Combined material-energy building environmental footprint model: assessment of future renovation scenarios

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ABSTRACT

TODO
> Residential buildings have a significant impact on the global emissions.
> There are many studies evaluating operational and embodied impacts of buildings separately.
> But not many integrate them, especially while considering the impacts of the materials on both embodied and in-use impacts.
> Thus we develop a interface where this material data can be integrated with models estimating in-use demands, givign a final LCA of buildings.
> We further add scenarios to estimate the maintenance phase of the building as well.
> Our results show clearly that our model helps estimate the in-use emissions better (more accurate).
> scenarios in this case, for new buildings, show that energy source change is effective but insulation addition is not always as effective to save building's impacts.
> Model can be used to test for other types of buildings, where the results on the same scenarios may vary.
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1. Introduction

Nearly one third of total global final energy consumption can be attributed to the buildings and buildings construction sectors (IEA, 2022). Together these two sectors are responsible for a large share of globally emitted greenhouse gases (GHG). The potential for emissions reduction presents a great opportunity for both newly engineered as well as already existing building stock (Jennings, Hirst, Gambhir et al., 2011).

GHG emissions are released throughout all lifecycle stages of buildings starting from construction, and ending with final demolition. Researchers distinguish between *operational emissions* from energy demand for space heating/cooling, lighting, ventilation and the use of appliances, and *embodied emissions* arising from extraction and processing of raw materials, manufacturing and transportation of building components, buildings construction, maintenance and renovation (Ramesh, Prakash and Shukla, 2010). Past studies estimated a rather small magnitude of embodied emissions compared to operational emissions accumulated over the complete life span of buildings, with the respective shares being 10-30% and 70-90% (Ramesh et al., 2010; Adalberth, 1997; Utama and Gheewala, 2009). However, nowadays, due to better insulation, enhanced building designs, and higher environmental performance of energy sources, the operational emissions have been decreasing, while the shares of embodied greenhouse gas (GHG) emissions increased (Chastas, Theodosiou, Kontoleon and Bikas, 2018). For these reasons, there is a shift from studies with a sole focus on operational energy demand and towards more comprehensive assessments that include both operational and embodied impacts (Ibn-Mohammed, Greenough, Taylor, Ozawa-Meida and Acquaye, 2013).

Assessment of energy demand, GHG of residential buildings, and potential mitigation pathways is possible by means of building stock models (Nägeli, Camarasa, Jakob, Catenazzi and Ostermeyer, 2018). They are commonly categorized into top-down and bottom-up approaches (Swan and Ugursal, 2009; Kavgic, Mavrogianni, Mumovic, Summerfield, Stevanovic and Djurovic-Petrovic, 2010; Keirstead, Jennings and Sivakumar, 2012; Reinhart and Davila, 2016; Sun, Haghighat and Fung, 2020). The former analyze aggregate energy consumption of the entire residential sector, and use historical data to understand future trends as a function of broader technological and econometric

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factors, such as income, fuel prices, technological advancements, and others. However, top-down models do not allow detailed analysis of buildings' environmental performance. In contrast, the bottom-up methods investigate characteristics of individual buildings and quantify their energy consumption and environmental impact depending on building properties. This allows for explicit modeling of e.g. renovation scenarios.

Buffat, Froemelt, Heeren, Raubal and Hellweg (2017) introduced a bottom-up model to estimate building space heating demands based on large-scale geographic information systems (GIS), and with high temporal resolution. By employing light detection and ranging (LiDAR) data in combination with digital elevation models and building footprint data, the authors were able to derive building geometries and accurate building volumes. At the same time, digital surface models with 30-minute temporal resolution of spatial climate data, allowed to evaluate solar gains through windows and shading effects while accounting for the surrounding topology. This study showed that in computing the spatially-explicit heating demand, the most sensitive parameters are room temperature and thermal transmittance (U-values) of materials in building components such as floors and walls. Despite recognizing the importance of the U-values, they have been artificially sampled for each building from a generic probability distribution constructed according to the building type and age range (in Buffat et al. (2017) approach). This approach lead to low accuracy of the U-values. A more comprehensive analysis requires primary data on the material composition of the buildings components.

Material data obtained from building owners and architects can be helpful in modeling existing buildings stocks. John (2012) provided material compositions for 12 residential buildings in Switzerland and their life cycle assessment (LCA) impacts. This study contains rich level of detail in the material data due to the collected information from architectural sources; at the same time, it does not account for spatial and temporal site conditions. This resulted in higher reliability of the computed embodied impacts compared to the operational emissions estimates.

The aim of this study is to provide a model that pays equal attention to more accurate estimation of both embodied and operational greenhouse gas (GHG) emissions of residential buildings. To this end, we (1) improve the GIS-based bottom-up energy demand model from (Buffat et al., 2017) by converting it to a interface that allows integration of external material data sources and user inputs; (2) replace the generic probabilistic U-values with building specific material composition data (John, 2012); (3) incorporate life cycle impact assessment data to assess building impacts from operational emissions, given more precise space heating estimates, and compute embodied emissions; (4) compare various renovation scenarios and their potential benefits and impacts, (5) finally, validate U-values, space heating demands and embodied GHG emissions with reported data. The primary output of this work is a interface that allows data inputs from users in case material data is available, and where different scenarios can be tested to estimate the LCA of buildings. Note that throught this paper, the LCA of building includes the construction, maintenance and operational phases of the building (and not the demolition and recycling phase).

We first provide the datasets used (Section 1.1), followed by discussion of our model, which estimates the total operational and embodies emissions of the building (Section 2). Then, we introduce a case study (Section 3) to validate and showcase our results (Section **??**). Finally we conclude the paper with further discussions and outlook (Section 5 - Section **??**).

1.1. Data

In the following, we provide a description of various datasets used in this research. The overview of the datasets is listed in Table 1.

1.2. Building properties

In this work we employ a dataset that contains information about high-level building properties. The main source of this data for Switzerland is the Federal Register of Buildings and Dwellings (FRBD) that collects the most important basic data about individual buildings (FSO, 2022). The Register has been established in 2000 on the basis of a buildings and dwellings survey, and is maintained by the Swiss Federal Statistical Office (FSO). Nowadays it contains a wide variety of building types with an extensive coverage of residential buildings. The specific building parameters provided by the FRBD are listed in Table 1, and include physical parameters, information on building's construction and renovation, as well as energy and warm water sources. In addition to the FRBD, Buffat et al. (2017) computed better estimates for building footprint areas that include sets of polygons describing geocoordinates, shapes and dimensions of each building in Switzerland.

