# Synthetic building stocks as a way to assess the energy demand and greenhouse gas emissions of national building stocks



Citation for the original published paper (version of record):
Nägeli, C., Camarasa, C., Jakob, M. et al (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.
http://dx.doi.org/10.1016/j.enbuild.2018.05.055

Energy & Buildings 000 (2018) 1–18

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

# Synthetic building stocks as a way to assess the energy demand and greenhouse gas emissions of national building stocks

Claudio Nägeli[a,*], Clara Camarasa[a], Martin Jakob[b], Giacomo Catenazzi[b], York Ostermeyer[a]

[a] Chalmers University of Technology, Department of Architecture and Civil Engineering, Sustainable Building Group, Gothenburg, Sweden
[b] TEP Energy GmbH, Zürich, Switzerland

ARTICLE INFO

*Article history:*
Received 23 November 2017
Revised 22 May 2018
Accepted 30 May 2018
Available online xxx

*Keywords:*
Building stock modeling
Bottom-up model
Synthetic building stock
Synthetic population
Building archetypes
Building energy modeling
GHG emissions

ABSTRACT

In Europe, the final energy demand and greenhouse gas (GHG) emissions of residential and commercial building stocks account for approximately 40% of energy and emissions. A building stock model (BSM) is a method of assessing the energy demand and GHG emissions of building stocks and developing pathways for energy and GHG emission reduction. The most common approach to building stock modeling is to construct archetypes that are taken to representing large segments of the stock. This paper introduces a new method of building stock modeling based on the generation of synthetic building stocks. By drawing on relevant research, the developed methodology uses aggregate national data and combines it with various data sources to generate a disaggregated synthetic building stock. The methodology is implemented and validated for the residential building stock of Switzerland. The results demonstrate that the energy demand and GHG emissions can vary greatly across the stock. These and other indicators vary significantly within common building stock segments that consider only few attributes such as building type and construction period. Furthermore, the results indicate a separation of the stock in terms of GHG emissions between old fossil fuel-heated buildings and new and refurbished buildings that are heated by renewable energy. Generating a disaggregated synthetic building stock allows for a discrete representation of various building states. This enables a more realistic representation of past building stock alterations, such as refurbishment, compared with commonly used archetypes, and not relying on more extensive data sources and being able to accommodate a wide variation of data types. The developed methodology can be extended in numerous manners and lays groundwork for future studies.



## 1. Introduction

### 1.1. Background

In Europe, final energy demand and greenhouse gas (GHG) emissions of residential and commercial building stocks account for approximately 40% of energy and emissions [1,2]. In addition, the building stock has been identified as one of the largest and mostly untapped potential targets for improving energy efficiency and mitigating GHG emissions [1,2]. An overview of its potential is required to develop targeted measures that make use of it; for this, an accurate assessment of the distribution of energy and GHG emissions across the stock is required. However, this assessment can be challenging because of the poor availability and quality of data as well as the complex system of interactions across the stock, such as building stock developments, building alterations, and single technology measures.

Building stock models (BSMs) offer a method of assessing the energy demand and environmental impact of building stocks, and can demonstrate pathways for reducing GHG emissions and energy demand by considering the conflicts and synergies between various strategies and technological solutions at a stock level [3,4]. They have been used to evaluate policy scenarios [5–7], the potential for renewable energy sources [8,9], and energy planning on an urban scale [10–12]; assess life cycle performance [13]; and study the heat island effect [14], refurbishment strategies [15], and health impacts [16]. BSMs are differentiated according to two distinct modeling approaches: top-down and bottom-up [3,17].

Recent developments in the field have focused on bottom-up methodologies as disaggregate data has become more readily available [3,4,10]. They have the advantage of being specific technologies, and therefore, can model building stock changes more easily, through unprecedented technological developments and policy interventions. Bottom-up models typically estimate the energy de-

* Corresponding author.
*E-mail address:* claudio.naegeli@chalmers.se (C. Nägeli).

https://doi.org/10.1016/j.enbuild.2018.05.055

mand of representative buildings in the stock and aggregate the results to the stock level [3]. They can be applied at different scales: from transnational to national [6,18–20], and from urban [12,21,22] to district scale [23,24], using data from various levels of disaggregation. Most BSMs assess the stock using representative buildings in terms of archetype or sample buildings [17]. Archetype buildings are artificially constructed buildings considered to represent a certain class of buildings in the stock (typically segmented according to building type, age, and/or size) [24]. Sample buildings, however, are existing buildings taken to be representative of a given section of the stock [18].

Both archetype and sample building modeling make it easy to describe and analyze the building stock even with limited data availability, and furthermore, to create new scenarios relatively quickly [5,7,25]. However, they present restrictions in terms of the complexity that can be modeled. They are especially limited in the representation of heterogeneity in the building stock in terms of size, building state, occupancy, and user influence [26,27]. These modeling approaches are sensitive to assumptions from representative buildings, because any error in the description is extrapolated in the aggregation process [25]. Thus, the uncertainty of results can be substantial, although this is not often reflected or assessed in modeling practices [10].

There has been a rise in BSMs being developed for urban building stocks [10,28]. Typically, urban BSMs forego the use of representative buildings and use individual building microdata such as 3D city models, building registries, and/or energy performance certificate data, which is combined using GIS. However, these models rely on archetypical information to fill data gaps for many building characteristics (e.g., *U*-values and heating system efficiency) [21]. More recent approaches use probabilistic data to define uncertain parameters [29], based on which it is possible to calibrate and validate models on a building level using energy consumption data [26,30,31]. This is especially crucial to adequately represent previous energy efficiency measures in the stock, to not overestimate future reduction potentials [10]. However, missing micro-level data such as 3D building models makes it difficult to transfer advances in building stock modeling from an urban to a national scale.

### 1.2. Aim

This paper presents he methodology of synthetic building stock modeling to address shortcomings (of conventional BSM approaches) through generating a synthetic building stock as a midpoint between individual building data and sample or archetypical buildings. We make use of methodologies developed for the generation of disaggregated synthetic populations of individuals and households based on aggregate data [32]. Synthetic populations are simplified representations of an actual population in the form of artificially generated microdata from aggregate distributions or sample data. They are widely used in microsimulations and agent-/individual-based models, where micro-level data is required but often not available (e.g., because of privacy protection). Synthetic populations have been applied in fields such as activity-based transportation models [32] and land-use models [33], as well as in the study of epidemic diffusion or policy impacts [34]; furthermore, they have been applied in models such as ILUTE [35] or UrbanSim [33]. Similarly, in relation to buildings, they have been proposed for modeling occupant behavior [36] or housing location choices in land-use models [33,37]. In this paper, we adapt the methodology for creating synthetic populations to generate synthetic microdata on building stocks for use in building stock (energy) modeling. The methodology enables the creation of synthetic microdata on building stocks describing individual buildings and their usage as an alternative to aggregate average archetype buildings. This will allow BSMs to more adequately describe the heterogeneity of building stocks in size, building state, occupancy, and user influence, even in data-poor cases (e.g., in applications on a national scale) or in cases where data is available only at an aggregate scale.

This study aims to contribute to the field's development by:

- Describing a methodology for generating a synthetic building stock that can be used in building stock modeling.
- Showcasing application of the developed methodology based on the residential building stock of Switzerland.
- Showing the distribution of energy demand and GHG emissions of the residential building stock of Switzerland.

The following section outlines the methodology for generating a synthetic building stock (Section 2.1), the building stock energy and environmental impact assessment model used to evaluate the generated stock (Section 2.2), and its adaptation to the residential building stock of Switzerland (Section 2.3). The assessment results of the generated stock are presented in Section 3 and discussed in Section 4. Finally, Section 5 summarizes the findings with respect to the stated aims and provides an outlook for future research.

## 2. Methodology

The proposed building stock modeling methodology is split into two main parts (see Fig. 1): synthetic stock generation and building stock assessment by means of analyzing the synthetic stock in terms of different indicators. The generation of a synthetic building stock follows three steps:

1. The first step is building stock initialization, during which the synthetic building stock is structured in terms of factors such as type and age according to structural data of the real building stock, typically available from national statistics or registries (Section 2.1.1).
2. The second step is building characterization, during which synthetic buildings are further characterized according to the attributes required for building stock energy and environmental modeling. These include building geometry and energy relevant parameters (e.g., original *U*-values). This is performed using distributions of archetypical data on building attributes and/or sample data (Section 2.1.2).
3. The third step is updating building characteristics, during which various attributes of individual synthetic buildings are updated with regards to past refurbishment, maintenance measures and other alterations, to represent their current state (e.g., in terms of current *U*-values or energy carrier; Section 2.1.3). Aggregate sales data (e.g. of windows or heating systems) or sample data from surveys (such as [59]) are used to validate this step.

Subsequently, the generated synthetic stock is assessed and calibrated using the building stock assessment model, which calculates the resulting energy demand of each generated building as well as their environmental impact. The results of the individual buildings are then aggregated to a stock level.

Synthetic stock generation in conjunction with the building stock assessment model were implemented in Python, making use of the libraries SciPy [38], Numpy [39], Pandas [40], ipfn [41], and matplotlib to visualize the results [42].

### 2.1. Synthetic building stock generation

Multiple methodologies have been developed and applied to creating synthetic populations. Literature mostly distinguishes between sample-based (also called reweighting) and sample-free (or synthetic reconstruction) methodologies [43,44]. Sample-based methods use a sample micro-dataset as a basis, which is adapted

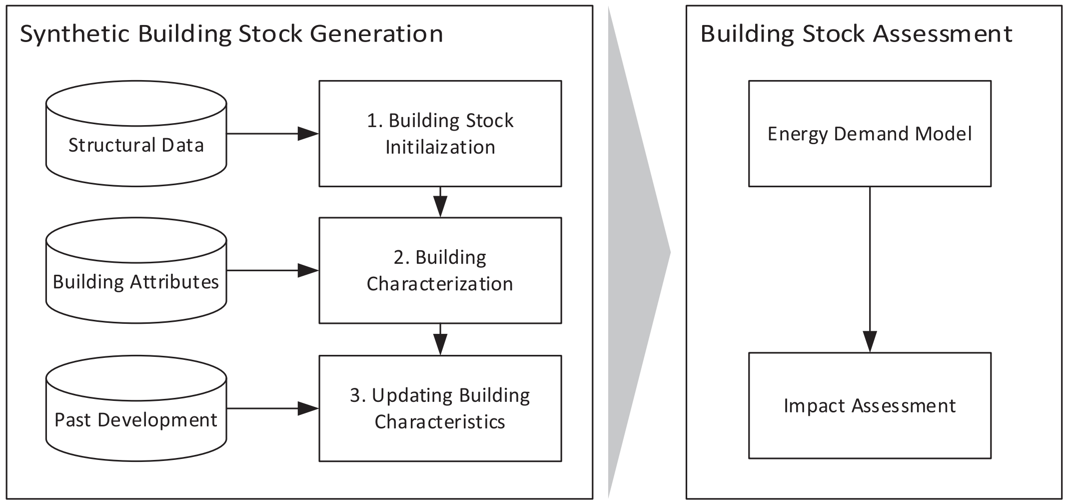


**Fig. 1.** Process for generating a synthetic building stock for use in building stock modeling.

to fit aggregate distributions of the whole stock; for example, by applying iterative proportional fitting (IPF) [32]. IPF adapts the elements of a data table in that the marginal totals along various dimensions equal a defined distribution [37]. A sample-free approach is used where no micro-dataset is available. It builds a synthetic population by iteratively assembling the population based on known distributions of characteristics from aggregate datasets through Monte Carlo random sampling [34]. Although both are viable methods, this study applies a sample-free approach, because often no suitable micro-dataset is available to apply a sample-based approach.

A synthetic population is not simply a construction of records of each individual person, but also their organization and structuring into households. Similarly, the synthetic building stock can be thought of as not just generating individual records of buildings in the stock but also of the various usages in the building. These different usages can not only be various individual dwellings in a building (as in the case study of this paper), but also non-residential usages in mixed-use or non-residential buildings. This allows modeling at both a building and sub-building level (e.g., differentiating occupancy attributes and appliance equipment rates across various dwellings in one building).

The synthetic building stock can be sized flexibly in that the number of buildings generated can be adapted. Therefore, it is possible to recreate an individual record for each building in the stock. However, this is only of limited use because national building stocks typically consist of several million buildings, even for small countries. Therefore, the computational demand to run a BSM would increase significantly for larger countries. To limit the computational time in the assessment of a BSM, a synthetic building stock can be limited to a representative sample stock, thereby creating representative building functions the same as representative samples in surveys as they each represent a portion of the stock. All results of the building stock assessment can later be scaled. The scaling factor is determined based on the number (or another indicator such as gross floor area) of representative buildings chosen for each cluster of the stock.

Fig. 2 shows a representation of the synthetically created buildings that result from adapting this study's methodology. The main attributes of a building include building type and construction year, and they are directly defined at the building scale; the technical systems of each building are then defined individually. Thus, each building comprises several building envelope components, a heating system, and ventilation concept (either natural or mechanical). Each of these technical components is described by an installation or retrofit year as well as its technical characteristics. Each building can have multiple use areas with a different usage type or one to several dwellings (housing units) in case of residential buildings (cf. Fig. 2).

