Bottom-up LCA building stock model: tool for future building-management scenarios

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ABSTRACT

Residential buildings have a substantial impact on global environmental impacts. In this paper we present a model that assesses impacts from materials (embodied impacts) as well as from heating (operational impacts) for all residential buildings in Switzerland. Our model builds on an existing high-resolution spatio-temporal building stock model, which estimates the space heating demand of buildings, based on building property and site data. In this work we additionally include the impacts of materials extraction, production, transportation, and disposal of building components (floors, roofs, walls, ceilings and windows). Our model already comes with a site- and building-specific default parametrization for all buildings, but it is developed as a tool that allows architects and planners to adapt building and site data with specific information to increase the accuracy of the environmental assessment of the current buildings and future building-management scenarios. We applied the model to ten Swiss buildings and assessed a selection of building-management scenarios to illustrate the application of the tool. The results show that our model accurately estimates thermal and ventilation heat transmittance, operational space heating demands, and operational and embodied climate-change impacts for the considered buildings. The detailed modeling results for the ten case study buildings outperformed the simplified version of the model with generic default values for material building composition (using age-grouped building archetypes), emphasizing the importance of adding detailed material information in building life cycle assessments. Therefore, a focus should be placed on obtaining accurate material inventories of buildings in future research. The here-developed model allows for easy integration of such detailed material inventories, overwriting the provided default values.

1. Introduction

Nearly one third of the total global final energy consumption can be attributed to the buildings and building 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 et al., 2011).

GHG emissions are released throughout all lifecycle stages of buildings starting from construction, and ending with final demolition, and are typically estimated using the life cycle assessment (LCA) methodology (Hauschild, 2018). 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 et al., 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 the embodied emissions increased (Chastas et al., 2018). For these reasons, there is a shift from studies with a sole focus on operational energy demand towards more comprehensive assessments that include both types of impacts (Ibn-Mohammed et al., 2013).

Assessment of energy demand, GHG of residential buildings, and potential mitigation pathways is possible by means of building stock models (Nägeli et al., 2018). They are commonly categorized into top-down and bottom-up approaches (Swan and Ugursal, 2009; Kavgic et al., 2010; Keirstead et al., 2012; Reinhart and Davila, 2016; Sun

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et al., 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 factors, such as income, fuel prices, and technological advancements. However, top-down models do not allow detailed analysis of buildings' environmental performance in scenarios of building rennovation or changed user behavior (e.g. windos opening, indoor temperature). 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 et al. (2017) introduced a bottom-up model with high temporal resolution to estimate building space heating demands based on large-scale geographic information systems (GIS). 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 elevation 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. A sensitivity analysis (Buffat et al., 2017) 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. Despite recognizing the importance of the U-values, they were sampled for each building from a simplified probability distribution constructed according to the building type and construction period. This approach lead to low accuracy of the U-values.

A more comprehensive analysis requires primary data on the material composition of the building components. It can be obtained from building owners, planners and architects. These datasets can be helpful in better estimations of not just the U-values, but also the embodied emissions of buildings. One of the ways to include them lies in providing an interface to the building stock models, where model users can input additional building data to overwrite the 'default' values used in the model of Buffat et al. (2017). As the total emissions of a building are affected by multitude of parameters, the possible user inputs should not be restricted to material data, and should incorporate other building properties such as its volume, geometry, ventilation flow rates. Such interfaces exist as propriety software platforms or Building Information Models (BIM) (Azhar, 2011; Anand and Amor, 2017). They allow inputs on multiple different properties of building (e.g. including building piping systems, etc.) and in some cases also integrate material related impacts to estimate building's environmental impacts (Soust-Verdaguer et al., 2017).

But these tools have limited flexibility on data interoperability with respect to user inputs, i.e. if building planners input data e.g. configurations of windows in one of these models, the output data is not always integrable with other models specialised in other forms of input data e.g. building energy systems (Sun et al., 2017; Bernstein and Pittman, 2004). Also, none of the existing BIMs compare in complexity to the building stock models i.e. the ability to handle different data and integrate them from various sources e.g. building materials, energy sources and demands, climate and site data, especially for estimation of operational energy of the building. Thus, there is a clear need of a tool that combines flexible user inputs with elaborate building stock models.

The aim of this study is to provide a model that accurately estimates building impacts from materials (embodied impacts) and operational energy demand for all buildings in Switzerland. We develop our model as a stepwise tool and allow for integration of specific building and site data from users to increase the accuracy of the assessment. For example, we improve the GIS-based bottom-up energy demand model from (Buffat et al., 2017) by enabling the replacement of generic U-values with building specific material composition data. To illustrate the application of the new model, we apply it to a case study of ten Swiss residential buildings containing detailed building data that, among other information, includes material compositions (John, 2012). For this case study, we also evaluate the impacts of hypothetical scenarios including building renovation and exchange of heating source (energy carrier). Finally, we validate U-values, space heating demands and embodied greenhouse gas (GHG) emissions with reported data from the case study.

The paper is laid out as follows: first, we provide the datasets used in the study (Section 2), followed by the description of the developed model, which estimates the total operational and embodied emissions of the buildings (Section 3). Then, we introduce the case study (Section 4) and show the model's output for 10 buildings including validation of the results (Section 5). Finally, we present the discussions, outlook and conclusion for this study (Sections 6- 7).

2. 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.

2.1. Building properties

The main source of the high-level building properties data for Switzerland is the Federal Register of Buildings and Dwellings (FRBD), which collects 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 hot 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 based on the Swiss cartographic SwissTLM dataset (Fan et al., 2014) and OpenStreetMap (Schmassmann and Bovier, 2010).

2.2. Dimensions of 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 dataset described above, these models were used to derive dimensions and configurations of building components. These include statistical estimations of walls and their areas, number of floors, orientation and location of windows (Buffat et al., 2017, 2019).

2.3. Materials of building components

The materials and their amounts 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 3.2). This information can be provided as material composition or material intensity data.

Material composition can be defined as different materials constituting the layers of the building components, and their thickness 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, remote sensing for outer layers, as well as from literature sources. In case it is not available, we use default data on material intensities instead (see next paragraph).