Table 1
An overview of the datasets used in the model

Category	Dataset source	Parameters
Building properties	Federal Register of Buildings and Dwellings (FSO, 2022)	Building identifier number Canton and municipality Number of floors Number of accommodation units Type and year of construction Year of renovation Energy reference area Heating and warm water sources
	Buffat et al. (2017)	Geocoordinates Footprint area
Building components	Digital elevation models (swisstopo, 2022)	Building volume External and inner wall areas Number of floors Roof area Windows dimensions
Materials of building components	Material intensities based on: - (Heeren and Fishman, 2019) - (Heeren and Hellweg, 2019) - (Gauch et al., 2016)	Materials used in: - façade - walls and windows - roofs and ceilings - floors
	Material compositions from: - literature sources - architects and planners - building owners	
Material properties	Literature sources (see comprehensive list in the SI excel	Thermal conductivities of: - walls and windows - roofs and ceilings - floors
Site data	Climate (MeteoSwiss, 2022)	Daily mean temperature
	Solar radiation (Müller et al., 2015)	Global irradiance Direct normal irradiance Cloud albedo
	Digital elevation models (swisstopo, 2022)	Geocoordinates Shading effects
Environmental data	Life cycle inventories from ecoinvent (Wernet et al., 2016)	Energy and material inputs in product systems Emissions to and from the natural environment
	Life cycle impact assessment (Stocker, 2014; Myhre et al., 2014)	Global warming potential values for greenhouse gases
	KBOB platform (Koordinationskonferenz der Bau- und Liegenschaftsorgane der öffentlichen Bauherren) (KBOB, 2022)	Impacts per kilograms of various construction materials

1.3. Building components

The Swiss Federal Office of Topography (swisstopo) is a crucial source of geoinformation data in Switzerland. It is responsible for the collection, management and provision of official geodata and the provision of spatial services (swisstopo, 2022). Swisstopo has a long history of developing high-resolution digital elevation models of Swiss landscape such as (1) digital surface models (DSMs) that incorporate all items above ground, and (2) digital terrain models (DTMs) outlining the bare ground natural terrain, excluding natural and built surface objects. Following previous research in combination with the building properties dataset described above, these models were used to derive building volumes, areas of walls, number of floors, configuration of windows and other attributes of various building components to estimate building heat demands (Buffat et al., 2017; Buffat, Heeren, Froemelt and Raubal, 2019).

1.4. Materials of building components

The type and amounts of materials used in building components constitute life cycle inventories that are needed to estimate buildings embodied emissions. At the same time, component areas and material data allows for the computation of the heat losses from walls, roofs, ceilings, floors and other components of a building during its operational phase (see Section 2.2). This information can be provided as material composition or material intensity data.

Material composition can be defined for various building components, and is expressed as thickness of each constituting material in the component's cross-section. The composition includes but is not limited to construction, cover, finish, and insulation materials. For instance, floor composition might include combination of insulated wood panel, bitumen membrane, cement cast plaster floor and concrete floor slab. Material composition data can be collected from architects, planners and building owners, as well as from literature sources. In case it is not available, we use the material intensities of buildings instead.

Material intensity is the total mass of a construction material present in an entire building divided by the building's volume (or sometimes its floor area). In this work, we assembled a dataset with mass-to-volume ratios of minerals, metals, timber, brick, concrete, and combustible materials for typical Swiss buildings based on a literature review (Heeren and Fishman, 2019; Heeren and Hellweg, 2019; Gauch et al., 2016). Due to the changes in material technology and policies on sustainable construction, materials used in the construction of buildings evolve significantly over time. This is reflected in the developed dataset by choosing the typical buildings and allocating their respective material intensities based on the construction periods, each spanning at least 15 years. We validated the constructed dataset with (1) an existing building model from an architecture firm, and (2) the study on waste from building materials conducted by the Federal Office of Environment (Guerra and Kast, 2015) (see SI excel).

1.5. Material properties

Each construction material has different physical properties that determine its contribution towards the overall emissions of a building. In our model, one such important property is thermal conductivity - the rate at which the heat is conducted through material (Bird, 2002). It is measured in watts per meter-kelvin $[W/mK]$, ranging from 0.01 W/mK for gases and all the way up to 1000 W/mK for metals, where lower values point to better insulators. Based on various literature sources, we have collected thermal conductivity of 165 materials, including timber, concrete, insulation, and other materials of varying densities (see SI excel). Subsequently, thermal conductivities allow us to compute thermal transmittance, or U-value, that is the heat transfer coefficient describing how well a building component conducts heat (see Section 2.2).

1.6. Site data

In addition to the building and material datasets described above, the location of buildings significantly affects their environmental performance. For instance, **climate** conditions, such as local air temperature and solar radiation, influence heat flows between building components and its surroundings. To compute time-series of heat losses, Buffat et al. (2017) used the temperature data collected by the Swiss Federal Office of Meteorology and Climatology MeteoSwiss for the years 1994-2013 that contains daily mean temperature values on the 1.6 km in longitude and 2.3 km in latitude resolution (MeteoSwiss, 2022). To account for the effects of solar radiation, the authors employed the spatially and temporally explicit surface **solar radiation** dataset Heliosat (SARAH) provided by the Satellite Application Facility on Climate Monitoring (Müller et al., 2015). It contains solar radiation data for the entire Switzerland given on a 30 minute basis, and on a 3.8 km in longitude and 5.6 km in latitude grid. Combining these datasets with the **digital elevation models** that can account for the shading effects of neighboring structures, provides a more complete picture about the contribution of site conditions to building performance.

1.7. Environmental data

In order to compute operational and embodied emissions of buildings, life cycle assessment environmental data is needed. In this work we used ecoinvent - a well-established **life cycle inventory** (LCI) database that contains

(1) datasets on energy and material inputs in a wide variety of product systems present in global supply chains, as well as (2) natural resources taken from the natural environment and emissions released to the water, air and soil (Wernet et al., 2016). We focus on the climate change **life cycle impact assessment** method, with the global warming potential values of greenhouse gases estimated in the Technical Report by the Intergovernmental Panel on Climate Change (IPCC) (Stocker, 2014; Myhre et al., 2014). For the materials, we employ data available on the **KBOB platform** (Koordinationskonferenz der Bau- und Liegenschaftsorgane der öffentlichen Bauherren) (KBOB, 2022). KBOB datasets were originally based on ecoinvent. They contain impact assessment results for various construction materials, while taking into account services, transport and energy systems representative specifically for the building sector in Switzerland. For example, climate change impacts are given in kilograms of CO_2 equivalents per kilograms of materials.

2. Model

All the above mentioned data come from various model estimations and different literature sources. However, to obtain an accurate estimation of the building related emissions, it is preferable to obtain measured values from architects and building planners. Thus, in our model we make a provision for these model "users" to input the building properties, their components and their material compositions. We have developed a tiered model to take this input from the users, and thus estimate the final emissions of the building, as shown in Figure 1. All user prompts, examples of user provided values, and default model values are listed in SI excel. For this model, we use a specific user case study gathered by John (2012) and this is detailed in Section 3.

