RESIDENTIAL LAND-USE DENSITY AND BUILDING ENERGY CONSUMPTION: A CASE STUDY OF THE CITY OF GAINESVILLE, FLORIDA

By

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To my family and friends

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LIST OF ABBREVIATIONS

2D	Two-dimensional.
3D	Three-dimensional.
ACPA	Alachua County Property Appraiser.
AHS	American Housing Survey from U.S. Census Bureau.
BTU	British Thermal Unit. A traditional unit measurement of the energy required to cool or heat one pound of water by one degree Fahrenheit.
CAMA	Computer-Assisted Mass Appraisal system. A generic term referring to software systems that provide real-estate appraisal services for property tax purposes.
CBECS	Commercial Building Energy Consumption Survey from EIA.
CO2	Carbon dioxide.
CREEDAC	Canadian Residential Energy End-use Data Analysis Centre.
DOE	U.S. Department of Energy.
DU/acre	Dwelling Units/acre. Housing or residential land-use density unit measurement.
eGRID	Emissions & Generation Resource Integrated Database from EPA.
EIA	U.S. Energy Information Administration (DOE EIA).
EPA	U.S. Environmental Protection Agency.
EU-27	European Union with 27 member states (from Jan 1, 2007 to June 30, 2013): EU-25 + Bulgaria and Romania.
EUI	Energy Use Intensities (in kWh/sq m/year or kBtu/sq ft/year).
FAR	Floor Area Ratio.
FDOR	Florida Department of Revenue.
FRCC	Florida Reliability Coordinating Council
GHG	Greenhouse Gas.

GIS	Geographical Information System.
GRU	Gainesville Regional Utilities.
GWh	Gigawatt-Hour = 1 million kWh.
kWh	Kilowatt-Hour. Unit measurement of energy equals to 1,000 watt hours or 3.6 megajoules.
LCA	Life-Cycle Assessment.
LOESS	Locally Weighted Regression.
LOWESS	Locally Weighted Scatterplot Smoother.
MFR	Multi-Family Residential home.
NAL	Name, Address, Legal file. Certified tax roll file.
NCDC	National Climate Data Center.
NCEP/NCAR	National Center for Environmental Prediction-National Center for Atmospheric Research.
NEL	Net Energy for Load
NNR	NCEP/NCAR's 50-year Reanalysis (data).
NRCan	Natural Resources Canada.
NRI	National Resources Inventory (statistic reports) from U.S. Department of Agriculture (USDA).
NRTEE	National Round Table on the Environment and the Economy (Canada).
NSDI	Cadastral National Spatial Data Infrastructure from the Federal Geographic Data Committee (FGDC).
OLS	Ordinary Least Squares (Linear Least Squares) regression method.
PREC	Program for Resource Efficient Communities.
PUM	Public-Use Microdata Samples from U.S. Census Bureau.
RDBMS	Relational Database Management System.

RECS	Residential Energy Consumption Survey from EIA.
SFA	Single-Family Attached home.
SFD	Single-Family Detached home.
Sq m	Square meter or m2.
Sq mile	Square mile or mile2.
Sqft	Square Foot.
T&D	Electricity transmission and distribution.
TYSP	Ten-Year Site Plan. Submitted to Florida Public Service Commission.
UHI	Urban Heat Island.
USDA	U.S. Department of Agriculture.

Abstract of Thesis Presented to the Graduate School
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To date, studies investigating the energy consumption associated with urban development patterns have focused mainly on the transportation sector. These studies suggest that more efficient land use and high-density urban development is more likely to lead to shorter travel times, more energy-efficient transportation, more cost-effective delivery of services, and an overall lower carbon footprint. Yet, there is growing interest in better understanding the correlations between urban form and residential building energy consumption.

In service to this emerging body of knowledge, this study examines the correlation between net land use density and annual energy consumption per residential dwelling unit within the city of Gainesville, Florida. Spatial and residential energy consumption datasets used for the analysis model are based on Alachua County Property Appraiser and Gainesville Regional Utilities (GRU) records. A 3D geospatial visualization model was developed; an inferential and a descriptive analysis were conducted to investigate the correlation between annual per dwelling unit energy consumption (in equivalent kWh per utility meter) and net land use density (in DU/acre

per meter associated parcel). Correlative insights and suggested research next steps were derived from the results of the statistical and graphical interpretation.

CHAPTER 1
INTRODUCTION

Background

As the cities around the world continue to grow economically as well as spatially, the global rising demand of energy has caused the anthropogenic Greenhouse Gas (GHG) emissions to increase at a steep rate. Managing urban energy consumption and future energy demand, as a part of energy conservation efforts, is one of many strategies to mitigate GHG emissions.

Efficient land-use patterns and high-density urban development is more likely to lead to efficient energy utilization. The direct impact between the urban form and energy efficiency, mostly regarding transportation, has long been studied. This study looks into the significance of how urban land-use density contributes to community energy consumption, particularly in the City of Gainesville, FL.

Objectives

The main objective of this study is to determine if a statistically significant correlation exists between land-use density and annual energy consumption per residential unit in Gainesville, Florida. Other objectives include creating visual representations of land-use density and annual energy consumption of the studied geospatial area, so that insights of the relationship can be derived from the statistical and graphical interpretation.

Hypothesis

The null hypothesis (H_0) to be tested in this research states that there is no statistically significant correlation between land-use density and annual energy consumption per residential unit in the city of Gainesville, FL. The alternative hypothesis

(H_1) states otherwise, that there is a statistically significant correlation between land-use density and annual energy consumption per residential unit in the city of Gainesville, FL.

Scope and Facts

Gainesville Regional Utilities (GRU) is a municipal electric, natural gas, water, wastewater, and telecommunications utility system, owned and operated by the City of Gainesville, Florida and is the 5th largest municipal electric utility in Florida. The City of Gainesville is the county seat of Alachua County, located in North Central Florida. It has population of 123,903 as of April 2012 (City Of Gainesville, FL, 2012), and contains approximately 55,989 housing units (U.S. Census Bureau, 2011). Gainesville is also home to the University of Florida and Santa Fe College.

As a part of the energy conservation effort, the City of Gainesville, Florida has committed to adopt clean energy strategies. GRU has the most solar energy installed in Florida, and is currently pursuing biomass as a renewable energy source to meet the city energy needs for the next three decades.

This study was conducted using the GRU monthly electric billing data from residential utility customer within the GRU service area. Figure 1-1 shows GRU electric facilities and service boundary. Its service area includes the City of Gainesville and the surrounding urban area, with the zip codes from 32601 to 32609, 32614, 32615, 32641 and 32653.

GRU's Residential Energy Consumption Profile

Currently, residential consumers are responsible for 30 percent of the total energy consumption in Florida (EERE, 2013; EIA, 2012), compared to 37% of overall residential electricity consumption in the U.S. (EIA, 2012). The 2012 energy

consumption for residential use in Gainesville, Florida alone was about 44.5% (GRU, 2013).

Based on 2011 statistics, residential electricity consumed in the state of Florida is 113,554 GWh (Florida Public Service Commission, 2012, p. 12), while GRU's residential consumption is 805 GWh (GRU, 2013, p. 32). At the same time, GRU's 2011 average kWh per residential customer is 9,829 kWh, and is much lower compared to the rest of Florida, which is 13,567 kWh per residential customer. GRU generates approximately 0.9% of the total energy load in the state of Florida (Florida Public Service Commission, 2012).

Figure 1-2 shows history and forecast of GRU's residential energy consumption and number of customers from 2003 to 2022.

Although the number of GRU customers is increasing from year to year, overall the average energy consumption per customer has been declining. GRU has managed and continues to reduce its average residential energy consumption more than the overall Florida's residential consumption, as shown in the graph's trend line. In Figure 1-3. FL trend line slope, around 0.36% per year, has been far more moderate than GRU's, which is around 1.06% per year.

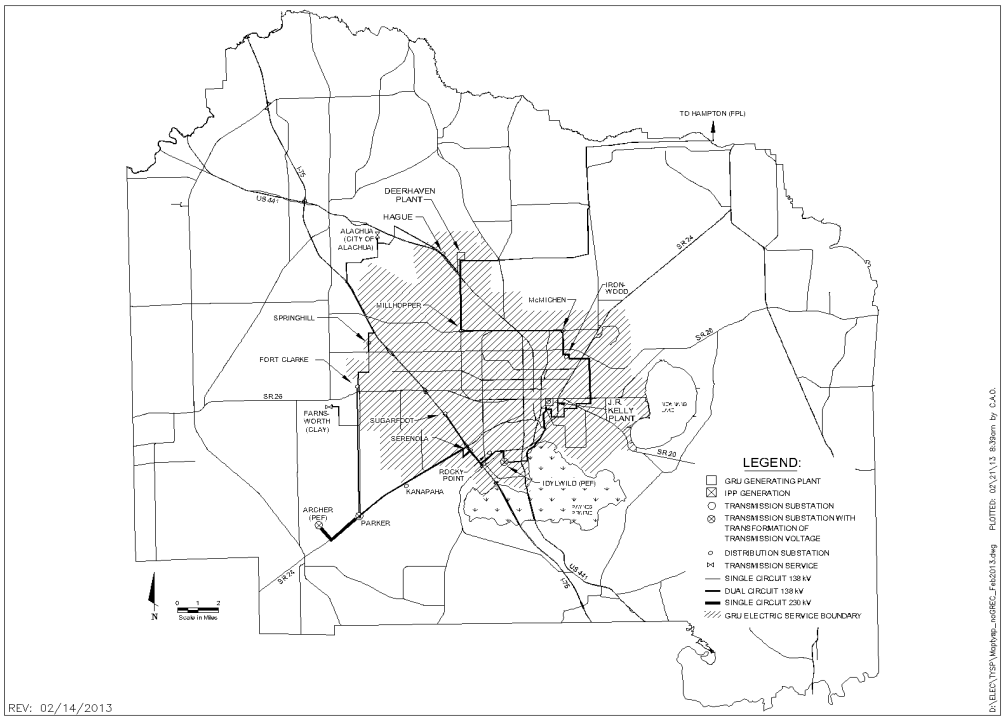


Figure 1-1. GRU electric facilities and service boundary, Alachua County, FL (GRU, 2013, p. 9).

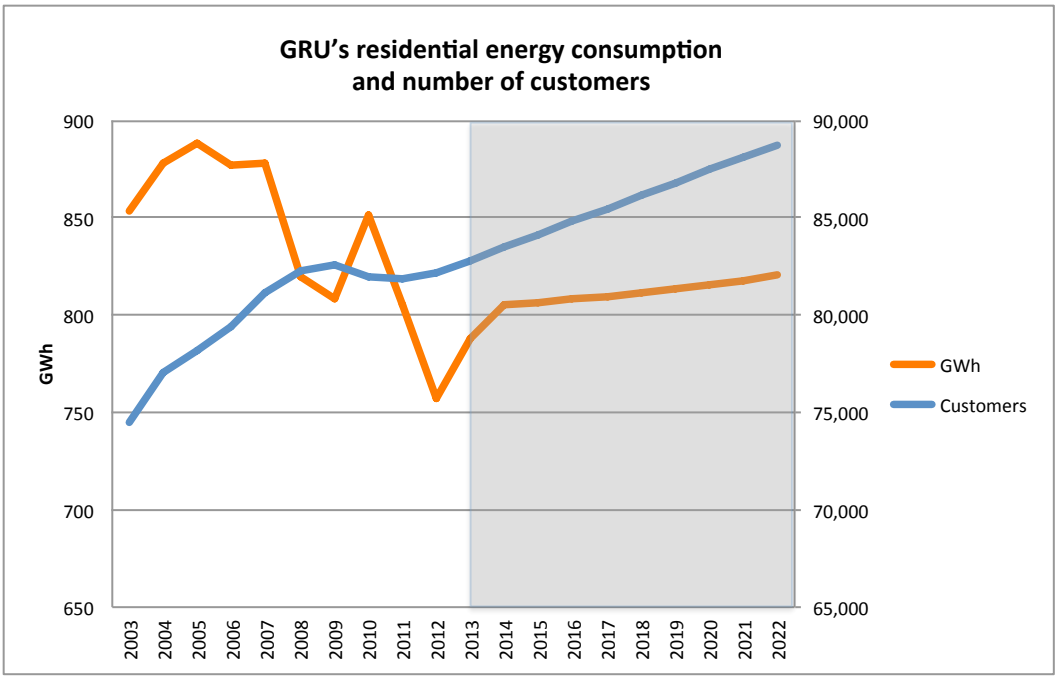


Figure 1-2. GRU's residential energy consumption and number of customers (GRU, 2013, p. 32).

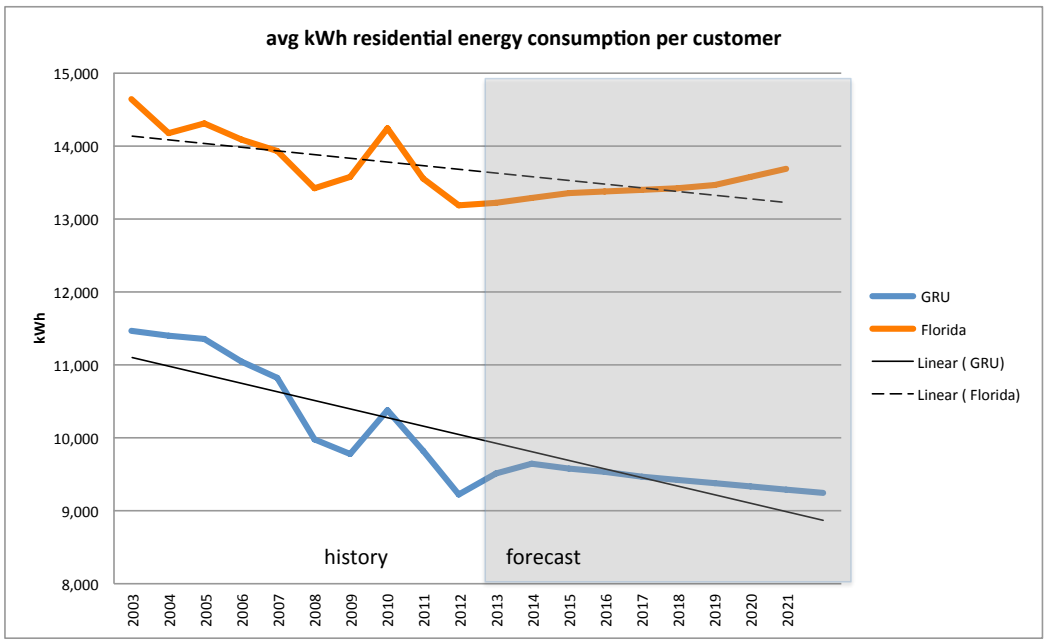


Figure 1-3. GRU's and Florida's average kWh per customer (GRU, 2013; FRCC, 2012, p. 2).