Material intensity is the total mass of a construction material present in an entire building divided by its volume (or sometimes its floor area). Due to the changes in material technology and policies on sustainable construction, materials used in the construction of buildings evolve significantly over time. Thus, we developed a material intensity dataset for typical buildings categorised based on their construction periods, each spanning at least 15 years (see SI excel Sheet 2). The dataset includes mass-to-area ratios of minerals, metals, timber, brick, concrete, and combustible materials for 5 types of typical Swiss buildings based on their construction period (<1945, 1946-1960, 1961-1980, 1981-2000, >2000). This dataset was derived using (1) multi-family building footprint area and building volume estimations from construction periods taken from a building model developed by an architecture firm in Zurich, (2) mass to volume ratio of each material in the building from Gauch et al. (2016); Heeren and Hellweg (2019); Guerra and Kast (2015) and the building model estimations provided by the architecture firm, and (3) validation of the derived material intensities with generic values provided for all Swiss buildings by Heeren and Fishman (2019).

2.4. 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

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 (address) Number of accommodation units Type and year of construction Year of renovation Energy reference area Heating and hot water sources
	- Swiss cartographic SwissTLM dataset (Fan et al., 2014) - OpenStreetMap (Schmassmann and Bovier, 2010)	Geocoordinates Footprint area Building volume
Dimensions of building components	Digital elevation models (swisstopo, 2022)	Statistical estimations of : - External and inner wall areas - Number of floors - Roof area - Windows location and orientation
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 Sheet 1)	Thermal conductivities of: - walls and windows - roofs and ceilings - floors
Ventilation data	Ventilation rates (Murray and Burmaster, 1995)	- Air flow rates
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
Life cycle data of background processes	Life cycle inventories from ecoinvent (Wernet et al., 2016)	Energy 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

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 Sheet 1). 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 3.2).

2.5. Ventilation data

Building's ventilation significantly affects its heat losses, and thus the final space heating demand of the building. There are two types of broad ventilation systems (Santamouris and Wouters, 2006): (1) natural ventilation, where the inner and outer pressure differences in the building drive the ventilation flow of the building, and (2) mechanical ventilation, which uses fans and other mechanical systems to provide air flow in the building (it is mostly centralised for all apartments in the building). In our model, the default ventilation rates are set up for natural ventilation using probabilistic distributions provided quarter-yearly by Murray and Burmaster (1995). The model allows for overwriting these default values including mechanical ventilation without energy recovery.

2.6. Site data

In addition to the building and material datasets, 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 site conditions as inputs for the heat demand model.

2.7. Life cycle data of background processes

We used ecoinvent version 3.8, cutoff system model as data source for background inventories of heating energy supply, electricity and transport (Wernet et al., 2016). We quantify climate change impacts (or GHG emissions) **life cycle impact assessment** method, with the global warming potential values for 100 years from the Intergovernmental Panel on Climate Change (IPCC) (Stocker, 2014; Myhre et al., 2014). We use this indicator here because studies (Wang et al., 2016; Röck et al., 2020) show that GHG emissions (or climate change impacts) are crucial for the performance evaluation of buildings and to meet the global GHG reduction targets for building industry. Many indicators are available for decision-making related to environmental assessment but Steinmann et al. (2016) shows that out of 135 indicators, only 6 indicators, including climate change impacts, can capture maximum variance of environmental impacts. Thus for the purpose of this paper (and case study) we showcase results for GHG emissions and if needed, our model can be used do other impact assessments for further impact assessments of buildings. For the material impacts, we mostly employed LCA data available on the **KBOB platform** (Koordinationskonferenz der Bau- und Liegenschaftsorgane der öffentlichen Bauherren) (KBOB, 2022). In some cases, where the background inventory data was outdated, we used the ecoinvent v3.8. It contains GHG emissions from the production and disposal of various construction materials, building services, transport and energy systems representative specifically for the building sector in Switzerland. Note that the background processes in ecoinvent and KBOB are compatible with each other because (i) KBOB LCA data was based on the older ecoinvent version 2.2 (KBOB, 2022), and (ii) ecoinvent reports the changes to its processes for each new database version allowing to track the data updates from ecoinvent version 2.2 to 3.8 (Ecoinvent, 2023).

3. Model

The above described data for deriving default input parameter values was taken from various models and literature sources. In order to obtain more accurate estimates of GHG emissions for a particular building, it is preferable to replace the generic default values with the building's specific data that can e.g. be provided by architects and building planners.