The tiers are laid out with this objective: To calculate the total emissions of the building, the final tier (tier 5) gathers data on operational emissions from calculations of space heating demand (tier 4), while for embodied emissions, the material data, components and properties are gathered (from user) in first three tiers (tier 1-3). The tiers are detailed below, while the processes are explained in detail in Sections 2.1-2.3. The model described here is developed on Python3 [1] to complement Buffat et al. (2017), and is available as a Github repository [2]. At each tier of the model a python dictionary [3] is taken as an input from the user or the model default values (and a pandas dataframe [4] is produced as an output) for each building, and then passed onto the next tier.

Tier 1: The first step in the model is to obtain the **building properties** for a given building. For this, the user is prompted with the first question on providing a unique building identifier. The unique identifiers in the databases of our model which contain the building properties (FSO, 2022; Buffat et al., 2017) are the building ID and the geocoordinates. For swiss buildings, this ID is the "Eidgenössische Gebäudeidentifikator (EGID)" or unique federal building identifier allocated to each building. Based on this user input on the identifier, model helps locate the user building in the database and thus assign its building properties. But in some cases, the model is not able to find the exact match of the ID and/or geocoordinates, due to the missing information on ID or approximate geocoordinates provided by the user. In that case, the model either prompt users with further questions on other building properties or uses a "least distance approach" to find the building closest in terms of building properties. As we use this approach for our case study, it is further detailed in Section 3.1.

Tier 2: After the building properties are obtained, the user is prompted to list the different **building components**. If the user does not have the information on the components, the building components are allocated based on the digital elevation model by Buffat et al. (2017). If the user has the information on the building component, i.e. the walls, roofs and floors, the user is further prompted to provide information on the **material compositions** of the components as well. Either in the case when the user does not have the information on the components or on the material compositions of the components, the model allocates the default values of the **material intensity** for the building based on its construction year. If the user has the information on material composition, then the model allocates the materials and their thicknesses to the various building components defined in the last tier for the building.

Tier 3: The tiers above collect the information on the building materials, components and properties. If the material information is available with the users, the materials listed by the users are linked to their respective **material properties**. The thermal conductivities and the thickness of the material (from the material properties and material compositions) for the provided components help calculate the thermal transmittance (U-Values) of the components

[1] https://www.python.org/
[2] https://github.com/rhythimashinde/building-model
[3] https://docs.python.org/3/tutorial/datastructures.html#dictionaries
[4] https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.html

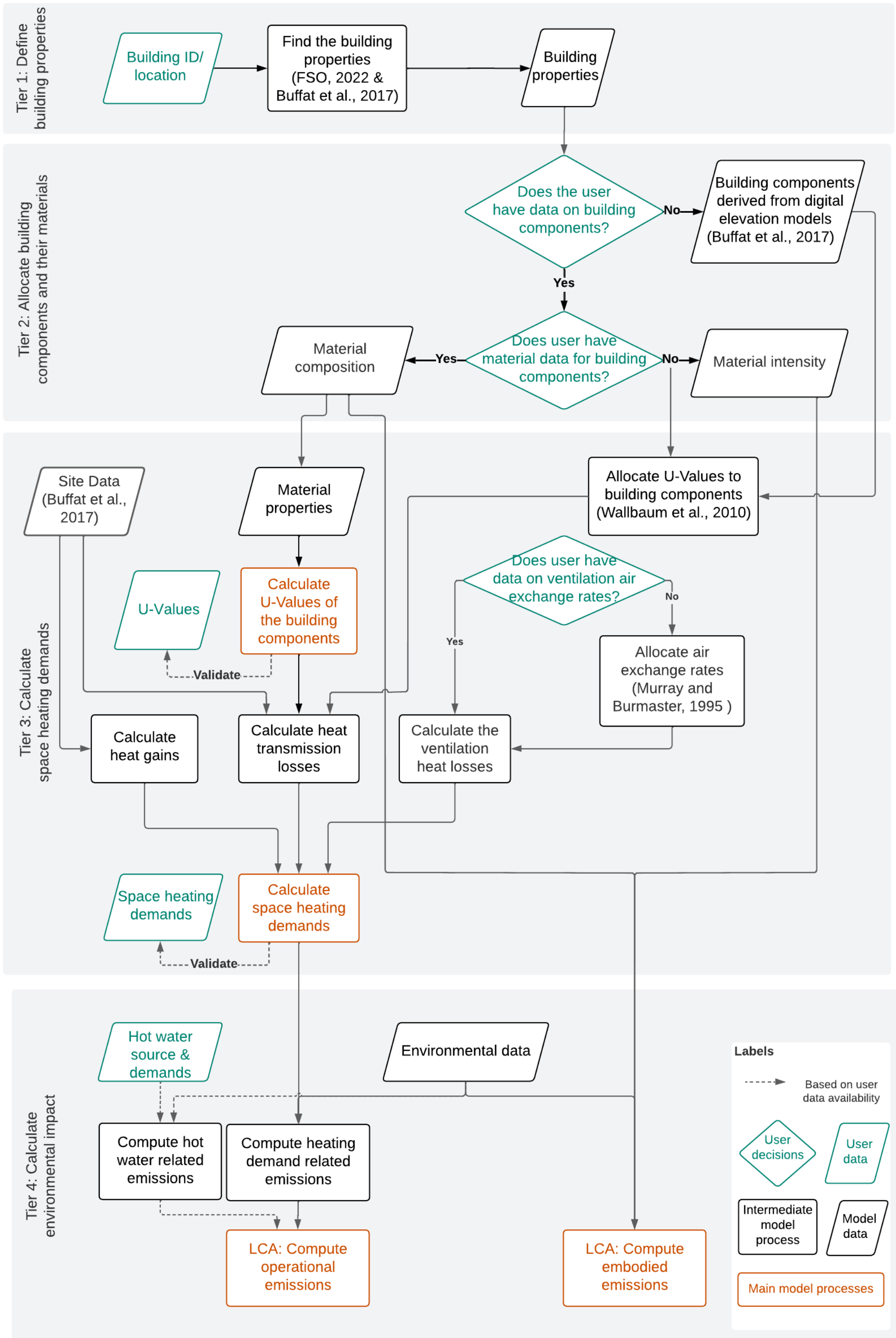

Figure 1: Methodological approach for material-data integration and validation

(Section 2.1). In case the material information is not available with the users, the model allocates U-Values to each building component directly, based on the construction year of the building and derived from Wallbaum, Heeren, Jakob and Martius (2010). Once the U Values are allocated to the building components, the model estimates the heat transmission losses, which finally contributes towards the space heating demand of the building (Section 2.2). As the ventilation losses based on the air exchanges rates, either provided by the user or Murray and Burmaster (1995), and the heat gains also contribute to the space heating demand, we calculate them in this tier. We also make provision for validation in the model based on the availability (with users) of the U-Values of the components or the space heating demands (preferably measured) of the building.

