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Where if? Using spatial, building-stock-driven simulations to explore construction circularity strategies in Gothenburg, Sweden

Jonathan Cohen ^{*} , Maud Lanau , Leonardo Rosado , Jorge Gil 

Department of Architecture and Civil Engineering, Chalmers University of Technology, Sweden

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ABSTRACT

Recycling construction materials can significantly reduce the environmental impact of the construction and demolition sector. However, implementing circularity strategies requires a spatially refined understanding of material stock dynamics. This study introduces a stock-driven and rule-based simulation that forecasts – over space and time – material stocks, flows, and associated embodied carbon resulting from construction, renovation, and demolition activities. It enables the exploration of how urban parameters, such as the recycled content of new constructions, demolition rates, renovation rates, and different types of new construction, influence material flows and embodied carbon.

Using Gothenburg's residential building stock, the simulation's capabilities are demonstrated by tracking eight building materials along with their embodied carbon over time, across the parameters, and for two scenarios: a baseline, and a policy on energy efficiency. Results show that prioritizing renovation over demolition consistently reduces embodied carbon impacts, while increasing material circulation further enhances these benefits. Additionally, aligning new housing typologies with the composition of materials released from demolitions improves resource efficiency, although in the Gothenburg case, varying the share of single- versus multi-family housing has limited influence on overall outcomes.

The primary contribution of this study is the model developed for evaluating the interactions between demolition, renovation, and material circulation in a spatially and temporally explicit manner. The model provides urban planners with actionable insights into the spatiotemporal dynamics of material supply, supporting more informed strategies for transitioning toward a sustainable and circular construction sector.

1. Introduction

The construction and demolition (C&D) sector is responsible for developing, maintaining, and replacing building stocks that provide key services to society (e.g., housing, shelter, and more) (Pauliuk & Müller, 2014). In doing so, the sector generates substantial environmental impacts – both resource-wise, through resource extraction and waste generation, and carbon-wise, through embodied and operational emissions. Environmental targets are being set around the world to dematerialize and decarbonize the construction sector. For example, the European Union set a reduction target of 55% of greenhouse gas emissions by 2030 (90% by 2040) as compared to 1990 (European Commission, 2024), and to increase resource efficiency and minimize waste generation (European Commission, 2020). These regulations intensify pressure on the C&D sector to adopt more resource- and carbon-efficient practices, with the circular economy (CE) being

increasingly regarded as a guiding framework (Alhola et al., 2019; Gallego-Schmid et al., 2020; López Ruiz et al., 2020; Munaro et al., 2020). The EU renovation wave – aiming to cut down emissions and energy consumption from buildings – also translates into construction material demand and waste generation unless CE strategies are implemented (European Commission, 2020). Despite the increased momentum of these strategies, according to Vigier et al. (2023) carbon footprint reductions are low and narrow, especially when looking at actions delivered by leading cities. Moreover, diversity in frameworks to assess CE in cities obscures the identification of effective strategies to move forward a sustainable urban agenda (Papageorgiou et al., 2021).

The concept of circular construction encompasses various aspects, from material reuse and recycling, through design for deconstruction, resource efficient design, circular business models, to data-driven tracking and management of materials to support decision-making (European Circular Economy Stakeholder Platform, 2021). In this

^{*} Corresponding author.

E-mail address: Jonathan.cohen@chalmers.se (J. Cohen).

paper, the focus is set on material recirculation, i.e., material reuse and recycling, and on data-driven support to decision-making. More specifically, the focus is on a known barrier to wide-scale implementation of circularity, namely the lack clarity on the supply of secondary materials that actors may expect (López Ruiz et al., 2020; Purchase et al., 2021). Indeed, construction actors require a solid understanding of the dynamics of construction materials throughout C&D activities, including the too-often oversimplified (or overlooked) renovation activities; those make for a non-negligible part of the sector's material flows and environmental impacts (Li et al., 2022a; Liu et al., 2022).

Gaining knowledge on the dynamics of construction materials was already identified two decades ago as critical to support resource efficiency in the C&D sector and support data-driven policies to address the climate crisis (Rees, 1999; Yeheyis et al., 2013). Until recently, the quantification and analysis of the materials consumed (inflows), discarded (outflows), and accumulated over time in building stocks (material stocks) was primarily performed *a*-spatially, effectively treating the territory under analysis (e.g., a city) as a black box that consumes, accumulates, and discards materials (Athanasiadis et al., 2015; Cohen, 2024; Newman, 1999). Forecast of construction and demolition waste (CDW) quantities has also been performed based on waste statistics, using prediction models and machine learning techniques (inter alia, Fang et al., 2024; Jafari & Mousavi, 2024; Maged et al., 2024; Song et al., 2017). In addition to focusing primarily on pattern detection rather than delivering a prospective, dynamic stock-flow model, these types of studies are not spatially resolved. But the spatialization of information is crucial for construction actors to develop large-scale and long-term circular strategies, such as planning for and implementing a network of secondary material warehouses, moving towards a paradigm of “design according to availability”, and similar strategies (Lanau et al., 2024; Wuyts et al., 2022).

Material stock and flow analysis (MSFA) quantifies the stocks and flows of materials in a system, usually over time, to understand how materials are extracted, used, stored, and discarded. This is widely used in research on the built environment within the fields of industrial ecology, urban metabolism, and the circular economy (Lanau et al., 2019). Over the last decade, researchers in MSFA have developed modelling approaches to enable spatial and/or temporal granularity of model outputs. These model outputs refer to *how much, where, and when* materials are needed for construction, stocked as buildings during their use phase, replaced through renovation and maintenance, and discarded from demolition or deconstruction. As shown in the brief review of MSFA approaches below (Section 2), studies have been conducted across all parts of the temporal spectrum: retrospectively using historical data, statically looking at a specific year, and prospectively through scenario development. In contrast, spatial differentiation of results has only been achieved for retrospective and static studies; results of prospective studies remain largely *a*-spatial (Zhang et al., 2022). The closest precedent to a highly spatially refined *and prospective* MSFA study is that of Heeren and Hellweg (2019a) on the Swiss residential building stock. In their study, the authors advanced a bottom-up, building-level model for Swiss residential stocks using 3D GIS data and probabilistic lifetime modelling. Their framework explicitly links stocks, inflows, and outflows and enables spatially granular prospective analysis. However, as explained by the authors, “the results are only representative for groups with more than ca. 400 buildings”, i.e., the minimum group size needed to maintain the stochastic representativeness of the model.

This persistent lack of spatialization of prospective MSFA complicates the task of guiding actors and policies in the inherently spatial domains of construction and urban planning (Zheng et al., 2025). Actors in these sectors require detailed insights into the spatial dynamics of future construction activities, and into how planning decisions affect the spatial distribution and magnitude of material stocks and flows, and the potential for material recirculation. Moreover, spatial assessment can provide urban policy makers with a fundamental layer of information that can be integrated with green and blue infrastructure, enabling

better decision making (Giacomelli et al., 2025). Accordingly, researchers have been calling for a spatial turn in urban metabolism (Bahers et al., 2022) and industrial ecology (Schiller et al., 2025) research. (Bahers et al., 2022; Schiller et al., 2025).

1.1. Aim, objectives, and methodological contribution

Against this background, the aim of this article is to develop, present, and showcase a *spatially explicit* prospective stock-driven model that simulates future dynamics of construction activities – including new construction, renovation, demolition, and material recirculation – and estimates the associated avoided carbon emissions. To achieve this aim, the following objectives are set: (1) To develop a spatially explicit and rule-based simulation of the material demands and waste generation from residential stock development, and (2) to use the model to explore the impact of different policy scenarios in Gothenburg (Sweden) on the city's resource use and (avoided) carbon emissions.

This study addresses the spatialization gap of prospective MSFA by combining three key modelling approaches: the lifetime approach, the bottom-up approach, and spatially explicit agent-based modelling (ABM). More specifically, the MSFA approach developed in the works of Müller (2006) and Sartori et al. (2016) – which already combines the bottom-up and the lifetime approaches – is spatialized using agent-based modelling (ABM, see next section). The methodological cornerstone of the model introduced in this paper pertains to the solution used to preserve stochastic variability: rather than aggregating buildings into groups large enough to be stochastically representative, repeated city-wide simulations are performed at the building level, producing stochastically representative results for each building. Such integration of spatial simulations with MSFA modelling enhances both the methodological and analytical yields of results. Indeed, the model quantifies and maps the material stocks and flows resulting from different rates of (i) construction, (ii) renovation, (iii) demolition, and (iv) material recovery. With the resolution of the model at the building level, it is possible to identify not only when but also *where* materials are likely to be freed from the stock. The status of each residential building can also be identified at any point in the future, and various circularity scenarios can be explored spatially and temporally.

In this paper, Section 2 clarifies the theoretical background underpinning this study. Then, Section 3 describes the architecture and core principles of the general model, while Section 4 demonstrates the model's applicability and capabilities using the case of residential buildings in Gothenburg (Sweden), including a parameter exploration to quantify changes in material flows (MF) and embodied carbon (EC) (Section 4). Finally, Section 5 discusses the model and implications of adopting such modelling frameworks to address resource efficiency and environmental impacts in the C&D sector.

2. Theoretical background

This section covers the interdisciplinary theoretical background underpinning the modelling method developed in this article. First, the lifetime approach to temporalize MSFA is introduced (Section 2.1), followed by the bottom-up approach that can be used to spatialize MSFA (Section 2.2). Agent-based modelling and simulations are also introduced (Section 2.3), as well as a short summary on the importance of dashboards and visualisation strategies to communicate research outcomes and inform policies and actions.

2.1. Temporalizing material stock and flow analysis: The lifetime approach

The top-down MSFA method builds on the mass-balance principle: the change in stock is the difference between inflows and outflows of material over time. For retrospective studies, inflow data is retrieved from historical statistics. For prospective studies, future inflows can be

assumed to be driven by the demand for floor area, itself tied to socio-economic indicators such as population and number of persons per dwelling (Müller, 2006).

In contrast to inflows, outflow data is notoriously hard to track down. To estimate outflows, the concept of lifetime is used, which refers to the time lag between a material's entry into a system (e.g., building construction) and its subsequent release by demolitions (Krych et al., 2025; Pauliuk et al., 2024). In the lifetime approach, lifetime probability distributions reflect the probability of a product (e.g., a building) to be demolished at a specific time. Demand-driven modelling and lifetime approach have been applied and further developed in numerous studies, especially on the Norwegian dwelling stock (Sandberg et al., 2016, 2017; Sartori et al., 2016). These studies include that of Sartori et al. (2016), who developed a general algorithm that uses lifetime, renovation cycles (both expressed as probability functions), and convolutions to model the construction, renovation, and demolition activities of a building stock.

While these modelling approaches allow for retrospective modelling, the spatialization of the results is highly limited by the low spatial resolution of input data, typically only available at the national or sub-national level. This limitation restricts the possibility of detailed insights into the location and composition of material stocks and flows, which urban planners and local policy need to better plan cities and regions. In this regard, the bottom-up approach has allowed the spatialization of retrospective and static results.

