ADDRESSING URBAN BUILDING ENERGY MODELING (UBEM)
DATA NEEDS: A CASE STUDY IN A LOW RESOURCE
COMMUNITY

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Presented to
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By

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ADDRESSING URBAN BUILDING ENERGY MODELING (UBEM) DATA NEEDS: A CASE STUDY IN A LOW RESOURCE COMMUNITY

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<td>Agent-Based Modeling</td>
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<td>ACH</td>
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<td>ACS</td>
<td>American Community Survey</td>
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<td>AHS</td>
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<td>ARC</td>
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<td>ASHRAE</td>
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<td>BPS</td>
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<td>CFL</td>
<td>Compact Fluorescent Lamps</td>
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<tr>
<td>COP</td>
<td>Coefficient of Performance</td>
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<td>ECB</td>
<td>Energy Cost Burden</td>
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<td>EER</td>
<td>Energy Efficiency Ratio</td>
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<td>EUI</td>
<td>Energy Use Intensity</td>
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<td>GIS</td>
<td>Graphical Information System</td>
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<td>GPF</td>
<td>Grove Park Foundation</td>
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<td>HOLC</td>
<td>Home Owners’ Loan Corporation</td>
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<tr>
<td>HSPF</td>
<td>Heating Seasonal Performance Factor</td>
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<tr>
<td>HVAC</td>
<td>Heating, Ventilation, and Air Conditioning</td>
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<td>IECC</td>
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<td>LIHEAP</td>
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<td>MVU</td>
<td>Minimum Viable UBEM</td>
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<tr>
<td>PNNL</td>
<td>Pacific Northwest National Laboratory</td>
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<tr>
<td>RECS</td>
<td>Residential Energy Consumption Survey</td>
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<tr>
<td>SAIPE</td>
<td>Small Area Income and Poverty Estimates</td>
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SEER  Seasonal Energy Efficiency Ratio
TDS  Travel Demand Survey
TMY  Typical Meteorological Year
UBEM  Urban Building Energy Modeling
UHI  Urban Heat Island
UMI  Urban Modeling Interface
WWR  Window-to-Wall Ratio
SUMMARY

Urban Building Energy Modeling (UBEM) is a method of simulating the energy usage of a grouping of buildings, at the scale of a neighborhood or city, rather than the typical simulation of a single building. This can be a powerful tool to reduce current energy usage, through testing retrofit scenarios on the existing building stock, and to guide future planning efforts. This switch in simulation scales is crucial to move towards more sustainable and resilient cities.

One critical limitation in UBEM is data availability to develop representative archetypes for an area of study. An UBEM requires a lot of geometric and non-geometric data to simulate the energy use patterns of an area. Necessary geometric data include building footprint, building height, number of stories, and window-to-wall ratios. These data are relatively less challenging to source as compared to the non-geometric building properties required for a study. This includes the building program, conditioning systems type and efficiency, operations schedules, internal loads, occupancy patterns and behavior, and building envelope construction. This information is used to generate archetypes that define the characteristics of all buildings in a study area.

The issues of data availability are even more severe in low resource communities, where default values will not be representative of lived experiences. This thesis identifies critical obstacles and highly sensitive parameters related to building occupants, envelopes, and systems when simulating the energy use of underrepresented communities. It also argues for the inclusion of socioeconomic factors when developing archetype definitions for an UBEM, particularly in a low resource neighborhood. Ignoring socioeconomic and demographic factors in the models may result in inaccurate simulations that do not capture
the realities of underrepresented areas. This has the potential to further compound the inequalities the neighborhoods already face.

This thesis addresses data availability issues, in all urban contexts, by establishing a list of readily available data sources as well as a multi-step, theoretical framework that can be used to gather the data required to run an accurate UBEM that considers the surrounding socioeconomic factors. This framework starts by translating any available data sources that can be used to define building parameters for the neighborhood. Any gaps that remain after using available datasets should be filled with data that can be translated from other relevant studies. If the required data do not already exist and there are no data from a different study that can be used, data must be collected or generated specific to the study.

This framework is demonstrated through a case study in the Grove Park neighborhood of Atlanta, Georgia. This majority-minority, low- to moderate-income neighborhood was selected based on a relationship with a local community organization. 110 single-family households were modeled. The results of the study analyze current energy use patterns, compare neighborhood-specific archetype definitions to default residential archetype templates, and look at the neighborhood’s performance under future weather scenarios. The results are validated against national energy consumption data.

The study shows that within a single neighborhood the energy use intensity (EUI) can vary by up to 92 kWh/m² based on building envelope condition and occupancy patterns. Default archetype inputs can dramatically underestimate or overestimate the energy use of households in a low resource community. Looking at energy performance under both current and future weather scenarios allows for energy efficiency strategies that are beneficial to the neighborhood now while increasing future resiliency.
CHAPTER 1 INTRODUCTION

As global populations shift from rural to urban areas it is particularly important to turn attention there to help reduce energy usage. Currently, urban areas use approximately 70% of the world’s energy (Natanian and Auer 2020) and are one of the highest contributors to global CO2 emissions (Mat Santamouris 2013). This means that urban areas hold significant potential to reduce global energy use and emissions.

One method of addressing current and future energy use in urban areas is Urban Building Energy Modeling (UBEM). UBEM provides a method of simulating buildings’ operational energy use at the scale of a neighborhood or city, rather than the typical simulation of a single building. An UBEM study can help to guide retrofitting efforts on the existing building stock and future planning scenarios for proposed development. This switch in scales is crucial in reducing current energy use and planning more sustainable and resilient cities.

UBEM is still a relatively young field of research. Since 2011, there has been a steady increase in the number of publications on this topic each year, but it still requires significant consideration and research to make the tool more useful to researchers, architects, planners, policymakers, and government agencies (Ali et al. 2021). Issues related to data, time, and resources must be addressed moving forward to further the use of UBEM across all urban areas.

As research in UBEM continues and the tool is used more frequently, it is critical that socioeconomic factors are coupled with the model. Building Performance Simulation (BPS) has a history of using standard inputs that introduce bias to the models and fail to account for a variety of cultural, racial, and economic backgrounds. Examples of this can
be found in typical occupancy schedules, which only account for a standard nine to five workday and exclude anyone working jobs with changing schedules and/or multiple jobs (O’Brien et al. 2017), as well as typical thermal comfort standards, which are based on middle-aged, white males and ignore how race, age, and gender may impact occupants’ perceived comfort (Fabbri 2015). Furthermore, default inputs ignore the impact that varying cultural backgrounds and practices have on energy usage patterns (Al-Mumin, Khattab, and Sridhar 2003). When models are built using these default inputs, they further compound the bias inherent in the way building performance is considered.

In UBEM, as with all BPS, the model is only as representative of an area as the inputs are. In underrepresented communities, where default values do not capture the residents’ lived experiences, the models fail to capture the realities of the neighborhood. Most current data sources and UBEM workflows are designed around ideal urban settings and do not account for the realities of majority-minority and low-income neighborhoods. Socioeconomic factors help produce representative UBEM in all areas but are especially important in low resource communities. In other, more typical urban conditions default values will be closer to lived experiences, they do not currently face the same levels of energy insecurity, they are not as energy cost burdened, and they are not as vulnerable to climate change. If the results of an UBEM study with default inputs are used to dictate resource allocation and shape urban policies, the already disadvantaged communities will continue to be overlooked and the problems they currently face will be exacerbated.

This thesis uses “low resource” and “underrepresented” to describe any community or grouping of people that “are marginalized and underserved in society” (Fish and Syed 2020). Vulnerability, particularly as it relates to natural disasters, can be defined as “a set
of conditions characterizing a group of people or a particular location as sensitive to stressors and perturbations, which typically include disasters and environmental hazards” and can be related to biophysical, political, social, and economic conditions (Mueller and Dooling 2011). Income levels, diversity and minority status, access to transportation, and community resources all play a part in defining underrepresented areas.

1.1 Research Gap

Critical work is being done to utilize and improve UBEM studies. However, challenges still prevail in data availability required to complete a study. Representative inputs, beyond default values, are even more challenging to source. Data sources and workflows to develop archetype definitions for UBEM must be expanded upon. While looking for available data sources, it is important to account for socioeconomic factors to ensure that data are tailored to the neighborhood being modeled. Socioeconomic factors should be included in all UBEM studies, but they are particularly important in low resource communities.

1.2 Research Questions

• What impact do socioeconomic and demographic factors have on energy usage and UBEM studies? How can they be incorporated?

• What data sources are available to generate UBEMs? What steps should be taken if there are no existing data required for an UBEM?

• Can existing data sources be used to generate representative UBEMs in low resource communities?
1.3 Research Aims

This thesis presents a workflow to source data required for archetype inputs in a residential UBEM study while considering the socioeconomic standing of the study area. While the approach is generalizable to all urban areas, the thesis is specifically focused on underrepresented communities. Specifically, this thesis document aims to:

- Argue for the consideration and inclusion of demographic and socioeconomic factors in all UBEM studies;
- Highlight critical obstacles and key parameters (related to people, envelope, and systems) and urban inequalities that are more sensitive in the context of racial, income, and resource inequalities;
- Identify readily available data sources that can be used to inform archetype inputs across all urban areas;
- Establish a framework that can be used to generate archetype inputs while considering socioeconomic factors; and
- Demonstrate this process in a low resource community through a case study of a residential UBEM in the Grove Park neighborhood of Atlanta, Georgia.

1.4 Research Significance

The workflows presented in this thesis are applicable to all urban areas and can help to address data scarcity across all UBEM. Understanding the relationship between socioeconomic factors and energy use patterns is not unique to low resource communities, but it is particularly important in them. The current lack of representation in UBEM is problematic as it can further compound the inequalities the neighborhoods already face.
Furthermore, by partnering with a local community organization, this work is also significant in demonstrating ways that UBEM can be used to address issues and goals present in a low resource community.

1.5 Thesis Overview

This thesis is structured as follows. Chapter 1 introduces the research and research aims. Chapter 2 covers a literature review of current UBEM practices and challenges. Chapter 3 presents available data sources that can be used to develop inputs for an UBEM. Chapter 4 moves through the process of translating these data sources into UBEM inputs with a case study in an underrepresented neighborhood in Atlanta, Georgia. Chapter 5 presents and validates the results of this case study. Chapter 6 discusses the results and limitations of the study as well as future work. Chapter 7 concludes the thesis. Appendix A provides a sample archetype input template.
CHAPTER 2 LITERATURE REVIEW

This literature review identifies key issues currently facing UBEM and explores how these challenges differ in various urban settings, including low resource communities.

2.1 Methodology

This scoping review, as defined by Arksey and O’Malley, is used to summarize existing research and identify the literature gap surrounding the integration of socioeconomic factors in UBEM (2005). The literature review was conducted through both keyword searches and relevant citations. First, major databases, including Google Scholar, Science Direct, and Scopus, were searched using combinations of keywords related to both UBEM and representation to source initial publications. There was a limited number of publications that overlapped these two areas, and most of the literature found falls into just one of the two broad categories. Sample keywords include “UBEM”, “archetypes”, “energy use”, “vulnerability”, “representation”, “socioeconomic”, “demographics”, and “climate change”. The results from these keyword searches were analyzed for relevance to the subject matter. Sources from the relevant citations in these papers were also included. 83 total sources are included in the literature review. Of these sources 88% are journal articles, 7% are conference papers, and the remaining 5% come from other sources including book chapters, reports, and news articles. Most of the sources, 73%, were published as of 2016. Only sources published in English were reviewed.

2.2 Urban Building Energy Modeling Approaches

Urban energy modeling looks at broad energy usage across urban areas. An UBEM only captures one side of urban energy use, typically overlooking the energy impacts of
urban transportation as well as the embodied energy in buildings and infrastructure and instead focusing on the operational energy of buildings (Abbasabadi and Ashayeri 2019).

UBEM is the practice of simulating the energy use patterns and needs of a grouping of buildings. These studies can be carried out on tens of buildings, just one block, all the way up to tens of thousands of buildings, encompassing an entire urban area (Hong et al. 2020; Reinhart and Cerezo Davila 2016). They move beyond the scale of a single building energy model and look at energy use patterns across urban areas. This shift in scales allows for decisions that reduce the energy use of a grouping of buildings and plan for sustainable and resilient future development. By modeling a grouping of buildings together, the Inter-Building Effect will also be captured and the impacts of the surrounding urban context on heating and cooling energy use will be captured, which will increase the overall accuracy of the model (Pisello et al. 2012; Han, Taylor, and Pisello 2017).

UBEM studies can be either top-down or bottom-up. Top-down models rely on larger data trends from the region of study and work to identify relationships between energy use patterns, sourced from historic energy use data, and other econometric and technological factors (Lim and Zhai 2017). They require fewer data and computing power than bottom-up approaches, but since they rely on existing data rather than a simulation of the energy use itself they are limited in their ability to evaluate future energy scenarios, and they typically cannot be used at a small spatial or temporal scale (Cereo Davila et al. 2017).

Taking an opposite approach, bottom-up studies examine more closely operational energy processes. These models can be statistics-based, which use measured inputs and outputs of procedures rather than simulating the process itself, or physics-based (Nageler
Building physics models use archetypes to represent a broader grouping of buildings within the simulated urban context based on shared characteristics (Torabi Moghadam et al. 2017). The archetypes hold all the non-geometric information of buildings in the simulation. The building stock is first segmented into different groups based on defining properties, which can include building typology, use, age, and systems. Then, values are assigned to these archetypes representative of the constructions, systems, and loads of the grouping of buildings. The archetypes can represent anywhere from tens to thousands of buildings within the area of study. Having templates that represent these values for groups of buildings, rather than defining each building individually, significantly reduces the amount of time and information needed in a study. The values assigned to different parameters in the archetype can be either a fixed value in a deterministic archetype or a probability distribution in a stochastic archetype depending on the intended use of the simulation (Pasichnyi, Wallin, and Kordas 2019). It is best practice to use fixed values for parameters that have little uncertainty or effect on the results and use probabilistic inputs for any parameter that is assumed to have a bigger impact on the results or has more uncertainty (Hedegaard et al. 2019).