Tier 4: Once the space heating demands are calculated for a building, based on the **environmental data** (in this case, the emission factor per unit of space heating demand) and the building properties (i.e. the space heating source), the final operational emissions of the buildings are calculated. In case the hot water demands and source is also present with the user, the emissions related to hot water demands are calculated. These emissions then are added to the space heating demand related emissions to calculate the total operational emissions of the building. Based on the material information of the building (either material composition or intensity) and the environmental data (in this case, the emission factor per unit of material used), the embodied emissions of the building are calculated (Section 2.3).

2.1. Calculate U-Values

In the first tiers (tier 1-2) of the model, the user is prompted to provide the building properties, the components and their materials compositions, which is primarily the construction and insulation materials used in the walls, roofs, and floors of the building. The purpose of gathering this information is to estimate that how each of the building component which is exposed to the outer air or (un)heated spaces of the building losses the heat and thus affect building's 'heat transmission losses' ($Q_{T,c}$, detailed in Section 2.2 and equation 3). Heat transmission losses for a building are primarily defined by the thermal transmittance (U-Value) of the components of the building.For a component (c) of the building, U-Value (U_c) is calculated based on each material (i), it's thickness (t) and its thermal conductivity (k) as shown in equation 1.

$$U_c = 1/\sum_i (t/k) \tag{1}$$

If the user does not have the material composition data for any component, the model allocates the U-Value for that component based on the construction period and renewal (renovation) rate of the building as estimated by Wallbaum et al. (2010); Heeren, Jakob, Martius, Gross and Wallbaum (2013). This also means that when the data from the user is missing, the model allocates an approximate U-Value to all buildings with same construction and renovation periods, which can lead to differences from the actual heat losses in the building. Note that the final components which are used in the model are floors, roofs, and walls against outside air, floors and walls against unheated spaces, and walls against adjacent heated spaces. If there are multiple components of one of those listed above, e.g. walls against outside air, for the sake of model simplification, we select the average U values for that component of the building.

2.2. Calculate space heating demand

Based on the allocated or calculated U-Values, the goal of tier 3 of the model is to calculate the total space heating demand to estimate the final operational emissions in the last tier (tier 4). In our model (as in Buffat et al. (2017)), the space heating demand is defined by SIA-380/1 (2009), which is a building heat model used in Switzerland to verify that buildings meet the heating insulation obligations. The model estimates the heat demand of a building using a monthly steady-state method while providing fairly accurate results across different building stocks. The model defines the heat demand of a building (Q_h) as in the equation 2, where, $Q_{T,c}$ are the heat transmission losses, Q_V are the ventilation heat losses, and Q_G are the heat gains associated to the building.

$$Q_h = \sum_t Q_T + Q_V - Q_G \tag{2}$$

Heat Transmission losses($Q_{T,c}$): are the losses due to the different building components (c) including windows, walls, floors and roofs of the building. As shown in equation 3, they are measured based on the temperature differences between heated and unheated areas (Δ_T), area of the components (A_c), their U-Values (U_c) and reduction factors (b_c) due to reduced thermal losses e.g. walls against unheated rooms.

$$Q_{T,c} = A_c * U_c * \Delta_T * b_c \tag{3}$$

Ventilation losses(Q_V): are modelled based on the volume of the building, which is derived from the digital elevation models as in Buffat et al. (2017). It also depends on the air exchange rates affected by the presence of inhabitants and their behavioral changes (e.g. keeping the window open), which is derived from Murray and Burmaster (1995), where the rates are provided from a probability distribution. Finally, the building elevation and the specific heat storage capacity of air affect the ventilation heat losses for a building. In our model, we also prompt the user to provide the air exchange rates (if available), to replace this probabilistic estimation of user behavior from Murray and Burmaster (1995).

Heat Gains(Q_G): for a building are defined by the degree of utilisation of heat gains(η_g), solar heat gains (Q_S), heat gains from electric devices(Q_{iE}) and heat gains from the inhabitants(Q_{iP}), as shown in equation 4. Here, the solar heat gains are derived from the site data i.e. the solar radiation data, the window size and orientation , energy conductivity of a window, and the shadowing effect of the neighboring building as estimated in the digital elevation models from SIA-380/1 (2009). The electricity heat gains are estimated based on typical electricity heat gains per year and the energy reference area for the building. Finally, the heat gain from inhabitants is modelled from the occupants and heat produced per inhabitant (Buffat et al., 2017). In our model, the users can additionally update the occupancy, the energy reference area of the building and the window sizes and orientations to update the heat gains, but this is not provided in our case study.

$$Q_G = \eta_g * (Q_S + Q_{iP} + Q_{iE}) \tag{4}$$

2.3. Life cycle assessment

The goal of this study with respect to LCA was to compute operational and embodied emissions of buildings. We consider the construction, maintenance and operation phases of the buildings, but exclude demolition and recycling processes. In line with the state-of-the-art research, the functional unit was chosen as one square meter area of dwelling over one year (1 $m^2 \cdot$year), and the lifetime of all the buildings was assumed to be 80 years (Ianchenko, Simonen and Barnes, 2020). LCAs were performed with Brightway - an open source Python library for advanced LCA calculations (Mutel, 2017).

To estimate the **operational emissions**, LCIA was conducted for the computed space heating demand for each building, where the specified heating source was matched against the ecoinvent LCI database (version 3.8, cutoff system model) Wernet et al. (2016). The foreground system for the **embodied emissions** was constructed based on the material composition dataset (Section 1.4) linked to the KBOB platform (Section 1.7).

Environmental performance for the climate change impact category is assessed via the 100-year time horizon GWP values of hundreds greenhouse gases based on the IPCC report (Stocker, 2014). This LCIA method was implemented for ecoinvent environmental flows by Bourgault (2020). Final LCIA scores are expressed in kilograms of CO_2 equivalent (kg CO_2-eq) per square meter area and one year. Naturally, this analysis can be easily extended to other impact categories and LCI databases.

3. Case study

In this paper, to test the model, we use a case study data of 12 Swiss buildings provided by John (2012), and collected from Swiss architects and planners. The dataset of these 12 buildings (constructed post 2000) serve as a good case study for us to test how the model works with different types of buildings and variations in user data . The major advantage of this dataset is the information on every building's properties, components and their material composition in details. This data also includes annual heat demand and the thermal resistance of the building components (U values) of the building. This helps us further in validating our model results. Additionally, the case study also contains information on the ventilation air exchange rates and the hot water demands and sources for some buildings, which help us estimate the operational emissions better than estimations from Buffat et al. (2017). The basic characteristics of these buildings are laid out in the Table 2 below, and the details are provided in SI excel.