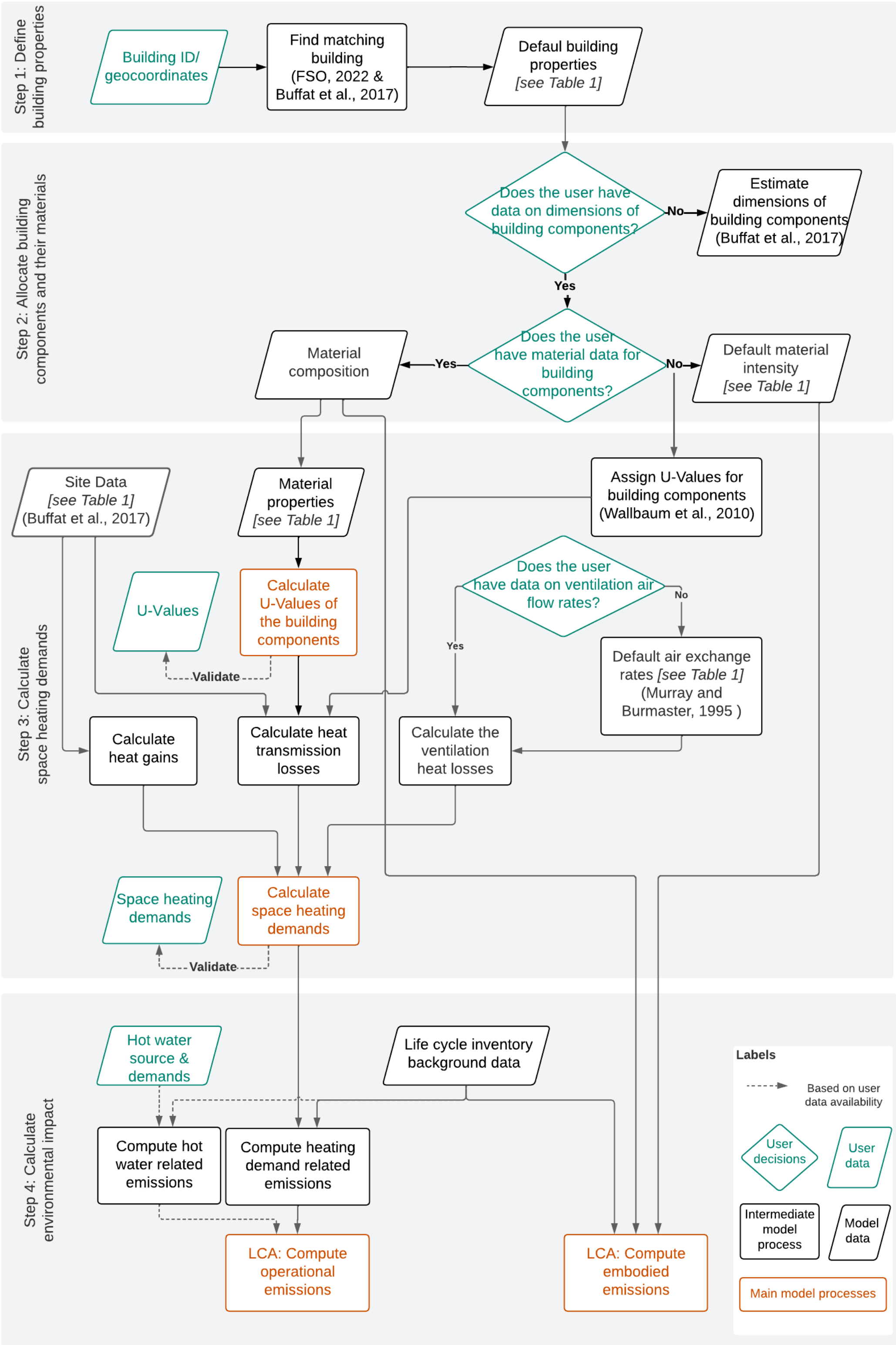

Figure 1: Methodological approach for material-data integration and validation

Thus, we developed a stepwise model that makes a provision for such model "users" to input additional data (Figure 1). The steps were laid out in the order of sequential user inputs, and with the objective of calculating the total emissions of a building. The final step 5 collects data on (1) operational emissions due to the space heating demand computed in step 4, and (2) embodied emissions which need the building components and material properties data gathered (from a user) in the steps 1-3. This model can also be used in a tiered approach based on the extent of information provided by the user. For example, if the user provides no information, the model assigns default values to building data.

The described model was developed in Python[1] to complement the model of Buffat et al. (2017), and is available as a Github repository[2]. At each step of the model, default building characteristics are combined with available user inputs and passed onto the next step. The implemented user prompts, examples of user provided inputs, and default model values are listed in the SI excel Sheet 3. In the following, we first provide an overview of the stepwise model, then detail the model calculation processes in Sections 3.1-3.3.

Step 1: The user inputs the unique building identifier or building geocoordinates (e.g. derived from address of the building, if provided), from which the stepwise model derives the **building properties** (FSO, 2022; Buffat et al., 2017). For Swiss buildings, the identifier is "Eidgenössische Gebäudeidentifikator (EGID)", or unique federal building identifier, assigned to each building in Switzerland. Based on the user input, the model locates the building and assigns it default building properties (see Table 1 for a list of these properties). In cases, when the model is not able to find the exact match due to missing information, it prompts the user with further questions on other building properties, and then employs the "least distance approach" that finds closest building in the database, where "closest" refers to similarity in terms of building properties. As we use this approach for our case study, it is further explained in Section 4.1.

Step 2: The user is prompted to provide the information on different **building components**, such as surface areas of walls, roofs and number of floors. If no data is available, the building components dimensions are derived with the digital elevation models (Buffat et al., 2017). Then, the user is asked to provide information on the components and their respective **material compositions**. In case the detailed material compositions are unknown, the model assigns the default **material intensity** values for the building based on its construction year. If the user can provide data on materials composition and thickness, then the step-wise model assigns this data to the various building components.

Step 3: Each material is linked to its respective **material properties** (Table 1). Knowing the thermal conductivities and thicknesses of materials in a building component, one can calculate the component's thermal transmittance, also called the U-value (see Section 3.1). In case the users cannot provide the material compositions, the stepwise model selects default U-values for each building component based on its construction year (Wallbaum et al., 2010). Once the U-values are assigned to the building components, the model estimates the heat transmission losses, which contribute towards the building's space heating demand (Section 3.2). In this step, we also account for the heat gains and ventilation losses based on the air exchange rates, either provided by the user or default values taken from Murray and Burmaster (1995). Notably, we make provision for the model validation if the user provides the U-values of the building components, and the space heating demand of the building (preferably measured).

Step 4: Finally, the model estimates total building GHG emissions (Section 3.3). Operational emissions are computed (1) combining the modeled heat demand with emission factors per unit of space heating demand and the space heating source (part of the building properties compiled in step 1); (2) combining hot water demands and the background inventories for hot water supply (with different boiler technologies), in case hot water demand is given by the user. Embodied GHG emissions are calculated based on the collected/ default material data combined with the KBOB LCA data.

3.1. Calculate U-values

In the steps 1-2, the user is prompted to provide the construction and insulation materials used in the walls, roofs, ceilings, windows, doors and floors of a building. The purpose of gathering this information is to estimate how each of the building components contributes to heat losses and space heat demand given its exposure to the outer air or (un)heated spaces of the building such as basements (see Section 3.2). These heat transmission losses are denoted as Q_T and are primarily defined by the thermal transmittance, or U-Value, of the building components. For a component c, its U-Value U_c is calculated based on the properties of constituting materials:

[1] https://www.python.org/
[2] https://github.com/rhythimashinde/building-model

$$U_c = \left(\sum_i \frac{t_i}{k_i} \right)^{-1}, \tag{1}$$

where t_i is the thickness (m) and k_i is thermal conductivity (W/mK) of a material i. Note that the considered U-values (W/m^2K) fall into 5 categories: (1-3) floors, roofs, and walls against outside air (external walls), and (4-5) floors and walls against unheated spaces (e.g. the shared walls). If there are multiple U-values in one of the categories listed above, e.g. several walls against outside air, then we select the average U-Value for that category. If no material composition data is available for a building component, the model resorts to default U-Value based on the construction period and last year of rennovation as estimated by Wallbaum et al. (2010); Heeren et al. (2013).

