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<https://doi.org/10.15760/etd.5287>

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THESIS APPROVAL

The abstract and thesis of Shem C. Heiple for the Master of Science in Mechanical Engineering presented June 8, 2007 and accepted by the thesis committee and the department.

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ABSTRACT

An abstract of the thesis of Shem C. Heiple for the Master of Science in Mechanical Engineering presented June 8, 2007.

Title: Using Building Energy Simulation and Geospatial Modeling Techniques to Determine High Resolution Building Sector Energy Consumption Profiles

A technique is presented for estimating hourly and seasonal energy consumption profiles in the building sector at spatial scales down to the individual taxlot or parcel. The method combines annual building energy simulations for city-specific prototypical buildings and commonly available geospatial data in a Geographical Information System (GIS) framework. Hourly results can be extracted for any day and exported as a raster output at spatial scales as fine as an individual parcel (<100m). This method can be applied to virtually any large US city to obtain day-specific estimates of electricity and natural gas consumption within the residential and commercial sectors. The resulting profiles can be used to estimate anthropogenic sensible and latent waste heat emissions associated with building energy consumption. The target application for this approach is urban scale atmospheric modeling in support of urban heat island and air quality studies. In such applications the inclusion of high spatial and temporal resolution waste heat data represents a significant advancement.

USING BUILDING ENERGY SIMULATION AND GEOSPATIAL MODELING
TECHNIQUES TO DETERMINE HIGH RESOLUTION BUILDING SECTOR
ENERGY CONSUMPTION PROFILES

by

SHEM C. HEIPLE

A thesis submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE
in
MECHANICAL ENGINEERING

Portland State University
2007

Dedication

i

Dedicated to my beautiful wife, Psalms, who continuously shows me Christ's love.

Acknowledgments

This research was supported by the National Science Foundation under Grant No. 0410103. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

The following thesis, while an individual work, benefited from the insights and direction of several people. It is difficult to overstate my gratitude to my advisor, Dr. David Sailor for unwavering commitment to helping see this project through to its final completion, and his equally generous and wise guidance during its development. I could not have done it without him. I would also like to thank Dr. Mark Weislogel for causing me to love mathematics through his intense enthusiasm for the subject, Dr. Gerald Recktenwald for all his programming advice, Dr. Graig Spolek for the enjoyable time spent with him working on the green roof project and Dr. Melissa Hart for answering all my random questions.

Most importantly, I would like to thank my family and friends who brought me into Life, and who have always loved me unconditionally.

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1 Introduction

Cities are often warmer than their less developed surroundings – a phenomenon referred to as the urban heat island [1, 2]. This phenomenon is governed in large part by significant differences between the energy budgets of cities and the countryside. As has been pointed out by various researchers [3, 4] the emission of waste heat from energy consuming activities plays a significant role in the development of the Urban Heat Island (UHI). Until recently, however, there have been relatively few studies of the urban climate that have explicitly included waste heat (anthropogenic heating) in their analyses [5, 6]. One reason for this is the relative difficulty in obtaining the necessary data for estimating spatial and temporal profiles of anthropogenic heating. While simplified methods have been introduced in the literature (e.g., [6]) these approaches have limited spatial and temporal accuracy associated with numerous assumptions that are required in mapping available coarse-scale data to hourly city-scale profiles. As urban climate and air quality modelers continue to refine their spatial scales of analysis there is a growing need for improved methods for estimating urban waste heat emissions. As a starting point it is important to first estimate detailed profiles of energy consumption within the building and vehicle sectors. These data can then be propagated into corresponding estimates of latent and sensible heat emissions.

The objective of this study was to develop a method that predicts energy consumption for the residential and commercial sectors at a high spatial and temporal resolution for major U.S. cities. The goal was to develop a method that uses readily available data resources so that the method can be easily applied to all major U.S.

cities. The development of this method and its application to a case study city (Houston Texas, USA) is presented in the following sections. Where appropriate the results of the method are aggregated and compared to available coarse-resolution energy consumption data.

2 Anthropogenic Heating Overview

Anthropogenic heating results from sensible waste heat rejected from energy consuming activities within the urban environment. The majority of this waste heat comes from end-use energy consumption that is divided into residential, commercial, industrial and transportation sectors. Waste heat emitted from power generation facilities serving, industrial, residential and commercial sectors must also be considered for urban areas that have such facilities within the area of interest. In the US the residential and commercial sectors make up 22% and 18% of total annual energy consumption, respectively. The industrial and transportation sectors consume 32% and 28% respectively [7]. The present analysis necessarily focuses on energy consumed in the residential and commercial sectors. Analyses of industrial and transportation energy consumption must be addressed using different approaches and are left for future studies.

Energy consumption within the commercial and residential sectors is a result of Heating, Ventilation, and Air Conditioning (HVAC), and internal loads in buildings. The proportion of energy consumed for each end use depends upon numerous factors including building type, local climate and season. Nationally, 45% of the annual energy consumed in commercial buildings is for HVAC, 29% for lighting and office equipment and 15% for water heating [8]. In the residential sector these proportions are 53% for HVAC, 29% for lighting and appliances, and 17% for water heating [9]

Much of the energy that is consumed in buildings is eventually released into the outdoor environment as sensible heat either through intentional ventilation,

exfiltration, long wave radiation, or conduction through the building shell.

Depending upon the mode of heat exchange there is a delay between time of energy consumption and time of eventual emission into the outside environment. It is important to note, however, that not all energy consumed in buildings is rejected as sensible waste heat into the atmosphere. Specifically, much of the energy used for domestic water heating exits the building through pipes and into a sewage system. A small portion of energy consumption by appliances is converted to latent heat (e.g. coffee makers and ranges). Sensible waste heat exhausted from air conditioning systems is rarely the same as the energy consumed by their mechanical systems. For example, evaporative cooling can decrease sensible waste heat by converting some sensible heat to latent heat to meet building cooling loads. Conversely, dehumidification, usually in combination with space cooling, increases sensible waste heat by converting latent heat to sensible heat. Hence, it is important to note that development of building energy consumption profiles is only a first step in obtaining anthropogenic heat emission profiles.

Before introducing the present research it is useful to review relevant past studies. These studies, summarized in the following sections, fall into two categories: those that focus on building energy estimates from existing load data and those that simulate energy consumption in individual buildings for the purpose of aggregating to larger scales (bottom-up approach).

2.1 *Building Energy Consumption Estimates from Existing Load Data*

Ichinose et al. [3] used detailed building load survey data to develop diurnal profiles of energy consumption for 9 building types representative of the residential and commercial sector buildings in Tokyo. These data were linked to a geospatial building database for Tokyo, resulting in a high resolution representation of energy consumption and waste heat emission. Since Ichinose's model was based on detailed building load survey data specific for Tokyo it is not readily applied to other regions. In another approach, referred to as the "top-down approach" in the remainder of this paper, Sailor and Lu [6] disaggregated U.S. monthly state-level consumption data to a city census tract scale based on diurnally varying population densities. Monthly consumption estimates were applied to regional and national diurnal profiles for summer and winter seasons. One of the major advantages of this approach was that it could easily be applied to any U.S. city. Although it achieved greater temporal and spatial resolution than other studies, the approach was based on a population density formulation with inherently large uncertainties related to the modeling of diurnal and spatial profiles of population. Diurnal profiles in the scope of this study are the hourly energy consumption patterns over the course of a day for a season or month. Furthermore, diurnal variability in natural gas consumption was assumed to be governed by diurnal temperature fluctuations in the same way that monthly natural gas consumption responds to seasonal variations in temperature. In the approaches of Ichinose and Sailor the diurnal consumption variability is limited to biannual and monthly averages respectively. Because the diurnal profiles in both approaches were

derived using historical consumption data, they are also limited in their predictive power with respect to changes in human behavior, and building technologies.

Many statistical approaches have been developed for utility load forecasting purposes to predict diurnal end-use electricity consumption in the building sectors. These approaches rely on extensive historical load data (often 3-5 years of hourly data), and are typically applicable to the relatively coarse scale of the entire utility service territory. Hourly electricity load profiles for FERC (Federal Energy Regulatory Committee) control areas or for utility companies with peak demand greater than 200 megawatts are available nationally through FERC [10]. Control areas generally encompass entire cities. While providing the needed information for aggregate utility-scale or in some cases city-scale load forecasting, the FERC data do not give insight into spatial variability within urban areas.

At the individual building level, several surveys have collected whole-building and sub-metered electricity data for both residential and commercial buildings. For example, the End-Use Load and Consumer Assessment Program (ELCAP) [11,12] of the 1980s collected hourly end-use electricity data for 454 residences and 140 commercial buildings in the Pacific Northwest. Another large study conducted by Pacific Gas and Electric Company (PG&E) collected hourly end-use loads for 750 residences in Northern and Central California [30]. The ELCAP database was used to characterize building archetypal consumption patterns for both the residential [11] and commercial [12] sectors. Whole building load data were used with weather and demographic survey data in a hierarchical regression model to predict load shapes. Unfortunately, whole building or end-use load data are not widely available across the

US. Another major drawback of statistical models is the lack of hourly non-electric load data--natural gas, fuel oil and LPG--which comprise 61% [9] and 46% [8] of national residential and commercial energy consumption, respectively.