Hybrid models, or the combination of a physics-based simulation with a statistical approach to calibrate the results, lead to the most accurate UBEM studies (Johari et al. 2020). A number of tools currently exist, and more are being developed, to support physics-based and hybrid UBEM simulations (Ferrando et al. 2020). Useful applications of bottom-up UBEM models can include guiding urban planning and new neighborhood design decisions, energy efficiency and carbon reduction strategies for the existing building stock by archetype, individual building-level recommendations, and buildings-to-grid
integration (Ang, Berzolla, and Reinhart 2020). Bottom-up models have recently been gaining significant attention because they can provide highly detailed spatiotemporal results, have the ability to test a range of design and retrofitting scenarios, and can act as an urban planning tool (Reinhart and Cerezo Davila 2016). For these reasons, this thesis will be focusing on hybrid, bottom-up models.

2.3 Challenges in UBEM

While great strides have been made in improving accuracy in UBEM, as well as reducing simulation time and effort, there are still challenges facing the field today. Some of the biggest challenges faced by UBEM at large are amplified in the context of underrepresented communities.

2.3.1 Data Availability

Several categories of data are required when completing an UBEM study, including data to run the simulations and validate the results. Significant challenges in data availability, data inconsistencies, and data quality persist (Ali et al. 2021) which limits the widespread adoption of UBEM.

For physics-based and hybrid bottom-up models information on building geometries and properties are required. Necessary geometric information includes building footprint and geometry (which can be simplified to reduce simulation times), number of stories, roof height, conditioned floor area, orientation, window-to-wall ratios (WWR), and thermal zones (Cerezo Davila, Reinhart, and Bemis 2016; Hedegaard et al. 2019). Common archetype parameters include building age, building size, typology, program, ownership model, building systems, operations schedules, internal loads, occupancy patterns and
behavior, building envelope construction and properties, and airtightness (Hong et al. 2020; Sokol, Cerezo Davila, and Reinhart 2017). Many cities have the public data required to support an UBEM, however, a lack of standardization across departments and cities makes these data difficult to access and implement in a study. It is also still frequently missing information on the buildings’ WWR, construction types, mechanical systems, appliances, and more which must be filled in from other data sources (Y. Chen et al. 2019).

Calibration and validation of UBEM results is essential to reduce uncertainties, compounded by simplifications made at all steps of the process, as well as to ensure the reliability of the results of the study (Ferrando et al. 2020; Johari et al. 2020; Reinhart and Cerezo Davila 2016). The most common calibration and validation approaches rely on data related to annual or monthly energy use for one, some of, or all the buildings included in an UBEM study (Delmastro, Mutani, and Corgnati 2016; Hedegaard et al. 2019). Based on privacy restrictions and data availability, most studies are calibrated based on aggregated data that represents the whole study area. This leads to highly accurate results for the overall study, but the results of any individual building in the study area can be highly inaccurate (Reinhart and Cerezo Davila 2016). Using data at a finer spatial scale, such as a block, and at a finer temporal scale, such as monthly or hourly as opposed to yearly, allows the results of a study to be used for more decisions, including the estimation of daily or seasonal peak demands as opposed to only city-scale decisions (Cerezo Davila et al. 2017).

When metered data are not available, other approaches to validation rely on a comparison to national energy use consumption statistics (Ali et al. 2021). Examples of this can be seen in a study developing building stock archetypes in Ireland (Ali et al. 2019) and a study that modeled the entire city of Boston based on building age and use (Cerezo
While this method is not as accurate as measuring against measured data it ensures the results of the study are plausible and is not restricted based on data availability.

Before running the simulation and obtaining the results, monthly electricity and natural gas data can be used to calibrate the input parameters for archetypes in a study, a process that is integrated into some tools including the Commercial Building Energy Saver (Y. Chen, Hong, and Piette 2017). Several methods to automatically calibrate UBEM using probabilistic inputs for key parameters have been proposed, including a method that continually updates the model based on building performance over time to track the actual performance of retrofitting measures and maintain a calibrated UBEM for future studies (Nagpal, Hanson, and Reinhart 2018) and parametric archetype inputs that can be automatically calibrated, before the simulation runs, based on measured annual data (Y. Chen, Deng, and Hong 2020). Several studies refer to Bayesian statistics as a viable framework to increase accuracy and eliminate uncertainty from models in a semi or fully automated process (Braulio-Gonzalo et al. 2016; Cerezo Davila et al. 2017; Sokol, Cerezo Davila, and Reinhart 2017). This approach goes beyond just reducing the gap between simulated and metered data by moving through an iterative process based on individual parameter uncertainties and likelihoods (Ferrando et al. 2020).

However, the data used for calibration and validation are limited in availability. Useful applications of UBEM are currently limited to cities in which measured data are available (Hong et al. 2020) or can be generated specifically for the study (Passe et al. 2020). Furthermore, sources of uncertainty in the data include the use of proxy data or the need to adjust the measured data to match the scale of the study (Keirstead, Jennings, and
Sivakumar 2012). Increased energy disclosure laws, like those already in place in several cities and states, will make more national energy data publicly available (Kontokosta, Reina, and Bonczak 2020). There are fewer pressures for, and requirements of, single-family residential buildings to publish energy data and therefore calibration of this building typology becomes more difficult (Pasichnyi, Wallin, and Kordas 2019). Moving forward, access to measured data at a building level, by occupancy type, and at a district level may increase accuracy in UBEM (Cerezo Davila, Reinhart, and Bemis 2016).

2.3.2 Data in Underrepresented Communities: Systemic Racism and Bias in Urban Data Collection Methods

While there are demonstrated issues of data availability and completeness in all urban settings, these issues are even more prevalent in low-income and minority neighborhoods. Developing areas are less likely to have data available (Keirstead, Jennings, and Sivakumar 2012). Underrepresented neighborhoods are more resistant to data collection due to lack of community engagement, lower access to telephone and internet services, and language barriers (Passe et al. 2020). Data collection and maintenance in underrepresented communities must be improved before UBEM can be adopted.

The national census database, and other urban surveys, can be used to gather some information on an urban population, including socioeconomic status and demographics (Torabi Moghadam et al. 2017), but these data are often incomplete or inaccurate. Current urban surveying techniques routinely discount the urban poor and vulnerable populations. The US census has historic problems in miscounting vulnerable demographics. A decision to end counting on the 2020 census in October, after significant impacts from the COVID-
19 pandemic, threatens the representation of Latinos, Native peoples, and undocumented immigrants for the next decade (Wang 2020).

Other urban and household surveying methods use standardized practices to allow for comparisons of results, but these standard practices repeatedly underrepresent the urban poor due to factors including population mobility, rapid urbanization, unplanned settlements, unregistered settlements, transformations in the sociodemographic structures within cities, and non-traditional dwelling and family arrangements (Elsey et al. 2018). Standard definitions of households, which allow for comparability in survey results, are designed to collect data on closed households, with fixed membership, and are therefore not suited towards counting open household units, which use flexible membership and multiple support networks to cope with poverty and in response to certain cultural practices (Randall and Coast 2015). These surveys often omit, sometimes intentionally, the “poorest of the poor” including people who are homeless, in institutions, nomadic, in disjointed households, or living in slums or other areas posing security risks (Carr-Hill 2013). To decrease bias in these data sources the structures and systems that have historically and continue to sustain systemic racism and inequalities must be acknowledged (K. S. Brown et al. 2019). When data from these surveys are used to inform UBEM studies they will not accurately or adequately address the realities and needs of these communities. This has the potential to influence the allocation of resources and policy decisions, which will further disadvantage these neighborhoods.

### 2.3.3 Archetype Definition

Outside of the issues in accessing data, challenges prevail in generating suitable archetypes to accurately model diverse building conditions, performance characteristics,
and use patterns (Torabi Moghadam et al. 2017). Research is ongoing to increase accuracy in many different ways including; Using probabilistic inputs for parameters with high uncertainty or impact on simulation results (Cerezo Davila et al. 2017); Calibrating unknown and uncertain probabilistic archetype parameters against measured energy data using Bayesian calibration (Sokol, Cerezo Davila, and Reinhart 2017) or a sensitivity analysis and k-fold approach (Battini, Pernigotto, and Gasparella 2019); Utilizing remote sensing to calculate archetype inputs, including WWR (Dochev et al. 2020). However, even with these steps, it is difficult to capture the complexities and realities of the urban fabric (Hedegaard et al. 2019; Hong et al. 2020). Typical reference occupancy factors used in UBEM studies have been shown to be inaccurate for both commercial and residential settings (Barbour et al. 2019; Happle, Fonseca, and Schlueter 2020). Uncertainties in key parameters, such as occupancy patterns and infiltration rates, can significantly impact the results of a study as they are difficult to accurately model but are also among the most sensitive parameters (Reinhart and Cerezo Davila 2016). Occupant behavior affects the energy use of building equipment, lighting, heating, and cooling (El Kontar and Rakha 2018). Infiltration rates heavily influence the heating and cooling demands of a space, and how they are modeled can significantly impact the results of an energy simulation (Happle, Fonseca, and Schlueter 2017).

Potential solutions to overcome this obstacle include leveraging advances in occupant-centric urban data (Salim et al. 2020) or integrating urban mobility models (Johari et al. 2020). The latter approach can be seen in both the Urban Modeling Interface (umi) and CitySIM tools (Ferrando et al. 2020). Efforts to develop standard, national archetype libraries can reduce the time pressures and further the adoption of UBEM to
municipalities that do not have the resources to go through the lengthy, data-intensive process themselves (Cerezo Davila, Reinhart, and Bemis 2016). These standard archetypes will be similar to the US Department of Energy (DOE) Commercial Reference buildings and act as both a benchmark performance measure and a reference point to develop more situation-specific archetypes (Carnieletto et al. 2021). There is an effort to make national representative archetypes for over a dozen countries in Europe through the TABULA project (Loga, Stein, and Diefenbach 2016).

2.3.4 Defining Archetypes in Underrepresented Communities

The issues in generating representative archetypes are intensified in the case of underrepresented communities. High uncertainty parameters become even more sensitive in low-income and minority communities where these factors deviate even further from the expected norm or published values. The literature demonstrates that energy use patterns and building characteristics differ with socioeconomic factors and minority status and therefore these must be considered when developing archetypes. Factors that can influence energy use profiles, particularly in a residential setting, include the number of occupants, size of the dwelling, dwelling typology, ownership model, household income level, minority status, gender, education level, occupation, property and land value, and density of public and private schools in the area (Aydinalp, Ugursal, and Fung 2002; Delmastro, Mutani, and Corgnati 2016; Z. Ding et al. 2017; Lam 1998; Ma and Cheng 2016; Tso and Yau 2003). Default values, which are frequently sourced from building codes and other available literature (Sokol, Cerezo Davila, and Reinhart 2017), will not be representative of underrepresented communities and therefore reduce the accuracy of the study.
Several considerations lead to these differences in energy use profiles. In a residential setting, appliances can use the majority of the energy (Hiller 2015), and there is a link between income levels and the estimated number of appliances in a residence (Filogamo et al. 2014). Particularly, a dryer, dishwasher, and electric stove/oven have been shown to significantly impact energy use profiles (McLoughlin, Duffy, and Conlon 2012). Furthermore, appliance efficiency and performance tend to be worse in low-income households leading to higher Energy Use Intensities (EUIs) among this demographic (Kontokosta, Reina, and Bonczak 2020). Beyond just the number of appliances, occupancy behavior and use of electricity is shaped by learned behaviors and various socioeconomic factors including income, age, and education level (IEA 2013). Different cultural practices can shape occupancy patterns and behaviors as well (Tso and Yau 2003).

It is important to capture socioeconomic considerations in occupancy schedules because they are widely recognized as a primary contribution to building energy use (Hoes et al. 2009). Default inputs are often based on over-simplified, static reference models that ignore the varied nature of occupant behaviors (Hong et al. 2018). For instance, default occupancy models assume a standard nine to five workday that does not account for alternate job types or multiple jobs (O’Brien et al. 2017). Default occupancy schedules also ignore varied cultural practices (Al-Mumin, Khattab, and Sridhar 2003). Heating and cooling habits are also impacted. Homes in low-income and minority status areas do not always have the systems or ability to achieve indoor comfort (Passe et al. 2020). Beyond the lack of access to heating or cooling equipment, income level affects setpoint schedules (M. Santamouris, Kapsis, et al. 2007).
Outside of the energy use profile, the physical properties of buildings in underrepresented communities will also vary, and typically underperform. Building envelopes of homes in low-income areas are frequently under-insulated or lack insulation entirely and are overall in worse condition than homes in higher-income areas (M. Santamouris, Kapsis, et al. 2007; M. Santamouris, Pavlou, et al. 2007). Air infiltration rate has significant impacts on the heating and cooling loads of a building and therefore is an important parameter to consider (Happle, Fonseca, and Schlueter 2017). In low-income houses, air leakage is up to 145% higher than in non-low-income houses (Bradshaw, Bou-Zeid, and Harris 2014). These envelope conditions lead to an increase in infiltration rates and overall make it so that parameters defined by literature or based on American Society of Heating, Refrigeration, and Air-Conditioning Engineers (ASHRAE) standards and other codes do not reflect the realities of low-income and minority communities.