CHAPTER 2
LITERATURE REVIEW

This literature review looks into the theory-based and empirical research that exists on the correlation between urban density and energy consumption. In the 1970s, the research on urban form and energy consumption gained momentum due to the energy crises that took place in that decade. This circumstance propelled the research on energy consumption efficiency in relationship to the impact of urban form. However, the interest subsided along with the fall of oil prices in the 1980s. Currently, the return of high energy prices and the growing concerns over global climate change has put the research in this area back on the agenda (Safirova, Houde, & Harrington, 2007; Norman, MacLean, & Kennedy, 2006).

Based on the 2010 statistics, as shown in Figure 2-1, buildings in the U.S. accounted for 41% of primary energy consumption (19% commercial and 22% residential), while industry and transportation sectors consumed only approximately 31% and 28% respectively (EERE, 2012).

Past studies on the relationship between urban form and energy consumption are mostly focused on transportation, travel patterns and urban heating. Most researchers would agree that efficient land use and high-density urban development is likely to lead to shorter travel times, energy-efficient transportation, cost-effective delivery of services, lower energy consumption and overall lower carbon footprint.

Despite the fact that overall energy consumption in buildings is higher than the energy consumption in transportation sector, there was not much attention given to this related issue. According to Ewing and Rong (2008), this is understandable due to the dependency of the transportation sector on oil as source of energy and the geopolitics

that make headlines. In fact, energy consumption in buildings plays a significant role in global Greenhouse Gas (GHG) emissions. The direct impact of the urban form and energy efficiency, or more specifically, the significance of urban development density towards the community energy consumption, has yet to be studied extensively (Safirova, Houde, & Harrington, 2007).

Housing Type and Energy Consumption

Ewing and Rong (2008) studied the impact of urban form on residential energy consumption in the U.S. based on county sprawl indexes. The authors argued that there are direct and indirect causal paths and that urban form can affect residential energy use. The direct impact is the loss of electricity through transmission and distribution (T&D) from generating sites to the residential area, where the loss in less dense urban area is expected to be higher due to the longer transmission line. However this impact is less significant, since the T&D loss only represents 7% of the total electricity generated in the U.S.

The other indirect impacts are through intermediate variables such as housing type and size, formation of urban heat islands (UHIs), house ownership, household income, number of members and ethnic background. The housing size relates to the required space heating and cooling areas; more energy is needed for a bigger house compared to a smaller one. Likewise, more energy is needed for a detached house compared to an attached one of the same size, due to the exposed surface area. The UHI effect is caused by object surfaces that absorb heat and the lack of natural cooling properties, such as tree shading and evapotranspiration. Excess heat from space heating and cars also contribute to higher temperatures, and this translates to higher energy demand for summertime cooling, especially in the Southern region. However,

the housing effect is more dominant than the UHI effect, and the authors came to conclusion that, "… urban sprawl can be said to inflate residential energy consumption and associated greenhouse gas emissions regardless of location." (p. 22)

Other studies also showed that single-family detached housing (SFD) have consistently consumed more energy compared to multi-family housing (Kaza, 2010; Owens, 1990). However, SFD normalized energy consumption per area is consistently lower than other housing types. On the one hand, SFDs are more efficient in term of energy consumption per area, but on the other hand, they tend to be larger in size and thus higher in total energy consumption. This dichotomy illustrates the "rebound-effect", where the gains in efficiency are offset by the consumption increases, as described by Haas, Auer, and Biermayr (1998):

> They [several economists] argue that increases in energy efficiency will lead to cheaper prices for service provided and to a substantial increase in service and energy demand. This increase will outweigh the conservation effect to a large extent and, hence, make conservation programs useless. (p. 195)

Kaza found that multi-family units within large apartment blocks consumed 50% to 60% less energy, but only 10% to 20% less within smaller blocks, compared to single-family house (Kaza, 2010, p. 6576), and later concluded that,

> Changing housing type mix makes a difference only when replacing single family residences with multi-family units in large apartment blocks. For the most part, other types of housing types do not promote savings in energy use across the consumption spectrum for all uses. (p. 6582)

Additionally, this finding is also in agreement with other authors, such as Owens (1990). Due to the lack of data, Kaza (2010) is inconclusive in regard to how the influence of climatic factors at the micro-scale affects residential electricity consumption.

Critiques

Randolph (2008) commented on Ewing and Rong's (2008) findings and argued that the reduction in energy consumption is better achieved through residential energy efficiency improvement, rather than through land use, density and housing type modification. Likewise, Staley (2008) argued that although Ewing and Rong's analysis is empirically sound, the data and methods used do not justify the conclusions. Furthermore, Staley's critiques focused more on the policy analysis. He argued that policies, which promote energy conservation and innovation incentives leading to energy efficiency improvements are more preferable than fostering density and smaller housing type.

Urban Density and Energy Consumption

While most of the studies in the literature focused only on the transportation sector, and showed that the high-density urban areas consume less energy per capita than in low-density suburban areas, Larivière & Lafrance (1999) found that electricity consumption in high-density urban areas is lower than in low-density areas. Focusing specifically on electricity consumption and using a dataset of 45 densely populated cities in Québec, Canada, the authors modeled electricity consumption per capita as a function of urban density, demographic, economic, and climatic factors.

Larivière & Lafrance's (1999) model showed that by increasing the density of an urban area by the factor of 3, from 360 persons/sq mile to 1,080 persons/sq, the electricity consumption would decrease by 7%. The authors concluded that compared to gasoline use, the effect of the population density is less significant, and pointed out that the change in urban design and land-use policy in those cities would not have a huge impact on reducing overall electricity consumption (p. 62). This suggested that density is

only one of many other important factors in lowering the electricity consumption per capita.

Another study was conducted by Norman et al. (2006), employing Life-Cycle Assessment (LCA) approach on the analysis of the energy consumption and GHG emissions associated with the residential density in the city of Toronto, Canada. According to the authors, Toronto's development trends and housing styles are quite similar to those of the relatively compact central core and suburban sprawl patterns common to many major cities in North America.

LCA represents a broader approach to examining the environmental impacts of an entire building, in which the material and energy flows are quantified and analyzed, including upstream and downstream processes. Upstream processes of the building include raw material extraction, production, transportation and building construction, while downstream refers to operation, maintenance and demolition of the building (Treloar, Love, Faniran, & Iyer-Raniga, 2000). Newton, Tucker, & Ambrose (2000) characterized this as embodied (embedded) energy, operating energy and maintenance energy (pp. 76-77).

In Norman et al.'s (2006) model, the analytical framework utilized for estimating energy use and GHG emissions includes three diverse components; construction materials, building operations, and public/private transportation. After summing the results of each individual component, the authors concluded that the low-density suburban development consumes 2.0 to 2.5 times more energy and GHG emissions compared to the high-density urban core development per capita. At the same time, low-urban density consumes 1.0 to 1.5 times more energy and GHG emissions

proportionally, than the high-density urban core development per unit of living space (p. 19).

While overall added results of the three components shows the difference in energy consumption between the low and high-density urban areas, on the building operations component alone, low-density and high-density developments in terms of energy and GHG emissions per unit of living space, are nearly equal. On the other hand, the low-density development consumes energy twice as much as the high-density, if the functional unit is changed from per unit of living space to per capita (p. 19).

In a more recent study, Wilson (2013) examined the correlation between residential electricity consumption and building characteristics using a unique dataset. The objective of his study, according to the author is to provide empirical evidence that supports or refutes the assertion that more compact urban form matters with respect to residential electricity consumption, including how the way that residential subdivisions are configured.

Focusing on SFD housing units, the author raised two questions. First, whether there is a relationship between urban form and electricity consumption for SFD housing in Illinois, post covariates adjustment (i.e. household and structural characteristics, climatic and other mitigating factors), and second, what are the implications of the first findings for how residential subdivisions are designed and built (p. 63).

The required data for the model were collected from three Illinois counties (Adams County, Macon County, Champaign County). They are based on local residential utilities consumer mail surveys, including residential energy consumption

records over the last 12 months, as well as the data from Residential Energy Consumption Survey (RECS) 2005. Using linear regression method, the seasonal and annual electricity consumption pattern was determined as a function of demographic, climatic, structural, technological, behavioral and urban form factors.

Previous literature suggested that the "Empirical evidence establishing the influence of climatic factors at the micro-scale on residential electricity consumption is sparse (Ewing & Rong, 2008), despite strong conceptual arguments in favor of a connection." Other findings by Holden (2004), and also by Holden and Norland (2005), discovered that there was evidence of a density effect with lower consumption observed in more densely developed areas; therefore, the authors argued in favor of more compact urban form (Wilson, 2013, p. 64).

Based on the model, Wilson (2013) observed that the most consistent predictors of residential electricity consumption are climate days, household size, number of bedrooms, and heating equipment. Moreover,

> The general relationship between the net density of the subdivision and summer electricity usage is negative, but when cooling degree days are lower than average the downward slope of this relationship is steeper than when the number of cooling degree days is higher than average.

Therefore the author concluded that "the negative relationship observed between net density at the subdivision level and summer electricity usage is consistent with arguments in favor of more compact development patterns and is interpreted in the context of the heat island effect." Finally, "urban form characteristics matter at the micro-scale and reiterates the potential value of compact residential development for managing residential electricity consumption, and by extension, greenhouse gas emissions." (p. 70).

The author argued that, “homes in subdivisions that are more compact and less peripheral are likely to reap benefits in the form of reduced electricity consumption.”

Geospatial Energy Consumption Modeling

The advance of geospatial technologies allow energy consumption studies to utilize Geographical Information System (GIS) in mapping the related analytical data (energy consumption profiles, base electricity loads, heating and cooling loads) to their actual geographical locations. The result is a geo-visual analytic model, in which the data can be explored and validated geospatially in two-dimensional (2D), as well as three-dimensional (3D) maps. Kraak (2003) argued that this interactive and dynamic environment is helpful to generate hypotheses, develop problem solutions, construct knowledge and stimulate the visual thinking.

To study the anthropogenic heating effects in building sector, Heiple and Sailor (2008) developed a modeling technique to predict energy consumption for residential and commercial sectors at a high spatial resolution. A high-resolution spatial data of any given day’s hourly results at individual parcel level can be obtained when detailed building energy simulations of prototypical buildings with GIS geospatial data are integrated. The data should contain the building characteristic’s information such as building types sizes and geographical location.

The city of Houston, TX, was selected as the case study city since it has historical extreme heat and pollution in summertime, and it is one of the densest U.S. cities with a high level of energy consumption per capita. Thus it is likely that Houston’s local climate is influenced by waste heat emitted from its buildings. The authors claimed that the same method could be applied to virtually any major city in the United States to

estimate day-specific residential and commercial electricity and natural gas consumption.

Min, Hausfather, and Lin (2010) presented a novel approach, using five-digit zip code high-resolution level information to model residential energy by end use and fuel type for the entire territory of the United States. The authors developed four models for space heating, space cooling, water heating, and also appliance energy end uses, based on the RECS 2005 dataset. They found large variations between residential energy use characteristics both within and across different regions of the country, with significant difference of and distribution by fuel of residential energy consumption in urban and rural areas. Model outputs by fuel type for each zip code include electricity, natural gas, fuel oil, propane and other (e.g. wood, solar, coal, etc.) were spatially mapped using GIS software.

The authors suggested possible research applications for the developed models, including examining factors in rural-urban residential energy consumption and fuel use patterns; estimating residential end use costs in combination with fuel-specific price data and examining the impact of various residential energy conservation actions, based on zip codes or regions.

Howard et al. (2012) proposed a model to estimate the building sector energy consumption for four primary end-use intensities including base electric, space cooling, space heating, and water heating in New York City. The end-use intensity is measured in kWh/sq m floor area. With the annual electricity and natural gas consumption data provided by the New York City Mayor's Office of Long-Term Planning and Sustainability and also information derived from Residential Energy Consumption Survey (RECS)

2005 and Commercial Building Energy Consumption Survey (CBECS) 2003, the annual end-use energy consumption data were developed by performing a robust multiple linear regression resulting in information about total fuel intensities for 8 different building types (residential 1–4 family, residential multi-family, office, store, education, health, warehouse and other commercial). Finally, based on the zip code level clusters for four primary end-users, the annual end-use energy intensities were applied to building floor area across New York City to determine the spatial distribution of the energy consumption.

Brief Summary

Table 2-1 summarizes the studies in reviewed literatures of residential energy consumption. Studies in the reviewed literature on urban density and its relationship with building energy consumption have been inconclusive. Several authors argued that high-density development reduces energy consumption (Ewing & Rong, 2008; Holden, 2004; Holden & Norland, 2005; Wilson, 2013), while others believed that the link between urban density and energy consumption is sparse (Larivière & Lafrance, 1999; Norman, MacLean, & Kennedy, 2006). This reflects the fact that this relationship between urban density and aspects of sustainability remains a debatable issue (Kaza, 2010; Echenique, Hargreaves, Mitchell, & Namdeo, 2012; Wilson, 2013).

While energy consumption in buildings is influenced by some spatial and non-spatial factors, such as building types, attributes, use, occupancy and weather, the complex interactions between those factors make it difficult to conclude with confidence that any one specific urban form will be more energy efficient than another (Owens, 1990, p. 63; Doherty, Nakanishi, Bai, & Meyers, 2009).

Moreover, according to Doherty et al. (2009), there is no one-size-fits-all solution for optimizing the energy consumption within the built environment per se, where comparison between locations will be ambiguous (i.e. comparison between countries or even within a country). On the other hand, by analyzing the forms of energy consumption separately, it may be possible to assess differences in performance at different levels.

Table 2-1. Overview of studies on building energy consumption in reviewed literatures.

Author	Variables	Dataset	Analysis Methodology
Ewing & Rong (2008)	Housing type and size, formation of UHIs, house ownership, household size, income and ethnicity, HDDs, CDDs. Sprawl index as measure of urban form.	Sprawl index: U.S. Census, NRI reports from USDA; Residential energy use: RECS 2001 from EIA; Housing stock: PUMS 2000, AHS 1998, 2002. Climatic data: HDD, CDD from RECS including NCEP/NCAR Reanalysis (NNR); Others: ESRI-GIS Data & Map 2005.	OLS (Ordinary Least Squares) regression
Kaza (2010)	Housing type, size and year-built, house ownership, household income, urban index, avg energy price, climate: HDDs, CDDs.	RECS 2005 derived from householder interviews, mailed questionnaires and energy consumption data provided by utilities companies.	Quantile regression
Larivière & Lafrance (1999)	Electricity consumption, economy and demography (population density, population, household income, std land wealth per capita, etc.), housing type, energy profile, climate, etc.	Demography data: Statistics Canada 1992; Electricity consumption data: Hydro-Québec 1991; other data from various organizations.	Linear regression

Table 2-1. Continued

Author	Variables	Dataset	Analysis Methodology
Norman et al. (2006)	Building materials, building operations, public/private transportation, urban density, GHG emissions.	Various data sources for urban infrastructure materials; Residential energy use/GHG emissions: NRCan 2003; SFD & apartments data: NRCan 2003, CREEDAC 2000, Statistics Canada 1999. Trans-portation: NRTEE 2003, University of Toronto 2003, Kennedy 2002, City of Toronto, etc.	Life-Cycle Assessment (LCA) analysis
Wilson (2013)	Housing and household characteristics, electricity consumption, demographic, climatic, structural, technological, behavioral, urban form.	RECS 2005; Electricity consumption from local utilities and other data from residential mail survey.	Linear regression
Heiple & Sailor (2008)	Building type (commercial and residential), building uses, floor space, weekly occupancy duration, building age; climate: annual HDDs, CDDs; Energy consumptions, incl. Energy Use Intensities (EUI).	RECS and CBECS for building prototypes. Parcel GIS data from NSDI.	eQuest – building simulation program from U.S. DOE.