### 2.1.1. Building stock initialization

First, the synthetic building stock is initialized based on structural data on the building stock (see Fig. 1). The structural data describes the make-up of the building stock in terms of number of buildings. Such data is typically available from national statistical offices and describes the stock according to features such as building type, construction period, and size. From that dataset, a representative sample is drawn to initialize the synthetic stock and create the individual representative buildings. In case the building stock should be reconstructed in its entirety, the sampling can be omitted, and instead, the individual records are created according to the number of buildings of the aggregated structural dataset. The result of step one is a structure of individual building records that when aggregated represents the structural input data and can be further characterized in step 2.

### 2.1.2. Building characterization

The second step aims to further characterize the initialized stock. It defines all further building attributes required for the generated synthetic building stock to be used in building stock modeling (cf. Fig. 1). These attributes can be defined through selecting single characteristics from a building typology or through Monte Carlo sampling from a distribution. The underlying data for this can vary depending on availability. It can either come from statistical offices, building standards, and surveys on parts of the stock, as well as other reports.

Ideally, available data provide a distribution of a certain attribute across the entire stock or part of it, which allows for sampling that attribute directly from the data. However, for most attributes, available data sources do not have representative distributions for the building stock, but rather average values with a lower and upper bound. In this case, the probability distribution can be constructed based on these minimum and maximum values, similar to in life cycle inventory databases, to be able to run Monte Carlo simulations [45]. Normal or log-normal distributions can be selected for most continuous variables (e.g., $U$-values). Log-normal is suitable for skewed distributions as well as attributes that are positive and cannot be smaller zero. Uniform distribution can be chosen for selective attributes where no clustering occurs near a mean value (e.g., building orientation). Lastly, discrete attributes

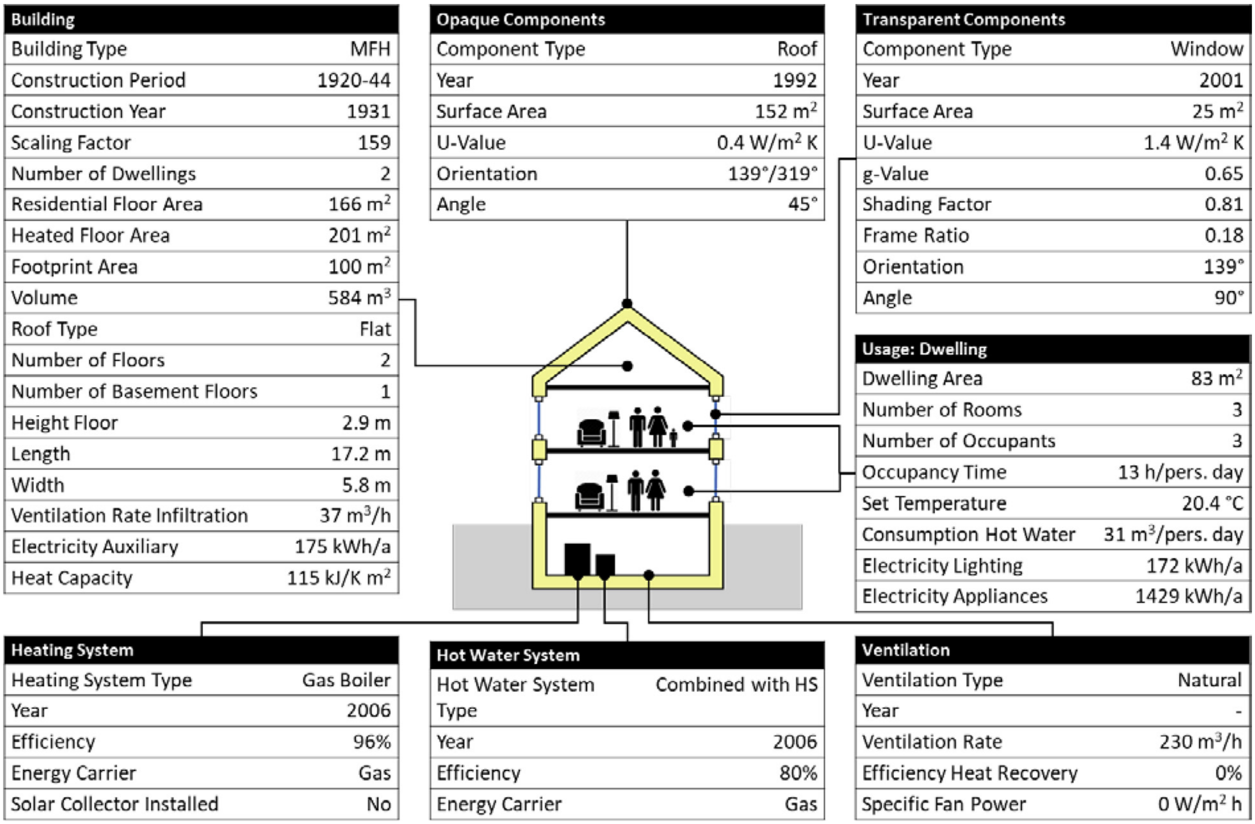


**Fig. 2.** Example representation of a synthetically created building through the application of the described methodology in the case study of the Swiss residential building stock with examples for the different elements (one per type; multiple opaque components exist, and there can be multiple dwellings per building) and characterizing attributes.

(e.g., number of occupants) can be defined as a binominal distribution or shares (e.g. shares of buildings with a basement).

In contrast to households, buildings have more correlated attributes; the most notable is building geometry (i.e., wall, roof, floor, and window areas), where surface areas cannot be individually randomly estimated because they relate to each other to make a complete building. Therefore, rather than choosing these attributes individually, a simple "shoebox" geometry of the building is constructed to estimate the surface areas. The shoebox model is estimated based on the total floor area within the building, the number of floors, and the aspect ratio between the building's length and width, as well as a glazing ratio of the façade to estimate the window areas. Subsequently, the total floor area is divided by the number of floors to obtain the footprint area. The length and width are then assumed based on the aspect ratio between the two (or vice versa, depending on data availability). From this, the total façade area can be calculated based on the building perimeter, number of floors, and floor height of the building. The façade area is reduced if the building is determined to be attached on one or two sides. The resulting façade area can be subdivided between opaque wall area and window area using a glazed surface area factor. The roof area is calculated based on the assigned roof type of the building. In case the building was assigned a flat roof, the roof area is equal to the footprint area, whereas for pitched roofs, the area is calculated according to the roof slope. The floor area is defined equal to the footprint area; however, depending on whether the building has a basement or not, it is defined as being toward the ground or unheated rooms.

*2.1.3. Updating building characteristics*

This step calibrates the current state of the building in terms of past upgrades and refurbishment measures. It can be skipped in case the available data sources are up to date and cover the current state of the stock accurately. However, in most cases, especially the data on *U*-values and type of heating system installed cover the state of the building as it was originally built and not its current state. In that case, this step is necessary to consider these upgrades.

This can be achieved in two stages:

1. The year of the last intervention is defined for each building component whose state requires updating. For recent buildings, this might be the same as the year of building construction. However, older buildings have all undergone one or more alteration in their lifetime.
2. If a measure has been implemented, how the building component was altered is assessed. The resulting efficiency improvement is related to the year in which the measure is estimated to have been implemented.

Thus, the year of the last intervention is estimated endogenously by the model. For each individual building component, the last intervention year is estimated through an estimated lifetime based on the Weibull distribution. The Weibull distribution was selected because it is often used to estimate the lifetime of building components [47,48]. However, other probability distributions such as the Gompertz distribution, Gamma distribution, or a fixed lifetime could also be used [46]. The distributions can be fitted based on real duration data or estimated based on average renovation intervals. Based on the fitted distribution, the year of the first intervention can be estimated starting from the year of construction. This process is repeated until the year of the next intervention surpasses the base year for which the synthetic building stock should be representative of.

If a component is altered in a given year, how it is changed is assessed. In case of building envelope components, this would mean first assessing whether the intervention has an effect on the energy efficiency (i.e., added insulation or exchanged windows) compared with pure maintenance measures (i.e., repainted walls or windows). This can be done through a random choice based on data on the share of renovations with an energy efficiency effect, compared with pure maintenance measures, or through evaluation of a micro-economic discrete choice model [24]. The resulting efficiency improvement of the component (be that an envelope component or a HVAC system) can then be defined based on the efficiency standard of that year (e.g., typical insulation thicknesses/*U*-values or heating system efficiencies).

## 2.2. Building stock assessment

The generated synthetic stock is assessed according to its energy and GHG emissions using the building stock assessment model described below. The model is split into two parts, an energy demand model and an impact assessment model. The energy model first calculates the buildings' energy demand in terms of useful energy for space heating and domestic hot water (Section 2.2.1). Based on the heating demand and the installed heating system in the buildings, the final energy demand is calculated according to the split of energy carriers and energy services (i.e., space heating and domestic hot water) as well as the electricity loads for lighting, appliances, and auxiliary electricity (i.e., ventilation and pumps). This is fed into the impact assessment model, which calculates the primary energy and GHG emissions of the buildings' use phase (using primary energy and emissions factors from the literature; see Section 2.2.2).

### 2.2.1. Energy demand model

First, the energy demand model calculates the useful energy demand for space heating using a monthly steady-state energy balance based on the norm ISO EN 52016-1 [49] (or the equivalent Swiss norm SIA 380/1:2016 [50]) based on the building physics parameters and usage data defined during the building characterization step. The internal electrical loads and hot water demand are calculated at an individual building use area scale as specified during the building characterization step, and then aggregated to the building scale. Based on the calculated useful energy demand for space heating and hot water, final energy demand is estimated depending on the heating system efficiencies. Different conversion efficiencies are applied for space heating and hot water generation to account for the different temperature levels and losses in distribution within the building. Solar thermal collectors are assessed separately based on a monthly energy balance of the possible production and demand from domestic hot water and/or space heating. In case that monthly production exceeds actual demand, the production is limited to cover this demand. Thus, no seasonal storage is assumed. A detailed description of the model can be found in Appendix B.

The energy demand model is set up to account for not only the stock variability in terms of physical characteristics, but also in terms of occupant related attributes such as demanded indoor temperature or varying hot water use. The average indoor temperature of the building is defined based on the average of the set temperature of each building usage (e.g., for each dwelling) in the building.

However, as research of the performance gap has revealed, the realized indoor temperature is notably lower for inefficient buildings compared with newer energy efficient buildings [51,52]. This is considered through the use of adjustment factors for indoor temperature depending on the energy efficiency standard of the building according to [52] (see Appendix B for a mathematical description of the implementation of the approach). The approach of Loga et al. [52] considers three reduction factors: (1) a reduction of the internal temperature during the night, (2) a reduction of the average internal temperature caused by limited (or unheated) spaces within the heated floor area, and (3) the user influence through reduced heating to save costs. Each of these factors depends on the energy efficiency of the building and results in a reduction of the average indoor temperature from the set temperature the more inefficient the building is.

### 2.2.2. Impact assessment

In this last step, the model calculates the direct and indirect GHG emissions and primary energy demand of the building's use phase's final energy demand. The GHG emissions as well as total and non-renewable primary energy are then calculated using emission and primary energy factors of various energy carriers. For the case study of the residential building stock of Switzerland, these were based on [53] and are listed in Appendix D. In case of electricity, the emission and primary energy factors for the consumption mix was used. The resulting emissions and primary energy demand are split depending on different energy services. Considering the GHG emissions and primary energy demand of the building, indicators such as GHG emissions and energy use per m$^2$, per building, or per occupant, are generated.

## 2.3. Case study: residential building stock of Switzerland

The methodology was applied to the residential building stock of Switzerland in 2015. Aggregate structural data comes from the building and dwelling register (BDR), which holds data on all residential buildings and dwellings in Switzerland. The buildings are described based on building type, construction period, number of floors, number of dwellings, and heating and hot water systems. The BDR is not up to date regarding the installed heating and hot water systems, and has been shown to be outdated in many instances [54]; these shares were therefore adapted during the calibration procedure (see Appendix C). Dwellings are similarly described according to the building type, construction period, dwelling size, and number of rooms. The structuring of the registry in separate records on buildings and dwellings allows for a joint generation of a building and dwelling stock. Fig. 2 presents a flowchart of the implemented process of synthetic stock generation, which is further described in the following subsections.

### 2.3.1. Building stock initialization

Based on aggregate data of the BDR on the building and dwelling stock, an initial sample for both stocks is generated separately and then combined to initialize the stock (see Fig. 3). The building stock sample is generated first. To limit the computational time in the BSM assessment, the building stock size is limited to a representative sample stock of 10,000 synthetic buildings. Once the initial building stock sample is generated, the interval class attributes from the BDR for number of floors (e.g., 10 + floors), number of dwellings (e.g., 6–9 dwellings) and the construction period (e.g., 1920–1944) are interpolated for each individual building in the generated sample to obtain a numerical value. For open-ended class intervals (e.g., 10 + dwellings), which are not delimited on both sides, an exponential distribution is assumed and calibrated using aggregate data. For example, the number of dwellings in buildings with 10 or more is calibrated so that the total number generated matches the distribution of the dwelling stock.