2.2 Bottom-Up Approach: Simulating Prototypical Buildings

Building energy consumption modeling is commonly used in industry as an analysis tool for building design but also has many research applications. By modeling a small set of buildings that is representative of buildings in a particular region and sector, researchers can estimate hourly profiles of energy consumption by fuel type as well as other key building characteristics. For example, Huang [13] simulated nearly 500 building prototypes to assess the potential of cogeneration in 13 major U.S. cities. In another study, Sezgen et al. [14] used output from commercial prototype simulations to create a forecasting system (Commercial End-Use Planning System, COMMEND 4.0) used by utility companies. A similar building simulation project developed commercial building electricity end-use load shapes for the Pacific Gas and Electric company (PG&E) by reconciling simulation results to metered whole building hourly loads from existing buildings within PG&E's service area [15]. A more recent study, using updated building prototypes from previous studies, determined building component (e.g., wall insulation, HVAC equipment, windows, lighting) contributions to space heating loads for the entire U.S. building stock [16]. Using computer simulations of building energy consumption (building simulations) to estimate diurnal profiles has several advantages over the top-down approach. First, nationwide residential and commercial building stock information is readily available

and updated every several years by the U.S. Department of Energy in their Residential Energy Consumption Survey (RECS) and Commercial Building Energy Consumption Survey (CBECS)[17, 18]. The RECS and CBECS are national statistical surveys, conducted on a quadrennial basis. They collect energy-related data for occupied primary housing units and commercial building stock within the U.S. They are the largest and most exhaustive sources of building consumption estimates for the U.S. Unfortunately, only annual energy consumption information is collected for each fuel type. Building simulations, on the other hand, can estimate hourly consumption rates for combustion fuels such as natural gas providing information that is important, but not available through top-down energy consumption resources. Building energy simulations also create models in which energy consumption that does not lead to atmospheric waste heat emission (e.g., domestic hot water usage and energy consumption resulting in latent heat) can be quantified and the time lag between usage and emission can be estimated. Finally, prototypical building simulations can be used to quantify the potential effects of energy efficiency and heat island mitigation strategies. Conversely, this approach can be used to estimate the building energy consumption impacts of climatic factors such as climate change and the urban heat island.

3 Method

The present research uses building energy simulation software in conjunction with a suite of prototypical buildings—the bottom-up approach—to estimate detailed profiles of building energy consumption. Prototype buildings were modeled using a comprehensive building energy simulation program (eQuest from the US Department of Energy – see www.doe2.com for documentation). The present study differs from past building simulation studies in that it seeks to estimate total end use consumption patterns and is not concerned with assessing the market value of individual building components. Therefore, individual building prototypes were defined only for groups of building types that share similar diurnal and seasonal energy consumption patterns and intensities and have similar natural gas and electricity consumption ratios. Building simulations were validated by comparing simulated annual Energy Use Intensities (EUI [$\text{kWh}/\text{m}^2/\text{yr}$ or $\text{kBtu}/\text{ft}^2/\text{yr}$]) with data from existing buildings. As needed prototype simulation parameters were adjusted using information from similar relevant studies until all simulation prototype EUIs were within 10% of existing building types.

Existing buildings within the study area were matched to building prototypes using GIS parcel (tax lot) data containing information on existing building type and building floor space for each tax lot. Total energy consumption for each existing building was calculated by multiplying the corresponding prototype's EUI by the actual building's floor space. Annual building energy consumption for the entire study area (E_{city}) was then calculated by:

$$E_{city} = \sum_{i=1}^N \left(A_i \sum_{j=1}^M EUI_j \cdot P_{ij} \right) \quad (1)$$

where A_i is the floor space for each existing building, EUI_j is the energy usage intensity predicted for the building prototype category, N is the number of buildings, M is the number of prototype categories, and P_{ij} is the matrix defining the mapping of buildings into each of the categories (if building i is in category j , $P_{ij}=1.0$, otherwise $P_{ij}=0.0$).

Energy consumption totals were also differentiated by building sector, fuel type and month. This allowed totals from the bottom-up approach to be compared against the top-down approach—where state-wide values had been disaggregated to the city level using population and climate weighting and sensitivity factors [20]. This process is illustrated in Fig. 1.

Figure 1: Block diagram of building simulation and validation steps. Rectangular blocks represent information sources and curved blocks represent processes.

After prototype simulation and validation, hourly load outputs from the simulations were used to calculate diurnal energy consumption profiles for each building prototype. Diurnal consumption profiles $Q_p(h)$, also known as load shapes, were calculated by taking the average consumption for each hour over a specific day of week and time duration, usually a season or month:

$$Q_p(h) = \frac{1}{nA_p} \sum_{i=1}^n Q_i(day, season) \quad (1)$$

where n is the set of days within the season that have the same day of the week, A_p is the building prototype floor space, and Q_i is the day and season specific average consumption value. The resulting $Q_p(h)$ is a vector with unique consumption values for each hour of the day. Prototype diurnal profiles were then matched to existing buildings using the parcel GIS. Diurnal energy consumption for existing buildings was estimated by multiplying corresponding prototype consumption profiles by building floor space. The resulting profiles allow for hourly estimation of energy consumption at the parcel scale.

In order to use the resulting parcel-level profiles as input to an atmospheric model, energy consumption at the parcel level must be aggregated up to the atmospheric model's spatial resolution. This can be achieved by first overlapping the atmospheric model's grid on the parcel GIS. Buildings then can be sorted by the grid cells in which they are located and by their building type. Diurnal consumption profiles ($Q_{cell}(h)$) representing the entire grid cell are then obtained by:

$$Q_{cell}(h) = \sum_{j=1}^n Q_j(h) \sum_{i=1}^n A_{ji} \quad (2)$$

where n is the number of buildings within a grid cell.

4 Application to a Case Study City: Houston, TX USA

Houston Texas was selected as the case study city for this research because it experiences frequent summertime episodes of extreme heat and pollution. Furthermore, as one of the most populous U.S. cities in a state with high levels of per capita energy consumption it is likely that Houston's local climate is influenced by waste heat emitted from building energy consumption.

Houston's climate is hot and humid with summer electric peaking energy consumption. Our study area extends just beyond the city limits encompassing an area with a population of 2,400,000. Although Houston's energy consumption is predominantly driven by energy intensive industries, it has a dense commercial urban core that is centrally located within the city.

4.1 Overview of Survey Data Resources (RECS and CBECS)

The Residential Energy Consumption Survey (RECS) and the Commercial Building Energy Consumption Survey (CBECS) were used to define building prototypes. Of the data available in these surveys the most notable for the present study are: general building uses, floor space, annual heating and cooling days, weekly occupancy duration, age of buildings and HVAC systems. All estimates from the survey were weighted by building floor space:

$$\bar{\alpha} = \frac{\sum_{i=1}^n \alpha_i A_i W_i}{\sum_{i=1}^n A_i W_i} \quad (3)$$

where a represents any scalar value for a surveyed building (e.g., EUI, HDD, CDD weekly occupancy duration), A is the building floor space and W is the weight factor or number of buildings that the surveyed building represents within the national or regional building population.

Both RECS and CBECS present multiple options for aggregating data so that the aggregation represents a statistically valid estimate of the characteristics of the buildings within some region. These regions are defined based on either spatial proximity (census regions and divisions) or on climate similarity (climate zones). Figures 2 and 3 illustrate the definitions of these regions. RECS also reports state level residential information for the four most populated states - Texas, New York, California and Florida.

Figure 2: EIA Census regions and divisions. Reproduced from the Energy Information Administration [17].

Figure 3: EIA Climate zones. Reproduced from the Energy Information Administration [17].

Previous studies of regional consumption characteristics generally focused on a single representative city that experienced climate similar to the regional average [14].

Typical meteorological year (TMY) data for the selected city would be used as input for the region's building simulations. Regional simulation outputs were then compared against regional EUI estimates from the RECS and CBECS. Because the present study is interested in estimating city-specific consumption, a region within the surveys must be selected such that regional averages from the surveys are close to those for the specific city under study. Survey data from two spatial domains--the

West South Central Region and the state of Texas—were initially considered for assessing existing commercial and residential buildings, respectively (see Fig. 2). Even state-specific residential EUI estimates are not a good representation of residential energy use in the city of Houston, however, because of intrastate climate variation. Aggregating survey data based on climate similarity instead of spatial location gave a building population with energy consumption that is more representative of Houston. So, climate regions were selected based on similarity of their yearly HDD and CDD with those of Houston (heating and cooling degree days are determined using a 65 °F base). The SW Central Division region and the Texas state region had average climates that were substantially different from Houston. Climate zone 5, on the other hand, with average HDD of less than 4000 and an average CDD over 2000 was closer to the average climate of Houston (Fig. 3), and was therefore selected as the basis for prototype building development. To achieve better agreement between Zone 5 data and Houston, buildings with HDD < 400 were excluded from the RECS and CBECS data and average building characteristics were recalculated. This resulted in average degree days shown in Table 1.

Table 1: Comparison of HDD and CDD.

	HDD	CDD
RECS climate zone 5	1430	2779
CBECS climate zone 5	1800	2839
2001 Houston airport	1524	2701
TMY Houston	1771	2898

Houston TMY data were used in the building simulations rather than actual 2001 data because results were compared not only to two different survey years but also to previous prototypical simulation studies that used the same TMY data.

4.2 CBECS Prototype Selection

The CBECS has 18 predefined building types for the commercial building stock. After assessing the total contribution of energy consumption of each building type, building categories were combined and reduced to eleven types. Building types which did not represent a significant amount of consumption were grouped together into a general building category. Retail and office buildings, accounting for 48% of commercial energy consumption in Houston, were divided based on floor space, into large ($> 2,323 \text{ m}^2$ or $25,000 \text{ ft}^2$) and small buildings ($\leq 2,323 \text{ m}^2$ or $25,000 \text{ ft}^2$). Building types were further grouped by primary heating fuels (electric or non-

electric). Because fuels other than electricity and natural gas are less than 5% of commercial energy consumption for zone 5, and because these other fuels typically have the same end-uses as natural gas, they were not modeled explicitly - their net energy consumption was simply added to natural gas consumption estimates (NG+). Building age is also a significant factor affecting consumption, but could not be differentiated because of sample size limitations. The prototype definition process resulted in 22 commercial building prototypes (Fig. 4). For this study building types were defined as the building categories shown at step two on the left side of Fig. 4. Building prototypes were defined as building types grouped by primary fuel type at step 3 in this figure.