Table 2-1. Continued

Author	Variables	Dataset	Analysis Methodology
Heiple & Sailor (2008)	Building type (commercial and residential), building uses, floor space, weekly occupancy duration, building age; climate: annual HDDs, CDDs; Energy consumptions, incl. Energy Use Intensities (EUI).	RECS and CBECS for building prototypes. Parcel GIS data from NSDI.	eQuest – building simulation program from U.S. DOE.
Min et al. (2010)	Housing type, size and year-built, urban index, household demography; Climate: HDDs, CDDs; Electric price.	RECS 2005; Climatic data: NCDC 2009; Emission data: eGRID from EPA; Zip codes, household demography, housing types, etc.: U.S. Census 2000; Fuel price from EIA 2005.	OLS regression
Howard, et al. (2012)	Building characteristics: building type, total floor area. Electricity consumption: base electric, space cooling, space heating, and water heating. Total fuel consumption.	RECS 2005; CBECS 2003; annual electricity & gas consumption data from NYC Mayor's Office of Long-Term Planning and Sustainability.	Robust multiple linear regression.

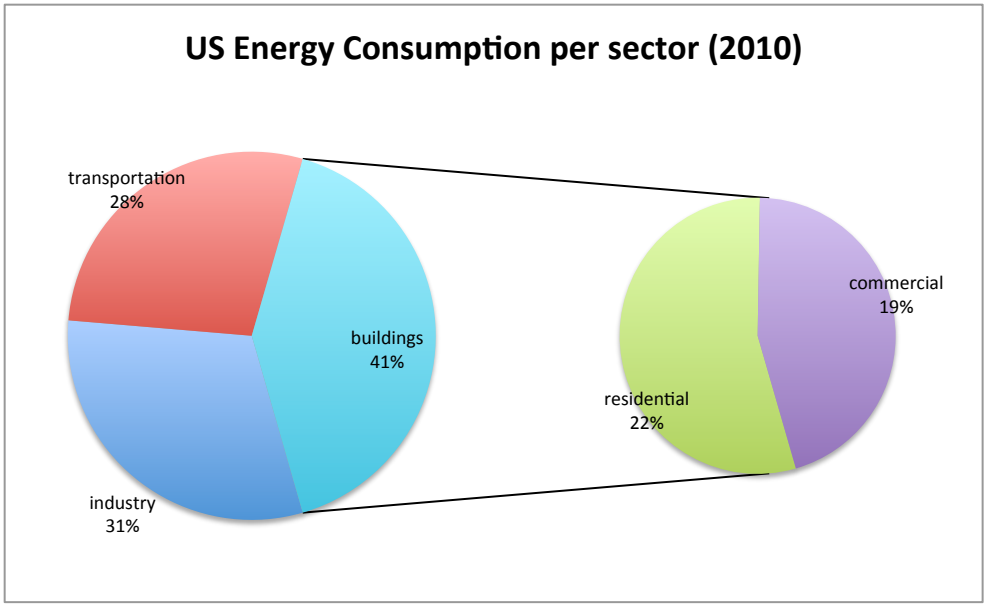


Figure 2-1. U.S. Energy Consumption per Sector - 2010 (EERE, 2012).

CHAPTER 3
METHODOLOGY

Strategy

The spatial and residential energy consumption datasets used for the visualization and analysis model are based on Alachua County Property Appraiser (ACPA) and Gainesville Regional Utilities (GRU) records. The GRU's energy consumption data used in this thesis is based only on 2012 consumption data, provided by Program for Resource Efficient Communities (PREC) at the University of Florida. This thesis-study is a part of PREC's larger research project, which relates to PREC's joint cooperation with GRU.

The raw data was provided in comma separated text file format, and was later processed, cleaned and stored in a relational database management system (RDBMS). It is common for a logically interconnected relational data model to be stored in several tables where each has a relationship to the other tables in the form of one-to-one, one-to-many and many-to-many.

The data mining multi-step process includes data extraction, filtering, transformation, merging and integration. These steps are required to generate the data in the correct format for visualization and analysis. Conventional database tools available in MS Office 2013, such as Power Query in MS Excel and Query feature in MS Access, are used for the data mining purposes. The processed results are later stored in mySQL database as cleaned and ready to use data. This will subsequently be used for further queries using MS Access and MS Excel to generate the results for the graphs and ArcGIS data feed. The diagram in Figure 3-1 shows the required block

processes, from data mining to the generation of the clean data format, ready for the model.

A geospatial visualization model was developed using ArcGIS latest available version 10.2. Subsequently, a descriptive analysis based on the graphs generated from the data was conducted to investigate the correlation between annual per dwelling unit energy consumption (in equivalent kWh per utility meter) and net land use density (in DU/acre per meter associated parcel).

Data Sources

The following databases were used in building the analysis data model. A complete list of the database tables and their data fields can be found in Appendix A, and the metadata of CAMA 2012 database related table is listed in Appendix B.

1. CAMA 2012 database is Alachua County Property Appraiser (ACPA), public downloadable Computer-Assisted Mass Appraisal (CAMA) database. The database was downloaded in August 2013 from ACPA's GIS Service Center online website (ACPA, 2012). The dataset tables required for the analysis data model are as follows:

    - Parcel: This table has 109,176 unique parcel records. The "PIN" field is used as primary identifier for each unique parcel of the data model.
    - Address: This table has 123,854 parcel related addresses.
    - Building: Building table has 88,927 records associated with Parcel in one-to-many relationship.

2. ACPA's "Public GDB" file is similar to CAMA 2012, only it is in ArcGIS GDB file format instead of MS Access.

3. GRU consumption database (GRU_CY2012) with datasets comprised of approximately 82,122 GRU residential electric customers with individual utility

billing records from total 85,500 premises; and 2,051,908 consumption-billing records of the year 2012.

- GRU Premises table: This table has 85,500 unique premises associated with 51,462 unique parcels. Each premise has a physical address consists of premise house number, street name, premise unit, city, state and zipcode.
- meter_type: This field contains the meter type: E, G or W. “E” stands for Electricity, “G” for Gas, and “W” for Water consumption.
- date_to: This field stands for Meter Read Date.
- is_cancellation: This field stands for Cancelled Bill Status. Cancelled if marked with an “X”.

4. NAL 2013 database is Name, Address, Legal (NAL) database of Alachua County.

- Parcel_ID: The table has 100,441 unique parcel records.
- LND_SQFOOT: This stands for Land Size in Square Feet. Later converted to acre.
- TOT_LVG_AREA: This stands for Total Living Area in Square Feet.

Data Preparation

Data transformation and cleansing are required prior to importing the data from above mentioned sources into the analysis data structure. The following lists the required steps.

GRU Consumption Database (GRU_CY2012)

- Excluded all non-electric billing records. The GRU residential utility consumption database consists of all utility billing records from 2008 to 2012, including electric, water and gas totaling about 3.6 million records; only the electric billing records are used.
- Upon examination of the electric billing records, there are some records, which do not have any Parcel ID associated with them. These records were excluded along with the records that have “is_cancellation” status marked with an “X".

- The street addresses in the Premise dataset were converted into the geospatial address locations in geodetic latitude and longitude coordinate format and respective columns were added (“latitude”, “longitude”).

- All natural gas consumptions were converted to its kWh equivalent (expressed in ekWh units) by multiplying it with 29.30722.

ACPA/CAMA 2012 Database

- Excluded all records in Parcel table, which has no PIN number (PIN is empty).

- Determined the quantity of units per parcel (Dwelling Units or DU) by grouping the parcels in the Address table together.

NAL 2013 Database

- Converted the “Parcel _ID” format from “00000 000 000” to “00000-000-000”.

- Converted the value “LND_SQFOOT” from square feet to acre by dividing it with 43,560 and store the new value in a new “size_acre” column.

- Following fields were selected for the calculation of DU/acre: “Parcel_ID”, “LND_SQFOOT”, “size_acre” and “TOT_LVG_AREA”.

- For DU/ac calculation, acre unit can be derived from the field “LND_SQFOOT” value by dividing it with 43,560.

Outliers Detection

A simple deviation method can be used to filter out premises energy consumption outliers within each parcel. Outliers records could be easily detected by examining their standard deviation values, σ. Records with σ values, which lie within x times its standard deviations $(\mu \pm x\sigma)$ of the median, are included for further calculation, otherwise they are discarded. The threshold x value used here is 4, so that the $ekWh_i$ value must be within four times its standard deviations, which corresponding to the 99.99 percentile of the normal distribution.

The total $ekWh$ of a parcel is equal the sum of all energy consumption of its premises, and can be expressed as follow:

$$ekWh_p = \sum_{i=1}^{n} ekWh_i \tag{3-1}$$

If μ_p is the median value of energy consumptions of all premises within the parcel, and n is the number of premises within the parcel, then the parcel's standard deviation σ_p can be expressed as follow:

$$\sigma_p{}^2 = \frac{1}{n}\sum_{i=1}^{n}(ekWh_i - \mu_p)^2 \tag{3-2}$$

To determine the test value x of the $ekWh_i$:

$$x_i{}^2 = \frac{(ekWh_i - \mu_p)^2}{\sigma_p{}^2} \tag{3-3}$$

All premise records with its x value > 4 are considered to be outliers and will be discarded. Figure 3-2 below shows an overview of the each record's standard deviation value on a chart. The purpose of this chart is to provide a quick eye-level observation of the whole dataset to easily spot outliers if they exist. Later these outliers will be removed from the dataset using common SQL statement. As an example, there are a few records, which exceeded the 4σ threshold in the dataset. One of them is premise #7000052152, which has σ > 12, as shown in Figure 3-2.

Data Grouping and Aggregation

GRU Premises table has 85,500 unique premises associated with 51,462 unique parcels in a one-to-many relationship, where one Parcel is linked to one or many

Premises (see Figure 3-3). At least one premise record exists and can be linked to the related parcel record.

After the process of data preparation steps described above, to determine the number of the premises of each parcel, the grouping and counting of parcels is necessary. This can be done using SQL statement i.e. *SELECT DISTINCT (Parcel_ID), count(*) as premise_count FROM GRU_Premises;*

Although NAL11P201302 data table has a NO_RES_UNITS field, that should indicate the number of residential units of the parcel, there are some discrepancies between these numbers and the numbers obtained from the GRU_Premises' premise count, as shown in Table 3-1. Since the energy consumption is directly derived from GRU database, it is more relevant to use the number resulted from premise count rather than those from NAL11P201302 data table.

To calculate the parcel's density ($density_p$) expressed in DU/ac unit, the premise count of each parcel ($premise\_count_p$) is divided by the acre value obtained from converting "LND_SQFOOT" (LND_SQFOOT_p) as described in data preparation above.

$$density_p = \frac{premise\_count_p}{LND\_SQFOOT_p} \times 43{,}560 \ \ {}^{DU}/_{ac} \tag{3-4}$$

To reflect the energy consumption per dwelling unit of each parcel, the sample median method is used to calculate the average energy consumption (ekWh) of all premises on each respective parcel.

The aggregated dataset required for the rendering of the 3D model in ArcGIS should at least have the following fields: *Parcel_ID, du_acre, avg_ekWh*. Data used for scatter plots only require two fields, *du_acre* and *avg_ekWh*. In order to obtain a single

du_ac data point, all du_acre rows need to be grouped together based on their values with respective *avg_ekWh* values averaged.

Visualization Tasks and Method

The visualization tasks for generating the data model include:

1. A visual representation of land-use density, and
2. a visual representation of average energy consumption per residential unit density in Gainesville, Florida.

The visualization method utilizes the aggregated data in combination with the GIS database (Public GDB-File) downloaded from ACPA's GIS Service Center online website (ACPA, 2012) to generate the 3D model in ArcGIS, as shown in the process diagram in Figure 3-4.

Using the Parcel layer from the Public GDB database, the aggregated data table "Parcel_ID" field was joined with the "PIN" field with a *INNER JOIN* method, where only matching records from both tables are selected. The symbology of the Parcel layer was set to show the value of "avg_ekWh" based on the graduated colors from green to red in 25 steps. This will map the average energy consumption value to its designated color.

Regression Method

Locally Weighted Regression (LOESS) method was used to fit the residential energy consumption and density model to data. Loess is a nonparametric regression method, which does not require a predetermined definition of the relationship between the dependent and independent variables, but is defined based on the information derived from the data. Loess method is a generalization of the preceding LOWESS

method, an acronym for Locally Weighted Scatterplot Smoother, and is used most frequently as bivariate scatterplot smoother (Cleveland & Devlin, 1988; Jacoby, 2000).

Compared to parametric regression methods used in the reviewed literature, such as Simple Linear Regression, Ordinary Least Squares (OLS), Quantile regression methods etc., the nonparametric method used in LOESS addresses some limitations faced by the parametric regression methods. Parametric fitting is broadly used, and is a very effective way to construct a relationship between the variables if the structure in the data conforms to the type of function that is fitted by the smoothing algorithm. However, the exact functional form is mostly unknown. Nonparametric approach such as Loess can be used to "locate a smooth curve among the data points without requiring any advance specification of the functional relationship between the variables." (Jacoby, 2000)

Suppose that n number of observations on two variables, x and y, and the iteration $i = 1\ to\ n$. The plotted points in a bivariate scatterplot are the ordered pairs (x_i, y_i). The whole model can be expressed in the following relationship:

$$y_i = \hat{g}(x_i) + \varepsilon_i \tag{3-5}$$

Where $\hat{g}$ is the regression function or observed fitted value, and ε_i is the random error or the residual value. The $\hat{g}(x_i)$ should approximate the true unobserved value, in which the approximation is attained by fitting a regression line within a chosen neighborhood of the data point x_i.

Loess is not strictly a descriptive tool. According to Jacoby (2000): "the statistical theory for local regression models has been worked out, so it is possible to incorporate an inferential component into a loess analysis." (p. 594) Moreover,

> Statistical inference with a loess smooth curve is usually grounded in least-squares theory (Cleveland & Devlin, 1988), and it requires several assumptions. Specifically, the observed fitted values, $\hat{g}(x_i)$, are now viewed as estimates that should approximate, as closely as possible, the true but unobserved fitted values, $\hat{g}(x_i)$. Furthermore, the residuals about these fitted values should be gaussian. That is, the $y_i - g(x_i)$ should be independently and identically distributed according to a normal distribution, with a mean of zero and a constant variance. When these assumptions are met, direct generalizations of traditional least-squares methods can be employed to perform statistical tests.

To test the null hypothesis (H_0) of no functional dependence between Y and X variables on a single loess curve, it employs an F distribution (or ratio of standard deviation) with $(df_{loess} - 1)$ and $(n - df_{loess})$ degrees of freedom:

$$F = \frac{(TSS_Y - RSS_{loess})/(df_{loess} - 1)}{(RSS_{loess})/(n - df_{loess})} \tag{3-6}$$

In the above equation, RSS_{loess} is the sum of squared loess residuals, df_{loess} is the degree of freedom associated with the predicted curves, and n is the number of data points.