3.2. Calculate space heating demand

The goal of step 3 is to calculate the total space heating demand in order to later estimate the final operational emissions. As in Buffat et al. (2017), the space heating demand is quantified using the apporach of SIA-380/1 (2009), which is a building heat model used in Switzerland to verify that buildings meet the heating insulation obligations. The SIA model estimates the heat demand of a building based on the EN ISO 13790 norm [3]. It defines the heat demand (MJ) of a building Q_H summed over time periods t as follows:

$$Q_H = \sum_t \sum_c Q_{T,t,c} + Q_{V,t} - Q_{G,t}, \tag{2}$$

where Q_T are the heat transmission losses, Q_V are the ventilation heat losses, and Q_G are the heat gains. Note that in this model, using site-specific climate datasets with a time resolution t of half an hour.

For each component c including windows, walls, floors and roofs **heat transmission losses** Q_T were quantified based on the component surface area A_c (m^2), its U-Value U_c, the temperature difference $\Delta_{T,c}$ (K) between indoors and outdoors (for external walls and roofs), and reduction factor b_c due to reduced thermal losses from surfaces whose thermal conductivities are unknown, e.g. soil and for surfaces where the temparature differences are negligible e.g. shared walls:

$$Q_{T,t,c} = A_c \cdot U_c \cdot \Delta_{T,t,c} \cdot b_c \tag{3}$$

Ventilation losses Q_V depend on the air exchange rates a ($1/h$) affected by the behavior of inhabitants, such as keeping the windows open. The rates are derived from a probability distribution from Murray and Burmaster (1995). Additional to the air exchange rates, the losses are modelled by taking into account the volume V (m^3) of the building, which is either given by the user or calculated from the output of the digital elevation models (Buffat et al., 2017), and the specific heat storage capacity of air s ($MJ/m^3.K$):

$$Q_{V,t} = a \cdot V \cdot \Delta_{T,t} \cdot s \tag{4}$$

In addition to including these various contributors, our stepwise model prompts the user to provide the air flow rates, f (m^3/h) to estimate the air exchange rate a and replace the probabilistic values in the model whenever possible:

$$a = \frac{f}{V} \tag{5}$$

Heat gains Q_G of a building include solar heat gains Q_S (MJ/m^2), cumulative heat gains from electric devices Q_E (MJ/m^2) and cumulative heat gains from the inhabitants Q_P (MJ/m^2), weighted by the degree of utilisation η_g of the heat gains:

[3] https://www.iso.org/standard/41974.html

$$Q_{G,t} = (Q_{S,t} + Q_{E,t} + Q_{P,t}) \cdot \eta_g \tag{6}$$

Here, the solar heat gains are derived from the site data that considers the solar radiation at different times of the day, sizes and orientations of windows in a building, energy conductivity of each window, and the shadowing effect of the neighboring building as estimated in the digital elevation models. The electricity heat gains are based on typical Swiss electricity heat gains per year and the energy reference area of the building (SIA-380/1, 2009). The heat gain from inhabitants is modelled from the occupancy period and heat produced per inhabitant (Buffat et al., 2017). The stepwise model allows the users to update and overwrite the default values for occupancy, the energy reference area of the building and the windows size and orientations to refine the estimations of the total heat gain, by updating the window to facade ratios as assumed in the space heating demand estimation model.

Note that in Buffat et al. (2017) analysis for space heating demand, there are some approximations, specifically including window configurations, ventilation rates, room temperatures, heat gains due to electricity, thermal storage capacity and time of refurbishments of the building. These approximations are based on various studies which provide a distribution for these values, e.g. the thermal storage capacity for the buildings is sampled from a triangular distribution provided by Saner et al. (2013), and the facade to window ratios are sampled from Wagner et al. (2015a). As Buffat et al. (2017) model performs a monte-carlo simulation for by sampling different values from these distributions in each run, the results for space heating demands are obtained as a range of values, contributing to uncertainty in the heat demand estimations.

3.3. Life cycle assessment

In the LCA, we consider the construction, maintenance, operation and disposal phases of the buildings. The functional unit was chosen as one square meter area of dwelling per one year lifetime (1 m^2a). Therefore, embodied emissions were divided by the anticipated lifetime of the buildings. LCAs were performed with Brightway - an open source Python library for advanced LCA calculations (Mutel, 2017).

To estimate the **operational GHG emissions**, the computed space heating demand for each building and the specified heating source was matched against appropriate background processes in ecoinvent. We additionally included the climate impacts from hot water consumption, electricity consumption, and the ventilation (electricity) demands.

The foreground system for the **embodied emissions** was constructed based on the material composition dataset (Section 2.3) linked to the KBOB platform (Section 2.7). For the embodied GHG emissions, we used the following stages: raw material extraction, processing, manufacturing, transportation, replacement and disposal of the material to the building location, as detailed in SIA 2032 standard [4].

Environmental performance for the climate change impact category is assessed via the 100-year time horizon GWP values of numerous 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.

4. Case study

To demonstrate how the user inputs can be incorporated into the developed stepwise model, we use a case study data that was collected from Swiss architects and planners (John, 2012). This dataset represents 10 relatively modern residential buildings constructed post 2000, and serves as a reasonable case study to test the stepwise model performance. One major advantage of this 'reported' dataset is the availability of detailed information on buildings properties, components, material compositions. Moreover, this data includes annual space heating demands of the buildings and thermal transmittance values of the building components that were used for the validation of the model results (see Figure 1). Additionally, the dataset contains information on the ventilation air exchange rates and the hot water demands for most of the buildings. Note that the data on energy demand was estimated here based on the SIA-380/1 (2009) standard, unlike other building information which is directly reported by the building architects and planners. The basic characteristics of these buildings are laid out in Table 2, and the details are provided in the SI excel Sheet 4-6.