Figure 4: Block diagrams depicting the selection process for building prototypes within the CBECS and RECS.

4.3 RECS Prototype Selection

Residential buildings are categorized as either multi-family residential (MFR) or single-family residential (SFR). SFR buildings include detached, attached and mobile homes. MFR units are apartments or condominiums containing two or more housing units. Although MFR buildings generally have larger EUIs than SFR buildings, it is reasonable to assume that their diurnal consumption patterns are similar

because they share the same use as SFR buildings. At the national level average MFR EUIs are 164.4 kWh/m^2 (52.1 kBtu/ft^2), whereas SFR EUIs are 137.6 kWh/m^2 (43.6 kBtu/ft^2). However, the EUIs for zone 5 show less difference—MFR EUI = 137.2 kWh/m^2 (43.5 kBtu/ft^2) and SFR = 128.1 kWh/m^2 (40.6 kBtu/ft^2)—respectively. Sorting housing units by occupancy was initially considered, but was rejected as there was little variation of EUI within each housing type. Although, RECS does not report duration of occupancy, it does differentiate between housing units that are occupied or unoccupied during the day. At the national level EUIs were only 2.5% greater for housing units that were occupied during the day. For zone 5, however, EUI estimates were actually 1.7% smaller for daytime occupied housing units. So, based on the survey data, daytime occupancy plays a small role in energy consumption and was therefore not used to classify building prototypes.

Based on past prototypical building studies, residential buildings were also sorted by year of construction (pre-1980 vs. post-1979). After vintages had been defined, buildings were then sorted by primary heating fuel type. As was done for the commercial sector, residential sector energy consumption associated with fuel types other than electricity and natural gas was simply added to the natural gas consumption estimates (NG+). The total contribution of fuel types other than electricity and natural gas in the residential sector was 1.7%. The residential prototype definition process resulted in 8 building prototypes as shown in the right side panel of Fig. 4.

4.4 *Building Energy Simulations*

Using the prototype definitions in Huang [13] as a starting point we derived additional building inputs where new information was available. Huang's study reported building prototype information for older and newer vintages. Because we did not differentiate between building vintages for the commercial sector, Huang's vintage input values were averaged based on total vintage floor space within Houston. The goal for each building prototype definition was to balance the accuracy of modeled energy consumption profiles with level of detail and complexity of the simulation process. We used DOE-2 in conjunction with eQUEST for all building simulations (both available from and documented by the U.S. Department of Energy at www.DoE2.com). eQUEST has an extensive library of default values for building characteristics for several building types. Default values supplied within eQuest were used for building features that had a minor impact on energy consumption (i.e., hot water tank insulation, interior finish, door types).

In defining prototypes we used many of the building prototype simulation practices established in Huang [13]. Building physical features, such as walls and windows were equally distributed along the four building faces to avoid directional bias errors. Building internal complexities for commercial buildings were simplified by using a well established technique that separates internal areas into five zones - four perimeter zones and one core (Figure 5). Floors between the ground and top floors share the same thermal characteristics. Therefore, only one middle floor was modeled for buildings with more than three stories. Space loads resulting from the floor were then multiplied by the number of middle floors (Figure 5) and incorporated

into the building HVAC plant system. Building insulation and other envelope values were estimated taking into account that many buildings are not at current building standards. Therefore, building codes were not directly applied to define building characteristics. Instead, we used envelope values from Huang's study that were estimated from historic building codes, building conditions and human comfort levels.

The National Renewable Energy Laboratory has created the Building America Benchmark Definition [24] for Residential buildings. This benchmark was based on building industry knowledge and other end-use studies such as ELCAP. It developed building energy simulation inputs that are representative of "standard" building use. The Department of Energy's Building Energy Data Book [25] and Huang's [16] study were used to define characteristics the single family residential (SFR) prototypes. We used these parameters in conjunction with the Building America Benchmark, RECS, and Huang's [16] study to develop internal load shape, power densities and occupancy and HVAC schedules.

The zoning strategy used for commercial buildings was not used with the SFR prototypes because the building foot print area was too small for distinct core and perimeter thermal zones. Instead SFR prototypes were zoned according to space use (Figure 6): bedroom, general living and unconditioned garage. This allowed lighting schedules that differentiate bedrooms from general living spaces to be used. Multi-family residential (MFR) prototypes were modeled by adjusting the yearly hourly loads from the SFR simulations to the RECS MFR EUIs. The MFR prototypes were not explicitly modeled because the extensive simulation inputs available for SFR

prototypes were not available for MFR prototypes and because the SFR and MFR building types share the same usage patterns and consumption characteristics.

Key simulation inputs for each building prototype are summarized in appendix A.

Figure 5: eQuest screen shot of large office prototype. External geometry is depicted (top of figure), with plan view (bottom of figure) perimeter/core zone configuration common to all commercial buildings.

Figure 6: eQuest screen shot of single family residential prototype. External geometry is depicted (top of figure), with plan view (bottom of figure) zoning by space classification.

Building schedules are a major determinant of load shapes. The ELCAP study concluded for commercial buildings within the Pacific Northwest, that time alone can explain approximately 70% of hourly load variation [12]. Occupancy, internal loads, HVAC operating schedules, and DHW use are some of the many building characteristics that are modeled in building energy simulation programs using schedules (assumed hourly profiles). Internal load shapes, such as lighting, office

equipment and cooking, not only contribute to the building load, but also affect space conditioning loads by supplying “free heating” to conditioned spaces [21]. A literature review by Abushakra [22] examined existing typical internal load shapes from monitored commercial buildings and methods to develop them without end-use hourly load data. Although the review covered most commercial building types, it focused on office buildings. In the present work, reported internal load shapes were used where readily available. Lighting load shapes were based on office building profiles developed by ASHRAE [23].

4.5 *Fuel Ratio Adjustment*

Fuel ratios (R) are the ratio of non-electric (NG+) to electric EUIs. Obtaining typical fuel ratios for each building type allows energy consumption for each fuel type to be disaggregated and compared to EIA state total and aggregate hourly loads from utility companies. The model cannot capture all the variation in end-use consumption fuel types because the building prototypes were classified by the primary heating fuel used. For commercial building prototypes, secondary heating and the DHW (domestic hot water) fuel type is associated with the building’s primary heating. However, it is common to have mixed fuel type uses for an individual building (e.g, natural gas primary heating with electric secondary heating). End-use by fuel type distribution for the city level is not known. In order to compensate for the mix of fuel uses in existing buildings not captured by the prototype buildings, total prototype floor space was adjusted so that the model’s combined fuel ratio for building types matched that for

existing building types. This was done by first calculating average building type

EUIs for both NG+ and electricity:

$$EUI_{NG} = P^{NG} EUI_{NG}^{NG} + (1 - P^{NG}) EUI_{NG}^{ele} \quad (4)$$

$$EUI_{ele} = P^{NG} EUI_{ele}^{NG} + (1 - P^{NG}) EUI_{ele}^{ele} \quad (5)$$

where P^{NG} is the fraction of prototype buildings for a building type based on total floor space that use NG+ (rather than electricity) for primary heating. *EUI* is energy use intensity for the building types and prototypes (building *EUIs* are on the left side of equations 5 and 6 and building prototype *EUIs* are on the right). Subscripts in these equations denote the type of fuel consumption for both building types and prototypes and superscripts denote the primary heating fuel for the building prototypes. Energy usage intensities for the model's building types with the same fuel ratio as existing building types are obtained by:

$$EUI_{NG} = P^{adj} EUI_{NG}^{NG} \quad (6)$$

$$EUI_{ele} = P^{adj} EUI_{ele}^{NG} + (1 - P^{adj}) EUI_{ele}^{ele} \quad (7)$$

In these equations P^{adj} represents the adjusted percentage of building prototype floor space using NG+ for primary heating that will cause the model's building type fuel ratio to be equal to that of the existing building type. This factor can be evaluated by setting the fuel ratios from CBECS equal to the model's fuel ratios and combining equations 7 and 8:

$$P^{adj} = \frac{R \cdot EUI_{ele}^{ele}}{R(EUI_{ele}^{ele} - EUI_{ele}^{NG}) + EUI_{NG}^{NG}} \quad (8)$$

4.6 Overview of Parcel Geographical Information Systems

Geospatial mapping of building energy consumption is limited by the availability and detail of geospatial data. GIS databases often include information that is crucial for energy use mapping as well as supplemental data that can help inform building prototype simulation modeling. Building floor space and building type are necessary for geospatial mapping. Other commonly available GIS information useful for building prototype simulations, but not critical to geospatial mapping, are building materials, HVAC systems, building height and primary fuel type. Depending on the region, much of the information necessary for geospatial mapping and building prototype simulation is contained in parcel-scale GIS databases. Fortunately, collection of parcel information is federally mandated. Tax assessors, usually at the city or county level, are responsible for reporting on site assessment of individual parcels. Although all parcel information is collected, the degree to which this information is available in GIS format varies by city, county and state.