2.4 Importance of Accurate UBEM

Beyond the ways in which UBEM studies inadequately address underrepresented communities at the scale of a building or small grouping of buildings, there are larger challenges at the urban scale that low resource communities face that UBEM must also address.

Low-income and minority communities currently experience adversity in terms of their energy use and microclimates. It has been shown that both low-income and minority households face increased energy cost burdens (ECBs), a relationship of the total amount of money spent on energy to net income (Kontokosta, Reina, and Bonczak 2020). This can be partially attributed to the inefficiency and poor performance of the housing stock in underrepresented communities. Furthermore, dangerously high indoor air temperatures and
the risk of overheating during a heatwave disproportionally affect minority, low-income, and elderly populations (Holmes, Rajkovich, and Baker 2017). There is a clear and demonstrated link between lower socioeconomic standing and increased urban heat stress from localized Urban Heat Island (UHI) effects (B. C. Mitchell and Chakraborty 2018). Factors that increase sensitivity to extreme heat events include being elderly, non-white, under poverty levels, and having a low education level (Xu et al. 2021). Current UBEM practices typically neglect the effects of microclimates, including UHI, to avoid increasing the complexity of the model (Cerezo Davila, Reinhart, and Bemis 2016) and based on limited computing power (Johari et al. 2020). However, local weather data are important for accurate UBEM results, as TMY files can both significantly overestimate and underestimate electricity and gas use, based on the season (Li 2020).

At a larger urban scale, underserved communities face many other adversities more frequently than other urban areas. Low resource urban settings are associated with worsened health, both physical and mental. Health issues in low-income urban areas can be attributed to deprivation of both material and social elements and can be linked to income, education level, population density, access to water, and sanitation practices (Stephens et al. 1997). Urban areas across the board are more susceptible to disease transmission, but particularly urban slum-like conditions. In a recent study on the transmission of the Covid-19 virus in urban settings, key parameters including population density, derelict living conditions, lower-income level, high-risk occupations, and untreated water were all linked to higher transmission rates (Mishra, Gayen, and Haque 2020). Furthermore, poor urban environments also have a demonstrated link to higher non-communicable diseases including injury and mental health, which stem from poor and
unsafe living conditions, alcoholism, crime, gender-based discrimination, environmental hazards, and housing instability (Elsey et al. 2018). Criteria including air pollution, water quality and availability, sanitation practices, traffic noise, population density, public transportation options, and food supply can all be linked to urban health (Kjellstrom et al. 2007). Unequal access to quality greenspace in urban settings further propagates health inequality in urban living. Low-income and low resource communities typically have less access to quality green space, which in turn means they cannot equally benefit from the physical and psychological health benefits that green urban spaces provide (Braubach et al. 2017). Access to quality parks in an urban environment has shown a positive correlation with physical activity and a negative correlation with obesity rates, two strong indicators of overall public health (Macfarlane et al. 2020).

Low-income urban areas are also disadvantaged in terms of transportation options. High-income areas have better proximity to transportation options which continues to privilege them in terms of new development opportunities and furthers urban segregation (Tiznado-Aitken, Muñoz, and Hurtubia 2018). Spatial inequalities are further propagated by the distribution of public right-of-way street trees. Publicly funded street trees vary with income, minority status, and homeownership model, and leave communities without the benefits of street trees which include reducing UHI, reducing air pollution, increasing property value, and reducing aggression and crime (Landry and Chakraborty 2009).

Policies aimed at helping disadvantaged communities must closely understand the physical and social realities of these environments to best implement changes. The Low-Income Home Energy Assistance Program (LIHEAP) was started in 1981 to help low-income houses with heating and cooling needs, energy crisis assistance, and
weatherization, but the methods of allocating funds are outdated and do not equitably support present-day homes across the country (Kaiser and Pulsipher 2002). Weatherization programs, like the one LIHEAP offers, are being underutilized in low resource neighborhoods due to a lack of knowledge of the available resources as well as the perceived effort of utilizing these resources being far greater than the benefits of weatherization in the community. Policies to overcome these barriers should focus on leveraging social norms and community leaders (Huang et al. 2019). An UBEM study can only show the significant opportunities for energy savings by promoting weatherization in underserved communities where buildings are demonstrated to underperform, but it requires knowledge of the community to create policies that will be successful in accomplishing these goals.

2.5 Impact of Climate Change in Low-Income and Minority Communities

Climate change has the possibility to, and likelihood of, amplifying existing urban inequalities. Events including heatwaves, flooding, and landslides as well as the mitigation strategies to respond to these events all disproportionately affect people who live in low-income and low-socioeconomic neighborhoods (Reckien et al. 2017). As the climate changes these events will cause more damage to underrepresented neighborhoods, which will in turn further disadvantage the areas. With changing climate patterns and the frequency of heatwaves increasing (O’Neill and Ebi 2009) the risk level for these communities already exposed to more heat stress also increases. More frequent incidents of extreme rainfall-induced flash flooding is another risk of climate change that threatens the urban transportation infrastructure and stormwater management systems (Kermanshah, Derrible, and Berkelhammer 2017) particularly in underrepresented communities. Not only
are they more vulnerable to adverse effects from climate change, but they also have fewer resources and knowledge to adapt to these changes (Passe et al. 2020; Shi et al. 2016).

2.5.1 Resiliency Strategies

The 2021 winter storm in Texas highlights the importance of climate adaptation and resiliency strategies in urban planning. For long-term urban planning and climate adaptation strategies to be equitable and inclusive, they must both recognize and challenge existing socioeconomic inequalities in present-day cities (Chu, Anguelovski, and Roberts 2017). Current adaptation strategies tend to protect or prioritize high socioeconomic groups and ignore the urban poor, by omission, or actively displace and/or negatively affect disadvantaged areas, by commission (Anguelovski et al. 2016). Equitable, rather than equal, distribution of resources should be embedded in all resilience plans to acknowledge and account for social, cultural, and political differences as cities plan for resilience (Meerow, Pajouhesh, and Miller 2019). Mueller and Dooling highlight the importance of understanding the existing populations and current conditions of neighborhoods before making any redevelopment plans to avoid reinforcing existing vulnerabilities (2011).

UBEM tools can be used to understand existing conditions and plan for future development and resiliency strategies. Both top-down and bottom-up models can be used to predict performance under future climate scenarios (Im, Srinivasan, and Jia 2020). UBEM can act as an instrument to implement various decarbonization strategies and other energy adaption approaches, including energy communities, and test their performance (Bukovszki et al. 2020). By utilizing morphed weather files that predict future climate scenarios, UBEM studies can be used to predict an urban environment’s performance in various weather scenarios as well as test the effectiveness of design strategies to increase
resilience to climate change (Jagani and Passe 2017). Many cities, particularly those on coasts or in desert climates, identified UBEM as helpful in testing and identifying adaptation and resiliency strategies in the face of climate change and extreme weather events (Reyna et al. 2018). Applications of UBEM to plan for future climate scenarios must carefully consider the realities of all urban areas to not further disadvantage low resource communities in the face of climate change.

2.6 Current Representation Practices in UBEM

One area of research within UBEM of prominence to this work is the limited studies starting to point towards the importance of accounting for socioeconomic and demographic factors in UBEM. The connection to demographics and energy use patterns is acknowledged but rarely integrated in current practice. While socioeconomic factors can be a primary input of top-down modeling approaches (Brøgger and Wittchen 2018) they have been historically ignored in bottom-up models (Johari et al. 2020). They are important to consider in terms of defining occupancy patterns and relating energy models with socioeconomic models to better understand this relationship (Hong et al. 2020). Socioeconomic factors are mentioned as a potential way to segment the existing urban stock into archetype definitions (Pasichnyi, Wallin, and Kordas 2019). Furthermore, calls to integrate data-driven modeling approaches can bring socioeconomic factors into archetype construction allowing for more accurate urban models (Abbasabadi and Ashayeri 2019). Some socioeconomic factors, specifically ownership model, education level, and occupation, were identified as barriers to residential retrofitting opportunities and therefore require stronger integration into existing UBEM workflows (Delmastro, Mutani, and Corgnati 2016). Previous work shows the possibility of integrating UBEM
results and Graphical Information System (GIS) to provide interactive spatiotemporal visualization of energy use, the impacts of different energy efficiency strategies, and neighborhood demographics (Krietemeyer and El Kontar 2019).

2.7 Minimum Viable UBEM

Much like in other BPS, the amount of detail required while setting up an UBEM is dictated by the intended use of the results. A Minimum Viable UBEM (MVU) determines what level of detail and calibration efforts are required based on the intended application of the study (Ang, Berzolla, and Reinhart 2020). This ensures that the model can reliably answer questions while still minimizing effort and cost. As the requirements of a study evolve, and as the application changes, so will the requirements of the MVU. For example, an UBEM used for urban planning can rely primarily on standard inputs, including the US DOE reference buildings, with very little customization. However, a study being used to make building-level recommendations requires significantly more detailed information, including metered data for calibration.

The concept of the MVU is particularly important to consider in low resource communities. The lack of readily available data is already a limitation to these studies, and time and cost resources are at a premium. Understanding the intended use of the model, as well as the required level of detail to accurately answer these questions, can be a method of producing reliable models with less effort.
CHAPTER 3  UBEUM DATA SOURCES

This chapter focuses on publicly available data sources that can be used to generate relevant residential model inputs in the United States. It builds off work from the UBEUM scoping review, which identified commonly used data sources. These include metered data from utility companies (Delmastro, Mutani, and Corgnati 2016; Sokol, Cerezo Davila, and Reinhart 2017; Torabi Moghadam et al. 2017), local and national government databases and records (Cerezo Davila, Reinhart, and Bemis 2016; Y. Chen, Hong, and Piette 2017; Y. Chen, Deng, and Hong 2020), mandatory disclosure laws (Kontokosta, Reina, and Bonczak 2020; Ma and Cheng 2016), field measurements (Hedegaard et al. 2019; Hiller 2015; Salim et al. 2020), community engagement through surveys and questionnaires (Hiller 2015; Passe et al. 2020; M. Santamouris, Kapsis, et al. 2007; Tso and Yau 2003), and third-party map and geospatial databases (Hong et al. 2020). GIS databases are frequently used to access geospatial data on buildings, including geometric properties and age (Torabi Moghadam et al. 2017; Ferrando et al. 2020).

The identified datasets are split into two categories; data that can be used to qualify the socioeconomic demographics of the neighborhood in Section 3.1, which is especially important in the context of an underrepresented neighborhood, and data that can be used to generate archetype inputs considering the socioeconomic factors in Section 3.2. Sources listed here are limited to those that are nationally applicable or are commonly available in all major metropolitan areas across the country. Local data sources, that are maintained by the state or local government, community organizations, or other third-party entities can also be useful in this process but vary by area.
3.1 Population and Neighborhood Demographics

US Census Bureau

The US Census Bureau generates and maintains data about all aspects of the people and economy in America. While they maintain a variety of databases, the primary population data programs are the Decennial Census and the American Community Survey (ACS) (US Census Bureau 2017). The Decennial Census is completed every decade to get an accurate count of the population and demographics in the US (US Census Bureau 2021a). The ACS is conducted every month, and the data are released every year, to supplement the information from the census (US Census Bureau 2021b). This includes more detailed information on education, housing, employment, and transportation not covered by the decennial census. While the census surveys everyone in the country, the ACS provides estimates based on a sampling of the population. The census and ACS data are reported at varying scales from a national level, down through the state, tract, zip code, and block level. Together, they provide the most complete picture of the population demographics of an area.

Small Area Income and Poverty Estimates

The Small Area Income and Poverty Estimates (SAIPE) from the US Census Bureau provides information on different poverty indicators at the scale of a state, county, or school district (US Census Bureau 2020c). It uses survey data and statistics to model income and poverty estimates in the area. It provides information on both total people living in poverty as well as children living in poverty. SAIPE data are typically used by federal, state, and local governments to allocate funding. Based on the established
connection between low-income households and energy use patterns it is essential to understand poverty levels when completing an UBEM.

**Home Owners’ Loan Corporation Maps**

The Home Owners’ Loan Corporation (HOLC) maps, more commonly known as “redlining” maps, were developed in the 1930s as part of a larger effort to stabilize the housing market after the great depression (Aaronson, Hartley, and Mazumder 2020). These maps were drawn up for over 200 cities across the country in an effort to determine the lender’s risk level of a mortgage in these areas. Each area, rated as either “Best,” “Still Desirable,” “Definitely Declining,” or “Hazardous” was evaluated on the quality of the housing stock, history of sales and rent in the neighborhood, neighborhood amenities, and racial and ethnic profile of the residents (Nelson et al., 2016). Most of the neighborhoods with high ratings were predominantly white, while most neighborhoods with black, immigrant, and working-class residents were rated lower.

In areas that were rated “Hazardous,” or colored red on the maps, lenders refused to give mortgages. The impacts of this historic lack of investment can still be felt, in some neighborhoods, today. Racial and economic segregation in cities, stemming from redlining, persists (B. Mitchell 2018). A 2018 report from the National Community Reinvestment Coalition shows that; 74% of the neighborhoods graded “Hazardous” are currently low- to moderate-income; 64% of the neighborhoods graded “Hazardous” are currently majority-minority neighborhoods; Cities in the South have shown the least change in the “Hazardous” grading over time. Although these maps were created years ago and do not reflect the neighborhood today, they can still be an indication of the state of an area.
Distressed Communities Index

The Distressed Communities Index (DCI) developed by the Economic Innovation Group combines the demographics of a neighborhood into a single impact percent and well-being rating (EIG 2020a). Areas at the zip code, county, state, and congressional district level are evaluated based on education level, poverty rate, employment rate, housing vacancy rate, income, change in employment, and change in the number of establishments. Each area is given a total distress score, out of 100, and sorted into one of five ratings; “Prosperous,” “Comfortable,” “Mid-tier,” “At Risk,” and “Distressed.” It can be used to show inequalities across smaller areas as well as identify trends in specific areas. It demonstrates the combined impacts of population demographics on an area.