Next, the dwelling sample is generated based on the size of the building stock sample by summing up the number of dwellings of each building in the building stock. The generation of both building and dwelling stocks before they are merged guarantees that

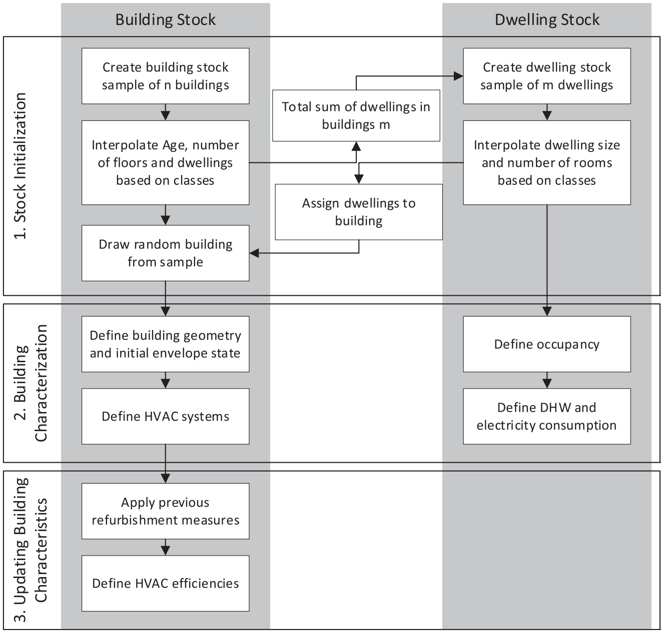


**Fig. 3.** Flow chart describing the process for generating a synthetic building and dwelling stock.

both stocks match the overarching structure of the input data. In a similar manner to the buildings, the dwelling characteristics are assigned by interpolating between the various class boundaries, or extrapolated using an exponential function in case of open-ended classes, to assign a numerical value to each attribute.

In the last step of stock initialization, the building and dwelling stocks are combined. This step is performed iteratively by picking a building at random from the generated building stock sample and assigning the defined number of dwellings to the building based on the building type or construction period. However, some restrictions are placed on the selection of dwellings to limit inconsistent combinations. These restrictions attempt to limit the generation of buildings with an unrealistically small floor area compared with the number of floors. Therefore, restrictions are set so that if there are between 1 and 0.5 dwellings per floor, no dwellings smaller than 70m$^2$ are picked. If there were even less than 0.5 dwellings per floor, then only dwellings larger than 150m$^2$ are picked. In all other cases, no restrictions related to the sampling of dwellings are set.

### 2.3.2. Building characterization

Next, the generated building stock is further characterized through Monte Carlo sampling as described in Section 2.1.2, based on distributions generated from various data sources, statistical offices [55], building standards [50,56,57], and other reports [22,58–62]. A complete overview of the data sources and chosen distribution types for all input parameters can be found in Appendix A.

First, the building geometry (wall, roof, floor, and window areas) is generated through a shoebox model as described in Section 2.1.2. For this, the total heated floor area of the building is estimated by multiplying the sum of the dwellings' floor area by a factor of + 15% and + 20% for single and multi-family houses, respectively, to account for factors such as circulation area and construction area, as proposed in [63]. After the surface areas of the individual components are estimated, the physical properties of the different building components are defined, such as *U*-value, g-value (or SHGC), and frame-to-glazing ratio for windows, as well as angle, orientation, and shading factor. Each of these parameters is defined as well through Monte Carlo sampling based on different distributions depending mainly on building type, construction period, and building component type. The orientation of the whole building is assigned randomly based on a uniform distribution. The orientation of the individual building components is then defined accordingly.

The space heating and hot water system, as well as whether a solar collector is installed, is already contained in the structural data of the BDR. The efficiencies of the system are then defined based on the step to update building characteristics described in the next section. Most residential buildings in Switzerland are naturally ventilated; however, especially in newer buildings, ventilation systems with heat recovery are increasingly common. The share of residential buildings equipped with ventilation systems with heat recovery is estimated based on data from [22]. The ventilation rate is defined based on the building type, age, and the ventilation system installed, and divided between infiltration and natural/mechanical ventilation depending on the system type.

For the individual dwellings, the number of occupants is based on binominal distributions generated from household size data from [55]. The average occupancy time per day and person is then defined based on average values for residential use from the building standard [56]. Similarly, the hot water consumption as well as electricity use for lighting and appliances are defined based on building standards [50,57] individually for every dwelling. Lastly, the set temperature is defined on the dwelling scale to consider the individual heating behavior of building occupants.

### 2.3.3. Updating building characteristics

The lifetime distributions for this step are estimated based on average renovation rates for each building component for various building types and construction periods from an empirical study [59] and standard building lifetimes [64,65]. Furthermore, [59] provides the share of renovations with an effect on the energy efficiency (i.e., added insulation or exchanged windows) compared with pure maintenance measures (i.e., repainted wall or windows) for building envelope components. In the second step, this data is used to assess whether the building component was renovated with an energy efficiency retrofit or only maintained. In the case of energy efficiency retrofit, the *U*-value of the building component (and the SGHC in case of windows) is updated based on data from [58,60] on the commonly applied insulation thicknesses and window standards in a given renovation period. Similarly, the heating and hot water system efficiency is defined depending on the updated installation date of that system based on the lifetime distribution, according to Section 2.1.3. The efficiency of the systems is then determined based on the installation year, according to data from [22]. Similarly, the heat recovery efficiency and the specific fan power of the ventilation systems are determined based on data from [60].

## 3. Results for the Swiss building stock

In this section, the results of the synthetic building stock generated for Switzerland and its analysis with a BSM are described. First, the structure of the synthetic building stock is described. Subsequently, the results of the stock assessment model are presented according to various levels of aggregation.

### 3.1. Structure of the stock

Fig. 4 shows the structure of the generated synthetic building and dwelling stock, comparing the results to the distribution of the input data used. As seen in both figures, this approach can reproduce the distribution of the input data. However, some deviations occur because the synthetic stock is generated based on a

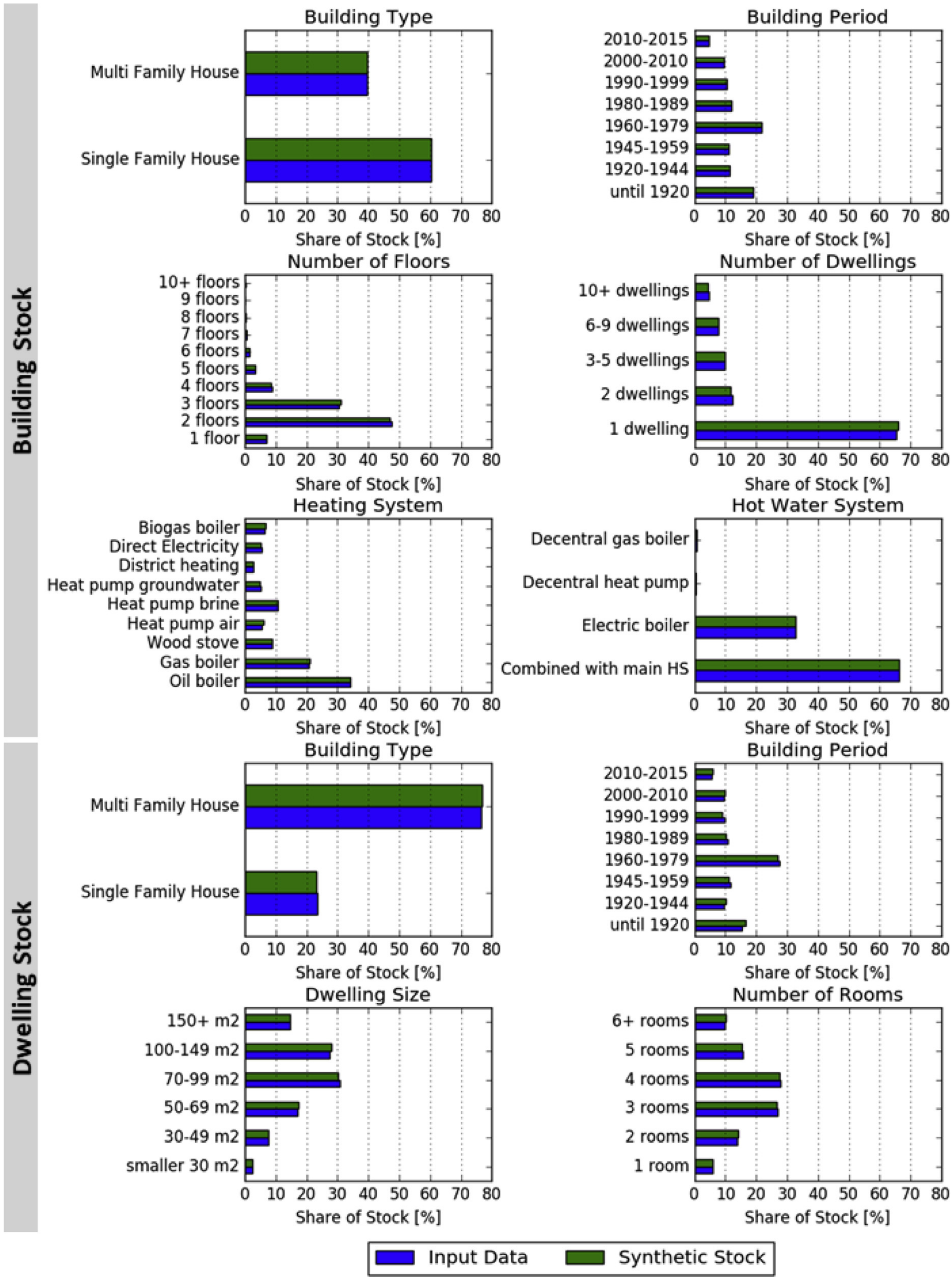


**Fig. 4.** Distribution of various attributes across the created synthetic building (top) and dwelling (bottom) stock based on the initialization step. The synthetic stock data are shown in green and the input data in blue bars. The shares are weighted based on the number of buildings/dwellings in the stock.

**Table 1**
Summary of indicators across the modeled synthetic building stock, which is compared with the indicators based on the national statistics on household energy consumption [66].

| Indicator | Statistics 2015 | Total | Per heated floor area | Per building | Per citizen |
|---|---|---|---|---|---|
| Final energy | 64.4 TWh | 67.2 TWh | 135.4 kWh / $m^2$ | 41,230 kWh / building | 8,111 kWh / capita |
| Total primary energy | 106.4 TWh | 110.0 TWh | 221.6 kWh / $m^2$ | 67,502 kWh / building | 13,280 kWh / capita |
| Non-renewable Primary energy | 91.1 TWh | 82.2 TWh | 165.5 kWh / $m^2$ | 50,417 kWh / building | 9,919 kWh / capita |
| GHG emissions | 12.3 mil. $tCO_2$-eq. | 12.8 mil. $tCO_2$-eq. | 25.7 $kgCO_2$-eq / $m^2$ | 77,837 $kgCO_2$-eq / building | 1.54 $tCO_2$-eq / capita |

random sample of 10,000 buildings instead of the 1.6 million residential buildings that exist in Switzerland. Moreover, Fig. 6 shows that the deviation from the input distribution is more significant for dwellings than buildings. This is because the synthetic dwelling stock is generated from a stratified sample based on the number of dwellings required to populate the synthetic buildings. This stratification leads to a slightly increased distortion in the dwelling stock as the deviations in the building stock are passed on to the synthetic dwelling stock. This distortion is, however, kept minimal by calibrating the number of dwellings assigned per building depending on the construction period (see Appendix C for details).

### *3.2. Impact assessment of the stock*

The aggregated results of the modeled synthetic building population are summarized in Table 1 and compared with data based on national energy statistics from [66]. Reference values for primary energy and GHG emissions can also be calculated based on the energy statistics and the primary energy and emission factors listed in Table 3 in Appendix D. The stock is analyzed based on its total useful energy demand for heating (space heating and hot water), final energy demand (for space heating, hot water, appliance use, lighting, and auxiliary energy), primary energy (both total primary energy and non-renewable) alongside its GHG emissions. Results are shown both as a total as well as averages per heated floor area, building, and citizen. The total final energy demand is overestimated by 4% from the national statistics, which is also mirrored in the other indicators. The exception is non-renewable primary energy, where the modeled results are lower than the statistics. A more detailed comparison between modeled results and statistics can be found in Appendix C.