The Federal Geographic Data Committee (FGDC) subcommittee for Cadastral Data was chartered in 2002, to implement a federal initiative for collecting, standardizing, and converting parcel data to a centralized GIS. This program is known as the Cadastral National Spatial Data Infrastructure (NSDI). In 2003 the FGDC

surveyed state, county and city governments [26] to assess the number of parcels in the United States and the degree to which parcel data have been converted to a GIS. With 34 states reporting relevant information it was estimated that data for 61% of parcels in these states were available in digital format. Thirteen states had more than 70% of their parcel data in GIS format. Larger cities typically had higher rates of converted parcels. The FGDC also reported that communities with populations over 250,000 are likely to have an active parcel GIS conversion effort underway, if not already completed. The results of the FGDC have been compiled in an extensive web enabled interactive inventory of U.S. areas with GIS parcel data including contact information and URLs for state, county and city jurisdictions (<http://www.nationalcad.org>). To further investigate the availability of GIS-based data useful for bottom-up energy consumption analysis, we examined the ten largest cities in the U.S. In all cases, city parcel GIS data were either publicly available or available for purchase from the county or city. Building type or land use classification of parcels was available for all cities. In most cases geospatial building floor space, as well as additional information applicable to building simulations, were also available. For cities lacking building floor space information in their parcel GIS data, this information could be obtained through the local county or state tax assessor office and then linked to a geospatial database through parcel IDs. Three-dimensional building orthomography (aerial remote sensing imaging), which can be used in place of floor space information, is also becoming a common addition to larger city's GIS data bases. As a result, the methods employed in the present study can be readily adapted for use in modeling many other large U.S. cities.

4.7 *Geospatial Mapping*

The City of Houston Planning and Development Department maintains the City of Houston Geographical Information System (COHGIS) [27]. COHGIS is updated annually and contains cadastral information for the greater Houston metropolitan area. The Cadastral database includes Harris County parcel layers with over 800,000 parcels. Parcel data contains a multitude of fields including land use classification, building floor space and year of building construction (Figure 7). Harris county land use code and land use group fields were used to determine the building type. There are 245 land use codes and 11 land use groups. For parcels with buildings within the tax lot, the land use code and group describe the building use. Land use codes and land use groups were used to match the building types defined in the building prototype selection process to each parcel containing a building. For example, a parcel with a land use code 345 “discount department stores” would be associated with the retail building prototypes. A parcel with a land use code 104 “residential 4 family or more” would be associated with the MFR building prototypes. A parcel with a land use group 4 “office” would be associated to the office building prototypes. Use codes were also used to identify vacant buildings.

To ensure the completeness of the data set, parcels with use codes defining non-vacant buildings were analyzed to ensure the floor space was provided. Hospital and public school parcels consistently had missing floor space. For hospital and school parcels missing floor space information, the average floor space calculated from existing floor space parcel data was used.

Appendix B outlines the processes for mapping parcels to an atmospheric grid domain, sorting and binning parcels by building type and grid cell and then applying building prototype energy consumption profiles (Equation 2). Programming code used in these processes is supplied at the end of Appendix B.

Figure 7: Atmospheric grid domain (228 km^2) encompassing Houston and the COHGIS parcel layer (left). Sample grid cells and parcels depicted on the right.

5 Results

5.1 *Aggregate Energy Consumption*

All simulation prototype EUIs were adjusted to within 10% deviation of existing building types, with the exception of a 15% difference for retail building types. Internal lighting and equipment power densities were the only parameters adjusted (adjusted power densities for each simulation prototype are given in appendix A). The retail simulation prototype was not adjusted to a 10% deviation because the needed additional adjustments were inconsistent with previous simulation studies and engineering judgment. Figure 8 compares simulation building type and zone 5 (RECS and CBECS) EUIs. Restaurants had the largest EUI (887.2 kWh/m^2 or 281.4 kBtu/ft^2) due to large internal loads from cooking appliances. Warehouses had the smallest EUI of (83.8 kWh/m^2 or 26.5 kBtu/ft^2) because of low occupancy, low hours of use and an average unconditioned area of 70%.

Figure 8: Comparison of EUIs for RECS and CBECS EUIs against simulation building prototypes.

Figure 9: Percentage of city wide floor space and annual energy consumption by building types for Houston.

Figure 9 shows the percentage of total existing building floor space and predicted percentage of annual building energy consumption for each building type in Houston. Note that although restaurants comprise of only 0.4% of Houston's building floor space, they consume 2.1% of the total energy. The amount of building information available to define a building simulation prototype is proportional its net impact on city wide energy consumption. SFR prototypes, consuming 42.3% of the city's total energy had the most comprehensive building information. Office building prototypes, consuming 15.3% of the city's energy, also had an abundance of building information, including statistically defined internal power density schedules. Undefined building types lumped into the "Other" building type accounted for only 6.6% of the energy consumption.

Aggregated averaged daily energy consumption totals predicted by our model were compared against the top-down approach (see Table 2). This was done to ensure that the model accurately predicts the magnitude of total energy consumption. Table 2 shows that both approaches predicted similar citywide daily average consumption in both the residential and commercial sectors with the bottom-up model predicting 3.7% less consumption than the top-down approach in August and 2.3% more in January. Large differences were found when citywide diurnal energy consumption was compared. In August (see Figure 10) the bottom-up model predicted lower values for the overnight or off hours (24:00 – 6:00). Consumption in the bottom-up model lagged the top-down approach during the morning and peaked much later at 18:00. In January (see Figure 11), off hour energy consumption rates were similar for the two methods, but a large early morning peak attributed to space heating consumption for

building warm up was much greater for the bottom-up model. Although Houston has a relatively hot climate with mild winters, the winter peaks caused by space heating are similar in magnitude to the summer peaks caused by space cooling. This similarity is because heating efficiencies are much lower than space cooling efficiencies.

Table 2: Sum of daily energy consumption for August and January.

	August		January	
	Top-down	Bottom-up	Top-down	Bottom-up
	(MWh)	(MWh)	(MWh)	(MWh)
Residential	62,735	59,077	73,818	78,414
Commercial	45,853	45,483	49,888	48,161
Total	108,588	104,554	123,706	12,657

Figure 10: August average daily energy consumption for Houston for both the bottom-up and top-down approaches.

Figure 11: January average daily energy consumption for Houston for both the bottom-up and top-down approaches.

5.2 Spatial Energy Distribution

To understand how spatial variation in energy consumption might affect atmospheric model results, it is necessary to aggregate the predicted parcel level energy consumption results to a much coarser resolution common in atmospheric modeling applications. For this study we aggregated up to a resolution of 1.33 km which is comparable to the scale commonly employed in urban meteorological modeling. Results at this scale for the bottom-up model are compared against the top-down approach in Figures 12-15. In this figure the height of each extruded grid cell is proportional to its hourly energy consumption. Four snap shots are presented in this figure at six hour intervals. Results from the bottom-up model are displayed on the top with the top-down approach displayed on the bottom. Water bodies (Galveston Bay and Houston) are evident on the East.

The bottom up model predicts large variance in energy consumption with generally higher levels near and in the downtown core. Houston's downtown core is clearly highlighted by two grid cells with large energy consumption. The downtown core had a peak energy consumption of 102 W/m^2 in the early afternoon in August compared with 118 W/m^2 in January. The top-down approach does not capture downtown core peaks, predicting peak consumption of 6 W/m^2 for both August and January W/m^2 .

Spatial variation in energy consumption is caused by variations in building density (i.e. the amount of floor space), and the mixture of building types within each grid cell. Each grid cell has a unique mixture of building types and thus a unique diurnal profile. As shown in Figures 12-15, however, spatial variation in energy

consumption caused by the mixture of building types is insignificant when compared to the spatial variation caused by building density. Results from the bottom-up method show that the fraction of city wide energy consumed by each grid cell is relatively constant throughout the day (i.e. the magnitude changes but the general shape of the 3-dimensional plots stays the same). If the mixture of building types, or unique diurnal profiles, had greater effect on consumption, there would be a greater change in the overall shape of the plots for each hour. As shown in Figures 12-15, however, the spatial distribution of energy consumption peaks over the commercial building dominated commercial core even during the evening hours when the residential sector peaks. Variation caused by building types is insignificant because of the large variations in building density and because the commercial and residential sectors are well mixed. In contrast, the top-down method assigns either a residential or commercial profile to grid cells based on the dominant sector. Since the top-down approach does not account for building density variation, all grid cells within any sector have a single value of energy consumption within any hour. As a result, this method is not capable of capturing the large spatial variation caused by changes in building density in each grid cell.

An important result of this spatial analysis is that the top-down modeling approach reveals relatively little variation in energy consumption at grid scales commonly employed in urban scale atmospheric modeling. The bottom-up approach, on the other hand, reveals significant variation in energy consumption across the city.

Bottom-Up
August 5:00 – 6:00

Top-Down
August 5:00 – 6:00

Figure 12: Energy consumption at 1.33 km grid cell resolution for the 5:00– 6:00 hour interval.

Bottom-Up
August 12:00 – 13:00

Top-Down
August 12:00 – 13:00

Figure 13: Energy consumption at 1.33 km grid cell resolution for the 5:00 – 6:00 hour interval.

Bottom-Up
August 17:00-18:00

Top-Down
August 17:00-18:00

Figure 14: Energy consumption at 1.33 km grid cell resolution for the 17:00 – 18:00 hour interval.

Bottom-Up
August 24:00 – 1:00

Top-Down
August 24:00 – 1:00

Figure 15: Energy consumption at 1.33 km grid cell resolution for the 24:00 – 1:00 hour interval.

6 Discussion and Conclusion

The Houston case study revealed that the bottom-up method can accurately capture total building energy consumption. This was demonstrated by comparing total daily city-wide aggregate energy consumption results against the top-down approach that is accurate at the city level (Table 2). Key information sources (i.e. GIS and building energy surveys) are available for most large U.S. cities and therefore the method is widely applicable. The time intensive process of creating a set of prototype building simulations is the largest shortcoming of this method. However, much of the simulation structure, once created for one city, can be used for other U.S. cities.

A significant challenge in the building simulations was defining realistic average operating schedules. Most notable were various binary HVAC schedules that could not be readily averaged for a single prototype building. For example, some buildings in each commercial building type operated 24 hours day, but the HVAC schedules were defined to represent the majority of buildings, excluding hotels and hospitals, which had distinct off-hour set back periods. This resulted in a small over prediction of daytime consumption while underestimating nighttime consumption. To overcome this shortcoming, additional prototypes could be defined for 24 hour operation.