Table 2
Basic information on 12 Swiss buildings used in this model as case study (John, 2012)

	Canton	Construction year	Accommo-dation units	Built surface area [m²]	Heating source	Energy standard
mfh01	Zurich	2012 (8022)	111	2350	Electric heat pump water brine (343 kW)	MINERGIE
mfh02	Schwyz	2011 (8022)	2	190.2	District heating	MINERGIE-ECO
mfh03	Bern	2011 (8022)	3	163.4	Electric heat pump water brine	MINERGIE-P
mfh04	Zurich	2010 (8021)	4	240	Electric heat pump water brine (16.7 kW)	SIA 380
mfh05	Zurich	2007 (8021)	132	2218	Electric heat pump water brine (92 kW)	MINERGIE-P-ECO
mfh06	Bern	2006 (8021)	3	777	Wood pellet heating (67.2 kW)	MINERGIE-P-ECO
mfh07	Zurich	2011 (8022)	89	1810	Modulating condensating boiler (kW 200)	MINERGIE
mfh08	Lucerne	2011 (8022)	6	375.3	Electric heat pump water brine (24.9 kW)	MINERGIE-P-ECO
mfh09	St Gallen	2008 (8021)	4	135.15	Electric heat pump, air water (4.2 kW)	MINERGIE-P-ECO
mfh10	Zurich	2012 (8022)	10	411	Near/ district heating from cogeneration	MINERGIE
mfh11	Bern	2012 (8022)	22	665	Electric heat pump water brine (40.8 kW)	MINERGIE-P-ECO
mfh12	Lucerne	2008 (8021)	10	168.75	Electric heat pump water brine (28.1 kW)	

3.1. Allocate building properties

To include the case study as the user data, the first step in the model (Figure 1) is to find the building properties for the user provided building IDs or geo-coordinates. To maintain the anonymity of the buildings, in this case study, the information on these identifiers is missing and thus we use a two step approach here to find the building properties. We first prompt the user to provide three of the building properties (for all the 12 buildings): the year of construction, municipality, and height of the building. These building properties are chosen because they are found easily with the users and are least likely to be measured wrong or affected by the renovations in the building over its lifetime. But in case the model fails to find a unique match (either no match or a set of buildings), we use a "least distance approach" for finding the closest match of building, in terms of the building properties. For our case study, as we always find multiple buildings instead of a unique building to match the databases in the model, we have used the 'least distance' approach, which means we find the closest (least root mean square difference) building in terms of the building properties matching the user building. The matched building properties to further compute the emissions are shown in SI excel.

3.2. Scenario assessment

Based on the data gathered in this case study, and the model steps discussed in the section 2, we can calculate the total embodied and operational emissions of the building. But for this case study, we also present the steps for estimating renovation related emissions of building. For the same, we have introduced two sets of scenarios in this model. The focus of these scenarios is to estimate the potential savings in the emissions of the building. In our model, scenarios directly update the building properties data and thus update the final operational and/or embodied emissions. The two scenarios are explained below with steps for model modifications.

Adding insulation: A common practice to reduce the heat demand of the building (and thus the operational emissions and also the energy bills) is to reduce the thermal losses of the buildings. This is usually done by insulating the buildings further with adding insulation layers, or replacing the existing insulation layers with better materials. For our case study, we follow Ostermeyer, Nägeli, Heeren and Wallbaum (2018), which states standard or efficiency refurbishment scenarios based on the existing building type. The former refurbishment leads to the resulting U-value of the refurbished building components between the legal minimum (SIA 280) and the MINERGIE standard. This means the U Values for walls $< 0.15\ W/m^2K$, and for windows $< 1\ W/m^2K$. The latter form of refurbishment transitions towards a passive-house or MINERGIE-P which means the U Values for walls approx. $0.10\ W/m^2K$, for roof $< 0.15\ W/m^2K$, for floor $<0.15\ W/m^2K$, for windows $< 0.6\ W/m^2K$

Changing heating source: Additional to insulation changes (which affects both the operational and embodied emissions), the change in heating sources can be quite influential to reduce the operational emissions of the building. In the case study of 12 buildings, we have electric heat pump (brine water) ($0.033\ kgCO_2eq/MJ$), district heating ($0.00019\ kgCO_2eq/MJ$), wood pellet ($0.013\ kgCO_2eq/MJ$), or natural gas ($0.065\ kgCO_2eq/MJ$) as the primary heating or hot water sources. The only case where a heating source change could make a difference is the natural gas source, as it has a high impact per unit of energy used. As the district heating heavily depends on the location of a building, based on the second least environmental impact, the scenario introduces a change of natural gas source to the brine water heat pump source.

Note that the purpose of the scenario assessment here is to showcase that the users of this model (e.g. building owners, policy makers, architects) can introduce many more renovation scenarios (e.g. in Fishman, Heeren, Pauliuk, Berrill, Tu, Wolfram and Hertwich (2021); Heeren and Hellweg (2019); Mastrucci, Marvuglia, Benetto and Leopold (2020)) or even create potential scenarios to check for the changes in the building emissions based on different renovations to make better building related renovation choices.

4. Results and Validation

In the following section, based on the methods discussed above, the results are laid out for the estimated U values (section 4.1) and heat demands (section 4.2) for impacts in operational phase of (for case study of 12 Swiss) buildings are laid out. Then, to incorporate the impacts of all the construction, maintenance and operational phase, the LCA results with the scenario results are discussed (Section 4.3 and Section 4.4).

4.1. U values

In this section, we present how the U values calculated in our model vary compared to the reported U values for the 12 swiss buildings. The following Figure 2 show an example with the calculated (in our model) and reported U values (from John's data) for two building components (roof and external walls) of few buildings. As can be seen in the graph, the calculated and the given values are not significantly different, which confirms the U values calculation implemented in the model. In the SI excel we also show these U values for all the building components for all the buildings, compared to the reported U Values and the U Values which are estimated for these buildings by the Buffat et al. (2017) model.

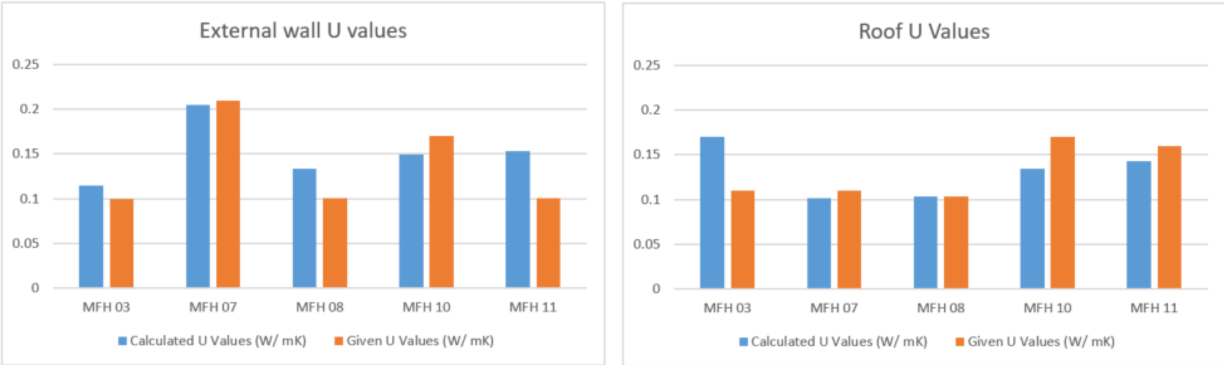

Figure 2: Results of U Values for 5 example buildings: calculated (in our model) vs reported by John (2012)

