Modeling Energy and Material Use of Buildings at Urban Scale

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In the past decade, scientific efforts to address the urgency of energy consumption and greenhouse gas (GHG) emissions from the building sector have increased. Buildings in the U.S. account for 39% of energy use and 38% of GHG emissions, contributing to adverse environmental and climate change impacts. Commercial buildings are responsible for approximately half of the total energy consumption. Given that more than 80% of the U.S. population lives in cities and urban areas, the role of urban buildings in energy consumption and emissions has become more crucial. Research about simulating energy consumption, modeling material use, and assessing the environmental impacts of buildings has increased; however, there are still issues that need to be addressed especially at the urban scale. The goal of this dissertation was to advance the sustainability of buildings by investigating the energy consumption and the embedded materials of existing building stocks. The energy use of buildings in the presence of climate change throughout the 21st century was estimated by integrating machine learning and climate change science. Most regions in the U.S. will experience increase in energy use. Further, to understand the trend of building energy use and evaluate the impacts of energy efficiency strategies at the urban scale, an urban building energy model was developed. This model also introduced a novel photogrammetry and imaging framework. The outcomes revealed that energy use was correlated to building use type and the implementation of efficiency strategies reduced energy use effectively. The gaps and barriers in analyzing the material stock of buildings were identified by the critical

review of the state of the art in this field to understand how building material stock analysis can contribute to and improve the circular economy of buildings. Finally, quantifying the accumulated materials and renovation flow of a building stock showed that brick and concrete had the highest share of accumulated materials and renovation flow. Moreover, there were significant variations in material distribution of different building components. The knowledge about the type, quantity, and time of availability of materials upon renovation and demolition was crucial for closing the resource loop and reducing waste.

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Nomenclature

GHG	Greenhouse Gas
ML	Machine learning
ANN	Artificial neural network
MLR	Multiple linear regression
XGBoost	Extreme gradient boosting
CBECS	Commercial Building Energy Consumption Survey
EUI	Energy use intensity
HVAC	Heating, ventilation, air conditioning
SVM	Support vector machine
LAC	Los Angeles County
IPCC	Intergovernmental Panel on Climate Change
RCP	Representative Concentration Pathway
BEND	Building ENergy Demand
CASCaDE	Computational Assessment of Scenarios of Change for Delta Ecosystem
EIA	Energy Information Administration
HDD	Heating degree days
CDD	Cooling degree days
MAE	Mean absolute error
RMSE	Root mean squared error
U.S. DOE	U.S. Department of Energy
GCM	General Circulation Model
NASA	National Aeronautics and Space Administration
NEX-GDDP	NASA Earth Exchange Global Downscaled Daily Projections
RF	Random forest
AI	Artificial intelligence
API	Application Programing Interface

ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CBES	Commercial Building Energy Saver
DEM	Digital Elevation Model
DER	Distributed Energy Resources
DSM	Digital Surface Model
EC	Energy conservation
fov	field of vision
GIS	Geographic Information System
ID	Identification
KS	Kolmogorov-Smirnov
LED	Light Emitted Diodes
LiDAR	Light Detection and Ranging
PDF	Probability distribution function
PE	Percent error
RECS	Residential Energy Consumption Survey
SVS	Street View Static
TMY	Typical Meteorological Year
UBEM	Urban building energy model
USGS	United States Geological Survey
WPRDC	Western Pennsylvania Regional Data Center
WWR	Window to wall ratio
MSA	Material stock analysis
MFA	Material flow analysis
MEP	Mechanical, electrical, plumbing
LCA	Life cycle assessment
BIM	Building Information Model
GDP	Gross domestic product
PVC	Polyvinyl chloride
LDPE	Low density polyethylene

MIC	Material intensity coefficient
VCT	Vinyl composite tile
OSB	Oriented strand Board
GCM	Global climate model
EE	Embodied energy
PFAS	Per-and polyfluoroalkyl substances
GPR	Ground penetrating radar

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1.0 Introduction

1.1 Energy Use and Materials of Buildings at Urban Scale

In the past decade, scientific efforts to address the urgency of energy consumption and greenhouse gas (GHG) emissions from the building sector has increased. Buildings in the U.S. account for 39% of energy use and 38% of GHG emissions [1], contributing to adverse environmental and climate change impacts. Commercial buildings are responsible for approximately half of the total energy consumption. Given that more than 80% of the U.S. population lives in cities and urban areas, the role of urban buildings in energy consumption and emissions has become more crucial. Buildings are also the largest generator of waste [2] and the main consumer of raw materials by being responsible for 50% of total use of raw materials, globally [3, 4]. In the U.S. alone, 600 million ton of waste was generated due to construction and demolition activities in 2018 [5]. Thus, the building sector is a major cause for resource depletion and a significant source of pollutants and waste discharges beyond the capacity of the environment. As the consequences of climate change increase and building stocks age, there is a need for especial emphasis on the building sector, a major negative contributor and a major positive solution provider [6].

Effective mitigation and adaptation strategies for the building sector in face of climate change are tied to knowledge about how buildings will consume energy in the future. Furthermore, with the increasing interest in reducing energy and emissions from the building sector, several cities established ambitious energy reduction goals and provided incentives for energy conservation strategies or measures. However, achieving these goals needs a thorough understanding of the trend of building energy use and the impacts of energy conservation strategies on the overall energy reduction of buildings in a city. Urban building energy models (UBEMs) are being more prevalently used to investigate building energy use at the city scale, but they are usually dependent on assumptions and disparate in terms of methods and data, which prevent them from accurately estimating energy use and simulating impacts of conservation strategies. Besides energy, building materials are important for the sustainability of the building sector.

While there have been notable efforts to reduce embodied energy and environmental impacts of new buildings through design, use of locally available materials, and less energy-intense materials and construction practices [6, 7], there is an expressed need to reduce demolition and renovation waste from existing buildings and close materials loop. Material stock and flow analysis enable the practical implementation of circular economy to close the material loop; however, building material stock analysis (MSA) is relatively nascent and there are gaps and barriers, especially in the U.S. that need to be addressed.

1.2 Research Goals and Objectives

The goal of this research was to mitigate the problems, which were discussed above, by developing machine learning and physics-based models to investigate the energy use of buildings under climate change, identify the trends of energy use, and assess the impacts of energy conservation measures at the urban scale. Additionally, this research advanced the circular economy of buildings and filled the gaps by a comprehensive review of state of the art in building MSA as well as modeling material stock and renovation flow of an existing building stock. This work achieved these goals by answering the following research questions:

1. Can machine learning methods be implemented to predict the shift in commercial buildings' energy use as a result of climate change in the future?
2. What is the framework for obtaining essential parameters to develop a UBEM in order to mitigate data disparity and reduce assumption dependency? And can a UBEM be used for both identifying trends of energy use and evaluating the impacts of energy conservation measures for a commercial building stock?
3. Are there any gaps and barriers in the current literature about building MSA? And what are the quantity and type of accumulated materials and materials, which will become available due to renovation, in the different components of an existing commercial building stock?

To answer the research questions, the following research objectives were developed and completed:

1. Develop and test machine learning (ML) models using a publicly available national building database, the Commercial Building Energy Consumption Survey (CBECS) [8].
2. Employ the ML model, selected in Objective 1, to estimate building energy use under climate change throughout the 21st century.
3. Create a framework for developing and validating a UBEM for a commercial building stock with a focus on photogrammetry and image processing and employ the UBEM to investigate the energy use and the impacts of energy conservation measures.
4. Review and evaluate the current state of literature about building MSA in the context of circular economy to identify gaps, barriers, and future opportunities. Create a model to analyze the accumulated materials and renovation flow of different components of a commercial building stock.

5. Develop a multi-layer map that integrates outcomes from Objectives 3 and 4.

1.3 Broader Impacts

This research focused on two major factors that affect the sustainability of the building sector: energy use and material. First, this work coalesced diverse viewpoints and technical terminology of data science and climate change science to build the connection between machine learning's predictive ability and climate change projections. Further, the disparity in the required data for creating UBEMs and the dependency of previous UBEMs on assumptions were addressed by developing a framework, which provided a comprehensive summary of useful data resources, and introducing photogrammetry and image processing methods. These contributions will facilitate the reproducibility of research in this area; thus, more cities can establish realistic energy reduction targets and make informed decisions about mandating energy efficiency strategies based on urban scale models. The patterns of energy consumption in different commercial buildings of Pittsburgh, PA along with reduction potentials at an urban scale were shared with the City of Pittsburgh's Division of Sustainability and Resilience, the Green Building Alliance, and policy makers that work toward a carbon-neutral city.

The findings of this research regarding material stock and renovation flow have been shared with the City of Pittsburgh to aid the city officials in expanding the deconstruction policy beyond the city-owned condemned buildings. Additionally, the results of our research about the accumulated materials' location, quantity, type, and time of availability have been presented to local companies that work on second-hand construction materials and building waste management in order to help these companies enhance their business models. The outcomes of this research have been published in peer-reviewed journal articles and shared with engineering, industrial ecology, and academic communities at conferences such as CIRP Life Cycle Engineering, Architectural Engineering Institute Conference, Building Performance Analysis Conference & SimBuild, and International Symposium on Sustainable Systems and Technology.

1.4 Intellectual Merit

This research introduced a new approach to estimating the energy use of commercial buildings under climate change by synthesizing the power of machine learning and the future weather projections. Additionally, most urban energy models have been developed depending on publicly available databases. These databases usually lack detailed information regarding buildings' parameters; hence, urban models rely on coarse national data or engineering assumptions to proceed. This work addressed this limitation by introducing photogrammetry and image processing, implementing geographic information system (GIS), and compiling a modeling structure to map required data and resources. Further, the overall accuracy of urban scale models has been impacted by the consistent performance of residential buildings; thus, this research focused on the development of a UBEM for commercial buildings to improve the field and the current knowledge. Ultimately, incorporating circular economy strategies in the building sector like reusing and repurposing materials demands a thorough knowledge of the location, quantity, and type of stockpiled materials in buildings of a city. This knowledge is scarce to date, especially in the U.S. Also, there is a need to differentiate between materials that are accumulated in various components and to emphasize on the components with high frequency of maintenance, repair, and renovation like windows and roofs. The field of building circular economy will benefit from this research project, which addressed the aforementioned gaps.

2.0 Predicting Building Energy Use under Climate Change Using ML Models

The research presented here addresses objectives one and two. Specifically, it answers the question 'Can machine learning methods be implemented to predict the shift in commercial buildings' energy use as a result of climate change in the future?' The content of this chapter was published in a peer-reviewed journal:

Mohammadiziazi, R., & Bilec, M. M. (2020). Application of machine learning for predicting building energy use at different temporal and spatial resolution under climate change in USA. *Buildings*, *10* (8), 139.

2.1 Introduction

Urban areas account for nearly 67% of total energy consumption worldwide [9]. As the population shifts from rural areas to cities, the energy consumption in cities will continue to rise [10, 11]. Understanding energy use in cities and associated greenhouse gas (GHG) emissions, is critical to solving energy and policy goals. Yet data related to urban energy use is disparate and diverse, especially in the area of building energy use. In London buildings consumes 61% of the city's energy which is two times higher than the share of transportation [12]. Further, the rising dependency of city residents and workers on appliances, office equipment, and space conditioning has led to the increase in building energy use [9, 13]. For example, space conditioning comprises almost 31% of the total energy use of Shanghai, China [14]. Given the pressing nature of climate change, there is an immediate need to develop fast and reliable methods to understand urban building energy use in the sector that accounts for 40% and 30–40% of total energy use in U.S. and the world, respectively [8, 15, 16].

Urban buildings are comprised of many types, from residential to commercial, and the fabric of the urban environment is shifting as new buildings are constructed, while existing buildings remain unchanged or are renovated. Understanding the energy use of existing buildings remains challenging as their vintage, material properties, and renovations lead to a high uncertainty in predicting building energy use.

In addition to these challenges, climate change will exacerbate building energy use modeling and predictions. Climate change and extreme weather events like heat waves may have positive or negative effects on energy use of this sector. Therefore, analyzing buildings at large scale and how they consume energy during operation in accordance to different factors such as weather condition, geographic region, building activity (use type), etc. will improve our understanding and aid policy makers and city planners in making informative decisions regarding regional energy and climate change mitigation policies as well as resiliency planning [17-19].

Machine learning (ML) may offer promise, and several researchers have explored this space in the context of building energy use [20-29]. ML approaches are less difficult to pursue than physics-based approaches that rely on heat and mass transfer and requires extensive "input" information [21]. However, disparate methods, databases, temporal resolutions, results, and recommendations related to ML have emerged. Thus, the body of literature was reviewed to analyze gaps and opportunities.

Ahmad et al. established a comparison between artificial neural network (ANN) and random forest when predicting energy use (energy for heating, cooling, and ventilation) of a hotel with hourly resolution [20]. They used ten predictors that presented weather condition, time, and booking status. Through a stepwise technique, hyperparametric ability of ANN and random forest were explored in order to introduce the models' controls (number of hidden layers for ANN, depth of trees and number of tested predictors at tree nodes for random forest) that provided the closest predictions [20]. Yalcintas et al. used ANN and multiple linear regression (MLR) models to predict office buildings' electricity use in nine U.S. census divisions, separately [30, 31]. The input predictors that were used in their ANN models varied from those that were used in the MLR models to achieve the best possible predicting performance. Among the predictors only age and number of floors were related to buildings and remaining predictors presented weather condition and operation of buildings [30]. Robinson et al. [32] used Commercial Building Energy Consumption Survey (CBECS) data for training, testing, and evaluating ML models [8]. Then, compared the predictive performance of eleven ML-based models and two linear models that were built using five variables from CBECS. This study reported that extreme gradient boosting provided the best goodness-of-fit in estimating annual energy use. Further, the authors validated this model through applying it to the New York City benchmark dataset and reported that the model performed well on an unseen dataset by having low magnitude of errors [32]. In these studies, ML-based models were reported to provide better performance (lower error) compared to linear models; however, these studies were limited by the numbers and type of predictors used. The diversity of a building's use type, often used to develop prediction models, is another factor that may affect performance.

Deng et al. selected a subset of CBECS data that was limited to office buildings, and they compared the performance of six models in predicting annual total energy use intensity (EUI), HVAC EUI, lighting EUI, and plug load EUI [33]. Random forest and support vector machine (SVM) were found to have better performance on total EUI prediction; however, different results were reported for other end uses. Errors obtained from different models for HVAC EUI showed great discrepancy; however, for lighting EUI models showed close performance. Finally, the study showed that random forest model had the lowest values of errors for plug load EUI [33].

In order to examine whether addressing the identified gaps have positive effect on prediction accuracy in this study, first, the scope was expanded to all commercial building use types available in CBECS, as Deng et al. focused only on office buildings. Second, this study used more than a hundred predictors via CBECS data to develop our ML models.

In addition to ML disparities and gaps, the existing research also shows inconstancies related to integrating climate change models into energy modeling. Several research projects developed methods and tools to project future weather and studied trends of energy consumption in relation with weather variability [34-45], but it is not clear which approach is the most promising as many scenarios present large ranges, making it difficult for decision makers to enact policies. For example, in the thorough work by Reyna and Chester, they employed a physics-based approach to develop a bottom-up model and map the combined effect of climate change and energy efficiency policies for the residential building stock of Los Angeles County (LAC), CA between the years 2020 and 2060 [35]. The stock was clustered into eighty-four archetypes, based on construction period, use type, and climate zone, further electricity and natural gas consumption were simulated utilizing EnergyPlus [46]. The morphing technique was used to create hourly weather profiles, for forty-one years, based on four climate change scenarios established by Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (RCP2.6, RCP4.5, RCP6, RCP8.5) [47]. The authors ran numerous simulations and reported results that showed under RCP2.6 and RCP8.5 electricity demand will increase between 41% to 78% and 47% to 87% over different policy scenarios for LAC, respectively.

Similarly, Dirks et al. reported annual buildings energy use of three years (2004, 2052, 2089) based on the IPCC fourth assessment report's moderate scenario across U.S. [36, 48]. For this study, 26,000 energy models that encompassed a variety of building use types, envelope characteristics, size, etc. and resembled U.S. building stock were created using Building ENergy Demand (BEND), an energy simulation platform. Dirks and colleagues obtained the downscaled daily precipitation, minimum and maximum temperature, which are required as inputs for energy models, from Computational Assessment of Scenarios of Change for Delta Ecosystem (CASCaDE) dataset. Results for the late 21st century suggested that change in annual electricity use will consistently increase over different census divisions, ranging from 9% to 30%. On the other hand, for mid-century, annual electricity will change inconsistently across different regions ranging from 4% decrease to 19% increase [36].

In another approach, Christenson et al. adopted a method which integrated degree days, building thermal loss, internal gain, and solar gain to develop an equation and quantify the energy demand under climate change in Switzerland [39]. The heating demand was projected to reduce (13% to 87%) for various temporal and spatial spans; however, it was suggested that cooling demand projection needed additional study [39]. In summary, energy use has predicted to rise or lower, with high variations, in different regions over different temporal periods and it deserves further exploration.

The review of the existing literature has revealed that there are inconsistencies in the use of ML in urban building energy models. Some questions remain. At the same time, drawing general conclusions about algorithms' accuracy is not realistic since every data has a unique characteristic. To address these challenges and summarize, robust machine learning methods were applied to predict commercial buildings' annual energy use under projected heating and cooling degree days

(HDD and CDD) by IPCC across U.S. during the 21st century. Publicly available data via CBECS dataset was utilized to develop ML models. Specifically, statistical and ML algorithms were applied to the CBECS micro dataset to explore:

- Which of the statistical and ML algorithms (multiple linear regression, single regression tree, random forest, and extreme gradient boosting) provide a better predictive ability of building energy use intensity by comparing the goodness-of-fit?
- How many predictors will affect the performance of the model, and what are the type (e.g., age, number of occupants, etc.) and combination of the predictors?

2.2 Materials and Methods

This section describes the seven phases that were developed and employed to answer the two questions. Phase one, data and data preprocessing, clarifies the sources of data and the steps to prepare the dataset, such as predictor selection and feature engineering. In the second phase, a concise characterization of the four models is provided. The third phase, cross validation, focuses on techniques to address uncertainty and minimize bias in developing prediction models. To experiment with the effects of the number, type, and combination of predictors on the accuracy of energy use prediction, three groups of predictors (every group consists of different number and combination) were built (phase four, forming groups of predictors). Phase five, model performance, presents detail information on the metrics that are utilized to validate and evaluate strength of each model in predicting energy use of commercial buildings. These metrics establish the foundation for further comparing and selecting the best model. The next phase uses U.S. climate regions and census divisions' boundaries to generate smaller geographic regions with less weather variability, and the visualization of the higher resolution regions is demonstrated. Finally, the climate change phase explains climate change scenarios, obtaining weather projections based on the scenarios, and integration of weather projections into the best ML model to study the energy use change.

2.2.1 Data and Data Preprocessing

The U.S. Energy Information Administration (EIA) has published ten issues of CBECS since 1979. CBECS is a national-scale survey with a dataset about energy use and parameters that affect energy use of commercial buildings. The dataset is gathered through questionnaires filled out by buildings' representative or energy suppliers or both parties. This work used CBECS microdata from 2012 [8]. The micro dataset includes 6,720 commercial buildings across U.S. with detailed information on 491 variables, such as, envelope attributes, mechanical systems, renovation status, operation, occupancy, weather, and energy end use; thus, the variables are either categorical or continuous.

One goal was to include as many commercial buildings as possible, and not focus on a standard commercial office building. 847 buildings were removed from the CBECS dataset that are more industrial or processing related, these included manufacturing industrial complexes, central physical plant on complexes, plants that produce district steam, plants that produce district hot water, plant that produce district chilled water, plant that produce electricity, and central plants. The interquartile range analysis was conducted to remove outliers since regular models are prone to put high weight on outliers that will result in poor performance and low reliability [49]. Based on my experience in building energy modeling, use type plays an important role in the magnitude of energy use; for example, food service usually consumes more energy than office buildings.

Hence, an interquartile range analysis was performed for every use type, separately and upper and lower thresholds were estimated based on 1st and 3rd quartiles for all use types [50]. Figure 1 shows the distribution of commercial building use types. Ultimately, the dataset included 5,252 buildings.

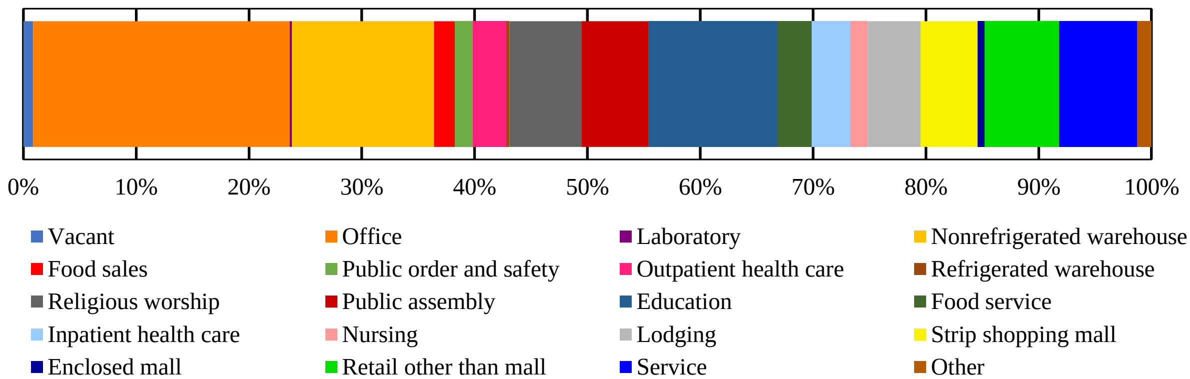


Figure 1 Distribution for building use types in the dataset

In the development of the models, the input variables are called predictors and the building's annual EUI is the target variable. The primary statistics of the EUI are displayed in Table 1.

Table 1 Primary statistics of annual EUI (kBtu/ft2) in the dataset

Minimum	Maximum	Median	Mean	Standard Deviation
0.0	754.4	57.3	75.9	73.9

A list of 114 predictors was developed based on consulting with building energy experts and using building energy modeling [32, 33, 51]. Table 2 is a partial list of the predictors for brevity, with the entire list of predictors along with descriptions in Appendix A, Table A.1. In summary, the dataset includes 5,252 observations (buildings) and 114 predictors.

Table 2 Partial list of input predictors used for developing prediction models. Note: * indicates that the feature engineering technique was applied to the predictors (see Appendix A, Table A.1 for entire list)

CBECS ID	Description	Categorical/ Continuous	Group 1	Group 2	Group 3
HDD65*	Heating degree days	Continuous	✓	✓	✓
CDD65*	Cooling degree days	Continuous	✓	✓	✓
WKHRS*	Total hours open per week	Continuous	✓	✓	✓
NWKER*	Number of employees	Continuous	✓	✓	✓
OE*	Office equipment	Continuous	✓	✓	✓
PUBCLIM	Building America climate region	Categorical	✓	✓	✓
PBA	Principal building activity	Categorical	✓	✓	✓
WLCNS	Wall construction material	Categorical	✓	✓	✓
RFCNS	Roof construction material	Categorical	✓	✓	✓
GLSSPC	Percent exterior glass	Categorical	✓	✓	✓
YRCONC	Year of construction category	Categorical	✓	✓	✓
HEATP	Percent heated	Categorical	✓	✓	✓
COOLP	Percent cooled	Categorical	✓	✓	✓
ENRGYPLN	Energy management plan	Categorical	✓	✓	✓
WINTYP	Window glass type	Categorical	✓	✓	✓

Pre-processing of the data required two steps of feature engineering for continuous predictors and factorial design for categorical predictors.

Feature engineering through scaling was applied to the predictors in Table 2 indicated with an "*" to improve the models' accuracy. Feature engineering converts variables into new forms to be more compatible with machine learning algorithms [52, 53]. Equation 2-1 was utilized for scaling in which z_i is the scaled value of a predictor, x_i is original value of a predictor, $\bar{x}$ is mean of original values, and σ represents standard deviation of original values.

$$z_i = \frac{x_i - \bar{x}}{\sigma} \qquad (2\text{-}1)$$

Several categorical predictors have two or more categories, therefore requiring recoding via available techniques (e.g., dummy coding, effects coding, etc.) to be readable by regression-based algorithms [52]. Dummy coding, which is described as a factorial design that creates pairwise comparisons for categorical variable, was used [54]. A categorical variable with *h* categories is converted to *h-1* dummy variables. For instance, the principal building activity or use type (e.g., office) is a predictor with twenty categories (1 to 20) which was recoded into nineteen dummy predictors. Every dummy predictor has a value of 0 or 1. Table A.2 in Appendix A provides a description of categories for all categorical predictors.

2.2.2 Prediction Models

EUI was calculated via the annual energy use (kBtu) and the floor space (ft^2) and is the target variable in our models. The annual energy use is the sum of electricity, natural gas, fuel oil, and district heat as indicated in CBECS.

In order to employ a prediction model for climate change analysis, a determination of what statistical or ML algorithm was explored. While there is a broad list of ML models, random forest and extreme gradient boosting were selected to predict annual EUI of buildings. Random forest manages multi-dimensional datasets, that encompass numerous predictors easily and it provides higher training speed compared to other ensemble algorithms, since it can work with a subset of predictors at every node of every tree. Other advantages of random forest are low bias and impartiality regarding non-linear predictors. Likewise, extreme gradient boosting (XGBoost) manages non-linearity of data; however, it requires longer training time because trees are formed sequentially (a detailed description of random forest and extreme gradient boosting are provided in subsequent sections). In addition to these advantages, research on predicting building energy use has mostly suggested that ensemble methods provide better performance compared to other ML models or deep learning models such as neural network [20, 32, 33]. Multiple linear regression and single regression tree were included because they require fewer control parameters; if they provide promising prediction of a dataset, using complex ML models may not be reasonable. Thus, utilizing these four models establishes a sufficient comparison ground. The next subsections further describe the four models.

2.2.2.1 Multiple Linear Regression

Unlike simple linear regression that models a target variable based on one predictor, multiple linear regression finds linear connection between several predictors and a target variable [55]. In general, this connection can be described through the following formula in which *k* predictors are noted as x_{i1}, x_{i2}, …, x_{ik}, Y is target variable, and α_0, α_1, …, α_k are regression coefficients, Equation 2-2.

$$Y=\alpha_0+\alpha_1 x_{i1}+\alpha_2 x_{i2}+\ldots+\alpha_k x_{ik} \tag{2-2}$$

The algorithm determines coefficients through minimizing the sum of square of residual for *n* observations (every observation constitutes of *k* predictors and a dependent variable y_i) that is described in Equation 2-3 in which e_i is residual:

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}\left(y_i - \alpha_0 - \sum_{j=1}^{k}\alpha_j x_{ij}\right)^2 \tag{2-3}$$

2.2.2.2 Single Regression Tree

A prediction tree aims to model the nonlinear relation between sets of predictors and a target variable through classification if the target is categorical or regression if it is continuous. A regression tree starts from a root node by splitting data into two sub-nodes. In the root node, linear regression is implemented using all predictors to determine the one that partitions data in a way that minimizes the impurity of sub-nodes. The splitting procedure continues recursively at each sub-node until the measured impurity reaches the predefined threshold [56]. The threshold in the model in this work is defined as when data stops converging. Eventually, the value of the target variables at final nodes are averaged and reported as the predicted value of that branch.

2.2.2.3 Random Forest

Sometimes, results obtained from a single regression tree may show high variance and low accuracy. In order to manage this variation, an ensemble method called bagging has been proposed [57]. In this method, rather than creating one tree based on the original dataset, many smaller datasets consisting of fewer numbers of observations are randomly selected from the original dataset. Further, regression trees are built for every smaller dataset, separately. Ultimately, the predictions from several regression trees are averaged and reported as the final outcome [57].

Random forest, an ensemble ML method, follows the similar strategy as bagging through construction of several classifications or regression trees [58]. The main difference of bagging and random forest is that when splitting nodes of trees, this step is not determined through testing all predictors. If the original dataset includes m number of predictors, m/3 predictors are randomly selected and tested to partition data at each node. For forests which solve classification problems, the number of predictors tested at each node is $\sqrt{m}$ [59].

Since, the model in this work aims to predict annual EUI, a continuous variable, the m/3 predictors are tested at every node of every tree to split data and minimize impurity of sub-nodes. Potential advantages of random forest are reduction in bias and overfitting. However, the required computational power may increase in comparison with multiple linear regression and single regression tree [60].

2.2.2.4 Extreme Gradient Boosting

Another ensemble method is gradient boosting in which series of trees are constructed. Unlike random forest, trees are not independent. Each tree is formed by learning from the error of the previous tree and tries to improve its performance. The improvement occurs by first forming the loss function of the first tree, which is defined as deviation of the actual and predicted value, Equations 2-4 and 2-5, then minimizing the loss function through estimating the negative gradient, Equation 2-6. The second tree is fitted to the negative gradient and predicted values, obtained from the first tree, and is updated by adding predicted results obtained from second tree. This recursive process continues until the model stops converging or the model reaches predefined number of trees [61]. y is true value of target variable, $F(x)$ is projected value of target variable, and n is the number of observations in Equations 2-4, 2-5, 2-6.

$$L = \big(y, F(x)\big) = \frac{\big(y - F(x)\big)^2}{2} \tag{2-4}$$

$$J = \sum_{i=1}^{n} L\big(y_i, F(x_i)\big) \tag{2-5}$$

$$y_i - F(x_i) = -\frac{\partial J}{\partial F(x_i)} \tag{2-6}$$

2.2.3 Cross Validation

Generally, to reduce bias and address data uncertainty of statistical or ML models, cross validation is conducted. In a k-fold cross validation, the dataset is equally clustered to k folds. For each unique cycle, one-fold is reserved as a testing set and $k - 1$ folds are combined and serve as the training set. Selection of k should satisfy the tradeoff between the number of sufficient data samples in the training set and testing set.

In this study, a 5-fold cross validation was conducted with over ten rounds of iteration to have sufficient data samples (observations) for testing the models (see Figure 2). The original dataset (group 3, see Figure 3) was divided into five partitions each containing 20% of data samples. Four partitions were considered as the training set for developing a model and the remained one was employed as the testing set to evaluate the efficiency of model on an unseen dataset. Figure 2 shows a summary of cross validation process. For each algorithm, there was a total of fifty models (5 CV × 10 iterations).

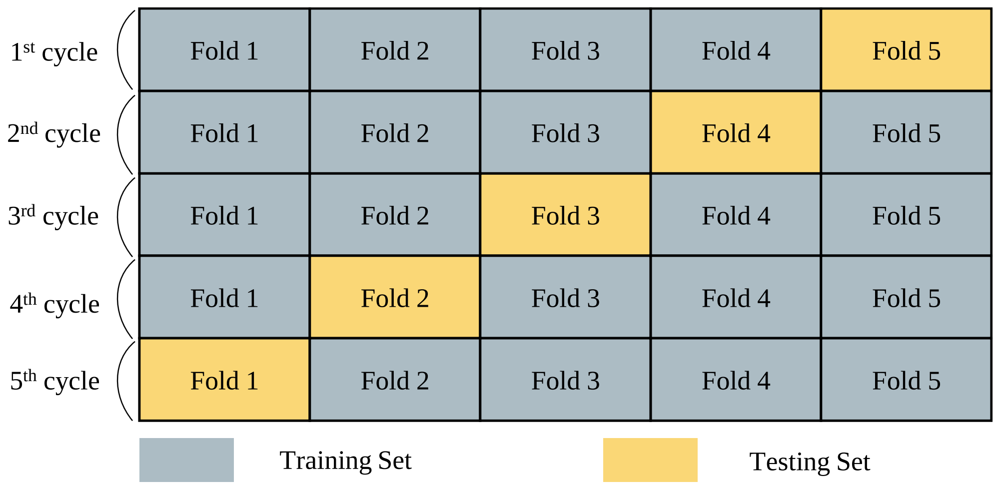


Figure 2 Five-Fold cross validation

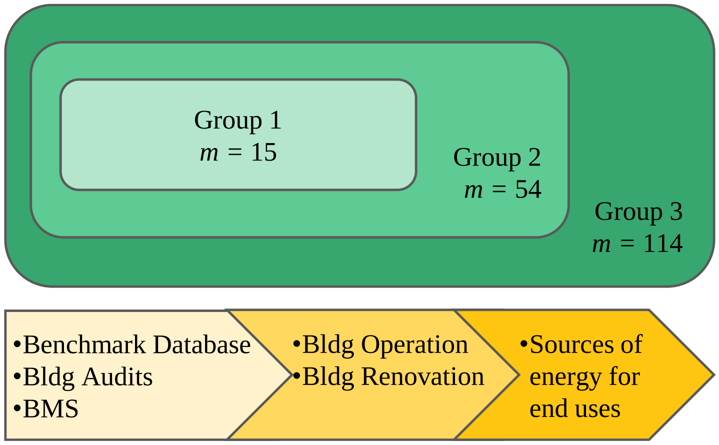


Figure 3 Three subsets of CBECS dataset (group 1–3) used for experimenting impact of number, type, and combination of predictors on prediction error. *m* is the number of predictors in each group. Types of predictors that were added to each group are shown. Note: Bldg and BMS refer to building and building management system, respectively

2.2.4 Forming Groups of Predictors

Previous articles have suggested that discrepancies in the number, type, and combination of input predictors may impact the magnitude of prediction errors [32, 33]. To explore this issue, a stepwise approach in which three subsets of CBECS data were created and used to develop prediction models based on random forest. The first subset which is referred to as group 1 are predictors that are either commonly found in benchmarking databases (e.g., age, use type, HDD, CDD, etc.) or can be obtained by simple building audits and building management systems (e.g., energy management plan, window type, etc.) (see Table 2). Group 2 expands upon the number of predictors in group 1 and encompasses parameters that provide more detailed information about a building's operation as well as any renovations (e.g., existence of cafeteria, existence of laboratory equipment, lighting upgrade, insulation upgrade, etc.). Lastly, group 3, which is considered as the original dataset, includes all predictors from groups 1 and 2 as well as new predictors that explain sources of energy use for heating, cooling, cooking, water heating, and electricity generation (e.g., district heat used for water heating, electricity used for cooking). Figure 3 displays the relationship of groups 1–3 and a full description of each group is provided in Appendix A, Table A.1. Performance metrics of models created for every group are compared and presented in the results of this chapter.

2.2.5 Model Performance

The common method of evaluating the performance of prediction models in building energy modeling is estimating the errors that are known as performance metrics [25, 30, 32, 33, 62, 63]. The errors show how the reported EUI varies from predicted EUI obtained from different models. Mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) are three metrics that are utilized to select the model that provides the closest predictions to reported EUIs, Equations 2-7 to 2-9.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{2-7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{2-8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}\left(y_i - \left(\frac{\sum_{i=1}^{n} y_i}{n}\right)\right)^2} \tag{2-9}$$

In above equations, $\hat{y}_i$ is the predicted EUI, y_i is the reported EUI derived from CBECS dataset, and n is the total number of data samples. Every performance metric represents different aspects of variation between reported and predicted values. For instance, MAE explains the average error over entire sample while RMSE penalizes larger errors. Coefficient of determination illustrates the proximity of values to a regression line. Thus, estimating the three metrics establishes a comprehensive foundation for models' comparison.

2.2.6 Integrating Geographic Regions into Dataset

Weather is a key parameter in energy demand of buildings and thus it is always considered in energy and climate analysis. For instance, commercial reference buildings created by U.S. Department of Energy used sixteen climate regions to represent several weather conditions [51]. Unlike U.S. DOE, CBECS used lower spatial resolutions (less specificity with regards to location) to classify climate regions which increase weather variability within the regions. To reduce this variability, defining new boundaries with higher spatial resolution (enhanced specificity with regards to location) is beneficial. In addition, policies regarding climate change are usually established at regional or state level. Thus, in order for the results of our climate change analysis to be interpretable and meaningful for policy makers and planners, they should be aggregated according to these higher resolution boundaries.

The specific location of buildings is not reported in the CBECS dataset to reserve confidentiality; although, two variables in the dataset related to buildings' location were presented: 1) climate region and 2) census divisions. The 2012 CBECS issue had four categories under climate regions as shown in Table 3 [8, 64] and nine categories under census divisions which are originally defined by the Census Bureau. The two variables were cross-referenced to form higher resolution boundaries which are referred as geographic regions in this chapter.

The cross-referencing process resulted in eighteen geographic regions that are depicted in Figure 4 and the coding scheme is presented in Table 3. Further, every building in the dataset was assigned to a geographic region based on the coding scheme. As an example, a building in a very cold/cold climate that is in New England has a geographic region code of 1,1.