Table 3-1. Some examples of discrepancies between premise count and the value from NO_RES_UNTS of NAL11P201302.

Parcel_id	premise_count	NO_RES_UNTS
03812-007-000	2	1
04305-003-001	247	176
04314-102-096	3	1
04333-001-002	201	1
06014-008-002	3	4
06655-053-036	9	1
06655-200-000	173	15
06680-022-000	249	792
06680-023-000	254	20

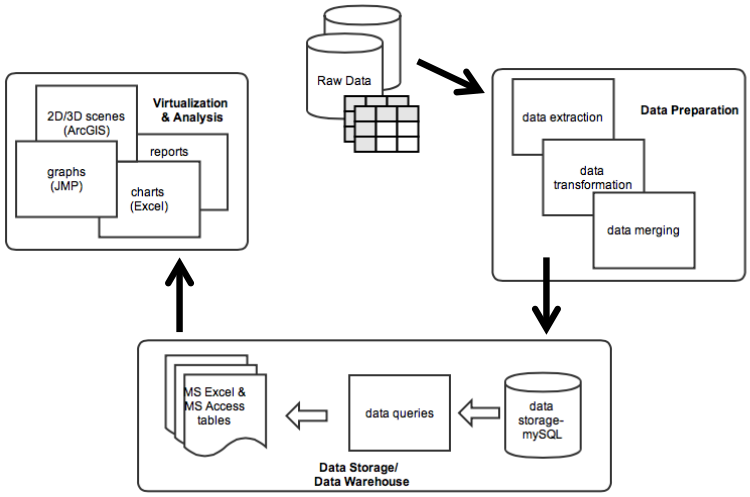


Figure 3-1. Process diagram of data preparation from the raw format to output results.

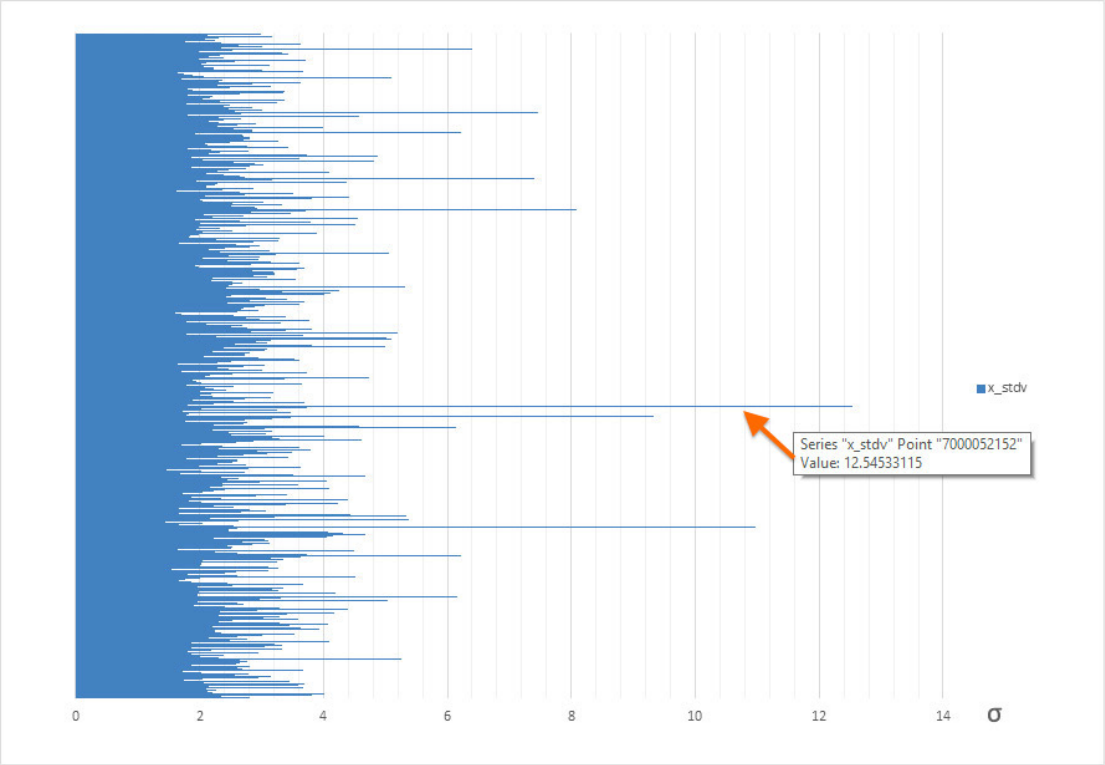


Figure 3-2. A chart to quickly spot outliers.

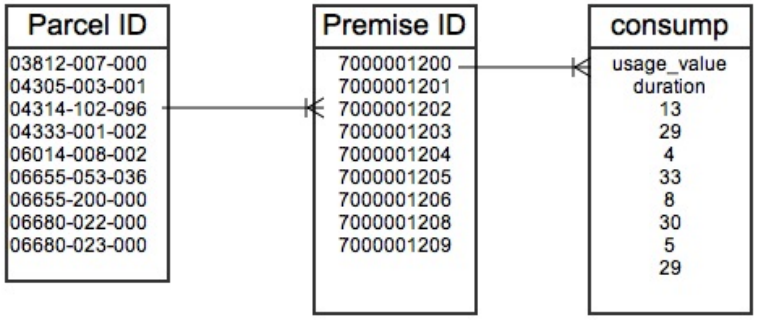


Figure 3-3. A one-to-many relationship between Parcel ID - Premise ID tables and Premise ID - monthly consumption data tables.

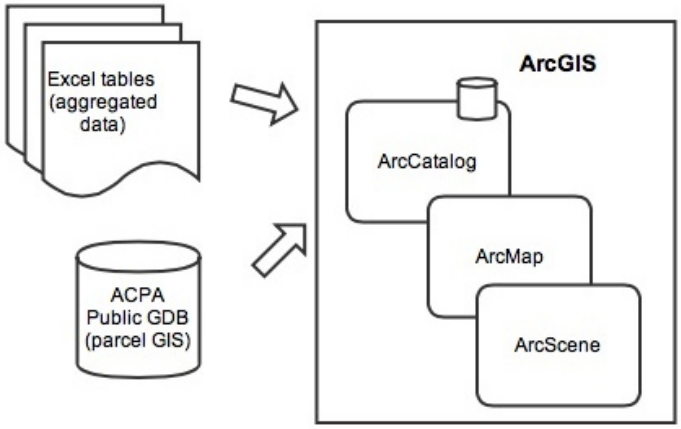


Figure 3-4. Process diagram of data use for 3D modeling.

CHAPTER 4
VISUALIZATION

Land-Use Density

A 2D visual representation of land-use density was generated using ArcMap. Projected coordinate system used for this rendering was the State Plane coordinate system (NAD_1983_StatePlane_Florida_North_FIPS_0903_Feet), and as Basemap layer, ESRI_Imagery_World_2D and ESRI_StreetMap_World_2D map service was used. The symbology of the Parcel layer was set to map the value of “du_ac” based on the graduated colors from green to red in 25 steps. Both services are connected to ArcGIS online server on *http://services.arcgisonline.com/ArcGIS/rest/services*.

The hi-resolution residential density map generated by ArcMap provided an overall sense of the residential land-use density of the city of Gainesville, FL, as shown in Figure 4-1. Each parcel was mapped to a specific color based on its calculated density value. The color legend of the density (DU/ac) values is presented in Figure 4-4.

The figure 4-2 shows the Cabana Beach Apartments and Rockwood Villas private condos areas on the map using ESRI_StreetMap_World_2D as Basemap.

Energy Consumption per Residential Unit Density

A 3D map representation of the average annual energy consumption per residential unit density was modeled using ArcScene. The intensity of the energy consumption of each residential land parcel is represented by a spectrum of colors, from green to red to indicate low to high energy use. Additionally, the height of the column bar extruded from the parcel represents the overall unit density, expressed in DU/ac (see Figure 4-3). The color legends, both for density and ekWh values, are shown in Figure 4-4.

The 3D model provides a quick observation method to identify and to evaluate an entire or partial spatial area of interest. Information can be read and analyzed directly from the model including the parcel size, the parcel land-use density by the heights of the bar extruded from the parcel, and the parcel's energy consumption (see Figure 4-5, 4-6, and 4-7).

Normal Distribution of the Energy Consumption

A geospatial visualization of the normal distribution of residential average annual energy consumption values was rendered, to provide a better insight into the actual per parcel distribution of energy consumption values. As shown in Figure 4-8 and a close-up look as in Figure 4-10, the colors on the visualized map indicate the standard deviation values of the average energy consumption per land-use density.

The σ or standard deviation values are represented in the color legend in Figure 4-9, and the curve on the right shows the normal distribution of the ekWh values (average energy consumption values), with the dotted vertical lines denoting the standard deviations.

With the geospatial mapping of the ekWh normal distribution values, it is much easier to identify the spatial areas with the average annual energy consumption based on their deviation values from the mean.

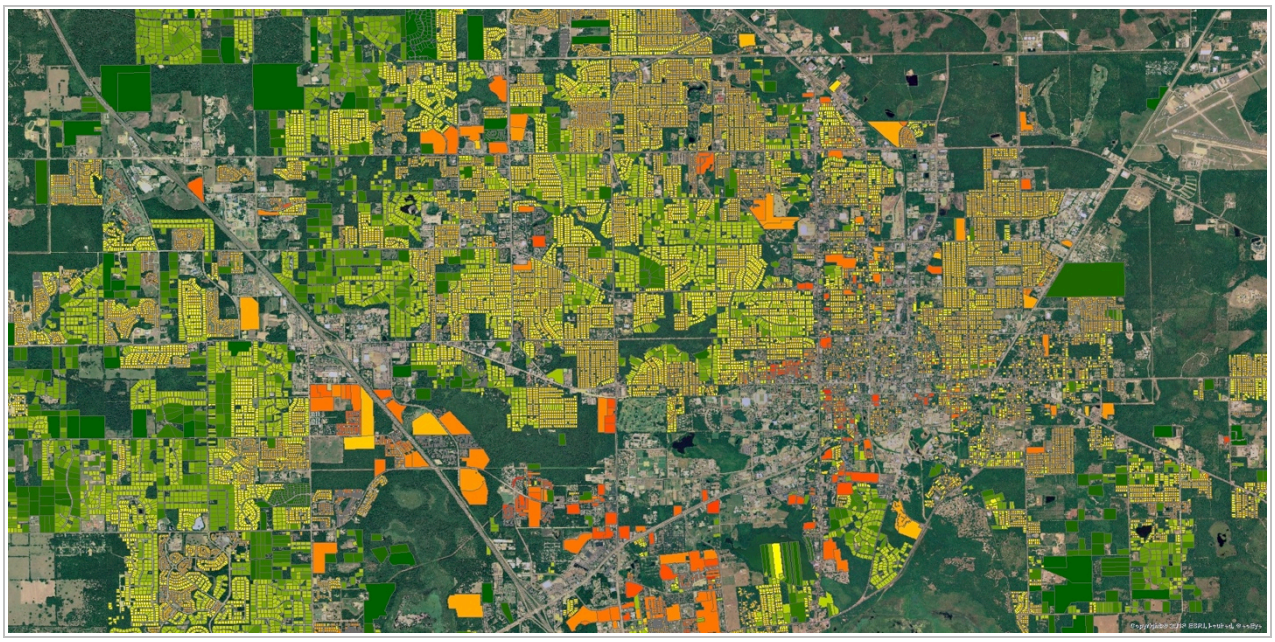


Figure 4-1. Gainesville map generated by ArcMap color-codes each residential land parcel based on its DU/ac density (map scale 1:40,000).

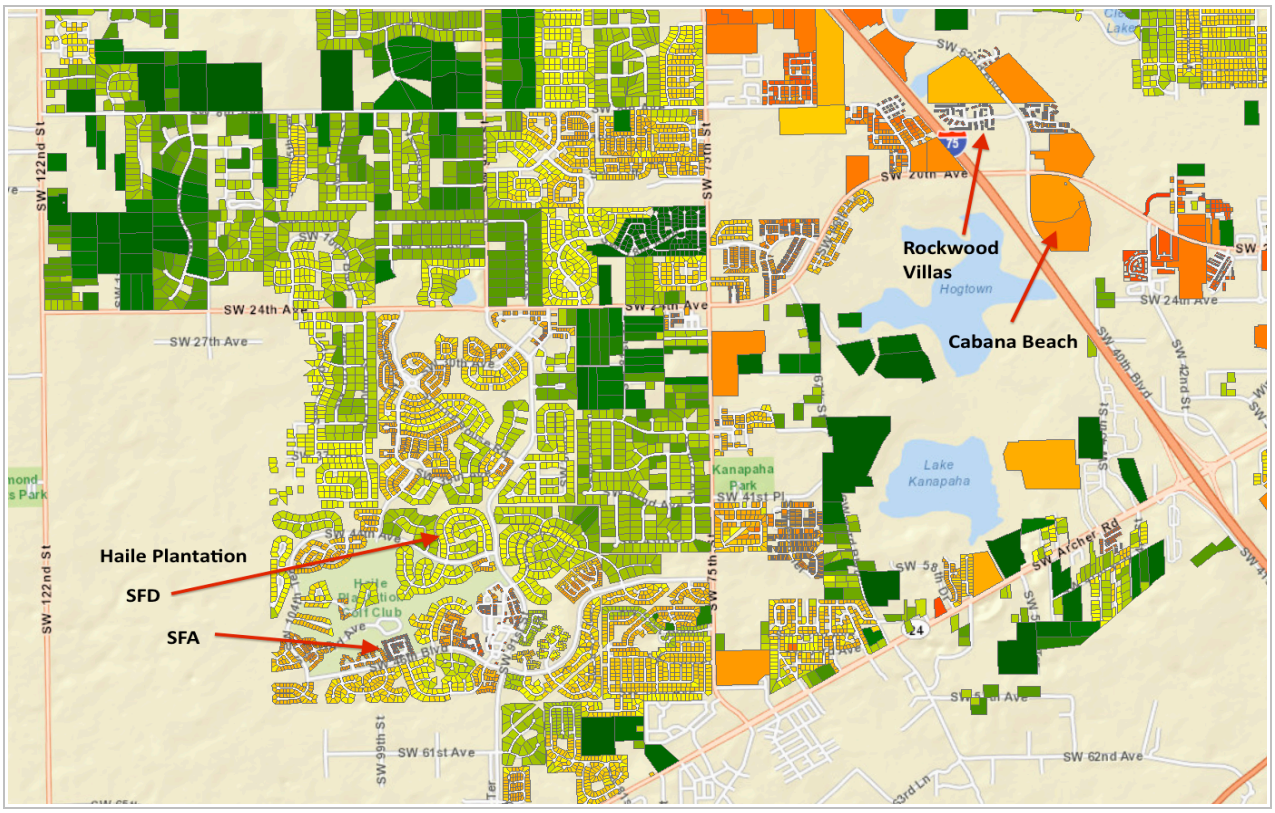


Figure 4-2. The ArcMap rendering shows the land-use density of Cabana Beach - Apartment and Rockwood Villas complex (map scale 1:25,000).