2.2. Spatializing material stock and flow analysis – the bottom-up approach

In the bottom-up approach, material stocks are inventoried “piece by piece” by multiplying two core datasets: the inventory of commodities under analysis, and the commodities' typical material intensities. In such studies, the nature of inventory data shapes the nature of the results: a spatial building inventory allows for spatialized results. Geo-spatial static bottom-up MSFA have been performed at various level of spatial resolution and geographic boundaries, using a variety of data sources such as cadastral data, paper maps, and satellite data (Haberl et al., 2021; Lederer et al., 2021). Floor area of buildings has been used widely as it can be turned into material demand using material intensity coefficients (MIs, average amount of material per dimensional unit) as shown in various contexts such as Sweden, Germany, USA and China (Gontia et al., 2019; Guo et al., 2019; Hu, 2023; Jegen et al., 2025; Kolkwitz, 2025). For instance, in Zhang et al. (2022) a novel methodology is presented to predict building types and therefore estimating in space carbon sinks and hot spots, concluding that CO₂ emissions were greatly affected by building typologies and plot sizes, rather than other factors such as administrative boundaries.

Machine learning is also increasingly used in static MSFA to infer building and component information from data sources that are otherwise incomplete or unavailable. For example, Dai et al. (2024) applied deep learning and computer-vision techniques to imagery and footprint data to recognize and quantify individual building components, supporting material quantification at the element level. Dai et al. (2025) also used machine learning with exterior building features and facade imagery to predict interior component stocks (e.g., interior wall lengths and room configurations) across large UK residential stocks. Even more recently, Q. Liu et al. (2026) used machine learning trained on urban morphology features to predict construction year and floor space to support bottom-up MSFA where detailed 3D data are unavailable. Together, these approaches generate enriched building- and component-level outputs that can be integrated into static bottom-up MSFA frameworks to improve spatial (and material) details.

Retrospectively, the bottom-up approach is used by collating historical maps into a sequence of snapshots at different timesteps (Li et al., 2022b; Miatto et al., 2019; Tanikawa et al., 2015; Tanikawa & Hashimoto, 2009). Stock and flow dynamics at- and between

timesteps can then be inferred using MIs and by comparing building shapes on (digitized) historical maps to identify demolition and new constructions (Li et al., 2022a; Tanikawa & Hashimoto, 2009).

Prospective studies, however, have only been performed with no or very low spatial resolution. To the extent documented in the literature, no study exists that models MSFA of the built environment in both a prospective and highly spatialized fashion (Fig. 1). This modelling gap can be traced back to the key parameter of stock-driven dynamic MFAs: the lifetime probability distribution. More precisely, the application of probability distributions requires a large enough number of buildings (let N denote the number of buildings) for it to be representative (Soonsawad et al., 2022). To fit this requirement, buildings are aggregated into building stock segments of at least N buildings – effectively de-spatializing stock modelling and results. The methodological challenge of spatializing prospective MSFA modelling of construction materials therefore lies in applying the lifetime probability function to individual buildings without losing the spatial resolution. In this context, spatially explicit simulations are particularly useful.

With an N -run spatial simulation on the same building stock, each building is effectively represented N times, and the probabilistic behaviour can be applied to each building while maintaining full building-level spatial resolution.

2.3. Simulating MSFA with agent-based modelling

ABM is a computational modelling approach that simulates the interactions of autonomous agents with defined behaviours and attributes. Due to the complexity of C&D activities, ABM is a relevant modelling approach allowing researchers and policy makers to incorporate agents that account with detailed behaviours, that allows them to interact with their virtual environment and between them, among other features. Urban challenges are seen as complex systems because factors cannot be fixed and are usually interdependent of each other (Fang et al., 2005). For instance, the demolition of a single building follows a complex process where real estate, planning and other societal factors play a central role, making the activity of forecasting demolitions challenging (Kohler & Hassler, 2002; Pomponi & Moncaster, 2017).

ABMs have been used to study various urban challenges such as transportation (Somanath et al., 2025), residential waste sorting (Cohen et al., 2025) or industrial symbiosis (Raimbault et al., 2020). With regards to modelling C&D activities, the use of ABMs remains very limited. In their review on ABM and simulations in the construction sector, Khodabandelu and Park (2021) found only five studies focusing on C&D waste management, all of which used stakeholders as agents. More recently, Yu et al. (2024) developed an ABM simulation for the study of potential material reuse and matchmaking, viewing contractors of deconstruction and construction projects as agents. In a recent contribution, Alibaş et al. (2025) develops an ABM and demonstrates its utility in the German case. Their model successfully described the dynamics of renovations and building operations. Despite being a bottom-up and spatial model, the results are presented at country level, allowing national policy to evaluate their current actions and targets.

Ultimately, the strength of ABMs and their simulations to explore scenarios goes beyond the possibility of including complex interactions, as they enable the consideration of temporal and spatial aspects, and by setting buildings as autonomous agents following specific sets of rules (heuristics), the lifetime model of MSFA can be applied at the building level through repeated simulations.

2.4. Interactive visualizations and decisions support systems

These recent contributions and applications increasingly rely on large datasets and complex methodologies describing material flows, life cycle impacts, and spatially distributed processes. This complexity creates significant challenges for communication, interpretation, and decision-making among diverse stakeholders, including planners,

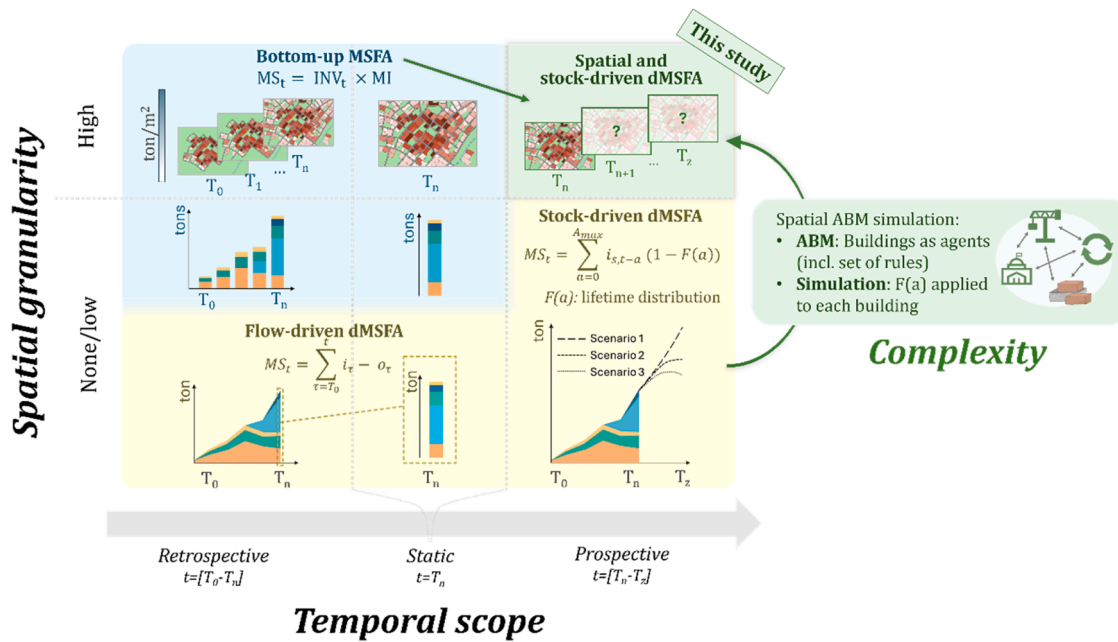


Fig. 1. Spatial resolution and temporal scope of various stock modelling approaches. In blue, the bottom-up material stock and flow approach. In yellow, dynamic MFA approaches. In green, the contribution of this paper: the integration of three approaches. Current MS is calculated using the spatial bottom-up stock approach, to which lifetime is applied to each building through simulations, while ABM is used to apply various rules to the buildings (e.g., probability of demolition depending on building age). The result is a dynamic MSFA that is spatially-refined, prospective, stock-driven, and bottom-up. Acronyms and indices: a : building age (from 0 to A_{max}), $F(a)$: lifetime distribution function, i : inflow at time τ (τ from T_0 to t), INV : inventory, MI : material intensity, MS : material stock, o_τ : outflow at time τ (τ from T_0 to t), t : time, T_0 : past time point, T_n : past or current time point ($T_n > T_0$), T_z : future time point ($T_z > T_n$).

engineers, and policymakers. Interactive visualization has been identified as a key approach to address these challenges, as it enables users to explore complex datasets dynamically while improving transparency and understanding of results (Fishman et al., 2021; Font Vivanco et al., 2019). However, such approaches remain underutilized in practice, and current tools in industrial ecology are often presented through static reports that are difficult to interpret and apply in real-world decision contexts. This limitation is particularly critical in the built environment, where decisions must account for multiple criteria, long time horizons, and spatial variability (Muzioeva et al., 2026). A comprehensive review of visualization strategies and the importance of such techniques as decision support tools has been studied by Chen et al. (2017)

3. A spatially explicit and prospective model of construction material dynamics

The ABM model presented here is based on dynamic MFA (Fig. 1), with each residential building being an agent following heuristics (i.e., rules). It can be used to simulate future material flows and their EC for any given location, if the data inputs (real or synthesised) match the data standard used in the model. This section provides a comprehensive description of the model, beginning with the data requirements and input parameters (Fig. 2a), and then outlining the resulting overall model functioning (Fig. 2b) and its governing rules (Fig. 2c).

Following the presentation of the general model, the case of the residential building stock in Gothenburg is introduced as a case study to illustrate its application to track the flow of various construction materials and its EC. This sub section outlines data sources, processing, assumptions, and scenario definitions used to instantiate the model. Given that data availability differs across local contexts, the data specification described here are specific to Gothenburg.

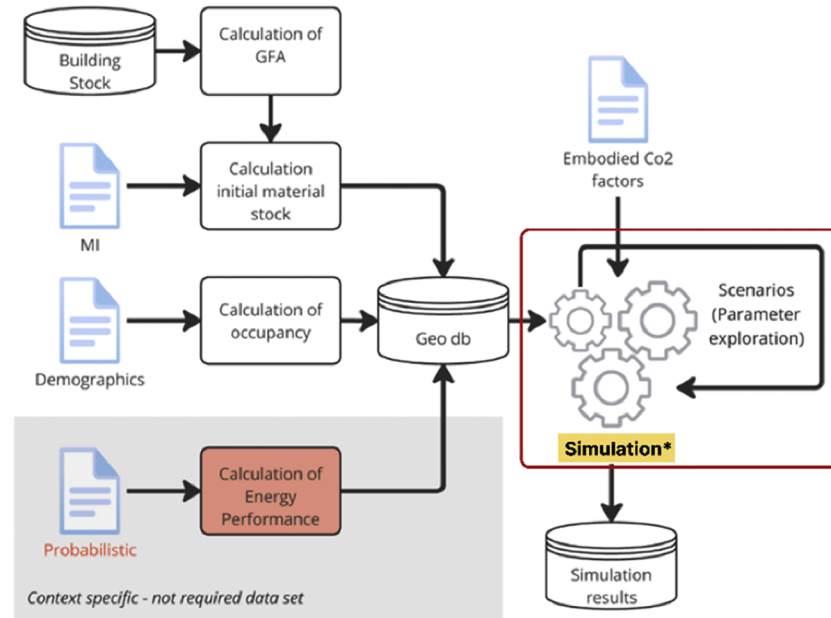
3.1. Data requirements, input parameters, and model outputs

3.1.1. Data requirements

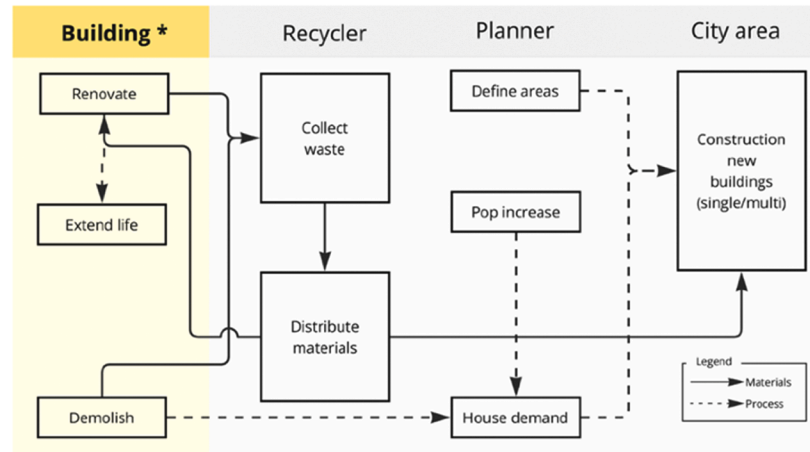
A variety of data sources and domain-specific expertise were combined into the general data architecture and processing steps described in Fig. 2a. Those are summarized below.