The distributions of the energy demand and GHG emissions across the synthetic building stock is shown in Figs. 5 and 6, and are differentiated according to the construction period and heating system of the building. The distributions are weighted based on the representative heated floor area of a given building in the stock. The results show that the distribution of all indicators varies greatly, both within the stock as a whole, and within each construction period or heating system. The useful energy demand follows a long-tailed distribution across the stock. However, the remaining indicators (i.e., final energy, total and non-renewable primary energy, and GHG emissions) do not follow such a clear distribution and show two peaks. The specific final energy demand has a clear secondary peak, which is made up mostly by buildings with a heat pump (cf. Fig. 6), which have a significantly lower final energy demand for heating and hot water compared with buildings with other heating systems. The separation of the two peaks is amplified by the fact that most buildings with a heat pump have been built since 2000, as seen in the data from the BDR [55]. These buildings already have a lower than average space heating demand because of the higher efficiency standard of the building envelope. This peak can also be seen for the distributions of the primary energy demand (both total and non-renewable), albeit less pronounced because of the different primary energy factors of the various energy carriers, where the efficiency gain from the heat pump in terms of final energy is partially lost because of the higher primary energy factor. Even so, in terms of non-renewable primary energy, the buildings with the lowest demand are shown to be buildings with a wood-based heating system (cf. Fig. 6). In terms of GHG emissions, the highest share is buildings emitting 5–10 $kgCO_2$-eq per $m^2$ and year. The more pronounced peak compared with the other indicators comes from the fact that Switzerland has a relatively GHG-non-intensive electricity consumption mix (the production is mostly from hydro and nuclear power, complemented by somewhat more carbon-intensive imports; see [53,67]). This favors buildings with heat pumps compared with non-electricity based heating systems in addition to the already lower final energy demand. Furthermore, a notable share of single-family houses that are heated with wood can be seen, as well as multi-family houses in cities connected to the district heating grid, which decreases the GHG emissions of these buildings compared with buildings with fossil heating systems. The second peak and long tail of the distribution comprises the buildings that have an oil or gas boiler, which still account for 34% and 20% of the stock, respectively (cf. Fig. 4).

The distribution of the various results according to both building type and construction period are visualized in Fig. 7. For all indicators, a trend towards lower energy demand and GHG emissions can be seen for both building types for the more recent construction periods. Nevertheless, the variation of the various indicators for each construction period is very large, especially for the earlier construction periods. This is also highlighted by the rather large number of outliers.

When comparing the two building types, both the median as well as the variation of the different indicators seems to be lower for multi-family houses compared with single-family houses. The average lower median of multi-family houses is caused by the generally more compact building geometry, which leads to a lower specific heat demand compared with single-family houses. An exception to this trend is the category of single-family houses from the construction period until 1920. Here, the median GHG emissions and non-renewable primary energy are lower for single-family houses compared with multi-family houses of the same period. This originates from this period's higher share of wood-heated single-family houses. The lower variation of the different indicators for multi-family houses may stem from the fact that building attributes defined on the dwelling scale are averaged across multiple dwellings in a multi-family house. This leads to a lower variation of the resulting energy demand, and therefore, a lower variation of the other indicators.

## 4. Discussion

The discussion's structure is in two sections. First, general methodological findings are discussed, and then additional insights are derived from the case study.

### *4.1. Discussion of the methodology*

#### *4.1.1. Advantages of synthetic building stocks*

The methodology described in this paper improves on the generally used archetype approach of building energy models in nu-

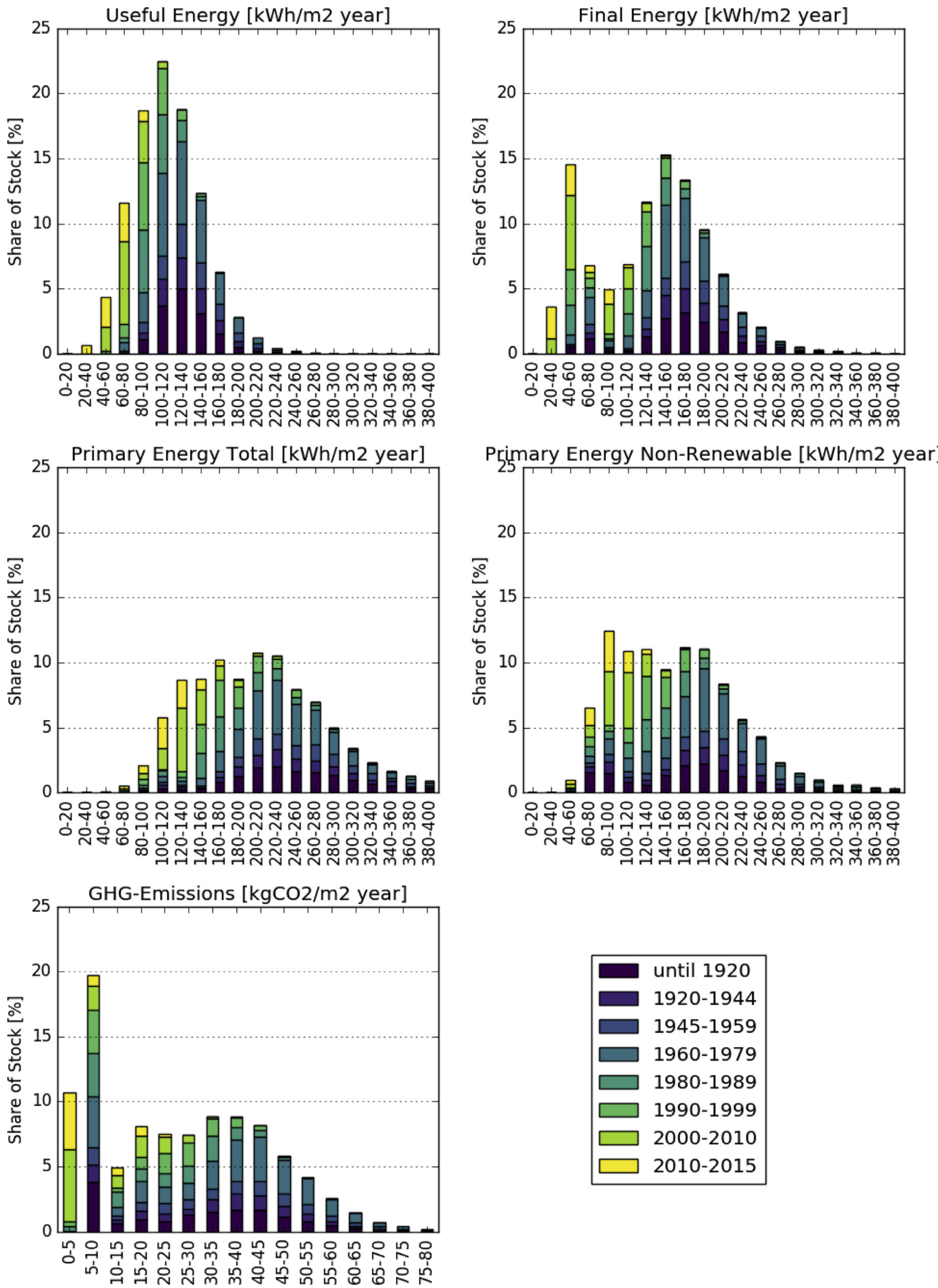


**Fig. 5.** Distribution of specific useful energy demand (only for space heating and DHW), final energy, primary energy (total and non-renewable), and GHG emissions across the synthetic building stock according to construction period. The shares are weighted based on the representative floor area in the stock.

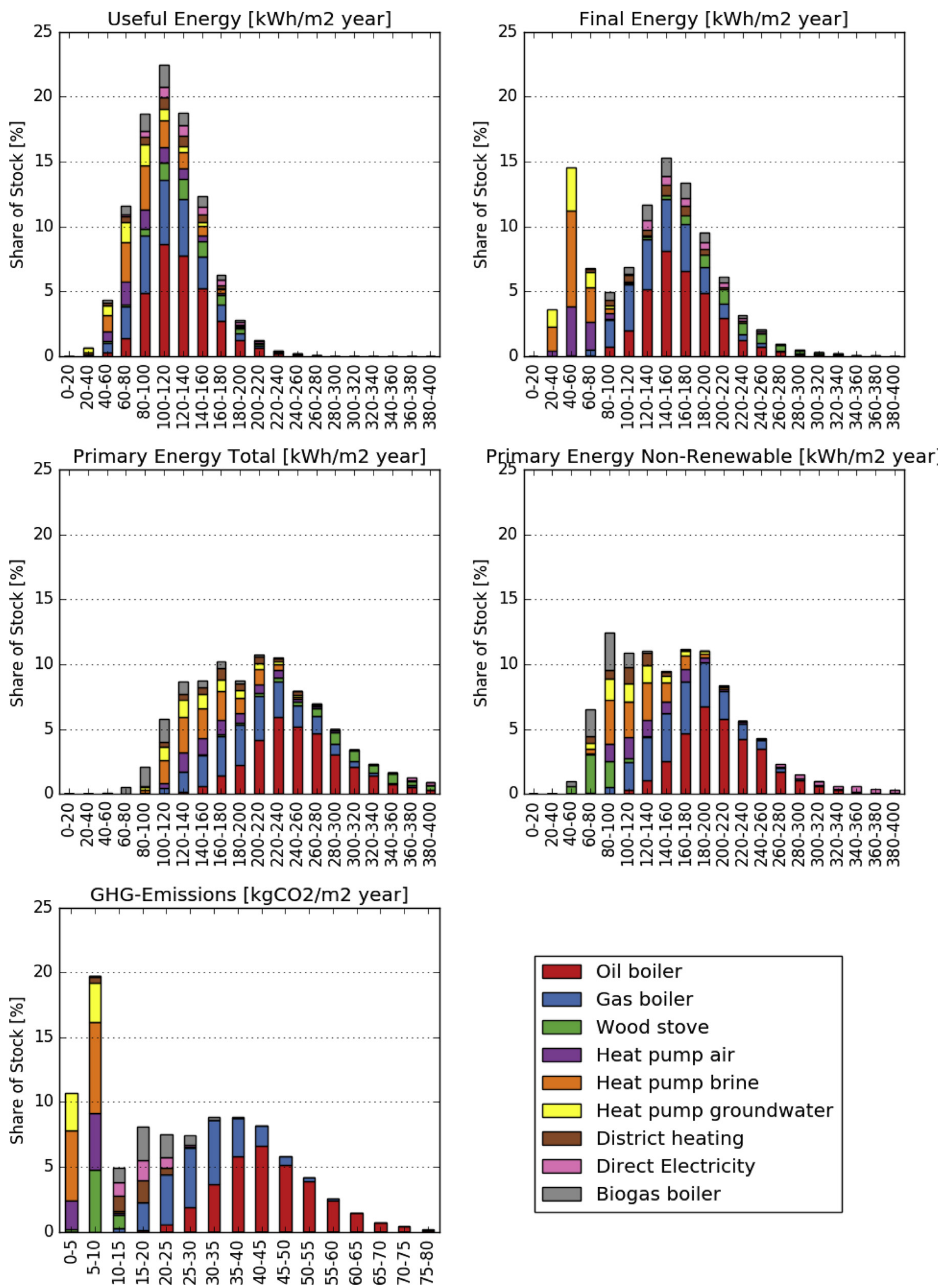


**Fig. 6.** Distribution of specific useful energy demand (only for space heating and DHW), final energy, primary energy (total and non-renewable), and GHG emissions across the synthetic building stock according to main heating system type. The shares are weighted based on the representative floor area in the stock.

