparation): Operationalizing the stock-flow-service nexus for economy-wide material flow analysis - an explorative implementation for the case study USA.

Streeck, Jan; Dammerer, Quirin; Wiedenhofer, Dominik; Krausmann, Fridolin (2021): The role of socio-economic material stocks for natural resource use in the United States of America from 1870 to 2100. In *Journal of Industrial Ecology* 140, p. 1880. DOI: 10.1111/jiec.13166.

Streeck, Jan; Pauliuk, Stefan; Wieland, Hanspeter; Wiedenhofer, Dominik (in revision_a): A review of methods to trace material flows into final products in dynamic material flow analysis - from industry shipments in physical units to monetary input-output tables.

Streeck, Jan; Wieland, Hanspeter; Pauliuk, Stefan; Plank, Barbara; Nakajima, Kenichi; Wiedenhofer, Dominik (in revision_b): A review of methods to trace material flows into final products in dynamic material flow analysis: a comparative application of methods to the USA and EXIOBASE3 regions.

Tanikawa, Hiroki; Fishman, Tomer; Hashimoto, Seiji; Daigo, Ichiro; Oguchi, Masahiro; Miatto, Alessio et al. (2021): A framework of indicators for associating material stocks and flows to service provisioning: Application for Japan 1990–2015. In *Journal of Cleaner Production* 285, p. 125450. DOI: 10.1016/j.jclepro.2020.125450.

U.S. Energy Information Administration (2018): Residential Energy Consumption Survey (RECS). Table HC10.1 Total square footage of U.S. homes, 2015. Available online at https://www.eia.gov/consumption/residential/data/2015/hc/php/hc10.1.php, updated on May 2018, checked on 8/9/2022.

U.S. Energy Information Administration (2021): Commercial Buildings Energy Consumption Survey (CBECS). Table B7. Building size, floorspace, 2018. Available online at https://www.eia.gov/consumption/commercial/data/2018/bc/html/b7.php, checked on 8/9/2022.

United States Census Bureau (2022): Characteristics of New Housing. Definitions - Survey of Constuction. Available online at https://www.census.gov/construction/chars/definitions/#f, checked on 9/28/2022.

Unlu, Gamze; Min, Jihoon; Kishimoto, Paul; Maczek, Florian; Krey, Volker (in preparation): MESSAGEix-Materials (tentative).

US Census Bureau (2021): American Community Survey Data. Available online at https://www.census.gov/programs-surveys/acs/data.html.

van Vuuren, Detlef P.; Stehfest, Elke; Gernaat, David E.H.J.; Doelman, Jonathan C.; van den Berg, Maarten; Harmsen, Mathijs et al. (2017): Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. In *Global Environmental Change* 42, pp. 237–250. DOI: 10.1016/j.gloenvcha.2016.05.008.

Wiedenhofer, Dominik; Fishman, Tomer; Lauk, Christian; Haas, Willi; Krausmann, Fridolin (2019): Integrating Material Stock Dynamics Into Economy-Wide Material Flow Accounting: Concepts, Modelling, and Global Application for 1900–2050. In *Ecological Economics* 156, pp. 121–133. DOI: 10.1016/j.ecolecon.2018.09.010.

Wiedenhofer, Dominik; Streeck, Jan; Plank, Barbara; Grammer, Benedikt (in preparation): From Economy-Wide Material Flow Accounting to Analysis: Advancing Wiedenhofer et al. (2019).