Table 3 Coding scheme for geographic regions

Climate Region (Code)	Census Divisions (Code)	Geographic Region Code
Very Cold/Cold (1)	New England (1)	1,1
	Middle Atlantic (2)	1,2
	East North Central (3)	1,3
	West North Central (4)	1,4
	Mountain (8)	1,8
	Pacific (9)	1,9
Mixed-Humid (2)	Middle Atlantic (2)	2,2
	East North Central (3)	2,3
	West North Central (4)	2,4
	South Atlantic (5)	2,5
	East South Central (6)	2,6
	West South Central (7)	2,7
Hot-Humid/Hot-Dry/Mixed-Dry (3)	South Atlantic (5)	3,5
	East South Central (6)	3,6
	West South Central (7)	3,7
	Mountain (8)	3,8
	Pacific (9)	3,9
Marine (5)	Pacific (9)	5,9

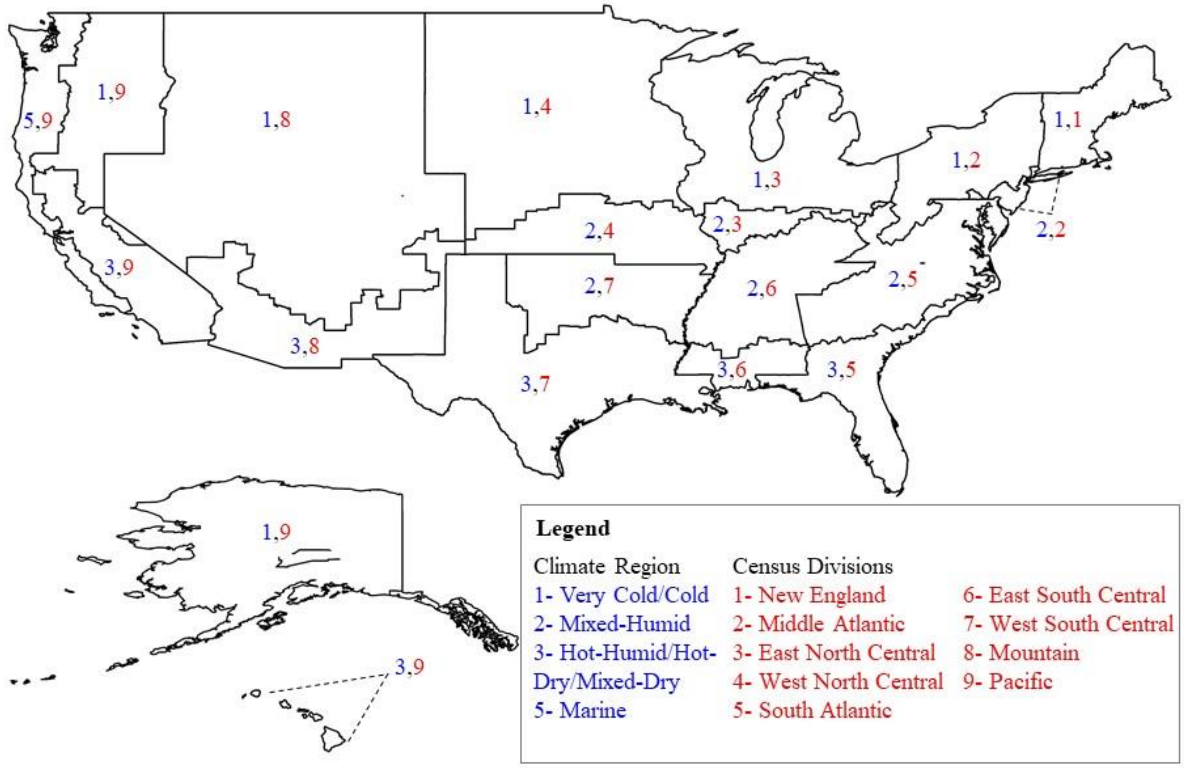


Figure 4 U.S. Geographic regions. Geographic regions are specified by unique codes that consist of climate regions and census divisions. #,# refers to climate region (blue text) and census division (red text), respectively

2.2.7 Climate Change

The prediction of the annual EUI of commercial buildings in the presence of climate change is a primary focus of this chapter. In this portion of the chapter, first climate change scenarios were introduced and then data acquisition was discussed.

In the fifth assessment report, IPCC proposed four pathways, known as Representative Concentration Pathway (RCP), RCP 8.5, RCP 6.0, RCP 4.5, RCP 2.6, for the possible range of radiative forcing and associated uncertainties [47]. For each pathway, a concentration of greenhouse gases (GHG) and the radiative forces are projected until 2100. In the most optimistic pathway (RCP2.6), due to the projected concentration of GHG, the radiative forcing is projected to increase by almost 0.95 (Btu/h.ft^2) before 2100 and then reduce. Whereas, for RCP8.5 the projected radiative forcing is 2.69 (Btu/h.ft^2) by 2100 and maintain an increasing trend after 2100. The radiative forcing will hit 1.43 (Btu/h.ft^2) and 1.90 (Btu/h.ft^2) by 2100 and will have the same amount after 2100 for RCP4.5 and RCP6.0, respectively. Additionally, the numerical models that are called General Circulation Models (GCMs) can simulate reactions of the climate due to increasing amount of GHG emissions [65, 66]. To make the GCM results functional for practical purposes such as regionalization, downscaling methods are usually implemented [37]. For example, National Aeronautics and Space Administration (NASA) used downscaling to create a database, called NASA Earth Exchange Global Downscaled Daily Projections (NEX-GDDP), that contains projection of minimum temperature, maximum temperature, and precipitation under RCP4.5 and RCP8.5 with 15.5 mi × 15.5 mi spatial resolution, which is important when predicting building energy use.

Critical to building energy use is not only the aforementioned regional data, but also degree days. HDD is the summation of the deviation between the average daily temperature and 65 °F over a year, when the average temperature is below 65 °F. CDD is the summation of deviation between average daily temperature and 65 °F over a year when the average temperature is above 65 °F. EIA considered 65 °F as the reference temperature for CBECS. Selection of HDD and CDD as weather variables had two reasons. First, relationship between degree days and building energy use has been proven [67-69]. For example, Kennedy et al. showed a correlation between annual EUI and HDD of several countries where increase in HDD led to increase in annual EUI [69]. Second, degree days are almost the only weather-related variables that are available in national-level energy surveys (e.g., CBECS) or regional benchmarking databases.

For this chapter, a publicly available visualization tool was used. The tool was developed by the Partnership for Resilience and Preparedness, a public-private organization working to data accessibly and climate resilience. One of the organization's key features is that they processed NEX-GDDP raw data and created a visualization tool. For this work, their projected degree days was used for the time period of 2030 to 2080 [70]. Future degree days, as inputs for climate change analysis, are associated with uncertainty. One approach to account for input uncertainty is scenario analysis in which values of input parameters vary over every scenario [71]. Hence, the projected values of HDD and CDD under two scenarios, RCP4.5 and RCP8.5, were imported to the model to address this uncertainty.

Since CBECS does not provide exact locations, the goal was to find locations that have the closest HDD and CDD (for 2012) values to those of buildings in the dataset and use these locations for future HDD and CDD projection for climate change analysis. With this goal, first, the HDD and CDD for the year 2012 along with projected values for six years (2030–2080) of 650 locations in U.S. were gathered from the visualization tool [70].

These locations were clustered based on the geographic regions (see Section 2.2.6) in an attempt to build a cross-referencing algorithm with CBECS. The algorithm first identifies a location that has the nearest 2012 values (HDD and CDD) for every building in the dataset. Secondly, it assigns projected degree days for six years in future to every building. In order to ensure that gathered data (labeled population 1) properly represents CBECS's climatic predictors (population 2), variability of the two populations were tested using F-test. The null hypothesis of this test is the equality of the variance of the two population ($h_o\colon \sigma_1^2 = \sigma_2^2$) which is shown in Table 4 and is not rejected for all regions. This result suggests that gathered climatic data of 650 locations properly represents CBECS. Upon completion of cross-referencing, twelve new datasets

(2-scenarios × 6-years) were created and imported to the best fitted model separately to predict EUI.

Table 4 Results of testing variability of two populations for both HDD and CDD

Geographic Region	HDD F-Value	CDD F-Value	Critical F-Value	Null Hypothesis
1,1	0.767	0.723	1.471	Not Rejected
1,2	0.737	1.033	1.729	Not Rejected
1,3	1.355	1.383	1.410	Not Rejected
1,4	0.972	1.392	1.432	Not Rejected
1,8	1.403	1.312	1.408	Not Rejected
1,9	1.800	0.730	1.808	Not Rejected
2,2	0.317	0.507	2.342	Not Rejected
2,3	0.964	1.367	3.296	Not Rejected
2,4	0.511	0.644	1.803	Not Rejected
2,5	1.367	1.375	1.498	Not Rejected
2,6	1.153	1.129	1.556	Not Rejected
2,7	1.119	1.279	1.554	Not Rejected
3,5	1.501	0.643	1.565	Not Rejected
3,6	1.481	0.671	2.349	Not Rejected
3,7	0.949	0.582	1.599	Not Rejected
3,8	0.862	1.127	1.751	Not Rejected
3,9	1.234	0.344	2.43	Not Rejected
5,9	1.668	1.464	1.737	Not Rejected

2.3 Results

2.3.1 Performance Validation

Results in Table 5 and Table 6 show that random forest and XGBoost outperformed the other two algorithms; furthermore, random forest improved the testing set's MAE by nearly 12%, 11%, and 4% compared to multiple linear regression, single regression tree, and XGBoost, respectively. Likewise, implementation of random forest has decreased RMSE by almost 16%, 14%, and 6% in comparison with multiple linear regression, single regression tree, and XGBoost, respectively (see Table 6). Similarly, R^2 shows that random forest model has yielded closer linear relationship between reported and predicted EUIs in comparison with other models (see Table 7).

Table 5 Mean absolute error of annual EUI of different models for training and testing sets (mean ± standard deviation). Performance improvement by comparing random forest model with other models (%) is provided in the last two columns

Algorithm	**Mean Absolute Error (MAE)**		**Improvement of Random Forest (%)**	
	Training set	Testing set	Training set	Testing set
Multiple linear regression	29.80 ± 0.28	31.58 ± 0.89	61.13	12.03
Single regression tree	25.99 ± 0.35	31.25 ± 0.98	55.42	11.10
Random forest	11.58 ± 0.09	27.78 ± 0.75	---	---
XGBoost	27.63 ± 0.50	28.89 ± 0.78	58.07	3.82

Table 6 Root mean square error of annual EUI of different models for training and testing sets (mean ± standard deviation). Performance improvement by comparing random forest model with other models (%) is provided in the last two columns

Algorithm	**Root Mean Square Error (RMSE)**		**Improvement of Random Forest (%)**	
	Training set	Testing set	Training set	Testing set
Multiple linear regression	43.29 ± 0.53	46.07 ± 2.26	61.69	15.63
Single regression tree	36.37 ± 0.58	45.41 ± 2.44	54.40	14.40
Random forest	16.58 ± 0.20	38.87 ± 2.12	---	---
XGBoost	38.87 ± 0.82	41.25 ± 2.52	57.34	5.77

Table 7 R^2 of annual EUI of different models for training and testing sets (mean ± standard deviation)

Algorithm	**Coefficient of Determination (R^2)**	
	Training set	Testing set
Multiple linear regression	0.66 ± 0.006	0.61 ± 0.029
Single regression tree	0.76 ± 0.006	0.62 ± 0.034
Random forest	0.95 ± 0.001	0.72 ± 0.028
XGBoost	0.72 ± 0.012	0.69 ± 0.034

In addition to performance metrics, required computational power may be a crucial factor in selecting the best model. Although the CBECS micro dataset is not considered a very large dataset, it is important to estimate the computational power in terms of total run time for every model, especially because it will be beneficial for future researchers that may work with larger and multi-dimensional datasets. Table 8 lists total run time of models using the same central processing unit while no other software programs or applications were in use. Random forest and extreme gradient boosting have more computational power. It is worthwhile to address that the required computational power for hyperparametric models such as random forest and extreme gradient boosting is highly sensitive to parameters that control them for example number of trees, number of predictors tried at every node of a tree, depth of trees, loss function etc.

Table 8 Computational power recorded for different models over ten iterations and 5-fold cross validation

Algorithm	Running Time (hour)
Multiple linear regression	0.28
Single regression tree	0.06
Random forest	5.97
XGBoost	6.13

2.3.2 Experimenting with a Combination of Predictors on Model Performance

As explained in Section 2.2.4, three groups were formed to investigate the sensitivity of the model's performance to the number, type, and combination of predictors. Since random forest (RF) was found as the most promising model (Section 2.3.1), the sensitivity analysis was done using RF. Changing the combination of predictors imported into the RF model improved the learning process of random forest. In comparing groups 1 and 2 (Figure 3), the MAE decreased 7% for the training set and 2% for the testing sets. The combination of predictors in group 3 improved the MAE by 15% and 10% for training and testing sets in contrast with group 1 (see Table 9). The RMSE's reduction was equal to MAE's reduction when comparing groups 1 and 2 (Table 10). Comparing groups 1 and 3, RMSE was lowered by 17% and 12% for training and testing sets, accordingly. In like manner, the standard deviations of MAE and RMSE obtained through combination of cross validation and multiple iterations have reduced. Improvements of R^2 in correlation with combination of predictors and changes in computational power are presented in Table 11 and Table 12.

Table 9 Mean absolute error of annual EUI for three groups of predictors for training and testing sets used in the Random Forest model (mean ± standard deviation)

Algorithm – Group	Mean Absolute Error (MAE)	
	Training set	Testing set
Random forest – Group 1	13.61 ± 0.13	30.76 ± 0.95
Random forest – Group 2	12.72 ± 0.13	30.20 ± 0.93
Random forest – Group 3	11.58 ± 0.09	27.78 ± 0.75

Table 10 Root mean square error of annual EUI for three groups of predictors for training and testing sets used in the Random Forest model (mean ± standard deviation)

Algorithm – Group	Root Mean Square Error (RMSE)	
	Training set	Testing set
Random forest – Group 1	20.05 ± 0.35	44.23 ± 2.67
Random forest – Group 2	18.72 ± 0.31	43.35 ± 2.57
Random forest – Group 3	16.58 ± 0.20	38.87 ± 2.12

Table 11 R^2 of annual EUI for three groups of predictors for training and testing sets used in the Random Forest model (mean ± standard deviation)

Algorithm – Group	Coefficient of Determination (R^2)	
	Training set	Testing set
Random forest – Group 1	0.93 ± 0.002	0.64 ± 0.036
Random forest – Group 2	0.94 ± 0.002	0.65 ± 0.031
Random forest – Group 3	0.95 ± 0.001	0.72 ± 0.028

Table 12 Computational power recorded for three groups of predictors used in the Random Forest model

Algorithm – Group	Running Time (hour)
Random forest – Group 1	1.59
Random forest – Group 2	3.62
Random forest – Group 3	5.97

2.3.3 Impacts of Climate Change on EUI

Deriving from CBECS data, office buildings include the largest portion of commercial buildings by having 18.3% of total floor space [8]. Although the RF model was comprehensive and included all use types defined by EIA, this section focuses on results obtained for office buildings for the purpose of brevity. Percentage of change in EUI for office buildings under RCP4.5 and RCP8.5 over six years during the 21st century is shown in Figure 5 and Figure 6, respectively. It should be noted that the percent change is averaged over every geographic region separately and the comparison baseline is the EUI in the year 2012.

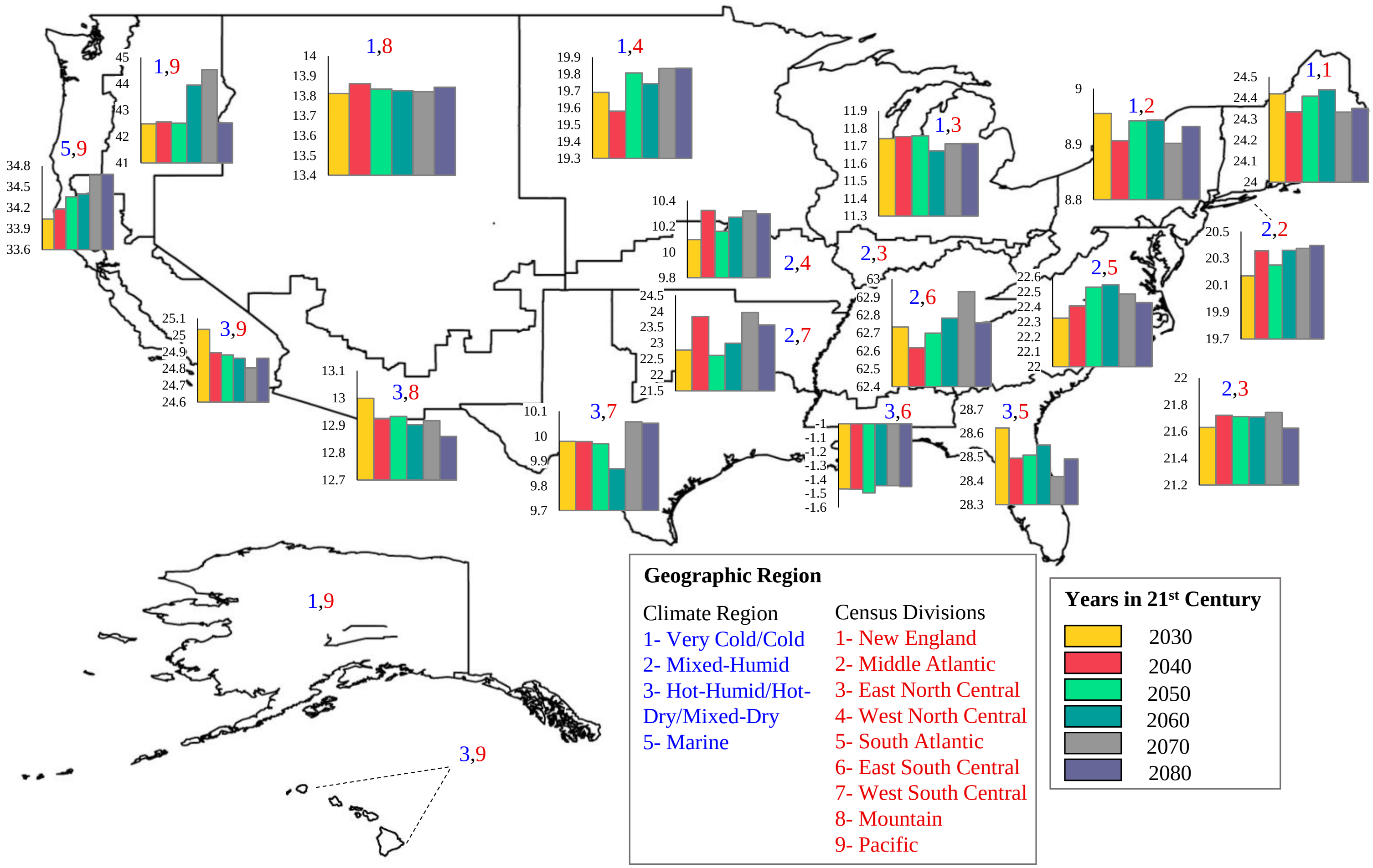


Figure 5 Change in EUI (%) compared to 2012 EUI for office buildings under RCP4.5 during the 21st century for different geographic regions. Note: Y-axes change per geographic region

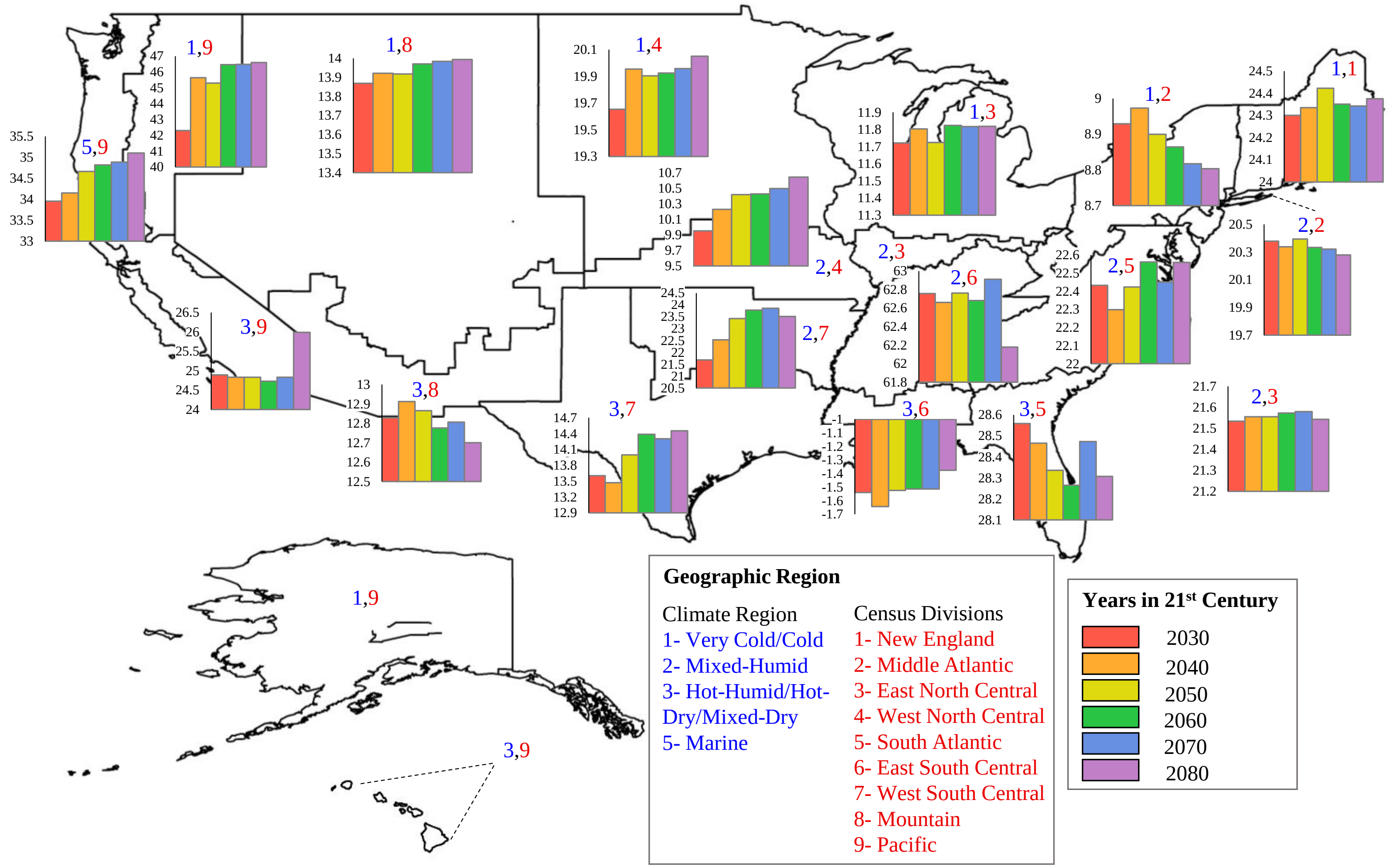


Figure 6 Change in EUI (%) compared to 2012 EUI for office buildings under RCP8.5 during the 21st century for different geographic regions. Note: Y-axes change per geographic region

In region 1,1, EUI will increase almost 24% in 2030 with slight change throughout the century due to projected change in HDD and CDD. The average EUI of office buildings under RCP4.5 will increase by 9% in region 1,2 during 2030. In the same region, energy use is predicted to increase 8.8% in late 21st century under RCP8.5. Likewise, due to RCP8.5, in region 1,4 there will be 19.6% and 20.1% energy use intensity increase at the beginning and end of the century, respectively. The most drastic EUI change in very cold/cold climate has been predicted for region 1,9 (comprising parts of Washington, Oregon, and California) as result of the highest climate change scenario (42.3% and 46.6% increase at 2030and 2080, respectively).

The largest change across mixed-humid climate is projected for region 2,6 (Tennessee, Kentucky, northern Alabama and northern Mississippi) with average EUI growth of 62.7% during all time spans for both climate change scenarios. As shown in the graphs, EUI fluctuation in this region is not considerable throughout the century (ranging from 62.2% to 62.9%). Although predictions obtained from random forest model show that regions located in the mixed-humid climate will experience almost the same increase or decrease in energy use at late 21st century as early 21st century, the result for region 2,7 shows more variation during the century. In this region based on RCP8.5, office buildings are predicted to consume 1.8% more energy per square footage during 2080 as opposed to 2030 (see Figure 6).

Interestingly, during the 1st temporal period in region 3,6 (parts of south Alabama and Mississippi) the EUI of office buildings will be reduced by 1.5% under RCP4.5 and 1.6% under RCP8.5 (see Figure 5 and Figure 6 for percent reduction throughout the century). Whereas, in the rest of geographic regions within hot-humid/hot-dry/mixed-dry climate, the EUI is showing an increasing trend. In order to find the reason for the moderate reduction trend in region 3,6, we looked at the weather condition in 2012 and compared it with 2020. This comparison showed that 81% of buildings in region 3,6 located in cities where the annual CDD were higher in 2012 than 2020. This means that 2012 was a particularly hot year in region 3,6; therefore, the EUI in this region showed moderate decreasing patterns in the future and under climate change scenarios compared with 2012. As displayed in Figure 6, the projected increase in the EUI for region 3,9 in 2080 (almost 26%) is notably distinct from the projected increase in the same region for other years throughout the 21st century (around 25%). The likely reason for this distinction may be the difference between the average annual CDD of 2080 and that of 2012, which is considerably higher than the differences between the average annual CDDs of the other five years and 2012. Finally, based on random forest model, EUI will gradually escalate from 34% increase at the beginning of the century to 35.1% increase by the end of century for the marine climate (region 5,9 contains parts of Washington, Oregon, and California) under RCP8.5. These EUI is projected to rise by 34% (year 2030) and 34.7% (year 2080) under RCP4.5 for the same geographic region. The increase projected for 5,9 is consistent with finding by Reyna and Chester [35].

2.4 Conclusions

Since previous studies have drawn a different conclusion from applying ML to various subsets of the CBECS dataset [32, 33], first the performance of simpler and complex statistics-based algorithms on a subset of CBECS, that contains all commercial building use types and more than a hundred predictors, were investigated to single out the one that provides better goodness-of-fit to proceed with climate change analysis. Then, the ability of the prediction model that was developed using random forest algorithm in capturing the change in energy use intensity of commercial building as result of climate change was assessed.

As presented earlier, multiple linear regression model showed higher error rates for training and testing sets compared to random forest and XGBoost which demonstrates the non-linear correlation of predictors and target variable. Although the computational power estimated for multiple linear regression model was less than random forest and XGBoost models, more convenient development and less power-intensive do not compensate for its poor performance. While the magnitude of MAE and RMSE that were obtained for random forest and extreme gradient boosting were slightly high considering the mean value of annual EUI (presented in Table 1), these results were similar to findings by Deng et al. [33]. For instance, Deng et al. found that MAE and RMSE of random forest were 27.0 ± 1.1 and 35.4 ± 1.8, respectively for a subset of CBECS dataset that only included office buildings. In this chapter, random forest provided marginally better prediction for total EUI than extreme gradient boosting whereas Deng and colleagues showed that both random forest and SVM outperformed other models [33]. It was concluded that this difference was probably due to the difference in the combination of input predictors of models which shows that selecting input predictors have impacts on the final outcome and the fact that [33] developed the models for office buildings. Additionally, the choice of the models' controls for hyperparametric models such as number of trees, loss function, depth of trees, etc. between two studies is another potential reason for this variation. The better performance of both random forest and extreme gradient boosting was reflective of non-linearity and complex interaction of building-, occupant-, operation-, and weather-related predictors and annual energy consumption of commercial buildings at national scale. The random forest model was used over extreme gradient boosting to proceed with both the experiment (Section 2.2.4) and the climate change analysis because of the following reasons: 1) lower error rate and higher coefficient of determination as discussed above, 2) less computational power (higher running speed), 3) indifference to non-linear predictors, and 4) more convenient tuning of parameters.

An experiment was conducted in Section 2.2.4 where three groups of predictors were created. Further, random forest models were developed using every group separately to analyze impact of number and various types of predictors on models' performance. Results depicted that incorporating building operation- and renovation-related predictors (group 2) in the model improved performance marginally compared to group 1. On the other hand, performance of the model developed for group 3, that contained predictors describing energy sources used for various purposes (end uses) in buildings in addition to other predictors, showed considerable improvement over groups 1 and 2. Thus, it can be concluded that variables that describe energy sources for different purposes for instance "electricity used for main heating", "natural gas used for water heating", etc. have high contribution in predicting energy use and enhance the model. This is because energy source may influence the coefficient of performance and age of mechanical, HVAC, and hot water systems/equipment of buildings. Furthermore, these variables aid explaining complicated nature of the dataset. Another finding to be address is that incorporating more input predictors to achieve a better model did not lead to overfitting because training set's and testing set's errors (MAE, RMSE,), and R^2 have reduced and increased, respectively.

As climatic analysis has suggested, EUI of commercial buildings will be affected by changes in two weather-related parameters (HDD and CDD). Most of geographic regions are predicted to have increase in energy use which conveys that increase in cooling demand due to warmer future will exceed the presumable reduction in heating demand. Moreover, space heating requires more energy than cooling [72], so presumable reduction in heating is not significant which will lead to overall energy use increase. Although the impact of changes in HDD and CDD is considerable when comparing energy use intensity of six years throughout 21st century to energy use intensity in the year 2012, changes in energy use intensity between these six years are not significant. The insignificant changes may be due to two reasons: 1) generalization of the ML model, 2) reciprocal effects of building energy use and climate change. A well-generalized ML model is not affected by minor variations of few predictors. In the case of this work, since degree days changes minimally from one year to another year in future, the predicted energy use does not change considerably. However, since degree days is projected to change significantly compared to recorded HDD and CDD for the year 2012, the predicted energy use intensity shows noticeable changes. In conclusion, a well-generalized building prediction model does not reflect minor changes in weather-related predictors on the final target variable. Secondly, climate change in general and variation in degree days in specific are known to be the result of GHG emissions. Since operation of the building sector depends on the combustion of fossil fuels, the main source of GHG emissions, directly (i.e., coal, natural gas, petroleum) and indirectly (electricity generation) [1, 73], there is probably a reciprocal cause and effect between variation in degree days and building energy use. This is another reason for insignificant energy use intensity change of six studied years. This possibility opens discussion regarding future work. Outliers, imputed values for some data samples, lack of occupants' behavior, correlation between predictors, and complex interaction between predictors and annual EUI in CBECS dataset are challenges of interpretability of the model. In order to solve this challenge and better explain how the prediction model based on random forest has made decisions, SHAP analysis could be conducted in future works. SHAP is a deep learning framework that explains which predictors are more relevant for certain predictions or clarifies overall performance of a model through multiple visual means such as dependence plot, model explainer, and prediction explainer [74, 75].

Detail and reliable data enhance predicting ability of ML and artificial intelligent approaches. However, majority of energy benchmarking efforts in U.S. cities like Philadelphia, New York, etc. lacks information regarding occupant-, operation-, HVAC system-, and weather-related parameters. Therefore, launching movements toward collecting more comprehensive regional building datasets in future is crucial to evaluate counteraction of building energy consumption and climate change at finer spatial scale using ML approaches. Policy makers and urban planners can advocate for allocating budgets to gather building dataset. Also, they can use the results of this work as a future road map of building energy use in presence of climatic variation.

3.0 Development and Validation of an Urban Building Energy Model

The research presented in this chapter addresses objective three. Specifically, it answers the question 'What is the framework for obtaining essential parameters to develop a UBEM in order to mitigate data disparity and reduce assumption dependency? And can a UBEM be used for both identifying trends of energy use and evaluating the impacts of energy conservation measures for a commercial building stock?'. The content of this chapter was published in a peer-reviewed journal:

Mohammadiziazi, R., Copeland, S., & Bilec, M. M. (2021). Urban building energy model: Database development, validation, and application for commercial building stock. *Energy and Buildings*, *248*, 111175.

3.1 Introduction and Background on Urban Building Energy Modeling

In the past decades, scientists have addressed the urgency of energy consumption and greenhouse gas (GHG) emissions from different sectors including the building sector. The building sector in the U.S. accounts for 39% of energy use with commercial buildings responsible for approximately half of this portion [1]. The continuous and growing rate of urbanization has resulted in urban buildings becoming the center point of energy consumption and GHG emission reduction strategies and ambitious targets. In this context, cities and countries around the world have formulated short-term and long-term energy and environmental goals that include energy reduction [76], shifting towards renewable energy sources [76], and selecting building materials with less environmental impacts [77]. For example, Los Angeles, California planned to reduce energy use per floor area of buildings 22% and 44% by 2025 and 2050, respectively [78]. Another example is California Title 24 which mandates new buildings to be equipped with photovoltaic systems for electricity generation [79]. The City of Pittsburgh, a member of the 2030 District Network and accounting for nearly 25% of floor spaces committed to this network, has established building energy and water reduction goals [80]. Achieving these goals for all cities and regions requires actionable and effective energy conservation (EC) strategies for buildings, especially existing buildings through renovation and retrofit. In addition to the demand side, launching actions and planning for renewable energy generation and supply systems, distributed energy resources (DER) [81], and district heating and cooling systems can also aid in accomplishing the energy goals. For regional decision makers to institute practical and effective energy efficiency policies and climate actions, thorough understanding of energy use of buildings in an urban area is essential.

Critical to understanding energy use is data and information about energy consumption and characteristics of buildings. Some cities have building energy data obtained through disclosure and benchmarking laws, along with voluntary approaches including the aforementioned 2030 District [80, 82, 83]. However, there are a significant number of cities and areas that lack benchmarking ordinances and laws. Another challenge facing of local governments is budget limitations for enforcement and processing of the data into meaningful reports and visualizations. Hence, urban energy modeling tools and frameworks can be beneficial to overcome these challenges, as they can enable studying trends of citywide building energy demand, evaluating impacts of EC strategies on heating and cooling energy consumption, finding hotspots related to energy and emissions, and identifying suitable locations for developing district energy systems.

In this chapter, a modeling structure, established based on advanced imaging and remote sensing techniques, was proposed and used for acquiring data and simulating urban building energy use. This structure was designed to maximize the use of actual data as a substitute for secondary data or assumptions and provide a road map to extract information from resources and standards. The commercial buildings in Pittsburgh, Pennsylvania were selected to develop and test the modeling structure. In addition, the outcomes of this research aim to aid the city in its efforts toward reducing energy and emissions and combating climate change.

Urban scale studies are categorized into two major approaches - top-down and bottom-up [84, 85]. The top-down approaches encompass macro-level variables and adopt statistical or machine learning methods to explore the energy use of buildings at a large spatial scale in relation to socio-economic aspects (e.g., income, education) [86]. For instance, Mostafavi et al. [87] developed a model based on the Residential Energy Consumption Survey (RECS) to predict residential energy use based on several factors, such as household size and ages of the occupants. While top-down approaches provide a broad view of energy demands, their ability to associate building- or stock-level characteristics with energy consumption are limited. Alternatively, bottom-up approaches (e.g., cluster analysis and urban building energy modeling) can incorporate individual buildings characteristics into the modeling process and study energy use at finer spatial scale such as building-, neighborhood-, zip code-level. One bottom-up approach is cluster analysis in which the energy use of a building stock is examined based on different characteristics or features of buildings such as use type, ownership status, and thermo-physical attributes [88, 89]. Conducting cluster analysis for a historic district in Italy, Lucchi et al. [89] concluded that geometric and thermo-physical features had higher correlation to building energy use compared to building age and can be utilized for energy demand assessment. Using cluster analysis requires extensive information about features and energy use of all buildings at scale. Another bottom-up approach is urban building energy modeling.

While definitions of this emerging area are evolving, the literature is gathering consensus that urban building energy models (UBEM) are bottom-up, physics-based models that unlock the capability of spatiotemporal energy demand analysis in an urban area. These models couple heat and mass transfer mechanisms of clusters of buildings with 3D models to simulate energy use [90, 91]. Principally, UBEMs are developed using either building prototypes or archetypes. In order to create *prototypes*, buildings are clustered into groups and for every group average values of *geometric parameters* (e.g., height, aspect ratio) along with predominant classes for non-geometric parameters (e.g., window U-value, HVAC coefficient of performance) are determined and utilized to create energy models. On the other hand, *archetypes* are groups of buildings that only share similar *non-geometric parameters* which are determined based on predominant classes for every group. Defining archetypes for an urban building stock will be described in detail further in this chapter. Many studies have explored urban building energy modeling for different cities worldwide [92-103]. These studies have been reviewed to identify gaps and best practices (see Table 13).