Past efforts to model the urban climate have often neglected waste heat emitted from anthropogenic sources. Recent UHI studies [3, 31] indicate a 1-3°C temperature rise within the urban canopy boundary caused by anthropogenic waste heat. While an increasing number of studies are pointing out the need to include waste heat in

atmospheric model simulations of cities, the difficulty in obtaining suitable energy consumption profile data has hampered modeling efforts.

The small number of urban climate modeling studies that have included anthropogenic waste heat have generally assumed that energy consumption is equivalent to anthropogenic sensible waste heat emissions. Little research has been conducted on the relative fraction of energy consumed that should be attributed to either sensible or latent heat. In the building sector, most of the latent heat emission is caused by the conversion of sensible to latent heat in air conditioning systems. Building energy simulations used in the bottom-up method can analyze these phase change processes. For example, many larger buildings use evaporative condensers to reject internal heat collected by an air conditioning system. Much of the heat is rejected from the condenser by evaporation which results in latent waste heat emission. Building simulations report hourly heat rejection from the condenser. By applying published condenser inlet and outlet dry bulb and wet bulb operating condition to the total heat rejection, the sensible and latent heat emission can be determined. Furthermore, a portion of a buildings' energy consumption that is converted into internal heat within the building is delayed from being emitted as waste heat by the buildings' thermal mass. This causes a time lag between energy consumption and waste heat emission. The typical top-down modeling approaches do not provide a framework that can analyze this transient heat transfer process. However, building simulations already account for thermal mass effects in order to calculate heating and cooling loads. DOE2, the building energy simulation program used in this study, solves for external surface and internal temperatures necessary for

analyzing time lag, but does not provide this information in its standard reports.

Also, DOE2 is not an open source code, restricting researchers from extracting this information from the simulations by modifying the program. Therefore, other simulation programs must be used for this application, e.g. Energy Plus, that either provides this information or allows the user to modify the source code. The bottom-up modeling approach discussed here will enable atmospheric modelers to address these two crucial issues.

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Appendix A – Building Simulation

Table A.1: Simulation inputs for Large Office building prototypes.

LARGE OFFICE > 25, 000 ft ²			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	211	Building floor space (ft ²)	103,000
% total commercial floor space	27.8%	Number of floors	7
Envelope		Operating Hours	
Window to wall ratio	45.5	Average operating hours	70.4
Window R-value	1.54	Weekday operating hours	12.0
Window shading coefficient	0.74	Weekend operating hours	5.2
Roof R-value	12.0	Internal Power Densities (W/sf²)	
Wall R-value	4.4		
Wall material	masonry	Unadjusted lighting	1.53
Roof material	built-up	Adjusted lighting	1.4
% conditioned floor space	100%	Unadjusted equipment	0.75
		Adjusted equipment	0.5
HVAC Sytems		Electric*	NG*
System type		VAV	VAV
% building stock w/sytem type		70.0%	70.0%
Heating plant		Electric Boiler	Gas boiler
Cooling plant		Hermetic centrifugal chiller	Hermetic centrifugal chiller
Plant Efficiencies			
Heating efficiency	0.63		0.94
Cooling COP	3.73		3.73
* Service hot water fuel type is the same as heating fuel type.			

Table A.2: Simulation inputs for Small Office building prototypes.

SMALL OFFICE < 25, 000 ft ²			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	52	Building floor space (ft ²)	6,213
% total commercial floor space	6.8%	Number of floors	2
Envelope		Operating Hours	
Window to wall ratio	18.5	Average operating hours	77.9
Window R-value	1.41	Weekday operating hours	13.0
Window shading coefficient	0.80	Weekend operating hours	6.4
Roof R-value	4.4	Internal Power Densities (W/sf²)	
Wall R-value	11.1		
Wall material	masonry	Unadjusted lighting	2.05
Roof material	built-up	Adjusted lighting	2.05
% conditioned floor space	100%	Unadjusted equipment	0.5
		Adjusted equipment	0.5
HVAC Systems		Electric*	NG*
System type	Packaged single zone	Packaged single zone	
	w/economizer	w/economizer	
% building stock w/sytem type	76.4%	76.4%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.63	0.94	
Cooling COP	3.51	3.51	
* Service hot water fuel type is the same as heating fuel type.			

Table A.3: Simulation inputs for Other building prototypes.

OTHER			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	124	Building floor space (ft ²)	10,736
% total commercial floor space	16.4%	Number of floors	1
Envelope**		Operating Hours	
Window to wall ratio	15.0	Average operating hours	70.0
Window R-value	1.52	Weekday operating hours	11.0
Window shading coefficient	0.80	Weekend operating hours	7.5
Roof R-value	4.0	Internal Power Densities (W/sf)**	
Wall R-value	12.0		
Wall material	masonry		
Roof material	built-up		
% conditioned floor space	70%		
		Unadjusted lighting	1
		Adjusted lighting	1
		Unadjusted equipment	0.8
		Adjusted equipment	0.8
HVAC Sytems		Electric*	NG*
System type	Packaged single zone	Packaged single zone	
	w/economizer	w/economizer	
% building stock w/sytem type	42.2%	42.2%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.94	0.76	
Cooling COP	2.47	2.47	
* Service hot water fuel type is the same as heating fuel type.			
** Typical values			

Table A.4: Simulation inputs for Large Retail building prototypes.

LARGE RETAIL > 25,000 ft ²			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	105	Building floor space (ft ²)	97,826
% total commercial floor space	13.9%	Number of floors	2
Envelope		Operating Hours	
Window to wall ratio	15.0	Average operating hours	88.0
Window R-value	1.54	Weekday operating hours	13.0
Window shading coefficient	0.77	Weekend operating hours	11.5
Roof R-value	4.1	Internal Power Densities (W/sf²)	
Wall R-value	11.9		
Wall material	masonry	Unadjusted lighting	1.88
Roof material	built-up	Adjusted lighting	1.2
% conditioned floor space	90%	Unadjusted equipment	0.4
		Adjusted equipment	0.4
HVAC Systems		Electric*	NG*
System type		VAV	VAV
% building stock w/sytem type		69.5%	69.5%
Heating plant		Electric Boiler	Gas boiler
Cooling plant		Hermetic centrifugal chiller	Hermetic centrifugal chiller
Plant Efficiencies			
Heating efficiency	0.94		0.63
Cooling COP	3.73		3.73
* Service hot water fuel type is the same as heating fuel type.			

Table A.5: Simulation inputs for Small Retail building prototypes.

SMALL RETAIL < 25, 000 ft ²			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	45	Building floor space (ft ²)	6,806
% total commercial floor space	29.8%	Number of floors	1
Envelope		Operating Hours	
Window to wall ratio	15.0	Average operating hours	65.6
Window R-value	1.54	Weekday operating hours	10.0
Window shading coefficient	0.84	Weekend operating hours	7.8
Roof R-value	3.7	Internal Power Densities (W/sf²)	
Wall R-value	10.8		
Wall material	masonry	Unadjusted lighting	1.93
Roof material	built-up	Adjusted lighting	1.93
% conditioned floor space	85%	Unadjusted equipment	0.4
		Adjusted equipment	0.4
HVAC Systems		Electric*	NG*
System type	Packaged single zone	Packaged single zone	
	w/economizer	w/economizer	
% building stock w/sytem type	65.0%	65.0%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.94	0.75	
Cooling COP	2.47	2.47	
* Service hot water fuel type is the same as heating fuel type.			

Table A.6: Simulation inputs for Warehouse prototypes.

WAREHOUSE			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	166	Building floor space (ft ²)	1,635
% total commercial floor space	21.9%	Number of floors	1
Envelope		Operating Hours	
Window to wall ratio	4.6	Average operating hours	51.0
Window R-value	1.52	Weekday operating hours	8.0
Window shading coefficient	0.84	Weekend operating hours	5.5
Roof R-value	9.0	Internal Power Densities (W/sf²)	
Wall R-value	3.2		
Wall material	masonry	Unadjusted lighting	0.8
Roof material	metal surf.	Adjusted lighting	0.8
% conditioned floor space	37%	Unadjusted equipment	0.3
		Adjusted equipment	0.3
HVAC Sytems		Electric*	NG*
System type	Packaged single zone w/economizer	Packaged single zone w/economizer	
% building stock w/sytem type	99.0%	99.0%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.94	0.75	
Cooling COP	2.43	2.43	
* Service hot water fuel type is the same as heating fuel type.			

Table A.7: Simulation inputs for Health Care building prototypes.

HEALTH CARE			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	24	Building floor space (ft ²)	114,414
% total commercial floor space	3.1%	Number of floors	8
Envelope		Operating Hours	
Window to wall ratio	25.0	Average operating hours	128.0
Window R-value	1.88	Weekday operating hours	24.0
Window shading coefficient	0.68	Weekend operating hours	24.0
Roof R-value	5.7	Internal Power Densities (W/sf²)	
Wall R-value	11.9		
Wall material	masonry		
Roof material	built-up		
% conditioned floor space	100%	Unadjusted lighting	2.2
		Adjusted lighting	1.2
		Unadjusted equipment	2.1
		Adjusted equipment	1.2
Service Hot Water			
Process flow (gpm)	22.5		
HVAC Systems		Electric*	NG*
System type		VAV	VAV
% building stock w/system type		60.0%	60.0%
Heating plant		Electric boiler	Gas boiler
Cooling plant		Hermetic centrifugal chiller	Hermetic centrifugal chiller
Plant Efficiencies			
Heating efficiency	0.94		0.75
Cooling COP	3.73		3.73
* Service hot water fuel type is the same as heating fuel type.			

Table A.8: Simulation inputs for Restaurant building prototypes.