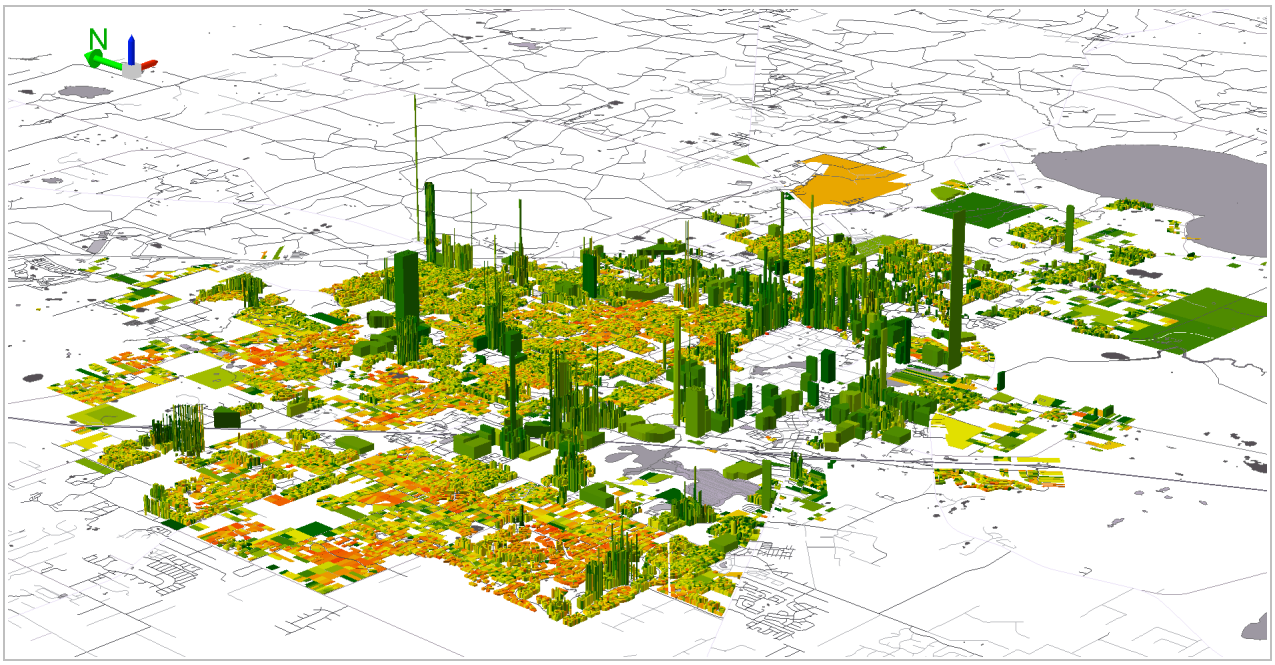


Figure 4-3. A 3D representation of average annual energy consumption per residential unit density of the City of Gainesville based on 2012 energy consumption data.

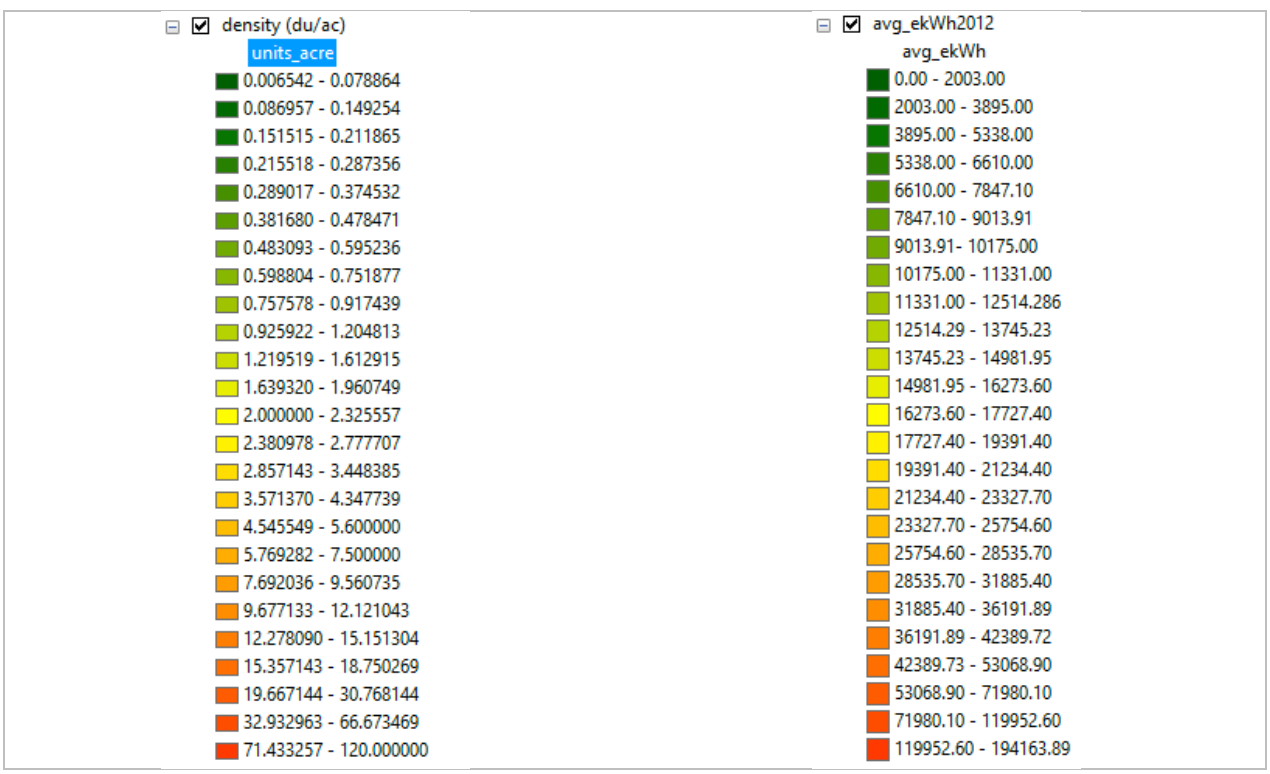


Figure 4-4. The color legends of density in DU/ac (on the left) and avg ekWh (on the right).

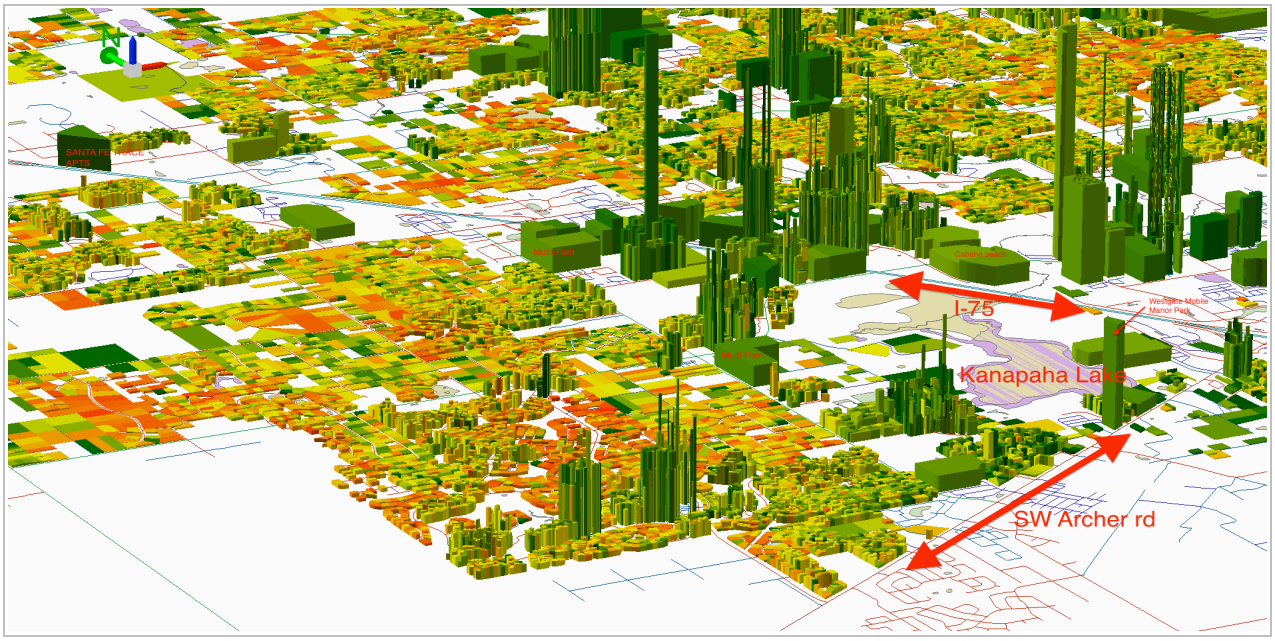


Figure 4-5. A closer look at southwest residential area, the corner between SW Archer road and I-75 in Gainesville, FL.

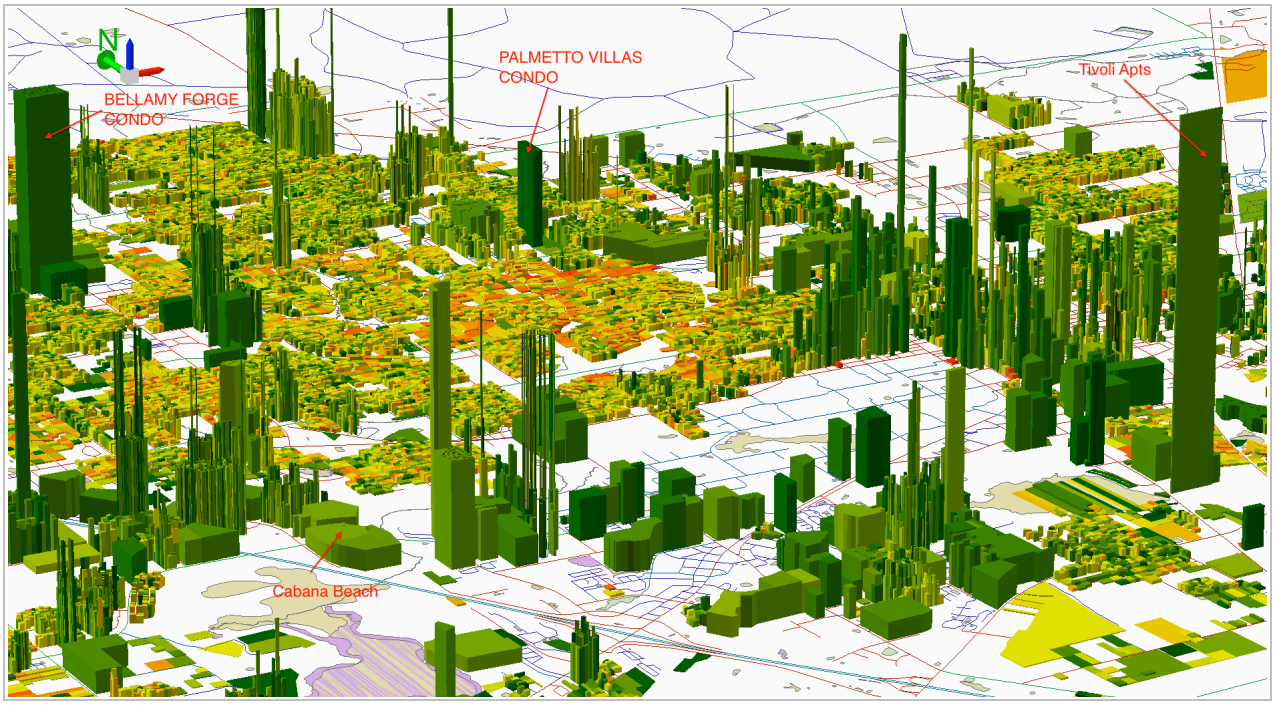


Figure 4-6. A scene from the SW overlooking the NW area of the city.

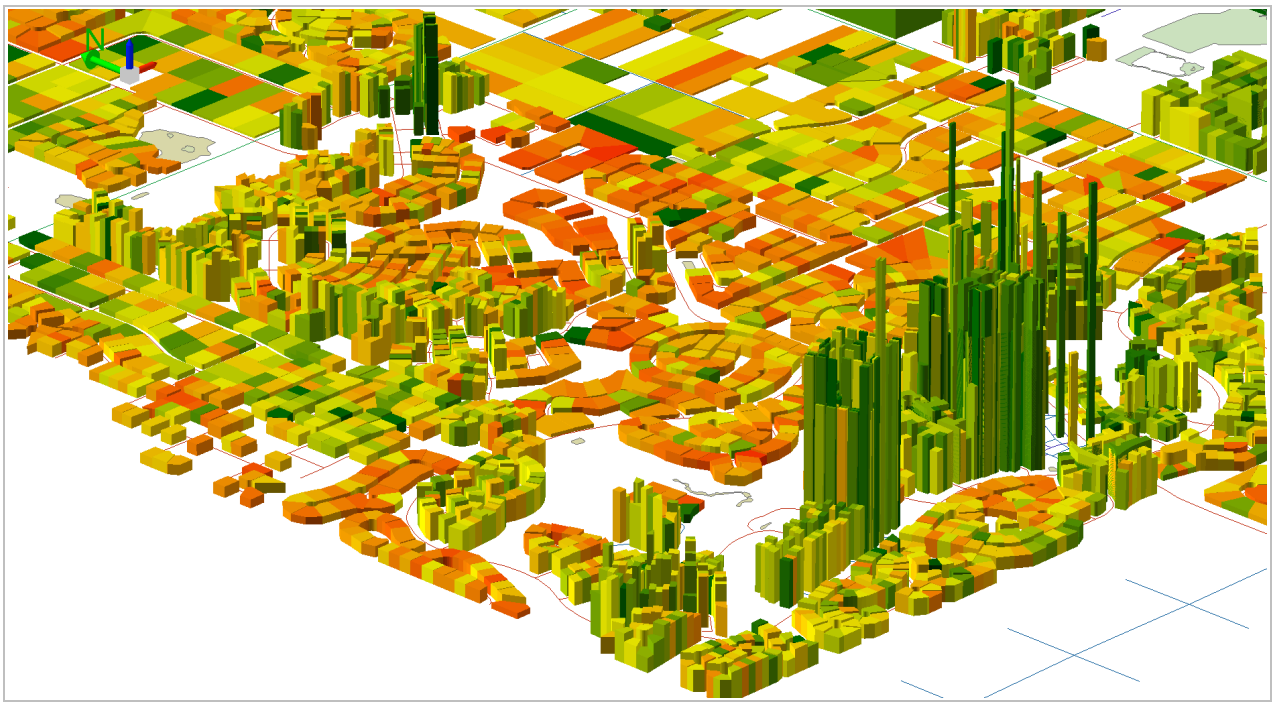


Figure 4-7. A detailed view of Haile Plantation subdivision, in the SW area of Gainesville, FL.