US Health Map

The US Health Map, maintained by the Institute for Health Metrics and Evaluation, provides health trends across the country at the county level (IHME 2018). It provides information, over time and split by sex, on common risk factors, mortality rates and causes, mortality risk, and life expectancy. The map also displays how the data have changed over the years to identify long term health trends of an area. Understanding the health risks and makeup of an area is important in holistically understanding a community and the challenges it faces as well as specific community vulnerabilities.

PLACES

Another health metric is provided by the US Center for Disease Control and Prevention in conjunction with the Robert Wood Johnson Foundation. PLACES builds off work from the 500 Cities Project and provides health and risk data by county, census tract,
and zip code level (CDC 2020). PLACES includes data on 27 indicators across health outcomes, prevention, and unhealthy behaviors.

3.2 Archetype Inputs

US Census Bureau

In addition to understanding the population of an area, the Decennial Census and ACS can be used to generate some archetype input parameters regarding occupancy density, occupancy behaviors, housing ownership model, housing condition, and mechanical systems.

American Housing Survey

The American Housing Survey (AHS) is a joint effort between the Department of Housing and Urban Development and the US Census Bureau (US Census Bureau 2020a). It provides the most detailed and up-to-date information on the existing housing stock in the US. It includes information on the size, composition, quality, and costs of the households and housing structures. Every other year a statistically representative sample of households, both occupied and unoccupied units, are surveyed to represent the entire residential building stock (US Census Bureau 2020b). This survey provides information on households both nationally and in select metropolitan areas longitudinally until a new sample is chosen. Data from the AHS related to household demographics, housing quality, home improvements, Heating, Ventilation, and Air Conditioning (HVAC) systems, appliances, and more can be used to generate archetype inputs related to residential occupancy, envelope, and mechanical systems.
**Residential Energy Consumption Survey**

The US Energy Information Administration’s Residential Energy Consumption Survey (RECS) provides data useful for generating archetype inputs (US-EIA 2015). These data are collected from a sampling of households and energy suppliers, and it aims to provide a nationally representative sample of energy use characteristics and patterns (US-EIA 2018). It provides information on housing characteristics and end-use energy consumptions correlated to demographic attributes including housing type, ownership model, household size, income, and geography. In addition to energy use and expenditure, it also provides information on housing characteristics that include available appliances, type of lighting, type of water heater, and available mechanical systems. These data can be used to generate archetype inputs related to building occupancy and mechanical systems as well as to validate UBEM results as explored in Section 4.7.

**Atlas of Rural and Small-Town America**

The Atlas of Rural and Small-Town America, from the US Department of Agriculture, provides county-level socioeconomic data (USDA ERS 2021). Despite the name, the atlas contains information on both urban and rural areas across the country. The data for each area are split into five broad categories; “People” includes information on population age, race, and household size and makeup; “Jobs” includes information on employment trends, unemployment, and jobs by industry; “County Classifications” includes information on rural, urban, metro, and nonmetro designations; “Income” provides information on household income and poverty; and “Veterans” provides demographic information on veterans. These data can be used to generate inputs related to household makeup and occupancy schedules based on employment information.
Like the Atlas described above, information from the US Bureau of Labor Statistics can be used to generate occupancy schedules based on the employment information and patterns of an area. They maintain several datasets related to occupation, employment and unemployment, workplace injuries, and more (US Bureau of Labor Statistics 2020b). These datasets are provided at a range of scales, from the state to zip code level. The Current Employment Statistics and Current Population Survey (CPS) provide information on the labor force, employment hours, and unemployment rates.

American Time Use Survey and Travel Demand Surveys

One of the datasets maintained by the US Bureau of Labor Statistics is the American Time Use Survey (ATUS). The ATUS is an effort to develop a national estimate of how and where Americans spend their time (US Bureau of Labor Statistics 2020a). The ATUS samples a subsection of households that have completed the CPS. Different houses are surveyed every month, and in the survey are asked a series of demographic questions as well as information on where and when each household member spent their time on the previous day, starting and ending at 4 am. The data are split so that 10% of the information is about each weekday, and 25% of the information is about each weekend day.

Like the ATUS, Travel Demand Surveys (TDS) look at where and when people spend their time with a greater emphasis placed on the modes of transportation used to get between these locations. These surveys are completed by the state government, local government, or metropolitan planning organizations in an area and focus on a specific city. They are often updated every decade. The Metropolitan Travel Survey Archive, maintained
by the University of Minnesota, provides a digital archive of various TDS from around the country. ATUS and TDS data can be used to generate occupancy schedules for UBEM.

*Construction Codes*

Construction codes, including building codes and energy codes, are used to set a standard of construction to protect public health and safety. They are based on national model codes and are adopted with revisions at the state or local level (Ching and Winkel 2018). Energy codes set minimum standards for the envelope performance of a building. The age of a structure can be correlated to construction codes of the time to develop relevant envelope inputs for an UBEM.

*Product Specification Sheets*

If the type and age of a heating and/or cooling system is known, product specification sheets can be used to determine mechanical system efficiencies and limits required in an archetype definition.

*City Datasets*

Individual municipalities collect and maintain information on their buildings. While most cities have ample data to support an UBEM, it lacks standardization (Y. Chen et al. 2019) and requires significant effort to pull the data together from multiple sources and file types (Y. Chen, Hong, and Piette 2017). The available information can vary between municipalities, but most city databases include information on buildings’ geometric and non-geometric properties. Most cities have information on buildings’ footprint, height, number of stories, building type and use, and year built. Additionally, tax assessor data provides information on building area, number of bedrooms, number of
bathrooms, condition of the structure, and mechanical systems. Building permit databases can be used to understand how buildings have been modified and improved over time (Cerezo Davila, Reinhart, and Bemis 2016; Hong et al. 2020).
CHAPTER 4 METHODS AND CASE STUDY

This chapter describes the workflow of using available datasets to generate archetype inputs for a specific urban context. An overview of the workflow is presented, and then a case study is used to demonstrate this process in Grove Park, highlighting the ability to generate representative residential archetype inputs.

4.1 Experiment Goals and Objectives

Data availability is a challenge across all UBEM, but it is a particular challenge in underrepresented areas (Heidelberger and Rakha 2021). This thesis addresses this issue by establishing a multi-step, theoretical framework to gather the required data to run an accurate UBEM that considers socioeconomic factors. Specifically, the workflow established in this section aims to answer the following questions:

• How can an UBEM consider the socioeconomic standing of the area of study instead of assuming ideal urban conditions?
• What available data sources support such a study?
• What steps need to be taken to translate the available data into neighborhood-specific building parameter inputs?
• What happens when there are insufficient data required for an UBEM?

The remaining sections of this chapter examine these questions through an overview of the workflow and a sample application in a case study.

4.2 Workflow

Figure 1 illustrates the necessary steps in conducting a bottom-up UBEM. The work is divided into four primary categories: defining an area of study, gathering the requisite
data, running the simulation, and validating the results. This approach is relevant to all urban areas but is particularly important in low resource communities.

**Figure 1** Methods Diagram. This research was divided into 4 main categories: Area of study definition, Data collection, Simulation, and Validation.

4.2.1 Area of Study

The first step in this process is defining an area of study. In a typical UBEM workflow, this step would only include defining the physical boundaries of the study area and then move on to categorizing the buildings by archetype. However, when including socioeconomic factors in an UBEM, it is important to identify the relevant population and built environment characteristics in this stage as well to have a complete understanding of the neighborhood before moving to the next stage. Key population demographics to consider include race, income level, age, education level, and occupation. Key built environment demographics include building typology, building age and condition, ownership model, and density. After characterizing the neighborhood, initial archetype classifications for all buildings within the area of study can be made.
4.2.2 Data Collection

After defining the area of study, data related to the climate, building geometry, and building properties are needed. Information on the building use and properties can be a significant limitation in UBEM, as outlined in the literature review. Therefore, the primary contribution of this thesis focuses on addressing this challenge. Figure 2 outlines a workflow to follow in sourcing data for any UBEM.

![Figure 2: Detailed workflow of the data collection process](image)

The process of generating information required in an UBEM starts with existing databases. Climate files and building geometry information are relatively less challenging to source than building properties. Historical climate files, in the typical meteorological year (TMY) format, are readily available for over 2,000 cities worldwide, and more recent,
local weather data can increasingly be sourced from services including Weather Underground (Hong et al. 2020). Building geometries are most often sourced from GIS data, which may include the building footprint, building height, and number of stories (Y. Chen et al. 2019). This provides a simplified extrusion of the building geometry, which is often a sufficient level of detail. More detailed geometries, including roof pitches or overhangs, may be necessary depending on the goals of the study (Johari et al. 2020).

The non-geometric building properties pose more challenges. Section 3.2 outlines several public, nationally available data sources that can be used to extrapolate these parameters. After all available data have been mined, the next step to filling in gaps in the requisite information is to find applicable data from other studies that can be translated and used in the new study area. Factors influencing the relevance of data in a new area include climate zone, population demographics, and built environment characteristics (Mantha, Menassa, and Kamat 2016). Lastly, if the required data do not exist and there are no data from a different area that can be translated then new data need to be collected or generated for the specific study (Passe et al. 2020). While this process can yield highly accurate results, and results that capture the qualitative experience of the occupants, it is also time-consuming and costly and should therefore be used as a last option (Mantha, Menassa, and Kamat 2016; Khosrowpour et al. 2018; Reinhart and Cerezo Davila 2016).

All the data that are collected are translated into one of three broad categories: climate data, 3D geometry of the study area, and building properties. The most sensitive building properties, identified in the literature review, relate to the buildings’ occupants, envelope, and mechanical systems. Once all the relevant information is organized, it feeds the simulation files required in the next stage.
4.2.3 Simulation

After collecting all required data, the information is translated into simulation files that are used to run the UBEM. These files include the weather data, 3D geometry of the neighborhood, and building archetypes. In this work, umi is used to run the simulations. Umi is a plug-in for Rhinoceros 3D that utilizes EnergyPlus to run heat-balanced physics model simulations of the urban energy usage. Beyond just operational energy use, umi can also integrate daylighting, outdoor comfort, and walkability simulations (Reinhart et al. 2013). To reduce simulation time, umi uses a shoebox approach to generate representative two-zone thermal models based on façade orientation, solar radiation, and geometric clustering. The results of these models, which represent the perimeter and core conditions at each “solar microclimate” are then weighted back up to the full scale of the simulation (Dogan and Reinhart 2017).

Available Simulation Tools

In a recent review by Ferrando et al., eight bottom-up UBEM tools were identified and compared; CitySim, SimStadt, umi, CityBES, OpenIDEAS, CEA, URBANopt, and TEASER (2020). Of these, only umi, CityBES, and URBANopt rely on EnergyPlus, a widely validated heat-balanced physics model (Crawley et al. 2004; Witte et al. 2001), to run the simulations. URBANopt is under development as an open-source software development kit that allows for the integration of multiple analysis types, as well as other tools, to customize workflows and outputs (El Kontar et al. 2020). For this research, a tool with an established front-end user interface was chosen instead. Umi was selected over CityBES because of the integration of additional simulations including walkability and daylighting.
4.2.4 Validation

The final step in the process is validating the results. Section 2.3.1 describes typical validation approaches in UBEM, which rely on access to metered energy data from the study area. When available, these data can also be used to calibrate the archetype inputs to the UBEM. However, access to these data are a big limitation in UBEM, and these data are particularly limited in both underrepresented communities and residential settings. In the absence of metered data, national energy use statistics can be used for validation.

4.3 Case Study – Grove Park

The ability to source representative data in a low resource community is demonstrated through a case study in the Grove Park neighborhood in Atlanta, Georgia.

4.3.1 Neighborhood Selection

The neighborhood of Grove Park was chosen for this case study based on an established relationship with the Grove Park Foundation (GPF), a community organization in the neighborhood. Grove Park is a low- to moderate-income neighborhood in Northwest Atlanta, Fulton County, GA, USA. Key demographics of the neighborhood, as outlined in a report from the Atlanta Regional Commission, include: an estimated population of 4,963 in 2017; 1,698 households with an average household size of 2.72; 38.3% of housing units are unoccupied, 38.3% are rented, and 23.4% are owner-occupied; 63.4% of housing units are single-family detached structures; The majority of the housing stock was built before 1970; 53.7% of households are nonfamily; 96% of residents are Black, which is around three times higher than the City of Atlanta; median household income is $23,055, and over half of the households have an income less than $25,000; 20.6% of residents hold some
form of college degree, and 14.4% of residents did not finish high school; 48.4% of residents work in the service industry, and 19.9% work in the retail trade industry (Atlanta Regional Commission 2018).

Historically, the HOLC maps designated Grove Park as “Definitely Declining,” with the remarks that “property, if acquired in this area, should be sold, rather than held” (Nelson et al. 2016). Today, the DCI rates the 30318 Atlanta zip code, including Grove Park, as 67.7% at risk. This is based on a combination of factors including below-average median household income and above-average housing vacancy rates and poverty rates (EIG 2020b). The United Way of Greater Atlanta, an organization focused on improving the lives of children in Atlanta through initiatives and funding, has a Child Well-Being Index that combines demographic factors on children, families, and communities to rate zip code areas on a scale from low to high well-being (United Way Atlanta 2017). The 30318 zip code has an overall well-being score of 50.9 out of 100. Some of the biggest issues facing the area are low birth weights, a low percentage of students reading at or above a 3rd grade level, a low percentage of students at or above 8th grade math levels, low high school graduation rates and college readiness, a high percentage of children living in poverty, a lack of household financial stability, and increased rates of housing cost burdens.