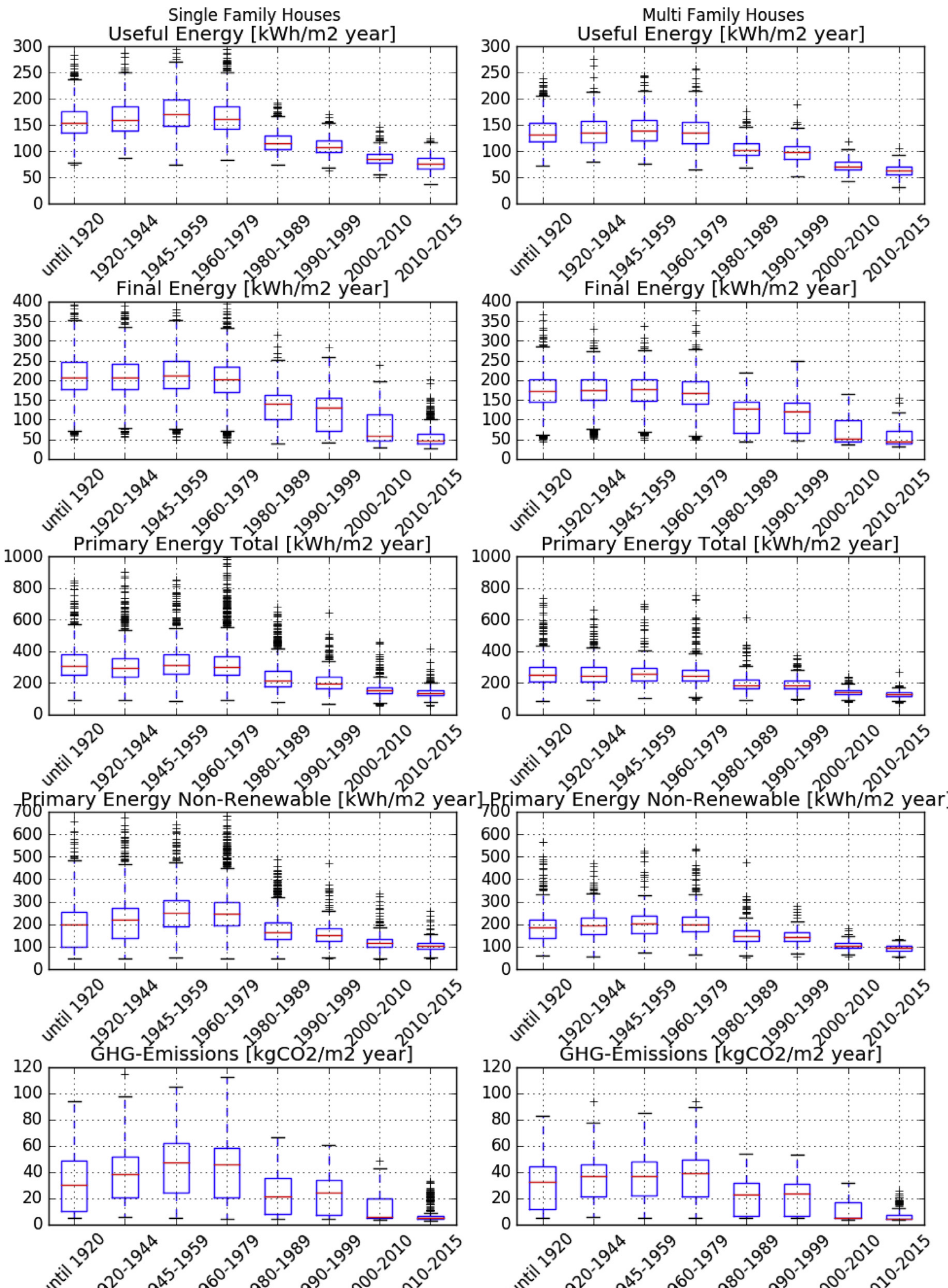


**Fig. 7.** Boxplot of the specific useful energy demand (only for space heating and DHW), final energy, primary energy (total and non-renewable), and GHG emissions across the synthetic building stock according to construction period and building type. Left-side: single-family houses; right-side: multi-family houses. The median is shown with a red line.

merous manners. It has the following advantages: (1) Generating numerous representative buildings and using input distributions makes it possible to consider the heterogeneity in the stock as well as the uncertainty and variation in the input data. (2) The method considers nonlinearities of interactions in the stock, such as the efficiency standard of the building envelope and the heating system. (3) The data need is not significantly higher than for the common archetype approach. (4) The possibility exists to consider various data types, including sample studies and surveys to calibrate distributions and reflect heterogeneity.

Generating numerous discrete representative buildings reproduces the heterogeneity in the building stock. The representative buildings represent a share of the stock just as building archetypes do, but they also reflect the heterogeneity in the stock in terms of past building stock alterations such as refurbishments, as well as variations of the occupancy and user influence across the stock. Past renovation measures are not considered an average improvement of the energy efficiency of a given archetype, but as a discrete event for a selection of the representative buildings. Variation in number of occupants, user influence, and other uncertain parameters are considered using probabilistic distributions of different parameters across the stock. Therefore, the synthetic stock can reproduce the variability and uncertainty of characteristics in the stock model and show how output variables at the building level vary across the stock.

The heterogeneity of the stock can have large implications when investigating energy conservation and GHG mitigation measures for the building stock as the effectiveness of energy efficiency measures differs between non-retrofitted, fully retrofitted, and partially (average) retrofitted buildings. Because of nonlinearities, the average of the individual results may not be equal to the results of an average situation. Thus, the synthetic stock model can provide a more detailed understanding of the distribution energy demand and GHG emissions in the existing stock, thereby providing a more robust basis for assessing future stock developments as well as investigate refurbishment strategies and policy interventions.

The increased level of detail of the method does not significantly increase the amount of data required compared with a conventional archetype approach. The data sources used are also the ones commonly applied in archetype modeling, but the data is processed to give a more detailed overview over the stock. Compared with an individual building approach (requiring data from each building), the synthetic building stock uses fewer, and more crucially, less sensitive data. All data sources that were used to generate the stock for Switzerland are publicly available. This, in theory, makes the method as broadly applicable as the archetype approach.

The method can accommodate a wider variation of data types compared with archetype approaches, particularly distributional information derived from surveys. Including such data sources strengthens the generated synthetic building stock because it helps to reproduce the heterogeneity in the stock. Being able to accommodate such different data sources and not relying on a single source (e.g., a complete building registry as an individual building-based approach would) makes the methodology easier to adapt to different situations of data availability, and therefore, more transferable to other cases.

#### 4.1.2. Critical review of the methodology

The current implementation of the methodology shown in this paper has some limitations. In particular, the following aspects should be considered: (1) The combination of building and dwelling types may lead to unrealistic combinations in some cases. (2) The different input distributions are assumed to be independent from each other; however, in reality, these may often be correlated with one another.

At this stage of implementation, the relationship between dwelling and building characteristics beyond the attributes of building type and construction period is often not explicitly considered. This may lead to unrealistic composition of dwelling types within a building because they are assigned randomly based on building type and construction period, which might also explain the large number of outliers in Fig. 7. This aspect was partially addressed by introducing restrictions on the size of the dwellings to be chosen from, yet no link was considered between dwellings in the same building when assigning dwellings. For instance, dwellings within the same multi-family building are more likely to belong to the same size group, which was not considered. However, with the methodology proposed, this could easily be considered if the underlying micro-level data or a sample thereof could be used as a basis for generating the synthetic stock.

In addition, the data quality could be improved when it comes to building characterization and updating, where representative data for the stock are often lacking altogether, and data must be used from many diverse sources. Hence, most attributes in these steps are defined independently from each other. This leads to unrealistic combinations of attributes in some of the synthetic buildings, because in reality, many attributes (e.g., the refurbishment status of various building components) are interconnected. This is shown in the results by the large number of outliers in Fig. 7. At a stock level, not enough data is available upon which and to what degree different building characteristics are linked to each other. Here, a remedy could be common sense assumptions, and more epidemiological studies on building energy use could help fill in the gaps in the long-term [68]. Such interdependencies could be implemented by introducing structured correlations between the various probabilistic distributions.

#### 4.1.3. Calibration

The calibration of the generated synthetic stock is an issue just as in all BSMs. The stock generated in this study was calibrated and validated at various scales in terms of structure, past refurbishment activities, and aggregate energy consumption. Be that as it may, a more detailed calibration could be performed by calibrating input distributions for the building characterization step based on energy consumption data, through using Bayesian methods as proposed by Sokol et al. [26]. However, this would require more detailed data on a representative sample of buildings across the stock to calibrate the input distributions. Furthermore, the availability of such a sample would mean that other methodologies for the generation of synthetic stocks such as the sample-based approach mentioned in Section 2 could be investigated. Calibrating the step for updating the building characteristics based on the current state of the building stock (e.g., gathered through surveys) is a valid approach; however, a more detailed longitudinal dataset tracking building stock developments over time (e.g., studies underlying the report by Jakob et al. [59]) might help to improve the underlying building component lifetime distributions [46], as well as the combination of different measures commonly applied in a building.

### 4.2. Discussion of case study results

Applying the synthetic stock methodology to the residential building stock of Switzerland demonstrates that the developed method can accurately reproduce aggregate results (cf. Table 1 and Fig. 9 in the appendix), and also provide information on the distribution of energy demand and GHG emissions within the stock (cf. Figs. 4–7). This is a clear value added compared with traditional approaches using building archetypes that are mostly based on averages.

The results for the Swiss residential building stock show that energy demand as well as GHG emissions can vary greatly across the building stock. This variation mainly arises from the energy standard of the construction period, building size, past retrofit measures that are unequally implemented, and most importantly, from the heating system's energy carrier. Moreover, varying factors under the user's influence (e.g., demanded indoor temperature, domestic hot water consumption, or ventilation rate) affect the distribution of energy demand and GHG emissions in the stock.

The results show that the variation within common classifications of building type and construction period can be much larger than the average differences between construction periods or building types (cf. Figs. 5 and 7). This highlights the limitations of an archetype approach because they are typically defined across these two dimensions. Therefore, the effectiveness of renovation measures are only to a certain extent explained by typical archetype variables such as construction period, but more so by the current state of the building (which varies widely as shown by the results). Considering these variations would therefore strengthen the usefulness of the results from BSMs to investigate refurbishment strategies and policy interventions.

The impact assessment of the generated stock shows that especially for final energy and GHG emissions, a division of the stock into two main clusters occurs: one cluster represents older, non-retrofitted and mostly fossil fuel-heated buildings, and the other represents newer buildings with a renewable energy-based heating system such as a heat pump. Although decarbonization of the heating supply could significantly reduce direct GHG emissions in all buildings, in Switzerland, these systems to date are mainly installed in newer buildings (and to a lesser extent in retrofitted buildings) that are already rather energy efficient. A large share of older, fossil fuel-heated buildings remains to be addressed.

## 5. Conclusion and outlook

This paper describes a new methodology for the generation of synthetic building stocks to be used in bottom-up building stock modeling. The method for generating the initial building stock per se comprises three steps: (1) building stock initialization, (2) building characterization, and (3) updating building characteristics. In a subsequent step, the generated synthetic building stock is assessed in terms of its energy demand and GHG emissions. The method was implemented for the residential building stock of Switzerland and calibrated based on the overall structure of the stock, the past renovation activities, and the aggregate energy demand of the building stock. This paper focused on the methodology development to generate synthetic building stocks for building stock modeling and helps set the scope for future work.

The methodology was applied and tailored to the building stock of Switzerland; nonetheless, the approach is transferable to other countries and other scales (e.g., a regional scale). However, such an application will depend on the size of the stock, model purpose, and data availability. Although the methodology can theoretically be applied to a stock of any size, it does not make practical sense to go below a stock size of several thousand buildings because at that scale, the stochasticity of the approach might lead to unrealistic results. One approach to remedy that would be oversampling (i.e., generating a synthetic stock that is larger than the actual stock, where each building has several representative buildings) or through a Monte Carlo simulation approach. Moreover, an application on a city scale may be feasible; for example, to inform a policy assessment. However, at that scale, building stock modeling results are often also used for energy planning purposes [69]. In that case, a synthetic stock is not enough, but rather data on the individual building are required. However, a building characterization approach can still be used to fill data gaps at a building level.

The developed methodology can be extended in numerous manners, which lay the groundwork for future work. A possible development would be to make the synthetic population spatially differentiated by distributing the population based on regions (e.g. cantons in Switzerland or NUTS regions), the municipality, or even down to a hectare raster level. Methodologies on how to spatially distribute a synthetic population exist and have been proven useful in transportation and land-use models [37,70]. Another further development is the extension of the approach to include non-residential buildings to encompass the complete building stock of a country. This would allow an improved representation of mixed-use buildings, which are typical for an urban environment. Data availability on the non-residential building stock is generally even poorer than for residential buildings, which limits this approach. One way to address this would be to use synthetic businesses as a proxy to estimate the non-residential floor space [37]. Another extension of the approach would be to combine the synthetic building stock with a synthetic population. This would make it possible to model occupant behavior in greater detail [36] or estimate the impact of changes in the building stock on the population, including social sustainability indicators (e.g., [71]).

The results of Switzerland demonstrate how the discrete representation of different building states in the synthetic building stock allows for a more realistic representation of past building stock alterations such as refurbishment. It also lays the groundwork for the development of a dynamic BSM based on a synthetic building stock using methodologies such as agent-based modeling. This can be applied both in terms of modeling decisions at the building scale, such as renovation and heating system substitution choices [24,72,73], or to model macro development through the integration of location choice and land-use models [33]. Such a dynamic model could be extended to include material attributes (such as wall constructions instead of *U*-values) as in the database developed by Ostermeyer et al. [74], to model the material intensity of the stock and its related embodied emissions and how it develops over time [75,76].

The combination of datasets to generate a synthetic building stock for stock modeling comes with many challenges, which were outlined in this paper. Although we demonstrated the feasibility of the use of synthetic building stocks from the available data sources, room exists for improvement with regards to data quality. In particular, in terms of the distribution of the combination of building attributes or previous building stock alterations, data is severely lacking. Here, more cross-sectional and longitudinal studies on the state and development of the building stock could increase understanding of these aspects at a stock level, while simultaneously improving the data basis for the generation of synthetic stocks and building stock modeling.

## Acknowledgments

The authors would like to thank the EIT Climate-KIC for funding the PhD studies of Claudio Nägeli and the project Building Market Briefs and the Swiss Federal Office of Energy for funding TEP Energy's contribution to the IEA-EBC Annex 70.

## Appendix

### *A. Description of input data and data sources*

Table 2.