[4] `http://shop.sia.ch/normenwerk/architekt/sia%202032/d/2020/D/Product`

Table 2
Basic information on 10 Swiss buildings used in this model as case study, taken from (John, 2012) (Note: 'mfh' refers to multi family houses)

Building identifier	Canton	Construction year	Accommo-dation units	Built surface area [m^2]	Ventilation flow rate [m^3/h]	Energy standard
mfh01	Zurich	2012	111	2350	14000	MINERGIE
mfh02	Schwyz	2011	2	190	0.3	MINERGIE-ECO
mfh03	Bern	2011	3	163	145	MINERGIE-P
mfh04	Zurich	2010	4	240	*not available*	SIA 380
mfh05	Zurich	2007	132	2218	*not available*	MINERGIE-P-ECO
mfh07	Zurich	2011	89	1810	11000	MINERGIE
mfh08	Lucerne	2011	6	375	0.3	MINERGIE-P-ECO
mfh10	Zurich	2012	10	411	*not available*	MINERGIE
mfh11	Bern	2012	22	665	4100	MINERGIE-P-ECO
mfh12	Lucerne	2008	10	168	0.34	*not available*

4.1. Compile building properties

To include the case study data as the user inputs, the first step is to assign building properties to each of the case study building given its ID or geocoordinates (Figure 1). As a general rule, we expect this data to be available to the users of the developed tool. However, the given case study does not contain information that uniquely identifies the buildings, since it is part of the open access doctoral thesis, where the anonymity of the buildings needed to be maintained (John, 2012). Thus, in this paper we use the following steps to find the building properties listed below, and the data for 10 matched building is given in the SI excel Sheet 8.

1. Prompt the user to provide three of the building properties: the year of construction, municipality and number of floors. These building properties were chosen because they are typically accessible to the user, and are least likely to be measured wrong or be affected by the renovations over the building's lifetime.
2. If the model fails to find a unique match and identifies a set of buildings instead, we employ the "least distance approach", where the model looks for a closest match of a building in terms of the provided building properties.

4.2. LCA assumptions and inventory datasets

The lifetime of all the buildings is assumed to be 60 years for the sake of consistency with John (2012). For each of the building, we directly use the material compositions provided by John (2012) for the floors, ceilings, internal and external walls, roofs, doors and windows. For the building component materials, the lifetime is chosen to be 30 or 60 years affecting the replacement related impacts of the building. Also, it was presumed that locally available material travels a distance of 50 kilometers from the production site to the building site by lorry.

Compared to John (2012), we employed the most recent version of the KBOB database from 2016 instead of ecoinvent version 2.2 for computing the impacts from building materials. Whenever material or inventory information is missing, we have used the ecoinvent version 3.8. We prioritized KBOB, since it is more specific for Switzerland and matched the level of detail of the data in John (2012) better than ecoinvent. Note that for the doors and windows (e.g. for the glazing), and for polyethylenes (PE) we have used the ecoinvent v3.8, because KBOB has higher impact values, which is not representative of the actual values across other literatures. We have also revised few assumptions made by John (2012). For example, all woods (solid spruce, oak, larch) used in the buildings are assigned to the timber wood inventory by John (2012), while we have chosen more appropriate wood materials. Another improvement was done for the composite materials e.g. timber battens with cellulose fibre insulation, are assigned based on the shares of the constituting components (10% of timber and 90% of cellulose).

For the operational emissions, we map the energy carriers for hot water and space heating demand to ecoinvent 3.8, as these are not available in KBOB. For hot water demand, we directly use the values provided by John (2012). For the electricity, we take the typical value from Nipkow et al. (2007), which states that in a household with 2 people, the annual consumption of household electricity equals 3500 kWh (= 12600 MJ). Electricity source for the electricity consumption and ventilation electricity demand were mapped to the Swiss electricity mix from ecoinvent.

Table 3
Maximum U-values for insulation scenarios.

renovation scenario	Max. U-values, W/m^{2}K			
	Walls	Windows	Roofs	Floors
Standard (Minergie)	0.15	1.00	-	-
Efficiency (Minergie-P)	0.10	0.60	0.15	0.15

Table 4
Climate change impacts of various heating sources.

Heating source	Impact per unit of energy kg CO_2-eq / MJ
Electric heat pump (brine water)	0.033
District heating	0.00019
Wood pellet	0.013
Natural gas	0.065

SI excel Sheet 7 provides the inventory dataset, which maps 187 unique building materials and 30 energy carriers of the selected buildings to the inventories listed in ecoinvent and KBOB database (including the material densities, their functional units and impacts).

4.3. Scenario assessment

Since renovations can significantly affect the environmental impact of buildings (Hasik et al., 2019; Itard and Klunder, 2007), we perform scenario assessment to estimate emissions related to renovations. In the following, we introduce two sets of scenarios, which focus on estimating the potential emissions savings. Note that in this paper the purpose of the scenario assessment is merely to showcase that the stepwise model allows the users to assess various renovation scenarios for informing environmental decision-making (see (Fishman et al., 2021; Heeren and Hellweg, 2019; Mastrucci et al., 2020) for possible renovation scenarios). In reality, the case study buildings (Table 2) would most likely not (yet) be up for rennovation, as they are rather new.

Adding insulation: A common practice in reducing the heating demand of a building is to reduce its thermal losses via additional insulation layers or replacement of the existing insulation with better insulation materials. In this work, we follow the study of Ostermeyer et al. (2018) that considers standard and efficiency renovation scenarios based on building types. The former scenario leads to the resulting U-Value of the refurbished building components between the legal minimum (SIA 280) and the MINERGIE standard[5], and the latter aims at transitioning towards a passive-house, such as MINERGIE-P (see Table 3).

Changing heating source: In addition to the insulation changes, which affect both the operational and embodied emissions, the change in heating sources can be quite influential to reduce the operational emissions. For the given case study, the primary heating and hot water sources with their respective climate change impacts are given in Table 4. The only case where changing a heating source could make a difference is the natural gas heating, because it has a comparatively high impact per unit of energy used. As the availability of district heating substantially depends on the location of a building, based on the second least environmental impact, in this scenario we introduce a change of natural gas to the brine water heat pump.

5. Results and Validation

In this section, we discuss the operational and embodied GHG emissions of 10 modern Swiss buildings. First, we show the estimated U-values of the building components in Section 5.1. Then, we compute the final space heating demands of the buildings in Section 5.2. Next, the space heating demand and the material composition of the buildings are used to conduct the LCA of the buildings in Section 5.3. Finally, we explore the potential effect of two renovation scenarios on the LCA results in Section 5.4.