3.1.1 Urban Building Energy Modeling – Residential Buildings

A review of the existing literature has revealed that several approaches for developing UBEMs have emerged to assess the energy consumption of residential buildings. In one of the earlier studies, Shimoda et al. [92] created 460 residential prototypes for Osaka, JP based on 23 household types (e.g., household with two employed members) and 20 dwelling types (e.g., detached house with floor area more than 150 m^2, apartment with floor area of 110-119 m^2) and simulated hourly energy use of every prototype over one year. Through accessing the number of buildings grouped under every prototype, the annual energy consumption of homes in the city was estimated. An 18% lower estimation from the model compared to the field surveys from 1999 was attributed to irregular occupants' behavior in using appliances, air conditioner, and lighting. Despite a comprehensive description of non-geometric parameters, it was unclear how the prototypes for the 3D models were developed, such as how to determine the geometric parameters or envelope properties.

Further, Cerezo et al. [93] and Sokol et al. [94] explored the importance of probabilistic approaches for determining non-geometric parameters of archetypes in Kuwait City, KW and Cambridge, Massachusetts, respectively in simulating the urban residential building energy use. In Kuwait City, their probabilistic approach focused on occupancy rate, lighting density, plug load, hot water peak flow, and heating/cooling set points; these parameters were modeled from either arrays of predefined values or Bayesian calibrations. Deterministic parameters (window to wall ratio, glazing type, wall material, roof material, cooling system) were gathered through in-person audits. When compared with the metered annual energy use, the Kuwait City results showed significant improvement in the model's accuracy due to using probabilistic approaches versus a deterministic approach (the mean error reduced from 16% (deterministic approach) to 1% (probabilistic approach)) [93]. However, calculation methods specifically related to window to wall ratio (WWR), an envelope property, were not clarified, for example, how were the in-person audits conducted.

Although these studies [92-94] and others listed in Table 13 [95, 96, 103, 104] investigated many aspects of residential UBEMs and proposed strategies to improve urban models, there are unexplored spaces especially regarding the diversity of envelope properties and building facades, along with reproducibility challenges. This chapter aimed to address these gaps.

Table 13 Overview of scopes in existing literature on urban building energy modeling. R, C, and EC are abbreviations for residential buildings, commercial buildings, and energy conservation, respectively

Articles	General building use type			Prototype vs Archetype		Envelope properties		Incorporating EC strategies	
	R	R and C	C	Prototype	Archetype	Not described/ Assumption	Actual/ Measured	High cost	Low/Medium cost
[92]	●			●		●		●	
[93]	●				●		●		
[94]	●				●	●			
[95]	●			●		●			
[96]	●				●	●			
[97]		●			●	●			
[98]		●		●		●			
[99]		●			●	●			
[100]		●			●	●			
[101]		●		●		●			
[102]			●		●	●		●	
[103]	●				●	●			
[104]	●			●		●			

3.1.2 Urban Building Energy Modeling – Commercial and Residential Buildings

As shown in Table 13, while the majority of UBEMs focused on residential buildings, in part due to less complexity of envelope properties and mechanical systems, some studies focused on both residential and commercial buildings [97-101]. In the absence of building- and energy-related data, Heiple and Sailor [98] used aggregated information from Commercial Building Energy Consumption Survey (CBECS) [31] and RECS [105] to create residential and commercial prototypes for Houston, Texas. The prototype building energy models, created using eQuest and DOE-2, simulated the daily energy use of the city. Through validating the aggregated results with the surveys data, the authors showed marginal difference between the model and survey results of 2.5% and -1.3% for August and January, respectively [98]. However, a gap remains related to the performance of various building types and which building type requires a more detail prototype. Ding and Zhou [101] utilized the prototype methodology to explore energy data scarcity of a city in China. First, they formed three prototypes, a residential apartment and two office buildings. Second, a building energy database was developed by stochastic analysis that encompassed various mechanical- and occupancy-related variables. Characterizing and modeling the city's buildings using aggregated information (e.g., [98]) or without accounting for actual use types, envelope properties, geometric parameters, and orientation (e.g., [101]) may lead to building energy performance challenges. The work in this chapter aimed to resolve these concerns for cities and areas, which suffer from data paucity, through our proposed modeling structure.

In a thorough study, Cerezo et al. [97] hypothesized whether developing a UBEM was feasible for residential and commercial buildings using publicly available Geographic Information System (GIS) data. To test the hypothesis, the authors created a model for Boston, Massachusetts and validated results based on CBECS and RECS since metered energy use data was not available for the city at the time of study. While Boston has a richer GIS data, which included building footprint, roof and ground heights, construction year, use type and number of floors, compared to many cities in U.S. like Pittsburgh, Pennsylvania, lack of both building archetypes and data were still introduced as major barriers by the authors [97].

3.1.3 Urban Building Energy Modeling – Commercial Buildings

To date at the time of this writing, only one study by Chen et al. [102] focused on two types of commercial buildings (office and retail) by developing a tool that automized creation of UBEM.

The tool generates 3D models of buildings based on footprint, height, and number of floors. The tool uses secondary data from Commercial Building Energy Saver (CBES) to build the energy models; it does not compile an archetype library that reflects on non-geometric parameters and envelope properties specific to an urban area. The modeling structure in this chapter intends to describe a holistic approach for developing databases and to mitigate dependency of UBEMs on secondary data, which is the key barrier to the converging UBEM outcomes and energy use of buildings in real-world. In this study, the pattern and variation of the energy consumption relative to different commercial buildings are also analyzed.

3.1.4 Objectives of the Chapter

The objectives of this chapter were to:

- Compile a unified modeling structure that maps methods, resources, and the steps essential to develop a comprehensive database of commercial buildings with a focus on actual envelope properties and façade reconstruction.
- Focus on commercial buildings to close the gap regarding the building use type.
- Validate the results of the UBEM with the actual energy data.
- Employ the model to evaluate impacts of low to medium cost EC strategies on the total energy use and different end uses which is not explored as shown in Table 13.

By achieving the objectives, this chapter aimed to contribute both to the field of urban building energy modeling and the region, while providing a path for other regions as well.

Based on the earlier discussion, the energy use of residential buildings has been investigated. The consistency in energy performance of residential stock has enhanced the overall results that focuses on this type of buildings. While some studies have included both residential and commercial buildings, the results of these models are still overshadowed by the consistent performance and simple characteristics of residential buildings. Increasing the knowledge about the energy performance of buildings at scale and improving UBEMs require special attention to commercial buildings. In addition, in the time of unforeseen crisis like Covid-19 pandemic, when there is a drastic energy demand shift from commercial to residential buildings, it is useful to have an urban model focusing on commercial building stock. This model will enable energy suppliers and utilities to estimate the energy demand reduction from the commercial stock and how the capacity could be directed toward residential buildings. While this is not the first investigation concentrating on commercial buildings [102]; it is the first, to our knowledge, that incorporates advanced imaging and remote sensing techniques to obtain envelope properties, which are not available in many city databases, and have been largely based on assumption and expert judgement in urban models. By using street-level digital images, the modeling related to the building envelope, especially WWR will be refined.

As mentioned, many regions have aggressive energy reduction goals without adequate planning. The region of this study, Pittsburgh, Pennsylvania, is a part of the 2030 District Network, in which each region or district commits to 50% reduction in building energy, water consumption, and emissions from transportation below a baseline by the year 2030. In Pittsburgh, the majority of its district is comprised of commercial buildings. This work, therefore, can provide policy makers, urban planners, and entities working towards these goals with actionable strategies to aid in ensuring success.

3.2 Materials and Methods

Development of a UBEM is a multi-layer process especially because in many cities, including Pittsburgh, the required data is not readily available and is scattered over various references or resources. This sub-chapter provides a detailed modeling structure regarding creating a comprehensive database and generating the model through five phases. Phase one describes the commercial buildings in the studied region together with available data. In the second phase, development of an archetype library is explained. The third phase presents a novel photogrammetry and image processing framework that was used to retrieve the envelope properties and for constructing the facades of buildings. To estimate the building's height, LiDAR analysis was conducted (phase four). Finally, integrating all the information to generate the urban model for commercial buildings is explained in phase five. A visualization, that displays the integration of these phases, is shown in Figure 7. Moreover, the graphical synthesis of methods and results is provided in Appendix B, Figure B.1.

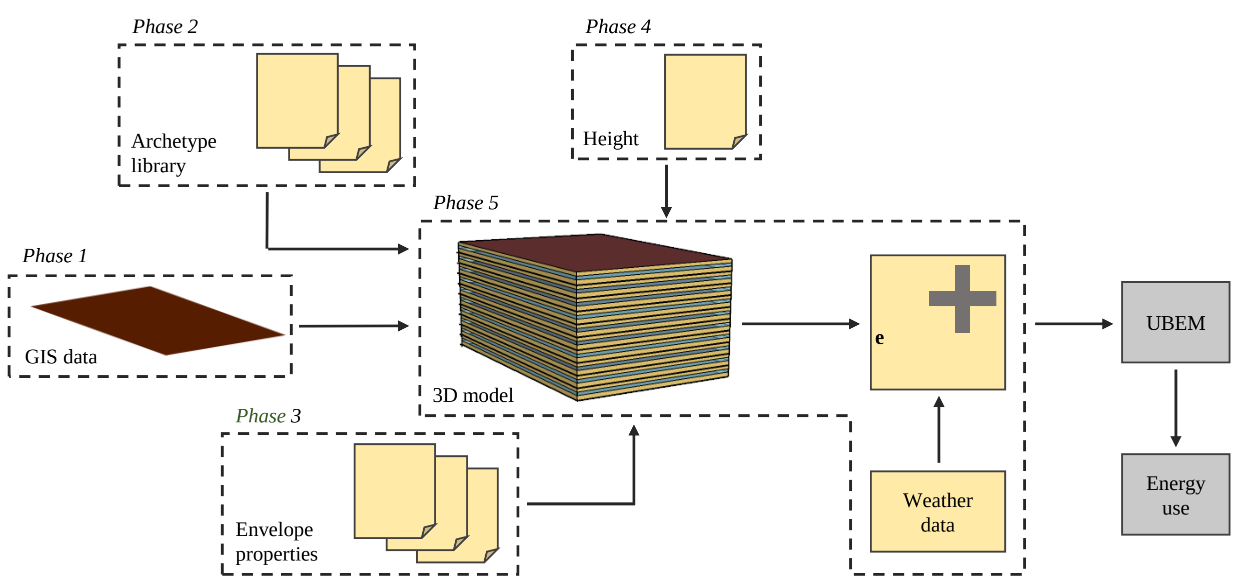


Figure 7 Graphical overview of generating the urban building energy model

3.2.1 Phase 1 – Description of the Commercial Buildings in the Studied Region

Pittsburgh is a city in western Pennsylvania located in cold climate (zone 5A) according to the U.S. DOE climatic boundaries [64]. The city houses the University of Pittsburgh and Carnegie Mellon University both with sizable commercial spaces. Recently, companies like Google, FedEx, and Facebook have opened offices in the city, which is another indicator of the growing commercial stock. This specific study contains a commercial building stock that belongs to the University of Pittsburgh and the City of Pittsburgh [17] and comprises total number of 209 buildings. This stock was selected because of a few reasons. First, the 2030 District goals motivated this work. Second, the commercial stock consisted of a variety of different commercial building use types. Table 14 shows the percentage of floor area for different use types. Finally, the actual annual energy use of buildings from 2017 was reported to our research team, which was used for validating the results. In addition to the actual annual energy use, the floor area, property tax identification (ID), and the construction year were provided to our team. Essential to urban energy modeling is geolocating buildings to identify the location on map, orientation, and footprint (i.e., polygon shape of a building plan). For this purpose, the geospatial data that included Pittsburgh's building footprint was obtained from the Western Pennsylvania Regional Data Center (WPRDC) in GIS format [106]. The property tax ID of the buildings was cross referenced with GIS data in order to identify the corresponding footprints. However, this information was insufficient to develop a UBEM; the additional input information for creating the model was the *geometric parameters*, *non-geometric parameters*, and *envelope properties*. The subsequent sub-chapters are allocated to illustrate how the missing information was gathered or measured.

Table 14 Percentage of floor area for different use types of the 209 commercial buildings in the studied region

	Commercial building use type							
	Education	Lodging	Office	Parking garage	Public assembly	Public order and safety	Warehouse	Other
Floor area (%)	31	24	14	7	14	5	1	4

3.2.2 Phase 2 – Archetype Library Development

Urban building energy modeling streamlines the modeling process by classifying buildings into homogenous groups, known as archetypes, that have similar characteristics [86]. One robust example is the TABULA project in which an archetype library was developed for the building stock of fifteen European countries [107].

Creating an archetype library consists of two major steps: classification and characterization [93, 108]. With respect to classification, buildings are 'binned' into groups based on one or more categories. In this research, the selected categories were based on two criteria: first, the categories must be available for all buildings; second, they should be relevant to energy consumption. According to these criteria, several categories have been proposed and utilized for classification by different studies such as use type, construction period, shape ratio, heating and cooling systems, and climate condition [88, 90, 98]. As Monteiro et al. suggested, defining more detailed archetypes increases the homogeneity of groups and may improve the precision or accuracy of urban energy models [95]. The challenge, in this regard, is that these categories are usually not available in public databases or are labor intensive to obtain for all the buildings in the stock or the city [93].

In this research, *use type and construction period* were used for classification; twenty archetypes were created for the commercial stock, comprised of eight commercial use types that were built during three construction periods (not all use types spanned the construction periods). Table 15 provides a list of the archetypes with additional descriptions. The majority of the publicly available resources like building codes, standards (e.g., ASHRAE standards), and surveys (e.g., CBECS) have included non-geometric parameters according to use type and construction periods [51]. Therefore, the classification of use type and construction period facilitated extracting these parameters of buildings from various resources during the characterization step.

Table 15 Archetypes defined by construction period and use type for the commercial building stock in Pittsburgh. The third column is a description of sub-categories that formed the broader use types. Note: sub-categories are coded by Latin numeric to avoid redundancy

Construction period	Commercial use type	Commercial use type sub-categories
Pre-1980	Education	School, college, university I
	Lodging	Dormitory, fraternity, sorority, nursing home II
	Office	Administrative office, social services, city hall III
	Parking garage	Multistory parking, underground parking IV
	Public assembly	Recreation center, senior center, library, museum V
	Public order and safety	Police station, fire station, medic center VI
	Other	Laboratory, observatory, mixed-use VIII
1980-2004	Education	I
	Lodging	II
	Office	III
	Parking garage	IV
	Public assembly	V
	Public order and safety	VI
	Warehouse	Non-refrigerated warehouse, distribution center VII
	Other	VIII
Post 2004	Education	I
	Lodging	II
	Public assembly	V
	Public order and safety	VI
	Other	VIII

Characterization is described as assigning values or classes of non-geometric parameters to every archetype. Drawing on the work from [93, 94], these parameters can be determined through either deterministic (single value or class for each parameter) or probabilistic (multiple values or classes for each parameter) approaches which both have their own advantages and disadvantages. The non-geometric parameters that are required for energy simulation depend on zoning (single zone or multi zone), the software engine used for simulation, and the thermal modeling approach. For this research, the three sets of non-geometric characterization parameters were occupancy, envelope composition, and mechanical/electrical systems. It was found that characterizing the archetypes via gathering information from several resources is cumbersome mostly because a thorough outline that can guide urban modelers on where to find a certain parameter does not exist. Therefore, Table 16 was compiled as a road map to fill this gap and aid future modelers in conducting urban studies.

Table 16 Outline of resources and references for developing an archetype library. Note: operating schedules encompass several sub-schedules like occupancy schedule, heating setpoint schedule, cooling setpoint schedule, HVAC schedule, etc.

	Non-geometric parameter	Resources/References
Occupancy-related	Operating schedules	- Engineering assumption - DOE commercial reference buildings [51] - Consulting with local experts
	Occupancy rate	- DOE commercial reference buildings [51] - Literature [109, 110]
	Plug and process loads	- DOE commercial reference buildings [51] - Literature [109-111]
	Ventilation rate	- Literature [109-111] - ASHRAE standards [112, 113]
	Service hot water demand	- Literature [114, 115]
Envelope composition	Roof	- CBECS [8] - ASHRAE standards [116-118]
	Window	- CBECS [8] - ASHRAE standards [117, 118] - DOE commercial reference buildings [51]
	Flooring	- ASHRAE standards [117, 118]
	Infiltration/Air leakage	- Literature [119] - DOE commercial reference buildings [51]

Table 16 (continued)

Mechanical/Electrical systems	Lighting density	- ASHRAE standards [117, 118] - DOE commercial reference buildings [51]
	HVAC system	- ASHRAE standards [117, 118] - DOE commercial reference buildings [51] - Consulting with local experts
	Water heating system	- Literature [120] - ASHRAE standards [117, 118] - Consulting with local experts

Some of the parameters needed modification or additional processing prior to being imported into the energy simulation. For example, ASHRAE standards on ventilation and indoor air quality [112, 113] specified the minimum ventilated air per occupant (cfm/person); however, the ventilation rate (cfm/m²) was needed for energy simulation in this study. Thus, the minimum ventilation (cfm/person) was divided by occupancy rate (m²/person), obtained from [51, 109, 110], and the ventilation rate was calculated for every archetype. Additionally, the predominant classes of roofs for all archetypes (e.g., built up, slate or tile shingle, asphalt, concrete, metal surfacing) were determined by analyzing CBECS data for climate zone 5A, where Pittsburgh is located. Further, based on these classes, roof compositions and corresponding specifications such as the u-value were extracted from ASHRAE standards on energy efficient design [116-118]. Determining specifications of windows (u-value and solar heat gain coefficient) and flooring for all archetype followed the same process as was done for roofs. Ultimately, the non-geometric parameters, that are listed in Table 16, formed the archetype library and were stored in a csv file used in energy simulation.

3.2.3 Phase 3 – Photogrammetry and Image Processing Framework

Envelope properties including external wall material, WWR, and floor count (number of floors above ground) are known to influence energy consumption [17, 121, 122], yet they have been under-reported in UBEMs due to cities' database deficiency and technological barriers. For instance, in the Boston work, WWRs were considered between 0.1 and 0.8 per use type based on authors' judgement [97]; how the WWR and external wall materials were determined was not clarified in other studies [96, 98]. As previously delineated in the introduction and background of this chapter, incorporating detailed envelope properties through reconstructing facades is one of the objectives of this research. To achieve this objective, a framework, comprising photogrammetry (acquiring façade images) and image processing (interpreting images), was developed and utilized.

Information about the surrounding environment and objects including building facades can be obtained by taking and analyzing aerial or street-level images. The quality and availability of aerial images are usually impacted by high-rise buildings in dense urban areas as they block vision of neighboring facades [123]. Hence, this framework was built using street-level images of facades obtained from Street View Static (SVS), which is an application programming interface (API) designed by Google to provide 360° images of numerous locations on the earth [124]. Employing SVS API provided the opportunity to download images in JPEG or PNG formats, that is not possible through regular Google Street View. Moreover, SVS API allowed for adjusting image attributes without using pointing devices, which mitigates randomness and enhances accuracy. To obtain the images, the buildings' centroids were found using GIS analysis to determine the latitudes and longitudes coordinates of the centroid points for all buildings. These coordinates were then imported to the SVS API for every building, separately, to access the façade images. As mentioned above, this semi-automatic API enables users to remotely control the attribute of an image by changing the vertical angel of camera (pitch), horizontal angel of camera (heading), field of vision (fov), and resolution (size) in order to find images with desired quality. Also, the remote-control capacity allowed me to check images and maintain consistency (similar pitch, fov, and size) for different facades, which is critical to determine the material of the facades. Ultimately, the images of all buildings were downloaded, stored, and further processed.

Agent-based processing was used for this research. Figure 8 illustrates the process. The external wall material (eight types as shown in Figure 8) and floor count were identified. According to the external wall type, the wall compositions and corresponding specifications were extracted from ASHRAE standards [116-118]. Accurate information about the floor count is important in energy simulations since it affects number of thermal zones. Next, the images were transferred into an area calculator software, SketchAndCalc, to measure the total area of the windows and the gross wall area, and then estimate the WWR, that is defined as area of window divided by area of wall above the ground [125, 126]. Following Equation 3-1, the WWR of building *i* with *n* facades was estimated. This process was replicated for all buildings.

$$WWR_i = \frac{\sum_{j=1}^{n} WWR}{n} \tag{3-1}$$

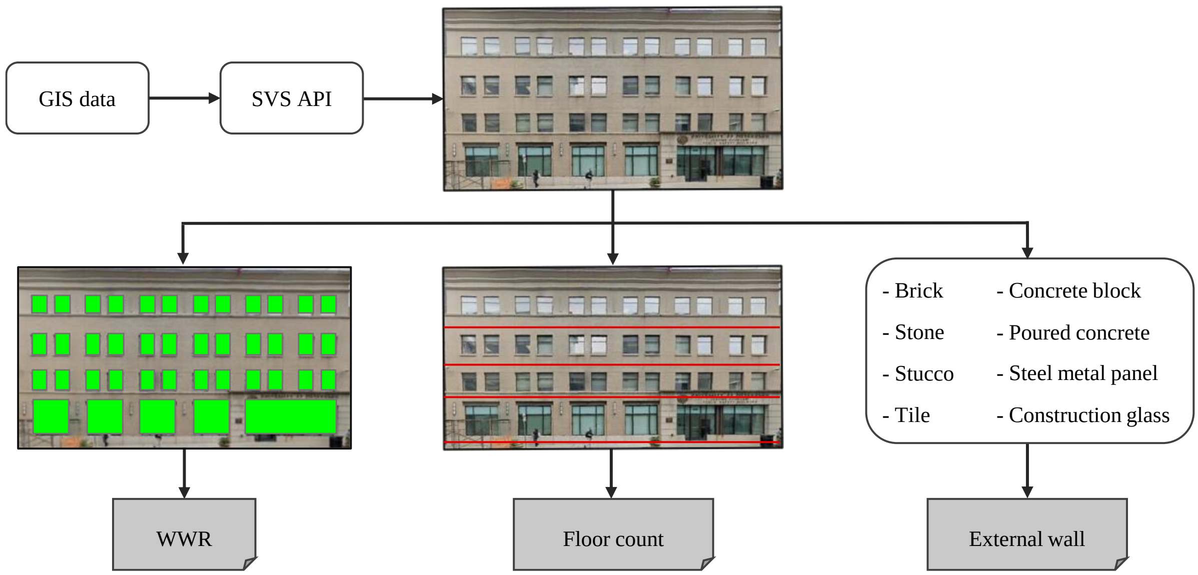


Figure 8 Process flow diagram of photogrammetry and image processing framework for retrieving envelope properties. SVS API and WWR refer to Street View Static API and window to wall ratio, respectively

In order to investigate the importance of including the measured WWR of buildings in every region and city, the WWR values of the studied buildings, estimated through this framework, were compared to values derived from CBECS [8] for the same commercial use types that were located in U.S. cold climate. As displayed in Figure 9, in Pittsburgh approximately 26% of commercial buildings have a WWR less than 0.1; on the other hand, based on CBECS data, almost 56% of buildings have a WWR less than 0.1. Also, the majority of the studied buildings (60%) have a WWR between 0.11 and 0.25; whereas, 29% of the buildings in CBECS fall into this category. The comparison reveals that employing CBECS would have resulted in underestimating WWR of Pittsburgh commercial buildings. This difference confirmed the fact that surveyed data like CBECS may not represent façade architecture and the WWR that are specific to a region or city. It should be noted that while selecting equal WWR intervals or ranges for this comparison would be beneficial, the WWR of buildings were specified as predefined ranges in CBECS rather than exact values [8]. Therefore, the predefined ranges in CBECS were utilized for this comparison.

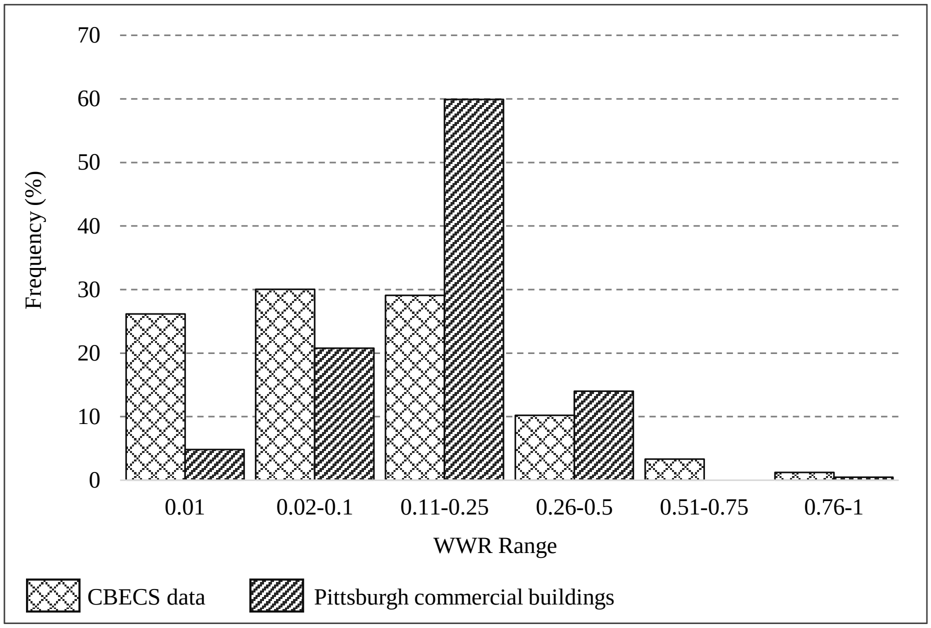


Figure 9 Comparison of measured WWR with WWR from CBECS [8]. WWR and CBECS stand for window to wall ratio and Commercial Building Energy Consumption Survey, accordingly

3.2.4 Phase 4 – LiDAR Analysis

GIS data at the municipal- or city-level is often 2-dimensional and lacks the elevation or height, a key geometric parameter for energy modeling. Some studies [93, 127] tried to reconstruct the volumetric models of buildings via visual inspection and site surveys, but logistics and time consideration can limit adoption at scale. Others [100, 104] used standard reference building heights but precision of this method remains uncertain [51, 128]. The height issue was addressed by using LiDAR analysis. LiDAR, Light Detection and Ranging, is a remote sensing technique to examine earth and objects on the earth. Figure 10 displays the procedure used in this work for determining the building height. Two sets of GIS compatible datasets were utilized: 1) the commercial building footprint in shapefile format (see section 3.2.1), 2) airborne LiDAR data in las format obtained from U.S. Geological Survey (USGS).

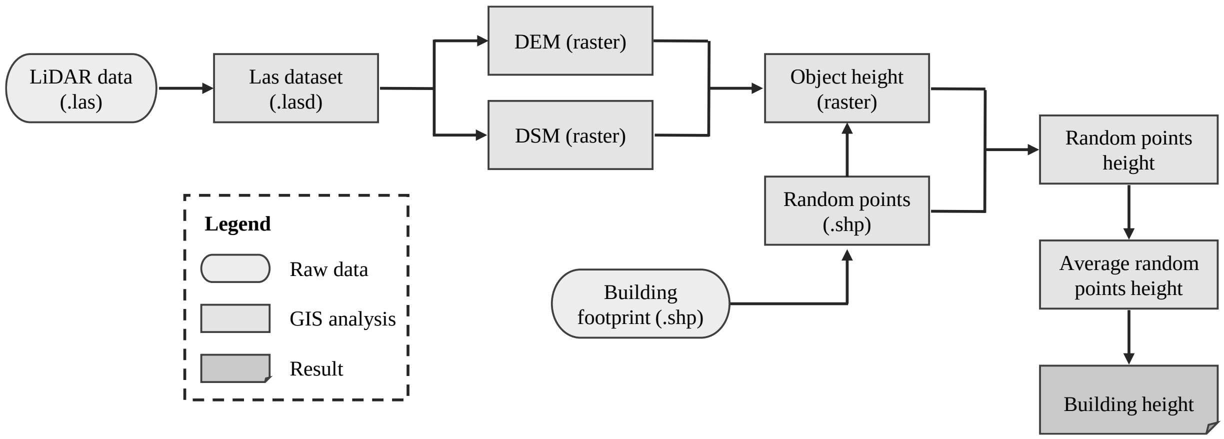


Figure 10 LiDAR analysis for building height estimation. DEM and DSM refer to Digital Elevation Model and Digital Surface Model, respectively. Note: the texts in the parentheses (e.g., shp) illustrate the file format of different stages of GIS-based analysis

The raw LiDAR data was adopted to create the elevation models; Digital Elevation Model (DEM) and Digital Surface Model (DSM). The DEM contains the elevation of the earth's surface with reference to a specific datum, whereas the DSM contains the elevation of different objects on the earth (i.e., buildings, city furniture, vegetation, and bridges) with reference to the same datum. Thus, subtracting the DEM's elevations from the DSM's elevations results in a new model that only includes the object's height above the earth. To distinguish the height of the commercial building from other objects across the city; first, the new height model was filtered in relationship to the building footprint. Next, several random points, that were inscribed by the building footprint, were generated and synthesized with the height model; therefore, every point was assigned a height. Sometimes roofs are pitched or having height variations, and reconstruction of these types of roofs was difficult and time consuming. So, a simplified approach was used in which heights of points (inscribed by a building footprint) were averaged for every building independently and considered as the final value of a building's height. While this simplification may affect precision of the thermal modeling, the associated error is negligible as it is averaged out when estimating the aggregated energy use for the entire stock.

3.2.5 Phase 5 – Urban Model Generation

When all required input information was gathered or estimated, an energy model of each building in the stock was generated to simulate energy use utilizing EnergyPlus, an open source program designed by U.S. DOE [46]. Model generation was a multi-step task that included creating 3D models, assigning envelope properties, defining thermal zones, and assigning non-geometric parameters to zones (see Figure 7).

The 3D models represented the volumetric shape and orientation of the buildings. In the most basic models, a combination of a rectangle footprint and height forms the volumetric shape that is known as a shoe box model. However, the goal of this research was to develop more detailed 3D models. The building footprints, from phase 1, were imported from ArcGIS to SketchUp, which is a drawing computer program, using Spirix Import Shapefile add-in tool, then they were extruded based on the buildings' height, from phase 4, to form the volumetric shapes. This approach provided a volumetric shape similar to the actual building. Next, the floor count and WWR, from phase 3, were assigned to the 3D models of every building, separately. It was assumed that windows were evenly distributed among facades and located one meter above the ground. Considering five thermal zones per floor, a common practice in energy modeling of individual buildings, increases both model generation and running time [97]. So, in order to have a multi-zone model and avoid run time issues, one thermal zone was defined for each floor of buildings. The boundary condition of the external walls, floors, and roof were completed in SketchUp and by leveraging the OpenStudio add-in tools. Upon completion of the 3D models, they were converted to idf format, the operational format of EnergyPlus, and imported into EnergyPlus.

To complete the energy modeling, according to use type and construction period, an appropriate archetype, from phase 2, was selected for a respective building and non-geometric parameters were appointed to different thermal zones of the building. As an example, one thermal zone in the archetype, that represented the lodging buildings constructed prior to 1980, was specified for laundry activities. The plug and process load of this zone was defined in a way that included energy consumption of laundry appliances such as washer and dryer. Weather variables such as dry bulb temperature, wind velocity, also have substantial impact on energy consumption. Typical Meteorological Year (TMY) data has been broadly used in building energy analysis as weather input. TMY data embodies 8760 sample points representing median values of weather variables for every hour over one year [129]. One of the recent TMY data is TMY3 for which hourly weather variables were calculated based on historical data between 1991 and 2005. For this urban model, TMY3 from the Pittsburgh International Airport weather station, which represented the average weather condition of Pittsburgh, Pennsylvania, was employed. Once the weather data was imported into EnergyPlus, the energy models were completed, and simulations were run for every building in the stock.

The simulation results were analyzed in section 3.3 to identify the pattern of energy use for different commercial use types and to validate the UBEM. The implications of different EC strategies on the annual energy use of the building stock were assessed through adopting the UBEM. Three EC strategies including temperature set points adjustment, upgrading lighting systems, and plug and process load reduction were selected. To implement these strategies, the primary values for heating and cooling set points, lighting density, and plug and process loads, which were determined during characterization, were modified in the energy models and simulations were run for every building again.

3.3 Results and Discussion

3.3.1 Energy Use Pattern Correlated with Commercial Use Types

The simulated annual energy use intensity (EUI) of the buildings was calculated and mapped as displayed in Figure 11. EUI is summation of energy consumed by various end uses including space heating, space cooling, ventilation, lighting systems, internal equipment and appliances, water systems (e.g., pumps), and water heating systems normalized by floor area. The simulated annual EUI, averaged over the use types, ranged from 74 kWh/m^2 to 1,302 kWh/m^2 for parking garages and warehouses, respectively. The high annual EUI for warehouse can be attributed to high intensity internal equipment and their schedules such as refrigerators and fans that are operating throughout the day without interruption. Buildings categorized as 'other' followed by education buildings had second and third highest average annual EUI. The former housed mixed-use spaces including offices, medical centers, restaurants, and retail stores which typically have higher energy consumption. The latter housed research activities, laboratories, and server rooms with high intensity equipment that resulted in greater energy consumption compared to the rest of commercial use types. Finding the lowest annual EUI for parking garages was expected given that these buildings did not have space heating and cooling, which dominated the energy use compared to the other end uses.

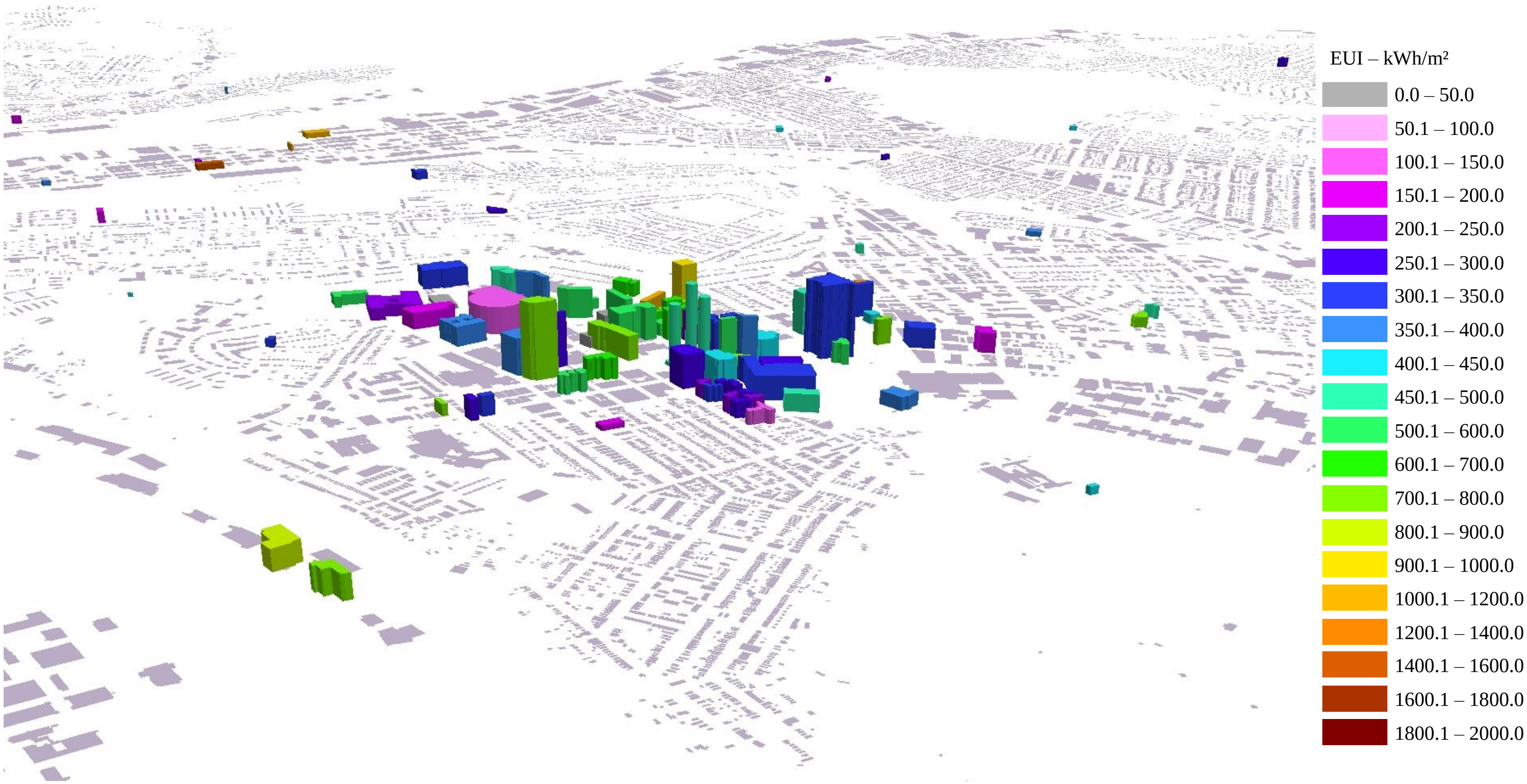


Figure 11 Simulated annual energy use intensity (EUI) of the commercial buildings in the urban building energy model (UBEM) for Pittsburgh, Pennsylvania. Note: we only included buildings for which we had actual energy use for this UBEM for validation purposes

Space heating, cooling, and lighting together comprised between 36% to 93% of the total energy use for various use types. Apart from parking garages with no heating systems, the share of space heating from total energy use was estimated at 23% for education buildings, which is the lowest compared to rest of use types in the stock. Two reasons can be posited. First, energy consumed by internal equipment and appliances (plug and process loads) dominated energy use of education buildings. Second, heat gain due to operation of these equipment compensated for heating and reduced space heating demand for this use type. Whereas, for lodging buildings, 65% of the total energy use was allocated to space heating since the majority of these buildings were dormitories and not 100% operational during the cooling season. Therefore, the energy consumed for space cooling along with the plug and process loads was reduced and resulted in heating became the dominant energy load. Aligned with significant impact of weather condition on trend of energy use, it was found that in this commercial building stock the share of space cooling from total energy use (0-12%) was fairly lower than that of space heating because Pittsburgh is located in a cold climate with severe winter weather and milder summers. Besides discrepancy in the simulated energy use pattern of different commercial use types, there were variations in the simulated energy use of buildings with similar use types.