**Table 2**
Description of input data and data sources. The table is structured according to the different steps in the method and the building stock assessment. Reading example: The attribute "Number of Buildings" has the unit #, the data table has values ranging from 1 to 53,997 and it is differentiated in according to building type, construction period, number of floors class, number of dwellings class, heating system type, hot water system type and solar system installed, it is not represented by a distribution and the source is [55].

| | Section | Attribute | Unit | Range of data | Differentiated according to | Distribution | Source |
|---|---|---|---|---|---|---|---|
| **1. Building stock initialization** | **Building stock** | Number of buildings | # | 1–53,997 | Building type, construction period, number of floors class, number of dwellings class, heating system type, Hot water system type, solar system installed | – | [55] |
| | **Dwelling stock** | Number of dwellings | # | 1–183,003 | Building type, construction period, dwelling size class, number of rooms class | – | [55] |
| **2. Building characterization** | **Building geometry** | Share roof type pitched | % | 19–100 | building type, construction period | – | [22] |
| | | Share buildings with basement | % | 70–90 | building type, construction period | – | [22] |
| | | height floor | m | 2.7–3 | Building type, construction period | Lognormal | [22] |
| | | Share one side attached | % | 0–20 | Building type, construction period | – | [22] |
| | | Share two sides attached | % | 5–50 | Building type, construction period | – | [22] |
| | | Aspect ratio (length/width) | – | 25–100 | Building type, construction period | Lognormal | [22] |
| | | Share glazing short side | % | 10–55 | Building type, construction period | Lognormal | [22] |
| | | Share glazing long side | % | 10–55 | Building type, construction period | Lognormal | [22] |
| | | Building orientation | ° | 0–180 | – | Uniform | – |
| | **Building envelope** | *U*-value | $W/m^2$ K | 0.16–2.4 | Building type, construction period, Building component type | Lognormal | [22,58,60,61] |
| | | *g*-value window | – | 0.45–0.78 | Building type, construction period | Lognormal | [22,58,60,61] |
| | | Window shading factor | % | 60–90 | – | Lognormal | [22,50] |
| | | Window frame ratio | % | 10–30 | – | Lognormal | [22,50] |
| | | Internal heat capacity building | $J/K\ m^2$ | 80,000 - 370,000 | – | Lognormal | [77] |
| | **Occupancy** | Number of occupants | # | 1–7 | Dwelling size class | Binominal | [55] |
| | | Occupancy time | h/persons day | 10–18 | – | Lognormal | [50,56] |
| | | Indoor temperature | °C | 18–22 | – | Lognormal | [50,56] |
| | | Consumption hot water | l/persons day | 30–50 | – | Lognormal | [50,56] |
| | **HVAC systems** | Share mechanical ventilation with heat recovery | % | 0–25 | – | – | [22] |
| | | Ventilation rate infiltration | $m^3/m^2h$ | 0.2–0.4 | Building type, construction period | Lognormal | [58,60] |
| | | Ventilation rate natural ventilation | $m^3/m^2h$ | 0.6–2.6 | Building type, construction period, ventilation system | Lognormal | [58,60] |
| | | Ventilation rate mechanical ventilation | $m^3/m^2h$ | 0.8–1.1 | Building type, construction period, ventilation system | Lognormal | [58,60] |
| | **Electricity use** | Electricity appliances | kWh/ year | 950–2526 | Number of rooms class | Lognormal | [57] |
| | | Lighting power | W | 150–1100 | Number of rooms class | Lognormal | [57] |
| | | Lighting full load hours | h/year | 150–1000 | Occupancy time | – | [57] |
| | | Electricity auxiliary | $kWh/m^2$ year | 3–4.5 | Building type | Lognormal | [57] |
| **3.** Updating building characteristics | **Building envelope** | lifetime | year | 10–200 | Building type, building component type, renovation period | Weibull | [59,64,65] |
| | | Share energy efficiency refurbishment | % | 25–90 | Building type, Building component type, renovation period | – | [59] |
| | | Insulation thickness after refurbishment | mm | 20–200 | Building type, building component type, renovation period | – | [22,58,60,61] |
| | | *U*-value window after refurbishment | | 1.1–1.8 | Building type, renovation period | – | [22,58,60,61] |
| | | *g*-value window after refurbishment | – | 0.54–0.7 | Building type, renovation period | – | [22,58,60,61] |

(*continued on next page*)

**Table 2** (*continued*)

| | Section | Attribute | Unit | Range of data | Differentiated according to | Distribution | Source |
|---|---|---|---|---|---|---|---|
| | **HVAC systems** | Lifetime | year | 15–40 | Building type, building component type, renovation period | Weibull | [59,64,65] |
| | | Efficiency space heating | % | 60–400 | Heating system type, year of installation | – | [22,60] |
| | | Efficiency hot water | % | 54–285 | Hot water system type, year of installation | – | [22,60] |
| | | Full load hours ventilation | h / year | 6098–8760 | Ventilation type | – | [22,60] |
| | | Efficiency heat recovery | % | 50–90 | Ventilation type, year of installation | – | [22,60] |
| | | Specific fan power | $W/(m^3/h)$ | 0–0.91 | Ventilation type, year of installation | – | [22,60] |
| **Building stock assessment** | **Climate data** | Solar irradiation | $kWh/m^2$ month | 4–168 | month, orientation | – | [78] |
| | | External temperature | °C | 0–16.8 | month | – | [78] |
| | **Energy carrier** | GHG factor | $kgCO_2/kWh$ | 0.03–0.3 | Energy carrier | – | [53] |
| | | PE total factor | kWh/kWh | 0.33–3 | Energy carrier | – | [53] |
| | | PE nonrenewable factor | kWh/kWh | 0.16–2.52 | Energy carrier | – | [53] |

*B. Energy demand model*

The energy demand model is based on a monthly steady-state energy balance based on the norm ISO EN 13790 [79] (or the equivalent Swiss norm SIA 380/1 [50]). It calculates monthly energy demand of each building for space heating, hot water, appliance use, lighting and auxiliary electricity use (ventilation, pumps, etc.).

The monthly space heating demand ($Q_{H,\,m}$) of the building is calculated based on the balance between the sum of all heat losses and gains for each month in the building according to below equation:

$$Q_{H,m} = Q_{T,m} + Q_{V,m} - \eta_{g,m}(Q_{S,m} + Q_{O,m} + Q_{E,m}) \quad (1)$$

Where $Q_{T,\,t}$ is the heat losses from transmission, $Q_{V,\,t}$ is the heat losses from ventilation, $\eta_{g,\,t}$ is the heat gains utilization factor, $Q_{S,\,t}$ is the heat gains from solar radiation, $Q_{P,\,t}$ is the heat gains from occupants, and $Q_{E,\,t}$ is the heat gains from electricity use in the building (lighting, appliances, etc.).

The heat losses from transmission ($Q_{T,\,t}$) are calculated for each component and summed up according to below equation:

$$Q_{T,m} = \sum_{c} U_c \cdot A_c \cdot \Delta T \cdot b_c \cdot t_m \cdot 24 \cdot 10^{-3} \quad (2)$$

Where $U_c$ is the $U$-value of the component in $W/m^2$ K, $A_c$ is the surface area of the component in $m^2$, $\Delta T$ is the temperature difference between internal and external temperature in K, $b_c$ is a reduction factor to account for surfaces with a reduction of thermal losses such as floors against ground or unheated spaces and $t_m$ is the length of month m in days.

The heat losses from ventilation ($Q_{V,\,m}$) from both active (natural or mechanical ventilation) and passive (through infiltration) ventilation are calculated according to below equation:

$$Q_{V,m} = \rho_a c_a \cdot \left(q_{v,act} \cdot (1 - \eta_{HR}) + q_{v,inf}\right) \cdot \Delta T \cdot t_m \cdot 24 \cdot 10^{-3} \quad (3)$$

Where $\rho_a c_a$ is the heat capacity of air in $Wh/m^3$ K, $q_{v,\,act}$ is the air exchange rate due to active ventilation in $m^3/h$, $\eta_{HR}$ is efficiency of heat recovery from ventilation in % and $q_{v,\,inf}$ is the air exchange rate due to infiltration in $m^3/h$.

The adjusted temperature difference ($\Delta T$) between the external and internal temperature is calculated based on Loga et al. [52] according to below equation:

$$\Delta T = f_n \cdot f_r \cdot f_u \cdot (T_{s,m} - T_{e,m}) \quad (4)$$

Where $f_n$ is the reduction factor for the nightly decrease of the internal air temperature, $f_r$ is the reduction factor for the partially heated spaces, $f_u$ is the reduction factor for user influence (e.g. blocking of building components through furniture, reduction of set temperature to save heating costs), $T_{s,\,m}$ is the set temperature in °C and $T_{e,\,m}$ is the external air temperature in °C.

The reduction factor for the nightly decrease of the internal air temperature ($f_n$) is calculated based on Loga et al. [52] according to below equation:

$$f_n = 0.9 + \frac{0.1}{h} \quad (5)$$

Where $h$ is the specific heat loss factor of the building in $W/m^2{}_{floor\ area}$ K.

The reduction factor for the partially heated spaces ($f_r$) is calculated based on Loga et al. according to Eq. (5).

$$f_r = \frac{1}{0.5\sqrt{h} \cdot {n_r}^2 + 1} \quad (6)$$

Where $h$ is the specific heat loss factor of the building in $W/m^2{}_{floor\ area}$ K and $n_r$ is the share of indirectly or partially heated spaces (e.g. stairways, etc.) in the thermal envelope.

The share of indirectly or partially heated spaces in the thermal envelope $n_r$ is estimated based on Loga et al. [52] according to below equation:

$$n_r = 0.25 + 0.2 \cdot \tan^{-1}\frac{A_D - 100}{50} \quad (7)$$

Where $A_D$ is the average dwelling size in the building.

The reduction factor for user influence ($f_u$) is calculated based on Loga et al. [52] according to below equation:

$$f_u = 0.5 + \frac{1}{1 + 0.5 \cdot h} \quad (8)$$

Where $h$ is the specific heat loss factor of the building in $W/m^2{}_{floor\ area}$ K.

The heat gains from solar irradiation ($Q_{S,\,m}$) are calculated for each window and summed up according to below equation:

$$Q_{S,m} = \sum_{C}^{Windows} I_G \cdot A_c \cdot g_c \cdot \left(1 - f_{frame,C}\right) \cdot f_{shading,C} \cdot t_m \cdot 24 \cdot 10^{-3} \quad (9)$$

Where $I_G$ is the global solar irradiation on the window surface in $kWh/m^2$, $A_c$ is the surface area of the window in $m^2$, $g_c$ is the solar gains factor of the window, $f_{frame,\,C}$ is the frame Ratio of the window, $f_{shading,\,C}$ is the shading factor of the window and $t_m$ is the length of month m in days

The heat gains from building occupants $Q_{O,\,m}$ are calculated according to below equation:

$$Q_{O,m} = n_O \cdot q_O \cdot t_O \cdot t_m \cdot 10^{-3} \tag{10}$$

Where $n_O$ is the number of occupants, $q_O$ is the heat gain from each person in W/person, $t_O$ is the occupancy time in h/day and person and $t_m$ is the length of month m in days

The heat gains from electricity use ($Q_{E,\,m}$) are calculated according to Eq. (10).

$$Q_{E,m} = (E_A + E_L + E_{Aux}) \cdot \frac{t_m}{365} \tag{11}$$

Where $E_A$ is the electricity use from appliances in kWh/year, $E_L$ is the electricity use from lighting in kWh/year, $E_{Aux}$ is the electricity use from auxiliary sources (pumps, ventilation, etc.) in kWh/year and $t_m$ is the length of month m in days.

The final energy for space heating ($E_H$) can be calculated according to below equation:

$$E_H = \frac{\sum_m^{12} \left(Q_{H,m} - f_{H,solar} \cdot Q_{solar,m}\right)}{\eta_H} \tag{12}$$

Where $Q_{H,\,m}$ is the monthly space heating demand according to Eq. (1) in kWh, $Q_{solar,\,m}$ is the heat provided from solar thermal collectors in kWh, $f_{H,\,solar}$ is the share of the heat provided by solar collectors used for space heating and $\eta_H$ is the efficiency of the heating system for space heating in %.

The monthly hot water demand ($Q_{HW,\,m}$) of the building is calculated according to below equation:

$$Q_{HW} = \rho_w c_w \cdot n_O \cdot V_{HW} \cdot t_m \cdot 24 \cdot 10^{-3} \tag{13}$$

Where $\rho_w c_w$ is the heat capacity of water in Wh/m$^3$ K, $n_O$ is the number of occupants, $V_{HW}$ is the daily hot water consumption per occupant in m$^3$/day person and $t_m$ is the length of month m in days.

The final energy for hot water ($E_{HW}$) can be calculated according to below equation:

$$E_{HW} = \frac{\sum_m^{12} \left(Q_{HW,m} - f_{HW,solar} \cdot Q_{solar,m}\right)}{\eta_{HW}} \tag{14}$$

Where $Q_{H,\,m}$ is the monthly hot water demand according to Eq. (13) in kWh, $Q_{solar,\,m}$ is the heat provided from solar thermal collectors in kWh, $f_{H,\,solar}$ is the share of the heat provided by solar collectors used for hot water and $\eta_H$ is the efficiency of the heating system for hot water in %.