- 1- **Building stock geodatabase.** This geodatabase is the foundation of the model. It contains building footprints enriched with archetypal information needed for MI allocation. This information includes each building’s use, year of construction, construction type, and height. Potential demolition year was estimated by adding a stochastic lifetime drawn from a truncated normal distribution. This approach provides variability in building lifetimes without modelling the demolition process explicitly (Petrović et al., 2021).
- 2- **Material intensity (MI).** MIs are values that quantify the amount of material required per unit area/volume of a specific structure. These values often differ depending on the decade of construction, the building structure and the local context. In the model, MIs are used to translate floor area into material requirements.
- 3- **Initial material stocks.** By applying their relevant MIs to each building (based on their archetypal characteristics), the initial material stock in the system is quantified.
- 4- **Population and occupancy factors.** Current population data and growth rates are the primary drivers of building demand. An estimate of the expected number of persons per building or square meter is required to effectively track whether the simulations are hosting an adequate number of residents.
- 5- **Embodied carbon (EC) factors.** EC refers to the total amount of greenhouse gas emissions (or its equivalents) associated with the material and construction processes of a building throughout its lifecycle, but excluding its operational use. In the model, EC factors include the lifecycle stages of raw material extraction, transport, and manufacturing. Operational emissions are out of scope. EC factors translate material quantities into EC, allowing an estimation of the

(a) Data integration architecture



(b) Simulation overview



(c) Building's heuristic

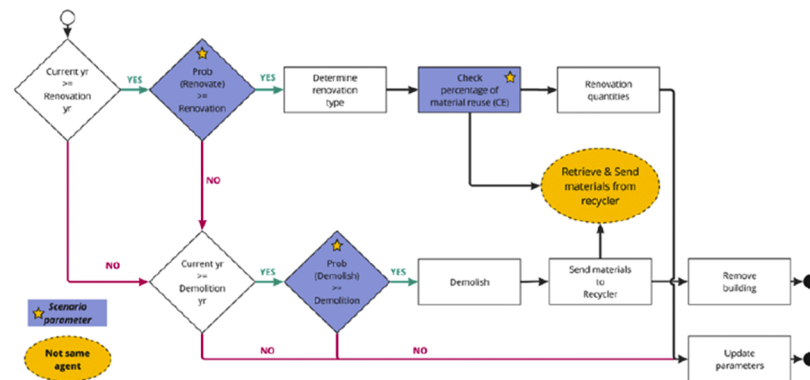


Fig. 2. Model elements and process rules for buildings. (a) general data architecture, including an example of optional data requirements. (b) Overall simulation process, agents and how materials flow in the model, and (c) rules followed by the building agent.

EC burden of construction activities. These factors are material-specific and expressed as weight of carbon equivalent per unit weight of material (kg.CO2e/kg.material). As such, they can be

multiplied by the building material composition (in kg.material) to obtain the building's EC.

6- **Optional datasets.** Additional building data can be integrated into the simulation to support specific inquiries. In this paper, the impact

of a policy mandating renovations of buildings with low energy performance is examined (see policy scenario in Section 3.4.2). Buildings' energy performance certificates (EPC) were thus integrated into the model.

A data set of the footprint of buildings in a given city needs to be enriched with the year of construction, material structure, number of floors (or height) and type of residential building. These parameters should be aligned with a local or approximate material intensity, so that the original database of building footprints can be enriched with the number of materials. Finally, using various data imputation techniques other building characteristics such as energy performance, could be inferred. The specific process of developing this main data will depend on data availability and granularity of each city and local context.

3.1.2. Input parameters

Besides these data sources and modelling assumption, five parameters of interest need to be specified throughout the simulation (see model demonstration in Fig. 4). These input parameters are made variable so that the users or researchers can explore what would happen under specific model configurations.

- **Proportion of single-family buildings.** New constructions can be single- or multi-family buildings. This parameter sets the building typology mix of new construction, determining which MI to use in the simulation.
- **Probability of demolition.** As a building approaches its demolition date, its actual demolition is based on a probabilistic mechanism. To incorporate stochasticity into the model, the modeller can determine the chances of demolition.
- **Probability of renovation.** Renovations follow a similar mechanism to that of demolitions. The modeller can determine the chances of renovation.
- **Recycled rate content of renovations.** Renovating a building triggers a material demand, whether recycled or virgin. This parameter specifies the percentage of recycled materials (in weight) to be used in renovations. When no specific materials are found, virgin ones are used.
- **Recycled content of new constructions.** Similarly to the one above, this parameter determines the percentage of recycled material used in new constructions. When no specific materials are found, virgin ones are used. This variable refers to the level of CE.

3.1.3. Model outputs: Key performance indicators

The model tracks the temporal and spatial evolution of the system regarding four main aspects:

1. **Building characteristics.** The history of all the buildings is recorded. For each simulated year, the model tracks whether a building has been renovated or demolished. Aggregating these attributes yields a description of the building stock at different points in time.
2. **Construction & Demolition dynamics.** This aspect encompasses the building stock. The model keeps track and reports the number of new constructions, demolitions and renovations.
3. **Material flows:** the flows of construction materials to and from the urban system due to C&D activities is recorded.
4. **Embodied carbon:** Total and per capita EC are calculated based on MI and EC factors (see Supporting Information).
5. **Embodied carbon savings:** Because the circularity strategies reduce the amount of material use, it is possible to capture carbon savings in each simulation. Savings in Co2e calculation is described below Eq. (1)

$$Co2e\ SAVINGS\ (\%)_{year} = \frac{\sum_{b=1}^N Circular\ EC_b(t)}{\sum_{b=1}^N EC_b(t)} \quad (1)$$

Where:

b is one building

N total amount of standing buildings

Circular EC is the embodied carbon contained in recirculated materials in new constructions and renovations

EC is the embodied carbon in the building (Circular EC + Non-Circular EC)

3.2. Model description and heuristics

The simulation is bottom-up, stock-driven, and rule-based, which means that each dwelling within the building stock is programmed with the same set of rules. This section describes in more detail the various agents in the simulation, the programmed rules and the various parameters in the model that allowed to determine different what-if scenarios.

Fig. 2b shows the overview of the simulation process, which features four agents: buildings, recyclers, planners, and city areas. Fig. 2c presents the heuristics followed by the buildings. The model was developed with GAMA v1.9 (Taillandier et al., 2019), a spatially explicit agent-based simulation platform. The model is available at the COMSES Library.¹

3.2.1. Agents in the simulation

The first agent is the simulation space itself (the **World** agent), in which the rest of the agents are placed and interact. The World initializes the simulation: the various files are loaded, variables are created, and parameter values are set. The World has the critical function of making the time-steps move forward so that all agents execute all their actions at every time step (or year). The World also aggregates information and performs calculations of the various KPIs of the system (see 3.1.2).

The **Building** is the main agent, acting as an independent decision-making entity that determines when to renovate or undergo demolition. These actions are based on the years or time-steps of the simulation- For example, 'demolition' is only triggered when a given building notices that the current year is greater than its year of demolition. Every 5 years (1 time step in the simulation), each building will face a renovation based on the input parameter of renovation. This means that if the parameter is set at 10%, about 10% of the buildings will be upgraded and this will extend the lifetime of the building. Renovation triggers a demand for materials, be they virgin or recycled. Both demolitions and renovations increase the amount of recycled material at the 'recycler' (see below). Fig. 2c shows the general rule followed by all the buildings agents.

The **Recycler** collects and distributes materials from renovation and demolition activities. As the building agent demands or supplies materials from renovations or demolition activities, the recycler accounts for material quantities. It also accounts for the demand for (virgin or recycled) materials for new building construction. This agent is scheduled at the end of each simulation step. Based on the amounts of materials used, the Recycler agent also calculates the EC generated during that simulation period.

The **Planner** sets the demand for new construction based on population increases and lost housing from demolitions. The model allocates the population increase between single-family and multi-family units based on the housing typology parameter (in percentage).

City Areas are grid squares (10 m by 10 m) based on an official population data grid. City Areas receive input from the Planner regarding the required number of buildings. At each step, City Areas

¹ <https://www.comses.net/codebases/eabb72fe-3a47-47b1-a0b7-0e384679fd35/releases/1.0.0/>

decide whether to allocate buildings within them. While the current model employs a random selection process, it is worth noting that it can incorporate diverse building rules, such as prioritising high-density areas or experimenting with alternative building sequences.

3.2.2. Temporal scope

The simulation runs from 2010 to 2100, in increments of five years. Such temporal granularity is deemed satisfactory for capturing the typically slow-paced changes of building stocks. (Ahmadian et al., 2019; Heeren & Hellweg, 2019b; Kohler, 2018; Simmonds et al., 2013), though it may be increased if required.

3.3. Initialization: loading information and assumptions

During initialisation, datasets are loaded (see Section 3.4.1) and assumptions and parameters programmed. Note that a distinction is made between assumptions (hardcoded but modifiable if required) and exploration parameters (user-modifiable via the simulation dashboard, see next subsection).

3.3.1. Assumptions

The function of determining a building's year of renovation or demolition goes beyond a simple correlation between the age, type, or condition of the buildings (Kohler & Hassler, 2002). Therefore, stochasticity was introduced to counter the otherwise simplistic assumption of a hard-set building lifetime. This step echoes the use of probabilistic building lifetimes in dynamic MFA (see for example (Pauliuk & Heeren, 2020; Sartori et al., 2016)). The developed model assumes the following:

(i) the demolition year is calculated by adding 80 years to the construction year, with an additional randomly generated offset between 10 and 20 years (Andersen & Negendahl, 2023) to account for variability in structural longevity Eq. (2):

$$D_{year} = C_{year} + y \quad (2)$$

Where:

D_{year} is the year of demolition.

C_{year} is the year of construction.

y is randomly uniformly distributed variable $N \sim (10, 20)$.

(ii) the renovation year is determined by adding a random value between 5 and 35 years to the base year of the starting simulation year Eq. (3):

$$R_{year} = starting_{year} + y \quad (3)$$

Where:

R_{year} is the year of renovation.

$starting_{year}$ is the year when the simulation starts.

y is randomly uniformly distributed variable $U \sim (5, 35)$.