The relationship with the GPF was leveraged to understand the residents’ experiences in the neighborhood. Instead of interfacing directly with the residents, which requires time to develop trust and a relationship, the GPF was used as a proxy for community engagement. They have knowledge of the common conditions and issues in the neighborhood through the trust they have built and maintained with the residents.
One primary goal of the GPF is to help the neighborhood residents secure healthy and safe housing. They accomplish this by first assessing what situation the residents are in, how they got in that situation, and what help they need. Often, that help comes in the form of critical home repairs, especially for senior residents in the area.

The biggest issue facing residents, according to the GPF, is that they do not have enough money to cover their living expenses. They are housing, transportation, and energy cost burdened. Total housing costs, mainly rent and mortgages, are very high compared to the residents’ income. The neighborhood is transportation burdened because of an absence of services, amenities, and transportation options in the area. Grove Park lacks key services, such as a grocery store, pharmacy, or bank, and key amenities, including restaurants. There are also very few opportunities for work in the area, meaning residents must travel farther for work and essential needs. Limited public transit options further compound the transportation cost burdens.

The city of Atlanta, as a whole, faces high levels of energy burdens, but these levels are particularly elevated among residents who are black, seniors, renters, and low-income. 36% of black households in Atlanta have an energy burden above 6%, meaning that more than 6% of the households’ income is spent on energy bills. 25% of low-income houses have an energy burden above 16% (ACEEE 2020). Some of the reasons that Atlanta faces these energy burdens include the high space heating and cooling demands, the aging housing stock, poor construction quality of low-income homes, and high upfront costs of energy efficiency measures (M. Brown et al. 2018). ECBs are high across Grove Park.

All of these cost burdens prohibit necessary home maintenance and repairs. The GPF helps with deferred maintenance by securing funding for critical and emergency home
repairs, including repairs to the roof, electrical systems, plumbing, and condition systems. These factors all demonstrate the vulnerabilities and energy burdens that Grove Park faces as well as the need to consider such socioeconomic parameters in an UBEM study.

In helping to inform the inputs of the UBEM, the GPF also makes sure that the results of the study can be useful to their mission in helping the neighborhood. The results of the UBEM can help to provide a better understanding of the need for and impact of home repairs in the neighborhood, both now and in the future. The study can also help to give context to the current realities of the neighborhood and bring to light issues that the neighborhood faces. By integrating socioeconomic factors into the UBEM workflow, the results will highlight the added energy and cost burdens in low- to moderate-income areas that default inputs might miss.

4.3.2 Archetype Classification

Within the Grove Park neighborhood, a specific subsection of buildings was chosen for the simulation. Single-family residential is the most common building typology in the neighborhood and one of the focuses of the Grove Park Foundation’s Neighborhood Investment Proposal (Grove Park Foundation 2019). 110 single-family residential structures across 10 blocks were selected as demonstrated in Figure 3. This specific area was chosen based on the diversity of structure conditions in the building stock.
Figure 3 The area of study is bound on the North by Baker Rd NW and Madrona St NW, on the East by S Evelyn Place NW, on the South by North Ave NW, and on the West by Emily Pl NW

Figure 4 Examples of each building archetype. The categorization was done by exterior visual analysis. Source: Google Maps

The selected building stock was categorized into initial archetypes based on the exterior conditions of the buildings. Four archetypes were defined: buildings in good condition, fair condition, poor condition, and vacant structures. Figure 3 shows the classification of each structure, and Figure 4 shows examples of each archetype from within the area of study. These four building conditions, as well as the criteria for inclusion in each of them, were developed based on the four classifications applied to residential
parcels in the 2012 Strategic Community Investment (SCI) Report, which provided information on the conditions of the residential housing stock in Atlanta based on a windshield survey (City of Atlanta 2013). Good buildings are well maintained with no visible defects or other aesthetic issues, fair structures have some minor signs of deterioration or aesthetic issues that do not compromise the structural integrity of the home, poor structures are not well maintained and show signs of deterioration with potential cracks in the windows however do not need to be demolished, and deteriorated, or vacant, structures show severe decay and structural issues (APD Solutions 2012).

The classification of each building was initially based on the 2012 data but updated based on a visual assessment of the structures conducted via Google Maps street view. Of the 110 buildings, 34 are in good condition, 44 are in fair condition, and 19 are in poor condition, and 13 are deteriorated and currently vacant. The ACS shows that over 90% of the vacant structures in the area are not for sale or rent and are instead likely to be demolished. In this UBEM they will be modeled as context structures only and will not have any energy use.

4.3.3 3D Model Construction

To generate the 3D file of the study area the building footprints and roads were generated using the Mosquito plugin for Grasshopper. There was no information related to building heights included, so the building footprints were extruded manually, either 3m for a single-story house or 6m for a two-story house, based on visual observations in Google Maps. The typical WWR in the neighborhood was derived via a visual inspection and estimated at 15% for all facades.
4.3.4 Weather File

A TMYx weather file from Atlanta, with data gathered from the Atlanta Fulton County Airport-Brown Field, was used in the study and sourced from the Climate One Building dataset to represent current weather conditions. This file was then morphed, using the Climate Change World Weather File Generator, to reflect potential weather conditions in 2080. This is an Excel-based tool that relies on the A2 emission scenario developed by the International Panel on Climate Change (Jentsch et al. 2013).

4.4 Archetype Inputs

Using the research methods detailed in Section 4.2.2 archetype inputs specific to Grove Park, and with the realities of the neighborhood in mind, were generated. Information related to key inputs identified in the literature review was prioritized.

4.4.1 Occupancy

In an UBEM, the primary inputs related to occupancy include the occupancy schedule, occupancy density, lighting use, and equipment use. The occupancy density is the number of people inside a given building, often expressed in the number of people per floor area (i.e., people/m²). The occupancy schedule gives a number, between 0 to 1, for every hour of the day and every day of the year that represents what percentage of the total occupants are present. Often, two 24-hour schedules are generated, one for weekdays and one for weekends, and they are applied consistently throughout the year. However, seasonal schedules and/or a separate schedule for every day of the week can be used. Similar schedules for the percentage of total lights and equipment being used are also required in the occupancy inputs.
**Persona Modeling**

This work utilizes a persona modeling approach to generate occupancy inputs. Persona modeling is the process of defining user archetypes that represent a grouping of target users with shared characteristics (Negru and Buraga 2012). It is widely used in Human-Computer Interaction, product design, service design, marketing (Nielsen 2013; Pruitt and Grudin 2003). Although not common in BPS, the process of generating user archetypes closely mimics the process of generating building archetypes in UBEM.

Occupancy profiles have previously been used to develop UBEM inputs, but they were developed based on available metered data as opposed to population demographics (El Kontar and Rakha 2018). Principles similar to this research’s persona modeling approach can be seen in some forms of occupancy modeling where occupants’ schedules and movement within an office building are adjusted based on their occupation (Feng, Yan, and Hong 2015). Another, similar approach to occupant modeling relies on agent-based modeling (ABM). ABM moves beyond fixed, default schedules and uses characteristics about building occupants, or agents, to dynamically simulate how they interact with each other and their environment (Berger and Mahdavi 2020). While computing resources limit the integration of ABM and UBEM, the persona modeling method used in this thesis aims to, in a fixed manner, predict the interactions of different groupings of residents with their environments based on shared characteristics.

In most other fields, personas are a single person, but in this case each persona represents one household and can encompass up to several residents. Traditionally in persona modeling, personal details are added to each persona to give them more life and humanize them. Each persona is given a name, a picture, and other personal details.
including hobbies to make them easier to design for and prevent them from becoming generic user descriptions (Goodwin 2005; Negru and Buraga 2012). While these steps to humanize the user are important when trying to design for a specific audience, in UBEM the goal is to generalize occupants’ behaviors. For this reason, the personas work better as generic descriptions of a household makeup. No family names, pictures, or other personal details were added to the household personas.

A combination of quantitative and qualitative sources was used to generate personas that most closely align with the current residents of the neighborhood. The GPF provided qualitative data about typical household makeups in the neighborhood, including the number, age, relationship, and occupation of residents. This engagement with the GPF was a stand-in for user interviews that are a typical part of the persona modeling process (Goodwin 2005). To minimize both the time and cost efforts of completing the UBEM, the community organization was in place of direct resident engagement.

Information on household makeups from the GPF was correlated to data from the ACS 5-Year Estimates from 2015-2019. Data at the census tract, census block group, and ZIP code tabulation area level were used to validate and supplement the personas established by the GPF. While it was established in the literature review that there are issues of systemic racism and bias in urban surveying methods, including the census, it is the most accessible population data. Using it in conjunction with the qualitative account of the neighborhood from the GPF made sure that groups that are not properly captured in the census are still represented by the personas.

The GPF and ACS established the typical household makeup, occupant relationships, occupancy patterns, and ownership model. The AHS was then used to add
additional information about each persona, including household income ranges and the
typical age of the household structure. This information is important to correlate data to
the personas. The combination of the ACS data, AHS data, and qualitative account of the
neighborhood from the GPF provided four representative personas in the neighborhood.
Each persona is described below.

*Persona 1*

Persona 1 represents a one-person household in Grove Park. This resident is a
senior, 65+, living on their own. They typically own their house, have an annual household
income of under $25,000 a year, and live in a house constructed before 1970. This resident
does not work and spends most of their time at home. Persona 1 makes up approximately
20% of occupied homes in the neighborhood.

*Persona 2*

Persona 2 represents a two-person household. These residents are young
professionals who are new to the Grove Park neighborhood. These residents follow a more
typical nine-to-five occupancy pattern during the week. There is a mix of homeownership
and renting in this persona. Typical household income will range from $50,000 to
$100,000. They occupy a mix of homes built from 1970 through to today. Persona 2 makes
up approximately 15% of occupied homes in the neighborhood.

*Persona 3*

Persona 3 represents a household of four members. The primary occupants of this
persona are a family, with two adults and two kids. However, this persona represents a
household with flexible membership. A room in the house may be rented out to an unrelated
individual, or other family members may spend varying amounts of time staying at the house. This persona rents their home rather than owning it. The houses range from homes built before 1970 through today, and the household income ranges from $25,000 to $100,000. Persona 3 makes up approximately 55% of occupied homes in the neighborhood.

**Persona 4**

Persona 4 represents a house of five unrelated residents who each rent a single room. These occupants pay a fixed rate for rent and utilities. The property is often neglected by the tenants and landlords. Specific information about the occupants’ income or employment status is unknown. Persona 4 makes up approximately 10% of occupied homes in the neighborhood.

**Occupancy Density**

In an UBEM, the total number of occupants in a building is determined by the occupancy density. This is a measure of the number of people per floor area, typically people/m². To determine the occupancy density of each persona the number of people in the persona was divided by the average floor area of the neighborhood. The occupancy densities of personas 1, 2, and 3 were calculated using the average floor area of all buildings in the study area, which is 133 m². The occupancy density of persona 4 was calculated using the average area of only the 2-story buildings in the study area, 286 m², since this persona is only present in 2-story houses, as described in Section 4.5.

**Occupancy Schedules**

Different occupancy schedules were developed for each of the four personas. The occupancy patterns of personas 1 and 2 were developed based on information from the
conversation with the GPF. Residents in persona 1 rarely leave their houses, and instead are home most of the time. The same occupancy schedule, which shows the resident home all 24 hours of the day, was applied to four days of the week. An individual schedule was assigned randomly to Tuesday, Thursday, and Sunday. In each of these schedules, the occupant is away from home for a few hours of the day; in the morning on Sundays, the afternoon on Thursdays, and the evening on Tuesdays. This reflects time the occupant may spend with friends or family, at a store, at a doctor’s appointment, at church, or anywhere else they typically go in a week. The occupancy schedule for persona 2 was copied from the Pacific Northwest National Laboratory (PNNL) residential prototype buildings. These residents typically work a nine-to-five job and follow default occupancy schedules. In this case, standard inputs are relevant.

The occupancy schedules for personas 3 and 4 could not be developed based on just information from the GPF. Both personas reflect households with flexible membership and with varying occupations and occupancy patterns. For both cases, data from the Atlanta TDS was used to generate occupancy schedules. This survey was conducted by the Atlanta Regional Commission (ARC) and the Georgia Department of Transportation in 2011 to understand travel in and around a 20 county region surrounding Atlanta (ARC 2011). This survey collected information from a statistically representative sampling of households during the spring and fall of 2011. Each household that participated provided a travel diary for one 24-hour period, starting and ending at 3 am, for all household members on an assigned travel day. Data was collected evenly for all five weekdays, but no data was collected on weekends.
The TDS has information from over 10,000 households in the region. All of the data could be clustered to develop typical occupancy behaviors for different user archetypes in the region if no personas had been developed (Rakha, Rose, and Reinhart 2014). However, since personas with household demographics had previously been established, the data were filtered down to match these personas. The data were initially filtered to be relevant to all of Grove Park, and then this subsection of the data were further filtered down individually for each persona. To be relevant to Grove Park, the data were filtered by county, area type, residence type, income, and race. Only households in the 10-county Atlanta region, as defined by the ARC, were included. These counties are Cherokee, Clayton, Cobb, DeKalb, Douglas, Fayette, Fulton, Gwinnett, Henry, and Rockdale. Only single-family detached and attached houses in a suburban residential area were included. Finally, only households with an annual income between $10,000 and $100,000 and households that reported their race as “African-American,” “Multicultural,” or that did not specify a race were included.