The monthly heat gains from solar thermal collectors ($Q_{solar,\,m}$) is calculated according to below equation:

$$Q_{solar,m} = I_{G,c} \cdot A_c \cdot \eta_{solar} \cdot t_m \cdot 24 \cdot 10^{-3}. \tag{15}$$

Where $I_G$ is the global solar irradiation on the collector surface in kWh/m$^2$, $A_c$ is the surface area of the collector in m$^2$, $\eta_{solar}$ is the efficiency of the solar collector and $t_m$ is the length of month m in days

The total final energy demand of the building is calculated according to below equation:

$$E_{tot} = E_H + E_{HW} + E_A + E_L + E_{Aux} \tag{16}$$

Where $E_H$ is the final energy for space heating in kWh/year, $E_{HW}$ is the final energy for hot water in kWh/year, $E_A$ is the electricity use from appliances in kWh/year, $E_L$ is the electricity use from lighting in kWh/year and $E_{Aux}$ is the electricity use from auxiliary sources (pumps, ventilation, etc.) in kWh/year

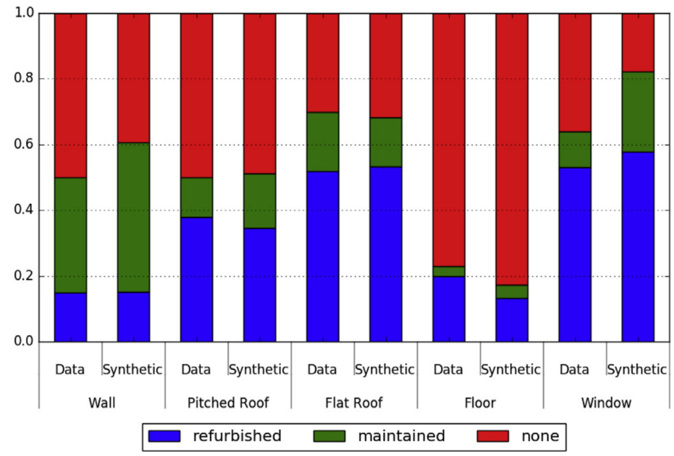


**Fig. 8.** Share of refurbished and maintained building components in the synthetic building stock as well as based on the calibration data from [59].

### C. Calibration

The calibration of the generated synthetic is done on multiple levels and along all three steps in the synthetic building stock generation as well as through the building stock model. The methodology described in step 1 guarantees that the generated building stock has the same structure as the input dataset. Albeit, some deviations through the random sampling of buildings can occur. These deviations are, however, limited due to the size of the generated building stock. The structure of the dwelling stock is dependent on the structure of the generated building stock sample. As a result, deviations in the structure of the building stock are passed along. What is more, the size of the generated dwelling stock is dependent on the chosen exponential distribution to convert the open-ended class “10 or more dwellings” into a numerical value. The exponential distribution was accordingly calibrated for each construction period, so that the generated dwelling stock reflects the input data of the actual stock both in size and structure.

The state of the building stock in terms of its energy demand is calibrated through different mechanisms. The already refurbished share of the synthetic stock can be calibrated with data from [59]. The calibration results of the building stock according to the past refurbishments is shown in Fig. 8. The deviation between the synthetic data and the data from [59] is larger compared to the deviation in the structure of the stock. The share of already refurbished flat roofs and walls is matched rather well by the generated synthetic stock, while the shares for pitched roofs and floors are slightly underestimated. The share of refurbished windows is overestimated, especially when also including the maintained share.

As a second calibration step, the model is calibrated against the aggregate level residential energy demand of Switzerland both in aggregate level and in the distribution of the household energy consumption according to the main energy carrier [66]. The BDR is not up to date on the installed heating and hot water systems and has been shown to be outdated in many instances, e.g. changes in heating systems in existing buildings have often not been recorded [54]. To calibrate the distribution of heating system the BDR data was adapted through the IPF routine to update the outdated data basis of the building registry (see Section 2.3.1). The resulting energy demand of the calibrated stock compared to national statistics on the household energy consumption [66] can be seen in Fig. 9. Although the distribution of the demand can be met by the model to large degrees, in overall the model still overestimates the demand by around 4% (Statistics: 64.4 TWh, Synthetic Stock: 67.2 TWh). The deviation is largest for Oil (0.7 TWh) and

**Table 3**
Primary energy and emission factors used in the impact assessment of the building stock model based on data from [53].

| Energy carrier | GHG emission factor [$kgCO_2$/ $kWh_{FE}$] | Primary energy total factor [$kWh_{PEtot}/kWh_{FE}$] | Primary energy nonrenewable factor [$kWh_{PEnonrenewable}/kWh_{FE}$] |
|---|---|---|---|
| Oil | 0.3 | 1.24 | 1.23 |
| Gas | 0.23 | 1.06 | 1.06 |
| Wood | 0.03 | 1.2 | 0.16 |
| Electricity | 0.1 | 3.01 | 2.52 |
| District Heat | 0.11 | 0.88 | 0.55 |
| Biogas | 0.13 | 0.33 | 0.3 |

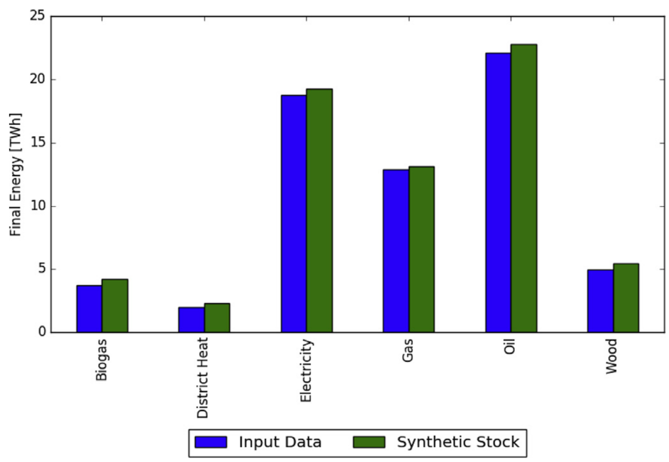


**Fig. 9.** Comparison of final energy demand of synthetic building stock (green bars) compared to statistical data (blue bars) from Switzerland from [66]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Wood (0.46 TWh) and smallest for Gas (0.3 TWh). The general overestimation of the demand can partially be explained by the fact that the building stock is modeled as if all buildings are permanently occupied. At any rate, there is a share of around 1.47% empty dwellings [55] as well as non-permanently occupied residences, which was not taken into account.

*D. Primary energy and emission factors*

Table 3.

## References

[1] M. Economidou, B. Atanasiu, C. Despret, J. Maio, I. Nolte, O. Rapf, Europe's buildings under the microscope: a country-by-country review of the energy performance of buildings, Build. Perform. Inst. Eur. (BPIE) (2011) ISBN: 9789491143014.
[2] IPCC, Summary For Policymakers, Intergovernmental Panel On Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, USA, 2014.
[3] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, M. Djurovic-Petrovic, A review of bottom-up building stock models for energy consumption in the residential sector, Build. Environ. 45 (2010) 1683–1697, doi:10.1016/j.buildenv.2010.01.021.
[4] A. Mastrucci, A. Marvuglia, U. Leopold, E. Benetto, Life cycle assessment of building stocks from urban to transnational scales : a review, Renew. Sustain. Energy Rev. 74 (2017) 316–332, doi:10.1016/j.rser.2017.02.060.
[5] N. Heeren, M. Jakob, G. Martius, N. Gross, H. Wallbaum, A component based bottom-up building stock model for comprehensive environmental impact assessment and target control, Renew. Sustain. Energy Rev. 20 (2013) 45–56, doi:10.1016/j.rser.2012.11.064.
[6] I. Sartori, N.H. Sandberg, H. Brattebø, Dynamic building stock modeling: general algorithm and exemplification for Norway, Energy Build. (2016), doi:10.1016/j.enbuild.2016.05.098.
[7] R. Mckenna, E. Merkel, D. Fehrenbach, S. Mehne, W. Fichtner, Energy efficiency in the German residential sector: a bottom-up building-stock-model-based analysis in the context of energy-political targets, Build. Environ. 62 (2013) 77–88, doi:10.1016/j.buildenv.2013.01.002.
[8] S.J. Quan, Q. Li, G. Augenbroe, J. Brown, P.P.J. Yang, A GIS-based energy balance modeling system for urban solar buildings, Energy Proc. 75 (2015) 2946–2952, doi:10.1016/j.egypro.2015.07.598.
[9] M. Jakob, H. Wallbaum, G. Catenazzi, G. Martius, C. Nägeli, B. Sunarjo, Spatial building stock modelling to assess energy-efficiency and renewable energy in an urban context, in: Proceedings of the International Conference on CISBAT, 2013, pp. 1047–1052.
[10] C.F. Reinhart, C. Cerezo Davila, Urban building energy modeling –a review of a nascent field, Build. Environ. 97 (2016) 196–202, doi:10.1016/j.buildenv.2015.12.001.
[11] M. Kohler, N. Blond, A. Clappier, A city scale degree-day method to assess building space heating energy demands in Strasbourg Eurometropolis (France), Appl. Energy 184 (2016) 40–54, doi:10.1016/j.apenergy.2016.09.075.
[12] A. Mastrucci, O. Baume, F. Stazi, U. Leopold, Estimating energy savings for the residential building stock of an entire city: a GIS-based statistical downscaling approach applied to Rotterdam, Energy Build. 75 (2014) 358–367. doi:10.1016/j.enbuild.2014.02.032.
[13] A. Mastrucci, E. Popovici, A. Marvuglia, L. De Sousa, E. Benetto, U. Leopold, GIS-based life cycle assessment of urban building stocks retrofitting- a bottom-up framework applied to Luxembourg, in: Proceedings of the EnviroInfo ICT Sustainability, 2015, pp. 47–56, doi:10.2991/ict4s-env-15.2015.6.
[14] A. Mavrogianni, M. Davies, Z. Chalabi, P. Wilkinson, M. Kolokotroni, J. Milner, Space heating demand and heatwave vulnerability: London domestic stock, Build. Res. Inf. 37 (2009) 583–597, doi:10.1080/09613210903162597.
[15] J.L. Reyna, M.V. Chester, The growth of urban building stock: unintended lock-in and embedded environmental effects, J. Ind. Ecol. 19 (2015) 524–537, doi:10.1111/jiec.12211.
[16] I. Hamilton, J. Milner, Z. Chalabi, P. Das, B. Jones, C. Shrubsole, M. Davies, P. Wilkinson, Health effects of home energy efficiency interventions in England: a modelling study, BMJ Open 5 (2015) e007298–e007299, doi:10.1136/bmjopen-2014-007298.
[17] L.G. Swan, V.I. Ugursal, Modeling of end-use energy consumption in the residential sector: a review of modeling techniques, Renew. Sustain. Energy Rev. 13 (2009) 1819–1835, doi:10.1016/j.rser.2008.09.033.
[18] É. Mata, A.Sasic Kalagasidis, F. Johnsson, Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK, Build. Environ 81 (2014) 270–282, doi:10.1016/j.buildenv.2014.06.013.
[19] É. Mata, A.S. Kalagasidis, F. Johnsson, A modeling strategy for energy, carbon, and cost assessments of building stocks, Energy Build. 56 (2013) 100–108, doi:10.1016/j.enbuild.2012.09.037.
[20] T. Csoknyai, S. Hrabovszky-Horváth, Z. Georgiev, M. Jovanovic-Popovic, B. Stankovic, O. Villatoro, G. Szendrő, Building stock characteristics and energy performance of residential buildings in Eastern-European countries, Energy Build. 132 (2016) 39–52, doi:10.1016/j.enbuild.2016.06.062.
[21] M. Österbring, É. Mata, L. Thuvander, M. Mangold, F. Johnsson, H. Wallbaum, A differentiated description of building-stocks for a georeferenced urban bottom-up building-stock model, Energy Build. 120 (2016) 78–84, doi:10.1016/j.enbuild.2016.03.060.
[22] Martin Jakob, G. Catenazzi, R. Forster, T. Egli, T. Kaiser, R. Looser, M. Melliger, C. Nägeli, U. Reiter, M. Soini, B. Sunarjo, Erweiterung des Gebäudeparkmodells gemäss SIA-Effizienzpfad Energie [Extension of the Building Stock Model according to the SIA Efficiency Path Energey], Swiss Federal Office of Energy, Bern, Switzerland, 2016.
[23] J.A. Fonseca, T. Nguyen, A. Schlueter, F. Marechal, City energy analyst (CEA): integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts, Energy Build. 113 (2016) 202–226, doi:10.1016/j.enbuild.2015.11.055.
[24] C. Nägeli, M. Jakob, B. Sunarjo, G. Catenazzi, A building specific, economic building stock model to evaluate energy efficiency and renewable energy, in: Proceedings of the International Conference on CISBAT, 2015, pp. 877–882.
[25] S. Moffatt, Stock aggregation: methods for evaluating the environmental performance of building stocks, Annex 31, Energy-Related Environmental Imapacts of Buildings, 2004.
[26] J. Sokol, C. Cerezo Davila, C.F. Reinhart, Validation of a Bayesian-based method for defining residential archetypes in urban building energy models, Energy Build. 134 (2017) 11–24, doi:10.1016/j.enbuild.2016.10.050.
[27] V. Aragon, S. Gauthier, P. Warren, P.A.B. James, B. Anderson, Developing english domestic occupancy profiles, Build. Res. Inf. 0 (2017) 1–19, doi:10.1080/09613218.2017.1399719.
[28] J. Keirstead, M. Jennings, A. Sivakumar, A review of urban energy system models : approaches, challenges and opportunities, Renew. Sustain. Energy Rev. 16 (2012) 3847–3866, doi:10.1016/j.rser.2012.02.047.
[29] C. Cerezo, J. Sokol, S. AlKhaled, C. Reinhart, A. Al-Mumin, A. Hajiah, Comparison of four building archetype characterization methods in urban building energy modeling (UBEM): a residential case study in Kuwait City, Energy Build. 154 (2017) 321–334, doi:10.1016/j.enbuild.2017.08.029.