3.3.2 Variations in the Simulated Energy Use of Buildings with the Same Use Type Were Identified

Frequency distributions for the annual simulated and actual EUIs and probability distribution functions (PDF) for annual simulated EUIs are shown in Figure 12a and 12b, accordingly. While the thermal zoning was similar for the buildings with the same use type, the simulated annual EUI varied for different buildings (see Figure 12b). This variation was because the solar heat gain and heat loss were different for buildings due to the diversity of the orientation and WWR, which their influential role on the energy use of buildings are well-studied in the literature [130-132]. Thus, it can be inferred that considering the actual building orientation, obtained from geospatial data, and the WWR, measured through photogrammetry and image processing, likely improved the urban model's accuracy. Moreover, incorporating the external wall material specific to each building and consequently wall composition, which impacts the heat transfer between buildings and unconditioned environment, was another reason for the variation of simulation results within one use type.

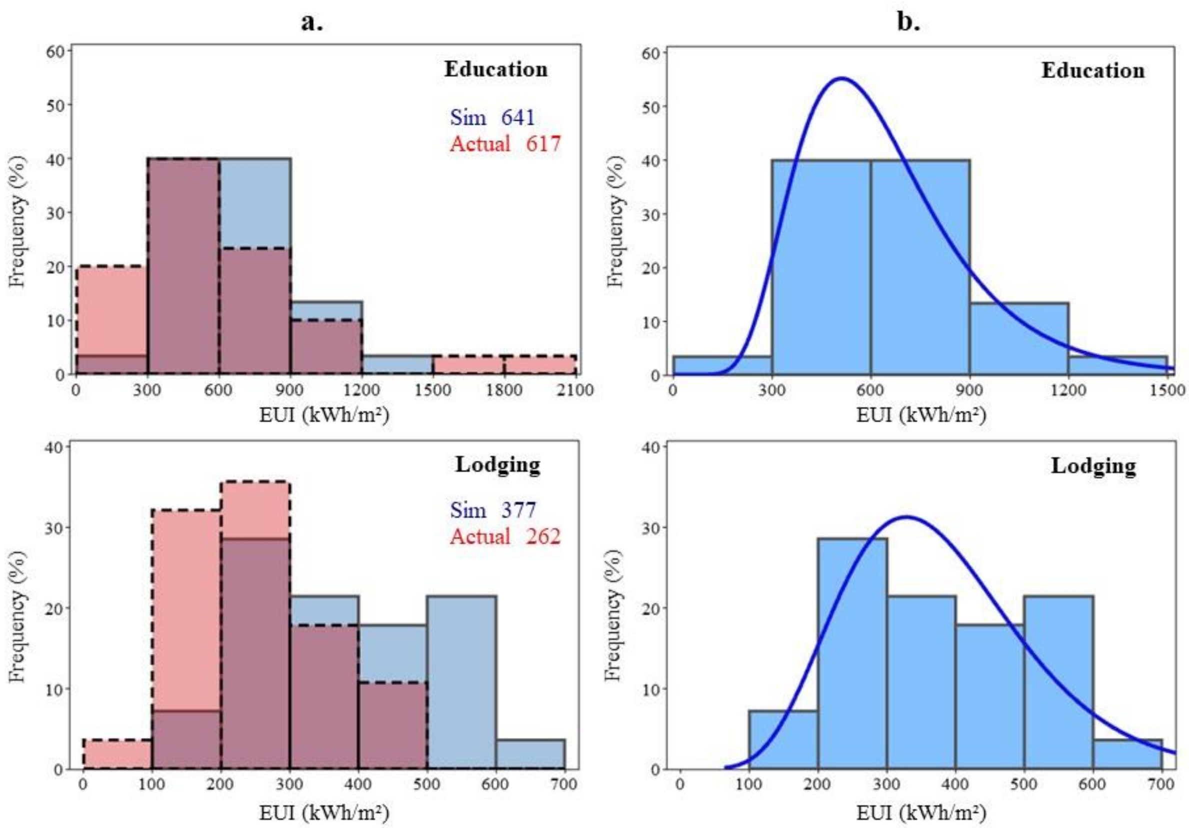


Figure 12 Energy use pattern for different use types. a) Frequency distributions of annual simulated and actual EUIs for eight use types; b) PDF and frequency distribution of annual simulated EUIs. The average annual simulated EUI (Sim) and the average annual actual EUI (Actual) are shown in blue and red texts, respectively

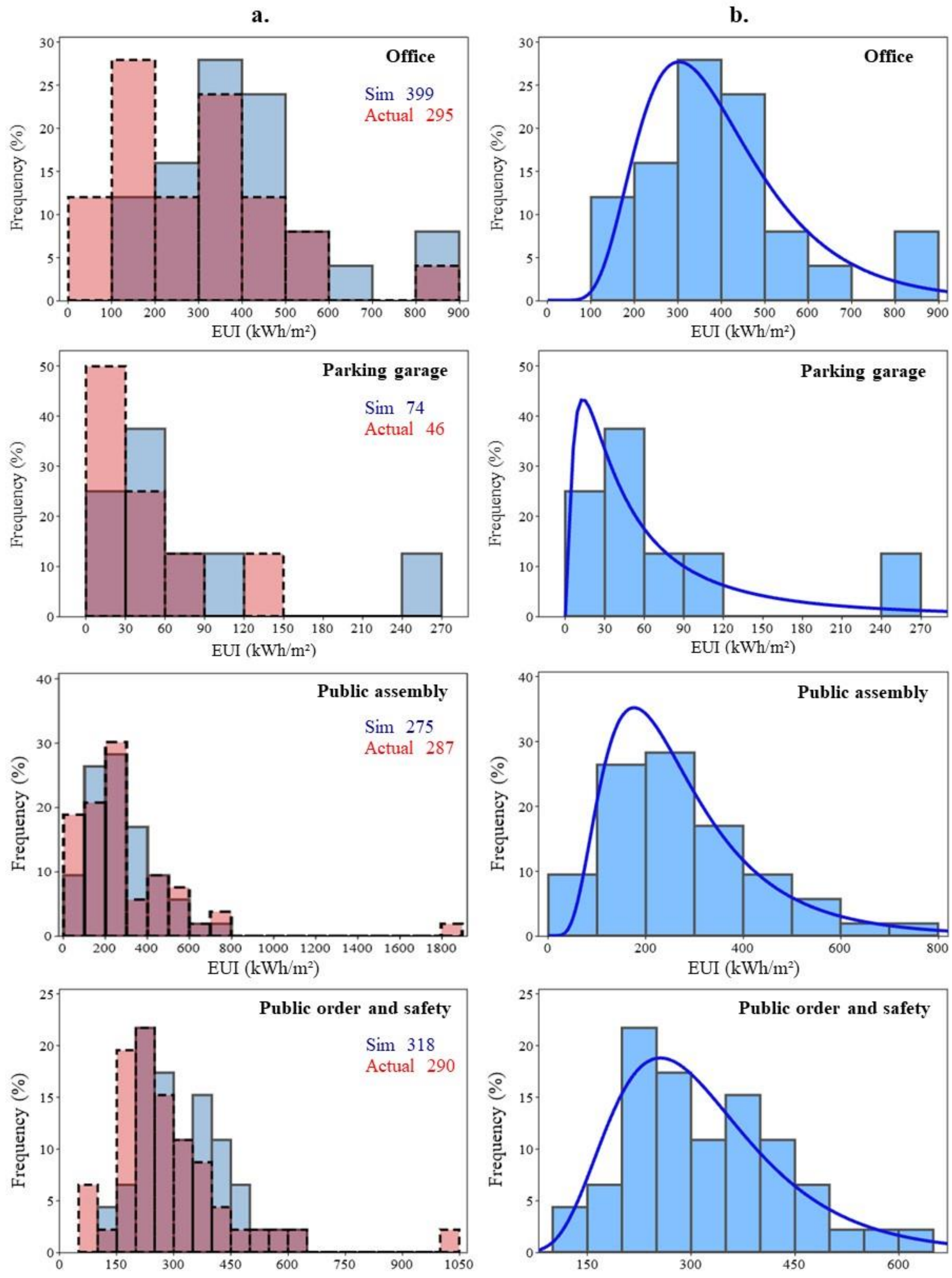


Figure 12 (continued)

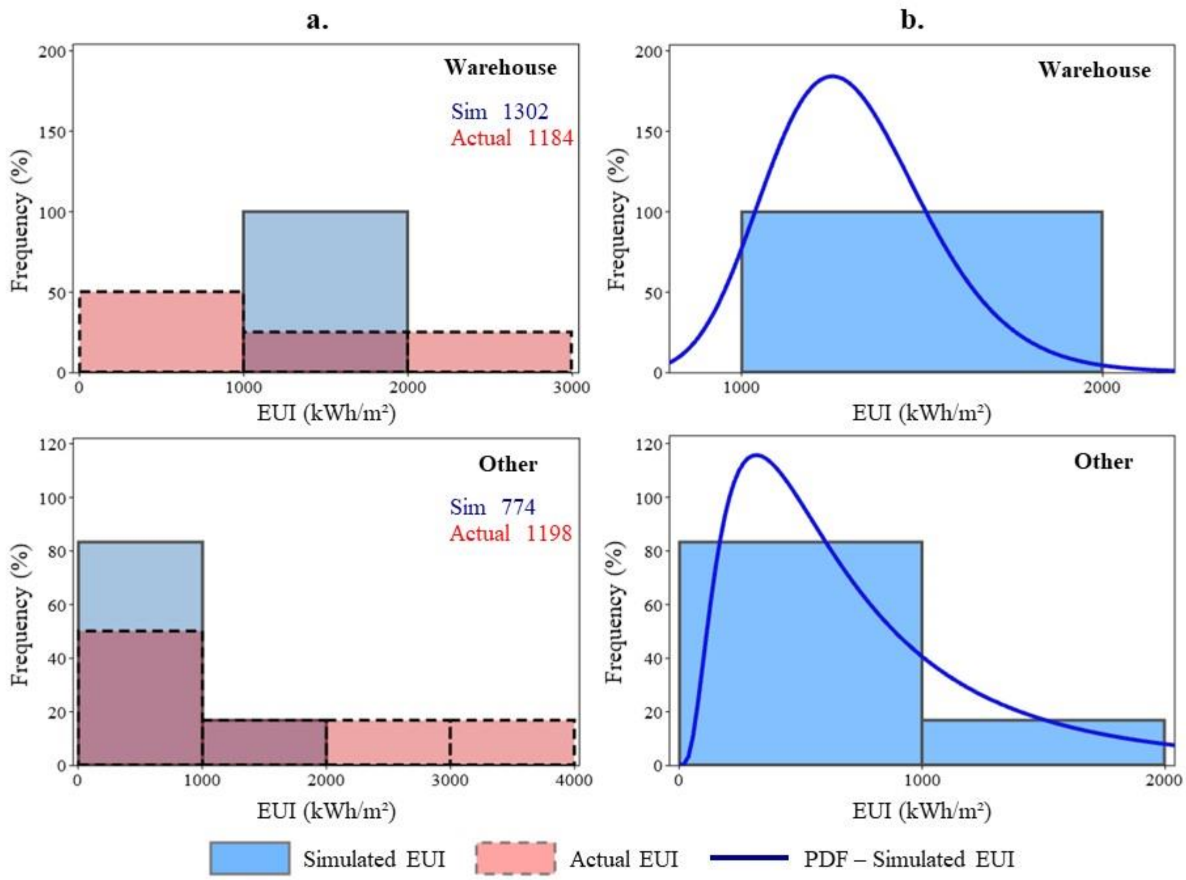


Figure 12 (continued)

The PDF of the annual simulated EUI for seven types of buildings (excluding lodging buildings) followed a lognormal distribution as shown in Figure 12b. Buildings with lower EUIs had higher frequency than buildings with high EUIs. Another important finding to be addressed is that PDFs were right-skewed; therefore, the higher EUIs are more scattered. Furthermore, through comparing the frequency distributions of simulated and actual EUIs (Figure 12a), it can be concluded that the UBEM's results were more concentrated whereas actual data were dispersed. This was mostly because when characterizing archetypes, the occupancy-related and mechanical/electrical systems parameters were assumed fixed for every archetype, which is a known limitation of UBEMs. Nonetheless in the real-world, these parameters differ for every individual building, consequently the actual EUI had a wider range. The simulated frequency distributions of the public assembly and public order and safety buildings showed more similarity with actual frequency distributions compared to the rest of use types. This similarity was likely due to less complex mechanical systems and occupancy-related parameters of public assembly and public order and safety buildings. By examining the average annual EUIs, presented in Table 17, the difference between the overall simulated and actual energy use was not significant in this building stock. Thus, it pointed to the conclusion that despite inherent complexity and diversity of commercial buildings, the UBEM was able to provide accurate estimation of energy consumption.

Table 17 Average annual simulated and actual energy use intensity for eight commercial use types and the overall studied building stock

Use Type	Average Annual EUI (kWh/m^2)	
	Simulated	Actual
Education	641	617
Lodging	377	262
Office	399	295
Parking garage	74	46
Public assembly	275	287
Public order and Safety	318	290
Warehouse	1302	1184
Other	774	1198
Overall	126	117

3.3.3 The UBEM Was Validated According to Actual Data

One of the contributions of this research was focusing on commercial buildings to advance the field. To examine the accuracy of the UBEM developed for solely commercial buildings without leveraging steady energy performance of residential buildings, it is imperative to validate results based on actual data. One path for validation is estimating and interpreting modeling error, which can be defined as deviation between simulated energy use and actual energy use [133]. Modeling errors can be generated from numerous sources from inaccuracy of simulation engine and the uncertainty of input information, to simplification applied to various stages of developing the model. In this order, the percent error (PE) was estimated using the aggregated energy use of each use type. The mean PE of the annual EUI was estimated based on Equation 3-2, where *Mean* EUI_{aj} was the average annual actual EUI for use type *j*, and *Mean* EUI_{sj} was the average annual EUI obtained from the UBEM for use type *j*.

$$Mean\ PE_j = \frac{\left|Mean\ EUI_{aj} - \ Mean\ EUI_{sj}\ \right|}{MEan\ EUI_{aj}} \times 100 \qquad (3\text{-}2)$$

As shown in Table 18, the mean PE varied according to the use type. The low PE for the education buildings was likely because most of these buildings belonged to the University of Pittsburgh and consulting with building managers aided our team in characterizing archetypes with greater similarity to real-world operation. The error for lodging, other, and office buildings were almost similar and can be mainly traced to various operating schedules and internal equipment. Surprisingly, comparing average simulated EUI with the average actual EUI of parking garages showed considerable difference (63%). Ventilation systems were defined during the archetype characterization for parking garages. However, some of these buildings were designed with vehicular barrier walls instead of external walls and used natural ventilation rather than ventilation systems (e.g., fans). So, their actual energy use was much lower than the simulated values, but this difference did not have a considerable impact on overall model error since the energy use of parking garages were low compared to other buildings.

Overall modeled PE was 7%, which is within acceptable range (1-15%) suggested by existing literature [97]. In addition to error estimation, two-sample Kolmogorov-Smirnov (KS) test was adopted to explore the similarity of distributions of simulated EUI and actual EUI. The benefit of the test is showing if the UBEM's outcomes represent the commercial building stock of

Pittsburgh and whether the distributions of energy use, acquired from the model, can be utilized in future to scale up outcomes to the entire city or not.

Table 18 Percent error (PE) and Kolmogorov-Smirnov (KS) test results for annual energy use intensity

		KS test	
Commercial use type	**Mean PE (%)**	**P-value**	**0: null hypothesis not rejected; 1: null hypothesis rejected**
Education	4	0.071	0
Lodging	44	0.012	1
Office	36	0.156	0
Parking garage	63	0.980	0
Public assembly	4	0.429	0
Public order and Safety	10	0.342	0
Warehouse	10	0.771	0
Other	35	0.474	0

The KS test is a non-parametric test providing insights on the statistical difference of two samples [134]. The null hypothesis is that the two distributions are not statistically different, and it is not rejected when the p-value is greater than a specific significance level. Usually, the significance levels are assumed to be 0.05 or 0.01. The p-values for every use type were compared with a significance level of 0.05. According to the results of KS test, displayed in Table 18, the null hypothesis was not rejected for all the buildings except lodging buildings, which confirms that distributions of simulated and actual EUI are not distinct. The statistical difference for lodging buildings may be correlated with operating schedules and other occupant behaviors, which can be addressed through implementing a probabilistic approach during the lodging archetype characterization to define occupant-related parameters. However, such this approach first requires comprehensive behavioral data that is not currently available, and second is computationally intensive. Another solution is to randomly select a sample of the lodging buildings, conduct occupants' surveys, and recalibrate lodging archetypes based on surveys in a future work. Regardless of minor difference for lodging buildings, from both error estimation and KS test results it can be concluded that the UBEM represented the commercial stock of Pittsburgh and verified to be accurate. So, it can be further employed to evaluate EC strategies.

3.3.4 Selected Energy Conservation Strategies Reduced Energy Consumption of the Commercial Stock by 2-5%

For policy makers and urban planner, broad knowledge about impacts of energy efficiency programs on energy performance of existing buildings at scale is essential as it aids them in refining codes and standards as well as structuring regional retrofit guidelines and regulations. On this basis the UBEM was utilized to assess energy reduction or savings of the studied building stock in concert with EC strategies. As mentioned earlier, three low to medium cost EC strategies [135]; temperature set points adjustment, upgrading lighting systems to LEDs, and plug and process load reduction were selected and applied. The rest of this section is allocated to discuss findings.

Raising cooling set point from 24°C to 25.5°C and lowering heating set point from 21°C to 20°C was the first strategy with no cost. The new temperature set points are within temperature spectrums that provide comfortable indoor environment for occupants [135, 136]. The cumulative energy use of the building stock prior to adjusting set points was simulated as 521 GWh which reduced approximately 5% after changing set points to new values in the UBEM. In addition to the cumulative energy use of the stock, the total EUI averaged over the entire stock reduced by 4% (see Table 19). Also, the impact of this EC strategy on dominant end uses (space heating, space cooling, and lighting) was estimated, which showed that the reduction in average cooling EUI (27%) was much higher than other two end uses.

Table 19 Percentage of energy use change due to energy conservation strategies. Positive values represent reduction and negative values represent increase

	Cumulative energy use (%)	Average total EUI (%)	Average heating EUI (%)	Average cooling EUI (%)	Average lighting EUI (%)
Temperature set points adjustment	5	4	9	27	0
Upgrading lighting systems to LEDs	4	10	-3	11	72
Plug and process load reduction	2	2	-1	2	0

Replacing traditional incandescent bulbs, which convert 90% of energy to heat, with Light Emitted Diodes (LEDs) is a well-known strategy to conserve energy. As reported by the Department of Energy, LEDs consume 4 to 5 times less energy than incandescent bulbs [137]. In order to examine the impact of this strategy on the building stock, lighting density (W/m^2) was reduced between 50% to 75% for different buildings. Shifting to LEDs resulted in percent decreases for the average total EUI, average cooling EUI, and average lighting EUI as presented in Table 19. On the other hand, average heating EUI increased by 3%. This is because heat generated from lighting system decreased when using LEDs and heating system should run more to compensate for the heat. Ultimately heating demand was simulated to be increased.

Utilizing more energy efficient internal equipment and appliances for example those with ENERGY STAR label would reduce plug and process loads. The amount of energy conserved varies greatly for different equipment and appliances. For instance, ENERGY STAR refrigerators and washers consume about 10% and 40% less energy, respectively than standard ones [138]. In this chapter, it was assumed that plug and process loads would reduce by 15% and energy savings was estimated. The average reductions for total and cooling EUIs were less than set point adjustment and upgrading lighting systems. Moreover, average lighting EUI was remained unchanged, as expected, and the average heating EUI showed a slight increase. When the plug and process load decreases, amount of rejected heat by equipment and appliances reduces. Thus, heating system would run more to meet the demand of buildings. Evaluating the EC strategies at an urban scale provided insights on how energy ecosystem of urban buildings would alter, and which strategy yielded higher promise.

3.4 Conclusions

This chapter described a holistic and detailed modeling structure for developing a UBEM focusing on commercial buildings. With the aim of increasing reproducibility of future UBEMs, an archetype library with sources was provided, along with proposing and implementing an advanced imaging technique to retrieve envelope properties and reconstruct façades as well as LiDAR analysis. The major findings of this chapter are:

- The WWRs between 0.11 and 1 had higher frequencies in the studied building stock (74%) when compared to CBECS buildings (44%). Therefore, using CBECS data, rather than measuring WWR based on photogrammetry and image processing framework, would have led to underestimating WWR.
- The average annual EUI for different building use types was simulated between 74 kWh/m² and 1302 kWh/m². This range showed that energy use of commercial buildings was highly related to use type.
- Validating the simulation results with actual data showed the overall acceptable PE of 7% for the studied building stock. The PE for different building use types were estimated between 4% (education buildings) and 63% (parking garages). Ventilation systems were considered when simulating energy use of parking garages; however, some of these buildings did not have

ventilation systems in real-world. Therefore, the average simulated EUI was somewhat higher than the average actual EUI for parking garages resulting in the highest PE compared to other use types.

- The KS test results revealed that the distributions of simulated and actual EUI were similar for seven use types (p-values were greater than 0.05). However, the p-value for lodging buildings was calculated as 0.012 showing that the distributions of simulated and actual EUI were statistically different for this use type. This difference can be attributed to variable schedules and occupant behavior.
- The average EUI of the studied building stock was reduced 2-10% as result of three EC strategies. All three EC strategies reduced the average cooling EUI (2-27%); whereas, upgrading lighting systems to LEDs and plug and process load reduction slightly increased the average heating EUI by 3% and 1%, respectively. These increases were because rejected heat from lighting systems and different appliances and equipment was declined; thus, heating demand increased.

In addition to providing policy makers, urban planners, and utility companies with insights about trends of energy use, the results of this research can be used to provide guidance about EC strategies for the commercial building stock at urban scale. So, relying on this information policy makers and urban planners can advocate for converting EC strategies from voluntary actions to regulations.

As part of future work, the model can be utilized to evaluate simultaneous implementation of the three EC strategies as well as more aggressive and high-cost strategies such as upgrading heating/cooling systems and improving envelope airtightness. Additionally, the environmental impact associated with energy consumption of the studied commercial buildings can be assessed through employing the amount of different energy sources. There are some studies that have integrated building energy use mostly at individual building-level with climate change based on physics-based or machine learning approaches [40, 139, 140]. The UBEM can be employed to predict changes in energy use of buildings in Pittsburgh, Pennsylvania region due to weather variation caused by climate change. Furthermore, the resiliency of energy supply network in time of extreme weather events (i.e., heat wave and cold wave) can be evaluated by meshing the UBEM with extreme meteorological year data. Technical aspects that require improvement are accessing documents of all buildings in the city, that includes basic data regarding buildings and their energy use, together with automating the photogrammetry and image processing framework. Artificial intelligence (AI) methods have been used to automize image processing especially in medical fields; therefore, it is planned to resolve current challenges and implement AI methods for façade image processing at urban scale.

4.0 State of Building Material Stock Analysis for Effective Circular Economy Strategies

The research presented here addresses objective four. Specifically, it answers the question 'Are there any gaps and barriers in the current literature about building MSA?' The content of this chapter was published in a peer-reviewed journal:

Mohammadiziazi, R., & Bilec, M. M. (2022 accepted). Building Material Stock Analysis Is Critical for Effective Circular Economy Strategies: A Comprehensive Review. *Environmental Research: Infrastructure and Sustainability*.

4.1 Introduction

Global material use is projected to increase from 89 Gt to 167 Gt between 2017 and 2060, along with the associated environmental impacts including carbon emissions from material production [141]. This projected increase in material use is due in part to the building sector that is needed to house and support our growing population [142]. The building sector in urban areas is responsible for the largest share of consumption of raw materials for producing construction materials and accumulated materials as well as significant amounts of waste generated during construction and demolition [2, 3, 142, 143]. In 2018, construction and demolition activities in the United States resulted in 600 Mt of waste which was more than double the amount of generated municipal solid waste [144]. In light of climate change, resource depletion, and waste generation, there is an urgent need to develop and implement innovative strategies.

Replacing the current linear economic system (i.e., take, make, and waste economy) with a circular economy system has been suggested as a solution for climate change, resource depletion, and waste management with a focus on plastic pollution [145]. Circular economy strategies such as reuse, recovery, design for disassembly, and extending lifetimes are intended to retain the primary value of materials and products, close the material loop, reduce natural resource extraction, reduce waste, and mitigate the environmental impacts of buildings. However, the practical implementation of circular economy strategies for the building and construction sector can be difficult. While some have proposed utilizing buildings as urban mines and secondary resources, extensive knowledge and information about building stocks are first needed to realize the potential. Simply put, one cannot mine without knowledge of where the material is located, along with the type, quantity, quality, and value of the material [146]. Information about buildings in several countries including the United States is usually disparate, sparse, and granular [139, 147, 148].

To overcome the data challenge and compile the information about accumulated materials in existing buildings, material stock analysis (MSA) and material flow analysis (MFA) can be employed. MSA and MFA explore the material's dynamic and metabolism at different temporal and spatial scales and are known as support tools to foster circularity. In the last twenty years, analyzing the stock of built environments (i.e., buildings, roads, railroads, bridges, water and sewer pipelines, and other civil infrastructure [149]) has gained attention and several researchers proposed different methods at neighborhood-, city-, and country-scale to understand metabolisms and estimate the quantity of available materials in these structures. Augiseau and Barles [150] summarized proposed methods and findings of thirty-one publications, between 1998 and 2015, that analyzed the stock and flow of non-metallic minerals in the built environment including road and railroad networks. They found that in many case studies recycling, reusing, or recovering current materials in the built environment may not meet the growing demand for buildings and infrastructure. For instance, using recycled construction waste as secondary material would decrease the need for new materials only by 7% in Vienna, AT. In another article, Lanau et al. [151] depicted a broad picture of the scope and approaches of 249 technical reports and articles covering both buildings and infrastructure, that were published prior to 2018. They found that cities and urban areas are responsible for the highest share of materials in the built environment and material accumulation in developed countries are generally higher than in developing countries. Goswein et al. classified methods, tools, and data of studies that investigated building materials, embodied energy, and emissions at the neighborhood or district level [152].

In this chapter, the gaps from the prior papers are addressed [150-152]. This work focuses on the MSA of buildings because buildings are highly diverse and have complex systems; therefore, they warrant close attention that may be overlooked when the entire built environment is aggregated. Unlike former review papers that narrowed their scope to specific materials [150], all types of metallic and non-metallic materials are included in this review. Moreover, this work covers the latest studies until 2021. The spatial scale is expanded to encompass studies at the neighborhood-, district-, city-, and country-level, which is referred to throughout this chapter as "at scale".

Circular economy strategies include the reuse and recovery of materials and components. The objective of this chapter is to advance the circularity of the building sector by analyzing the current body of literature with a focus on the MSA of buildings, and illustrate a new and updated paradigm in this area by accomplishing the following research goals:

- Characterize the scope, system boundary, and resolution of existing studies.

- Explore and classify the approaches to quantify and spatialize building materials, along with the gaps and limitations.
- Compile an inventory that contains the composition and quantity of materials in existing buildings in different parts of the world by extracting results from several studies.
- Discuss technological and data barriers, and remaining gaps as well as opportunities to improve this emerging field.

4.2 Method

To achieve the research goals, the narrative review method was adopted. First, Scopus, a citation database developed by Elsevier, was used to search for publications that were published after 2000 and contained “building material stock”, “building material flow”, and “building stock assessment” terms in the title, abstract, or keywords with an emphasis on the peer-reviewed journal and conference publications. More than 11,000 publications were found in the Scopus database under the aforementioned criteria; however, several irrelevant articles were included. The abstracts of all publications were reviewed through a rigorous process and 62 articles, which were directly related to the focus of building material stock analysis at scale and were published between 2001 and February 2021, were identified. The 62 articles were comprised of 59 research articles and 3 review articles. First, 59 research articles were categorized based on their main approaches. Second, the articles were clustered according to detailed methods that were utilized. Further, every article was investigated to extract the required information for synthesizing scopes and boundaries, archetype and material intensity, approaches, and materials inventory.

4.3 Progress in Material Stock Analysis of Buildings

The chronological trend of publication dates is displayed in Figure 13. This increasing trend can be attributed to recent interests in the circular economy, urban mining, resource reuse, innovations in Geographic Information Systems (GIS), aerial photogrammetry, and building disclosure policies (e.g., the state of California mandated buildings over 50,000 ft^2 to disclose basic building information like floor area as well as energy use data). As the area of building MSA evolves over time, the inclination to employ bottom-up approaches has risen (see Figure 13). In addition to the number of publications over time, the level of details has improved; for example, more types of material have been accounted in recent publications.

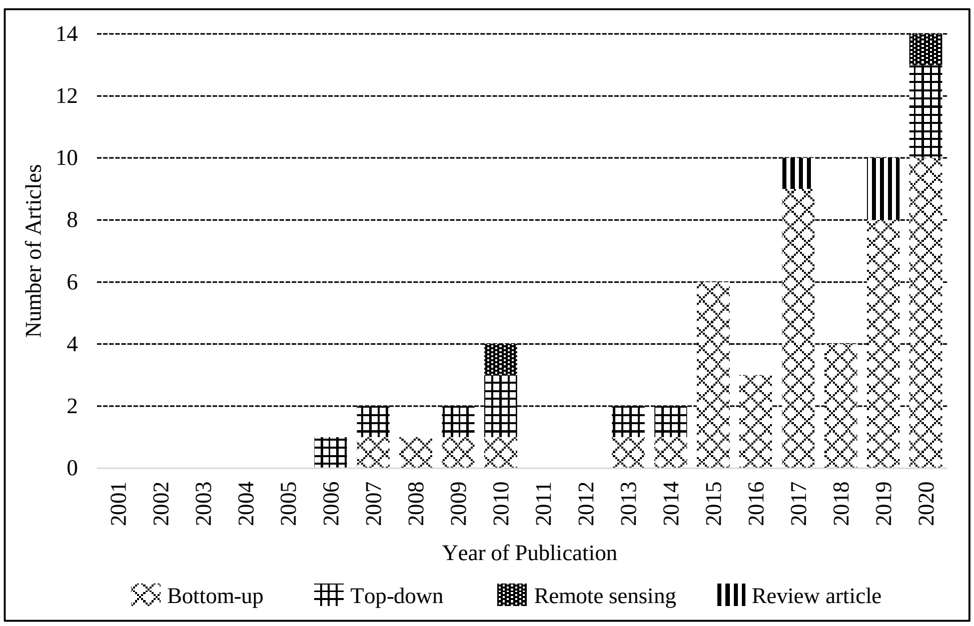


Figure 13 Number of articles on building material stock analysis at scale classified based on different approaches since 2001. The latest access date from the Scopus database was February 7, 2021

Of the 62 reviewed articles, 59 were research articles. The type and number of materials, that were included in these research articles, were investigated in accordance with their publishing year. As shown in Figure 14, in recent years researchers have been conducting more in-depth and comprehensive analyses of buildings by incorporating more types of building material in the stock analysis compared to the early 2000s. Out of 27 studies published from 2018 to 2021 and 20 studies published from 2014 to 2017, 23 (85%) and 15 (75%) studies estimated the quantity or calculated material intensity of more than one type of building material, respectively. However, this percentage was lower for studies published in the early 2000s (see Figure 14). Two studies proposed frameworks for MSA without quantifying or spatializing building materials [153, 154]. Turan et al. [153] and Lismont et al. [154] elaborated on classifying buildings into representative buildings or archetypes using manual and k-means clustering algorithms, respectively. Three articles reported the total accumulated building materials in different cities and countries without providing more disaggregated results regarding the type of materials [155-157]. This investigation shows that higher resolution and more holistic building stock assessments have been growing over time.

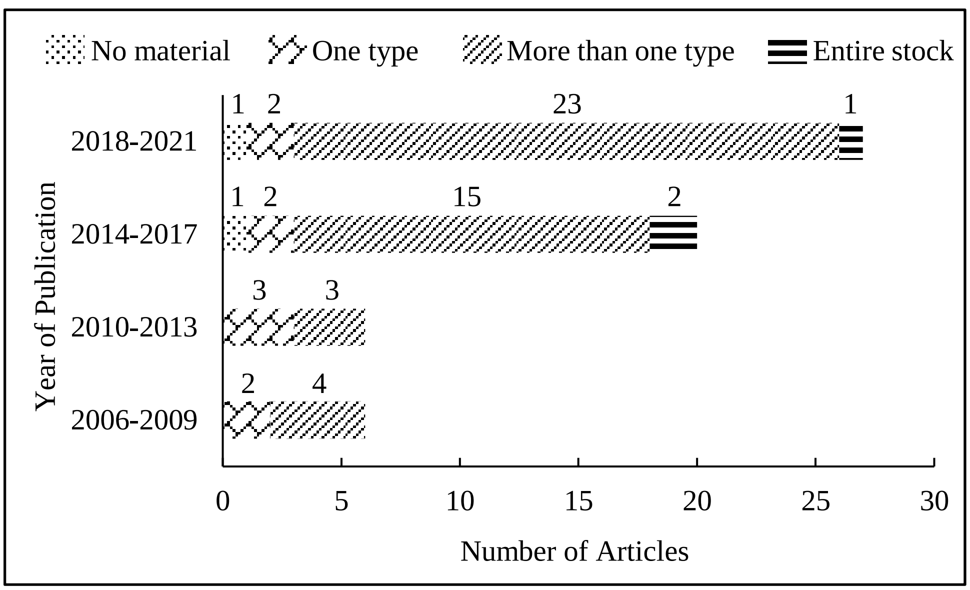


Figure 14 Temporal trend of articles with respect to the number of building materials, that were included in studies

4.4 Material Stock Analysis Scopes and Boundaries

The distribution of stocks of building materials at scale is influenced by scopes and system boundaries of studies. Thus, imperative to understand the in-use or accumulated material stocks of buildings is characterizing scopes and system boundaries. Scope and system boundary can be categorized into four groups: 1) building function or use type, 2) building components, 3) spatial or geographic boundary, 4) temporal resolution.

4.4.1 Building Function or Use Type

As required by the majority of codes and standards, the architectural, structural, and energy designs of buildings are determined based on their function. As a result, the composition and the amount of materials are affected by the building function. The functional system boundaries of reviewed articles mostly contained residential buildings (42%) or a combination of residential and non-residential buildings (52%); few articles limited their scope to solely non-residential buildings [158, 159]. Although there was not a definite explanation for the lower numbers of non-residential buildings, some factors were likely related to the complexity and diversity of construction techniques and structural systems. There is a need for an emphasis on non-residential buildings especially because they have a shorter average life span compared to residential buildings, which increases the frequency of demolition and consequentially the availability of reusable and recoverable materials [160].

While a consensus has been formed on categorizing building function into two broad categories (residential and non-residential), there has been less agreement about how to categorize building stock into different functional subcategories (e.g., non-residential municipal). There are overlaps and similarities between several functional subcategories both for residential and non-residential buildings, but distinct or disparate language was utilized by different articles; for example, institutional buildings may have similar functions as economic or education buildings. Nine residential and nineteen non-residential buildings subcategories were identified (see Table 20).