RESTAURANT			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	9	Building floor space (ft ²)	3,371
% total commercial floor space	1.2%	Number of floors	1
Envelope		Operating Hours	
Window to wall ratio	19.7	Average operating hours	99.0
Window R-value	1.52	Weekday operating hours	15.0
Window shading coefficient	0.80	Weekend operating hours	12.0
Roof R-value	3.9	Internal Power Densities (W/sf²)	
Wall R-value	11.9		
Wall material	masonry	Unadjusted lighting	2.2
Roof material	built-up	Adjusted lighting	2.2
% conditioned floor space		Unadjusted equipment	2.3
		Adjusted equipment	4
		Cooking**	15
Sevice Hot Water			
Process flow (gpm)			
HVAC Sytems		Electric*	NG*
System type	Packaged single zone	Packaged single zone	
	w/economizer	w/economizer	
% building stock w/sytem type	74.3%	74.3%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.94	0.75	
Cooling COP	2.43	2.43	
* Service hot water fuel type is the same as heating fuel type.			
** Cooking loads are NG for simualtion with NG heating.			

Table A.9: Simulation inputs for Lodging building prototypes.

LODGING			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	34	Building floor space (ft ²)	192,128
% total commercial floor space	4.5%	Number of floors	8
Envelope		Operating Hours	
Window to wall ratio	32.3	Average operating hours	162.0
Window R-value	1.55	Weekday operating hours	24.0
Window shading coefficient	0.78	Weekend operating hours	21.0
Roof R-value	5.0	Internal Power Densities (W/sf²)	
Wall R-value	13.0		
Wall material	masonry	Unadjusted lighting	1.18
Roof material	built-up	Adjusted lighting	0.6
% conditioned floor space	88%	Unadjusted equipment	0.72
Service Hot Water		Adjusted equipment	0.4
		Cooking**	3.25
Gallons/person/day	26		
HVAC Systems		Electric*	NG*
System type	four pipe fan coil	four pipe fan coil	
% building stock w/system type***	---	---	
Heating plant	Electric Boiler	Gas boiler	
Cooling plant	Hermetic centrifugal chiller	Hermetic centrifugal chiller	
Plant Efficiencies			
Heating efficiency	0.94	0.75	
Cooling COP	2.43	2.43	
* Service hot water fuel type is the same as heating fuel type.			
** Cooking loads are NG for simulation with NG heating.			
*** CBECS does distinguish buildings with four pipe fan coil system.			

Table A.10: Simulation inputs for Education building prototypes.

EDUCATION			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	51	Building floor space (ft ²)	91,797
% total commercial floor space	6.7%	Number of floors	2
Envelope		Operating Hours	
Window to wall ratio	24.8	Average operating hours	50.7
Window R-value	1.46	Weekday operating hours	10.0
Window shading coefficient	0.81	Weekend operating hours	0.0
Roof R-value	4.0	Internal Power Densities (W/sf²)	
Wall R-value	10.7		
Wall material	masonry		
Roof material	built-up		
% conditioned floor space	100%		
		Unadjusted lighting	1.8
		Adjusted lighting	1.8
		Unadjusted equipment	0.5
		Adjusted equipment	0.5
Service Hot Water			
Gallons/person/day	2		
HVAC Systems		Electric*	NG*
System type		Multi-zone	Multi-zone
% building stock w/system type**		—	—
Heating plant		Electric Boiler	Gas boiler
Cooling plant		Hermetic centrifugal chiller	Hermetic centrifugal chiller
Plant Efficiencies			
Heating efficiency	0.94	0.75	
Cooling COP	4	4	
* Service hot water fuel type is the same as heating fuel type.			
** CBECS does distinguish buildings with multi-zone system.			

Table A.11: Simulation inputs for Food Sales building prototypes.

FOOD SALES			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	9	Building floor space (ft ²)	5,727
% total commercial floor space	1.1%	Number of floors	
Envelope		Operating Hours	
Window to wall ratio	15.0	Average operating hours	227.0
Window R-value	1.55	Weekday operating hours	114.0
Window shading coefficient	0.81	Weekend operating hours	17.0
Roof R-value	4.4	Internal Power Densities (W/sf²)	
Wall R-value	10.3		
Wall material	masonry	Unadjusted lighting	1.2
Roof material	built-up	Adjusted lighting	1.2
% conditioned floor space	87%	Unadjusted equipment	2.4
		Adjusted equipment	2.4
		Refrigeration	2
HVAC Systems		Electric*	NG*
System type	Packaged single zone w/economizer	Packaged single zone w/economizer	
% building stock w/sytem type	84.8%	84.8%	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.94	0.74	
Cooling COP	2.41	2.41	
* Service hot water fuel type is the same as heating fuel type.			

Table A.12: Simulation inputs for Pre 1980 SFR building prototypes.

PRE 1980 SINGLE FAMILY RESIDENTIAL			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	569	Building floor space (ft ²)	2,344
% total residential floor space	36.7%	Number of floors	1
Envelope		% conditioned floor space	87%
Window to wall ratio	11%		
Window type	Double Clear 1/8in Air		
Ceiling Insulation (below attic)	R-11		
Wall Insulation	R-7		
Wall material	Wood frame, 2x4, 16 in. o.c.		
Roof material	Wood, standard framing		
Roof type	Unconditioned attic, 25° Pitch		
Ground floor exposure	Over craw space		
Operating Hours		Domestic Hot Water	
Average operating hours	14.9	Hot water use (gallon/day)	64.9
Weekday operating hours	14	Thermostat set points	
Weekend operating hours	17	Heating	71 °F
		Cooling	75 °F
Activity Areas (zones)			
Internal Power	General	Bedroom	Garage
% total of floor space	56%	31%	13%
Lighting (Wh/day/ft ²)	5	5	2
Equipment (Wh/day/ft ²)	9.8	4.7	0.1
Equipment % sensible load	71%	90%	100%
Equipment % latent load	0%	0%	0%
HVAC Systems		Electric*	NG*
System type	Central, Packaged	Central, Packaged	
	Single Zone	Single Zone	
Heating plant	Electric resistance	Gas furnace	
Cooling plant	DX cooling	DX cooling	
Plant Efficiencies			
Heating efficiency	0.96	0.80	
Cooling COP	2.00	2.70	
* Service hot water fuel type is the same as heating fuel type.			

Table A.13: Simulation inputs for Post 1979 SFR building prototypes.

POST 1979 SINGLE FAMILY RESIDENTIAL			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	569	Building floor space (ft ²)	2,344
% total residential floor space	31.7%	Number of floors	1
Envelope		% conditioned floor space	87%
Window to wall ratio	11%		
Window type	Double Clear 1/8in Air		
Ceiling Insulation (below attic)	R-32		
Wall Insulation	R-11		
Wall material	Wood frame, 16" o.c.		
Roof material	Wood, standard framing		
Roof type	Uncond. attic, 25° Pitch		
Ground floor exposure	Over craw space		
Operating Hours		Domestic Hot Water	
Average operating hours	14.9	Hot water use (gallon/day)	64.9
Weekday operating hours	14	Thermostat set points	
Weekend operating hours	17	Heating	71 °F
		Cooling	75 °F
Activity Areas (zones)			
Internal Power		General	Bedroom
% total of floor space	56%	31%	13%
Lighting (Wh/day/ft ²)	5	5	2
Equipment (Wh/day/ft ²)	9.8	4.7	0.1
Equipment % sensible load	71%	90%	100%
Equipment % latent load	0%	0%	0%
HVAC Sytems		Electric*	NG*
System type		Central, Var. Vol	Central, Var. Vol
		Var. Temp.	Var. Temp.
Heating plant		Heat pump	Gas furnace
Cooling plant		DX cooling	DX cooling
Plant Efficiencies			
Heating efficiency	2.80	0.80	
Cooling COP	2.70	2.70	
* Service hot water fuel type is the same as heating fuel type.			

Table A.14: Sources for commercial simulation prototype inputs.

COMMERICAL SECTOR			
SOURCES FOR SIMULATION INPUT			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	(4)	Building floor space (ft ²)	(2)
% total commercial floor space	(4)	Number of floors	(2)
Envelope		Operating Hours	
Window to wall ratio	(1)	Average operating hours	(3)
Window R-value	(1)	Weekday operating hours	(1)
Window shading coefficient	(1)	Weekend operating hours	(1)
Roof R-value	(1)		
Wall R-value	(1)	Internal Power Densities (W/sf²)	
Wall material	(1)	Unadjusted lighting	(1)
Roof material	(1)	Adjusted lighting	N/A
% conditioned floor space	(3)	Unadjusted equipment	(1)
		Adjusted equipment	N/A
HVAC Systems		Electric	NG
System type	(2)		(2)
% building stock w/sytem type	(2)		(2)
Heating plant	(1)		(1)
Cooling plant	(1)		(1)
Plant Efficiencies			
Heating efficiency	(3)		(3)
Cooling COP	(3)		(3)
Reference #	Source		
(1)	[16] Huang and Franconi, 1999		
(2)	[17] CBECS, 1999		
(3)	[14] Sezgen et al., 1995		
(4)	[27] COHGIS, 2005		

Table A.15: Sources for residential simulation prototype inputs.