Based only on the portion of the data that are relevant to all of Grove Park, individual datasets were pulled out for persona 3 and 4. Data for persona 3 were further filtered down by household size, household composition, and ownership model. Only households with three to six members, with at least one child, and who are renting were included. This resulted in data on a total of 49 households, 185 people, and 609 trips. Data for persona 4 were filtered down by ownership model, age, and student status. Only people who rent instead of own, are between 25 and 60 years old, and are not a student were included. This resulted in data on a total of 143 households, 191 people, and 836 trips. Using the trip data for each person a value of either 0 or 1 was assigned to every hour of
the day to represent when the occupant was away or home. These values were then averaged to develop individual occupancy schedules for each day of the week. Occupancy schedules for the weekend were generated by averaging all the schedules together.

**Equipment and Lighting**

In addition to the occupancy schedules and densities, the personas were used to develop information related to the equipment and lighting use patterns in the UBEM. For both equipment and lighting use, data on relative power use across the personas was available. However, specific equipment and lighting power densities were not available. Instead, they were sourced from relevant studies instead, and fall within typical residential ranges (Ahmad, Rafique, and Badshah 2014; ASHRAE 2017; Cerezo Davila et al. 2017; C. Ding, Feng, and Tian 2019; Sokol, Cerezo Davila, and Reinhart 2017).

For equipment use, data on the presence of appliances and electronics from the AHS and RECS was used to generate relative equipment power densities. The equipment power density is lowest in persona 1 because smaller and low-income households overall have less appliances and electronics. Personas 3 and 4 have the same equipment power densities because they have a similar number of residents and the same ownership model. Finally, persona 2 has the highest equipment density because higher-income and newer households are more likely to have more appliances and electronics. This persona is also the most likely to have the appliances with the largest impact on energy usage, including dishwashers and clothes dryers.

The equipment schedules are also impact by household demographics. Persona 1 uses the appliances and electronics less often because it is a smaller, low-income
household. Persona 2 uses their appliances more often because they are higher-income households but not as often as personas 3 and 4 which have more household members.

The lighting power densities and schedules were developed in a similar manner. The RECS has information on the number, type, and frequency of use of lights in a house. Personas 3 and 4 have the highest lighting power densities because they are renting and living in older houses, making them the most likely to have incandescent light bulbs. Persona 1 is a lower-income house but also typically owns their house, meaning they have a mix of incandescent bulbs, compact fluorescent lamps (CFL) bulbs, and LED bulbs. Persona 2 has the lowest lighting power density because newer houses and higher-income houses are more likely to have LED or CFL bulbs. Personas 3 and 4 run more lights more often throughout the day because they have more total household members and spend more time at home. Persona 2 does not spend as much time at home, but a higher household income correlates with using the lights for longer. Even though persona 1 spends the most time at home, they also have the least number of residents so use their lights the least often.

**Occupancy Inputs**

Key occupancy inputs are listed out in Table 1 and Figure 5a through Figure 5d. See Appendix A for an example umi template with all inputs.

<table>
<thead>
<tr>
<th>Table 1 Occupancy inputs by household persona</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Occupancy Density (people/m²)</strong></td>
</tr>
<tr>
<td>-----------------------------------------</td>
</tr>
<tr>
<td><strong>Equipment Power Density (w/m²)</strong></td>
</tr>
<tr>
<td><strong>Lighting Power Density (w/m²)</strong></td>
</tr>
</tbody>
</table>
Figure 5a Sample occupancy schedule for persona 1 - Tuesday

Figure 5b Sample occupancy schedule for persona 2 - Weekday
Figure 5c Sample occupancy schedule for persona 3 - Weekend

Figure 5d Sample occupancy schedule for persona 4 - Weekend
4.4.2 Building Envelope

The primary building envelope inputs required for an UBEM include the material properties and constructions of the exterior wall, roof, slab, and window constructions, and the building’s infiltration rate. These values are often sourced from the relevant building and energy codes at the time of construction, which establishes the minimum thermal performance of the envelope.

The age of a structure is often one of the criteria used to segment the building stock into archetypes because of the link between building age and energy performance (Aksoezen et al. 2015; Reinhart and Cerezo Davila 2016). However, the age of a structure does not give any indication of any renovations to the building over the years, which can be a better method for understanding the actual performance of a building (Cerezo Davila, Reinhart, and Bemis 2016). For this reason, the SCI designations and windshield survey described in Section 4.3.2 were used to segment the building stock in place of the structure’s age.

Tax assessor and building permit data from Fulton County and the City of Atlanta, respectively, were used to understand the age, state, and renovations of the buildings in Grove Park. The tax assessor data includes a variety of information on each building but most important to the envelope system was the building age. The permit database contains information on renovations to the buildings over the year, including updates to the envelope system. While building permit data can be very useful in understanding improvements to the structure, it does not include information on the performance of the building, just a general description of work done, and it is very time-consuming to sort through (Hong et
al. 2020). For this reason, building permits and tax assessor data were accessed for a random sampling of 15% of the structures from each envelope condition.

Based on the information from the windshield survey, tax assessor, and building permits, construction codes for each structure were identified to establish building envelope performance. The buildings in good condition were primarily renovated around 2017 according to the permits, so they are modeled to meet the 2009 International Energy Conservation Code (IECC) and 2012 International Residential Code. There are not many building permits for buildings in fair condition, but the permit database only has digital records starting around 2000. Based on the exterior condition of the house, it can be assumed that the buildings were renovated shortly before the building permits were digitized and therefore the 2000 IECC was used to establish envelope performance. Buildings in poor condition also do not have many building permits but do not show signs of recent renovation or maintenance. These buildings are modeled to meet the 1975 Standard 90 from ASHRAE.

**Building Envelope Inputs**

<table>
<thead>
<tr>
<th></th>
<th>Good</th>
<th>Fair</th>
<th>Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Façade R-Value (m²·K/W)</td>
<td>3.58</td>
<td>2.17</td>
<td>0.76</td>
</tr>
<tr>
<td>Roof R-Value (m²·K/W)</td>
<td>6.62</td>
<td>5.21</td>
<td>1.87</td>
</tr>
<tr>
<td>Slab R-Value (m²·K/W)</td>
<td>3.45</td>
<td>3.45</td>
<td>1.83</td>
</tr>
<tr>
<td>Window U-Value (W/m²·K)</td>
<td>1.85</td>
<td>3.7</td>
<td>5.9</td>
</tr>
<tr>
<td>Infiltration Rate (ACH)</td>
<td>0.35</td>
<td>0.5</td>
<td>0.6</td>
</tr>
</tbody>
</table>
Table 2 lists the thermal performance of the primary envelope components and the infiltration rates of the three building conditions.

4.4.3 Mechanical Systems

The primary inputs related to mechanical systems in an UBEM include the setpoints, schedules, and efficiencies of the heating and cooling systems. Unlike in most BEM programs, where both setpoints and setbacks can be scheduled, umi only accepts one heating and one cooling setpoint. The schedules describe seasonally when heating and cooling are available, and which hours of the day it is running. The coefficient of performance (COP) describes the efficiencies of the heating and cooling systems.

Conditioning Equipment

The process of generating mechanical system inputs started with a conversation with the GPF about the typical mechanical systems in the neighborhood. Through this conversation, it was revealed that most homes in the neighborhood do not have a combined HVAC unit. Primarily, only homes that were built in the last 30 years or significantly renovated in the past 10 years will have a combined unit. Most houses in the neighborhood have either a furnace or heat pump for heating, but some houses rely on portable gas heaters which pose safety concerns to the residents. A majority of the homes in the neighborhood, including most of the persona 1 homes, do not have central air conditioning. They instead rely on portable AC units, window AC units, or fans for cooling. The windshield survey revealed several window AC units across the study area, but they are not all functional according to the GPF.
In conjunction with the qualitative understanding of the conditioning systems from the GPF, available data sources were used to develop the archetype inputs. The tax assessor data on the subsection of houses described in Section 4.4.2 indicates most structures, across all envelope conditions, have central air heating systems powered by natural gas. The building permits and RECS data indicate that houses in good condition are likely to have a combined heat pump unit. The COPs of the heating and cooling systems for houses in good condition are based on a combined HVAC heat pump unit with a seasonal energy efficiency ratio (SEER) of 15.5 and a heating seasonal performance factor (HSPF) rating of 8.2. The efficiencies of the structures in fair and poor conditions are not based on a combined HVAC unit. The heating COP of both the fair and poor houses are based on a gas furnace, with the lower efficiency of the poor conditioning reflecting the age of the unit. The cooling COP of the fair condition is based on a portable AC unit with an energy efficiency ratio (EER) of 10. The cooling COP of the poor condition is based on a window AC unit with 9.8 EER.

*Setpoints*

The RECS also has information regarding system use habits across the country. This showed that houses are most likely to set their thermostat to one temperature and leave it there all day, regardless of if anyone is home or not. Houses with a higher income, or houses that were built more recently, are more likely to have and use a programmable thermostat to automatically adjust the temperature at scheduled times. Overall, the data did not show strong trends to suggest how scheduling could be applied to the Grove Park neighborhood. Additionally, the RECS contains information on typical set points. Nationally, typical heating setpoints range from 19.4° to above 23.3°. Typical cooling
Setpoints range from below 17.2° to 22.8°. No strong correlation between setpoints and demographic factors, including ownership model, age of structure, or household income, could be established.

Setpoints are affected in homes facing energy insecurity. From the RECS data, it was established that energy insecurity, defined as an inability to meet the basic energy needs of a household (Hernández 2016), affects 37 million homes in America and causes 13 million homes to leave their house at an unhealthy temperature to compensate. Low-income, black, and rented homes are more likely to leave their house at an unhealthy temperature due to energy insecurity. Homes constructed before 1970 and with inadequate insulation are also more likely to face energy insecurity.

Since usage patterns and setpoints specific to the neighborhood could not be established through existing data, relevant studies were used to find information on these habits. Specifically, studies regarding energy insecurity in low-income housing were referenced. These studies showed mixed results. Some low-income households use conditioning systems sparingly or at very conservative setpoints to lower energy bills (Langevin, Gurian, and Wen 2013; Hernández 2016). On the other hand, a lack of understanding about how conditioning systems work, as well as the need for warmness or coolness, can lead to increased energy consumption among low-income residents (C. Chen, Xu, and Day 2017; Langevin, Gurian, and Wen 2013).

The external studies referenced did not provide accurate heating or cooling setpoints for the neighborhood, and instead further complicated the problem. Since setpoints can significantly impact the energy usage of a household, and adjusting them provides a no-cost option to reduce energy usage in a neighborhood (Al-Mumin, Khattab,
and Sridhar 2003), they require further study through a community survey. The need for a community survey is compounded by the fact that energy insecurity can pose risks to occupant health, both by homes being left at unhealthy temperatures and through dangerous supplemental heating methods, such as a stove or oven (Hernández 2016). As a stand-in, before community data can be collected, the most common heating and cooling setpoints from the South Atlantic region, based on the RECS, are applied throughout the whole day and night across all personas.

**Mechanical Systems Inputs**

Based on data from the GPF, AHS, and RECS, heating and cooling system types are most strongly correlated first to building age and then to household income. For this reason, the system efficiencies are determined by the building envelope archetype rather than the persona definitions. These inputs are listed in Table 3. Once neighborhood specific system setpoints and schedules are developed they will be assigned to each persona since they are based on the occupants’ behavior. For now, these inputs are standard across all personas. The setpoint inputs are listed in

Table 4.

**Table 3 Mechanical system inputs by building envelope condition**

<table>
<thead>
<tr>
<th></th>
<th><strong>Good</strong></th>
<th><strong>Fair</strong></th>
<th><strong>Poor</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating System</td>
<td>Heat Pump</td>
<td>Gas Furnace</td>
<td>Gas Furnace</td>
</tr>
<tr>
<td>Heating COP</td>
<td>2.4</td>
<td>0.8</td>
<td>0.75</td>
</tr>
<tr>
<td>Cooling System</td>
<td>Heat Pump</td>
<td>Portable Unit</td>
<td>Window Units</td>
</tr>
<tr>
<td>Cooling COP</td>
<td>3.68</td>
<td>2.93</td>
<td>2.87</td>
</tr>
</tbody>
</table>
Table 4 Mechanical system inputs by household persona

<table>
<thead>
<tr>
<th></th>
<th>All Persons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating Setpoint (^\circ\text{C})</td>
<td>20</td>
</tr>
<tr>
<td>Heating Availability</td>
<td>24 hours a day, April 15(^{th}) – October 15(^{th})</td>
</tr>
<tr>
<td>Cooling Setpoint (^\circ\text{C})</td>
<td>21</td>
</tr>
<tr>
<td>Cooling Availability</td>
<td>24 hours a day, October 16(^{th}) – April 14(^{th})</td>
</tr>
</tbody>
</table>

4.5 Final Archetypes

The final archetypes developed for this study are a combination of the building conditions, assigned based on the windshield survey, and the typical household personas, developed based on information from the GPF and ACS. Characteristics of each persona were used to match them to building envelope conditions.

The vacant classification is the only archetype that does not have a persona attached to it as these structures are included in the UBEM as shading objects only and do not use any energy. Persona 4 was the first to be assigned to structures. Based on the characteristics of the persona, persona 4 is only present in two-story structures in fair or poor condition. Persona 4 is limited to two-story structures because there is a high number of occupants each renting an individual room, so they need more space overall.

Next, persona 1 was matched with specific structures. Persona 1 is only present in buildings in poor and fair conditions, as the senior residents live in older houses and have less money to maintain their homes. A Grasshopper script was used to randomly assign persona 1 to 20% of the remaining structures in poor and fair condition. This same process was repeated to assign persona 2 to 15% of the remaining structures in fair and good conditions.
condition. The young professionals in the neighborhood have higher incomes and live in newer houses. The remaining houses, approximately 55% of the occupied units, were all assigned to persona 3. Persona 3 is the most common and is present in houses in poor, fair, and good condition. This process resulted in nine final archetypes and one vacant classification, listed out in Table 5 and visualized in Figure 6.