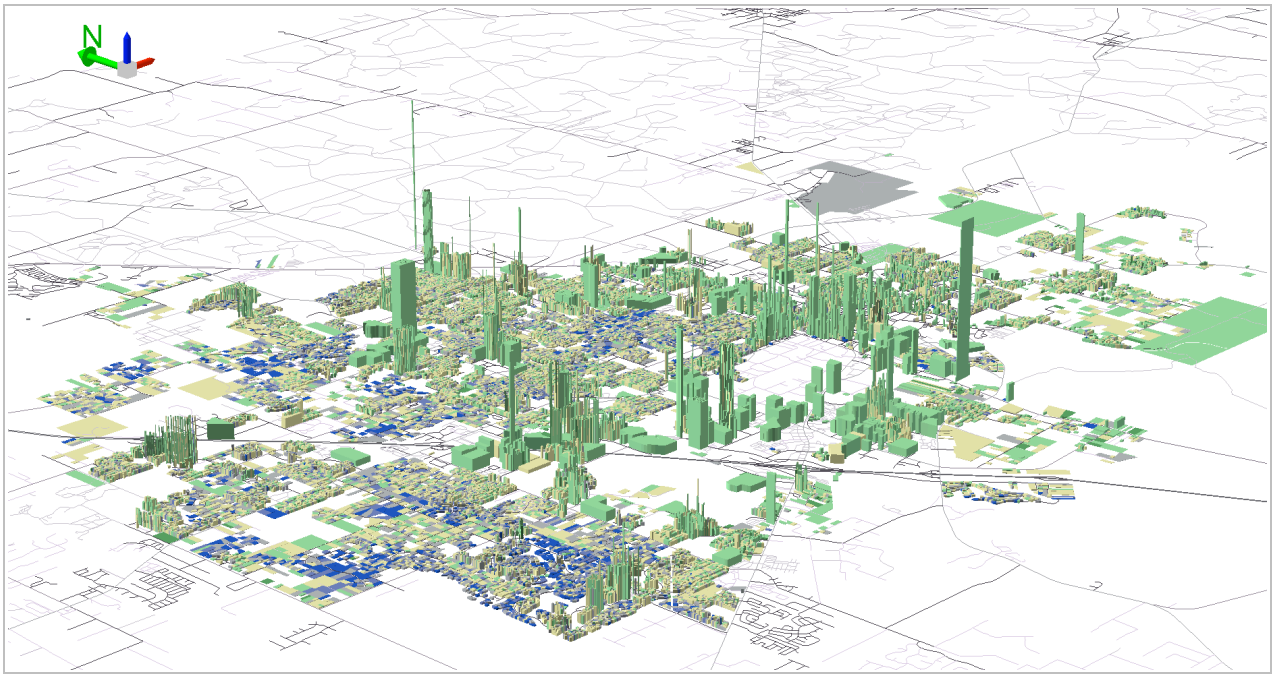


Figure 4-8. The colors on the map show the standard deviation values of the average energy consumption per land-use density.

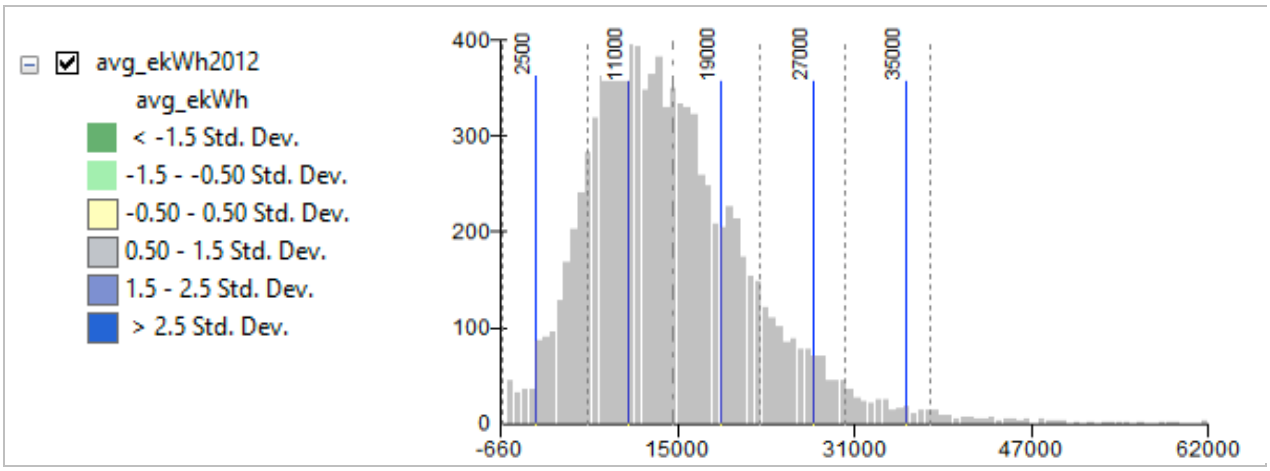


Figure 4-9. The σ legend, and the ekWh distribution curve.

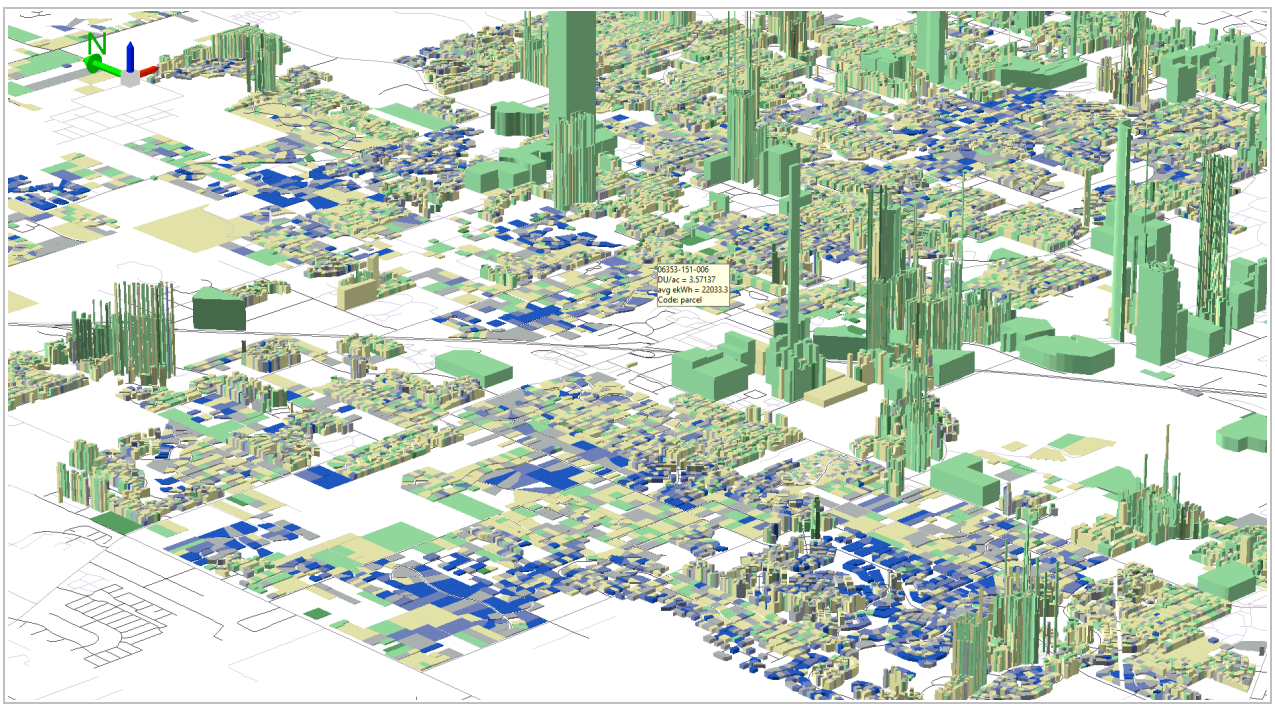


Figure 4-10. A close-up look at the spatial distribution of the σ values of the ekWh.

CHAPTER 5
ANALYSIS

A nonlinear, nonparametric regression model based on Loess fitting was constructed with the pre-processed data. The GRU residential energy consumption 2012 data (GRU_CY2012) was transformed, and the premises energy consumption values were aggregated to calculate the median ekWh of each parcel, as the dependent variable of the model. The density values, expressed in DU/ac as the independent variable of the model, were calculated from the GRU_CY2012 by linking and merging with the CAMA2012 and NAL2013.

A bivariate plot of the median of ekWh per land-use density can be generated based on the processed data, as shown in Figure 5-1. Based on eye-level observation of the plotted graph as in Figure 5-1 and 5-2, it can be seen that the density of the data points beyond 50 DU/ac is sparse. Further calculation of the data points' normal distribution within three standard deviations $(\mu \pm 3\sigma)$ from the median (or 99.7%), shows that $(\mu + 3\sigma) = 48.32$ and can be rounded up to 50 DU/ac:

- $n = 1218$
- $\sigma = 15.69751$
- $\mu = 1.223255$
- $(\mu + 3\sigma) = 48.31579$

The same fitted loess curve with adjusted density of 50 DU/ac is shown in Figure 5-3.

Examining the Loess Residuals

As in traditional regression methods, the purpose of plotting the loess residuals is to examine whether the smooth curve has sufficiently incorporated all feasible structure of the data points. From the equation 3-5, the loess residual values are defined as the

difference between the each observed Y values, and each of the corresponding fitted values of X:

$$\varepsilon_i = y_i - \hat{g}(x_i) \tag{5-1}$$

In finding the best fit parameter of the loess curve λ (lambda), which is the degree of the loess polynomial: when λ=0 the mean method is used, λ=1 the linear equation method is used, and λ=2, the quadratic equation method.

Among all the loess fitted residual plots in Figure 5-4 and 5-5, the latter with λ=2 (Quadratic equation) shows the lowest residuals and thus the best fit.

Arithmetic Means and Median Methods Comparison

To better reflect the energy consumption per land parcel, the total energy consumption value is normalized against the number of the residential units on the respective parcel. There are two ways to average the sum of the energy consumptions of all residential units, as defined in equation 3-1, over the number of the respective parcel. The median method is chosen because it better represents the average value of the skewed distribution of the residential unit's energy consumptions. A comparison curves for both arithmetic means and median methods on the overall energy consumption per unit density is shown in Figure 5-6.

Confidence Interval (CI)

The 95% confidence interval (CI) bands, as described in Jacoby (2000) are plotted around the loess fitting curve of median ekWh (2012) per DU/ac, as shown in Figure 5-7. The confidence bands are calculated based on the curve's standard error: CI = 95% and $z_{\alpha/2} = 1.96 \approx 2$.

Inferential Analysis

The loess curve graphs are generated using R statistical software version 3.0.2, and the fitted loess curve in Figure 5-3 has parameter information as follow:

```
Call:
loess(formula = y ~ x, data = data.frame(x = unit_acre, y = med_ekwh),
 span = 0.4205214, degree = 2)

Number of observations: 1189
Equivalent Number of Parameters: 9.35
Residual Standard Error: 7436
Trace of smoother matrix: 10.32

Control settings:
 normalize: TRUE
        span    :       0.4205214
        degree  :       2
        family  :       gaugasian
        surface :       interpolate   cell = 0.2
```

To test the hypothesis H_0 by applying the equation 3-6, following values are calculated from the data and residuals tables:

n = 1,189
TSS_Y= 98,882,024,133
RSS_{loess}= 65,125,684,362
and df_{loess}= 9.35

Using these values, the F distribution value and its distribution p-value can be determined:

$$F = \frac{(TSS_Y - RSS_{loess})/(df_{loess} - 1)}{(RSS_{loess})/(n - df_{loess})}$$

$$F = \frac{(98{,}882{,}024{,}133 - 65{,}125{,}684{,}362)/(9.35 - 1)}{65{,}125{,}684{,}362/(1189 - 9.35)}$$

$$F = 73.22675$$

and F distribution's p-value = 6.81875E-98 **< 0.0001**

It is apparent that the p-value of the F distribution is far less than 0.0001, thus the H_0 of no statistically significant correlation between land-use density and annual energy consumption per residential unit in the city of Gainesville, FL, can be rejected, and at the same time it is possible to accept the alternative hypothesis H_1.

Residential Energy Consumption per House Type

Additionally, from the GRU residential energy consumption 2012 and CAMA2012 databases, further data extraction can be performed to obtain the dataset for residential energy consumption per house type.

The scatterplot graph in Figure 5-8 and smoothed Loess curves in Figure 5-9, show the energy consumption of Single-Family Attached (SFA), Single-Family Detached (SFD) and Multi-Family house types, and the their distributions based on the land-use density are depicted in Figure 5-8. Following records quantity per house type are used for the calculation,

- SFA = 4,900 units
- SFD = 36,965 units
- Multi-Family = 33,801 units

SFD has the highest energy consumption from all house types; its average energy consumption per unit is higher than overall per unit's energy consumption. On the other hand, SFD energy consumption continues to decline as the land-use density increases and it is starting to match that from SFA starting about 13 du/ac. From all house-types, Multi-Family has the lowest unit consumption, and in this study, it is well represented through their normal distribution with 33,801 housing units.

Case Studies

Geospatial mapping of average annual energy consumption of the land-use density provides a helpful and quick overview of the whole area of interest and reveals otherwise hidden information. The interactive nature of the 3D model creates a virtual panoramic image that can be panned, zoomed and rotated in 360-degree view. This allows the selected residential areas to be compared and studied further, from a bird's-eye view down to the street level.

Some areas in Gainesville were selected for case studies, as depicted in Figure 5-10, are as follow:

- Cabana Apartments, Phase I & II (Multi-Family)
- Rockwood Villas (SFA)
- An SFA Condo in Haile Plantation, Unit 15
- An SFD in Haile Plantation, Unit 25 Ph. II

Table 5-1 summarizes the studied residential areas and their density. For example, the subdivision of Rockwood Villas has 227 housing units. Each unit is in its own respective parcel with land size of 1,307 sqft or 0.03 acre. Since there is only one housing unit per parcel, it gains a relatively high land-use density of $\frac{1}{0.03}$ = 33.33 DU/ac.

For comparison, Cabana Beach I Apartment's parcel has a huge 30.3 acre land size area (because it is shared across all units, includes all common areas), but achieves a land-use density of only $\frac{247}{30.3}$ = 8.15 DU/ac.

The 3D model of the average energy consumption per residential unit density in Figure 5-11 shows the differences in the land size of the parcels, between Rockwood

Villas and Cabana Beach Apt I & II. From the eye-level observation of the model, the following information can be easily identified:

- The land size among the parcels.
- The parcel's land-use density in DU/ac, indicated by the heights of the bars.
- The respective parcel's average energy consumption, indicated by the color spectrum, from green (low consumption) to red (high consumption).

The same as above, Figure 5-12 shows the close-up visualization of the areas of study in Haile Plantation, both the SFD area (development unit 25, Phase II) and SFA area (unit 15). Based on eye-level observation, the high-density areas, the low- density areas, and the parcel units that include their intensity of energy consumption can be identified.