RESIDENTIAL SECTOR			
SOURCES FOR SIMULATION INPUT			
Houston Stock Floor Area Data		Building Size	
Total floor space (million of ft ²)	(4)	Building floor space (ft ²)	(6)
% total residential floor space	(4)	Number of floors	(6)
		% conditioned floor space	(2,6)
Envelope		Operating Hours	
Window to wall ratio	(2)	Average operating hours	(5)
Window type	(2)	Weekday operating hours	(5)
Ceiling Insulation (below attic)	(2)	Weekend operating hours	(5)
Wall Insulation	(2)		
Wall material	(2)		
Roof material	(2)	Domestic Hot Water	
Roof type	(2)	Hot water use (gallon/day)	(5)
Ground floor exposure	(2)		
Internal Power		HVAC Systems	
% total of floor space	(6)	System type	(2,7)
Lighting (Wh/day/ft ²)	(5)	Heating plant	(2,7)
Equipment (Wh/day/ft ²)	(5)	Cooling plant	(2,7)
Equipment % sensible load	(5)	Plant Efficiencies	
Equipment % latent load	(5)	Heating efficiency	(3)
		Cooling COP	(3)
Reference #	Source		
(1)	[18] RECS, 2001		
(2)	[28] Huang et al., 1999		
(3)	[14] Sezgen et al., 1995		
(4)	[27] COHGIS, 2005		
(5)	[24] NREL, Building America Benchmark, 2005		
(6)	[25] DOE, Building Energy Data Book, 2006		
(7)	[29] Houston American Housing Survey, 1998

Figure A.1: January diurnal commercial sector energy consumption for Houston by fuel type.

Figure A.2: January diurnal residential sector energy consumption for Houston by fuel type.

Figure A.3: January diurnal combined (residential + commercial) sector energy consumption for Houston by fuel type.

Figure A.4: January diurnal combined (residential + commercial) sector energy consumption for Houston by sector.

Figure A.5: April diurnal commercial sector energy consumption for Houston by fuel type.

Figure A.6: April diurnal residential sector energy consumption for Houston by fuel type.

Figure A.7: April diurnal combined (residential + commercial) sector energy consumption for Houston by fuel type.

Figure A.8: April diurnal combined (residential + commercial) sector energy consumption for Houston by sector.

Figure A.9: August diurnal commercial sector energy consumption for Houston by fuel type.

Figure A.10: August diurnal residential sector energy consumption for Houston by fuel type.

Figure A.11: August diurnal combined (residential + commercial) sector energy consumption for Houston by fuel type.

Figure A.12: August diurnal combined (residential + commercial) sector energy consumption for Houston by sector.

Appendix B – Data Processing and Program Codes

The following section outlines the data processing steps used to create a domain of $Q_{cell}(h)$ by taking yearly hourly data outputted from the building prototype simulations and applying them spatially to a GIS (Figure 1 steps 3 and 4). The program codes used for data processing is supplied at the end of this appendix.

Data Processing steps:

1. Convert raw data from building prototype simulations to $Q_p(h)$ (Equation 2).

The Matlab script *profileGenerator.m* accepts a CSV file containing the yearly hourly NG and electricity energy use outputted from the building simulations for each building type. The script allows the user to specify the season duration, and days of the week to be processed. The user specified hours are then applied to equation 2. The script outputs a CSV file with eleven $Q_p(h)$ vectors for each building type.

2. GIS data processing

ArcGIS 9 was used for all GIS data processing. The GIS steps outlined in this section, although specific to the COHGIS database, are applicable to most parcel layers.

- a. Create an atmospheric grid domain.

In ArcToolbox use the Fishnet option from the Generate command to create a polyline grid based on the atmospheric grid domain. In ArcToolbox use the Feature to Polygon to convert the fishnet polyline to a polygon feature.

- b. Convert GIS parcel polygon layer to a point layer.

If the tax lot or parcel layer is a polygon, In ArcToolbox use the Feature to Point to convert it to a point layer.

- c. Index parcels to atmospheric grid cells.

In ArcToolbox apply the Intersect command to the polygon fishnet layer and the parcel point layer. Export the fishnet cell index, Usecode, Usegroup and building floorspace columns in CSV format from the layer created by the Intersect command.

3. Bin parcels by building types for each atmospheric grid cell and apply $Q_p(h)$ to the domain (Equation

For the COHGIS data set there are over 800,000 parcels. Python's library function was used to reduce the computational time associated with sorting such a large data set. The Python script *houston_Qf_grid.py* accepts the $Q_p(h)$ vector file created by *profileGenerator.m* and the CSV file with parcel data indexed to the atmospheric grid. Each parcel's Usecode or Usegroup is associated with a building type. Parcels are sorted by there Usecode or Usegroup and binned by grid cell and building type. The total floor space for each grid cell and building type is applied to $Q_p(h)$ (Equation 3) resulting in a $n \times m \times 24$ matrix with aggregate energy consumption for each grid cell and hour, where $n \times m$ is the atmospheric domain grid size.

Building codes (i.e Usecodes or Usegroups) for other GIS databases must be assessed and matched to there respective building types and manually entered into *houston_Qf_grid*'s sorting structure. Additionally, special care

must be taken to ensure the indexing order is the same as the atmospheric

grid domain for new GIS databases.

File name: *profileGenerator.m*

Programming language: Matlab

```
function profileGenerator

close all
% Synopsis:
%   Takes 8760 DOE2 outputs from for each building type and creates average
%   diurnal profiles for each building type for a user specified season or
%   group of month.
%
% Input:
% file is created from Excel file Compare_commercial_new...
% Spreadsheet "Pofile input" save data without headings into txt file...
% 'houRawLoads.txt'

data = load('C:\Python24\scripts\houston\houRawLoads.txt');

month = data(:,3);

%Specify season... example:(June-Sept)->(6,9)

sea_start = input('Specify start of season... example:June->6: ');
sea_end = input('Specify end of season... example:Sept->9: ');

monthIndex = find(month>=sea_start & month<=sea_end);
data = data(monthIndex,1:end);

%Specify days... example:(Mon-Friday)->(1,5)

day_start = input('Specify first day... example:Monday->1: ');
day_end = input('Specify last day ... example:Friday->5: ');

dayIndex = find(data(:,2) >= day_start & data(:,2) <= day_end);
data = data(dayIndex,1:end);

hour = data(:,1);
Q = data(:,4:end);
[numRow,numColumn] = size(Q);

%Create Electric profiles

count = 0;
for b = 1:2:numColumn-1
    count = 1 + count;
    for h = 1:24
        Qb = Q(:,b);
        Qhour(h) = mean(Qb(find(hour == h)));
    end
    Q_ele(count,1:24) = Qhour;
end

%Create NG profiles
```

```

count = 0;
for b = 2:2:numColumn
    count = 1 + count;
    for h = 1:24
        Qb = Q(:,b);
        Qhour(h) = mean(Qb(find(hour == h)));
    end
    Q_NG(count,1:24) = Qhour;
end

Qf = Q_ele + Q_NG;

csvwrite('C:\Python24\scripts\houston\houProfiles.csv', Qf)

disp('1 = Office')
disp('2 = Other')
disp('3 = Retail')
disp('4 = Warehouse')
disp('5 = Health')
disp('6 = Restaurant')
disp('7 = Lodging')
disp('8 = Education')
disp('9 = FoodSales')
disp('10 = SFR')
disp('11 = MFR')
BuildingType = input('Specify building profile to plot (1 - 11): ')

figure
subplot(3,1,1)
plot(1:24, Q_ele(BuildingType,:), 'o:')
title('Electric Qf');
xlabel('hour'), ylabel('W/sqft')

subplot(3,1,2)
plot(1:24, Q_NG(BuildingType,:), 'o:')
title('NG Qf');
xlabel('hour'), ylabel('W/sqft')

subplot(3,1,3)
plot(1:24, Qf(BuildingType,:), 'o:')
title('Total Qf');
xlabel('hour'), ylabel('W/sqft')

```

File name: *houston_Qf_grid.py*
 Programming language: Python

```

import csv
import operator

```

```

#Synopsis:

```

```

#1. For Houston Building energy data. Creates a matrix for MM5 input with
#   building energy values for the Residential and Commercial Sectors
#
#   input:
#
#   a) n x 4 comma delimited matrix from COHGIS for each tax lot with
#   columns:

```

```

#
#   Grid cells index, Usecode, Usegroup code, Building floor space
#
#   Default column HEADINGS
#   "FID_d5_ang", "USECODE", "USEGRP", "BLDGSQFT"

data = csv.reader(open('C:/COHGIS2005/myFiles/d5_grid_parcel.txt', "rb"))

#   b) Building type diurnal profiles from building sim model: 11x24 matrix
#       Units: W/sf/per hour
#       column: building type
#       row: hour

profileInput = open('C:/Python24/scripts/houston/houProfiles.csv', "rb")
##
##2. Creates comma delimited file n x 5 matrix to be linked to the COHGIS
##   with Qf for each our and grid cell.
##
##GIS_Qf.writerow(["Grid", "Hour", "COM_Qf", "RES_Qf", "Total_Qf"])

#####
#                               Declair variables                               #
#####

#default value for grig cells with no information.
default = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

# domain size (size of matrix)
rowSize = 129
columnSize = 129

# Grid size in m^2
gridSize = 1330*1330

#####
#                               Load anthropogenic profiles                               #
#####

office_p = profileInput.readline().rstrip().split(',') #1
other_p = profileInput.readline().rstrip().split(',') #2
retail_p = profileInput.readline().rstrip().split(',') #3
warehouse_p = profileInput.readline().rstrip().split(',') #4
health_p = profileInput.readline().rstrip().split(',') #5
restaurant_p = profileInput.readline().rstrip().split(',') #6
lodging_p = profileInput.readline().rstrip().split(',') #7
education_p = profileInput.readline().rstrip().split(',') #8
foodSales_p = profileInput.readline().rstrip().split(',') #9
SFR_p = profileInput.readline().rstrip().split(',') #10
MFR_p = profileInput.readline().rstrip().split(',') #11

#####
#                               Create dictionary                               #
#####

#1. Sorts usecodes into a dictionary by building type.
#2. Adds missing bldgsqft values for education,
#   hospitals and religious buildings.

#Default HEADINGS
#"FID_d5_ang", "USECODE", "USEGRP", "BLDGSQFT"