Table 5 Final archetypes by building condition and household persona

<table>
<thead>
<tr>
<th>Final Archetype</th>
<th>Building Condition</th>
<th>Persona</th>
<th># of Instances</th>
<th>% of Occupied Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Good</td>
<td>Persona 2</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>B</td>
<td>Good</td>
<td>Persona 3</td>
<td>23</td>
<td>24</td>
</tr>
<tr>
<td>C</td>
<td>Fair</td>
<td>Persona 1</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>D</td>
<td>Fair</td>
<td>Persona 2</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>E</td>
<td>Fair</td>
<td>Persona 3</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>F</td>
<td>Fair</td>
<td>Persona 4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>G</td>
<td>Poor</td>
<td>Persona 1</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>H</td>
<td>Poor</td>
<td>Persona 3</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>I</td>
<td>Poor</td>
<td>Persona 4</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>J</td>
<td>Vacant</td>
<td>N/A</td>
<td>13</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Figure 6 Final archetype distribution across the study area
4.6 Default Archetypes

The archetypes defined specifically for Grove Park in this study were compared against the results of two different default residential archetypes. The first default archetype referenced in this study is the masonry residential building that comes with umi. Umi downloads with a library containing four archetypes: an office building, a retail building, a masonry residential building, and a wood-framed residential building. All the archetypes downloaded with umi are designed to represent typical buildings in Boston, Massachusetts. No information is provided regarding the building age they represent. This was the only readily available template at the time of the study.

To have a comparison from a relevant climate zone, the second default archetype referenced in this study was adapted from a residential prototype building model developed by the PNNL. The selected PNNL file represents a single-family detached house, in climate zone 3A, with a gas furnace heating system and a slab foundation. It is modeled to meet the 2006 IECC.

The file was converted from an EnergyPlus file, designed for a single building energy simulation, to an umi archetype. Some of the information from the prototype building file was not challenging to pull directly into the umi template editor, including the lighting power density, infiltration rate, system setpoints, and system efficiencies, but some of the parameters required additional work. The EnergyPlus file gave most values in total numbers, instead of by floor area. This included the occupancy density, equipment power densities, and mechanical ventilation. To translate them to umi inputs they were divided by the conditioned floor area of the reference file. Instead of giving one total equipment
power density, the EnergyPlus file broke out total interior equipment energy usage by appliance. To translate this to one single equipment power density and one equipment schedule the total hourly energy use of all individual appliances was combined and divided by the floor area. Information on the domestic hot water usage was provided similarly, broken out by fixture. Since domestic hot water was not identified as a highly sensitive input in the literature review process, the same domestic hot water inputs from the umi Template were copied to the PNNL Template archetype. All building constructions in the PNNL reference file met the minimum 2006 IECC insulation values except for the slab construction. When converting the EnergyPlus file to umi additional insulation was added to the construction to correct this input.

Table 6 displays key parameter values for both default archetype templates. In each of the simulations using the default archetypes, every structure in the study area was assigned the same archetype. In the simulation using the adjusted archetypes, each of the structures was categorized into one of the 9 archetypes as described in Section 4.5

<table>
<thead>
<tr>
<th></th>
<th>Umi Template</th>
<th>PNNL Template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Façade R-Value (m²·K/W)</td>
<td>2.1</td>
<td>1.9</td>
</tr>
<tr>
<td>Roof R-Value (m²·K/W)</td>
<td>3.3</td>
<td>4.7</td>
</tr>
<tr>
<td>Window U-Value (W/m²·K)</td>
<td>3.2</td>
<td>3.7</td>
</tr>
<tr>
<td>Infiltration Rate (ACH)</td>
<td>0.35</td>
<td>0.67</td>
</tr>
<tr>
<td>Occupancy Density (p/m²)</td>
<td>0.025</td>
<td>0.014</td>
</tr>
<tr>
<td>Equipment Power Density (w/m²)</td>
<td>4</td>
<td>8.5</td>
</tr>
<tr>
<td>Lighting Power Density (w/m²)</td>
<td>7</td>
<td>2.5</td>
</tr>
<tr>
<td>Heating Setpoint (°C)</td>
<td>20</td>
<td>22.22</td>
</tr>
<tr>
<td>Heating COP</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Cooling Setpoint (°C)</td>
<td>24</td>
<td>23.88</td>
</tr>
<tr>
<td>Cooling COP</td>
<td>3</td>
<td>4.07</td>
</tr>
</tbody>
</table>

Table 6 Key parameter values from default archetype templates
4.7 Validation Approach

At the time of this study, no metered data were available for the Grove Park neighborhood. Instead, validation relies on national residential energy consumption values sourced from the 2015 RECS. An explanation of the data included in this survey can be found in Section 3.2. The RECS reports the national average EUI at 121.1 kWh/m². Looking at demographic characteristics relevant to Grove Park, the residential EUI should fall somewhere between 89.9 and 169.7 kWh/m². The low end, 89.9 kWh/m², is based on a house built between 2010 and 2015, and the high end, 169.7 kWh/m², is based on a house that is less than 1,000 SF. Other relevant reference points include urban households, which use on average 123.7 kWh/m², and households in the South Atlantic region, which use on average 106.6 kWh/m² (US-EIA 2015). The 2015 RECS results also show that in a single-family detached house, approximately 54% of the energy goes towards heating and cooling a house (US-EIA 2020).
CHAPTER 5   RESULTS

This section presents the results of the Grove Park case study. They are analyzed based on the current neighborhood energy performance, a comparison of the energy performance using the neighborhood-specific and default archetypes, a comparison of the energy performance under current and future weather scenarios, and a validation of the results against national energy use statistics.

5.1 Neighborhood Energy Performance

Table 7 Energy use by end use for final Grove Park archetypes

<table>
<thead>
<tr>
<th>Final Archetype</th>
<th>Total Energy (kWh/m²)</th>
<th>Heating (kWh/m²)</th>
<th>Cooling (kWh/m²)</th>
<th>Lighting (kWh/m²)</th>
<th>Equipment (kWh/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole Neighborhood</td>
<td>140</td>
<td>18</td>
<td>43</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>A</td>
<td>100</td>
<td>2</td>
<td>29</td>
<td>9</td>
<td>31</td>
</tr>
<tr>
<td>B</td>
<td>126</td>
<td>1</td>
<td>35</td>
<td>32</td>
<td>26</td>
</tr>
<tr>
<td>C</td>
<td>124</td>
<td>23</td>
<td>39</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>D</td>
<td>128</td>
<td>19</td>
<td>40</td>
<td>9</td>
<td>31</td>
</tr>
<tr>
<td>E</td>
<td>150</td>
<td>14</td>
<td>46</td>
<td>32</td>
<td>26</td>
</tr>
<tr>
<td>F</td>
<td>146</td>
<td>12</td>
<td>45</td>
<td>33</td>
<td>26</td>
</tr>
<tr>
<td>G</td>
<td>172</td>
<td>57</td>
<td>54</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>H</td>
<td>192</td>
<td>42</td>
<td>60</td>
<td>32</td>
<td>26</td>
</tr>
<tr>
<td>I</td>
<td>175</td>
<td>33</td>
<td>53</td>
<td>33</td>
<td>26</td>
</tr>
</tbody>
</table>

The simulation using the archetypes defined specifically for Grove Park and the current climate file resulted in an average EUI of 140 kWh/m². Across the individual archetypes, this value ranges from 100 kWh/m², for archetype A, to 192 kWh/m², for archetype H. Table 7 shows the energy intensities, total and broken down by archetype, across the neighborhood. Heating has the most variability between the archetypes, both by heating EUI and what percent of the overall EUI it makes up. While the cooling EUI varies...
from 29 kWh/m² to 60 kWh/m² across archetypes, it consistently makes up around 30% of the total EUI.

Figure 7 visualizes the monthly energy use intensities of all nine archetypes. The color coding is assigned primarily by building envelope condition and secondarily by persona classification. Across all archetypes, the energy use varies seasonally, peaking in summer and in winter months based on space conditioning needs.

![Total Energy Use](image)

**Figure 7** Total neighborhood monthly energy use, broken out by archetype

<table>
<thead>
<tr>
<th>Building Envelope Condition</th>
<th>Total Energy (kWh/m²)</th>
<th>Heating (kWh/m²)</th>
<th>Cooling (kWh/m²)</th>
<th>Lighting (kWh/m²)</th>
<th>Equipment (kWh/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>118</td>
<td>2</td>
<td>33</td>
<td>25</td>
<td>28</td>
</tr>
<tr>
<td>Fair</td>
<td>139</td>
<td>17</td>
<td>43</td>
<td>25</td>
<td>24</td>
</tr>
<tr>
<td>Poor</td>
<td>183</td>
<td>47</td>
<td>57</td>
<td>26</td>
<td>22</td>
</tr>
</tbody>
</table>
Figure 7 and Table 8 both look at the EUIs by building envelope characteristics. The total EUI is highest on buildings in poor condition and lowest on buildings in good condition, but there is overlap between the good and fair and the fair and poor in some months. Lower insulation levels and higher infiltration rates on the buildings in poor and fair condition drive higher energy usage. The differences in lighting and equipment energy use levels stem from the mix and rate of personas in each envelope designation.

Examining the EUIs by persona classification instead of envelope condition, persona 2 has overall the lowest EUI, as can be seen in Table 9 below. This is based on persona 2 having fewer household members, having newer appliances, and living in a house with better insulation and more efficient conditioning systems. On the contrary, persona 4 has the highest total EUI based on having the most household members and worse performing building insulation and conditioning systems. Personas 1 and 3 have very similar total EUIs. While persona 3 has more lighting and equipment use, they also have less heating use than persona 1.

<table>
<thead>
<tr>
<th>Persona</th>
<th>Total Energy (kWh/m²)</th>
<th>Heating (kWh/m²)</th>
<th>Cooling (kWh/m²)</th>
<th>Lighting (kWh/m²)</th>
<th>Equipment (kWh/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Persona 1</td>
<td>140</td>
<td>35</td>
<td>44</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>Persona 2</td>
<td>109</td>
<td>7</td>
<td>33</td>
<td>9</td>
<td>31</td>
</tr>
<tr>
<td>Persona 3</td>
<td>147</td>
<td>14</td>
<td>44</td>
<td>32</td>
<td>26</td>
</tr>
<tr>
<td>Persona 4</td>
<td>156</td>
<td>19</td>
<td>47</td>
<td>33</td>
<td>26</td>
</tr>
</tbody>
</table>

5.2 Archetype Comparison

This thesis compares two different, default, residential archetypes to neighborhood-specific archetypes defined specifically for this research to showcase how current default
templates do not capture lived experiences. As described in Section 4.6, the two default archetypes used as a point of comparison are the umi Template residential archetype and the PNNL Template archetype.

![Archetype Comparison](image)

**Figure 8** Comparison of default and neighborhood-specific archetype templates

Figure 8 showcases the average monthly energy use of the households, comparing the umi Template archetype, PNNL Template archetype, and neighborhood-specific archetypes defined for this study. The purple lines show the umi Template simulation results, the green lines show the PNNL Template simulation, and the black lines show the results of the Grove Park archetype simulation. For each simulation, the thin lines show the results of the individual structures, and the thick line shows the average monthly results.

Across the three simulations, there is an 81 kWh/m² difference in the average neighborhood EUI. The neighborhood EUI of the umi Template simulation was 96 kWh/m², of the PNNL Template simulation was 177 kWh/m², and of the adjusted
archetypes simulation was 140 kWh/m2. The umi Template simulation has the lowest total, heating, cooling, and equipment EUIs. The PNNL Template simulation has the lowest lighting EUI, but the highest total, heating, and equipment EUIs. The Grove Park archetype simulation has the highest lighting EUI. Both default templates have higher energy usage in the winter months than the summer months, whereas the neighborhood-specific templates use similar amounts of energy in summer and winter months.

In both default simulation runs the same template is applied uniformly across all structures in the study area, leading to very similar energy use intensities and the same energy use patterns for all houses. However, the simulation using the neighborhood-specific archetypes had each occupied building classified into one of nine archetypes defined for the study area. Each archetype has similar a EUI and energy use pattern, but across the neighborhood, these values vary significantly.

5.3 Future Weather Scenario

![Current Weather File](image)

**Figure 9a** Comparison of operational energy by month under current weather
Figure 9b Comparison of operational energy by month under future weather

Figure 9a and Figure 9b compare the normalized monthly energy use in Grove Park under current and future weather scenarios. In each graph, the thin grey lines represent individual buildings while the thick red line shows the neighborhood average. The archetype definitions were not adjusted, so the total energy used by lighting, equipment, and hot water did not change. The most prominent change in energy use comes from the cooling needs of the houses. The neighborhood EUI for cooling increased from 42 kWh/m² to 57 kWh/m². At the same time, the heating energy decreased from 18 kWh/m² to 10 kWh/m². This is based on the predicted increase of outdoor air temperature in all seasons, including the winter months. Table 10 compares the cooling and heating degree days across the two weather files, with a base temperature of 18.33°. The number of heating degree days drops by 33% between the two weather files, while the number of cooling degree days increases by 86%.
Table 10 Comparison of Heating and Cooling Degree Days

<table>
<thead>
<tr>
<th></th>
<th>Current Weather</th>
<th>Future Weather</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating Degree Days</td>
<td>1,616</td>
<td>1,048</td>
<td>-33</td>
</tr>
<tr>
<td>Cooling Degree Days</td>
<td>1,157</td>
<td>2,147</td>
<td>+86</td>
</tr>
</tbody>
</table>

Figure 10 Heating and cooling energy use under present and future weather

Figure 10 compares the monthly heating and cooling needs under each weather scenario, with the red lines representing current weather conditions and the teal lines representing future weather conditions. The thin lines display the average conditioning needs of each building archetype, and the thick lines display the neighborhood averages. While the overall need for heating decreases between the current and future weather scenarios, the heating use patterns stay consistent. However, the cooling use patterns change. Under current weather scenarios, the cooling use drops steadily from July to
September. Under future weather scenarios the cooling use continues to climb into, and peaks in, August before dropping off.