An aerial view of the two land parcels, Rockwood Villas and Cabana Beach Apt I & II can be seen in Figure 5-13, showing the layout of the parcels from above. Figure 5-14 shows the street-level view of the two land parcels. Subsequently, the aerial view of Haile Plantation, Unit 15 (an SFA) and Unit 25 Ph. II (an SFD) areas is shown in Figure 5-15 and Figure 5-16 their street-level view.

Finally, a comparison of the average annual energy consumption per residential unit in those five studied areas is shown in Figure 5-17. It can be seen, that the energy consumption of the SFD/Haile Plantation Unit 25 Ph. II is the highest among the other four parcels.

Table 5-1. Overview of studies on building energy consumption in reviewed literatures.

Name	Parcel_id	DU	acres	DU/ac	LND_ SQFT	TOT_ LVG_ AREA
Cabana Beach Apts I	06680-022-000	247	30.3	8.15	1319432	322845
Cabana Beach Apts II	06680-023-000	252	25.2	10	1097712	299051
Rockwood Villas	06680-030-xxx	227	0.03	33.33	1307	1106
an SFD (Haile Plant.)	06860-252-046	1	0.54	1.85	23522	3052
an SFA (Haile Plant.)	06860-150-014	1	0.03	33.33	1307	1088

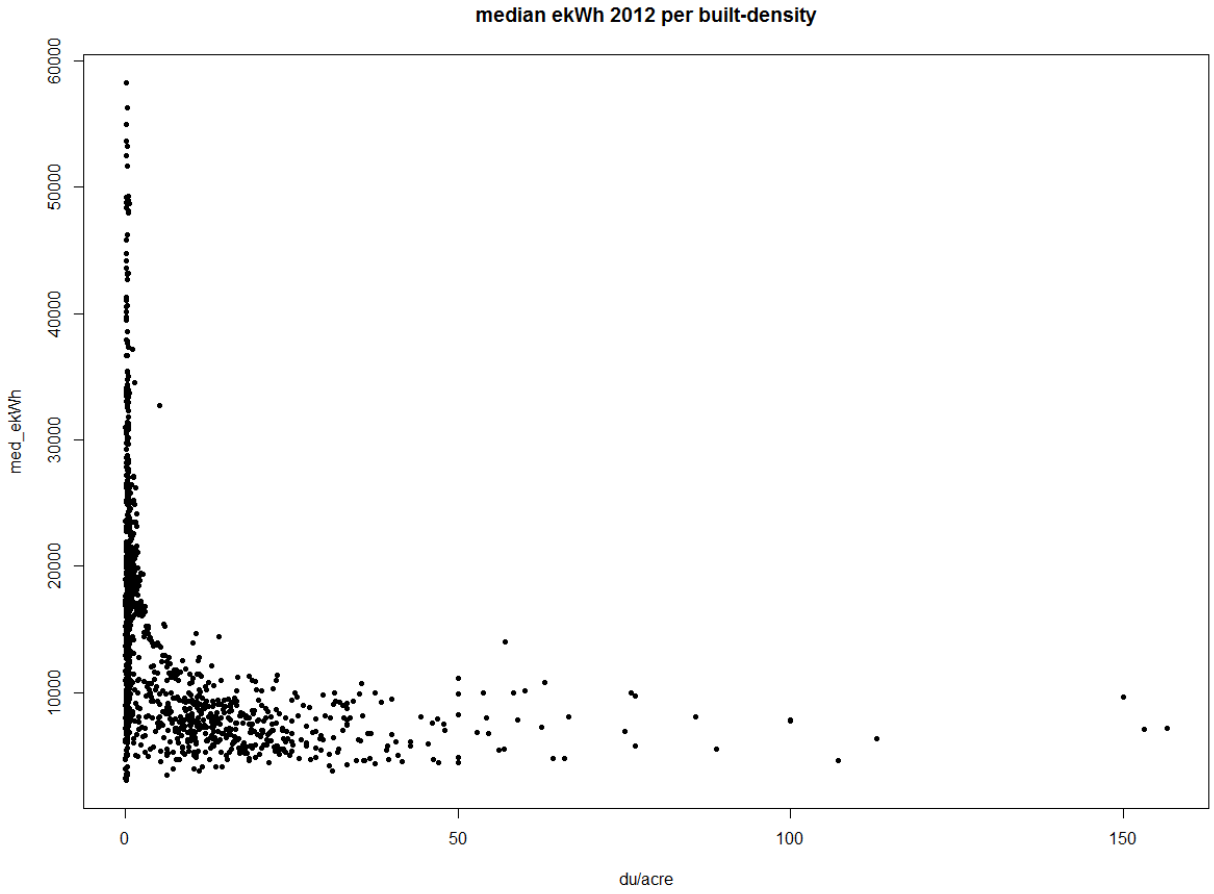


Figure 5-1. Bivariate plot graph of median ekWh (2012) per DU/ac.

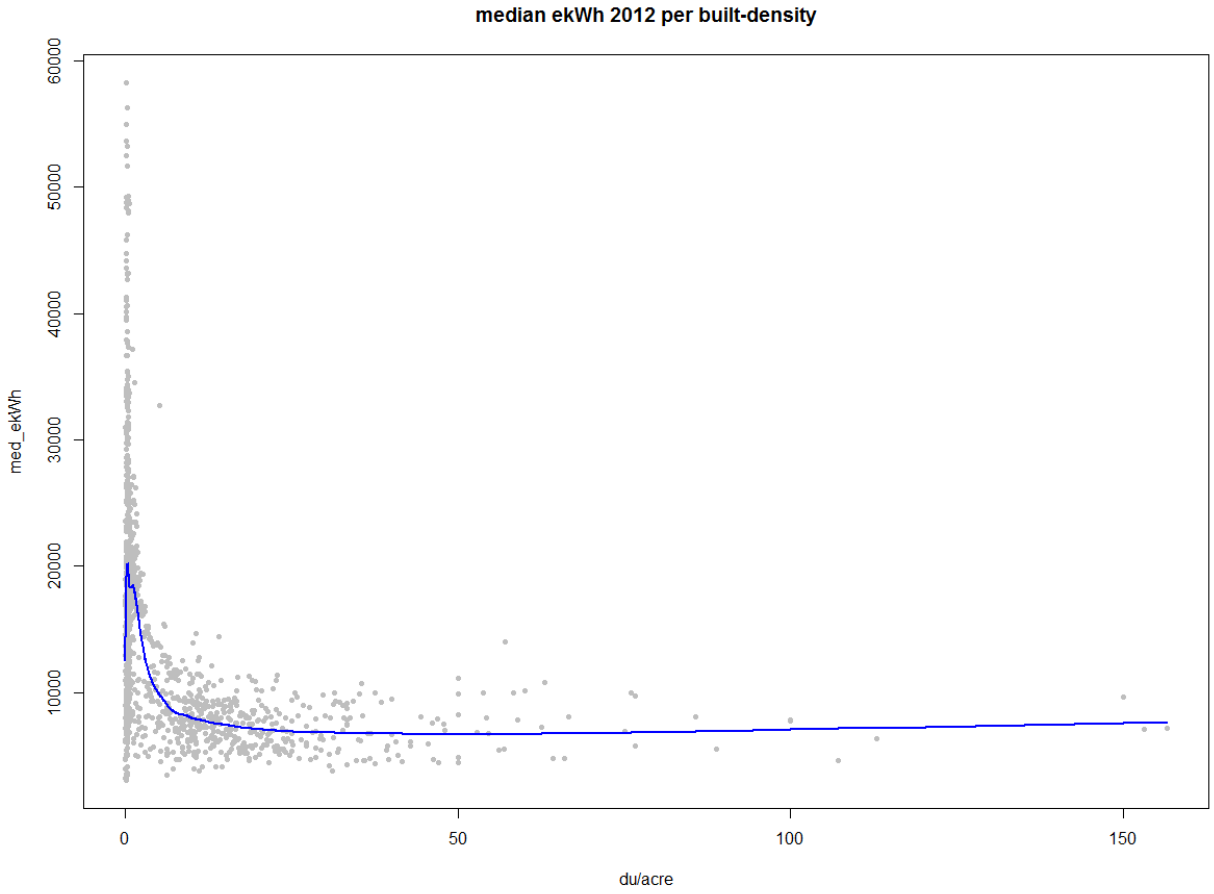


Figure 5-2. Fitted loess curve of median ekWh (2012) per DU/ac (up to 153 DU/ac).

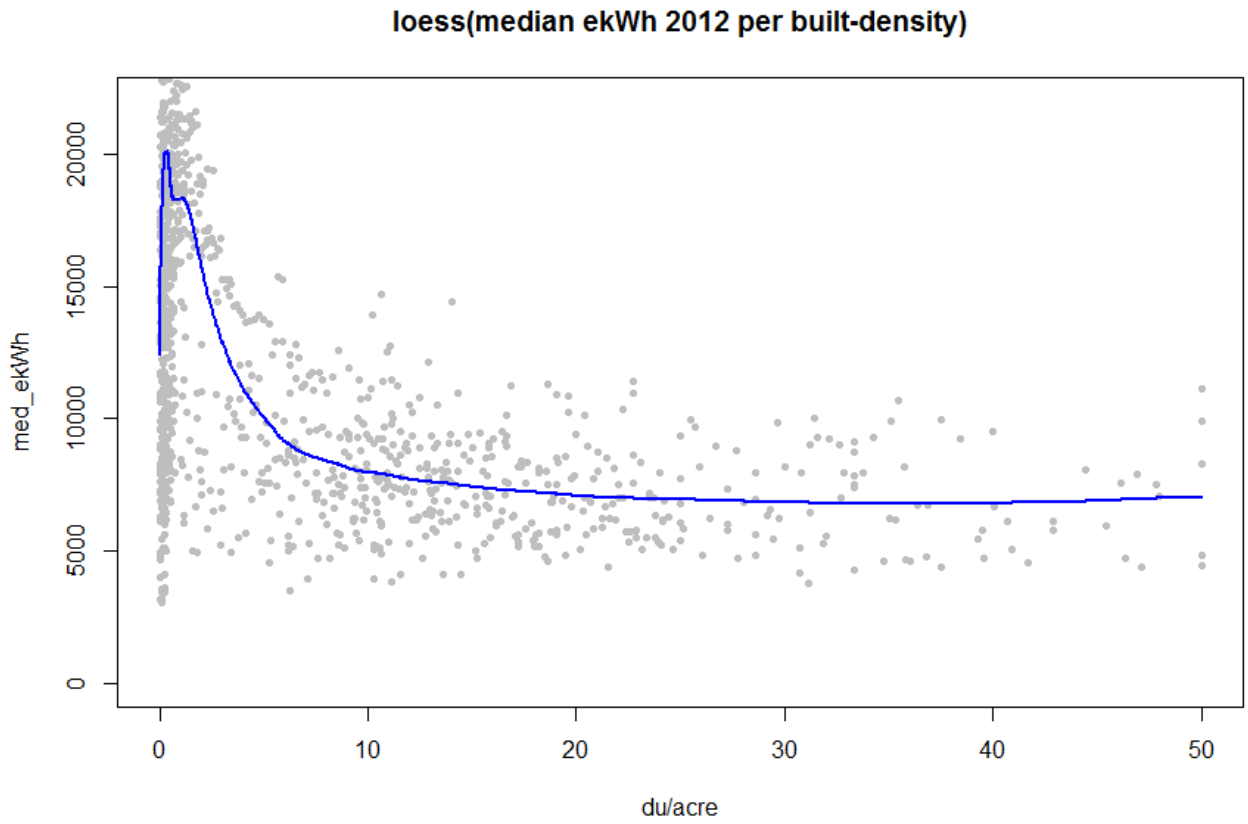


Figure 5-3. Fitted loess curve of median ekWh (2012) per DU/ac (limited to 50 DU/ac).

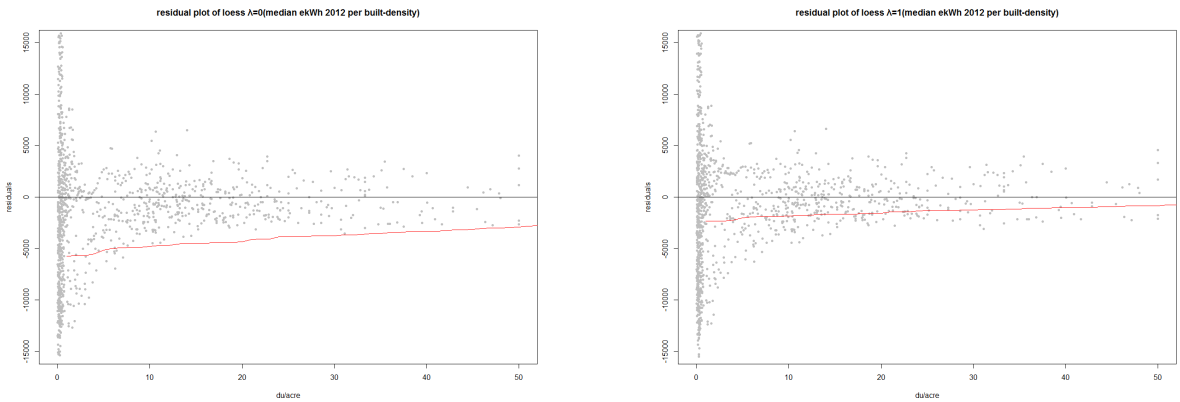


Figure 5-4. Residuals of loess fitted median ekWh (2012) per land-use density with λ=0 (on the left) and with λ=1 (on the right).