Noteworthy is that building lifetime assumptions can easily be turned into exploration parameters. While not the aim of the present study, assumptions on a building's lifetime are indeed a fundamental interest of material stocks and flows research (Cao et al., 2019; Kayo & Tonosaki, 2022).

3.3.2. Exploration parameters

Five main parameters are made available for exploration of scenarios, using the simulation dashboard (see model demonstration in Fig. 4).

- **Proportion of single-family buildings.** New constructions can be single- or multi-family buildings. This parameter sets the building typology mix of new construction, determining which MI to use in the simulation.
- **Probability of demolition.** As a building approaches its demolition date, its actual demolition is based on a probabilistic mechanism. To

incorporate stochasticity into the model, the modeller can determine the chances of demolition.

- **Probability of renovation.** Renovations follow a similar mechanism to that of demolitions. The modeller can determine the chances of demolition.
- **Recycled content of renovations.** Renovating a building triggers a material demand, whether recycled or virgin. This parameter specifies the percentage of recycled materials (in weight) to be used in renovations. When no specific materials are found, virgin ones are used.
- **Recycled content of new constructions.** Similarly to the one above, this parameter determines the percentage of recycled material used in new constructions. When no specific materials are found, virgin ones are used.

3.3.3. Heuristics for renovation, demolition, and construction activities

Fig. 2c describes the rules determining whether a Building undergoes renovation or demolition. It also highlights which conditions are affected by the model parameters.

First, for each year, the model compares the current year to the building's renovation year. If the renovation year has passed *and* the probability threshold for renovation is met, then the type of renovation is determined. Renovations include three types: small, medium, and big. These types determine the extent of the renovation and the amount of material needed. See Figure A2 in Supporting Information, to have a detailed understanding of the process behind renovations.

If the Building is not renovated, the current year is compared to the demolition year. If the demolition year has passed and the probability threshold is met, the building is demolished and its materials sent to the Recycler agent.

The need for new construction is determined by the Planner agent, who quantifies the number of demolished buildings and estimates the additional population to be housed in the next step. The number of new single- and multi-family buildings is calculated based on the ratio of single-family buildings set by the user (input parameter). Here, the size of each household is determined stochastically. The number of new buildings is then captured by the City area agent, which places them within the city area. Each area or quadrant of the city is filed proportionally, but this feature enables future model extensions to determine the placement of how the city will develop. Here the proportion of single and multi-family buildings becomes relevant as specific building materials are needed for one or the other residential typology.

Construction and renovation activities demand materials, while demolitions and renovations release materials into the system. These materials flows are calculated by the Recycler agent. Using the Circular Economy parameters, the modeller can decide the percentage of materials that the system should try to recirculate into construction and renovations. Based on the quantity of new materials needed an estimation of EC is generated.

Finally, building parameters are updated, such as the number of times it was renovated, the next renovation date, new demolition date or total amount of materials.

3.4. Model demonstration and results in Gothenburg, Sweden

The city of Gothenburg, Sweden (Fig. 3), was chosen as a case study based on data availability but also on the relevance of the research to the municipality. Gothenburg is the country's second largest city, with a population exceeding 600,000 residents. By 2035, the population is expected to grow by 150,000, creating pressure on the municipality to produce 45,000–55,000 adequate and sustainable new housing units within this timeframe (City of Göteborg, Planning and Building Committee, 2014). At the same time, Gothenburg has ambitious climate goals, including the reduction of climate impact from construction and renovation of buildings by 90% in 2030, compared to 2020. This ambition includes reducing per capita yearly carbon

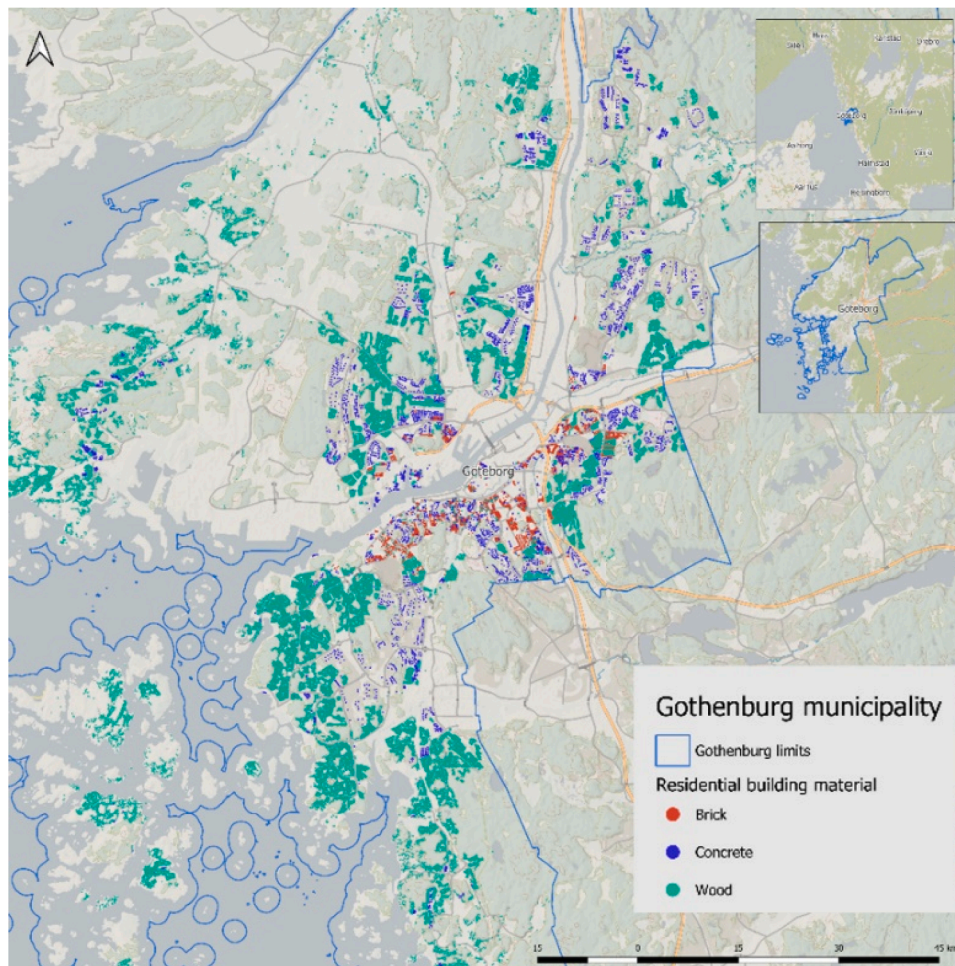


Fig. 3. Residential building stock (per structural material). Own elaboration using 2023 information from the Swedish mapping, cadastral, and land registration authority Lantmäteriet, based on [Gontia et al. \(2018\)](#).

emissions from 4.2 tCO₂e (in 2025) to 1.1tCO₂e by 2035 ([Göteborgs, 2021.](#), pp. 2021–2030). To meet this target, the city must increase its construction circularity and decrease the primary energy consumption to 12 MWh per capita. As such, the city must increase the energy efficiency of its residential buildings. All such potentially conflicting needs make Gothenburg relevant as a case study.

A baseline and a policy scenario are introduced (see [3.4.2](#)) and for both, simulation parameters can be changed.

3.4.1. Data collection and processing

All required data (listed in [3.1.1](#)) were retrieved for the case of Gothenburg; a detailed description of each dataset is available in the Supporting Information in Tables A3 to A8. An additional dataset was collected to support the enquiry into an energy-efficiency policy scenario, namely energy performance certificates (EPC) of Swedish residential buildings. EPCs rate the energy efficiency of residential buildings from A to G (most to least efficient) but are not available for all buildings. This incompleteness was addressed by assigning default energy rating based on the building's type and construction decade (Tables A7–A9 of the Supporting Information). The dataset of buildings with their year of construction, number of floors and main typology (single or multifamily) was obtained from Lantmäteriet (Swedish mapping, cadastral, and land registration authority). A total of 56,245 residential buildings was detected in the database and enhanced from previous works by [Gontia et al. \(2018\)](#) with building types and their materials. [Fig. 3](#), presents the footprint of the residential buildings and their main material types.

The resulting database encapsulates crucial details for each building, such as construction year, height, typology (single-family or multifamily), material composition, and energy performance ratings. It served as the foundation for initialising the simulation.

3.4.2. Assumptions and scenarios

The baseline scenario helps understand the model's behaviour by exploring the parameter space (i.e., all possible combinations of these parameters). As the exploration of five parameters resulted in an exponentially growing simulation, possible combinations were limited by restraining simulation parameters to only relevant values based on construction statistics and experts' input. As such, the probability of demolition was assigned three values (1%, 3%, and 5%), and all other parameters were explored from zero to one with increments of 0.25 (five values). This exploration yielded 1875 simulations to run, each replicated ten times to account for model uncertainty, resulting in 18,750 simulations for the baseline scenario.

Policy scenario. To showcase the usefulness of such simulation (both to researchers and decision-makers), a hypothetical yet informed scenario was explored under which Gothenburg Municipality would no longer accept buildings with low energy performance after 2045. Buildings with a level G in their EPC would be forced to improve their energy performance through renovation or face demolition. In this scenario, contextual knowledge was integrated into the model, and building heuristics were updated to consider EPCs. More specifically, renovations were assumed to improve the building's energy performance for 10 to 20 years ([Bekker, 2011](#)). To enable comparison with the

baseline scenario, the policy scenario was evaluated under the same parameter exploration and replicated five times (9375 simulations in total).

4. Results

4.1. Simulation dashboard

The simulation dashboard is shown in Fig. 4. It illustrates how the combination of ABMs and interactive platforms helps to communicate results and interact with the model. On the upper left, the control panel displays the input parameters of the simulation: demolition probability, renovation probability, renovation size (only small and big probabilities are needed, since the remaining is assigned to medium size renovations), and targeted percentage of reused materials in the system. Additionally, a panel for the policy scenario can be toggled on or off and its parameters determined.

The rest of the simulation dashboard consists of seven panels where various simulation outputs are tracked and graphed. These include the building dynamics (number of buildings having undergone renovation, demolition, and number of newly constructed buildings), material quantity being needed and freed from these dynamics, the rate of each energy rating across the stock, and the associated EC. In the bottom left, a geospatial overview of the simulation displays the evolution of the building stock over time, with buildings being represented as dots whose colour changes according to their status (renovations, demolitions, and new constructions).

4.2. Parameter exploration

The resulting embodied carbon (EC) for each simulation was averaged across each combination of parameters, producing a single EC value corresponding to a specific set of conditions: ratio of demolitions, ratio of renovations, percentage of recycled materials used in new

constructions, percentage of recycled materials used in renovations, and percentage of new single-family buildings constructed. These averaged values are presented in Appendix Table A14, encompassing a total of 1875 possible scenarios.

To facilitate interpretation of these results and demonstrate how multi-parameter scenarios can be explored more effectively, an interactive parallel plot was developed. Fig. 5 serves as a multimedia companion, allowing readers to independently investigate the generated results.

Panel (a) shows the initialized dashboard, where the scatter plot displays all resulting EC values from the simulations. The parallel plot on the right allows the user to trace each parameter combination corresponding to a specific scenario and its associated EC. Finally, the density plot at the far right depicts how EC values are distributed across all scenarios.