4.2. Heating demand

After allocating the U values for the building components to the buildings, the heat demands are updated using the Buffat et al. (2017) model. The following Figure 3 shows the calculated vs measured heat demand results. For comparison, in the same graph we also add the "old" calculated space heat demand results (with the simplified estimation of U values in Buffat et al. (2017)). As shown further in the Table 4.2, the current model shows a very high improvement in the final heat demand quantification compared to the previously simplified U values. the buildings with highest improvement in relative error [5] (mfh 03, 06 and 08) are also those where the U Values changed most due to the new quantification of U values and introduction of material composition. Also note that these are the buildings with some of the highest estimated heating demand. This provides a scope for our model to correct the "default" u values for these building typologies, improving the estimations of buildings' energy demands. Note that although the relative error reduces with the new model, the high error for some of the buildings (compared to the measured values) exist due to multiple reasons including the user behavior, etc. which is not included in the model currently (discussed more in Section 5). Also, it is important to note that the measured data referred to one particular year, which may not be representative for longer time periods.

4.3. LCA results

Allocating the material impact factor per material used in the building components, we estimate the embodied emissions of the building. This database of the material impacts for the 12 Swiss buildings used in the case study here is shown in the SI excel. The estimated embodied GHG are then added to the operational GHG (calculated via space

[5] relative error here is defined as the ratio of the difference between measured value and the calculated value, and the measured value

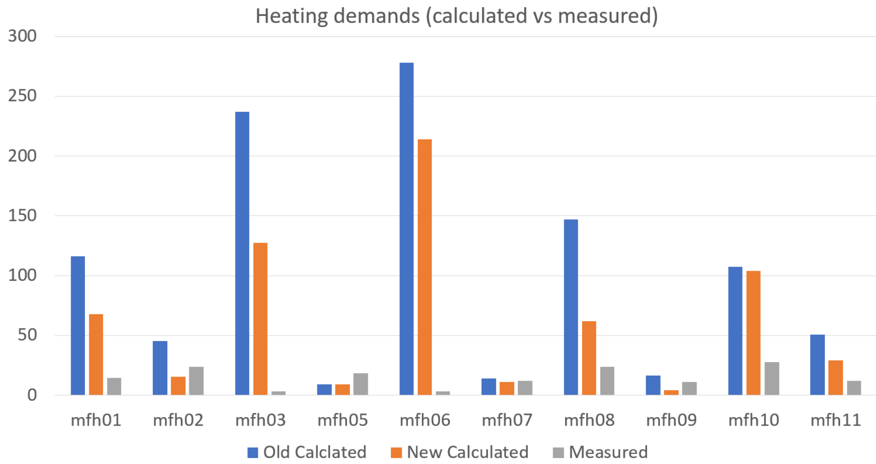

Figure 3: Heat demand estimation of the simplified (old) approach by Buffat et al. (2017) (left bar column), the updated model using accurate material specifications of each building (middle bar column), and reported values by John (2012) (right bar column)

Table 3
Relative errors [6] for the models in estimation of space heat demand

Building	Decrease in relative error	Relative error old	Relative error new
mfh03	33.22	70.79	37.58
mfh06	19.43	83.24	63.81
mfh08	3.55	5.14	1.58
mfh01	3.37	7.08	3.72
mfh11	1.81	3.27	1.47
mfh02	0.54	0.89	0.35
mfh10	0.11	2.86	2.75
mfh07	0.06	0.15	0.09
mfh12	0.00	1.00	1.00
mfh05	-0.01	0.50	0.51
mfh09	-0.15	0.46	0.61
Average	**5.63**	**15.94**	**10.32**

heating demand estimated in the above Section 4.2 above), to estimate the total GHGs for the building. The Figure 4 shows the Greenhouse Gas (GHG) emissions calculated annually per metresquare of the different buildings. The results show that the LCA of the buildings is rather high for the mfh02 and mfh06. One of the reasons explaining this could be the ratio of the building surface area per sq.m being the highest for these two buildings (96 m^2/ accommodation unit and 259 m^2/unit, respectively).

4.4. Scenarios

For showcasing how the model works with various scenarios, we have introduced two scenarios for two buildings mfh07 and mfh10 as they have a natural gas as a heating system which can be improved further (scenario 2). We keep the same buildings for further improvements in insulation (scenario 1) to study the effects of different scenarios on the same building. The changes as per the scenarios in the existing buildings' parameters e.g. the walls' insulation, or the heating systems

Listed in the Table 4.

Scenario 1- Insulation: For the first scenario of adding a layer of insulation, a new insulation material is added in the building walls which is not already present to effectively change the thermal conductivity of the walls and reduce the U values. This affects the LCA of the building in two ways: the additional material increases the embodied impact

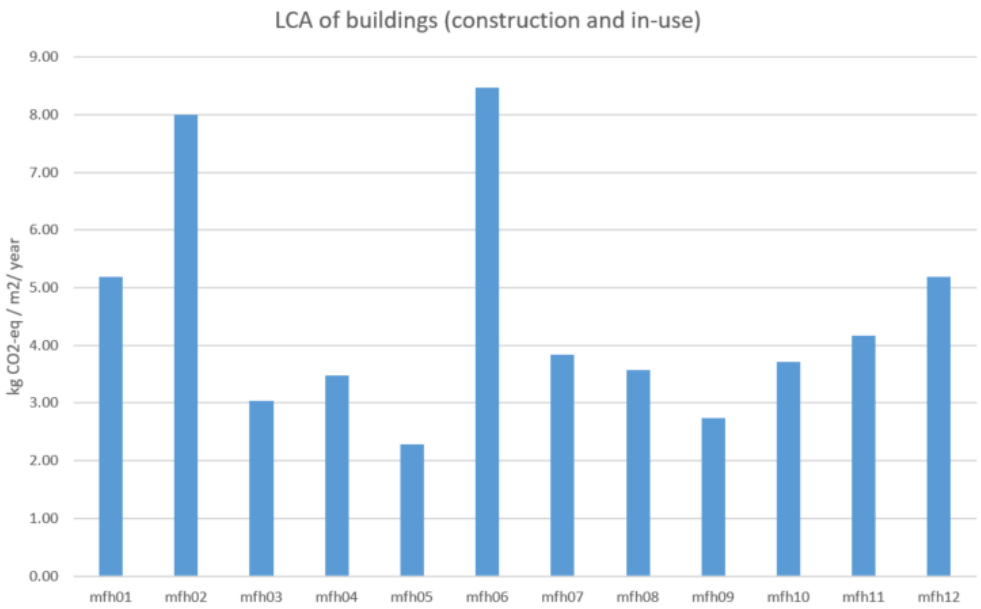

Figure 4: LCA (Greenhouse gas emissions) for all the buildings, split by the embodied and operational emissions. The lifetime assumed for all buildings was 80 years.