[5]https://www.minergie.ch/de/zertifizieren/minergie/

5.1. U-values

In Figure 2, we showcase the U-values reported by (John, 2012) and the U-values calculated in our model for the main building components: roofs, floors and walls (see also SI excel sheet 8).

We see that the calculated U-values of floors are in general slightly lower than the reported values, except for the buildings mfh03 and mfh10. Note that the U-values of building components are dependent on the thermal conductivities of the (various) constituting materials. Thus, one possible explanation of this underestimation is that the floors contain various insulation materials, such as glass wool mat, Extruded Polystyrene (XPS), phenolic foam and others, which have very low thermal conductivities, resulting in almost half of the materials with conductivity below 0.05 $W/m.K$ (see the plot on the right-hand side). Moreover, many of the reported insulation materials are not easily distinguishable, e.g. both "glass wool mat" and "insulation (glass wool)" get assigned thermal conductivity value 0.03 $W/m.K$ of a typical glass wool, which is one of the best insulating materials.

The calculated U-values for roofs and walls, respectively, are slightly overestimated compared to the reported values, with the exception of the buildings mfh08 and mfh10. Most of the walls and roofs contain different types of timber and concrete, for example "Timber battens with intermediate glass wool" and "Timber battens and counter battens with air cavity". The lower reported U-values show that the buildings in this case study have even better insulation properties than we estimate due to the presence of additional insulation layers that are missing in the reported inventories (e.g. rock wool, air cavity, and others).

Overall, the computed results are closer to the reported values than the default U-values. This is because we integrate all the materials and their thickness with their properties (thermal conductivity) to estimate the U Values. Also, Buffat et al. (2017) assumed the default U-value to be 0.21 $W/m.K$ for all roofs, floors and walls based solely on the construction period of the respective buildings (2010-2020 in the given case study).

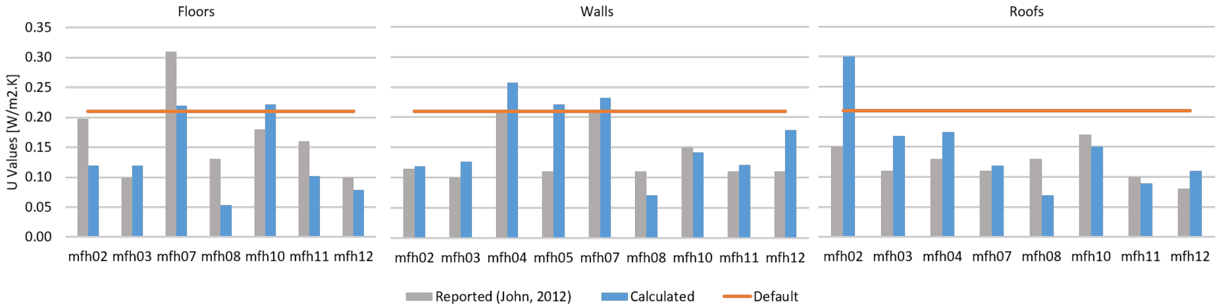

Figure 2: U Values of materials of floors, roofs, and walls for all buildings

5.2. Space heating demand

Figure 3 shows the reported space heating demands from John (2012), as well as the box plots of the calculated values from our model with the median values, and the default values estimated by Buffat et al. (2017). Table 5 provides the reported and median space heating demands. It also presents relative errors with respect to the reported values to quantify the performance of our and the default model.

To estimate the final space heating demand, Buffat et al. (2017) derives values of specific building parameters from their probabilistic distribution based on literature, and performs (1000) Monte Carlo simulations (MC) on them. For example, the facade to window ratios are assumed as a distribution based on Wagner et al. (2015b), and then a value is sampled in each run of the model. Thus, in Figure 3, we see a distribution of the space heating demands. In our model, the uncertainty from these iterations reduce slightly due to the presence of exact ventilation air exchange rates reported by John (2012), but some uncertainties e.g. the facade to window ratios still remain, giving slight uncertainties in the estimations.

One can see the highest reduction in the error is for the building mfh11. On one hand, it has the highest air exchange rate (0.58 $1/h$) compared to other buildings, which was not incorporated in the default model. On the other hand, there is a significant improvement in the U-values of the components compared to the default (old model value) ones for roofs and walls. In this case, the default values are 0.21 $W/m^2.K$ for both roof and walls. But with our estimations it is updated to 0.09 $W/m^2.K$ for roofs (where the reported value is very close i.e. 0.10 $W/m^2.K$), and 0.12 $W/m^2.K$ for

Table 5
Space heating demands and their relative errors (arranged in descending order of reduction in relative error of the model).

	Space heating demand values $[MJ/m^2a]$			Relative errors compared to the reported values		
	Reported Q_H^o	Calculated Q_H	Default Q_H^d	Error (calculated) r $\lvert Q_H - Q_H^o\rvert/Q_H^o$	Error (default) r_d $\lvert Q_H^d - Q_H^o\rvert/Q_H^o$	Reduction in error $r_d - r$
mfh11	23.00	90.16	170.87	2.92	6.43	3.51
mfh12	28.10	66.32	117.81	1.36	3.19	1.83
mfh02	106.00	167.97	230.77	0.58	1.18	0.59
mfh03	70.00	72.91	104.76	0.04	0.50	0.45
mfh10	115.00	109.88	159.12	0.04	0.38	0.34
mfh08	78.00	61.74	119.39	0.21	0.53	0.32
mfh01	129.60	104.13	80.59	0.20	0.38	0.18
mfh05	118.00	87.62	68.55	0.26	0.42	0.16
mfh07	48.00	43.28	42.61	0.10	0.11	0.01
mfh04	169.30	176.12	177.36	0.04	0.05	0.01

walls (where the reported value is also close i.e. 0.11 $W/m^2.K$). Both of these factors contribute to the higher quality estimate of the space heating demand. Similar effect can be observed for the buildings mfh02 and mfh12 with better U-value estimates compared to the default number.

For buildings mfh03 and mfh10, which have a very low model error, and a significant reduction of the error, very good estimations for the U-values are available not only for roofs and walls, but also for floors and windows. The case of mfh08 is interesting, because the calculated U-values are lower than the reported ones for all the building components, resulting in overall underestimation of the heating demand compared to the reported value. Thus, we can see that the material compositions have a significant effect on the estimations of the space heating demand.