### 5.4 Outcome Validation

The neighborhood EUI is 19 kWh/m² above the national average of 121.1 kWh/m². The values across the neighborhood range from 99 kWh/m² to 199 kWh/m², which is consistent with the expected range of 90 kWh/m² to 170 kWh/m². These points of comparison are averages based on building characteristics, not definitive values that all EUIs must fall between. Figure 11 displays the total EUI distribution compared to key reference points identified in the RECS data. The RECS data also provide insight into the typical end use breakdowns of the total energy use in residential settings. Typically, 54% of the total energy is used to heat and cool a housing unit. The remaining 46% of the energy use is divided between lighting (5%), water heating (17%), and all other appliances (US-EIA 2020). Across the study area, 44% of the energy use goes towards space conditioning, 18% is used for lighting, and 21% is used for hot water heating.
Looking at the differences in energy use by household persona and building envelope characteristics, rather than across the neighborhood, can also be used to validate the results. On average, households that rent instead of own use more energy. In this simulation, personas 3 and 4, who rent, used more energy than persona 1, who owns. Households with more than three members use more energy than households with one or two members, which holds true with personas 3 and 4 using more energy than personas 1 and 2. When utilities are included in rent the household energy usage tends to be higher, which is true of persona 4. The RECS shows that older homes use more energy and newer homes use less energy. This is consistent with homes in good condition using the least energy and homes in poor condition using the most energy in this simulation.
CHAPTER 6 DISCUSSION, LIMITATIONS, AND FUTURE RESEARCH

This section provides a discussion on the results of the simulations, the overall process, and future work that needs to be done to continue to develop the relationship of UBEM inputs and urban socioeconomic factors to accurately model low-income and majority-minority areas.

6.1 Discussion

The range in total energy use across the archetypes shows how the different building conditions and occupancy patterns in the neighborhood impact energy usage and ECBs across the neighborhood. This information can be used to develop energy efficiency strategies relevant to each archetype, building envelope condition, or persona.

Both an underestimation or overestimation in the simulation results by using the default templates can lead to decisions that do not support better neighborhood performance. For instance, in this case, if the PNNL Template file is used, the emphasis may be placed on reducing heating loads in the neighborhood. However, the adjusted archetypes show cooling loads to much more concerning, especially under the future climate scenario. The umi Template has a lower overall EUI and underestimates the ECBs in the neighborhood. Based on this template, replacing appliances with more efficient models would be the most cost-effective energy efficiency measure in the neighborhood. While this would still be beneficial, it does not tackle the biggest issues Grove Park.

Beyond the difference in overall EUIs and end use breakdowns between the two default and neighborhood-specific simulations, using the default templates lumps all the buildings in the study area together. It does not recognize any differences based on building
condition or occupants. When using the neighborhood-adjusted archetypes, different recommendations may be more appropriate for each of the different archetypes based on their energy performance instead of one recommendation for the whole neighborhood.

Running the simulation with both current and future weather scenarios enables resiliency planning. While there are issues with high energy use now, these numbers will continue to climb as the climate changes. By using both files, energy efficiency decisions can be made that have longer-lasting improvements in the neighborhood and make sure that the building stock is ready for new weather patterns. Proper resiliency planning requires a model that captures the realities of a neighborhood and targets the issues it is currently facing and will continue to face. In this case, that is the cooling demands of the neighborhood.

6.1.1 Model Calibration and Validation

As mentioned previously, this case study was limited by the lack of metered energy use data. While national statistics were used to validate the simulation results on an annual timescale, the archetype inputs could not be calibrated. The results are sufficiently validated within the national consumption range, but metered data specific to the neighborhood could be used to further understand the seasonal energy use patterns and burdens in Grove Park. Future steps of this work include calibrating and further validating the results based on metered data from the study area.

6.2 Data Limitations

Challenges prevail in the process of generating archetype inputs required an UBEM. First and foremost, the process of gathering, organizing, and translating the data for this case study was incredibly time consuming and required a fair amount of manual
organization and translation. Efforts to standardize the formats and language of datasets can help to make the process more automated and reduce the total amount of time required to set up an UBEM (Y. Chen et al. 2019).

There are also some limitations with the data sources themselves that can impact the results of the simulations. For instance, the TDS data that were used to develop occupancy schedules for personas 3 and 4 does not contain any information on weekend occupancy. Instead, all five weekdays were averaged together to make a weekend occupancy schedule. This may not be reflective of true weekend occupancy if occupants’ behaviors differ between the weekdays and weekends. These data are also not representative of any seasonal variations in schedules, such as children being home from school for the summer or summer hours at a job.

All the data being used is collected at differing spatial and temporal scales. For instance, the TDS data are specific to the metro Atlanta area, so highly relevant in terms of location, but was also collected 10 years ago in 2011. The information from the 2015 RECS is more recent but is collected nationally so it is not specific to the Atlanta region. While these data can be filtered by a variety of household demographics and can be used to get information specific to marginalized communities, it will not differentiate between these marginalized communities. The AHS, which is specific to Atlanta and from 2019, is the most relevant in terms of spatial and temporal scale, but also had less overall information. While all of these data are collected to be statistically representative of all household make-ups within the survey’s impact area, the data collection methods favor typical household arrangements. The data will not be as representative of alternative living situations, such
as the flexible family membership of persona 3 or the group house dynamic of persona 4, as it will be of the more typical living situations found in personas 1 and 2.

All the data used in this study were collected in or before 2019 and therefore does not reflect pandemic or post-pandemic life. Instead, this study reflects the energy use patterns of a pre-pandemic, business as usual scenario. Covid-19 has had, and will continue to have, considerable impacts on residential occupancy patterns and behaviors. When developing an UBEM it is important to keep in mind when the data were collected and how that can influence the results. Ultimately, the goal of the study determines the data requirements used for the inputs.

6.3 Software Limitations

There are some limitations built into the UBEM software that limit the model’s ability to capture all urban settings. While this discussion is only focused on limitations within umi, many other available bottom-up software tools face the same limitations.

Umi currently only supports fixed values for all archetype parameters. This helps to reduce the simulation time and required computing power, but also reduces the archetypes’ ability to accurately represent the diversity of the existing building stock. Stochastic inputs better capture real-world conditions but are not currently supported. In this simulation, all buildings encompassed by an archetype had the same value for each parameter. However, the ability to incorporate probabilistic inputs for some of the most uncertain or sensitive parameters would help to increase the accuracy of this study. For instance, plug loads vary with both the number of appliances in a household and the age of the appliances and can vary across houses within the same archetype.
The impact of fixed values is amplified in low resource communities, especially in parameters related to occupancy. Current tools limit the occupancy factors and schedules to single inputs. This does not allow the simulation to account for households with flexible memberships, which are more common in these urban contexts. In this study, persona 3 represents a household that may rent a room to an unrelated adult, have additional family members come to stay with them short or long term, or the children may spend time at another household based on joint custody arrangements. Umi currently cannot capture any of these living arrangements.

6.4 Future Work

While this research establishes a workflow for coupling socioeconomic factors and UBEM there is more work that still needs to be done. This workflow was only demonstrated and validated for residential buildings. Additional data sources will need to be identified for other building typologies and uses, including commercial, retail, and institutional uses. Each building typology poses its own challenges, particularly in underrepresented areas.

Based on the available datasets, as well as previous studies, there is a need for community data collection specific to HVAC setpoints and habits. This is particularly important to this study because setpoints can have a significant impact on the results of the simulation, occupant behaviors surrounding HVAC setpoints provide an opportunity to reduce energy usage at no cost to the resident, and adequate heating and cooling systems are an essential component of safe and healthy homes. The community survey could also be used to supplement available data related to occupancy density, occupancy schedules,
lighting schedules, and equipment power densities. The relationship with the GPF can be leveraged to facilitate the community survey process.

Default values were still used in some areas that were not identified as highly sensitive. Examples of this include information on hot water use, blind operation patterns, and natural ventilation habits. Although these parameters were not found to vary with the urban context or have a high impact on the results of the simulation, it becomes more important to consider them as the rest of the simulation is better adjusted to the specific study area. Additional data related to these parameters is needed moving forward.

The archetypes defined for this study will need to be manually updated as new data become available and as housing conditions change. The data sources used to develop the archetypes are routinely updated at different frequencies. As new versions of the datasets are published, with information more current to the neighborhood, non-geometric building parameters should be adjusted accordingly. Similarly, as the physical condition of the buildings change the envelope classifications must be updated accordingly. For instance, one of the buildings identified in poor condition for this study has recent building permits to update the interior, exterior, electricity, plumbing, and HVAC systems. After this work has been completed the structure will be reclassified to good condition. Also, as structures are demolished, built, and modified the 3D geometry of the neighborhood will need to be updated accordingly.
CHAPTER 7 CONCLUSION

This thesis aimed to tackle the issue of the extensive data needs by proposing a framework to develop archetype inputs for an UBEM specific to the urban context. This workflow is especially important and useful in low resource communities. Underrepresented neighborhoods that have fewer resources to devote to such a study. At the same time, vulnerable communities have a demonstrated need for a closer investigation to accurately simulate their energy use. UBEM focusing specifically on the needs of these communities can not only help to reduce current energy demands, and lower ECBs, but also plan for more resilient cities moving forward under climate change scenarios. Several limitations, including a lack of access to data and readily available archetypes as well as the time-intensive nature of setting up the model for a simulation, currently prohibit the widespread adoption of UBEM.

A case study in the Grove Park neighborhood of Atlanta shows the importance of accurate archetypes in understanding energy use patterns and lived experiences, as well as the potential impacts of climate change on them, in a low-income and majority-minority neighborhood. In underrepresented areas, default archetypes have the potential to significantly underestimate or overestimate total energy usage, pointing to the need for area-specific archetypes. While the results of the case study demonstrated that existing datasets can be used to generate validated archetypes specific to an urban neighborhood, additional work will further improve these workflows. Access to more area specific data, including occupancy behaviors and metered energy use data, will further increase the accuracy of the simulations. At the same time, automated workflows to generate and update the archetypes will reduce the amount of time and resources needed to complete a study.
As the results of UBEM are used to influence policies and allocate resources, a concerted effort should be made to include underrepresented neighborhoods and accurately reflect the entire existing building stock. The same challenges that UBEM faces are heightened in the context of underrepresented neighborhoods. These specific urban contexts must be explicitly and carefully considered.
APPENDIX A  SAMPLE ARCHETYPE DEFINITION

This appendix provides a sample archetype definition from the study. The “A” Archetype is copied below to demonstrate the structure of the file and inputs.

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"Roof": { 
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"Slab": { 
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  "LightingPowerDensity": 4.0,
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"DataSource": null,
"Name": "Archetype_A"
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"WindowSettings": [
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REFERENCES


City of Atlanta. 2013. “Strategic Community Investment Report (Parcel Study)
Frequently Asked Questions.” Department of Planning and Community

Crawley, Drury B, Linda K Lawrie, Curtis O. Pedersen, Frederick C. Winkelmann,
New, Capable, and Linked.” Journal of Architectural and Planning Research 21

Delmastro, Chiara, Guglielmina Mutani, and Stefano Paolo Corgnati. 2016. “A
Supporting Method for Selecting Cost-Optimal Energy Retrofit Policies for

Ding, Chao, Wei Feng, and Qin Tian. 2019. “Residential Building Archetype and API
Development for Urban-Scale Building Energy Consumption Platform: A Case

Differences in the Factors Influencing the Energy-Saving Behavior of Urban and
Rural Residents in China—A Case Study of Jiangsu Province.” Energy Policy 100:
252–59.

Dochev, Ivan, Philip Gorzalka, Verena Weiler, Jacob Estevam Schmiedt, Magdalena
Linkiewicz, Ursula Eicker, Bernhard Hoffschmidt, Irene Peters, and Bastian
Modelling Approaches and Remote Sensing for Input Data and Validation.”
Applied Energy 280.

Dogan, Timur, and Christoph F. Reinhart. 2017. “Shoeboxer: An Algorithm for
Abstracted Rapid Multi-Zone Urbanbuilding Energy Model Generation and

EIG. 2020a. “Distressed Communities Index - The Spaces Between Us.” Economic
Innovation Group.

EIG. 2020b. “Distressed Communities Index - Interactive Map.” Economic Innovation
Group.

El Kontar, Rawad, Ben Polly, Tanushree Charan, Katherine Fleming, Nathan Moore,
Software Development Kit for Community and Urban District Energy Modeling.”
In 2020 Building Performance Modeling Conference and SimBuild.

El Kontar, Rawad, and Tarek Rakha. 2018. “Profiling Occupancy Patterns to Calibrate
Urban Building Energy Models (UBEMs) Using Measured Data Clustering.”

Elsey, Helen, Ak Narayan Poudel, Tim Ensor, Tolib Mirzoev, James N Newell, Joseph P
Hicks, Christopher Cartwright, et al. 2018. “Improving Household Surveys and

115


Rakha, Tarek, C.M. Rose, and Christoph F. Reinhart. 2014. “A Framework for Modeling Occupancy Schedules and Local Trips Based on Activity Based Surveys.” In


US Census Bureau. 2020a. “American Housing Survey (AHS) - About This Survey.”