In several studies, residential buildings were clustered into single-family and multi-family based on the number of units. A few studies considered the adjacency of buildings (detached house, semi-detached house, and townhouse) [154, 161-165]. An important parameter is building height, which influences the quantity and composition of materials and consequently impacts the spatial distribution of accumulated materials in a region [159, 166]. For non-residential buildings, height was inherently considered in some of the subcategories; for example, industrial, retail, and warehouse buildings were usually considered as a single story, and office buildings were usually designed with multiple stories [159]. Despite the importance of height, it was rarely incorporated in defining residential subcategories and only a small number of studies acknowledged the difference between high-rise and low-rise residential buildings [162, 163, 165, 167]. As illustrated in Table 20, there is a notable disparity among different articles regarding language or terminologies that were utilized to describe functional subcategories. This disparity is a barrier to the reproducibility of building MSA research. To overcome this barrier, collective terminologies like the International Standard on Building and Civil Engineering Works Vocabulary can be employed to define functional subcategories [168]. In addition, using unified and coherent terminology enables businesses and companies to adopt the results of academic research for adaptive reuse (repurposing) of buildings based on their function. The building function categories and subcategories for all reviewed articles are provided in Table 20.

Table 20 Building function categories and subcategories for the reviewed articles. Note: factory, government, storage, and school and childcare facility are included as industrial, institutional, warehouse, and education subcategories, respectively

Reference	Author/s (year)	Residential									Non-residential																			Other
		Residential	Single-family	Multi-family	Detached House	Semi-detached	Townhouse	Terraced House	High-rise	Low-rise	Non-residential	Industrial	Commercial	Institutional	Office	Economic	Public	Retail	Hotel and	Warehouse	Hospital	Parking	Agriculture	Recreation &	Transportation	Education	Supply & Disposal	Municipal	Historical	
[161]	Mollaei et al. (2021)			■	■	■	■					■	■	■																
[162]	Ajayebi et al. (2020)					■		■	■	■			■		■															
[169]	Bradshaw et al. (2020)	■									■																			
[170]	Yang et al. (2020)	■										■					■													
[171]	Mao et al. (2020)	■										■	■				■			■		■	■	■		■		■	■	■
[172]	Gao et al. (2020)	■																												
[173]	Gontia et al. (2020)		■	■																										
[174]	Lausselet et al. (2020)		■																							■				
[175]	Lederer et al. (2020)	■										■	■																	■
[143]	Romero et al. (2020)			■				■																						
[176]	Guo et al. (2020)	■										■	■																	
[163]	Deetman et al. (2020)			■	■	■			■						■			■	■											■
[177]	Tazi et al. (2020)		■	■				■																						

Table 20 (continued)

[164]	Marinova et al. (2020)
[178]	Gontia et al. (2019)
[154]	Lismont et al. (2019)
[148]	Arora et al. (2019)
[179]	Miatto et al. (2019)
[180]	Heeren et al. (2019)
[181]	Mesta et al. (2019)
[182]	Han et al. (2018)
[183]	Gontia et al. (2018)
[2]	Stephan et al. (2018)
[184]	Cheng et al. (2018)
[185]	Schiller et al. (2017)
[186]	Condeixa et al. (2017)
[166]	Kleemann et al. (2017)
[187]	Stephan et al. (2017)
[159]	Schebek et al. (2017)
[188]	Mastrucci et al. (2017)
[189]	Surahman et al. (2017)
[190]	Schiller et al. (2017)

Table 20 (continued)

[191]	Kalcher et al. (2017)
[158]	Ortlepp et al. (2016)
[192]	Ortlepp et al. (2018)
[193]	Zamora et al. (2016)
[167]	Wiedenhofer et al. (2015)
[156]	Sugimoto et al. (2015)
[155]	Tanikawa et al. (2015)
[153]	Turan et al. (2015)
[194]	Reyna et al. (2015)
[195]	Ergun et al. (2015)
[196]	Han et al. (2013)
[197]	Hu et al. (2010)
[198]	Hu et al. (2010)
[199]	Tanikawa et al. (2009)
[200]	Lichtensteiger et al. (2008)
[165]	Bergsdal et al. (2007)
[201]	Hashimoto et al. (2007)

4.4.2 Building Components

Building materials are found in structural components (e.g., roof and floor elements, columns, beams, wall panels) and non-structural components (e.g., roof and wall insulations, windows, non-bearing partitions, interior finishes, mechanical, electrical, and pluming (MEP) elements [202]). The obsolescence or recovery paths of structural components are different from those of non-structural components. The former, which are chiefly made from masonry, wood, concrete, and steel, usually become available at the end of a building's lifetime [164, 203]. Although there is a growing interest among building professionals in industry and academia for reusing structural components and returning them to a service loop while preserving initial value, considerable shares are still recycled or discarded in landfills. Recycling of these components is either energy-intensive like steel or associated with significant downgrading like crushing concrete into aggregate for further use in recycled concrete and pavement. The challenge of reuse is linked to a lack of building standards and regulations for testing the integrity of used structural components, the complexity of transforming traditional structural design in a way that can incorporate mechanical and geometric properties of reclaimed components into the design process, and a lack of enterprises that can bridge the gap between deconstruction and new construction [204, 205]. On the other hand, non-structural components are easier to access, sort and handle upon deconstruction, which facilitates reuse. Further, these components such as MEP elements and windows are more frequently replaced during a building's lifetime due to weather and utilization stresses, which make their adaptive reuse economically and environmentally beneficial [206]. The different obsolescence characteristics of structural and non-structural components point to the necessity of specifying scope with respect to the type of components beyond summing up the volume or mass of materials when conducting material stock analysis [176].

To this point, 80% of reviewed studies analyzed materials accumulated in both structural and non-structural components without differentiating between the two component categories. Few articles (19% of reviewed studies) constrained their system boundaries to structural components [162, 167, 171, 185, 191, 197, 198, 207-209], whereas only Stephan and Athanassiadis [2, 187] quantified and spatialized materials in non-structural components (i.e., floors, external walls, internal walls, windows, doors, roofs, pipes, wires) of Melbourne's building stock. This evaluation reveals that future MSAs need to consider and distinguish between materials available from different components to enable appropriate planning for circular usage in alignment with the respective lifetimes.

4.4.3 Spatial Boundary

The total amount of accumulated materials within a region and the level of detail about the exact location of materials are impacted by the spatial boundary of a study. Six spatial boundaries (i.e., global, continent, country, city, district, neighborhood) in the current body of work were found. Deetman et al. [163] and Marinova et al. [164] developed global building materials models by using population and floor area per capita data and reported total accumulated building materials in the world. In one study, Wiedenhofer and colleagues [167] conducted a continent-scale MSA and estimated concrete and minerals in residential buildings of twenty-five countries that formed the European Union at the time of the study. Twenty-four articles analyzed the material stock of buildings for fourteen countries located in Asia, Europe, and North America. The highest frequency of country-scale studies belonged to Germany (five studies [158, 185, 190, 192, 210]), China (five studies [170, 196, 211-213]), and Japan (four studies [155, 201, 212, 214]) followed by Sweden (2 studies [173, 183]), Norway (2 studies [165, 215]), and Switzerland (2 studies [180, 200]). Twenty-four articles quantified or spatialized building materials of thirty-four cities across the world. The inconsistency between the number of articles and the number of cities was because few articles explored more than one city [161, 162, 189, 208]. For example, Guo et al. [208] and Surahman et al. [189] calculated the quantity of materials in buildings in fourteen cities in China and two cities in Indonesia, respectively. Likewise, Mollaei et al. [161] estimated the building materials of Kitchener and Waterloo in Canada, and Ajayebi et al. [162] developed a model to draw the spatial distribution of bricks in building stocks of Manchester, Bradford, and Leeds in GB. Among city-scale research articles, Beijing, CN, Shanghai, CN, and Vienna, AT have been investigated by multiple studies. Finally, five and three articles limited their geographic scopes to districts [143, 156, 176, 193, 199] and neighborhoods [153, 174, 207], accordingly.

The high variation in the spatial boundary of studies increase the difficulty when comparing and validating results. This variation also complicates the transferability of data and outcomes between different regions. A closer look at geographic location showed that the majority of studies (80%) were concentrated in European countries, Japan, and China, while 8% were conducted in North America, and the remaining studies (12%) located in Australia, Asia, and South America or covers the entire world (see Figure 15). Unfortunately, no studies were found in Africa. Note that a country-scale study by Fishman et al. [214], which included both U.S. and Japan, is considered in Japan and North America percentages. Figure 15 displays the number of articles in different countries that conducted building MSAs regardless of spatial boundaries. For example, as shown in Figure 15, three articles analyzed material stocks of buildings in the U.S. [193, 194, 214]; however, the spatial boundary of these articles varied. Fishman et al. [214], Reyna et al. [194], and

Marcellus-Zamora et al. [193] analyzed material stocks of the entire U.S. (country-scale), Los Angeles (city-scale), and University City in Philadelphia (district-scale), respectively.

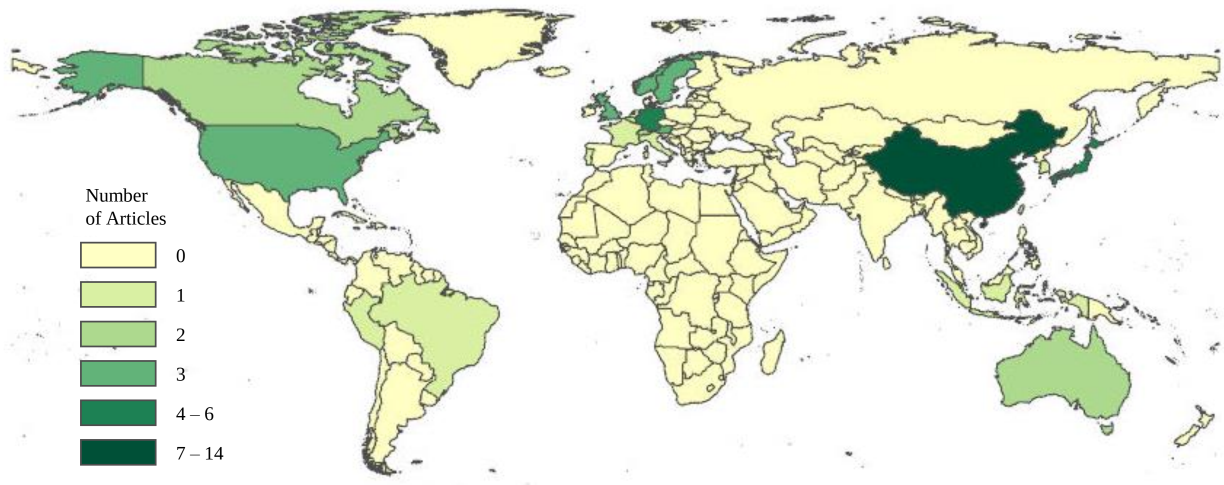


Figure 15 Number of articles in different countries with various spatial boundaries. Note: few articles analyzed building material stocks in more than one country

4.4.4 Temporal Resolution

While building stocks are inherently dynamic in relation to time due to variations in demand for new buildings, recurrent renovations, and maintenance during a lifetime, and demolitions at the end of life, materials have been analyzed both statically and dynamically. The temporal resolution affects the selected approach and outcomes of MSA, which is thoroughly discussed in section 4.6. In a static MSA, a time interval (e.g., one year) is selected and building material stock is represented for the chosen interval. Although the static approach does not provide insight into the trend of material accumulation over time, it does not suffer from the uncertainty associated with the inaccuracy of historical data or future projections. Several studies (32% of reviewed articles) utilized the static approach to estimate material stocks [143, 153, 154, 158, 159, 162, 169, 171, 177, 188, 192, 200, 208].

The dynamic approach accounts for the changes in stocks throughout time and can be classified into retrospective and prospective studies [150, 151]. Retrospective studies (34% of reviewed articles) employed either available maps or historical data to characterize building stock from past to present. Few retrospective studies analyzed building stocks by reconstructing GIS maps based on old sketches, paper maps, aerial images, and digital maps [156, 157, 176, 199]. On the other hand, several studies relied on historical data (e.g., population, floor area) [148, 155, 166, 173, 175, 178, 179, 181, 182, 193, 194, 196, 198, 214]. Prospective studies (8% of reviewed articles) predicted and characterized building stocks in the future [2, 161, 174, 180, 186, 187]. In addition to these dynamic approaches, retro-prospective studies investigated the building material's metabolisms from the past to future [163-165, 167, 172, 189, 197, 201, 207, 209]. The temporal span of dynamic MSA ranged from a few years to centuries. In one example, Marcellus-Zamora and colleagues [193] developed and validated a dynamic model to understand the material stock and flows of a neighborhood over eight years. However, Muller [209] assessed input flows, in-stock, and output wastes of concrete in the housing stock of the Netherlands between 1900 and 2100 through defining different scenarios.

4.5 Building Archetype and Material Intensity

Diversity in composition and intensity of materials among buildings are noticeable because of heterogeneity in design and availability of materials in different parts of the world and during various time periods. Nonetheless, obtaining and employing detailed data about materials for every individual building at scale is relatively difficult or not likely feasible. To overcome this challenge, the common practice is to define archetypes or typologies that represent groups of buildings with similar characteristics regarding materials. To classify a building stock into archetypes, the time of construction was prevalently utilized in the reviewed articles (see Table 21). In addition, other categories for archetype classification were building function, structure type, renovation state, urban vs rural, building height, floor counts, construction cost and lot size, and climate zone. As displayed in Table 21, the number of archetypes varied significantly. Classifying a building stock into more archetypes allows for capturing and integrating the diversity of buildings to a higher degree, which enhances accuracy. In addition to archetype classification, material intensity determination is an important factor.

Material intensity is one of the key parameters in MSA and indicates the quantity of a certain material per unit of a building such as mass per floor area, mass per building, mass per volume of a building, volume per building, and volume per volume of a building. More definite determination of material intensity for archetypes increases the accuracy of results and mitigates uncertainty. As shown in Table 21, several studies relied on previous literature as well as building standards, handbooks, and manuals for material intensity. The drawback of dependency on previous literature is that it may cause uncertainty propagation. Identifying and investigating sample buildings, that were representative of archetypes, through construction documents, life cycle assessment (LCA) inventories, and on-site inspection were other methods to determine material intensity. Moreover, data embedded in Building Information Models (BIMs) can be retrieved and employed to estimate the material intensity of sample buildings [153]. One-third of the articles in Table 21 evaluated sample buildings; however, straightforward procedures for on-site inspection and extracting material information from construction documents of old buildings were not described in these articles.

Advancements in determining the material intensity of building stocks require systematic collection and documentation of design and construction data to create comprehensive and publicly available inventories. Instituting policies and regulations that instruct design firms and construction companies to report the composition and quantity of materials in a building will help the creation of such inventories. In addition, leveraging technologies like BIM will not only facilitate documenting materials but also enable considering materials like plastics that are currently less considered in MSA of buildings. In Table 21, categories that were utilized for classifying archetypes, the number of archetypes, and how material intensity was determined as well as the units of material intensity are summarized. This table can be adopted for assessing the transferability of material intensity in different regions as well as employing material intensities in existing articles for future research.

Table 21 Summary of archetype classification and material intensity in reviewed articles

Reference	Author/s (year)	Archetype Classification			Material Intensity for Archetypes	
		Time of Construction	Other Categories	No.	Determination Methods/Resources	Unit
[161]	Mollaei et al. (2021)	- Before 1930 - 1930 – 1960 - 1961 – 1975 - 1976 – 1999 - 2000 – 2018	- Building function	15 [a]	- Existing literature [183, 194, 195, 216, 217] - Expert opinion	kg/m²
[162]	Ajayebi et al. (2020)	- Before 1850 - 1851 – 1945 - 1946 – 1970 - After 1971	- Building function	24	- Building standard, handbook, manual	#brick/m² [d]
[169]	Bradshaw et al. (2020)	---	- Structure type (concrete 1, concrete2, concrete 3, steel, stone, wood, wood-concrete)	7	- Evaluation of 303 sample buildings via on-site inspections	kg/m²
[170]	Yang et al. (2020)	- 1949 – 1959 - 1960 – 1979 - 1980 – 1989 - 1990 – 1999 - 2000 – 2015	- Building function - Structure type (brick-concrete, brick-wood, steel, steel-concrete, wood)	41 [a]	- Evaluation of 813 sample buildings via existing literature [h]	t/100m²
[171]	Mao et al. (2020)	- Before 1980 - 1981 – 2000 - 2001 – 2018	- Building function	36	- Evaluation of 1800 sample buildings via construction documents, existing literature, and expert opinion [h]	kg/m²
[172]	Gao et al. (2020)	- Before 1949 - 1950 – 1959 - 1950 – 1979 - 1950 – 2010 - 1950 – 2100 - 1960 – 1979 - 1965 – 1979 - 1980 – 1989 - 1980 – 1999 - 1990 – 1999 - After 2000	- Structure type (adobe-wood, brick-concrete, brick-wood, reinforced concrete) - Urban vs rural	21 [a]	- Building standard, handbook, manual - Existing literature [182, 211, 218-220]	kg/m²

Table 21 (continued)

[173]	Gontia et al. (2020)	- Before 1930 - 1931 – 1950 - 1951 – 1980 - After 1981		- Building function	8	- Existing literature [183]	kg/m²
[174]	Lausselet et al. (2020)	- 2019 – 2020 - 2021 – 2025 - 2026 – 2030 - 2031 – 2080		- Building function - Renovation state	16 [a]	- Construction documents	kg/m²
[175]	Lederer et al. (2020)	- Before 1919 - 1919 – 1945 - 1946 – 1980	- 1981 – 2000 - 2001 – 2015	- Building function	20	- Evaluation of 66 sample buildings via construction documents, LCA inventory, on-site inspection	kg/m³
[143]	Romero et al. (2020)	- Before 1919 - 1919 – 1939 - 1945 – 1964	- 1965 – 1983 - 1984 – 1992	- Building function	10	- Evaluation of 12,043 sample buildings via existing literature [221]	kg/m² kg/m³
[176]	Guo et al. (2020)	- Before 1950 - 1960 – 1979 - 1980 – 1989	- 1990 – 1999 - After 2000	- Building function - Structure type (brick-concrete, brick-wood, reinforced concrete)	24 [a]	- Existing literature [170, 220]	kg/m²
[163]	Deetman et al. (2020)	---		- Building function - Urban vs rural	12	- Existing literature [h]	kg/m²
[177]	Tazi et al. (2020)	- Before 1919 - 1919 – 1945 - 1946 – 1970	- 1971 – 1990 - 1991 – 2005 - 2006 – 2013	- Building function - Structure type (brick, concrete, stone, wood)	21 [a]	- Existing literature [h]	kg/m²
[164]	Marinova et al. (2020)	---		- Building function	4	- Existing literature [h]	kg/m²
[178]	Gontia et al. (2019)	- Before 1920 - 1921 – 1950 - 1951 – 1980 - After 1981	- Before 1930 - 1931 – 1980 - After 1981[b]	- Building function	17	- Evaluation of 15 sample buildings via construction documents - Existing literature [183]	kg/m²
[207]	Wang et al. (2019)	---		- Structure type (brick-concrete, steel)	2	- Existing literature [222-224]	kg/m²

Table 21 (continued)

[208]	Guo et al. (2019)	---		- Structure type (brick-concrete, reinforced concrete)	2	- Existing literature [219]	kg/m²
[148]	Arora et al. (2019)	---		- Building function	1	- Evaluation of 5 sample buildings via construction documents	kg/m²
[179]	Miatto et al. (2019)	- Before 1902 - 1903 – 1954 - 1955 – 1969	- 1970 – 1981 - 1982 – 1996 - 1997 - 2007	- Building function	30	- Building standard, handbook, manual - Existing literature [h]	kg/m²
[180]	Heeren et al. (2019)	NS		NS	NS	- Existing literature [225]	kg/m³ [c]
[181]	Mesta et al. (2019)	---		- Building function - Structure type (adobe, brick, reinforced concrete)	3	- Evaluation of 120 sample buildings via building standard, construction documents, expert opinion, on-site inspection	kg/m²
[182]	Han et al. (2018)	- Before 1960 - 1960 – 1980 - 1980 – 2000 - 2000 – 2010		- Structure type (brick-concrete, reinforced concrete)	8	- Existing literature [213, 220, 226]	kg/m²
[183]	Gontia et al. (2018)	- 1880 – 1890 - 1880 – 1900 - 1890 – 1900 - 1890 – 1910 - 1900 – 1910 - 1910 – 1920 - 1920 – 1930 - 1930 – 1940 - 1930 – 1950 - 1940 – 1950	- 1940 – 1960 - 1950 – 1960 - 1960 – 1970 - 1960 – 1980 - 1970 – 1980 - 1980 – 1990 - 1980 – 2000 - 1990 – 2000 - 2000 – 2010	- Building function - Structure type (brick, brick-wood, concrete, wood)	46 [a]	- Evaluation of 46 sample buildings via construction documents	kg/m²
[2]	Stephan et al. (2018)	- Before 1900 - Before 1960 - Before 1980 - 1901 – 1960 - 1961 – 1970 - 1961 – 2015	- 1971 – 1980 - 1981 – 2000 - 1981 – 2006 - 2001 – 2006 - 2007 - 2015	- Building function - Building height (≤10m, >10m and ≤18m, ≥19m)	48 [a]	- Existing literature [227, 228]	kg/m kg/m² kg/m³ kg/#comp-onent

Table 21 (continued)

[184]	Cheng et al. (2018)	---		- Building function - Structure type (brick, reinforced brick, reinforced concrete, steel, steel-reinforced concrete, wood, other)	10	- Existing literature [229, 230]	kg/m²
[185]	Schiller et al. (2017)	- Before 1918 - 1919 – 1948 - 1949 – 1968	- 1969 – 1990 - After 1990	- Building function	16 [a]	- Existing literature [231, 232]	t/building
[186]	Condeixa et al. (2017)	---		- Building function - Floor counts	4	- Existing literature [g]	kg/m²
[166]	Kleemann et al. (2017)	- Before 1918 - 1919 – 1945 - 1946 – 1976	- 1977 – 1996 - After 1997	- Building function	15	- Evaluation of 66 sample buildings via construction documents, LCA inventory, on-site inspection - Existing literature [h]	kg/m³
[187]	Stephan et al. (2017)	- Before 1900 - Before 1960 - Before 1980 - 1901 – 1960 - 1961 – 1970 - 1961 – 2015	- 1971 – 1980 - 1981 – 2000 - 1981 – 2006 - 2001 – 2006 - 2007 - 2015	- Building function - Building height (≤10m, >10m and ≤18m, ≥19m)	48 [a]	- Existing literature [227, 228]	kg/m kg/m² kg/m³ kg/#component
[159]	Schebek et al. (2017)	- Before 1918 - 1919 – 1948 - 1949 – 1957 - 1958 – 1968	- 1969 – 1978 - 1979 – 1994 - 1995 – 2001 - After 2002	- Building function	96	- Evaluation of 19 sample buildings via construction documents, on-site inspection	kg/m³
[188]	Mastrucci et al. (2017)	- Before 1949 - 1949 – 1968 - 1969 – 1994 - After 1994		- Building function	8	- Building standard, handbook, manual - Existing literature [233, 234] - Expert opinion	kg/m² [c]
[189]	Surahman et al. (2017)	---		- Construction cost and lot size	3	- On-site inspection	kg/m³

Table 21 (continued)

[190]	Schiller et al. (2017)	---		- Building function	2	NS	NS
[191]	Kalcher et al. (2017)	- Before 1919 - 1919 – 1944 - 1945 – 1960 - 1961 – 1970	- 1971 – 1980 - 1981 – 1990 - 1991 – 2000 - 2000 - 2010	- Building function	8	- Existing literature [235-237]	m^3/m^3 [e]
[158]	Ortlepp et al. (2016)	---		- Building function	7	- Evaluation of 252 sample buildings via existing literature [238, 239]	t/m²
[192]	Ortlepp et al. (2018)	- Before 1918 - 1919 – 1948 - 1949 – 1978	- 1979 – 1990 - After 1991	---	5	- Evaluation of 36 sample buildings via construction documents	t/m²
[193]	Marcellus-Zamora et al. (2016)	---		- Building function	6	- Existing literature [h] - Expert opinion	kg/m²
[167]	Wiedenho-fer et al. (2015)	---		- Building function - Structure and envelope type - Climate zone	72	- Existing literature [233, 240]	Mt/building
[156]	Sugimoto et al. (2015)	- 1959 - 1971 - 1974	- 1981 - 2000	- Structure type (reinforced concrete, steel, wood) - Floor counts	20	- Existing literature [241]	kg/m²
[155]	Tanikawa et al. (2015)	---		- Structure type (reinforced concrete, steel, steel-reinforced concrete, wood, other)	5	- Existing literature [242]	kg/m²
[153]	Turan et al. (2015)	---		---	6	- Evaluation of sample buildings via BIM model [f]	kg/m²
[194]	Reyna et al. (2015)	- Before 1950 - 1950 – 1990 - After 1990		- Building function	42	- Existing literature [217, 243, 244]	NS
[195]	Ergun et al. (2015)	- Before 1930 - 1931 – 1960 - 1961 – 1975	- 1976 – 2000 - After 2001	---	5	- Evaluation of sample buildings via construction documents [f]	m³/building

Table 21 (continued)

[196]	Han et al. (2013)	- 1980s - 2000s	- Urban vs rural	4	- Existing literature [213, 245, 246]	kg/m²
[197]	Hu et al. (2010)	---	- Structure type (brick-concrete, concrete, shearing-force)	3	- Existing literature [246]	kg/m²
[198]	Hu et al. (2010)	---	- Structure type (brick-concrete, steel-concrete)	2	- Evaluation of sample buildings via construction documents [f]	t/100m²
[199]	Tanikawa et al. (2009)	---	- Building function - Structure type (brick, reinforced concrete)	3	- Existing literature [247]	kg/m²
		---	- Building function - Structure type (reinforced concrete, steel, wood)	4	- Building standard, handbook, manual	kg/m²
[200]	Lichtenste-iger et al. (2008)	- 1900 – 1925 - 1926 – 1950 - 1951 – 1975 - 1976 – 2000	- Building function	16	- Evaluation of 11 sample buildings via construction documents, on-site inspection	t/building
[165]	Bergsdal et al. (2007)	- Before 1900 - 1901 – 1920 - 1921 – 1940 - 1941 – 1945 - 1946 – 1960 - 1961 – 1970 - 1971 – 1980 - 1981 – 1990 - 1991 – 2001	- Building function	45	- Expert opinion	kg/m²
[201]	Hashimoto et al. (2007)	---	- Building function - Structure type (reinforced concrete, steel, steel-reinforced concrete, wood)	8	- Existing literature [248]	t/m²
[209]	Muller (2006)	---	---	---	- Amount of produced material per floor area	t/m²

[a] Not all categories exist in every time period.

[b] 3 time periods for non-residential buildings and 4 time periods for residential buildings.

[c] Material intensities were determined for every component (e.g., roof) of every archetype.

[d] Material intensity (#brick/m^2) represents the number of bricks per unit area of an external wall.

[e] Material intensity (m^3/m^3) represents the volume of timber in m^3 per gross volume of a building.

[f] Number of sample buildings was not specified.

[g] Books, databases, journal articles, or reports, which were used as existing literature, were not specified.

[h] Several books, databases, journal articles or reports were used as existing literature. Refer to the article.

LCA and NS refer to life cycle assessment and not specified, accordingly.

4.6 Approaches for Development of Material Stock Analysis

A detailed review of articles revealed different approaches for developing MSA. As displayed in Figure 16, the approaches can be clustered into bottom-up, top-down, and remote sensing. While selecting an approach to conduct MSA depends on the objectives of a study as well as available data and tools, it has impact on how the results of MSA can be utilized to redirect entire or some fractions of materials to a resource loop. Therefore, it is important to summarize and critically assess the advantages and shortcomings of these approaches, especially from the lens of the circular economy. Figure 16 demonstrates a basic sketch for the modeling structure of different MSA approaches. The directions of arrows indicate the steps for developing an MSA model that starts from acquiring input parameters or variables and ends with meshing the parameters with material intensity.

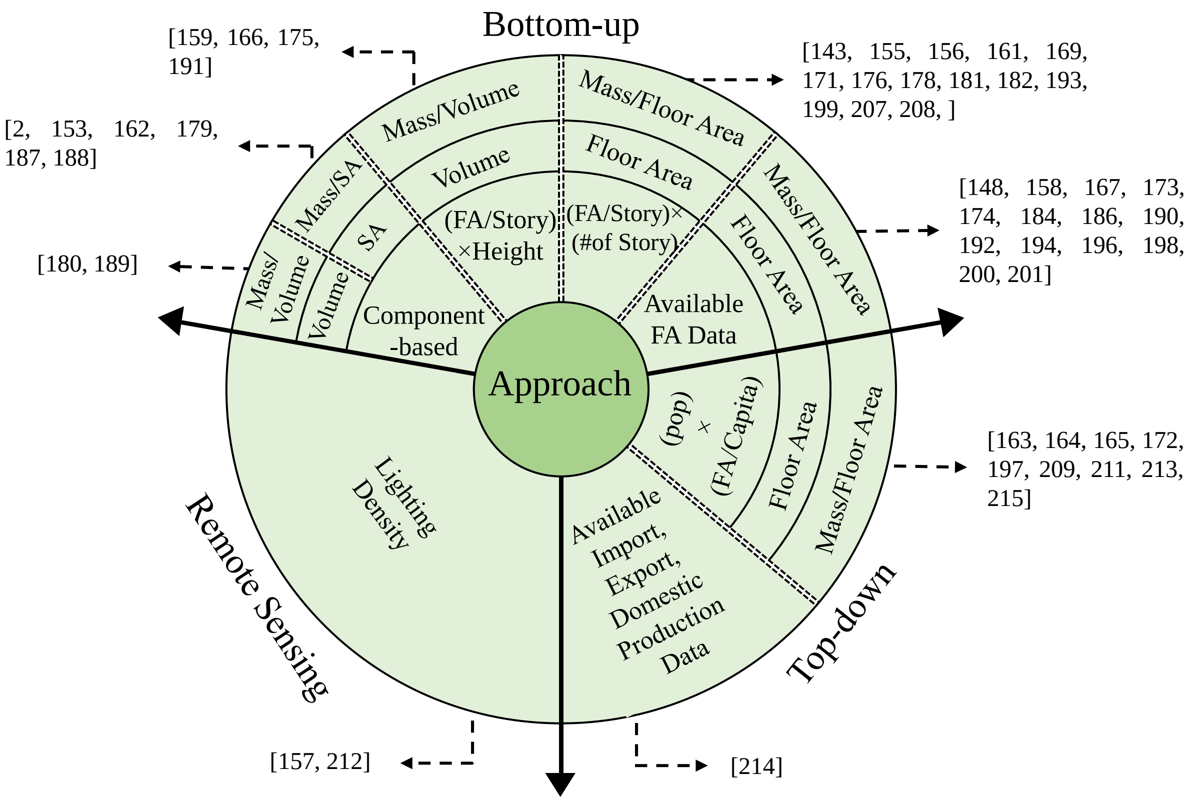


Figure 16 Approaches for quantifying and spatializing building materials at scale. Note: Surface Area (SA), Floor Area (FA), and Population (pop)

4.6.1 Bottom-Up Approaches

Primarily, bottom-up approaches are used to quantify and geolocate materials by combining *physical attributes* of buildings (i.e., floor area, volume, surface area) with *materials intensity*. These approaches provide the opportunity to produce finer results (usually at the building level) compared to other approaches. While the development of bottom-up models is data intensive and laborious, recent progress in GIS with increased data transparency and mandates in cities and municipalities have facilitated the creation of these models. To obtain the physical attributes of buildings, distinct methods were proposed and tested, which are critically reviewed in the rest of this sub-section.

Floor area from existing inventories. Some cities and countries have inventories containing either floor area of individual buildings [148, 174, 184, 186, 196, 201], that are coded based on a variety of identification (ID) tools such as property tax ID, or average floor area for different archetypes [173, 192, 194, 198]. Lausselet et al. [174] used the individual building floor area of an under-development neighborhood in combination with material intensity and quantified metallic and non-metallic materials. Similarly, Cheng et al. [184] and Condexia et al. [186] derived the floor area of every building from the Taipei City Construction Management Office and Rio de Janeiro Construction License databases, respectively to estimate accumulated materials at the city-scale. Hashimoto and colleagues [201] obtained the floor area of individual buildings from the Fixed Asset Prices Report and utilized it in conjunction with materials intensity to estimate the total materials embedded in the Japanese building stock. Gontia et al. [173] derived both the average usable floor area for every archetype and the number of buildings under different archetypes from national databases. Through multiplying the usable floor area and the corresponding number of buildings, the total floor area and further material stock of Sweden's residential buildings were calculated [173]. Using average floor area per archetype inhibits geolocating or mapping materials at building-level that is important to efficiently recirculate materials to consumption loop through different means (e.g., reuse, recycle, repurpose). Also, it causes over- or under-estimation of floor area, which exacerbates uncertainty of estimated materials.

Besides data about floor area, there are inventories or databases that contain the number of buildings. Wiedenhofer et al. [167] and Lichtensteiger and Baccini [200] extracted the number of buildings per archetype from available databases in European Union and Switzerland, accordingly. The former compiled the data from multiple sources (i.e., Eurostat, European Housing Statistics reports, and national databases of different European countries), and the latter obtained the data from a previous study [249]. In both studies, the number of buildings per archetype was multiplied by materials intensity in the form of mass per building of the corresponding archetype to estimate accumulated materials. Although incorporating the number of buildings per archetype resolved miscalculation due to using the average floor area of every archetype, in [167] floor area and in [200] floor area and structure type were not included for classifying archetypes and determining the material intensity, respectively (see Table 21). Thus, materials intensity in both studies did not reflect the influence of the diversity of building size or structure type on materials quantity and composition.

Floor area from GIS analysis. As displayed in Figure 16, floor area per story has been commonly employed in bottom-up models. This parameter is defined as the area of a representative polygon of a building and is obtainable from GIS databases. Utilizing the areas of polygons can provide two advantages. First, information about materials (i.e., amount and composition) can be geolocated at a building-level. The geolocation at this fine-scale allows local businesses and companies to plan for less destructive demolition and handling, sorting, storing, and trade of components and materials. Second, GIS-based software platforms like ArcMap offer drawing and geometric calculation tools. These tools enable the refinement of the representative polygons to match the real-world shape of buildings and a more accurate estimation of the polygon areas of the buildings.

Several studies obtained the floor area of every building in studied regions through multiplying floor area per story by floor counts (number of stories for a building), which were both available via GIS data of cities and countries [155, 161, 171, 182, 199, 207, 208]. For China, this method was adopted for many cities (e.g., Beijing, Shanghai) and the estimated floor area of individual buildings was combined with the material intensity to quantify material stock [171, 182, 207, 208]. Tanikawa and colleagues [155, 199] merged current digital maps (in GIS format) with old aerial photographs, paper maps, and ground-level photographs to construct a 4-dimensional GIS database of Japan and retrieve floor area per story and floor counts of buildings. Further, floor area per story was multiplied by floor counts and the material intensity to quantify and spatialize materials throughout time. The 4-dimensional GIS method, which was first introduced by Tanikawa, allowed for synthesizing time as the 4th dimension into GIS analysis and tracking materials over time. In addition, material geolocation offered the ability to draw the spatial distribution of materials across a region; for example, Tanikawa showed that 80% of building materials were concentrated in 20% of land in Japan, mostly in metropolitan areas [155]. In some cases, the floor counts were not readily available in GIS databases; thus, different methods have emerged to resolve this shortcoming.

Sugimoto et al. [156] conducted shadow analysis based on aerial images to estimate floor counts and complete the GIS database of a residential stock at the district-level. The accuracy of shadow analysis is tied to the quality of images and varies from image to image [250]. Moreover, the feasibility of applying this method to a larger scale or dense metropolitan area is not clear. Marcellus-Zamora and colleagues [193] utilized images from Google Earth's Street View to retrieve floor counts of new buildings in their studied region. For older buildings, with available height information in GIS database, the authors converted individual buildings' heights to floor counts assuming a floor-to-floor height of 3.6 m [193]. Similarly, Guo et al. [176] converted heights to floor counts based on a 3.5 m floor-to-floor height assumption. Another study determined floor-to-floor height according to building function [17]. Other articles used simple assumptions regarding floor counts to estimate total floor area and quantify materials [169, 178].

Acquiring floor counts through manual processing of aerial or street-level images is practical at a small spatial scale or for a limited number of buildings like [193]; however, implementing this strategy for a city or country requires automation of the process using artificial intelligence methods [251].