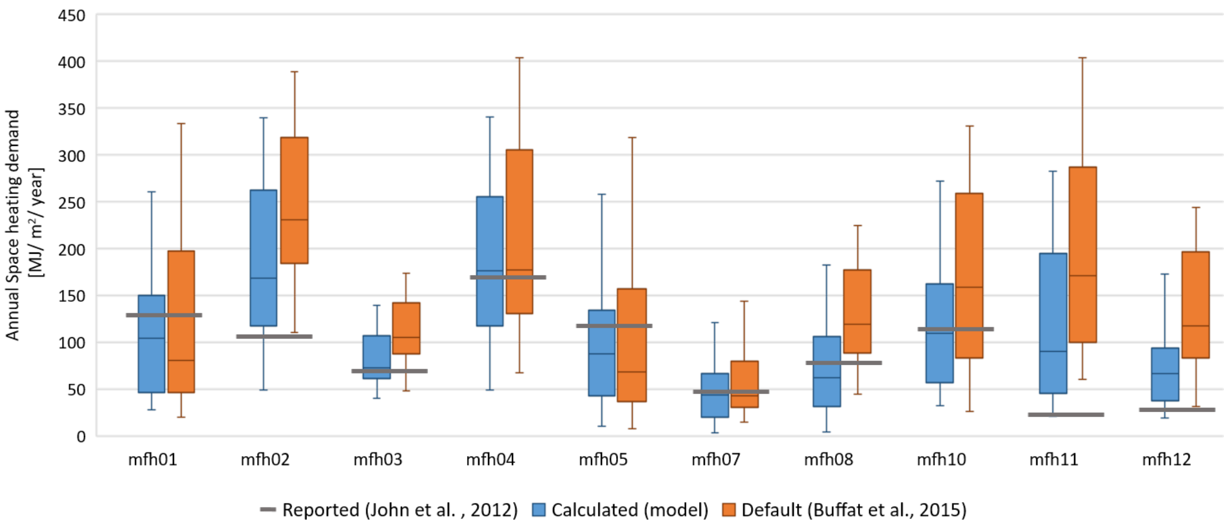

Figure 3: Heat demands for each building reported by John (2012) (left value), our calculated heat demands (middle box plot), and 'default' heat demand values by Buffat et al. (2017) (right box plot)

5.3. LCA results

Figure 4 shows the distribution of the Greenhouse Gas (GHG) emissions calculated annually per metresquare of the 10 buildings.It also shows each component contributing towards the embodied and operational emissions (reported by John (2012) , as well as calculated). As can be seen in both the figures and the detailed results in SI excel Sheet 9, our model estimates the LCA impacts for the given case study of 10 buildings quite accurately. Figure 4 shows that there is a higher share of the embodied emissions in each building, and this is justified for the 10 considered buildings which meet modern MINERGIE standards.

It should be noted that John (2012) uses ecoinvent 2.2. for emission calculation while we primarily use KBOB and ecoinvent 3.8. Thus, in some cases, we have differences e.g. though our model has fairly similar estimations when it comes to operational emissions, there are underestimations in some cases with hot water demand emissions. Similarly, for all building embodied emissions are slightly higher than those presented by John (2012). Thus, for this case study the emissions results are an approximate range for benchmark for validating our model, but they cannot be used as exact benchmarks as they use an outdated inventory database.

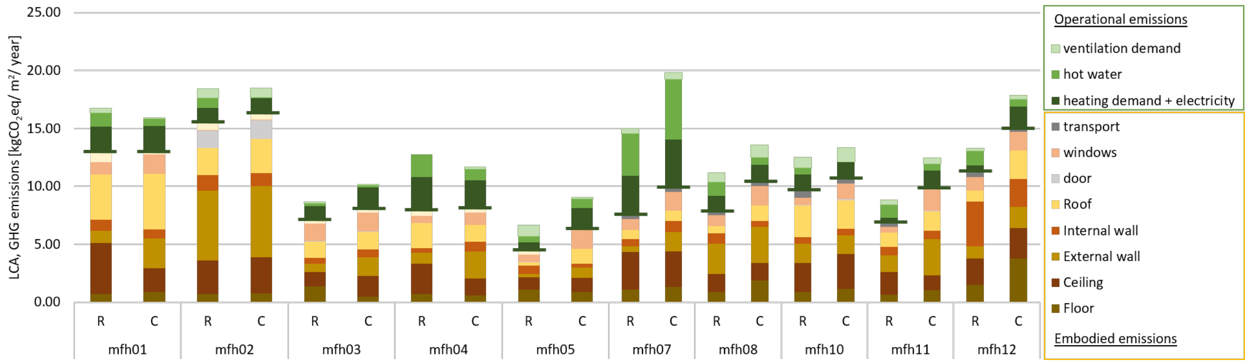

Figure 4: Greenhouse gas emissions for all buildings (GWP100a). Here R = Reported (John, 2012) and C = Calculated

5.4. Scenario assessment

In Table 6, we list how the parameters are changed for the buildings to implement the different renovation scenarios. We also list the final effect on the operational and embodied emissions based on these scenarios. Note that for this case study, we have implemented scenarios only for the buildings mfh07 and mfh10, as all other buildings already have a very good energy supply source except these two (i.e. natural gas), and thus the scope of improvement via renovations for other buildings was limited (especially for the second scenario).

Adding insulation: For this scenario we aim at reducing the U-values of walls by adding a layer of rockwool insulation to mfh07 and cellulose fiber to mfh10. This change affects the LCA of the buildings in two ways: the additional material increases the embodied impact of the building, while it reduces the energy impact from heating. As shown in Table 6, the insulation is not a very effective way for reducing the impacts in this case study, because either the effect is very minimal (e.g. mfh07) or the increase in the embodied emissions overpowers the slight reduction of the operational emissions (e.g. mfh10).

Changing heating source: For this scenario we chose to replace the natural gas systems in the two buildings to brine water heat pumps, as they have low impacts. Table 6 shows that the change in the energy source helps in reducing the impacts of both buildings. These improvements were higher for building mfh07 than for mfh10, because for the latter the original heating source was a co-generation heating unit with already rather low GHG emissions.