The control panel on the far left enables users to filter results based on key parameters such as demolition ratio, renovation rate, or levels of material circularity, as shown in panel (b). In this example, the filter has been applied to the demolition rate, selecting a specific subset of scenarios with the highest EC levels. These results correspond to a demolition rate of 0.5% and material circularity levels of 0%, regardless of renovation rates or new building typologies.

When the filter is applied to new building typologies, promoting 50% single-family units produces both the lowest maximum and minimum EC values. This outcome is linked to the fact that material outputs primarily originate from renovations and demolitions of single-family units; consequently, new construction typologies should align with the type of materials being released. Scenarios with minimum EC are observed when demolitions are limited to 0.1%, renovations are maximized, and circulated material levels are maintained at 25% for new constructions and 50% for renovations.

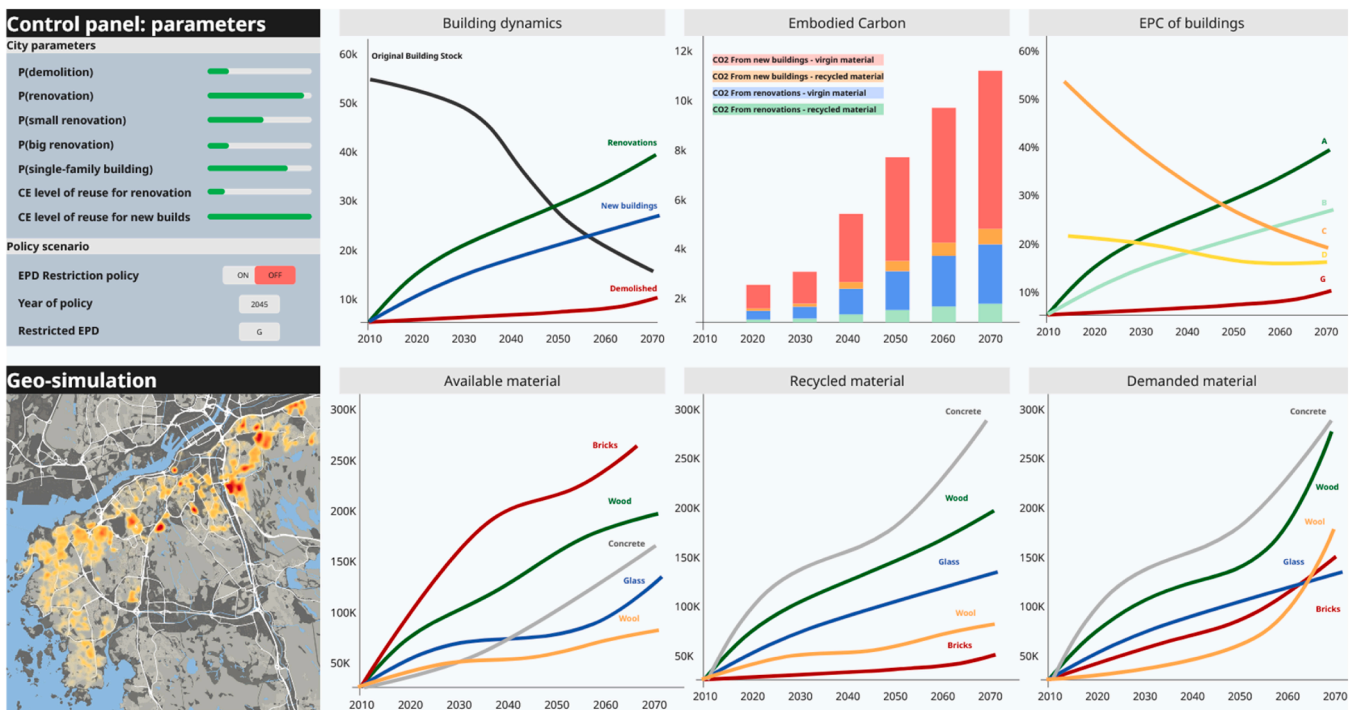
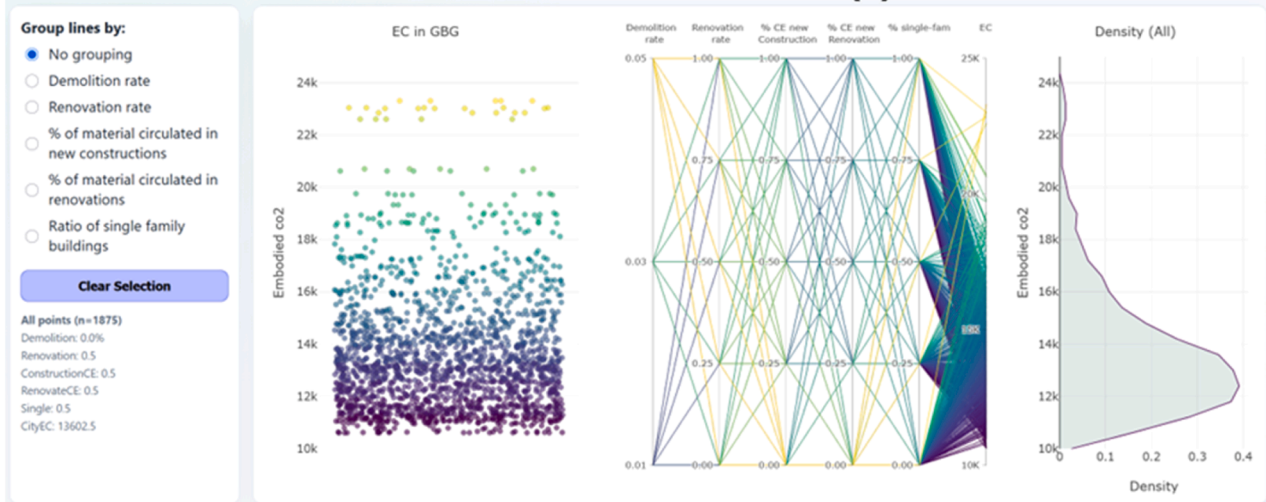


Fig. 4. Model dashboard in GAMA platform, including the control panel for parameters. The simulation tracks and graphs various output parameters, such as Building dynamics (in count of buildings), Materials in re use; Materials at recycler; Geo-simulation; Distribution of energy ratings over time (in %), Material demand; and (i) embodied carbon. For readability purposes the image has been enhanced to clearly show the model components. The model can be found in COMSES open model library presented in footnote 1.

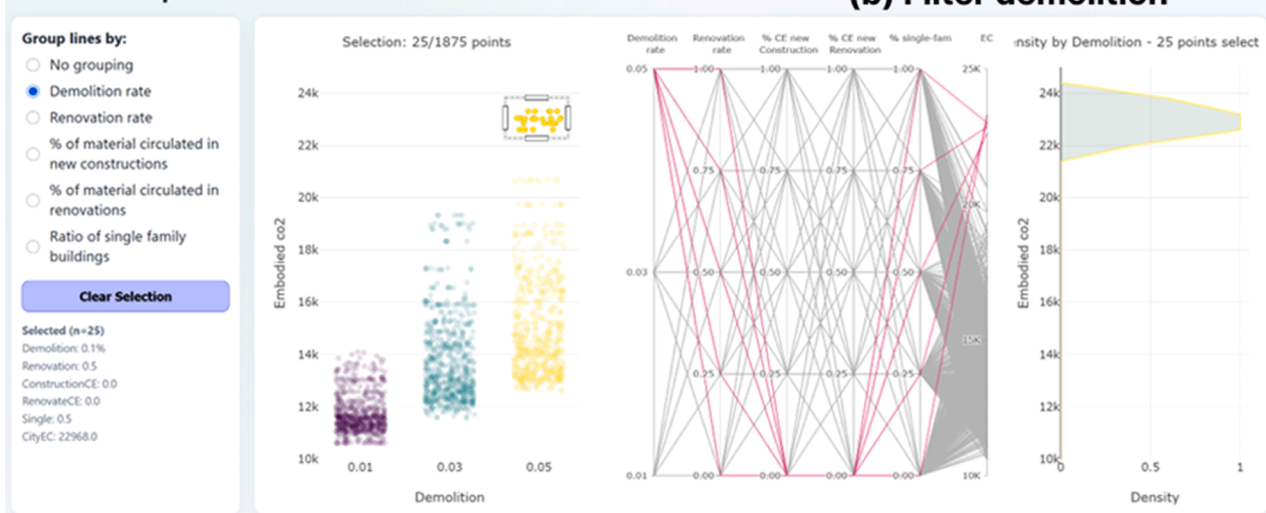
Parameter exploration in Construction Sector

(a) Initial dashboard



Parameter exploration in Construction Sector

(b) Filter demolition



Parameter exploration in Construction Sector

(c) Filter single buildings

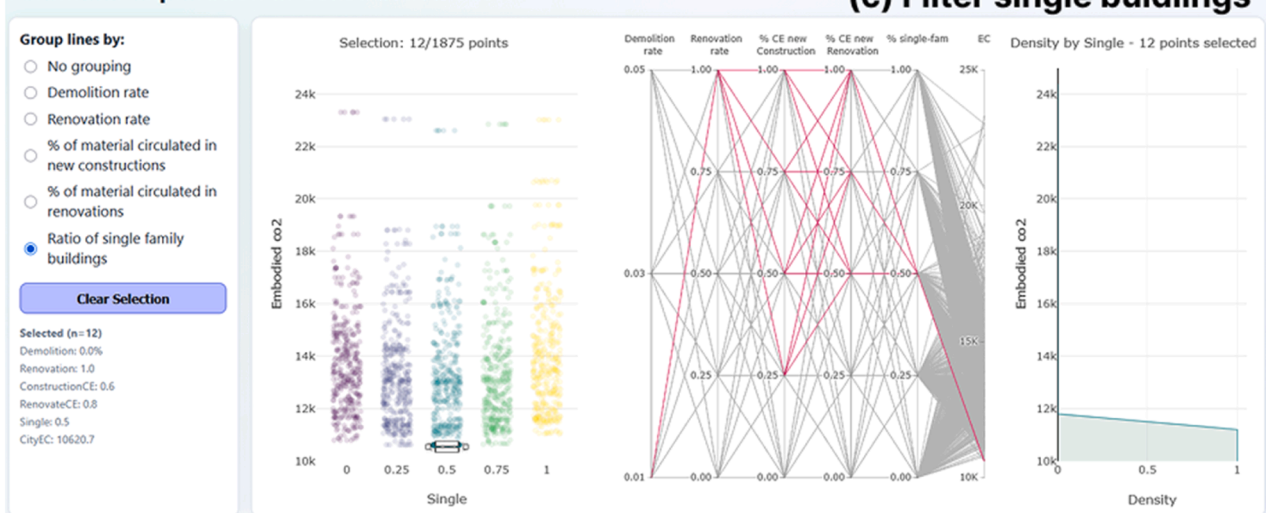


Fig. 5. Online and interactive dashboard of resulting simulations. Available data base of results and dashboard at <https://makijota.github.io/ConstructionSim/>.

4.3. Material availability and embodied carbon across the parameter space

Material quantities freed from demolition activities across the building stock are shown in Fig. 6, under different parameter combinations. The matrix of plots shows how material availability changes depending on demolition rate and the proportion of single-family buildings that will be constructed in the next period (with all other

parameters kept constant). Logically, freed material quantities increase as the demolition rate increases. Material-wise, bricks make up a large part of materials being released, pointing to the need for new buildings to integrate bricks into their design. The typology ratio of new constructions also impacts results. For example, the amount of available wool for insulation increases as the percentage of single-family buildings decreases (due of the material content of each building typology).