Some articles calculated the average floor area of archetypes via multiplying the average floor area per story by the average floor counts for every archetype. For example, Romero et al. [143] estimated the average floor area of ten archetypes (see Table 2) for a district located in London, GB, and quantified accumulated timber in residential buildings. Likewise, Mesta and colleagues [181] measured the amount of concrete, timber, brick, steel, and other materials in Chiclayo, PE's residential sector. Incorporating average values for archetypes instead of values for every individual building streamlines the complexity of the process and lessens computational challenges, but it may compromise the accuracy of outcomes.

Volume from GIS analysis. The height of a building impacts the fraction of in-use materials [159]. For instance, a one-story building (20L×20W×4H) has an equal floor area to a two-story building (20L×10W×4H); however, it contains a double amount of roofing materials and 33% less external wall materials. While height sometimes was implicitly considered in building function and consequently in the archetype classification of several studies, few articles progressed further and directly included height in the analyses [159, 166, 175, 191]. This method has been particularly popular in Austria and Germany. For Vienna, AT, floor area per story, and the height of individual buildings were obtained from the Municipal Department's GIS database and buildings' volumes were estimated [166, 175]. Combining with materials intensity (mass per volume of a building), the magnitude of several metallic and non-metallic materials was calculated and mapped. Applying this method at a country-scale, Kalcher et al. [191] multiplied the average floor area per story of different archetypes, obtained from the Austrian Statistical Office, by the average height (2.5 m or 3 m). The volume of archetypes was combined with the number of buildings and material intensity of timber for the corresponding archetype to calculate accumulated timber in Austrian's residential stock. The major barrier confronting the future of this method is that use of volume-based materials intensity is currently infrequent, as shown in Table 21. Therefore, materials intensity may not be transferred and used for building stocks that are less similar to building stocks, for which volume-based materials intensity are available.

Volume and surface area of components from GIS analysis. Geometric tools in GIS software platforms enable the calculation of surface area or volume of building components (e.g., roof, external wall, window). Synthesizing surface area or volume with materials intensity of different components provides the opportunity to list the accumulated materials in different components. Thus, component-level material analysis aids in more efficient return of materials into the resource loop and allows for distinguishing between the recovery paths of materials that can be retrieved from various components. As an example, timber from beams has a different recovery path compared to timber retrieved from doors and windows. Although some studies combined the surface area or volume of components with their materials intensity, the similar materials from different components were summed up and reported in an aggregated fashion [2, 153, 162, 179, 180, 187-189]. Therefore, the outcomes of these studies were not useful for identifying more circular obsolescence or recovery pathway with less downgrading based on building components.

4.6.2 Top-Down Approaches

The top-down approaches are established based on either the relationship between driving forces (e.g., population, lifestyle, gross domestic product (GDP)) and building material stock [84] or economic and trade data [150]. The benefits of these approaches are that they are less data-intensive compared to bottom-up approaches and they incorporate social- and economy-materials interactions. Hence, one is capable of employing these approaches to develop prospective materials stock models based on a variety of socio-economic scenarios in the future. Also, the conceptualizations that are illustrated by top-down models can be useful for policy making.

A model, that used population, lifestyle, and material intensity as input variables, was first introduced by Muller [209] and later employed by several other researchers [163-165, 172, 197, 211, 213, 215]. One of the metrics that represents lifestyle or living standards in a region is floor area per capita [252]. In Muller's model, the average floor area per capita was multiplied by population to estimate the floor area of buildings; further, the floor area was multiplied by the material intensity and total accumulated materials in Netherlands building stock were estimated [209]. Deetman et al. [163] and Marinova et al. [164] applied the same methodology to quantify building materials in 26 regions across the world. Although this top-down method unlocks the capability of large spatial scale analysis (e.g., country-scale and global-scale), it lacks information about the location of materials in a region. In addition, the accuracy of floor area per capita as one of the key variables is uncertain. Another drawback is that the population and the floor area per capita are usually aggregated over an entire building stock rather than being classified based on archetypes; thus, the end outcomes (floor area and quantity of materials) may vary significantly from real-world quantities.

As explained above, another type of top-down approach was based on economic and trade data. Fishman and colleagues [214] estimated the in-stock wood, steel, metals (i.e., copper, aluminum, tin), and minerals (i.e., stone, sand, limestone, gravel, clay) of Japan and the United States utilizing domestic production, import, and export data obtained from two previous studies [253, 254]. They calculated the in-stock materials in year *t* by estimating consumption in year *t* (sum of domestic extraction and import minus export) and survived materials from previous years. While estimation of accumulated materials can be provided by this method, there are two shortcomings. First, the accuracy and certainty of results are tied to the quality of trade data. Second, the data is usually at a country-scale, which inhibits the ability to locate and map materials.

4.6.3 Remote Sensing Approaches

A few studies leveraged satellite imagery to account for the material stock of buildings [157, 212]. He et al. [157] selected 260 circular sample points (with a radius of 50 m) in Jinchang, CN. Through analyzing satellite images for sample points, the total accumulated materials in buildings were roughly estimated. In another study, Hsu et al. [212] explored the relationship between nighttime light images and the quantity of accumulated steel in buildings of four Japanese cities, obtained from a previous study. They developed a linear regression model to correlate nighttime light and steel in buildings. Further, the linear regression model was utilized in conjunction with nighttime light images of Taiwan, South Korea, and China to estimate accumulated steel in buildings of these countries. Although this remote sensing method is rapid and beneficial in providing a broad perspective of steel in buildings, it does not offer specific information essential for circular usage of steel upon deconstruction of buildings.

In summary, bottom-up models provide more in-depth information about available materials in buildings compared to other approaches as they offer opportunities for locating materials and component-level analysis. While top-down and remote sensing approaches are viable to understand the balance of materials in the building sector and to depict a broad perspective for policy makers, they lack detailed information, which is necessary for using stockpiled materials as secondary resources.

4.7 Materials Inventory

One of the goals of this chapter was to compile an inventory of the composition and quantity of materials. This inventory serves two purposes. First, it can be employed to develop a global marketplace or blockchain-based network for secondary building materials. Second, it enables the adoption of the current body of knowledge for understanding the distribution of materials in buildings and validating future studies. A total of fifteen materials and "Other" were found in thirty-eight of the reviewed papers (see Table 22). The rest of reviewed papers (twenty-four) were not included in this inventory because of the following reasons: 1) they were review articles, 2) they did not estimate the quantity of materials, 3) they estimated the total material in the building stocks. There are a few details about the composition of materials in the inventory:

- Although concrete is made from aggregate and cement, some papers estimated concrete, aggregate and cement, separately.
- While one of the main ingredients of asphalt is aggregate, few papers reported aggregates separately.

- Minerals in construction include a wide range of materials. However, different papers categorized different materials as minerals. Also, some studies did not provide further specifications about what materials are considered as minerals.
- “Other” included a variety of materials in different papers.

In the class of papers that formed the materials inventory in Table 22, five papers solely focused on one material [143, 167, 197, 201, 209]. Twenty-eight papers reported that concrete or a combination of aggregate and cement had the highest mass compared to the rest of the materials. This statistic shows that researchers have paid special attention to concrete as one of the highest intensity materials in buildings. However, there are noticeable challenges, that require tremendous industrial, technological, and academic efforts. First, traditional concrete is one of the most essential building materials and the use of alternative materials with a lower level of degradation is currently less widespread in the construction industry. The second challenge is directly related to the circular economy. Upon demolition of a building, concrete components are usually crushed and used as aggregate in various forms like recycled concrete; thus, they typically do not retain the original value. Although recycled concrete reduces waste and slows the resource loop, it does not completely prevent resource depletion because new cement and additives are needed. Strategies like reusing and repurposing concrete components are nascent and need substantial research efforts to become industrialized. The integrity of recovered concrete components, disassembling, and shipping process along with the structural design of new buildings based on dimensions and specifications of recovered components are the roadblocks to reusing and repurposing these components.

Table 22 Mass of materials estimated and reported by the reviewed papers. The unit is in million metric ton. Note: NBHD and NS are abbreviations for neighborhood and not specified, respectively

Reference	Author/s (year)	Spatial Boundary	Country	Year of MSA	Concrete	Wood	Brick	Gypsum	Aggregate	Asphalt	Steel	Lime	Glass	Cement	Insulation	Aluminum	Copper	Minerals	Plastics	Other
[161]	Mollaei et al. (2021)	City	CA	2018	15	3.5	5.5	2	8.5	0.5	1.5									
[169]	Bradshaw et al. (2020)	Country	AG	2004	2.9	0.2			1.2		0.4									
[171]	Mao et al. (2020)	City	CN	2018		6.9	331.7		1233.9		42.6			632						23.2
[172]	Gao et al. (2020)	City	CN	2020	165	6	70	4		1	15	5	4							
[173]	Gontia et al. (2020)	Country	SE	2017		35.04	35.04		43.8		52.56							249.66		26.28
[175]	Lederer et al. (2020)	City	AT	2015	155.9	6.7	127.3				5.9		0.5		0.6				0.4	47.8
[143]	Romero et al. (2020)	District	GB	2016		0.1														
[176]	Guo et al. (2020)	District	CN	2018		0.4	4.7		15.8		0.9	0.7	0.1	3.6						
[163]	Deetman et al. (2020)	World		2020	286427	11516					16748		2269			1395	340			
[164]	Marinova et al. (2020)	World		2018	243000	10200					12000		1780			1200	190			
[178]	Gontia et al. (2019)	City	SE	2016		2	5.8		12.3	5.5	4.3							29.7		1.9
[207]	Wang et al. (2019)	NBHD	CN	2020	0.1		0.1													
[148]	Arora et al. (2019)	Country	SG	2016	125.7						6.5									
[179]	Miatto et al. (2019)	City	IT	2007	13.7	0.7	17.6				0.9									10
[180]	Heeren et al. (2019)	Country	CH	2015	527	31	203				17				17			276		2
[181]	Mesta et al. (2019)	City	PE	2007	14.1	0.2	5.6				0.4									4.2

Table 22 (continued)

[182]	Han et al. (2018)	City	CN	2010		5	95		330		20	10	2.4	70						
[184]	Cheng et al. (2018)	City	TW	2014	150.1	2.2	15.3				15.5		0.2			0.1				
[186]	Condeixa et al. (2017)	City	BR	2010	51.7	4.3	1.9		13.2		2.3	1.5	0.1	3.2					0.02	0.49
[166]	Kleemann et al. (2017)	City	AT	2013	152	7.4	129.2				5.9					0.1	0.1	30.4	0.6	55.2
[159]	Schebek et al. (2017)	City	DE	2011	0.7	0.0	0.3				0.1									
[188]	Mastrucci et al. (2017)	City	LU	NS	1.1	0.1	1.6				0.1									0.6
[189]	Surahman et al. (2017)	City	ID	2012	48	14.1	45.9	0.9	51		3			10.8						126.2
		City	ID		16	5.2	14.8	0.1	15.4		1			3.3						38.3
[190]	Schiller et al. (2017)	Country	DE	2010	6584	328	2128	168			883		331					4747	226	55
[158]	Ortlepp et al. (2016)	Country	DE	NS	2492	152	1325				532				59					2222
[192]	Ortlepp et al. (2018)	Country	DE	2010	1502.1	37.6	1089				187.8				37.6					901.3
[193]	Zamora et al. (2016)	District	US	2012	1.9		0.2		0.1	0.1	1.2									0.1
[167]	Wiedenhofer et al. (2015)	Continent		2009	14500													20500		
[214]	Fishman et al. (2014)	Country	US	2005		1530					790							36000		92
		Country	JP	2005		8200					970							96000		1600
[196]	Han et al. (2013)	Country	CN	2008		290	3760		21680	60	450	670	130	4850					10	10
[197]	Hu et al. (2010)	Country	CN	2005	559															
[198]	Hu et al. (2010)	Country	CN	2004-2008		1.58	4.8		111		21.9			25						
[199]	Tanikawa et al. (2009)	District	GB	2004	0.5	0.1	0.5		0.6											0.5
		District	JP	2004	6.8	0.1	0.1		2		0.6									0.5

Table 22 (continued)

[200]	Lichtensteiger et al. (2008)	Country	CH	2000		48.5	651.2	87.3	0.5	
[165]	Bergsdal et al. (2007)	Country	NO	2000	98	19.8				
[201]	Hashimoto et al. (2007)	Country	JP	2010						9500
[209]	Muller (2006)	Country	NL	2000	780					

Aggregate, brick, gypsum, stone, etc. are considered construction minerals. Four papers estimated that construction minerals had the highest quantity compared to the remaining materials [173, 178, 201, 214]. Gontia et al. [173] considered concrete, plaster board, etc. as minerals and found that minerals had the highest share in residential buildings in Sweden. Fishman et al. [214] reported that in the United States and Japan, construction minerals had higher percentages compared to wood and steel. As a variety of construction materials can be considered minerals, a more specific classification of the type of mineral materials or mineral products aids in selecting a proper strategy for recovering and returning materials or products to resource loop.

Besides concrete, minerals, and a combination of aggregate and cement, brick was reported as the material with the highest share in a few building stocks. Miatto et al. [179] and Mastrucci et al. [188] found brick as the most predominant material in Padua, IT and Esch-sur-Alzette, LU, accordingly. Among thirty-eight studies in the inventory, steel was quantified by thirty studies. The relatively high inclusion of steel in MSAs together with the facts that 98% of structural steel is returned to the resource loop provide a great source of data to create a marketplace for secondary steel. While the mass of plastics in buildings is significantly lower than the rest of the materials, the building and construction sector is recognized as one of the major consumers of plastics compared to other sectors [255]. From another perspective, plastics are lighter than most building materials; thus, a different denominator than mass such as environmental impacts may alter the distribution of materials. As displayed in Table 22, few papers estimated plastics accumulated in building stocks but, further disaggregation about the type of plastics such as PVC, LDPE, thermosets, etc. was not performed [166, 175, 186, 190, 196]. Overlooking quantification of plastics and identification of types of plastics in majority of reviewed articles is a substantial gap in the existing literature. To overcome environmental burdens caused by plastics pollutions and waste management difficulties, type and quantity of plastics should be estimated for building stocks.

4.8 Discussion

The increasing need to preserve natural resources, reduce demolition waste, and explore urban mining has prompted demands for more information and knowledge about available materials in different sectors including buildings. High monetary values, increase in consumption, and scarcity of some products or materials such as critical materials and rare earth elements [256, 257] have resulted in some knowledge about their accumulation and recovery, but the material stock analysis of buildings is a relatively new area. The remaining barriers and gaps for the progress of the field are:

- Reviewing the geographic location of the research papers, few to no studies analyzed material stocks of buildings in North America, South America, Africa, and Asia (except for China and Japan).
- Analyzing the embedded components in building stocks is currently overlooked. Only one study conducted a parallel analysis of material and component stocks [148].
- There is a lack of coherence in defining building function subcategories and a scarcity of differentiation between accumulated materials in structural versus non-structural components in the existing literature.
- The results of building MSAs are rarely validated.
- Limited data – especially publicly available data – about the design and construction system of buildings especially for older stocks not only complicates or hinders the development of

building MSA models but also compromises the calculation of materials intensities of archetypes. This shortcoming will result in propagating uncertainty of material quantification from archetypes to entire building stock.

- Another barrier pertains to deficiencies of GIS data. GIS data of buildings usually do not contain detailed geometric properties of buildings like the height or floor counts, especially in the United States. Although remote sensing methods like LiDAR analysis [147] and processing space-born sensor data [258] have been proposed to retrieve building height, this is an extra step in the creation of bottom-up material stock models. To resolve this barrier, cities and countries can consider making 3D models of existing buildings at scale. Practical applications of MSA results by urban mining and waste management companies are tied to the geolocation of materials, which is more feasible via bottom-up models. Hence, thorough GIS data not only helps with the development of bottom-up models but also increases the possibility of using outcomes of MSA in real-world applications.

The high concentration of building MSAs research in developed countries may be attributed to an abundance of design and construction technologies such as BIM software platforms in developed countries. Knowledge about the accumulated building materials in developing countries, where the frequency of construction and demolition is higher, is essential for opening more secondary resources and fostering the circularity of the building sector. Furthermore, emphasis on analyzing building component stock and differentiation between materials accumulated in various components will increase the possibility of reuse and adaptive reuse over recycling. In addition to filling these gaps, addressing data barriers is important.

Policy and decision-makers can contribute to solving data barriers through instituting regulations and policies, which enforce compiling and reporting composition, quantity, and specification of construction products and materials, as a part of the construction and renovation permit process. These regulations and policies would enrich publicly available building databases at the city- and district-scales. Additionally, specifications of products and materials like instructions for disassembly will aid in selecting end-of-life strategies.

4.9 Conclusions

Recently, discussion over the role of circular economy to achieve the United Nations Sustainable Development Goals of Responsible Consumption and Production has increased. The major motivation of this chapter was to coalesce the findings of existing building MSAs, which are needed as the cornerstone of circularity for the building sector. This chapter evaluated the existing literature in accordance with scopes, boundaries, archetypes and material intensities, and approaches to identify barriers, gaps, and opportunities in the field.

A major finding of this work showed that top-down and remote sensing approaches are less time-consuming to develop and offer a broad understanding of the balance of materials in building stocks; nonetheless, they are less informative for circular economy strategies compared to bottom-up approaches. Also, current data deficiencies may adversely impact both developments of bottom-up MSA models and accurate determination of material intensities of archetypes. Reviewing the studies showed that the mass of concrete was higher than other materials in the majority of studies while the mass-based distribution of other materials varied considerably. Finally, plastics and their specific types were rarely included in MSA studies, which rises a discussion about utilizing a different denominator than mass for analyzing the material stock of buildings in the future.

MSA can aid regional policy and decision makers. Understanding the distribution of material stocks in a region may aid in deciding on investing in technologies and equipment for construction material reuse. Furthermore, MSA outcomes can provide policy makers with information about materials that are widely available in a building stock; thus, they can consider incentives for designers and contractors. Given these benefits, it is useful to identify future opportunities, which can facilitate conducting building MSA research.

Convergence of building science's disciplines with MSA brings opportunities for assessing in-use materials of building stocks. One of these disciplines is physics-based urban building energy modeling. An urban building energy model contains 3D models of hundreds of buildings; therefore, it is a rich repository of geometric properties of buildings including height, floor counts, and footprint. The data from these models can be employed to resolve deficiencies in GIS data. Furthermore, classifying a building stock into archetypes is a common practice in urban building energy modeling. Available archetypes can also be utilized for archetype classification and determining material intensity for future MSA studies. There are models at the urban scale in several United States cities that can be beneficial for conducting building MSA. Mohammadiziazi et al. [147] created a comprehensive database of non-residential buildings in Pittsburgh, US, that contained geometric properties along with envelope properties (i.e., window to wall ratio and external wall materials). Also, Chen et al. [102] assessed energy conservation measures of offices and retail buildings located in six districts in San Francisco, US based on an urban building energy model. Heiple and Sailor [98] and Cerezo et al. [97] developed similar models for residential and non-residential buildings in Houston, US, and Boston, US, respectively. Moreover, Breunig and colleagues [259] projected floor area of residential and non-residential buildings in the state of California, US until 2050, which can be employed in concert with material intensity to create a prospective MSA. Another important point, which is can be addressed in future works, is related to ownership of construction materials and products. The general concept of MSA which is tracking construction materials over time and space can be employed to create an ownership system in which construction materials will be tracked and collected by original manufacturers to be disassembled and reused.

5.0 Quantifying and Spatializing Buildings Material Stock and Renovation Flow for Circular Economy

The research presented here addresses objective four. Specifically, it answers the question 'What are the quantity and type of accumulated materials and materials, which will become available due to renovation, in the different components of an existing commercial building stock?' The content of this chapter is currently under review:

Mohammadiziazi, R., & Bilec, M. M. (2022 submitted). Quantifying and Spatializing Commercial Building Material Stock and Renovation Flow for Circular Economy. *Journal of Cleaner Production*.

5.1 Introduction

All phases of a building's life cycle – material use, construction, maintenance and renovation, and deconstruction – result in resource use and depletion, environmental impacts, and waste. The rapid pace of urbanization and economic growth in nations have increased the amount of accumulated materials in buildings located in cities and urban areas [148, 260]. Thus, existing buildings in cities have the potential to serve as repositories of materials and products, in the context of urban mining. The re-use or repurposing of building stock materials, when needed, is a strategy in the circular economy for the built environment [261]. Our current linear system of take, make, and waste, has led to deleterious environmental impacts, while a circular economy may offer environmental benefits [262]. Despite the proposed benefits of a circular economy, currently, a portion of materials are recovered and returned to the resource loop while preserving their original values. In the U.S., 22% of construction and demolition waste (by weight) was used for manufacturing new products in 2018 and the remaining waste was either downgraded (54%) or sent to landfills (24%) [144]. The linear system has resulted in decreasing the value of the materials both in monetary terms and use, along with contributing to the landfilling of valuable materials.

Unlike knowledge about the *primary* resource of building materials and products that are widely accessible, there is a gap in knowledge about accumulated building materials. The practical implementation of circular economy in buildings requires an understanding of basic questions. What material is available in existing buildings? When will the materials be available? Where will the materials be located? How much material will be available from the renovation of buildings? Building material stock analysis (MSA) is a tool for tracking and mapping materials over time and space that can be used to answer some of the questions to aid in fostering a circular economy for the building sector. Given that in the U.S., 75% of raw materials that enter the manufacturing industry are used for producing building materials and products [3], and a significant magnitude of construction and demolition waste are generated every year (e.g., 600 million ton of construction and demolition waste in 2018) [5], the role of building MSA is crucial in achieving circularity, reducing environmental impacts, and reducing waste. Therefore, in this chapter, a bottom-up MSA model for a commercial building stock was developed. Pittsburgh, PA was used to actualize the MSA model and then analyzed the accumulated materials, explored the renovation flow of materials during a specific time period, and advanced the field by filling existing gaps in the current body of literature.

Analyzing the material stock of buildings is an emerging field that has been progressing among industrial ecology and building sustainability experts, in the last decade [162]. Approaches for conducting building MSAs can be categorized into three major classes: top-down, remote sensing, and bottom-up [150, 151, 263]. Muller [209] introduced a top-down method, which was later employed by several studies [163-165, 172, 197, 211, 213, 215], to assess the concrete stocks of residential buildings in the Netherlands. In this method, the author estimated the floor area of buildings by multiplying the population by floor area per capita. Then, the floor area was aggregated with the intensity of concrete and the accumulated concrete in the Netherland's residential buildings was calculated [209]. Gao et al. [172] used this top-down method to analyze the material stock of residential buildings in Shanghai, China. Their analysis showed that the accumulated materials increased 41-fold from 1950 to 2010, and the rural-urban transition regions had the highest accumulated materials compared to rural and urban regions because of more affordable housing prices for urban migrants [172]. The advantages of analyzing material stocks based on floor area per capita are that this method is timesaving, can be applied to large spatial scales, and can be utilized together with future projections of floor area per capita to predict material metabolism and accumulation in the future. Applying this top-down method at the global scale, Deetman et al. [163] projected that the demand for building materials would increase by 2050, and 71% of the demand for aluminum and 55% of the demand for steel, wood, and copper could be supplied from resources available in existing building stocks.

Another top-down method established inflows and outflows based on economic systems, such as the imports, exports, and domestic production of materials [263]. The difference between the flows was then assumed to be 'material stock' [214]. Using this top-down method, Fishman et al. [214] estimated the accumulated stocks of timber, minerals, iron, and other metals for the countries of Japan and the U.S., and they found that both countries had similar material stock per capita by 2005.

Similar to top-down methods, remote sensing methods are less time-consuming [263]. For example, He et al. [157] estimated the total volume of materials in the building stock of Jinchang, China through high-resolution satellite images and remote sensing techniques. The authors found that 5,513,171 m^3 of materials were accumulated in every hectare of land in 2015 [157]. Top-down and remote sensing approaches can provide a broad overview of the materials in existing buildings of a region, which are useful for policy and a general understanding of building material flow. On the other hand, both approaches are limited in the level of detailed information they can capture about material types and the location of materials at the individual building level, which are essential for answering the aforementioned questions and consequently implementing circular economy strategies. Thus, the bottom-up approach can be utilized to overcome these shortcomings.

In general bottom-up methods are capable of quantifying and spatializing material stock at the individual building level by combining variables that represent physical attributes of buildings (i.e., floor area, volume, surface area of components, volume of components), with material intensity coefficients (MICs). Physical attributes of buildings are obtained either from available inventories in cities and countries or through geographic information system (GIS). Several studies used the former to develop MSAs at the city- or country scale [148, 158, 167, 173, 174, 184, 186, 190, 192, 194, 196, 198, 200, 201]. Cheng and colleagues [184] derived the floor area and the MICs of buildings from the Taipei City Construction Management Office inventory and previous studies, respectively for quantification and spatialization of building material stocks in Taipei City, Taiwan. Their investigation showed that concrete (82%) had the largest portion of materials by mass followed by steel (8%) and brick (8%). Moreover, applying the lifetimes of buildings to their MSA model, the authors predicted the approximate time the materials would be available when buildings were deconstructed [184]. Examining the possibility of using this method at a country scale, Hashimoto et al. [201] obtained the physical attribute data of buildings and quantified the construction minerals of the Japanese building stock.

While utilizing physical attributes such as the floor area from available inventories bypasses GIS analysis, this bottom-up method does not account for a building's floor count or height, both of which could have a significant impact on the fraction of materials [159, 263]; thus, the outcomes are associated with uncertainty. To mitigate this uncertainty, a bottom-up method was introduced by Tanikawa and Hashimoto [199] for the first time in which the floor count of buildings was integrated with footprint area, obtained from GIS, to estimate the floor area of buildings [263]. Employing GIS also allowed for mapping and spatial analysis of materials. In the study, Tanikawa and Hashimoto [199] used their proposed method to analyze the building material stock of two urban areas in the UK and Japan over one hundred and fifty years. The 4d-GIS databases of the urban buildings were constructed from a combination of street-level photos, aerial photos, paper maps, and digital maps to estimate the footprint area and floor count, and further floor area of buildings over time. They found that for Salford Quays, UK, the building material stock increased from the mid-nineteen century until the 1980s and slightly decreased during the 1980s and 1990s. However, the building material stocks showed an increasing trend from 1855 to 2004 for Wakayama City, Japan [199].

In another study, Tanikawa et al. [155] developed the 4d-GIS database of the entire built environment (i.e., buildings, roads, railroads, airports, seaports, dams, water network) of Japan to assess the material stockpile between 1945 and 2010. Major findings of the study were that first, 43% of the material stock in the built environment was attributed to buildings, which placed buildings as the number one material-intensive sector compared to other built environment. Second, 80% of the materials accumulated in buildings were located on only 20% of the land, which formed major Japanese metropolitan regions [155]. These findings confirmed the significance of focusing on buildings in urban regions.

Several other studies employed this bottom-up method with [156, 161, 176, 178, 181, 182, 193, 207] or without [143, 169, 171, 208] temporal dimension. For example, Marcellus-Zamora et al. [193] estimated the floor area of buildings in a historic region located in Philadelphia, U.S. by multiplying the footprint area, derived from GIS, by floor counts. The total floor area was meshed with MICs of corresponding land use type and the total accumulated stock was estimated. The authors concluded that concrete (52%) and metal (35%) were the dominant materials in the studied building stock because of the abundance of both materials in buildings and their high density compared to other materials [193].

A few studies adopted and slightly modified the bottom-up method, introduced by Tanikawa, to estimate the buildings' volume via multiplying the height by footprint area, obtained from GIS. Buildings' volumes were integrated with volume-based MIC (e.g., mass per volume) to quantify accumulated materials in building stocks of cities [159, 166, 175] and countries [191].

The distinction between structural and non-structural components for both the integrity of reclaimed materials and cost of recertification perspectives results in unique obsolescence paths for structural and non-structural components [264]; hence, making decisions and planning for appropriate end-of-life strategies for returning materials to resource loops requires differentiation between materials from different components. GIS allows for estimating the surface area or volume of different components of buildings. Leveraging this ability of GIS, the surface area or volume of different components can be meshed with their corresponding MIC to account for building material stocks [2, 162, 179, 180, 187, 188]. Ajayebi et al. [162] estimated and mapped the quantity and embodied carbon of clay bricks, which were used in external walls, in three urban areas located in the UK. In another study that accounted for more than one type of material, Miatto et al. [179] calculated the surface area of building components using GIS and multiplied the surface area by the MIC of every component in mass per surface area to quantify the accumulated materials in residential and non-residential buildings of Padua, Italy. Miatto and colleagues' analysis showed that in the early twentieth century, brick was the dominant material, but the distribution changed in the 1980s, and concrete and mortar became dominant building materials in Padua, Italy [179]. Although some studies utilized specifications of building components (i.e., surface area, volume, material intensity) for conducting MSAs, the quantity of similar materials like wood from different components was summed and the results were aggregated. Therefore, differentiation between available materials from various components of buildings is currently overlooked in building MSAs.

In this chapter, the material stock and renovation flow of four components, which are frequently repaired and maintained during a building's lifetime, were analyzed including exterior walls, windows, roofs, and floors of selected commercial building stock in Pittsburgh, PA through a bottom-up method. In addition, the goal was to further advance building MSAs by using an imaging technique developed in chapter 3 [147]. The imaging technique reduces the dependency of bottom-up MSA models on assumptions regarding the physical attributes of buildings (i.e., the ratio of windows to exterior walls, floor count, exterior wall material) and differentiating between materials accumulated in different components of buildings. Also, the results were presented in a disaggregated material/component fashion for pragmatic circular economy solutions. Moreover, the rigorous review of building MSA articles in chapter 4 showed a scarcity of knowledge about building material stock in the U.S. [263]. Only two studies developed bottom-up MSA models in the U.S. without analyzing potential waste, generated due to renovation, [193, 194] and one study assessed the material stock of the country by top-down analysis of inflow and outflow data [214]. Therefore, focusing on a commercial building stock, the goal of this chapter was to enrich the knowledge about accumulated materials of existing buildings in the U.S. and provide policy makers, city planners, and local businesses with information about potential future material resources. This chapter addressed and discussed the following questions:

- What are the material composition and material intensity coefficient of different building typologies?
- What are the total accumulated materials of the studied building stock?
- What are the accumulated materials in different components?
- What are the total and annual material renovation flow between 2020 and 2030?
- What are the spatial configurations of total accumulated materials and renovation flow?

5.2 Materials and Methods

Developing a bottom-up MSA model for a building stock includes several steps. In this section, the overall modeling approach and a description of the steps are detailed. First, the case study buildings and the region of study are described (section 5.2.1). Next, the physical attributes, which are required for the bottom-up model, and methods of acquiring them are explained (section 5.2.2). The MICs for the four components are discussed in section 5.2.3. Finally, the methods of analyzing the material stock and the material renovation flows are presented (sections 5.2.4, 5.2.5). Figure 17 illustrates the overall modeling approach that was developed and utilized in this chapter.

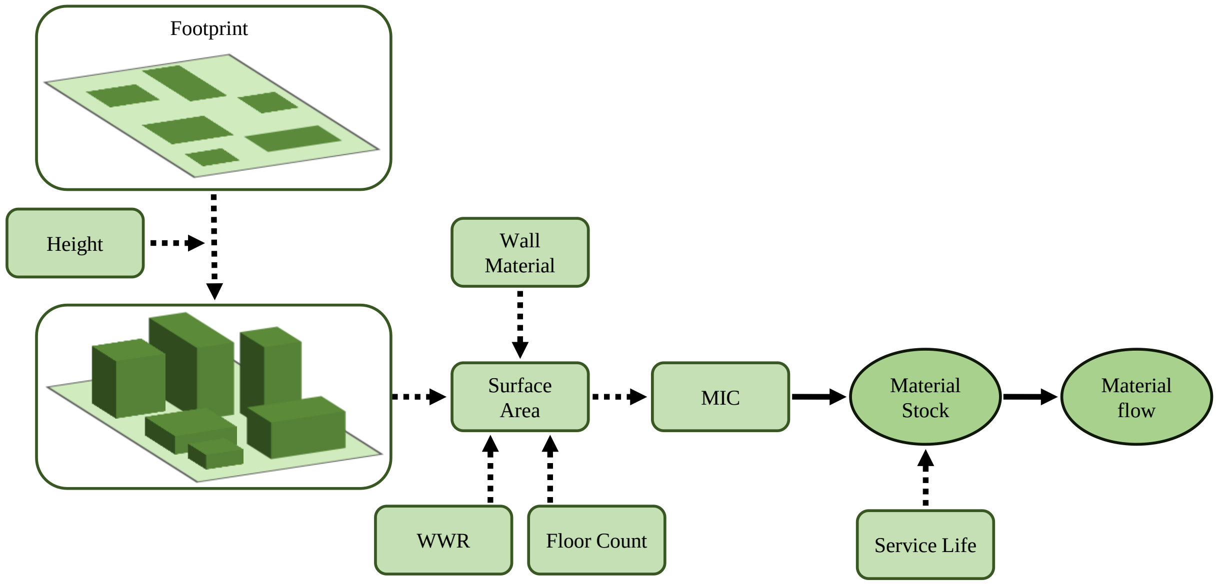


Figure 17 Overall modeling approach. Note: WWR and MIC stand for the window to wall ratio and material intensity coefficient, respectively [147]

5.2.1 Introduction to the Studied Commercial Building Stock

The studied commercial building stock is located in Pittsburgh, PA. Pittsburgh is a city in western Pennsylvania with around 302,000 population. There are a considerable number of both abandoned buildings and new construction. In addition, the building stock in Pittsburgh is aging, which could increase the frequency of repair, maintenance, and renovation. To address the challenges regarding commercial buildings and unlock potential opportunities for cycling reclaimed materials as resources, the focus of this research is on commercial buildings.

The studied commercial building stock contains eight use types with a cumulative floor area of 1,072,336 m². The floor area distribution of the building stock is displayed in Figure 18. Buildings with education (32%), lodging (20%), office (15%), and public assembly (15%) functions comprise a majority of the stock's floor area. While some building use types account for less floor area such as public order and safety buildings (5% of total floor area), there are more of them across the city that affects the spatial distribution of the materials.

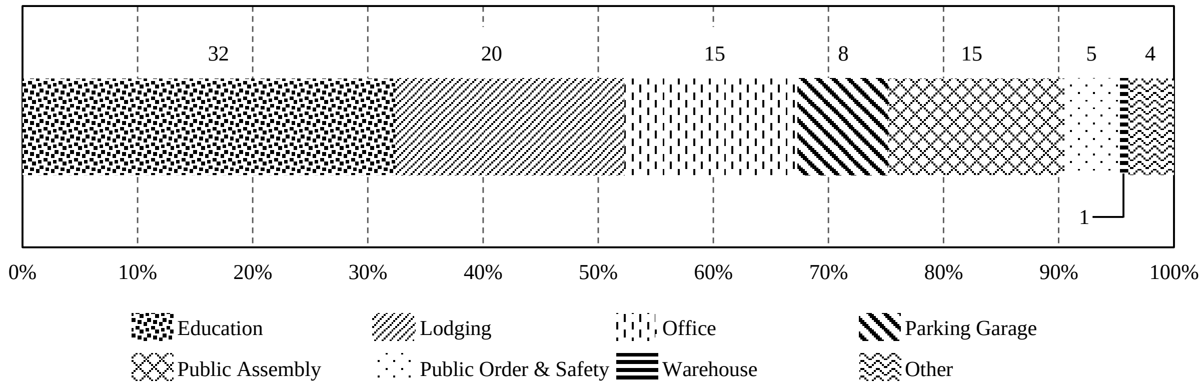


Figure 18 The floor area distribution of the studied commercial building stock based on building use type

5.2.2 Physical Attributes

This model includes four components: exterior wall, window, roof, and floor. The variable that represents the physical attribute in the model is the surface area of the components. *Footprint area*, *footprint perimeter*, *height*, *floor count*, and the *ratio of window to the exterior wall* are the essential parameters to estimate the surface area of the components.

The building footprint is defined as a polygon shape that describes the boundaries of the exterior walls of a building. GIS data, in the format of a shapefile, that contained building footprints of Pittsburgh, PA was downloaded from the Western Pennsylvania Regional Data Center (WPRDC) [106]. Using a combination of the addresses and tax property identifications (IDs), the footprints of the buildings that belonged to the studied stock were identified. The GIS-related analysis and mapping were completed in ArcGIS Pro, which is a software platform developed by Esri. The areas and perimeters of the footprints of the buildings were estimated using the geometric calculation tools in ArcGIS Pro, extracted from the software platform, and stored in a physical attribute library. The GIS data from the WPRDC lacked elevation information of buildings, specifically height and floor count.