In conclusion, in the case study investigated the benefit of adding insulation was low compared to changing the heating system. The reason is that both of the considered buildings already had followed the MINERGIE standard with an already reasonable environmental performance, and thus the change in the heating source or insulation only showed slight improvements. Here we merely wanted to demonstrate that one can do such analysis using our tool to introduce different renovation scenarios for buildings, and verify if and how these renovations are effective for reducing building emissions.

6. Discussion and Outlook

In this section, we reflect on the applicability of our model/ tool to more buildings, while discussing its the performance on the chosen case study.

Table 6
Changes in building parameters and total LCA impacts (emissions) due to the scenarios

		Building parameters			Emissions $[kg.CO_2 - eq]$		
		U Values for walls $[W/m^2.K]$	insulation material	energy source	embodied	operational	total
mfh07	base	0.23		natural gas	9.95	9.87	19.82
	scenario 1	0.12	rockwool insulation		10.27	8.63	18.89
	scenario 2			heat pump (brine water)	9.95	7.05	17.00
mfh10	base	0.14		natural gas (cogeneration unit)	10.67	2.68	13.35
	scenario 1	0.12	cellulose fiber		10.71	2.68	13.38
	scenario 2			heat pump (brine water)	10.67	2.10	12.77

6.1. Case study analysis

Due to reported data on **building properties** e.g. energy carriers, **dimensions and materials of building components**, **material properties** (i.e. their thermal conductivity), and **ventilation systems**, our model predicted the space heating demands and the overall embodied and operational emissions of the 10 buildings well. The median of the space heating demands as reported and calculated by our model ranges between 40-180 MJ/m^2a, which is comparable to the space heating demands (15-80 kWh/m^2a or 54-240 MJ/m^2a) presented for buildings constructed in 2011-2018 by Streicher et al. (2019). Similarly, our model estimates the emissions in the range of 10-20 $kgCO_2 - eq/m^2a$, which is comparable to the 15-35 $kgCO_2 - eq/m^2a$ in the literature review by Trigaux et al. (2021).

Note that all the case study buildings were recently built (2010-2020) and had comparatively low operational impacts due to effective insulation and low-impact heating sources. Thus, the model results would be different for other sets of buildings with lower insulation standards and fossil heating systems. Also, the case study used here had fairly detailed data on the material composition of the building, and in case of further missing user data, there would be more uncertainties in estimation of the final space heating demands and emissions.

6.2. Applicability of our tool

As seen from the case study, our model presents an improved way of calculating the LCA for the buildings, with the possibility for integrating data provided by users. We can also integrate data from other research in different regions, if similar site and buildings data is available to parameterize the model. For example, an extension of our study could potentially allow integration of approaches like Kleemann et al. (2016), which used construction data in combination with on-site investigations to characterize material composition of buildings in Austria; as well as Gontia et al. (2018), who created a material intensity database for residential buildings in Sweden that is based on architectural data and densities of construction materials. The step-wise approach in our method as presented in Figure 1 allows for large scale regional modeling while incorporating and assembling different data (based on different studies) for the building and the site, even if data is not provided by the building planners, and thus classifies our model as a truly bottom-up model.

The tool can be particularly useful for building planners and architects on evaluating the current operational (and embodied) emissions of buildings, but also the future emissions based on alternative building-management scenarios. For example, mfh11 and mfh12 which have higher estimation of heating demand as compared to old estimations) do not end up having a high operational emission. This is due to the overcompensation with the lower estimated hot water emissions. This is important finding as it highlights that in case of these buildings, the renovations for a heating system might not make any major difference as the hot water emissions might be lower than estimated. In addition, all the buildings in Table 2 are relatively new and well insulated, and in reality, they would probably not be the candidates for energy-related renovations.

Other effective scenarios as described in Ramírez-Villegas et al. (2019); Galimshina et al. (2021) like deep renovations, changing indoor temperatures, and heat recovery for ventilation systems can be further introduced in this model. Further policy measures on the entire regions e.g. on complete phase out of oil and fossil fuel energy sources in the buildings, as introduced in Nägeli et al. (2020) can also be simulated with our model, for estimating the efficiency of these polices and the actual GHG emissions saved per building. Also, with the current energy crisis and potential shortages, one of the recommended measure of lowering the room temperature to 18 degrees and its potential impacts can be evaluated using our model.

6.3. Limitations and recommendations

Even though our model provides fairly accurate results compared to the reported values for the embodied and operational emissions, there is scope for improving the model further. For example, the default values for ventilation currently do not consider mechanical ventilation, which is often implemented for newer buildings (as shown by our case study). Ventilation systems are sometimes also equipped with heat recovery, which could be integrated into the model by applying a reduction factor to the heat losses. Finally, our model does not yet assess biogenic carbon storage benefits of the materials (like woods) nor climate impacts from biogenic fuels. This can be introduced in the model further for improving the assessment of operational climate impacts. Also, the space heating demand values derived here are usually measured in duration of just limited years weather data (1994-2013), and thus they are not representative of space heat demands of buildings for longer periods (2011 and onwards). Having said that, with more information (in the right places), we can reduce the uncertainties of the model e.g. replacing the sampled values from distribution for facade to windows ratios to correct window areas and configurations. It can also help us get closer to actual heating demands by including further information for buildings e.g. the energy recovery of the ventilation systems.

7. Conclusion

In this paper, we created a tool and data pipeline to estimate life-cycle climate change impacts of buildings. The model is capable of incorporating data from users or existing studies, but provides default values in cases where primary data is lacking. The results show that heating demand estimations were substantially improved when building-specific primary data on materials were available. Our study also estimated the embodied emissions of building components fairly accurately for the case study of 10 buildings provided by John (2012). Therefore, our model shows that detailed material information is very important to accurately estimate of the overall operational and embodied GHG emissions of buildings. The scenarios assessed for the case study building show potential tradeoffs between embodied and operational impacts as well as overall environmental outcomes of various building management options. Thus, our tool can serve building planners, architects and potentially other actors (e.g. government and house owners) to assess the effectiveness of various measures in reducing environmental impacts of the buildings.

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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 1-2: Material intensities and material properties data, Sheet 3: Different user prompts in the model, Sheet 4-6: Case study data, Sheet 7: Final U-values and the energy demands, Sheet 8: LCA results, Sheet 9: ecoinvent and KBOB inventories associated to materials of buildings in the case study
Complete Code available on `https://github.com/rhythimashinde/building-model`

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