[30] A.T. Booth, R. Choudhary, D.J. Spiegelhalter, Handling uncertainty in housing stock models, Build. Environ. 48 (2012) 35–47, doi:10.1016/j.buildenv.2011.08.016.
[31] P. Symonds, J. Taylor, Z. Chalabi, A. Mavrogianni, M. Davies, I. Hamilton, S. Vardoulakis, C. Heaviside, H. Macintyre, Development of an England-wide indoor overheating and air pollution model using artificial neural networks, J. Build. Perform. Simul. 9 (2016) 606–619, doi:10.1080/19401493.2016.1166265.
[32] R.J. Beckman, K.A. Baggerly, M.D. McKay, Creating synthetic baseline populations, Transp. Res. Part A Policy Pract. (1996), doi:10.1016/0965-8564(96)00004-3.
[33] P. Waddell, UrbanSim: modeling urban development for land use, transportation, and environmental planning, J. Am. Plan. Assoc. 68 (2002) 297–314, doi:10.1080/01944360208976274.
[34] F. Gargiulo, S. Ternes, S. Huet, G. Deffuant, An iterative approach for generating statistically realistic populations of households, PLoS One 5 (2010), doi:10.1371/journal.pone.0008828.
[35] P. Salvini, E.J. Miller, ILUTE : an operational prototype of a comprehensive microsimulation model of ILUTE : an operational prototype of a comprehensive microsimulation model of urban systems, Netw. Spat. Econ. 5 (2005) 217–234.
[36] C.J. Andrews, M.S. Allacci, J. Senick, H.C. Putra, I. Tsoulou, Using synthetic population data for prospective modeling of occupant behavior during design, Energy Build. (2016), doi:10.1016/j.enbuild.2016.05.049.
[37] R. Moeckel, K. Spiekermann, M. Wegener, Creating a Synthetic Population, in: Proceedings of the Eighth International Conference on Computers in Urban Planning and Urban Management, 2003, pp. 1–18.
[38] SciPy developers, SciPy, 2018. (2018). https://www.scipy.org/index.html (accessed March 15, 2018).
[39] NumPy developers, NumPy, 2018. (2018). http://www.numpy.org/ (accessed March 15, 2018).
[40] Tom Augspurger, Bartak Chris, Phillip Cloud, Andy Hayden, Stephan Hoyer, Wes McKinney, Jeff Reback, Chang She, Masaaki Horikoshi, Joris Van denBossche, Pandas: Python Data Analysis Library, 2018 (accessed March 15, 2018). https://pandas.pydata.org/index.html .
[41] Damien Forthommme, ipfn 1.1.7, 2018. (2018). https://pypi.python.org/pypi/ipfn/1.1.7 (accessed March 15, 2018).
[42] John Hunter, Darren Dale, Eric Firing, Michael Droettboom, et al., Matplotlib 2.2.0, 2018. (2018). https://matplotlib.org/ (accessed March 15, 2018).
[43] M. Lenormand, G. Deffuant, Generating a synthetic population of individuals in households: sample-free vs sample-based methods, J. Artif. Soc. Soc. Simul. 16 (2013) 1–10, doi:10.18564/jasss.2319.
[44] K. Hermes, M. Poulsen, A review of current methods to generate synthetic spatial microdata using reweighting and future directions, Comput. Environ. Urban Syst. 36 (2012) 281–290, doi:10.1016/j.compenvurbsys.2012.03.005.
[45] R. Frischknecht, N.J. Editors, H. Althaus, G. Doka, R. Dones, T. Heck, S. Hellweg, R. Hischier, T. Nemecek, G. Rebitzer, M. Spielmann, Ecoinvent v2.0: overview and Methodology, (2007).
[46] A. Miatto, H. Schandl, H. Tanikawa, How important are realistic building lifespan assumptions for material stock and demolition waste accounts? Resour. Conserv. Recycl. 122 (2017) 143–154, doi:10.1016/j.resconrec.2017.01.015.
[47] N. Kohler, W. Yang, Long-term management of building stocks, Build. Res. Inf. 35 (2007) 351–362, doi:10.1080/09613210701308962.
[48] N.H. Sandberg, I. Sartori, H. Brattebø, Using a dynamic segmented model to examine future renovation activities in the Norwegian dwelling stock, Energy Build. 82 (2014) 287–295, doi:10.1016/j.enbuild.2014.07.005.
[49] ISO, ISO 52016-1:2017: Energy performance of buildings – Energy needs for heating and cooling, internal temperatures and sensible and latent heat loads Part – 1: Calculation procedures, 2017.
[50] SIA (Swiss Society of Engineers and Architects), 380/1: Heizwärmebedarf [380/1: Space Heating Demand], 2016.
[51] D. Majcen, L.C.M. Itard, H. Visscher, Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: discrepancies and policy implications, Energy Policy 54 (2013) 125–136, doi:10.1016/j.enpol.2012.11.008.
[52] T. Loga, M. Großklos, J. Knissel, Der Einfluss des Gebäudestandards und des Nutzerverhaltens auf die Heizkosten [The Influence of Building Standards and the User Behaviour on the Heating Costs], Institut Wohnen und Umwelt (UWI), Darmstadt, Germany, 2003.
[53] KBOB (Koordination Conference of Public Building Owners), Liste Oekobilanzdaten im Baubereich [List Life Cycle Assessment Data in the Building Sector], KBOB, Bern, Switzerland, 2016.
[54] UWE (Office for Environment and Energy Canton Luzern), Gebäude-Heizenergiebedarf - Methodik zur Schätzung des Heizenergiebedarfs der Wohngebäude mittels kantonalem Gebäude- und Wohnungsregister [Building Heating Demand - Method for the Estimation of the Heating Demand of Residential Buildings using the Canton, Bau-, Umwelt- und Wirtschaftsdepartement Umwelt und Energie (UWES), Luzern, Switzerland, 2013.
[55] SFOS (Swiss Federal Office of Statistics), Bau- und Wohnungswesen 2015 [Construction and Housing 2015], Swiss Federal Office of Statistics, Neuchâtel, Switzerland, 2017.
[56] SIA (Swiss Society of Engineers and Architects), Merkblatt 2024: Standard-Nutzungsbedingungen für die Energie- und Gebäudetechnik [Bulletin 2024: Standard Usage Conditions for Energy and Building Technology], Swiss Society of Engineers and Architect, Zürich, Switzerland, 2006.
[57] SIA (Swiss Society of Engineers and Architects), 380/4: Elektrische Energie im Hochbau [380/4: Electrical Energy in Buildings], Swiss Society of Engineers and Architect, Zürich, Switzerland, 2006.
[58] M. Jakob, E. Jochem, K. Christen, Grenzkosten bei forcierten Energie-Effizienzmassnahmen in Wohngebäuden [Marginal Costs of Forced Energy Efficiency Measures in Residential Buildings], Swiss Federal Office of Energy, Bern, Switzerland, 2002.
[59] M. Jakob, G. Martius, G. Catenazzi, H. Berleth, Energetische Erneuerungsraten im Gebäudebereich: Synthesebericht zu Gebäudehülle und Heizanlagen [Energy Efficiency Refurbisment Rates in the Building Sector: Synthesis Report for the Building Enevelope an Heating Systems], Swiss Federal Office of Energy, Bern, Switzerland, 2014.
[60] M. Jakob, S. Kallio, C. Nägeli, W. Ott, R. Bolliger, S. Von Grünigen, Integrated strategies and policy instruments for retrofitting buildings to reduce primary energy use and GHG emissions (INSPIRE) - Generic strategies for buildings in Switzerland, Swiss Federal Office of Energy, Bern, Switzerland, 2014.
[61] Wüest und Partner, Energieplanungsbericht 1998 – Kontrollrechnung Sanierungstätigkeit [Energy Planning Report 1998 - Verification Calculation of Refuribishment Activities], Zürich, Switzerland, 1998.
[62] Wüest und Partner, Bauen, Markt und Energie - eine Standortbestimmung [Construction, Market and Energy - a location decision], Flums, Switzerland, 1994.
[63] R. Dettli, S. Bade, A. Baumgartner, M. Bleisch, Vorstudie zur Erhebung von Energiekennzahlen von Wohnbauten [Prestudy for the Survey of Energy Characterization Factors of Residential Buildings], Bern, Switzerland, 2007.
[64] IP BAU, Alterungsverhalten von Bauteilen und Unterhaltskosten - Grundlagendaten für den Unterhalt und die Erneuerung von Wohnbauten [Ageing Behaviour of Building Components and Maintenance Costs - Background Data for the Maintenance and Refurbishment of Residential Buildings], Bundesamt für Konjunkturfragen, Bern, Switzerland, 1994.
[65] Ulrich Agethen, K. Frahm, K. Renz, Erik Peter Thees, Lebensdauer von Bauteilen, Zeitwerte [Lifetime of Building Components, Time Values], Bund Technischer Experten e.V., Essen, 2010.
[66] FOE (Swiss Federal Office for Energy), Schweizerische Gesamtenergiestatistik 2015 [Swiss Energy Statistics 2015], Swiss Federal Office for Energy, Bern, Switzerland, 2016.
[67] R. Frischknecht, M. Tuchschmid, K. Flury, Primärenergiefaktoren von Energiesystemen [Primary Energy Factors of Energy Systems], ESU-services Ltd., Uster, Switzerland, 2012.
[68] I.G. Hamilton, A.J. Summerfield, R. Lowe, P. Ruyssevelt, C.A. Elwell, T. Oreszczyn, Energy epidemiology: a new approach to end-use energy demand research, Build. Res. Inf. 41 (2013) 482–497, doi:10.1080/09613218.2013.798142.
[69] S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi, Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches, J. Clean. Prod. 165 (2017) 811–827, doi:10.1016/j.jclepro.2017.07.142.
[70] D.M. Smith, G.P. Clarke, K. Harland, Improving the synthetic data generation process in spatial microsimulation models, Environ. Plan. A 41 (2009) 1251–1268, doi:10.1068/a4147.
[71] M. Mangold, M. Österbring, H. Wallbaum, L. Thuvander, P. Femenias, Socio-economic impact of renovation and energy retrofitting of the Gothenburg building stock, Energy Build. 123 (2016) 41–49, doi:10.1016/j.enbuild.2016.04.033.
[72] M. Hecher, S. Hatzl, C. Knoeri, A. Posch, The trigger matters : the decision-making process for heating systems in the residential building sector, Energy Policy 102 (2017) 288–306, doi:10.1016/j.enpol.2016.12.004.
[73] J. Busch, K. Roelich, C.S.E. Bale, C. Knoeri, Scaling up local energy infrastructure; an agent-based model of the emergence of district heating networks, Energy Policy 100 (2017) 170–180, doi:10.1016/j.enpol.2016.10.011.
[74] Y. Ostermeyer, C. Nägeli, N. Heeren, H. Wallbaum, Building inventory and refurbishment scenario database development for Switzerland, J. Ind. Ecol. 0 (2017) 1–14, doi:10.1111/jiec.12616.
[75] A. Stephan, A. Athanassiadis, Quantifying and mapping embodied environmental requirements of urban building stocks, Build. Environ. 114 (2017) 187–202, doi:10.1016/j.buildenv.2016.11.043.
[76] V. Augiseau, S. Barles, Studying construction materials flows and stock: a review, Resour. Conserv. Recycl. 123 (2017) 153–164, doi:10.1016/j.resconrec.2016.09.002.
[77] H. Wallbaum, N. Heeren, M. Jakob, M. Gabathuler, N. Gross, G. Martius, Gebäudeparkmodell SIA Effizienzpfad Energie Dienstleistungs-und Wohngebäude-Vorstudie zum Gebäudeparkmodell Schweiz [Building Stock Model SIA Efficiency Path Energy for Service and REsidential Buildings - Prestudy for the Buildign Stock Model Switzerland], Bern, Switzerland, 2009.
[78] SIA (Swiss Society of Engineers and Architects), Merkblatt 2028: Klimadaten für Bauphysik, Energie- und Gebäudetechnik [Bulletin 2028: Climate Data for Buildign Physics, Energy and Building Technology], Swiss Society of Engineers and Architect, Zürich, Switzerland, 2008.
[79] ISO, ISO 13790:2008 Energy performance of buildings — Calculation of energy use for space heating and cooling, 2006 (2008) 162.