Interestingly, variables like height that are required for developing bottom-up MSAs are usually available from studies that modeled building energy [97, 102, 147] and environmental impacts [187, 194] at the urban scale. In chapter 3, an urban building energy model (UBEM) for the commercial buildings of Pittsburgh, PA was developed [147]. In the UBEM [147], the height was estimated by conducting Light Detection and Ranging (LiDAR) analysis using a combination of the building footprints shapefile and raw LiDAR data, which was obtained from The National Map – Data Delivery dataset developed by the United States Geological Survey (USGS). The heights of the studied buildings were extracted from the UBEM and added to the physical attribute library. Moreover, the exterior wall material, floor count, and ratio of windows to exterior walls, known as the window to wall ratio or WWR, were estimated based on photogrammetry and an image processing framework, which was proposed and utilized for the UBEM [147]. Unlike other studies that relied on assumptions regarding exterior wall material, floor count, and WWR [17, 169, 176, 178], the values of these parameters for every building in the studied stock were estimated. The rest of this subsection explains the process of estimating the surface area of the components using the parameters that formed the physical attribute library.

5.2.2.1 Exterior Walls

The gross exterior wall area of every building in the studied stock was estimated by multiplying footprint perimeter and height. Further, the net exterior wall area, which excluded any fenestrations and openings, was calculated by subtracting the window area from the gross exterior wall area.

5.2.2.2 Windows and WWR

WWR is defined as the ratio of the area of windows or fenestrations to the gross exterior wall area. Thus, to estimate the window area of a building, the WWR was multiplied by the gross exterior wall area, which was obtained from the previous step (section 5.2.2.1). Some window assemblies like frames were measured in linear units. Therefore, it was assumed that for every 1 m^2 of the window there were 3 m of enclosing [227].

5.2.2.3 Roofs

Unlike steep roofs that are common in residential buildings, for commercial buildings, the roofs are often designed flat to accommodate heating, cooling, and ventilation systems. Based on the flat roof assumption, the roof area was considered equal to the footprint area of a building.

5.2.2.4 Floors

Building flooring systems can be classified into exposed and unexposed floors. An exposed floor has an interface with unconditioned spaces; whereas, an unexposed floor is adjacent to the conditioned spaces of a building. This classification is important because of its impact on the quantity of insulating materials, especially for buildings that were constructed in the past four decades when building designs must comply with energy efficiency codes and standards. According to this classification, the area of the exposed floor was assumed to be equal to the footprint area of a building. In addition, the area of the unexposed floor of a building was estimated as the product of footprint area and floor count minus one.

5.2.3 Material Intensity Coefficient

As discussed in the introduction, the development of bottom-up MSAs depends on both physical attributes and MICs. MIC indicates the quantity of a specific material per surface area of different components. Architectural and energy designs along with the contractor's choices of materials lead to a diversity of material composition (i.e., layer, assembly), thickness, density, mass, and dimensions, which are necessary to estimate MICs. This diversity complicates determining the material compositions and MICs of components for every individual building at the urban scale. Without building information models, it is relatively unfeasible and inefficient to access the construction documents and the bill of materials of hundreds of buildings to determine both material compositions and MICs. Therefore, the typologies or archetypes that represent groups of buildings with similar material compositions and MICs are defined to streamline the analysis. As shown in Figure 19, the studied commercial building stock was classified into twenty typologies based on *use type* and *construction period*. These two categories were selected for classification because they are most prevalently used by other articles [263]; hence, they facilitate transferring information about compositions and MICs from other building stocks to Pittsburgh's commercial stock. Also, using the construction period can reflect changes that have occurred in the construction industry over time due to technological improvements, materials' availability, and environmental concerns.

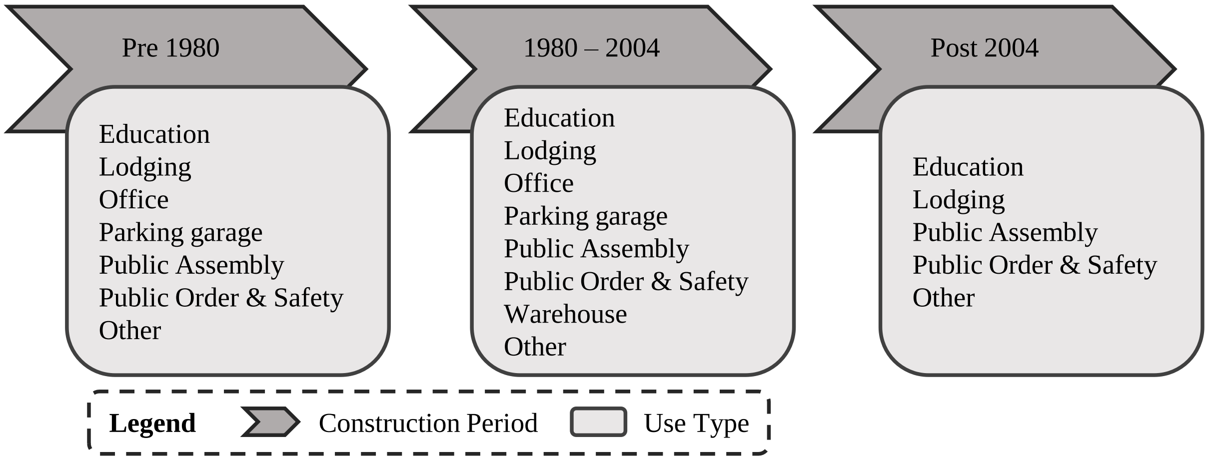


Figure 19 Typology classification for the studied commercial building stock based on use type and construction period [147]

The composition of the exterior walls for different typologies was compiled from multiple resources including the Commercial Building Energy Consumption Survey (CBECS) [8], Commercial Reference Building Models of the National Building Stock [51], and existing literature [2, 187]. The composition of exterior walls was also reflective of wall systems based on material type including stucco, brick, concrete, stone, metal, and wood, which were identified and recorded by photogrammetry and image processing (see section 5.2.2). For example, if the exterior walls of an education building constructed after 2004, were made of stucco, then the exterior walls were composed of six layers or assemblies; however, if the same building was made of brick, then the exterior walls were considered to be composed of five layers or assemblies (See Table 23). The MICs of different layers or assemblies of exterior walls in form of mass per surface area were estimated based on thickness and density or dimensions and weight. Windows were composed of three assemblies: pane, frame, and sealing. The type and MIC of panes for different typologies were extracted from CBECS [8] and a local manufacturing company [265], respectively. Like panes, the material type for frames of each typology was derived from CBECS, and the MIC was determined from reviewing technical specifications of multiple available products in the market.

Finally, the MIC of sealing was derived from the ecoinvent, which is a life cycle inventory database [266].

The compositions of the roof and the floor for different typologies were modeled based on consulting with construction companies and the CBECS [8]. To determine MICs, the thickness and density of several layers, which were installed on the roof and floor, were derived from the ecoinvent [266] and the Building Component Library, which is an online searchable library developed by the National Renewable Energy Laboratory [267]. Next, the MICs were calculated by multiplying thickness and density. However, there were few layers or assemblies such as vapor barrier and vinyl composite tile (VCT) for which required specifications were not available in the aforementioned sources. Thus, we searched and assessed the specifications of different products in the market and estimated the MICs. The material composition and the MICs of the four components for education buildings constructed after 2004 are summarized in Table 23. Moreover, the inventory that encompasses the material composition and the MICs of all typologies is provided in a google drive folder: https://docs.google.com/spreadsheets/d/1Tjli402XtfT7yY0O8DNIo_RIGCytAKWy/edit?usp=sharing&ouid=109256935135058741258&rtpof=true&sd=true.

Table 23 Composition and Material Intensity Coefficient (MIC) of education buildings constructed after 2004. OSB and VCT stand for oriented strand board and vinyl composite tile, accordingly

		Composition	Type of Material	MIC (kg/m²)	Service Life (year)
Exterior Wall	System 1 – Stucco	Stucco *	Cementitious	47.19	50-100
		Concrete block (8")	Concrete	455.78	Lifetime
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	4.12	Lifetime
		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
	System 2 – Brick	Brick	Brick	172.85	100
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	4.12	Lifetime

Table 23 (continued)

		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
	System 3 – Concrete	Concrete block (8")	Concrete	455.78	Lifetime
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	4.12	Lifetime
		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
	System 4 – Stone	Stone panel	Mineral	102.53	100
		OSB (7/16")	Wood	7.11	30
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	4.12	Lifetime
		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
	System 5 – Metal	Metal siding	Steel	11.53	50
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	15.87	Lifetime
		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
	System 6 – Wood	Wood siding	Wood	5.45	40
		Vapor barrier	Plastics	0.49	Lifetime
		Insulation	Insulation	19.79	Lifetime
		Metal Stud	Steel	6.40	100
		Gypsum board (1/2")	Mineral	9.98	40
Window		Double Pane **	Glass	32.12	30
		Frame	Aluminum	4.83	20
		Sealing	Plastics	0.29	30
Roof		Synthetic rubber membrane	Plastics	3.13	40
		OSB (5/8")	Wood	10.16	30
		Insulation	Insulation	33.11	Lifetime
		Vapor barrier	Plastics	0.32	Lifetime
Floor	Unexposed	VCT (1/8") ***	Mineral, Plastics	6.61	40
		Cement board (1/2")	Cementitious	11.72	50
		Plywood (3/4")	Wood	10.40	60
	Exposed	VCT (1/8") ***	Mineral, Plastics	6.61	40
		Cement board (1/2")	Cementitious	11.72	50
		Plywood (3/4")	Wood	10.40	60
		Insulation	Insulation	16.85	Lifetime

Note:

* The average service life was considered.

** The system consisted of two ¼" thickness panes filled with argon gas.

*** VCT was assumed to be comprised of 84% minerals and 16% plastics.

5.2.4 Material Stock

The accumulated material for one material type in a building was estimated as the product of the surface area of a component and the corresponding MIC, summed over different components based on Equation 5-1:

$$MS_{mn} = \sum_{ij} SA_{nij} \times MIC_{ijm} \tag{5-1}$$

Where MS_{mn} is the amount of material type *m* in building *n*; SA_{nij} is the surface area of component *i*, for building *n*, typology *j*; and MIC_{ijm} is the material intensity coefficient of material type *m*, for component *i*, typology *j*. The total accumulated material type *m* (MS_m) in the studied building stock and the total accumulated materials in the studied building stock (MS_T) were estimated according to Equation 5-2 and Equation 5-3, respectively:

$$MS_m = \sum_{n} MS_{mn} \tag{5-2}$$

$$MS_T = \sum_{m} MS_m \tag{5-3}$$

5.2.5 Material Renovation Flow

The material renovation flow can be calculated as the function of the service life of products, which form layers and assemblies, and the buildings' construction year between 2020 and 2030. It was assumed that no changes occur in technology and availability of construction materials during this time frame. Also, the selection of the 2020-2030 time frame was because of its alignment with the Pittsburgh 2030 District sustainability goals. The material renovation flow was estimated based on Equation 5-4 in which RF_{mny} is the quantity of flow of material type *m* in building *n* as a result of renovation in year y. MS_{mn} was calculated using Equation 5-1 and α was a determining factor, which specified whether a material will be replaced in year y or not. If the ratio of the difference between a specific year (y) and the construction year of building *n* (CY_n) to the service life of material type *m* that can be found in component *i*, typology *j* (SL_{ijm}) is an integer, then α is 1, which means that in year *y*, material type *m* in building *n* will be replaced. Otherwise, α is 0, which means that in year *y*, material type *m* in building *n* will not be replaced. The service life of materials was derived from the ecoinvent [266], Study of Life Expectancy of Home Components [268], and Building Materials Life Expectancy Chart [269].

$$RF_{mny} = MS_{mn} \times \alpha, \quad Where \begin{cases} \alpha = 1 \quad if \quad \dfrac{y - CY_n}{SL_{ijm}} \in Z^+ \\ \alpha = 0 \quad if \quad \dfrac{y - CY_n}{SL_{ijm}} \in Z^+ \end{cases} \tag{5-4}$$

The total renovation flow of material type *m* in the studied building stock in year *y*, and the total renovation flow of material type *m* in the studied building stock cumulated from 2020 to 2030 were calculated using Equation 5-5 and Equation 5-6, respectively.

$$RF_{my} = \sum_{n} RF_{mny} \tag{5-5}$$

$$RF_m = \sum_{y=2020}^{2030} RF_{my} \tag{5-6}$$

5.3 Results and Discussion

5.3.1 Material Stocks

The total mass of accumulated materials in the four components of the studied building stock was estimated as 256,085 mt or metric ton. Expectedly, most materials are accumulated in exterior walls (68%) and floors (27%), and the remaining 6% is accumulated in windows and roofs. Twelve material types were identified in the components (see Figure 20). Concrete and brick form the majority of the stock by representing 37% (94,692 mt) and 30% (77,611 mt) of the entire accumulated materials, respectively. Based on the MSA results, minerals (e.g., gypsum board, stone panel, terrazzo) and wood have 17% and 5% of total accumulated materials in the studied stock, accordingly. While insulation (2%) and plastics (less than 1%) have lower mass-based shares compared to other materials, they are inherently lightweight. Therefore, reclaiming and returning insulation and plastics to the consumption loop through circular economy strategies like reuse, adaptive reuse, etc. not only reduce the amount of waste and landfill pollution but also may be associated with considerable benefits from environmental impacts and resource depletion perspectives. Furthermore, the studied building stock locates in a heating-dominated climate zone, where compliance with energy codes and standards requires extensive air tightening measures for building envelopes. This makes the quantity of insulation available from exterior walls, roofs, and floors even more compared to cooling-dominated regions.

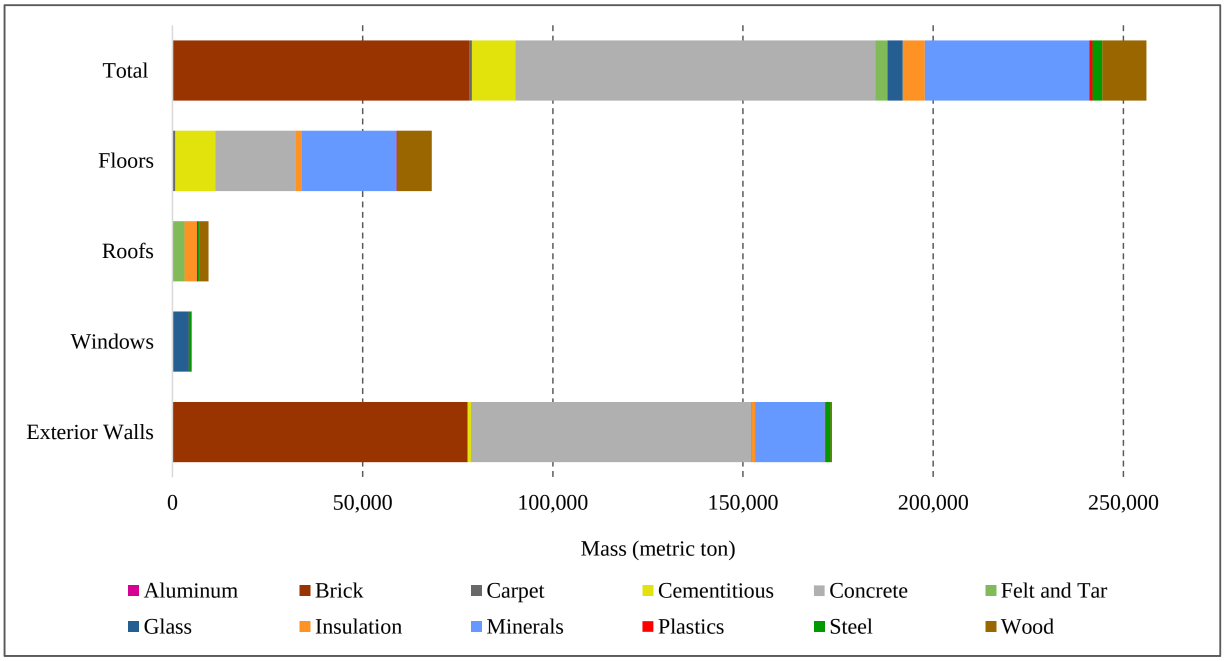


Figure 20 Total accumulated materials and materials in different components of the studied building stock

The spatial distribution of total accumulated materials in the studied buildings is illustrated in Figure 21. This distribution shows that in condensed urban neighborhoods with high-rise buildings like Oakland, Pittsburgh, where the University of Pittsburgh campus locates, the mass of accumulated materials is higher than in other neighborhoods. In addition to the total accumulated materials and their spatial distribution, another question that this work aims to address is what is the distribution or balance of accumulated materials in different components.

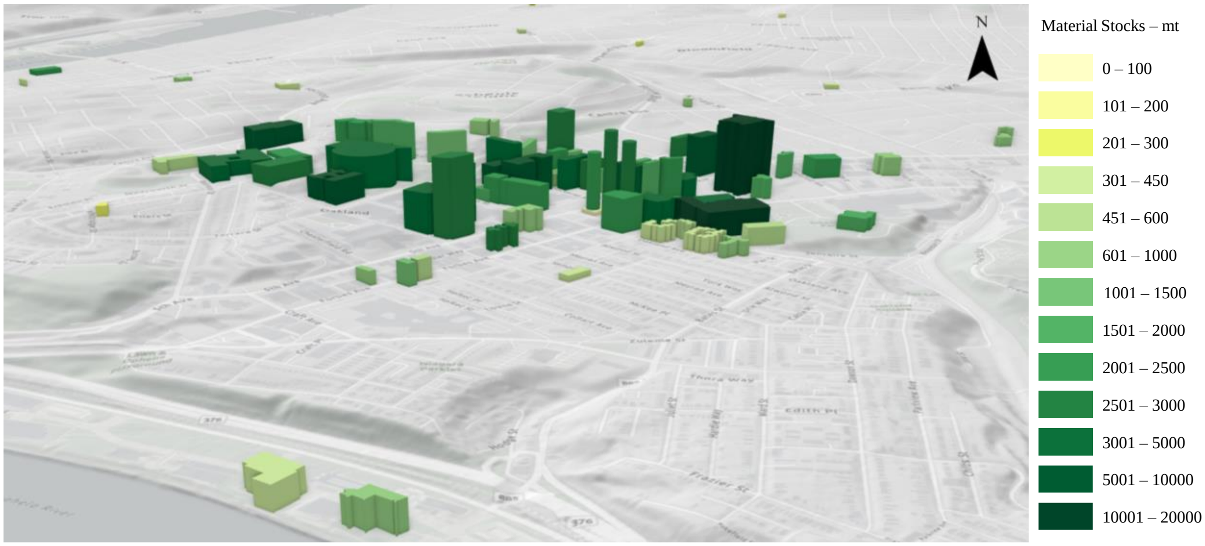


Figure 21 Spatial distribution of total accumulated materials in the studied building stock. Note: mt = metric ton

5.3.2 Material Stocks by Component

As displayed in Figure 20, nine out of twelve material types, which were identified in the four components, were found in exterior walls making this component a diverse repository of secondary materials. Cumulatively, 173,379 mt of materials are accumulated in the exterior walls from which brick and concrete together account for 87% by mass. Minerals comprise slightly more than 10% of the mass of the exterior walls. Cementitious, glass, insulation, plastics, steel, and wood each comprise less than 1% of the accumulated materials in the exterior walls. Pastes such as mortar that are usually used to bind the outer layer of walls such as bricks, concrete blocks, and stones were not accounted for in this analysis because their quantities can vary significantly among buildings.

Windows are the least diverse components in terms of material types. Expectedly, 77% of accumulated materials (by mass) in windows are glass. Glass is either found in windows or exterior walls and the majority of glass in the studied building stock exists in windows (98%); whereas only 2% of glass (by mass) are in the form curtain walls. Aluminum and steel that are utilized as the framing materials account for 8% (382 mt) and 14% (716 mt) of accumulated materials in windows, accordingly (see Figure 20).

There are 9,477 mt of materials accumulated in roofs, which makes this component the third material-intensive component before windows. Insulation and felt and tar constitute equal portions of roofs, each having 34% of total accumulated materials (by mass) in the component. While the cumulative surface area of exterior walls in the studied building stock is larger than that of roofs, the thickness and subsequently MICs of insulations installed in roofs are higher than the thickness and MICs of insulations in exterior walls. As an example, for education buildings constructed after 2004, the thickness of roof insulation was 12.5 cm, whereas the thickness of exterior wall insulation ranged between 4.5 cm to 7.5 cm based on the different wall systems. Hence, the total mass of roof insulation is 3,244 mt, which is approximately 4-times higher than the total mass of the exterior wall insulation (905 mt). This analysis confirms that roofs are potential mines for insulating materials. Plastics, steel, and wood comprise 4%, 4%, and 24% of the accumulated materials of roofs, respectively. Plastics used in roofs are mostly synthetic rubber membranes, which are installed as the outer layer, and vapor barriers that help keep moisture and water away from other roof layers and assemblies. Finally, 68,199 mt of materials are accumulated in floors, which puts floors in second place among the four components analyzed in this article. Minerals, concrete, and cementitious (i.e., cement boards, normal duty screed) account for 37%, 31%, and 15% of accumulated materials in floors. The considerable mass of flooring concrete is especially due to concrete used in parking garages’ pavements. It was found that insulation constitutes 2% of flooring materials because unexposed floors are designed without insulation. In addition, the MSA results showed less than 1% of plastics in floors, which has the lowest share among other components. The quantity (mass) of accumulated products in exterior walls, windows, roofs, and floors is provided in Appendix C, Tables C.1 to C.4.

5.3.3 Material Renovation Flow

As mentioned in the materials and methods section, the material renovation flow of the studied commercial building stock was analyzed during an eleven-year time period from 2020 to 2030. The cumulative amount of twelve materials, available as secondary resources due to renovation during this specified time period, is estimated as 43,069 mt. As displayed in Table 24, brick is identified as the material with the highest cumulative mass of renovation flow during the studied time period compared at 15,255 mt. Minerals and concrete account for the second and the third highest cumulative mass by having 8,514 mt and 8,003 mt, respectively. Considering the service life of insulating materials, the renovation flow of insulation is estimated as zero. This is because the insulating materials last for a building lifetime without requiring replacement. Plastics have the second lowest cumulative mass due to renovation in the specified period (see Table 24). The reason is that the majority of products, which are categorized as plastics, have the service life of a building lifetime. Besides, analyzing the cumulative quantity of renovation flow of different materials between 2020 and 2030, temporal analysis of the quantity of renovation flow for different material types is important as it provides valuable information for city planners and waste management businesses about when materials will become available as secondary resources due to renovating activities.

From the temporal analysis of material renovation flow, presented in Table 24, the highest quantities of aluminum, cementitious, concrete, felt and tar, glass, plastics, and wood are projected to become available as potential resources or wastes in 2020. In Table 24, cells' shades display the amount of renovation flow. Darker blue shades mean more renovation flow and lighter blue shades mean less renovation flow. The highest amounts of carpet (294 mt) and steel (96 mt) will be generated as the result of renovation in 2023. Also, 9,460 mt of bricks and 2,889 mt of minerals will become available in 2024 and 2028, respectively. To investigate the importance of renovation activities in buildings in relation to waste generation and the possibility of reclaiming and returning materials to the resource loop, a fraction of the materials renovation flow to the total accumulated materials was analyzed. The shortest service life of carpets has resulted in high replacement frequency from 2020 to 2030 by having a 110% fraction of the materials renovation flow to the total accumulated materials. Other materials with considerable replacement frequency are aluminum (67%), felt and tar (66%), and glass (55%). Brick, minerals, and plastics are each estimated to have a 20% fraction of the materials renovation flow to the total accumulated materials. While the estimated fraction for plastics is lower than many materials in the studied building stock, the adverse impacts of plastics on the environment and ecosystems because of significant decomposition time in a landfill may require special attention to plastics-based products. Circular economy strategies such as prolonging the service life of plastics-based products and producing plastics materials using thermosets, which facilitates the recycling process, can be possible mitigation strategies for use of plastics in buildings. Also, using materials with less detrimental impacts on the environment as a substitute for plastics in buildings may mitigate the adverse impacts. The spatial distribution of total material renovation flow cumulated over the eleven-year time period (2020-2030) is presented in Figure 22. Furthermore, the total quantity of products, which will become available as a result of renovation between 2020 and 2030 from exterior walls, windows, roofs, and floors, are provided in Appendix C, Tables C.5 to C.8.

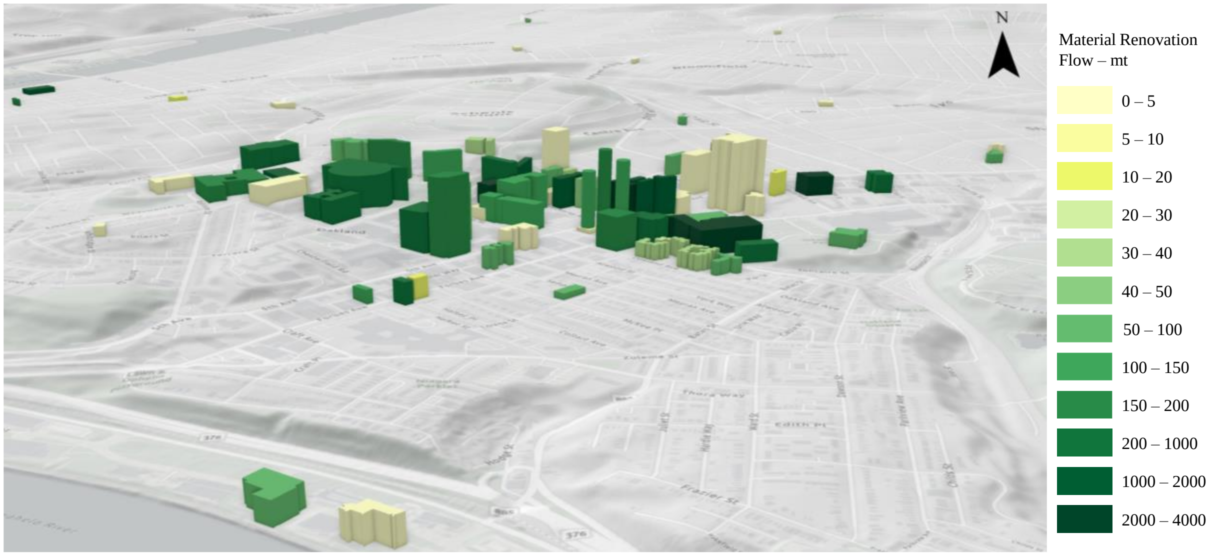


Figure 22 Spatial distribution of the total material renovation flow between 2020 and 2030 in the studied building stock. Note: mt= metric ton

Table 24 Renovation flow of different materials between 2020 and 2030 and the percentage of the total renovation flow to the total accumulated materials in the studied building stock. Darker blue shades mean more renovation flow and lighter blue shades mean less renovation flow. The unit of materials flows is in metric ton (mt)

	Material Types											
Year	**Aluminum**	**Brick**	**Carpet**	**Cementitious**	**Concrete**	**Felt and Tar**	**Glass**	**Insulation**	**Minerals**	**Plastics**	**Steel**	**Wood**
2020	95.6	0.0	74.7	638.0	3907.7	479.1	639.2	0.0	951.1	105.7	23.2	623.5
2021	0.0	1018.5	0.0	40.7	1736.2	273.5	10.4	0.0	285.2	0.9	7.2	52.7
2022	45.0	2973.6	111.8	132.6	0.0	384.6	346.6	0.0	113.2	3.5	41.1	229.9
2023	15.7	0.0	294.4	94.3	0.0	130.0	328.5	0.0	44.7	11.7	96.4	134.0
2024	14.9	9459.6	206.4	493.8	0.0	130.1	138.5	0.0	876.1	9.7	18.1	469.2
2025	31.2	0.0	0.0	227.5	940.3	225.3	231.6	0.0	2007.0	2.3	27.2	238.8
2026	16.5	1469.9	54.9	87.8	0.0	22.0	122.0	0.0	506.3	1.1	4.9	84.2
2027	1.6	0.0	0.0	112.2	0.0	29.8	12.7	0.0	630.4	0.1	1.8	99.5
2028	5.3	333.9	0.0	527.8	0.0	157.9	83.1	0.0	2889.1	9.7	34.2	544.8
2029	21.1	0.0	0.0	0.0	0.0	12.8	165.4	0.0	13.7	1.6	16.2	3.7
2030	10.9	0.0	74.7	540.6	1419.2	254.8	100.6	0.0	197.4	11.1	38.8	100.6
Total Renovation Flow	257.8	15255.5	817.0	2895.2	8003.3	2099.9	2178.6	0.0	8514.3	157.4	309.1	2581.0
Total Accumulated Materials	382.1	77610.6	742.3	11401.0	94691.8	3175.3	3981.5	5799.1	43303.4	784.6	2581.0	11632.8
Renovation Flow to Accumulated Materials (%)	67	20	110	25	8	66	55	0	20	20	12	22

5.4 Conclusions

In this chapter, the accumulated material stocks, projected to become available upon deconstruction, and the material renovation flow during a specific time period for a commercial building stock in the U.S. were analyzed. The work presented in this chapter fills the knowledge gap regarding building material stocks in the U.S. as well as analyzing materials stocks and renovation flow at the component level, which has been overlooked in the field of building MSA. Furthermore, leveraging a remote sensing technique and photogrammetry and image processing, actual building parameters for all buildings were estimated and used as inputs to develop the MSA model. One of the main findings of this work is that the exterior walls and floors are the largest repository of materials among the four components, which were included in this work, and concrete, minerals, brick, and wood have the highest mass among identified material types. Thus, to efficiently reclaim materials from exterior walls and floors upon deconstruction of buildings, nondestructive techniques should be employed.

Recent attention to energy efficiency has resulted in the increase of insulating materials to tighten a building's envelope. Since insulations are usually lightweight, their mass-based quantity is significantly lower than other materials like concrete or steel; however, a considerable amount of insulation is accumulated in the studied components, especially roofs. While it was found that plastics comprise less than 1% mass of accumulated materials in the studied building stock, the adverse implications of disposing of plastics in landfills justify the importance of time and financial investments to identify strategies, aligned with the circular economy, to return plastics to resource loop. Drawing on the results of spatial analysis, the spatial distribution of the accumulated material stocks is highly correlated to urban form and the neighborhood's compactness. Analyzing the material renovation flow of the studied building stock revealed that time is an essential factor that can contribute to effective planning for circular economy strategies and returning materials to the consumption loop after renovation.

The results of this work will aid in fostering the circular economy of the building sector; however, they are associated with uncertainty. The variable uncertainty, which is a limitation of this work, is related to both physical attributes and MICs. For physical attributes, the main variables that cause uncertainty are buildings' height and WWR which are estimated through LiDAR analysis and photogrammetry and image processing, respectively. Cities and municipalities can enforce reporting elevation and façade information of buildings as part of the construction and renovation permits process. Such information can be employed to compile comprehensive databases of buildings that may reduce the uncertainty of bottom-up MSA models and facilitate the development of these models. In addition, every building has a unique structure, design, and consequently unique MICs [155]; however, the bill of materials for buildings is often not publicly available especially in the U.S. Therefore, for determining MICs, publicly available databases and products' specifications were utilized. To address the variable uncertainty, which is attributed to MICs, a probabilistic bottom-up MSA model based on defining and utilizing distributions of MICs for different layers and assemblies can be developed in future. Furthermore, it was found that MSA models have utilized mass-based or in rare cases volume-based systems to analyze material stocks of buildings. These systems are constrained in capturing several advantages of returning materials to the resource loop such as potential impacts on natural resource preservation. Introducing and testing novel methods based on other denominators than mass or volume will advance the field of building MSA in the future. Ultimately, the scope of this model will be expanded to encompass all commercial and residential buildings in Pittsburgh, PA.

6.0 Visualizing Energy Use and Materials of a Building Stock

The research presented here addresses objective five.

Visualizing the results of modeling energy use (chapter 3), material stocks (chapter 5), and material renovation flow (chapter 5) of the commercial building stock in Pittsburgh, PA is beneficial for practical application of the outcomes by policy makers, planners, and stakeholders such as building owners and utility companies. For this purpose, an interactive map, which is a tool that enables users to explore the embedded information, was created.

The interactive map that is available online via https://arcg.is/0zjDO0 was comprised of three layers. The first layer contained the annual EUI of the studied commercial buildings, which were obtained from the UBEM. The second and third layers visualized the total accumulated materials and the cumulative renovation flow between 2020 and 2030 of the studied commercial buildings, respectively.

7.0 Conclusions and Future Work

7.1 Major Findings

The question about implementing ML models to predict building energy use in the future was answered by developing four statistical and ML models, comparing the prediction performance of models, and selecting the model with the best goodness-of-fit (chapter 2). The better performance of the random forest model, a non-linear algorithm, showed the non-linearity and the complex interactions of predictors in CBECS data. Using the random forest model in conjunction with climate change projections revealed that most office buildings across the U.S. will experience an increase in EUI due to increase in cooling demand in the future. While the estimated increase or decrease in EUI of office buildings was significant when compared to EUI in 2012, the estimated changes were insignificant when comparing the six future years (2030-2080). This was probably the result of the well-generalization of the random forest model and the interaction between building energy consumption and climate change. Although an ML model can be employed to predict the shift in building energy use under climate change, considering large geographic regions (low spatial resolution) with high weather variability may overlook weather conditions specific to a city or an urban area. Therefore, we conducted an urban scale study (high spatial resolution) and created a UBEM for a commercial building stock in Pittsburgh, PA. The UBEM can be integrated with climate change science for resolving the limitation related to spatial resolution.

The holistic modeling structure, which was developed in chapter 3, presented a multitude of data sources, which were required for the development of a UBEM, and resolved the data disparity in the field. Also, advanced imaging and GIS techniques like photogrammetry, image processing, and LiDAR analysis demonstrated that dependency on assumptions can be reduced. Validating the results of the UBEM for the commercial building stock of Pittsburgh, PA showed that while commercial buildings are more complex and less consistent in energy performance than residential buildings, acceptable accuracy was achieved. Moreover, the distributions of EUI of commercial buildings estimated by the UBEM were similar to the distributions of actual data for almost all use types. According to the outcomes of this research, the annual energy use of commercial buildings was highly related to their specific use type. Another finding of chapter 3 was that while low to medium cost energy conservation measures effectively reduced the energy use of the commercial building stock, achieving the ambitious goal of reducing energy use by 50% until 2030 demands more rigorous and more costly measures. In addition to energy use, the sustainability of buildings is tied to materials and their end-of-life management.

The question regarding the gaps and barriers in the current literature on building MSA were answered by a rigorous review of existing peer-reviewed articles (chapter 4). No studies in some parts of the world like Africa, lack of component analysis, limited data about building design and construction, and deficiency of GIS data were among the major gaps and barriers in the existing building MSAs. The results of this research showed that bottom-up approaches provided in-depth information about the accumulated materials; hence, outcomes were more useful for planning the circular economy strategies. Also, we found that while the building sector is one of the main consumers of plastics [255], plastics, which are lighter than most building materials, were rarely estimated in MSAs. Finally, policy makers and planners can leverage the distribution of accumulated materials in building stocks to consider incentives for designers and contractors that plan for strategies, which reduce building materials' disposal.

By developing a material stock and flow analysis model, the question of quantity and type of accumulated materials and renovation flow for a commercial building stock in Pittsburgh, PA was addressed (chapter 5). Our analyses revealed that exterior walls and floors had the highest shares of accumulated materials compared to windows and roofs. Concrete, brick, minerals, and wood were prevalently found in the studied components. Also, urban form and neighborhood compactness influenced the spatial distribution of accumulated materials. The temporal analysis of renovation flow between 2020 and 2030 determined the approximate time that a specific material type with a specific quantity will become available as a potential secondary resource. In addition, we found that the short service life of some materials such as carpet led to a considerable ratio of renovation flow to the total accumulated materials.