Table 4
Changes in building parameters introduced as per the scenarios

	Scenario 1: Insulation				Scenario 2: Heating	
	Old U Value for walls	New U Value for walls	Insulation material	+Material intensity (kg/m^2/year)	Old heating source	New heating source
mfh07	0.116	0.050	rockwool insulation	0.089	Natural Gas	Heat Pump
mfh10	0.16	0.033	cellulose fiber	0.468	Natural Gas	Heat Pump

of the building, while the additional insulation reduces the energy impact (usage) for heating the building. As shown in Figure 5, the insulation scenario shows for both the rockwool insulation in the mfh07 and cellulose fiber in mfh10 that the insulation is not very effective way for reducing the impacts. It should be noted the energy benefit of adding insulation is only about 5%, comparable to the second scenario of heating system change.

Scenario 2- Heating source change: For change in the heating source, we chose to convert the natural gas systems in the two buildings to brine water heat pumps, as they have low impact (district water incinerators have even lower impacts, but they can only be installed based on the location of the building). Figure 5 shows that the change in energy sources help in always reducing the impacts of the building. It should be noted that these are MINERGIE buildings with a very low impact already, and thus the change in the heating source or insulation doesn't necessarily show an improvement, but for other buildings, the case might be different based on their initial construct).

5. Discussion and Outlook

Takeaways and highlights from the model :

> Considering the results, for the case of the 12 buildings (new energy-efficient buildings, only around 10 years old), operational emissions rather low, so relatively the embodied emissions clearly show to have a significant impact.

> Note that the scenarios showcased here are performed for illustrating the capabilities of the tool developed here. All buildings in Table 2 are relatively new and well insulated, and in reality they would probably not be the candidates for the energy related renovations.

> The method improved the energy estimations for all of the buildings (still greatly deviating for the MINERGIE-P buildings, which have very low operational emissions)

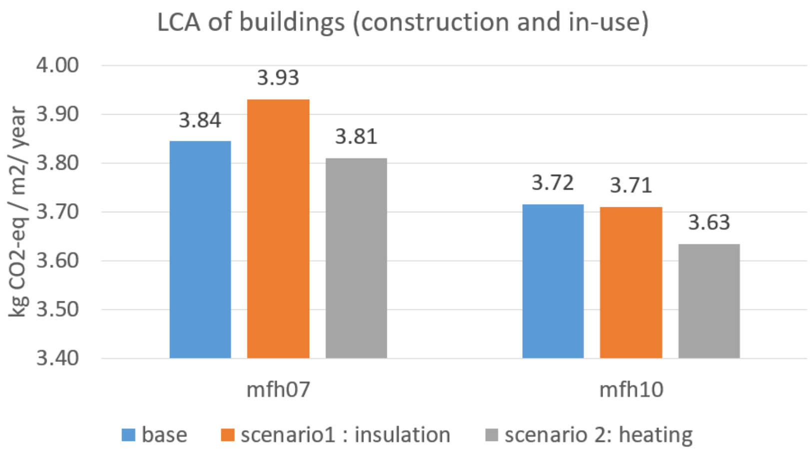

Figure 5: Scenario results: LCA (GHG) for two of the buildings (see Table 4 for Scenarios)

> The method proposed here presents an improved way of calculating the LCA for the buildings, with the possibility for integrating data provided by users. Tiered approach allows for large scale modeling while allowing for detailed assessment if data is not available.
> We can also integrate data from other research in different regions, e.g. an extension of our study can allow integration of approaches like Kleemann, Lederer, Aschenbrenner, Rechberger and Fellner (2016), which used construction data in combination with on-site investigations to characterize material composition of buildings in Austria; as well as Gontia, Nägeli, Rosado, Kalmykova and Österbring (2018), who created a material intensity database for residential buildings in Sweden that is based on architectural data and densities of construction materials. > Thus this is a truly bottom-up model while in comparison with other bottom up models (A detail analysis of bottom up model here Trigaux, Allacker and Debacker (2021))
> We also propose a framework to upscale the model by better estimation of U Values (even with missing material data) (Figure **??**)
> Results
> scenarios

Limitations and improvements of the model :
> Uncertainties in thermal conductivity for similar materials, but still good results in figure 4
> Electricity consumption and warm water source not included in LCA - but can be
> Currently only monthly scale of temporal data is used in the model right now, and this can be modified for different scenarios like solar
> User behavior is not included

6. Conclusion

> Buildings are high emitters, in their construction, maintenance and renovation phase.
Though these phases are well estimated across various studies, they are not always well connected to each other e.g. the materials impacting the embodies emissions, also affect the final operational emissions
> Our model creates a interface and a data pipeline to integrate the data from users or studies to better estimate the LCA of buildings.
> It also allows estimating LCA better for buildings with missing data.
> Our study shows significant improvement in the energy estimations compared to a high resolution energy space heating demand model (Buffat's)

> It also shows that not all renovations affect the buildings for lower environmental impact when both the energy and material emissions are considered together
> There is a possibility to improve this model further with better data sources from electricity and heating water sources, and user behavior.

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Authors contribution

All authors contributed to the presented study in conceiving and designing the analysis, and have reviewed and given approval to the final version of the manuscript. S.H. proposed the idea for this study and provided feedback throughout the project. R.S. conducted literature review, set up the models, performed the analytic calculations, the numerical simulations and drafted the paper. A.K. helped in writing and reviewing, and also contributing towards the LCA calculations in the model. All authors contributed to the writing of the manuscript. S.H. supervised the project.

Associated Content

Supporting_Information.xlsx
Sheet 1-10: Data preprocessing and description details, Sheet 11-13: Method and choice explanation, Sheet 13-24: Detailed and additional results on different consumption categories and household properties.
Complete Code available on `https://github.com/rhythimashinde/building-model`

References

Adalberth, K., 1997. Energy use during the life cycle of single-unit dwellings: examples. Building and environment 32, 321–329.

Myhre et al., G., 2014. Anthropogenic and Natural Radiative Forcing Supplementary Material. In Climate change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge university press.

Wernet et al., G., 2016. The ecoinvent database version 3 (part i): overview and methodology. The International Journal of Life Cycle Assessment 21, 1218–1230.

Gauch et al., M., 2016. Material- und energieressourcen sowie umweltauswirkungen der baulichen infrastruktur der schweiz. BAFU Bundesamt für Umwelt .

Müller et al., R., 2015. Surface solar radiation data set-heliosat (sarah)-edition 1. satellite application facility on climate monitoring. EUMETSAT Satellite Application Facility on Climate Monitoring .