Fig. 7 presents EC accumulation as added EC per new inhabitant

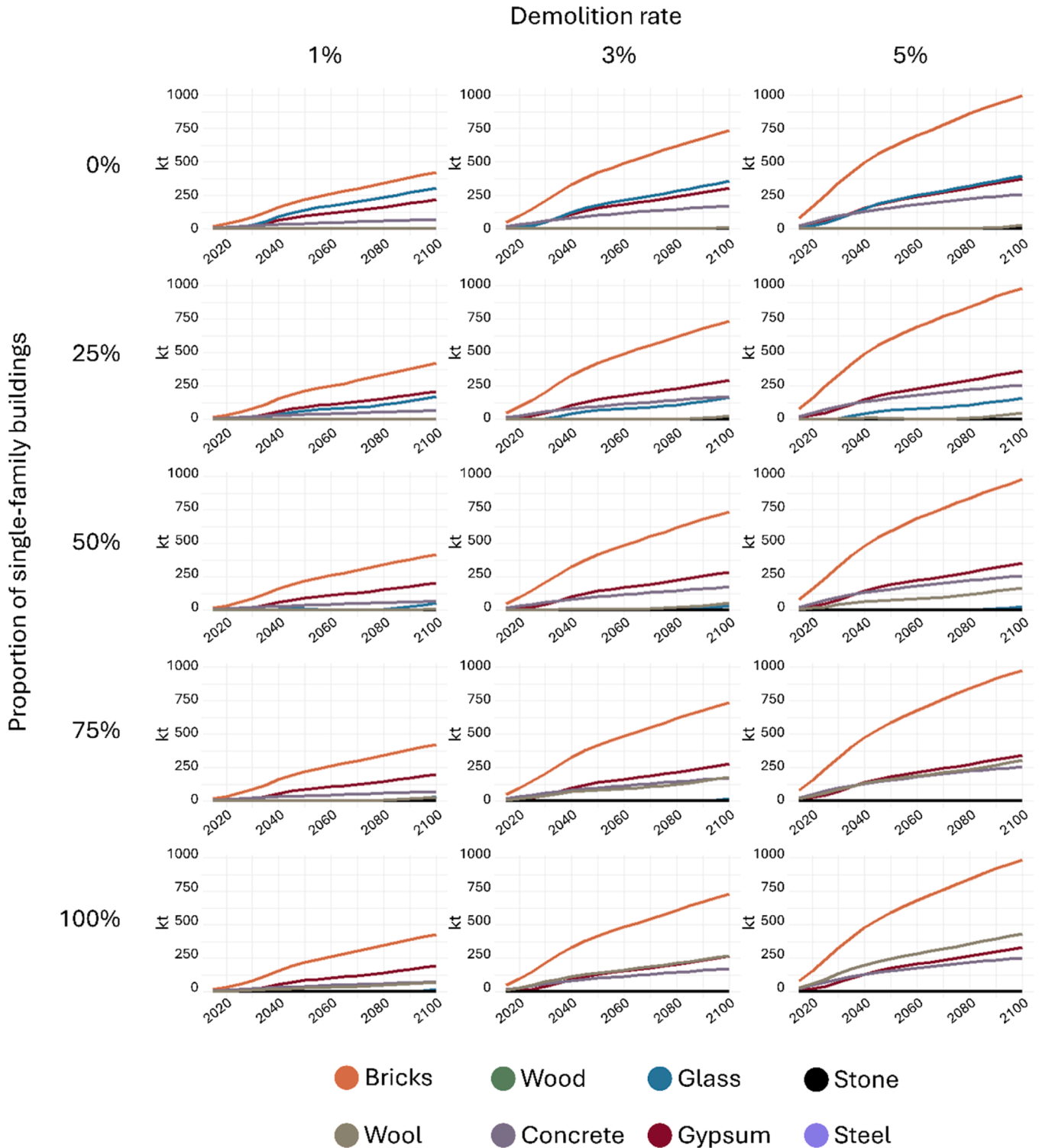


Fig. 6. Availability of construction materials (in kilotons) from 2020 to 2100, depending on the rate of demolition and on the proportion of new single-family buildings to be constructed.

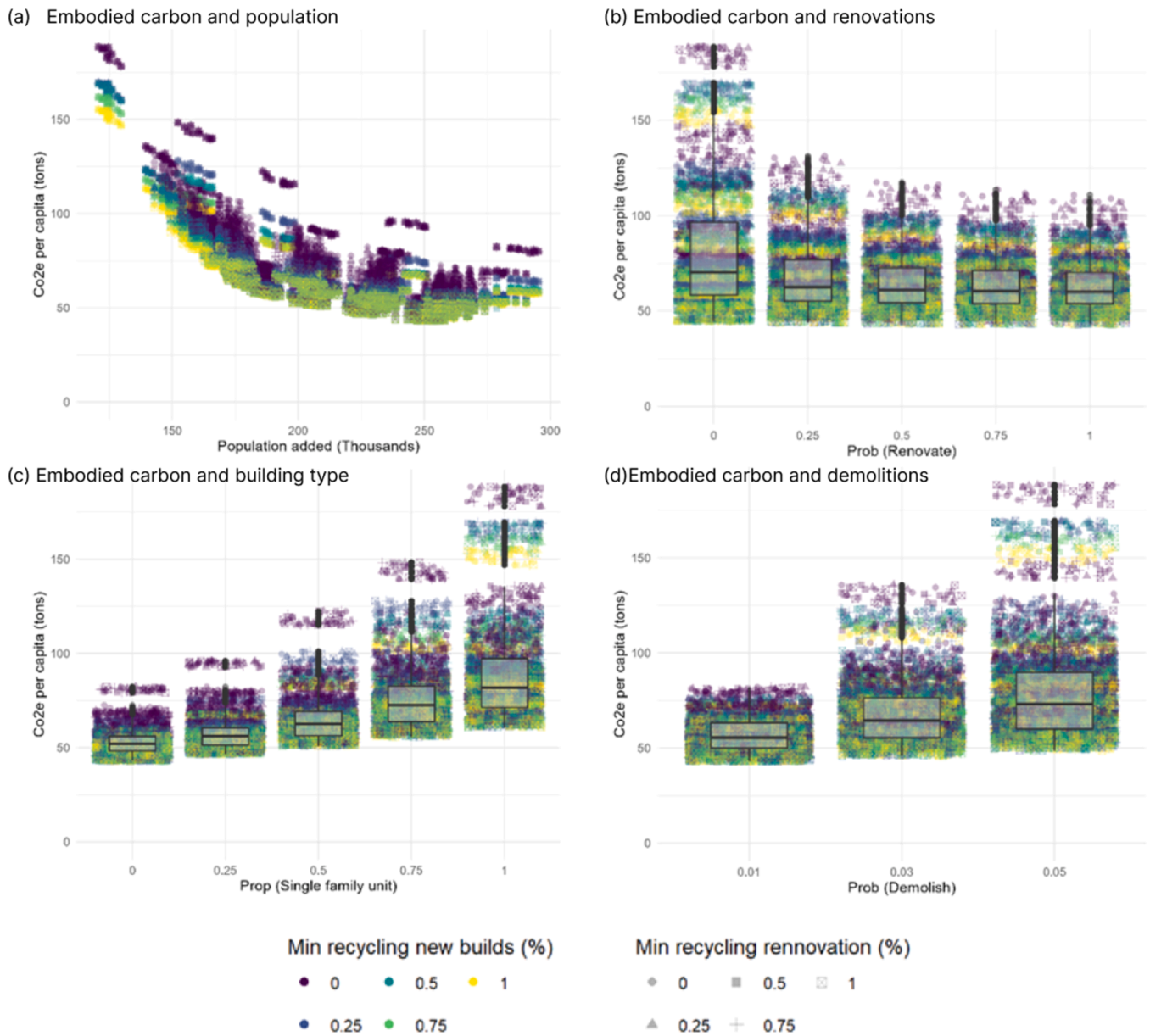


Fig. 7. Simulation results for selected variables. Total households, renovations, demolitions, and Single-family buildings. (a) Embodied carbon per capita and amount of households. (b) Embodied carbon per capita and probability of renovations. (c) Embodied carbon per capita and proportion of single-family buildings. (d) Embodied carbon per capita and probability of demolition.

(tCO_{2e} per capita) across the simulation parameter space. Each point represents the per-capita EC in 2100 for a given parameter setting; colour indicates the share of materials recirculated in new construction, and shape denotes the share of recycled materials used in renovations. All panels share a common y-axis.

Lower shares of recycled and recirculated materials are associated with higher per-added-capita EC. In Fig. 7a, increasing population additions correspond to a reduction in per-added-capita EC of approximately 0.63 tCO_{2e} per 100,000 additional inhabitants, with diminishing effects beyond ~300,000 inhabitants. Fig. 7c shows a positive relationship between per-added-capita EC and the share of newly built single-family units, consistent with their higher material intensity relative to multi-family buildings. Figs. 7b and 6d show that higher renovation rates slightly reduce per-added-capita EC, whereas higher demolition rates substantially increase it: average values rise from ~50 tCO_{2e} at a 1% demolition rate to ~65 and ~75 tCO_{2e} at 3% and 5%, respectively.

4.4. Spatial patterns of building dynamics

At every step of the simulation, the status of each building (i.e., untouched, renovated, or demolished) of each building across the city is recorded, resulting in a comprehensive spatially explicit prospective dataset. Fig. 8 shows the resulting demolitions at every simulation step and under the various parameter combinations. While the number of demolitions increases over time, the pattern of increase differs depending on the renovation rate, with a 5% renovation rate slowing down demolition. Indeed, a high renovation rate translates to more buildings being maintained and their end of life extended.

The spatially explicit nature of the model enables an understanding of where it is more likely for these demolitions to occur. Fig. 9a depicts such results in the form of a heatmap of the likely location of demolition activities under specific parameter combinations: probability of demolition (1%), proportion of single-family houses (25%), probability of

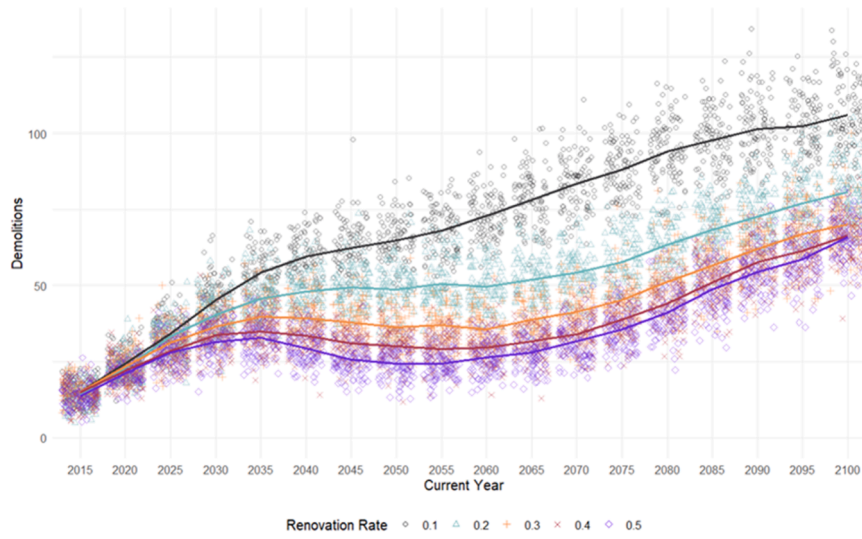


Fig. 8. Demolitions occurring during each time period for various parameter specifications. Specific focus to showcase the effect of the renovation probability ranging from 0.1 to 0.5.