7.2 Limitations

One limitation of developing and employing ML models to predict building energy use is that the accuracy of outcomes is confined to the quality of data. Although the CBECS dataset, which was utilized in chapter 2, was comprehensive in the number of predictors, most predictors were categorical. Thus, categories, which indicated ranges of values, were entered into a model instead of inputting the exact value of a predictor. The performance of prediction models in chapter 2 was validated based on different metrics; however, the results of impacts of climate change on energy use were not validated. A plan for validating and confirming these results is recommended as a part of future research in section 7.3. For simulating energy consumption at scale using a UBEM in chapter 3, there was uncertainty associated with characterizing the non-geometric parameters during the archetype development. While we tried to mitigate the impact of this uncertainty by close inspection of buildings in the commercial stock and consulting with building managers about operation and systems, lack of access to design documents of buildings and consequently their non-geometric parameters still remained as a limitation. Another shortcoming of this research pertained to photogrammetry. When acquiring images of various facades of a building utilizing SVS API, the goal was to maintain the consistency of the images' attributes. Nonetheless, to attain full coverage of façades, the image attributes of a few buildings were not consistent over different facades. Additionally, typical meteorological data from the weather station, located outside Pittsburgh, PA, may not represent the urban heat island in the City as well as the weather condition in 2017, which was employed as a base year for validating simulation results from the UBEM. Finally, the uncertainty of some variables including physical attribute and material intensity coefficient, which were utilized to analyze the accumulated materials and the renovation flow of the studied commercial building stock, was another limitation (chapter 5) that can be addressed by probabilistic approaches. Additionally, the scarcity of building MSA studies in the U.S. as well as the distinction between scopes and approaches of these studies [193, 194, 214] and the scope and approach of our study, presented in chapter 5, inhibited us from validating the outcomes of the building MSA model.

7.3 Future Work

Further research could be conducted to improve understanding of building energy consumption in presence of climate change, urban building energy modeling, and material stock analysis of buildings at the urban scale. First, the CBECS datasets that will be published in the future by EIA (e.g., a dataset for 2022 or later) are recommended to be used for comparing the energy consumption of office buildings in a specific year like 2022 with energy consumption from 2012. The results of this comparison may show how weather variabilities over one decade have affected energy consumption. Also, comparing data from 2012 with 2022 will help confirm the future trends of change in the energy consumption of office buildings that were obtained from the random forest model in chapter 2. The main barrier to this comparison at the time of this research was that the recent CBECS dataset published after 2012 encompassed information on commercial buildings from 2018 and did not contain the amount of electricity, natural gas, fuel oil, and district heat for buildings. Therefore, it could not be employed for validating the patterns of change in energy of buildings in different regions across the U.S.

In order to better understand how global warming and climate change will affect the energy for building cooling and heating, ML models can be developed to predict cooling and heating loads, separately. This will facilitate the interpretation of results in correlation with HDD reduction and CDD increase in the future. Also, it allows for identifying building features in different regions that have positive impacts on reducing energy and the environmental impacts associated with energy use. One challenge of studying building energy use is including prospective advancements in design, materials, and technology of buildings in the future. For instance, buildings will undergo changes, which are linked to renovation (e.g., upgrading envelope, HVAC systems, lighting) and use type adjustment, in the future. Scenarios that encompass individual change or multiple changes related to renovation and use type adjustment in buildings are recommended to be defined. Through scenario analysis, the energy consumption is suggested to be predicted considering variabilities in both weather conditions due to climate change and building's state due to renovation and use type adjustment.

Besides ML models, UBEMs enable the investigation of building energy consumption in presence of climate change at the city scale; thus, this ability of UBEMs will resolve the low spatial resolution problem of some databases like the CBECS. The weather files based on various climate change scenarios can be created by using high-resolution climate models or downscaling global climate models (GCMs). Running the UBEM with these weather files provides the total energy use of buildings as well as energy use by fuel type under climate change during the 21^{st} century. It is recommended for the future that a dynamic life cycle assessment model be paired with existing UBEMs' outcomes to calculate the environmental impacts of energy use under climate change. The dynamic analysis will then be able to capture the possible variabilities in future systems.

One of the main contributions of this work, described in chapter 3, was compiling the archetype library for eight types of commercial buildings built in three eras. The library will be published to facilitate building simulation. In addition, to reduce the uncertainty, which is associated with characterizing non-geometric parameters of archetype, employing a probabilistic method is recommended as a part of future work. In this method, distributions can be defined for every non-geometric parameter (i.e., occupancy-related, envelope composition, and mechanical/electrical systems). The parameters can be selected from distributions and the energy use can be simulated using the UBEM. Through several iterations, the non-geometric parameters that will result in the closest simulated energy use to actual energy use can be found and the archetype library can then be recalibrated.

Additionally, the scope of the UBEM could be extended to encompass the entire commercial buildings in Pittsburgh, PA. Imperative for this extension is to calculate the height and envelope properties of all commercial buildings. Thus, the automation of photogrammetry and image processing framework is needed to acquire façade images as well as WWR, floor count, and external wall type of all buildings.

Much work regarding the circular economy and MSA of the building sector could stem from the research presented in this dissertation. Repurposing or adaptive reuse can be a substitute for recycling building materials, which is often associated with downgrading. For instance, with ongoing discussions about improving the resiliency of coastal areas and riverbanks against the sea level rise, accumulated materials like concrete in existing buildings that will become available due to renovation and deconstruction could be repurposed for strengthening shores and riverbanks against sea level rise and flooding. The feasibility and benefits of repurposing and reusing of building materials and components should be studied from various aspects including structural integrity standpoint, environmental impacts, and health-related safety. As a suggestion, the quantity and location of materials from the MSA model in chapter 5 can be employed to estimate emissions from both transporting materials to shores and coastal areas along with installation.

Moreover, the embodied energy (EE) from renovation, known as recurrent EE, and EE from the demolition of a building stock are the functions of renovation flow and accumulated materials, respectively. First, subsequent work is recommended to assess embodied energy of renovation and deconstruction while considering the energy for disassembling components along with energy for handling, sorting, and storage of the second-hand building materials. The amount of stockpiled materials in a building stock, which were estimated in this dissertation, can be utilized for embodied energy calculation. Second, the ability and thoroughness of current LCA databases for assessing both the embodied energy and environmental impacts of building circular economy strategies (e.g., repurposing and reuse) are limited [270, 271] and open to more investigation.

Similar to the environmental impacts, investigating the health risks and hazards of returning building materials or products to the resource loop is necessary.

Many building materials and products contain chemicals and substances like asbestos, isocyanates, and per-and polyfluoroalkyl substances (PFAS) that are known to elevate health risks. Although the use of asbestos has been banned, there are still a considerable amount of materials and products in older buildings, which were constructed between the 1920s and late 1980s, that contain asbestos. Currently, other harmful chemicals are widely used in manufacturing building materials without any restrictions. For example, isocyanates are used to produce coating and adhesive materials. PFAS are detected in carpet, stone, and tile to increase water and stain resistance. Also, PFAS are extensively used to make composite wood products such as oriented strand board and plywood and to reduce corrosion and weathering. Despite knowledge about accumulated materials in buildings and the health risk of some materials, there are questions to be answered. First, how much of the accumulated materials in existing buildings contain harmful substances? Does disassembling components, which contain toxic chemicals, during deconstruction or renovation put construction workers and occupants at risk? Do weather-related stressors (e.g., wind, sunlight, precipitation) cause the release of chemicals from building materials; consequently, impact the safety of handling and storing second-hand building materials? How much of a closed loop can be achieved with the growing knowledge about the toxicity of some materials? The outcomes of the building MSA, presented in chapter 5 and Appendix C, can further be employed to explore the accumulated materials with harmful substances in a building stock and answer the above questions. Also, future research can be built upon this dissertation to assess the health risks due to weathering or aging while materials and products are still in-use in building stocks as well as when they are handled and stored.

Finally, building material identification at scale helps refine the inputs for modeling energy and materials. Hyperspectral or multispectral remote sensing technology allows for determining the type of impervious surfaces like roof materials based on spectral images. The images are processed to identify spectrums that are identical to those for different roof materials, obtained in laboratories. Information about roof surface materials will aid in determining the roof composition for every building in an urban area; thus, enhancing thermal specification for energy modeling and other specifications (i.e., thickness and density) for material modeling. Additionally, technologies in other disciplines like ground penetrating radar (GPR) can be utilized to find the envelope layer's type, thickness, and thermal specifications. Application of the GPR for every building in a city, although expensive and time consuming, can be used for a sample of buildings that represent archetypes or typologies.

Appendix A Supporting Information for Predicting Building Energy Use under Climate Change Using ML Models

Appendix Table A.1 Specific ID and detail description of predictors.

Predictors are from CBECS dataset that were used in creating prediction models. Every predictor is marked as group 1 and/or group 2 and/or group 3. Note: predictors that are indicated by '*' are continuous and their corresponding range and unit are listed in separate columns. The range of continuous predictors are prior to scaling

CBECS ID	Description	Categorical/ Continuous	Original Range	Unit	Number of Categories	Group 1	Group 2	Group 3
PUBCLIM	Building America climate region	Categorical	---	---	5	✓	✓	✓
PBA	Principal building activity	Categorical	---	---	20	✓	✓	✓
WLCNS	Wall construction material	Categorical	---	---	9	✓	✓	✓
RFCNS	Roof construction material	Categorical	---	---	9	✓	✓	✓
GLSSPC	Percent exterior glass	Categorical	---	---	7	✓	✓	✓
YRCONC	Year of construction category	Categorical	---	---	10	✓	✓	✓
WKHRS*	Total hours open per week	Continuous	168	Hour	---	✓	✓	✓
NWKER*	Number of employees	Continuous	6500	Person	---	✓	✓	✓
HEATP	Percent heated	Categorical	---	---	5	✓	✓	✓
COOLP	Percent cooled	Categorical	---	---	5	✓	✓	✓
ENRGYPLN	Energy management plan	Categorical	---	---	3	✓	✓	✓
OE*	Number of office equipment	Continuous	8540	Number	---	✓	✓	✓
WINTYP	Window glass type	Categorical	---	---	4	✓	✓	✓
HDD65*	Heating degree days	Continuous	10697	°F	---	✓	✓	✓
CDD65*	Cooling degree days	Continuous	5857	°F	---	✓	✓	✓
FREESTN	Freestanding building	Categorical	---	---	2		✓	✓
RFCOOL	Cool roof materials	Categorical	---	---	2		✓	✓
RFTILT	Roof tilt	Categorical	---	---	3		✓	✓
BLDSHP	Building shape	Categorical	---	---	12		✓	✓

Table A.1 (continued)

NFLOOR	**Number of floors**	**Categorical**	**---**	**---**	**3**	✓	✓
FLCEILHT	Floor to ceiling height	Categorical	---	---	2	✓	✓
NELVTR	Number of elevators	Categorical	---	---	2	✓	✓
NESLTR	Number of escalators	Categorical	---	---	2	✓	✓
RENOV	Any renovations	Categorical	---	---	3	✓	✓
RENRFF	Roof replacement	Categorical	---	---	3	✓	✓
RENWLL	Exterior wall replacement	Categorical	---	---	3	✓	✓
RENWIN	Window replacement	Categorical	---	---	3	✓	✓
RENHVC	HVAC equipment upgrade	Categorical	---	---	3	✓	✓
RENLGT	Lighting upgrade	Categorical	---	---	3	✓	✓
RENPLB	Plumbing system upgrade	Categorical	---	---	3	✓	✓
RENELC	Electrical upgrade	Categorical	---	---	3	✓	✓
RENINS	Insulation upgrade	Categorical	---	---	3	✓	✓
COURT	Food court	Categorical	---	---	3	✓	✓
OCCUPYP	Percent occupancy	Categorical	---	---	6	✓	✓
MAINHT	Main heating equipment	Categorical	---	---	8	✓	✓
MAINCL	Main cooling equipment	Categorical	---	---	9	✓	✓
HWRDHT	How reduce heating	Categorical	---	---	5	✓	✓
HWRDCL	How reduce cooling	Categorical	---	---	5	✓	✓
ECN	Economizer cycle	Categorical	---	---	3	✓	✓
WTHTEQ	Water heating equipment	Categorical	---	---	4	✓	✓
SNACK	Snack bar or concession stand	Categorical	---	---	3	✓	✓
FASTFD	Fast food or small restaurant	Categorical	---	---	3	✓	✓
CAF	Cafeteria or large restaurant	Categorical	---	---	3	✓	✓
FDPREP	Commercial or large kitchen	Categorical	---	---	3	✓	✓
KITCHN	Small kitchen area	Categorical	---	---	3	✓	✓
BREAKRM	Employee lounge, breakroom, or pantry	Categorical	---	---	3	✓	✓
OTFDRM	Other food prep or serving area	Categorical	---	---	3	✓	✓
HWTRM	Large amounts of hot water	Categorical	---	---	3	✓	✓
MEDEQP	Medical equipment	Categorical	---	---	3	✓	✓
LABEQP	Laboratory equipment	Categorical	---	---	3	✓	✓
MCHEQP	Machine equipment	Categorical	---	---	3	✓	✓
POOL	Indoor swimming pool	Categorical	---	---	3	✓	✓
HTPOOL	Heated indoor swimming pool	Categorical	---	---	3	✓	✓
RFGEQP	Refrigeration	Categorical	---	---	3	✓	✓
EQGLSS	Equal glass on all sides	Categorical	---	---	3		✓

Table A.1 (continued)

ELHT1	**Electricity used for main heating**	**Categorical**	**---**	**---**	**2**	✓
NGHT1	Natural gas used for main heating	Categorical	---	---	3	✓
FKHT1	Fuel oil used for main heating	Categorical	---	---	3	✓
PRHT1	Propane used for main heating	Categorical	---	---	3	✓
STHT1	District steam used for main heating	Categorical	---	---	3	✓
HWHT1	District hot water used for main heating	Categorical	---	---	2	✓
WOHT1	Wood used for main heating	Categorical	---	---	3	✓
COHT1	Coal used for main heating	Categorical	---	---	3	✓
SOHT1	Solar used for main heating	Categorical	---	---	2	✓
OTHT1	Other source used for main heating	Categorical	---	---	3	✓
ELCOOL	Electricity used for cooling	Categorical	---	---	2	✓
NGCOOL	Natural gas used for cooling	Categorical	---	---	3	✓
FKCOOL	Fuel oil used for cooling	Categorical	---	---	3	✓
PRCOOL	Propane used for cooling	Categorical	---	---	3	✓
STCOOL	District steam used for cooling	Categorical	---	---	3	✓
HWCOOL	District hot water used for cooling	Categorical	---	---	2	✓
CWCOOL	District chilled water used for cooling	Categorical	---	---	2	✓
OTCOOL	Other source used for cooling	Categorical	---	---	3	✓
ELWATR	Electricity used for water heating	Categorical	---	---	2	✓
NGWATR	Natural gas used for water heating	Categorical	---	---	3	✓
FKWATR	Fuel oil used for water heating	Categorical	---	---	3	✓
PRWATR	Propane used for water heating	Categorical	---	---	3	✓
STWATR	District steam used for water heating	Categorical	---	---	3	✓
HWWATR	District hot water used for water heating	Categorical	---	---	2	✓
WOWATR	Wood used for water heating	Categorical	---	---	3	✓
COWATR	Coal used for water heating	Categorical	---	---	3	✓

Table A.1 (continued)

SOWATR	**Solar used for water heating**	**Categorical**	**---**	**---**	**3**	✓
OTWATR	Other source used for water heating	Categorical	---	---	3	✓
ELCOOK	Electricity used for cooking	Categorical	---	---	2	✓
NGCOOK	Natural gas used for cooking	Categorical	---	---	3	✓
FKCOOK	Fuel oil used for cooking	Categorical	---	---	3	✓
PRCOOK	Propane used for cooking	Categorical	---	---	3	✓
STCOOK	District steam used for cooking	Categorical	---	---	3	✓
HWCOOK	District hot water used for cooking	Categorical	---	---	2	✓
WOCOOK	Wood used for cooking	Categorical	---	---	3	✓
COCOOK	Coal used for cooking	Categorical	---	---	3	✓
SOCOOK	Solar used for cooking	Categorical	---	---	2	✓
OTCOOK	Other source used for cooking	Categorical	---	---	2	✓
ELMANU	Electricity used for manufacturing	Categorical	---	---	2	✓
NGMANU	Natural gas used for manufacturing	Categorical	---	---	3	✓
FKMANU	Fuel oil used for manufacturing	Categorical	---	---	3	✓
PRMANU	Propane used for manufacturing	Categorical	---	---	3	✓
STMANU	District steam used for manufacturing	Categorical	---	---	2	✓
HWMANU	District hot water used for manufacturing	Categorical	---	---	2	✓
WOMANU	Wood used for manufacturing	Categorical	---	---	2	✓
COMANU	Coal used for manufacturing	Categorical	---	---	2	✓
SOMANU	Solar used for manufacturing	Categorical	---	---	2	✓
OTMANU	Other source used for manufacturing	Categorical	---	---	2	✓
NGGENR	Natural gas used for electricity generation	Categorical	---	---	3	✓
FKGENR	Fuel oil used for electricity generation	Categorical	---	---	3	✓
PRGENR	Propane used for electricity generation	Categorical	---	---	3	✓

Table A.1 (continued)

WOGENR	**Wood used for electricity generation**	**Categorical**	**---**	**---**	**2**	✓
COGENR	Coal used for electricity generation	Categorical	---	---	3	✓
SOGENR	Solar used for electricity generation	Categorical	---	---	3	✓
OTGENR	Other source used for electricity generation	Categorical	---	---	3	✓
DRYCL	Dry cleaning onsite	Categorical	---	---	3	✓
LOHRPC	Lit when open category	Categorical	---	---	6	✓
LNHRPC	Lit off hours category	Categorical	---	---	6	✓

Appendix Table A.2 Description of categories for the categorical predictors

CBECS ID	Description	Categories
PBA	Principal building activity	'01' = 'Vacant' '02' = 'Office' '04' = 'Laboratory' '05' = 'Nonrefrigerated warehouse' '06' = 'Food sales' '07' = 'Public order and safety' '08' = 'Outpatient health care' '11' = 'Refrigerated warehouse' '12' = 'Religious worship' '13' = 'Public assembly' '14' = 'Education' '15' = 'Food service' '16' = 'Inpatient health care' '17' = 'Nursing' '18' = 'Lodging' '23' = 'Strip shopping mall' '24' = 'Enclosed mall' '25' = 'Retail other than mall' '26' = 'Service' '91' = 'Other'
FREESTN	Freestanding building	1' = 'Yes' Missing='No'
WLCNS	Wall construction material	'1' = 'Brick, stone, or stucco' '2' = 'Pre-cast concrete panels' '3' = 'Concrete block or poured concrete (above grade)' '4' = 'Aluminum, asbestos, plastic, or wood materials (siding, shingles, tiles, or shakes)' '5' = 'Sheet metal panels' '6' = 'Window or vision glass (glass that can be seen through)' '7' = 'Decorative or construction glass' '8' = 'No one major type' '9' = 'Other'

Table A.2 (continued)

RFCNS	Roof construction material	'1' = 'Built-up (tar, felts, or fiberglass and a ballast, such as stone)' '2' = 'Slate or tile shingles' '3' = 'Wood shingles, shakes, or other wooden materials' '4' = 'Asphalt, fiberglass, or other shingles' '5' = 'Metal surfacing' '6' = 'Plastic, rubber, or synthetic sheeting (single or multiple ply)' '7' = 'Concrete' '8' = 'No one major type' '9' = 'Other'
RFCOOL	Cool roof materials	'1' = 'Yes' '2' = 'No'
RFTILT	Roof tilt	'1' = 'Flat' '2' = 'Shallow pitch' '3' = 'Steeper pitch'
BLDSHP	Building shape	'01' = 'Square' '02' = 'Wide rectangle' '03' = 'Narrow rectangle' '04' = 'Rectangle or square with an interior courtyard' '05' = '"H" shaped' '06' = '"U" shaped' '07' = '"E" shaped' '08' = '"T" shaped' '09' = '"L" shaped' '10' = '"+" or cross shaped' '11' = 'Other shape' Missing = Not applicable
GLSSPC	Percent exterior glass	'1' = '1 percent or less' '2' = '2 to 10 percent' '3' = '11 to 25 percent' '4' = '26 to 50 percent' '5' = '51 to 75 percent' '6' = '76 to 100 percent' Missing = Not applicable
EQGLSS	Equal glass on all sides	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NFLOOR	Number of floors	1 - 14 994 = 15 to 25 995 = More than 25
FLCEILHT	Floor to ceiling height	6 - 50 995 = More than 50
ELEVTR	Elevators	'1' = 'Yes' '2' = 'No' Missing = Not applicable
ESCLTR	Escalators	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

YRCONC	Year of construction category	'01' = 'Before 1920' '02' = '1920 to 1945' '03' = '1946 to 1959' '04' = '1960 to 1969' '05' = '1970 to 1979' '06' = '1980 to 1989' '07' = '1990 to 1999' '08' = '2000 to 2003' '09' = '2004 to 2007' '10' = '2008 to 2012'
RENOV	Any renovations	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENRFF	Roof replacement	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENWLL	Exterior wall replacement	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENWIN	Window replacement	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENHVC	HVAC equipment upgrade	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENLGT	Lighting upgrade	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENPLB	Plumbing system upgrade	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENELC	Electrical upgrade	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RENINS	Insulation upgrade	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COURT	Food court	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OCCUPYP	Percent occupancy	0 - 100 Missing = Not applicable
ELHT1	Electricity used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NGHT1	Natural gas used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

FKHT1	Fuel oil used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
PRHT1	Propane used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
STHT1	District steam used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HWHT1	District hot water used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WOHT1	Wood used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COHT1	Coal used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SOHT1	Solar used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTHT1	Other source used for main heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HEATP	Percent heated	0 - 100 Missing = Not applicable
MAINHT	Main heating equipment	'1' = 'Furnaces that heat air directly, without using steam or hot water' '2' = 'Packaged central unit (roof mounted)' '3' = 'Boilers inside (or adjacent to) the building that produce steam or hot water' '4' = 'District steam or hot water piped in from outside the building' '5' = 'Heat pumps (other than components of a packaged unit)' '6' = 'Individual space heaters (other than heat pumps)' '7' = 'Other heating equipment' Missing = Not applicable
ELCOOL	Electricity used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NGCOOL	Natural gas used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FKCOOL	Fuel oil used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

PRCOOL	Propane used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
STCOOL	District steam used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HWCOOL	District hot water used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
CWCOOL	District chilled water used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTCOOL	Other source used for cooling	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COOLP	Percent cooled	1 - 100 Missing = Not applicable
MAINCL	Main cooling equipment	'1' = 'Residential-type central air conditioners (other than heat pumps) that cool air directly and circulate it without using chilled water' '2' = 'Packaged air conditioning units (other than heat pumps)' '3' = 'Central chillers inside (or adjacent to) the building that chill water for air conditioning' '4' = 'District chilled water piped in from outside the building' '5' = 'Heat pumps for cooling' '6' = 'Individual room air conditioners (other than heat pumps)' '7' = '"Swamp" coolers or evaporative coolers' '8' = 'Other cooling equipment' Missing = Not applicable
HWRDHT	How reduce heating	'1' = 'Part of the Building Automation System' '2' = 'Programmable thermostat' '3' = 'Manually change thermostat' '4' = 'Manually shut down equipment' Missing = Not applicable
HWRDCL	How reduce cooling	'1' = 'Part of the Building Automation System' '2' = 'Programmable thermostat' '3' = 'Manually change thermostat' '4' = 'Manually shut down equipment' Missing = Not applicable
ECN	Economizer cycle	'1' = 'Yes' '2' = 'No' Missing = Not applicable
ELWATR	Electricity used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

NGWATR	Natural gas used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FKWATR	Fuel oil used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
PRWATR	Propane used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
STWATR	District steam used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HWWATR	District hot water used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WOWATR	Wood used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COWATR	Coal used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SOWATR	Solar used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTWATR	Other source used for water heating	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WTHTEQ	Water heating equipment	'1' = 'One or more centralized water heaters' '2' = 'One or more "point-of-use" water heaters' '3' = 'Both types' Missing = Not applicable
ELCOOK	Electricity used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NGCOOK	Natural gas used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FKCOOK	Fuel oil used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
PRCOOK	Propane used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
STCOOK	District steam used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

HWCOOK	District hot water used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WOCOOK	Wood used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COCOOK	Coal used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SOCOOK	Solar used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTCOOK	Other source used for cooking	'1' = 'Yes' '2' = 'No' Missing = Not applicable
ELMANU	Electricity used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NGMANU	Natural gas used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FKMANU	Fuel oil used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
PRMANU	Propane used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
STMANU	District steam used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HWMANU	District hot water used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WOMANU	Wood used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COMANU	Coal used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SOMANU	Solar used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTMANU	Other source used for manufacturing	'1' = 'Yes' '2' = 'No' Missing = Not applicable
NGGENR	Natural gas used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

FKGENR	Fuel oil used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
PRGENR	Propane used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
WOGENR	Wood used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
COGENR	Coal used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SOGENR	Solar used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTGENR	Other source used for electricity generation	'1' = 'Yes' '2' = 'No' Missing = Not applicable
TOGRID	Deliver electricity to grid	'1' = 'Yes' '2' = 'No' Missing = Not applicable
ENRGYPLN	Energy management plan	'1' = 'Yes' '2' = 'No' Missing = Not applicable
SNACK	Snack bar or concession stand	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FASTFD	Fast food or small restaurant	'1' = 'Yes' '2' = 'No' Missing = Not applicable
CAF	Cafeteria or large restaurant	'1' = 'Yes' '2' = 'No' Missing = Not applicable
FDPREP	Commercial or large kitchen	'1' = 'Yes' '2' = 'No' Missing = Not applicable
KITCHN	Small kitchen area	'1' = 'Yes' '2' = 'No' Missing = Not applicable
BREAKRM	Employee lounge, breakroom, or pantry	'1' = 'Yes' '2' = 'No' Missing = Not applicable
OTFDRM	Other food prep or serving area	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HWTRM	Large amounts of hot water	'1' = 'Yes' '2' = 'No' Missing = Not applicable

Table A.2 (continued)

MEDEQP	Medical equipment	'1' = 'Yes' '2' = 'No' Missing = Not applicable
LABEQP	Laboratory equipment	'1' = 'Yes' '2' = 'No' Missing = Not applicable
MCHEQP	Machine equipment	'1' = 'Yes' '2' = 'No' Missing = Not applicable
POOL	Indoor swimming pool	'1' = 'Yes' '2' = 'No' Missing = Not applicable
HTPOOL	Heated indoor swimming pool	'1' = 'Yes' '2' = 'No' Missing = Not applicable
RFGEQP	Refrigeration	'1' = 'Yes' '2' = 'No' Missing = Not applicable
LOHRPC	Lit when open category	'1' = '1 to 25 percent' '2' = '26 to 50 percent' '3' = '51 to 75 percent' '4' = '76 to 100 percent' '5' = 'Not lit at all when it is normally open' Missing = Not applicable
LNHRPC	Lit off hours category	'1' = '1 to 25 percent' '2' = '26 to 50 percent' '3' = '51 to 75 percent' '4' = '76 to 100 percent' '5' = 'Not lit at all during off hours' Missing = Not applicable
WINTYP	Window glass type	'1' = 'Single layer glass' '2' = 'Multi-layer glass' '3' = 'Combination of both' '4' = 'No windows'
PUBCLIM	Building America climate region	1' = 'Very cold/Cold' '2 '= 'Mixed-humid' '3' = 'Hot-dry/Mixed-dry/Hot-humid' '5' = 'Marine' '7' = 'Withheld to protect confidentiality'

Appendix B Supporting Information for Development and Validation of An Urban Building Energy Model

Table B.1 presents the predominant classes of roofs for different archetypes, which were extracted from CBECS data [8].

Appendix Table B.1 Predominant roof materials extracted from CBECS data

	Predominant roof material		
	Pre-1980	**1980-2004**	**Post 2004**
Education	Built-up (tar, felts, or fiberglass and a ballast, such as stone)	Built-up (tar, felts, or fiberglass and a ballast, such as stone)	Plastic, rubber, or synthetic sheeting (single or multiple ply)
Lodging	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Plastic, rubber, or synthetic sheeting (single or multiple ply)
Office	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Plastic, rubber, or synthetic sheeting (single or multiple ply)
Parking garage	Metal surfacing	Metal surfacing	Metal surfacing
Public assembly	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Metal surfacing	Metal surfacing
Public order and safety	Built-up (tar, felts, or fiberglass and a ballast, such as stone)	Built-up (tar, felts, or fiberglass and a ballast, such as stone)	Metal surfacing
Warehouse	Built-up (tar, felts, or fiberglass and a ballast, such as stone)	Metal surfacing	Metal surfacing
Other	Plastic, rubber, or synthetic sheeting (single or multiple ply)	Metal surfacing	Asphalt, fiberglass, or other shingles

Table B.2 provides the predominant classes of windows for different archetypes, which were extracted from CBECS data [8].

Appendix Table B.2 Predominant type of windows extracted from CBECS data

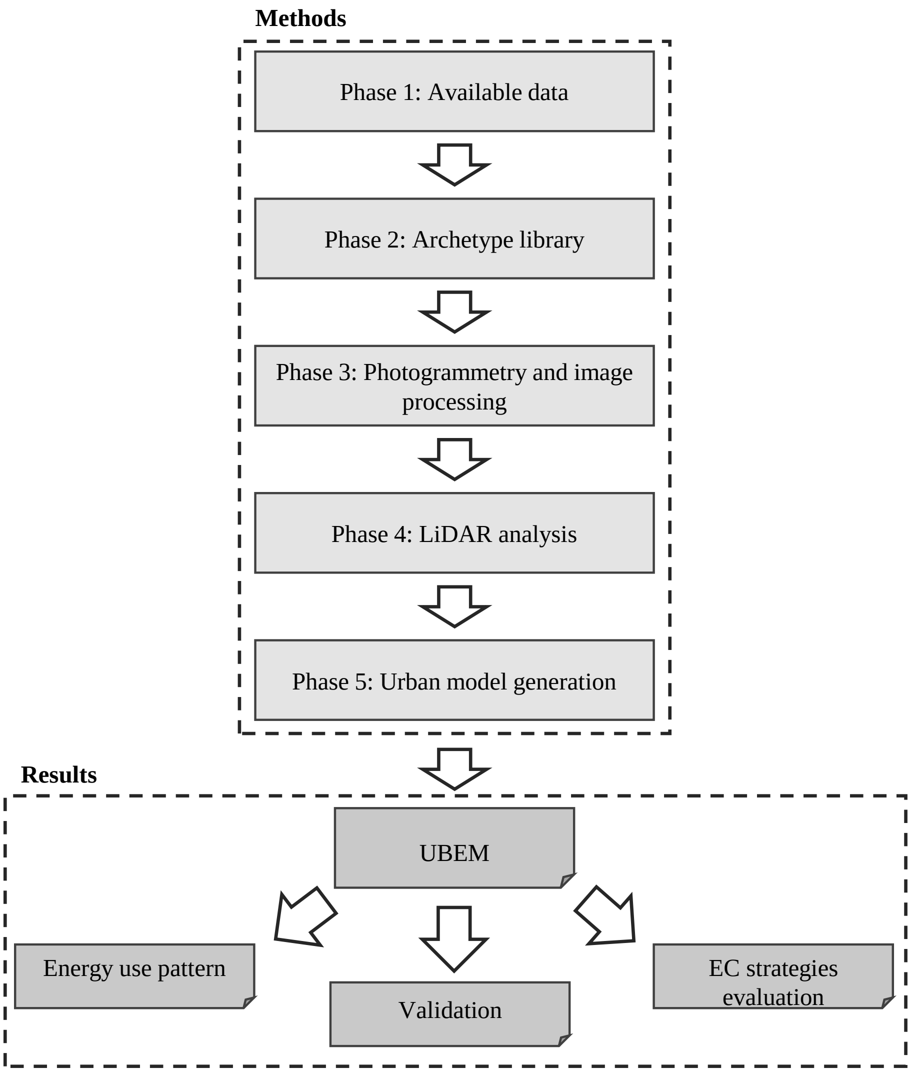
	Predominant roof material		
	Pre-1980	**1980-2004**	**Post 2004**
Education	Single layer	Multiple layer	Multiple layer
Lodging	Multiple layer	Multiple layer	Multiple layer
Office	Multiple layer	Multiple layer	Multiple layer
Parking garage	Single layer	Multiple layer	Multiple layer
Public assembly	Single layer	Multiple layer	Multiple layer
Public order and safety	Multiple layer	Multiple layer	Multiple layer
Warehouse	Single layer	Multiple layer	Multiple layer
Other	Single layer	Multiple layer	Multiple layer

The relationship between external wall materials and wall composition based on ASHRAE standard 90.1 are presented in Table B.3.

Appendix Table B.3 Classifying wall composition based on external wall materials

External wall material	Wall composition			
Brick, Stone, Stucco	Mass wall	Metal building wall	Steel-framed wall	Wood-framed wall and other
Concrete block, poured concrete	Mass wall			
Pre-cast concrete	Mass wall			
Sheet metal panels		Metal building wall		
Siding, shingle, tile			Steel-framed wall	Wood-framed wall and other
Construction glass			Steel-framed wall	

Figure B.1 displays the graphical synthesis of the proposed approach including methods and results.



Appendix Figure B.1 Graphical synthesis of the approach for the UBEM. LiDAR, EC, and UBEM stand for Light Detection and Ranging, energy conservation, and urban building energy model, respectively

Appendix C Supporting Information for Quantifying and Spatializing Buildings Material Stock and Renovation Flow for Circular Economy

Table C.1 to Table C.4 present the total accumulated materials by different products in exterior walls, windows, roofs, and floors.

Appendix Table C.1 Total accumulated materials in the exterior walls by different products

Product	Quantity (metric ton)
Stucco (1")	841.5
Concrete block (8")	69341.7
Gypsum board (1/2")	4742.7
Brick	77610.6
Stone panel (1-1/2")	13582.9
Concrete 25 MPa (15 cm)	4376.2
Reinforcement	130.2
Insulation (4.5 cm)	763.2
Insulation (5.99 cm)	120.4
Insulation (7.47 cm)	21.1
Metal Stud	1241.0
Vapor barrier	90.8
Metal siding	87.4
Wood siding	5.8
Plywood (1/2")	198.3
OSB (7/16")	135.7
Double Pane (1/4")	90.0

Appendix Table C.2 Total accumulated materials in windows by different products

Product	Quantity (metric ton)
Single and double pane (1/4")	3891.4
Frame steel	716.1
Frame aluminum	382.1
Plastics sealing	39.4

Appendix Table C.3 Total accumulated materials in roofs by different products

Product	Quantity (metric ton)
Felt and tar - 5 ply	1920.1
Felt and tar - 4 ply	1255.3
Plywood (5/8")	1201.2
Plywood (1/2")	883.3
Synthetic rubber membrane (90 mil)	301.9
Insulation (12.5 cm)	3243.7
Vapor barrier	33.2
Metal surfacing	406.2
OSB (5/8")	232.4

Appendix Table C.4 Total accumulated materials in floors by different products

Product	Quantity (metric ton)
Terrazzo (1")	23301.6
Cement board (1/2")	10115.3
Plywood (3/4")	8976.0
Carpet (1/2")	742.3
Paving concrete (6")	19554.6
VCT (1/8")	1995.5
Insulation (6.36 cm)	1650.7
Normal duty screed (4 cm)	444.3
Concrete substrate (10 cm)	1419.2

Table C.5 to Table C.8 present total material renovation flow cumulated between 2020 and 2030 by different products in exterior walls, windows, roofs, and floors.

Appendix Table C.5 Total material renovation flow in exterior walls cumulated between 2020 and 2030 by different products

Product	Quantity (metric ton)
Stucco (1")	0.0
Concrete block (8")	0.0
Gypsum board (1/2")	1054.0
Brick	15255.5
Stone panel (1-1/2")	1088.4
Concrete 25 MPa (15 cm)	0.0
Reinforcement	0.0
Insulation (4.5 cm)	0.0
Insulation (5.99 cm)	0.0
Insulation (7.47 cm)	0.0
Metal Stud	0.0
Vapor barrier	0.0
Metal siding	19.8
Wood siding	5.8
Plywood (1/2")	0.0
OSB (7/16")	0.0
Double pane (1/4")	0.0

Appendix Table C.6 Total material renovation flow in windows cumulated between 2020 and 2030 by different products

Product	Quantity (metric ton)
Single and double pane (1/4")	2178.6
Steel frame	249.6
Aluminum frame	257.8
Plastics sealing	21.2

Appendix Table C.7 Total material renovation flow in roofs cumulated between 2020 and 2030 by different products

Product	Quantity (metric ton)
Felt and tar	2099.9
Plywood	366.7
Synthetic rubber membrane (90 mil)	55.0
Insulation (12.5 cm)	0.0
Vapor barrier	0.0
Metal surfacing	39.7
OSB (5/8")	33.6

Appendix Table C.8 Total material renovation flow in floors cumulated between 2020 and 2030 by different products

Product	Quantity (metric ton)
Terrazzo (1")	5945.5
Cement board (1/2")	2450.9
Plywood (3/4")	2174.9
Carpet (1/2")	817.0
Paving concrete (6")	6584.1
VCT (1/8")	507.6
Insulation (6.36 cm)	0.0
Normal duty screed (4 cm)	444.3
Concrete substrate (10 cm)	1419.2

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