Bird, R.B., 2002. Transport phenomena. Appl. Mech. Rev. 55, R1–R4.

Bourgault, G., 2020. Implementation of impact assessment methods in the ecoinvent database version 3.7.1. Ecoinvent Association: Zürich, Switzerland .

Buffat, R., Froemelt, A., Heeren, N., Raubal, M., Hellweg, S., 2017. Big data gis analysis for novel approaches in building stock modelling. Applied Energy 208, 277–290.

Buffat, R., Heeren, N., Froemelt, A., Raubal, M., 2019. Impact of ch2018 climate change scenarios for switzerland on today's swiss building stock, in: Journal of Physics: Conference Series, IOP Publishing. p. 012004.

Chastas, P., Theodosiou, T., Kontoleon, K.J., Bikas, D., 2018. Normalising and assessing carbon emissions in the building sector: A review on the embodied co2 emissions of residential buildings. Building and Environment 130, 212–226.

Fishman, T., Heeren, N., Pauliuk, S., Berrill, P., Tu, Q., Wolfram, P., Hertwich, E.G., 2021. A comprehensive set of global scenarios of housing, mobility, and material efficiency for material cycles and energy systems modeling. Journal of Industrial Ecology 25, 305–320.

FSO, 2022. Federal Register of Buildings and Dwellings. 22905270, Bundesamt für Statistik (BFS), Neuchâtel. URL: `https://dam-api.bfs.admin.ch/hub/api/dam/assets/22905270/master`.

Gontia, P., Nägeli, C., Rosado, L., Kalmykova, Y., Österbring, M., 2018. Material-intensity database of residential buildings: A case-study of sweden in the international context. Resources, Conservation and Recycling 130, 228–239.

Guerra, F., Kast, B., 2015. Bauabfälle in der schweiz-hochbau studie 2015. Bundesam t für Umwelt BAFU, Zürich .

Heeren, N., Fishman, T., 2019. A database seed for a community-driven material intensity research platform. Scientific data 6, 1–10.

Heeren, N., Hellweg, S., 2019. Tracking construction material over space and time: Prospective and geo-referenced modeling of building stocks and construction material flows. Journal of Industrial Ecology 23, 253–267.

Heeren, N., Jakob, M., Martius, G., Gross, N., Wallbaum, H., 2013. A component based bottom-up building stock model for comprehensive environmental impact assessment and target control. Renewable and Sustainable Energy Reviews 20, 45–56.

Ianchenko, A., Simonen, K., Barnes, C., 2020. Residential building lifespan and community turnover. Journal of Architectural Engineering 26, 04020026.

Ibn-Mohammed, T., Greenough, R., Taylor, S., Ozawa-Meida, L., Acquaye, A., 2013. Operational vs. embodied emissions in buildings—a review of current trends. Energy and Buildings 66, 232–245.

IEA, I.E.A., 2022. Buildings. URL: https://www.iea.org/topics/buildings. (accessed 2022-07-28).

Jennings, M., Hirst, N., Gambhir, A., et al., 2011. Reduction of carbon dioxide emissions in the global building sector to 2050. Grantham Institute for Climate Change report GR 3.

John, V., 2012. Derivation of reliable simplification strategies for the comparative LCA of individual and" typical" newly built Swiss apartment buildings. Ph.D. thesis. ETH Zurich.

Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., Djurovic-Petrovic, M., 2010. A review of bottom-up building stock models for energy consumption in the residential sector. Building and environment 45, 1683–1697.

KBOB, 2022. Koordinationskonferenz der bau- und liegenschaftsorgane der öffentlichen bauherren. https://www.kbob.admin.ch/kbob/de/home/die-kbob/plattform-oekobilanzdaten-im-baubereich.html. Accessed: 2022-11-23.

Keirstead, J., Jennings, M., Sivakumar, A., 2012. A review of urban energy system models: Approaches, challenges and opportunities. Renewable and Sustainable Energy Reviews 16, 3847–3866.

Kleemann, F., Lederer, J., Aschenbrenner, P., Rechberger, H., Fellner, J., 2016. A method for determining buildings' material composition prior to demolition. Building Research & Information 44, 51–62.

Mastrucci, A., Marvuglia, A., Benetto, E., Leopold, U., 2020. A spatio-temporal life cycle assessment framework for building renovation scenarios at the urban scale. Renewable and Sustainable Energy Reviews 126, 109834.

MeteoSwiss, 2022. Swiss federal office of meteorology and climatology meteoswiss. https://www.meteoswiss.admin.ch/. Accessed: 2022-11-23.

Murray, D.M., Burmaster, D.E., 1995. Residential air exchange rates in the united states: empirical and estimated parametric distributions by season and climatic region. Risk Analysis 15, 459–465.

Mutel, C., 2017. Brightway: An open source framework for life cycle assessment. Journal of Open Source Software 2, 236. URL: https://doi.org/10.21105/joss.00236, doi:10.21105/joss.00236.

Nägeli, C., Camarasa, C., Jakob, M., Catenazzi, G., Ostermeyer, Y., 2018. Synthetic building stocks as a way to assess the energy demand and greenhouse gas emissions of national building stocks. Energy and Buildings 173, 443–460.

Ostermeyer, Y., Nägeli, C., Heeren, N., Wallbaum, H., 2018. Building inventory and refurbishment scenario database development for switzerland. Journal of Industrial Ecology 22, 629–642.

Ramesh, T., Prakash, R., Shukla, K., 2010. Life cycle energy analysis of buildings: An overview. Energy and buildings 42, 1592–1600.

Reinhart, C.F., Davila, C.C., 2016. Urban building energy modeling–a review of a nascent field. Building and Environment 97, 196–202.

SIA-380/1, 2009. Thermal energy in building construction.

Stocker, T., 2014. Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge university press.

Sun, Y., Haghighat, F., Fung, B.C., 2020. A review of the-state-of-the-art in data-driven approaches for building energy prediction. Energy and Buildings 221, 110022.

Swan, L.G., Ugursal, V.I., 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and sustainable energy reviews 13, 1819–1835.

swisstopo, 2022. Swiss federal office of topography. https://www.swisstopo.admin.ch/en/home.html. Accessed: 2022-11-22.

Trigaux, D., Allacker, K., Debacker, W., 2021. Environmental benchmarks for buildings: a critical literature review. The International Journal of Life Cycle Assessment 26, 1–21.

Utama, A., Gheewala, S.H., 2009. Indonesian residential high rise buildings: A life cycle energy assessment. Energy and Buildings 41, 1263–1268.

Wallbaum, H.., Heeren, N.., Jakob, M.., Martius, G., 2010. Gebäudeparkmodell büro-, schul-und wohngebäude. vorstudie zur erreichbarkeit der ziele der 2000-watt-gesellschaft für den gebäudepark der stadt zürich schlussbericht report URL: https://doi.org/10.3929/ethz-b-000113514, doi:10.3929/ethz-b-000113514.