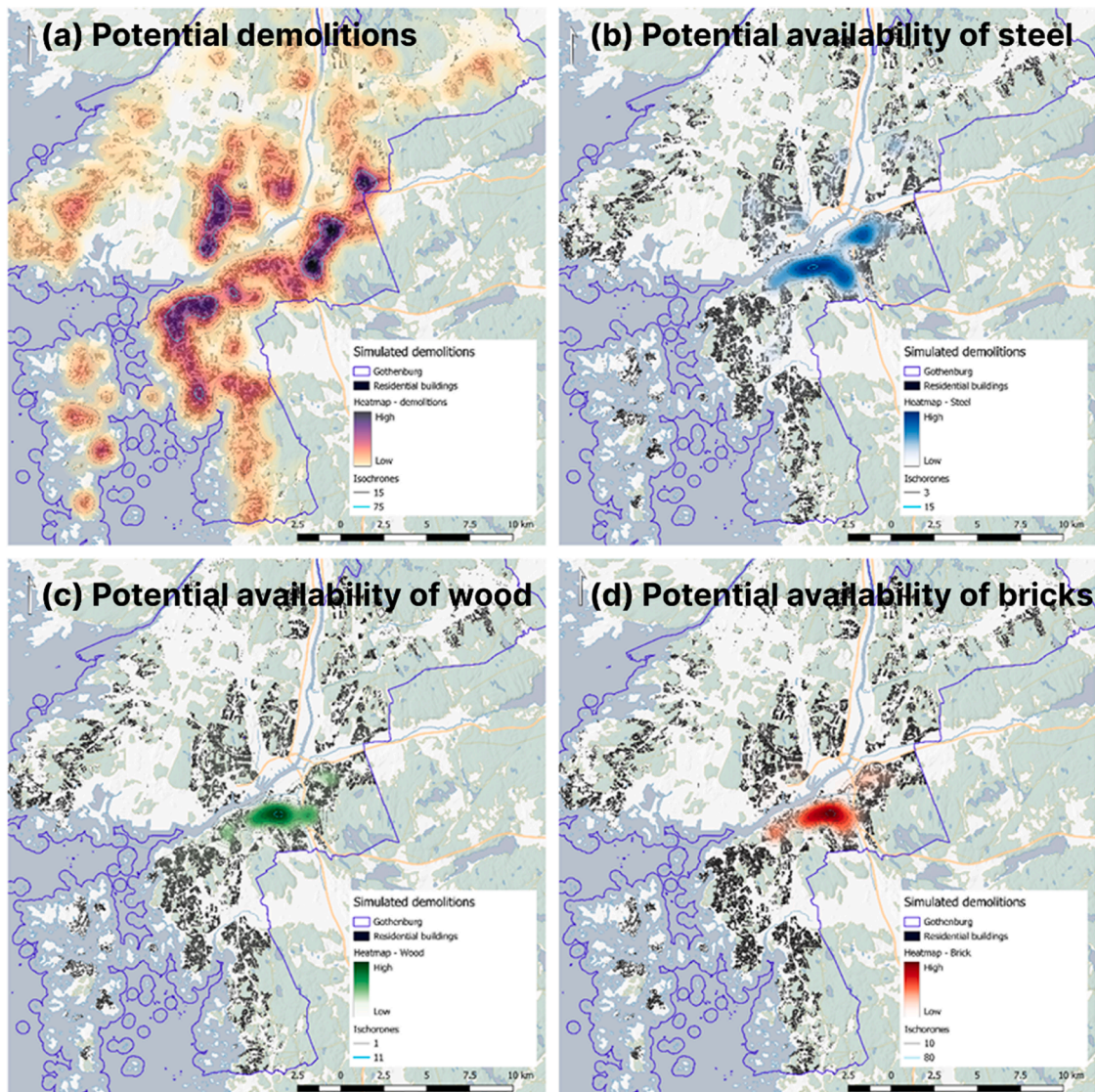


Fig. 9. (a) Heatmap of the probability of demolition across Gothenburg in 2100, translated into potential quantities of (b) steel, (c) wood, and (d) bricks.

renovation (25%), and recycling rate in new construction and renovations (25%). The selected parameter values are just an arbitrary combination to showcase how simulation outcomes can be visualized to provide insights. Such a demolition-likelihood map can also be translated into maps of likelihood of outflows of various materials across the city. For example, steel (Fig. 9b) is likely to become available in two specific hotspots around the city, while timber (Fig. 9c) and bricks (Fig. 9d) are likely to become available from the city core. Worth noting that these visualizations could also be generated for other parts of the model. For example, a heatmap of renovations and their demand for different materials, as a result that for every simulated period building status and material accounting is being recorded for later post processing.

4.5. Policy scenario: Upgrade of building stock's energy performance

The policy scenario was run with the following simulation parameters: probability of demolition (1%), proportion of single-family houses (25%), probability of renovation (25%), and recycling rate in new construction and renovations (25%). The analysis of the outcomes of the policy scenario – as compared to the baseline one – is facilitated by the temporally explicit nature of the simulation. In Fig. 10, the consequences of introducing the energy efficiency policy are illustrated for both the baseline scenario (left panels) and the policy one (right panels) from 2020 to 2100. Fig. 10a shows the number of buildings being built, renovated, and demolished. The figure shows that the policy scenario triggers more demolitions and new constructions than the baseline. Meanwhile, renovations happen earlier, with almost 40,000 building renovation expected by 2045, compared to 35,000 in the baseline. On the operational side of emissions, Fig. 10b shows the EPC rating profile of the building stock, with no G-rated buildings in the policy scenario by 2100. Fig. 10c displays the total demand for construction material (virgin and recirculated), which increases when the policy scenario is implemented. Finally, Fig. 10d displays the total added EC – differentiated between activities and material sourcing (virgin vs. recovered). The introduction of the policy on energy efficient buildings results in an increase in EC. This example demonstrates the sustainability analytics advantages brought by the simulation, as the EC impact of operational-focused policies is calculated. Readers are also encouraged to consult Supplementary Information for an exploration of the temporally explicit simulation results with statistical models.

5. Discussion

5.1. From spatialization gap to spatially explicit stock–flow simulation

Transitioning to a circular economy and effectively managing existing building and material stocks requires a detailed understanding of the quantity of potential secondary resources, but also of their location and time availability. This knowledge is crucial to organize a resource-efficient built environment at a wide-scale. Indeed, contrary to short-lived goods (e.g., food) and smaller long-lived goods (e.g., furniture), construction materials are bulky, heavy, and stay in use for long periods of time. The absence of detailed information about the timing and the location of material outflows therefore poses significant planning and logistical challenges to achieving a wide-scale circular construction sector.

In this paper, the spatialization gap of prospective stock and flow models is addressed by hybridizing three key system-based modelling methods – dynamic MFA, bottom-up MSA, and ABMs – within a spatial simulation framework. The result is a bottom-up, prospective, stock-driven, and rule-based simulation model that enables a spatially and temporally differentiated modelling of material stocks and flows.

The simulation goes beyond estimating stocks and flows; it provides the opportunity to look at how different rates of activities (i.e., renovations, demolitions, and recycling) impact the material dynamics

(amount location, and timing) across the city, and the resulting levels of EC savings. The city of Gothenburg was used as a case study to illustrate the various analytical potentials offered by the model. Additionally, the model was extended to showcase the versatility of the inquiries enabled by the simulation, as it is flexible enough to add datasets. In this paper, a scenario was explored under which energy-inefficient buildings are banned from the city and used EPC data as proxy for energy efficiency.

The results obtained after the various simulations, show expected results, providing evidence of the explanatory power of a model that incorporates simple dynamics of the construction sector. For example, as the probability for renovation increases, the overall number of demolitions is reduced, or as the ratio of newly residential buildings being single-family increases, the EC per capita tends to increase. Despite this, the model needs concrete data points and further validation to provide accurate results that can securely guide urban policy at the city scale. As also demonstrated in Alibaş et al. (2025) and Nägeli et al. (2020), the modelling of building stocks and EC can also benefit national policy by scaling up these bottom-up approaches. By enabling scenario building, these models can clearly show the changes of specific policies interventions reaching their intended targets.

5.2. Potential and comparative positioning of the model

One of the highlights of the model is that all modelling rules are followed by each building in the city, therefore offering a spatial granularity at the building level. Currently, the rules are simple and adjustable, which allows flexibility in the model. As showcased in this article, even with such simple rules, the model is capable of generating results across various parameters and to accommodate additional layers of data (e.g., EPCs) to refine scenarios. The simulation can integrate additional datasets to explore specific enquiries. In the demonstrated case, rules for renovation activities were incorporated and the model tracks the energy efficiency status of the building stock. Integrating this feature into the building stock model opens the door for further study of future energy demands and GHG emissions during the use stage of dwellings. Still, some limitations need to be highlighted when it comes to the use of EPCs for Gothenburg residential buildings, as it is an incomplete dataset. The attribution of EPC rating to a building based on its typology and age might lead to inaccuracies: buildings might already have been renovated since their construction. Notwithstanding such data quality issues, the model was successful in accommodation for additional data that support energy-regulation inquiry.

As far as the existing literature indicates (see Section 2), this is the first model that achieves a spatially detailed and prospective modelling of inflows, outflows, and stocks. Our approach offers high potential to advance spatially informed material stock and flow modelling, enabling more accurate assessments of timing and location of material changes. Despite these promises, in its current form, the robustness of the model outcomes is hindered by several key limitations. While these do not undermine the paper's primary methodological motivation – showcasing the feasibility and analytical power of spatially explicit stock-driven simulations – they still warrant careful discussion.

5.3. Constrained scope and opportunities for comprehensive model development

The model was instantiated for Gothenburg using empirical data as parameters. Yet, the results should be regarded as indicative: data unavailability and knowledge gaps constrained the model to a restricted simulation scope (this subsection) and to the adoption of coarse model assumptions (see next subsection).