```

```

print 'Commercial file headings'
print data.next()

COMfile = open("houComGIS_profiles.csv", "wb")
RESfile = open("houResGIS_profiles.csv", "wb")
writerCOM = csv.writer(COMfile)
writerRES = csv.writer(RESfile)

GIS_Qf = csv.writer(open('C:/COHGIS2005/myFiles/Qf_GISgrid.txt', "wb"))
writerIndex = csv.writer(open('Qf_index.csv', "wb"))

d = dict()
count = 0
print 'Creating dictionary'
print '.' * 20
for line in data:
    d.setdefault(int(line[0]), []).append([line[1], line[2], line[3]])
for key, values in d.items():
    sub_d = {}
    for i, line in enumerate(values):
        area = float(line[2])
        dontCount = 0
        usecode = line[0]
        if line[0] == '612' and area == 0: #school
            line[2] = 39226 # Average floorspace
            buildType = 'education'
        elif line[0] == '613' and area == 0: #university
            line[2] = 13760.37 # Average floorspace
            buildType = 'education'
        elif line[0] == '640' and area == 0: #hospital
            line[2] = 127413 # Average floorspace
            buildType = 'health'
        elif line[0] == '620' and area == 0: #religious
            line[2] = 6592 # Average floorspace
            buildType = 'other'
        elif line[1] == '4':
            buildType = 'office'
        elif operator.contains(['319', '370', '375', '373', '374', '375',
                                '376', '340', '341', '342', '343', '344',
                                '345', '346'], usecode):
            buildType = 'retail'
        elif operator.contains(['398', '397', '396'], usecode):
            buildType = 'warehouse'
        elif operator.contains(['362', '361', '383', '357',
                                '369', '640'], usecode):
            buildType = 'health'
        elif operator.contains(['321', '327', '328', '348'], usecode):
            buildType = 'restaurant'
        elif operator.contains(['314', '315'], usecode):
            buildType = 'lodging'
        elif operator.contains(['612', '613'], usecode):
            buildType = 'education'
        elif operator.contains(['324', '323', '326', '347', '348'], usecode):
            buildType = 'foodSales'
            count+= 1
        elif line[1] == '1':
            buildType = 'SFR'
        elif line[1] == '2':
            buildType = 'MFR'
        elif area > 0 and line[1] <> '5':
            buildType = 'other'

```

```

else:
    dontCount = 1
    sub_d.setdefault('empty', []).append(0)
    if dontCount == 0:
        sub_d.setdefault(buildType, []).append(float(line[2]))
    d[key] = sub_d
print 'finished creating dictionary.'

print '.' * 20

#####
#                               Sum up floor space in each grid cell                               #
#####

#Sums up floospace (sf) in grids cells by building type.

length = []
row = []
reverseIndex = range(rowSize*columnSize)
d_total = dict()

office_total = other_total = retail_total = warehouse_total = health_total\
               = restaurant_total = lodging_total = education_total\
               = foodSales_total = SFR_total = MFR_total = 0

reverseIndex.reverse()
for cellIndex in reverseIndex:
    if d.has_key(cellIndex):
        if d[cellIndex].has_key('office'):
            office_sum = sum(d[cellIndex]['office'])
            office_total+= office_sum
        else:
            office_sum = 0
        if d[cellIndex].has_key('other'):
            other_sum = sum(d[cellIndex]['other'])
            other_total+= other_sum
        else:
            other_sum = 0
        if d[cellIndex].has_key('retail'):
            retail_sum = sum(d[cellIndex]['retail'])
            retail_total+= retail_sum
        else:
            retail_sum = 0
        if d[cellIndex].has_key('warehouse'):
            warehouse_sum = sum(d[cellIndex]['warehouse'])
            warehouse_total+= warehouse_sum
        else:
            warehouse_sum = 0
        if d[cellIndex].has_key('health'):
            health_sum = sum(d[cellIndex]['health'])
            health_total+= health_sum
        else:
            health_sum = 0
        if d[cellIndex].has_key('restaurant'):
            restaurant_sum = sum(d[cellIndex]['restaurant'])
            restaurant_total+= restaurant_sum
        else:
            restaurant_sum = 0
        if d[cellIndex].has_key('lodging'):
            lodging_sum = sum(d[cellIndex]['lodging'])
            lodging_total+= lodging_sum

```



```

else:
    lodging_sum = 0
    if d[cellIndex].has_key('education'):
        education_sum = sum(d[cellIndex]['education'])
        education_total+= education_sum
    else:
        education_sum = 0
    if d[cellIndex].has_key('foodSales'):
        foodSales_sum = sum(d[cellIndex]['foodSales'])
        foodSales_total+= foodSales_sum
    else:
        foodSales_sum = 0
    if d[cellIndex].has_key('SFR'):
        SFR_sum = sum(d[cellIndex]['SFR'])
        SFR_total+= SFR_sum
    else:
        SFR_sum = 0
    if d[cellIndex].has_key('MFR'):
        MFR_sum = sum(d[cellIndex]['MFR'])
        MFR_total+= MFR_sum
    else:
        MFR_sum = 0
    d_total.setdefault(cellIndex, []).\
        extend([office_sum, other_sum, retail_sum, warehouse_sum,
        health_sum, restaurant_sum, lodging_sum, education_sum,
        foodSales_sum, SFR_sum, MFR_sum])
else:
    d_total.setdefault(cellIndex, []).extend(default)

grandTotal = office_total+other_total+retail_total+warehouse_total+\
    health_total+restaurant_total+education_total+foodSales_total
print 'Total square feet for COM Building types'
print
print 'office:      ', office_total
print 'other:       ', other_total
print 'retail:       ', retail_total
print 'warehouse:   ', warehouse_total
print 'health:      ', health_total
print 'restaurant:  ', restaurant_total
print 'lodging:     ', lodging_total
print 'education:   ', education_total
print 'food sales:  ', foodSales_total
print
print 'Grand Total:', grandTotal
print

print 'Percent square feet for COM Building types'
print
print 'office:      ', office_total / grandTotal
print 'other:       ', other_total / grandTotal
print 'retail:       ', retail_total / grandTotal
print 'warehouse:   ', warehouse_total / grandTotal
print 'health:      ', health_total / grandTotal
print 'restaurant:  ', restaurant_total / grandTotal
print 'lodging:     ', lodging_total / grandTotal
print 'education:   ', education_total / grandTotal
print 'food sales:  ', foodSales_total / grandTotal
print
print 'Grand Total:', grandTotal / grandTotal
print

```

```

print 'Total square feet for RES Building types'
print
print 'SFR:          ', SFR_total
print 'MFR:          ', MFR_total
print
print 'Grand Total:', SFR_total+MFR_total
print

print 'Percent square feet for RES Building types'
print
print 'SFR:          ', SFR_total / (SFR_total + MFR_total)
print 'MFR:          ', MFR_total / (SFR_total + MFR_total)
print
print 'Grand Total:', (SFR_total+MFR_total) / (SFR_total+MFR_total)
print

#####
#                               Apply Anthropogenic profiles                               #
#####

# multiply floorspace by 24 hour W/sf building type profiles

print 'Applying diurnal anthropogenic profiles to each grid cell'
print 'and writing to file "houComGIS_profiles.csv"...'

##### Commercial #####
d = {}
for hour in range(24):
    for cellIndex in reverseIndex:
        totalEnergy = sum([d_total[cellIndex][0]*float(office_p[hour]),
                           d_total[cellIndex][1]*float(other_p[hour]),
                           d_total[cellIndex][2]*float(restaurant_p[hour]),
                           d_total[cellIndex][3]*float(warehouse_p[hour]),
                           d_total[cellIndex][4]*float(health_p[hour]),
                           d_total[cellIndex][5]*float(restaurant_p[hour]),
                           d_total[cellIndex][6]*float(lodging_p[hour]),
                           d_total[cellIndex][7]*float(education_p[hour]),
                           d_total[cellIndex][8]*float(foodSales_p[hour])])\
                           /float(gridSize)
        row.append(totalEnergy)
    if len(row) == rowSize:
        row.reverse()
        writerCOM.writerow(row)
        row = []

##### Residential #####

for hour in range(24):
    for cellIndex in reverseIndex:
        totalEnergy = sum([d_total[cellIndex][9]*float(SFR_p[hour]),
                           d_total[cellIndex][10]*float(MFR_p[hour])])\
                           /float(gridSize)
        row.append(totalEnergy)
    if len(row) == rowSize:
        row.reverse()
        writerRES.writerow(row)
        row = []

##### Create Grid index #####
for hour in range(24):
    for cellIndex in reverseIndex:

```

```

        row.append(cellIndex)
        if len(row) == rowSize:
            row.reverse()
            writerIndex.writerow(row)
            row = []

##### Create GIS Qf #####

#GIS_Qf headings
GIS_Qf.writerow(["Grid", "Hour", "COM_Qf", "RES_Qf", "Total_Qf"])

GISIndex = range(rowSize*columnSize)
for hour in range(24):
    for cellIndex in GISIndex:
        COMtotalEnergy = sum([d_total[cellIndex][0]*float(office_p[hour]),
                               d_total[cellIndex][1]*float(other_p[hour]),
                               d_total[cellIndex][2]*float(warehouse_p[hour]),
                               d_total[cellIndex][3]*float(health_p[hour]),
                               d_total[cellIndex][4]*float(restaurant_p[hour]),
                               d_total[cellIndex][5]*float(lodging_p[hour]),
                               d_total[cellIndex][6]*float(education_p[hour]),
                               d_total[cellIndex][7]*float(foodSales_p[hour])])\
                               /float(gridSize)
        REStotalEnergy = sum([d_total[cellIndex][9]*float(SFR_p[hour]),
                               d_total[cellIndex][10]*float(MFR_p[hour])])\
                               /float(gridSize)
        GIS_Qf.writerow([cellIndex, hour+1, COMtotalEnergy, REStotalEnergy,
                           COMtotalEnergy + REStotalEnergy])

print 'thats all folks!'

print count

COMfile.close()
RESfile.close()

```