Building use types. The model focuses on residential buildings and would benefit from the inclusion of more building use types. Including non-residential buildings would enhance the quality and relevance of results, especially for the port and industrial city that is Gothenburg, which hosts a wide array of non-residential buildings, which are also

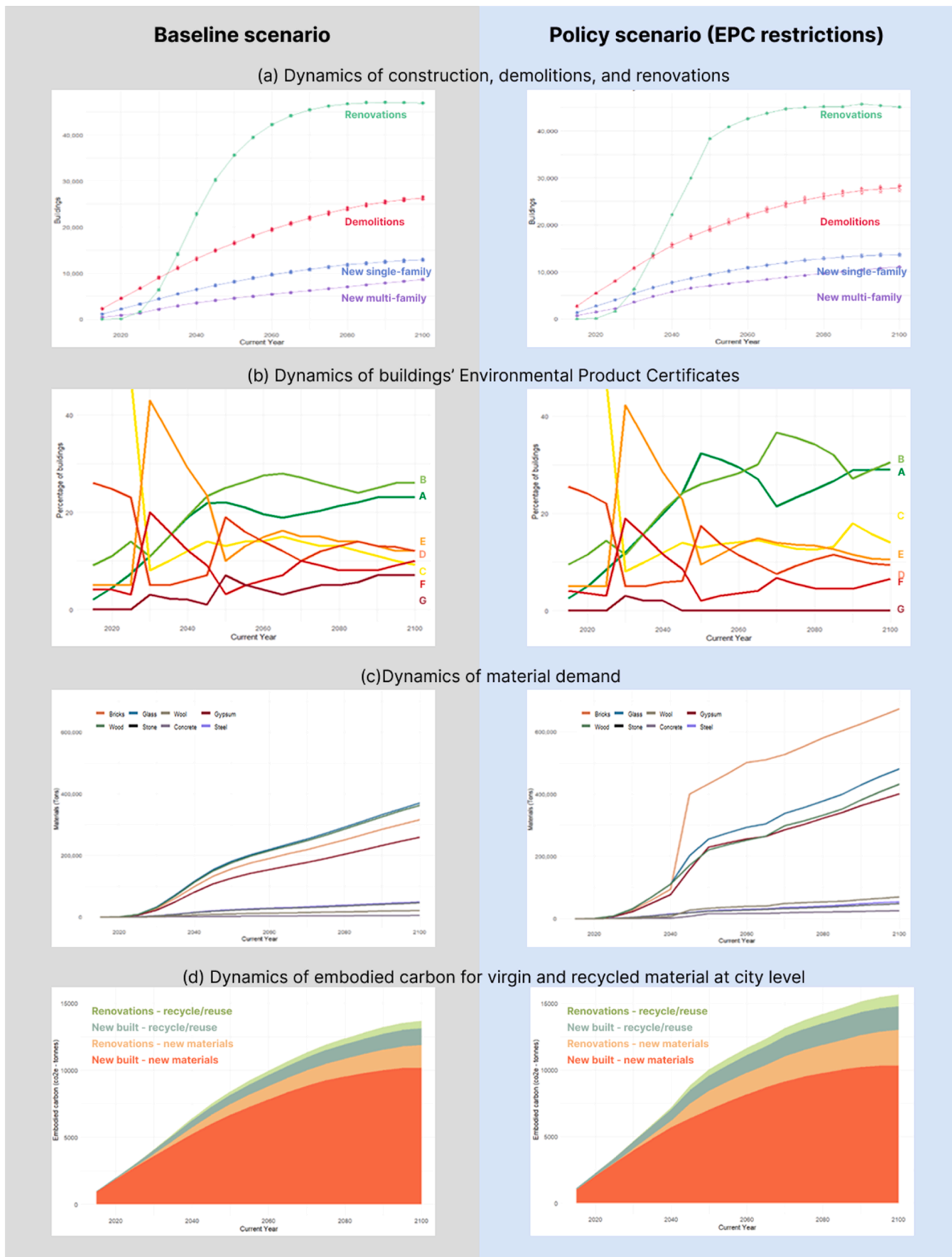


Fig. 10. Comparison of simulation results from 2010 to 2100 for the baseline scenario (left) and the policy scenario (right). Simulation results include the evolution of (a) building stock dynamics (i.e., new construction, renovation, and demolition); (b) the distribution of buildings' EPC levels (from A to G); (c), material stock demand (eight construction materials); and (d) evolution of the city's embodied carbon and potential embodied carbon savings.

more often subject to demolition processes than residential ones. Additionally, new constructions were restricted to two relatively recent building typologies from circa 2010, which may not fully represent current and near-future construction types. Expanding the set of typologies would enhance the model's analytical capacity. For example, including engineered-timber buildings would enable the exploration of short- and longer-term sustainability implications of prioritizing timber buildings which, while sustainable, do not easily integrate recovered construction materials.

Environmental accounting. Three aspects of environmental accounting warrant expansion. First, to limit computational costs, the model currently includes only eight construction material types. While these cover most material stocks, they do not provide a complete representation; additional materials—particularly carbon-intensive ones such as plastics—should be incorporated as computational efficiency improves. Second, the MI data relies on aggregated material categories, which required the use of average EC factors. Further disaggregation of MI's material categories would improve the robustness of EC estimates. Third, although the model captures new construction, renovation, and demolition processes, it does not account for logistics operations. Material transport distances and modes significantly influence the carbon impacts of construction circularity (Tsui et al., 2025). Incorporating logistical considerations would require introducing parameters for the location and scale of circular hubs, as well as assumptions regarding transportation modes (e.g., diesel trucks). This would improve the realism of the modelling and provide insights into how wide-scale construction circularity might look like in urban settings.

Building data granularity. The simulation treats each building as a monolithic entity, whereas buildings are composed of many parts with distinct material compositions and lifetime. This simplification leads to coarse estimates of material stock and flow. Incorporating MI and lifetime data at the building component level would offer a much-needed granular understanding of building and material stocks dynamics. A first step toward greater granularity would be to disaggregate buildings into their shearing layers (e.g., structure, skin, and space) (Brand, 1995) which are particularly relevant for the circular economy, as these layers have markedly different lifetimes: structural elements typically persist longest, while skin and space are replaced multiple times over a building's life. Modelling such intricate dynamics in MFA modelling increases realism. Here again, the computational capability of the model needs to be increased so it can accommodate such high data granularity.

Geographical boundary. In terms of geographical scope, the boundary is restricted to Gothenburg municipality. Restricting the boundaries to one single city hinders the capture of the interconnected nature of neighbouring municipalities. Enlarging the scope to a metropolitan, regional, or even national scale would help explore scenarios of sharing infrastructure and resources across administrative boundaries, leading to a more comprehensive and integrated approach to sustainability accounting and reflecting the interconnectedness of different areas and their shared impact on the environment.

5.4. Pathways to increased realism and research outlook

The previous subsection focused on limitations pertaining to the model's application. Here, the focus shifts to the model itself. Examining the foundational elements of the model highlights specific avenues for refinement that can improve the model's accuracy and applicability. In this context, the discussion explicitly outlines future research directions, so the simulation supports more robust analyses for urban planning and sustainability assessments.

Refining underlying assumptions. The model assumes all materials from demolitions and renovations are re-introducible into the market. As such, results should be viewed only as a "circularity potential," that assumes technical, legal, logistical, and economic feasibility. In reality, materials may be unsuitable for recirculation due to quality or contamination (e.g., asbestos) issues. Therefore, incorporating

recirculation ratios would improve realism. While it is easy to integrate into the simulation, data on such ratio is lacking. Future iterations of the model should extend the realism of the available technology to recycle CDW into ready to use materials or products (Yu et al., 2024). Another assumption constrained by data gaps is the model's initial condition: it starts with no materials at the recycler, meaning that material recirculation occurs only after renovations or demolitions. This assumption should be revised for more realistic results. Finally, as with any dynamic MFA, the probabilistic approach to demolitions, renovations, and future construction inevitably introduces uncertainty. Reducing this uncertainty requires more detailed information on local construction and demolition (C&D) activities, including a deeper understanding of building stock longevity and the factors driving renovations, demolitions, and new developments. In this regard, the study of building mortality and survival stock analysis is very relevant (Erik Bradley & Kohler, 2007). Such knowledge would enable more robust assumptions (e.g., building lifetimes) and parameters (e.g., renovation probabilities) within the simulation framework.

Integrating additional agency. The simulation assigns agency to individual buildings, which is sufficient to provide an overview of the scale of outcome differences across various scenarios. However, to better capture urban development dynamics, additional agencies should be integrated in the model in the long run. This would require evaluating diffusion mechanisms influencing decisions in the construction and demolition (C&D) sector. For example, (Chen et al., 2025) identified patterns and drivers of CDW generation in China at provincial and city scales through a retrospective spatiotemporal analysis. (Ding et al., 2021) forecasted demolition waste in Shenzhen (China) through an agent-based simulation of stakeholder behaviour, emphasizing socio-technical dynamics and policy levers. This focus on stakeholder decisions and policy incentives would be a valuable addition to the model, provided that a detailed local knowledge of construction practices and regulatory contexts is available.

Future iterations should also integrate spatial rules to enhance realism. For example, modelling urban densifications such as concentrating population growth in specific neighbourhoods, would improve accuracy, as the current approach assumes uniform population growth across the city. This would also allow the exploration of additional planning strategies and their environmental impacts. Therefore, future research should not only focus on identifying and better understanding C&D dynamics, but also on how those can be integrated into such simulations.

For all such refinements to be integrated into the model, a more computationally efficient approach to the model is needed. Transitioning to a graph-based model utilising nodes and edges presents an opportunity for accelerated simulations. This refined model can accommodate additional construction materials, higher modelling granularity (e.g., building shearing layers), but also transport dynamics and extend the staged actors by including for example, business model for recycling, a market for materials, an urban planning department that issues new construction and demolition permits and real estate developers and their business models.

The need for open science and transdisciplinary research. Throughout the study, it became clear that data availability and transparency of processes is a big limitation to the field of building stocks modelling. For example, the ratio of demolitions, past demolitions or accurate building typologies that match MC are difficult to retrieve. Therefore, this study has published the model for future research to use and hopefully improve. Publishing data, models, and methods secures the generalisation and replicability of results and increases transparency in general. Open data is also much demanded in Industrial Ecology (Pauliuk et al., 2019). Accordingly, the model's internal procedures, data inputs and assumptions are described in detail to ensure future research may improve and expand it, and the model is publicly available for use at COMSES, the computational model library (see footnote1).

Finally, a wide range of indicators and key performance indicators

(KPIs) are employed across the fields of urban metabolism, industrial ecology, and related sustainability-oriented disciplines. While this study focuses on EC, urban planners and decision-makers may prioritize other metrics, such as land availability. It is therefore essential that future research in industrial ecology, urban metabolism, and complex systems adopts open data practices and provides transparent access to developed models, enabling cumulative knowledge building and facilitating progress in sustainable built environment research. Close collaboration with practitioners and policymakers is also crucial to ensure that model assumptions align with real-world contexts and to enhance the robustness and relevance of simulation results.

6. Concluding words

This work bridges the spatialization gap in dynamic MFA, and tracks, quantifies, and locates the material dynamics of construction, renovation, demolition, and recycling over time and space. The model serves as a proof of concept that can be replicated in various contexts to showcase opportunities and challenges for the C&D sector in addressing future environmental goals. Nevertheless, as discussed above, both its underlying assumptions and scope need to be significantly improved before it can predict the future city. To this end, stakeholder collaboration and additional research (as described above) are direly needed, as well as empirical data to validate results. Still, as [Le Page and Perrotton \(2017\)](#) reflect, a model can be a learning tool to provide valuable insights. In other words, the model serves as a useful decision-support tool by acting as a virtual laboratory to explore the implications of urban policies, including demolition and renovation rates, material recirculation rates, and typologies of new constructions. It helps urban stakeholders understand how planning decisions affect material dynamics, circularity, and EC, thereby supporting informed decision-making toward sustainable urban development.

CRedit authorship contribution statement

Jonathan Cohen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Maud Lanau:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Leonardo Rosado:** Writing – review & editing, Supervision. **Jorge Gil:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.scs.2026.107554](https://doi.org/10.1016/j.scs.2026.107554).

Data availability

Data will be made available on request.

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