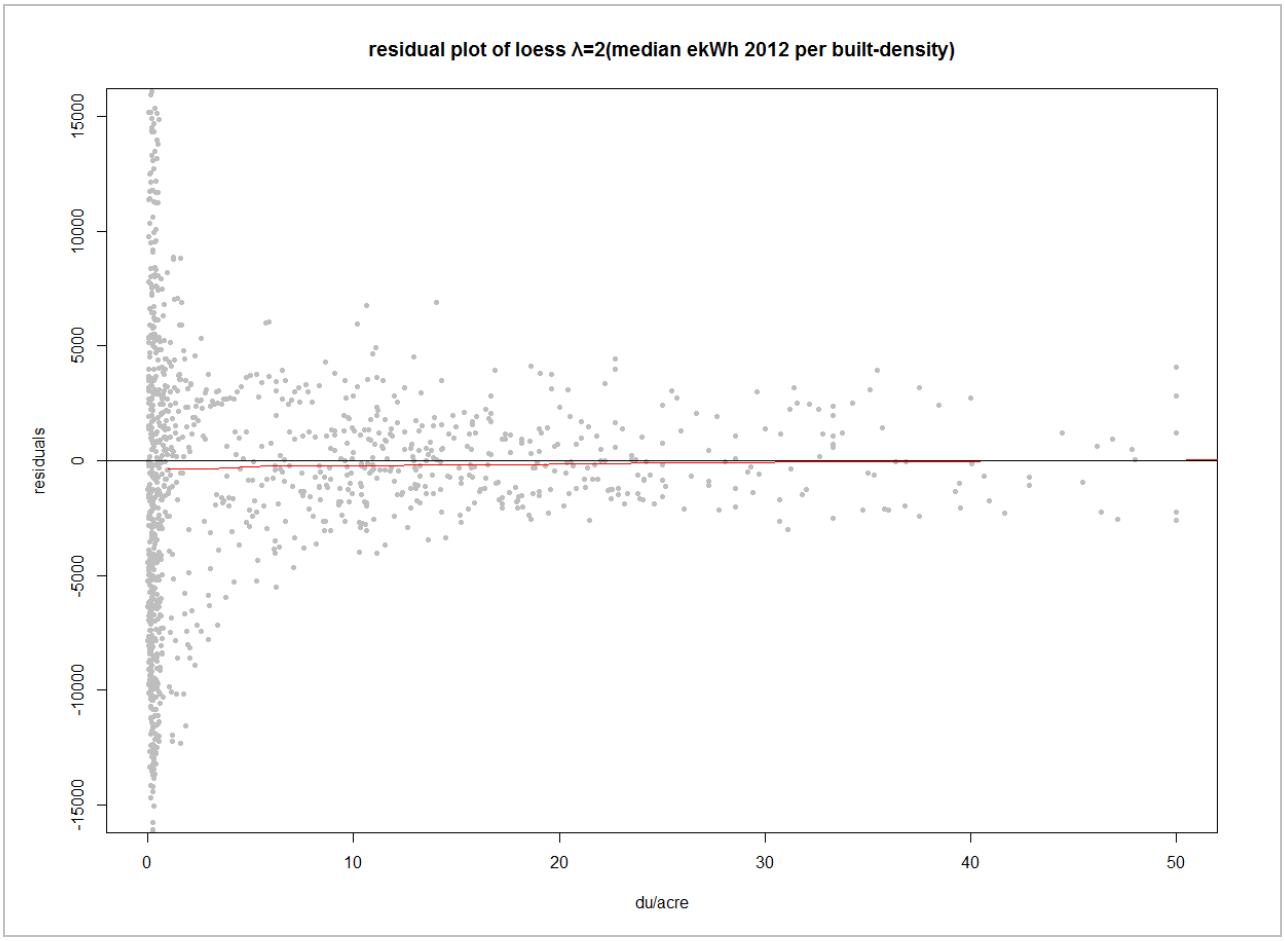


Figure 5-5. Residuals of loess fitted median ekWh 2012 per land-use density with λ=2.

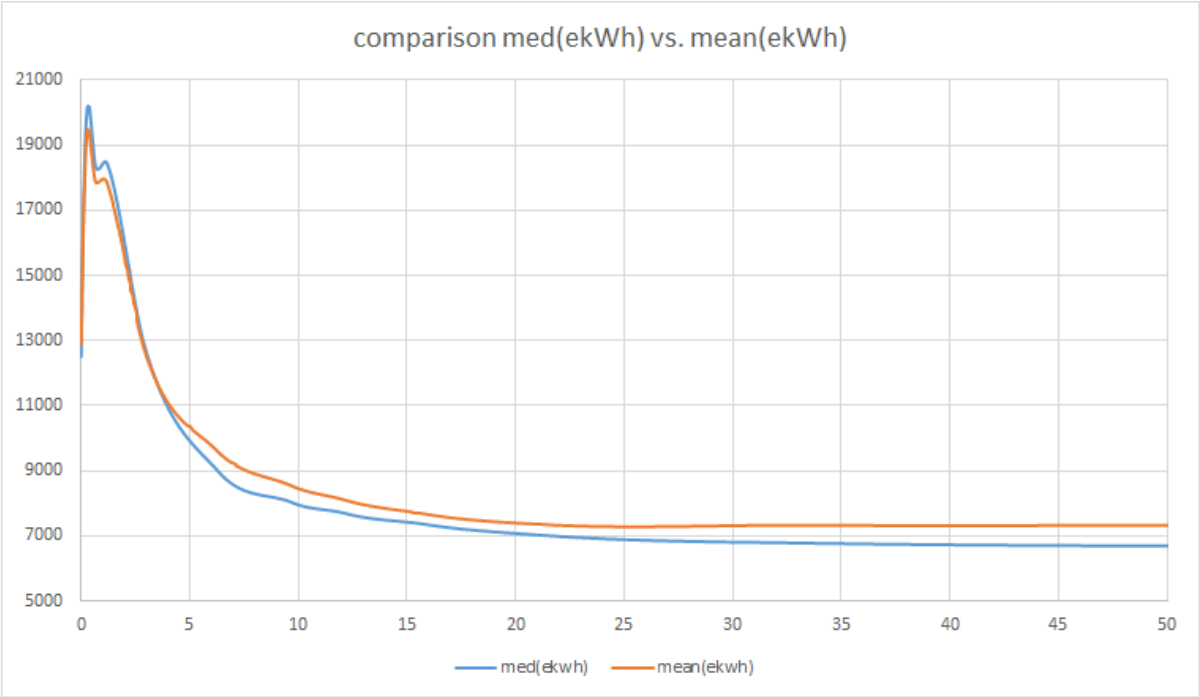


Figure 5-6. Comparison of energy consumption profiles normalized using arithmetic mean and median method.

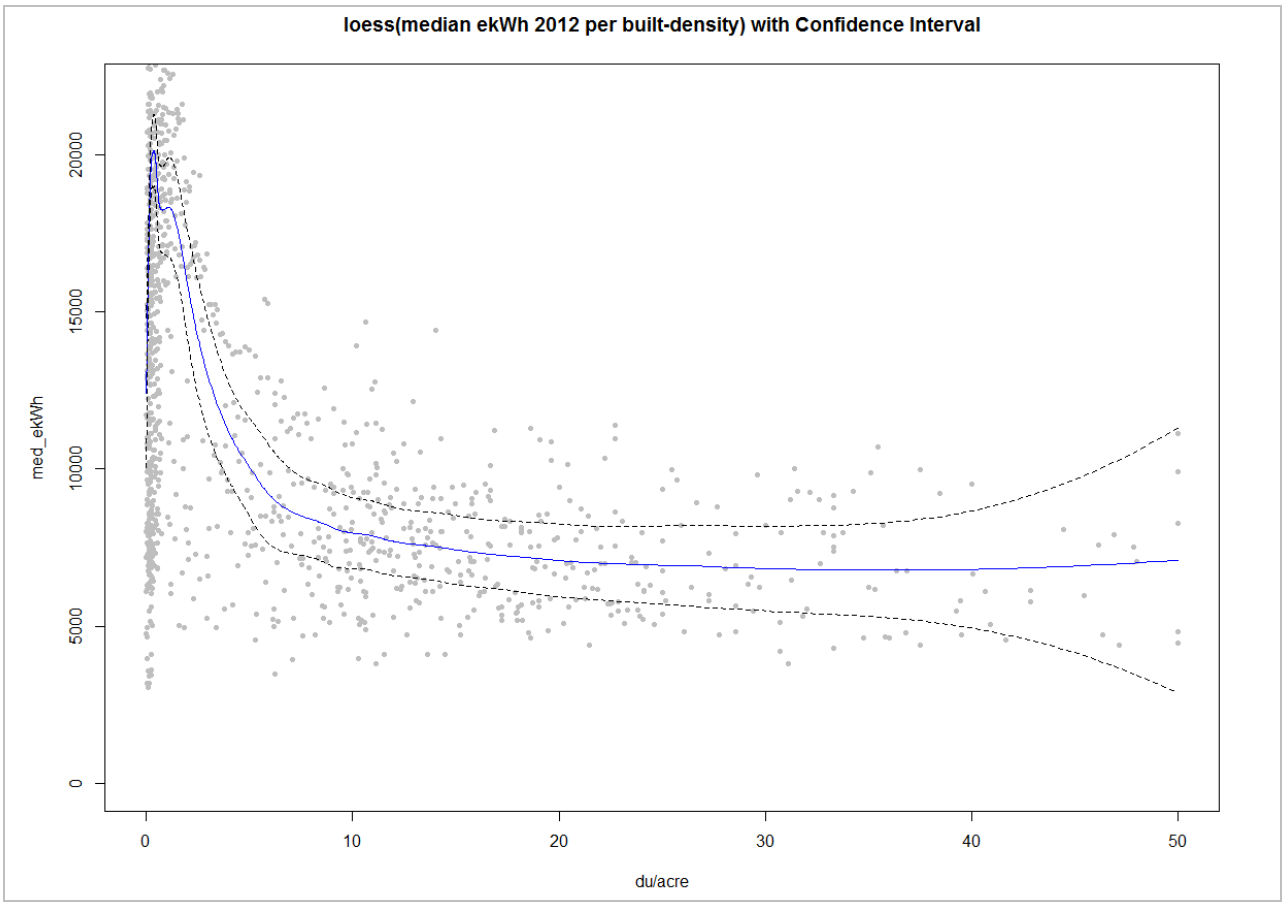


Figure 5-7. Median ekWh 2012 per DU/ac plotted with 95% confidence interval bands.

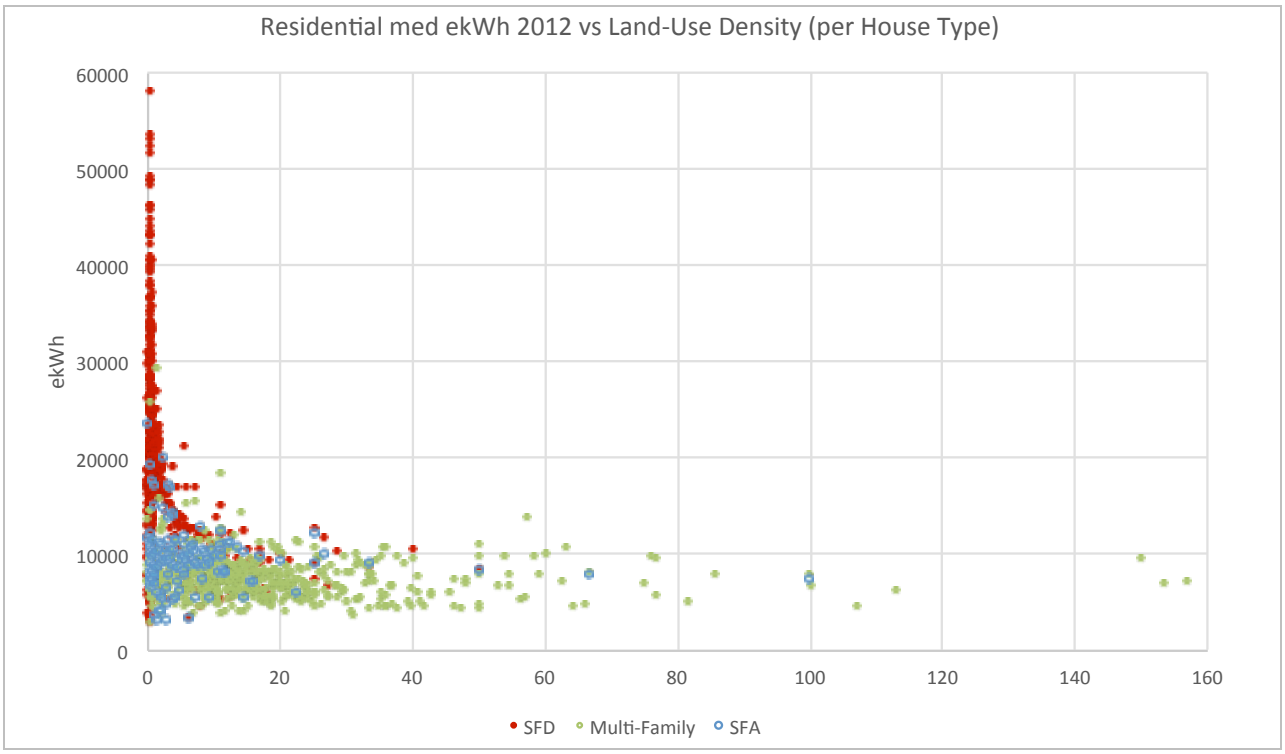


Figure 5-8. Res. energy consumption (2012) vs DU/ac scatterplot by house type.

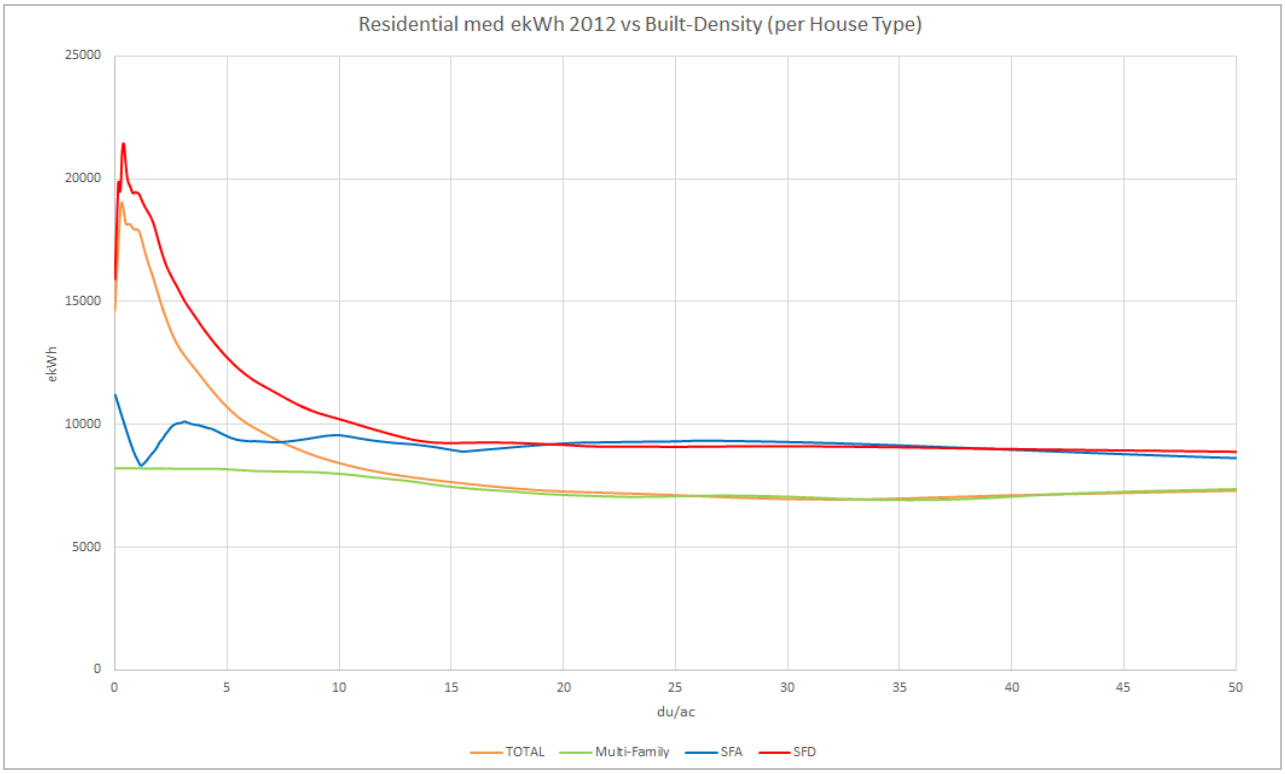


Figure 5-9. Residential energy consumption (2012) vs DU/ac by house type.

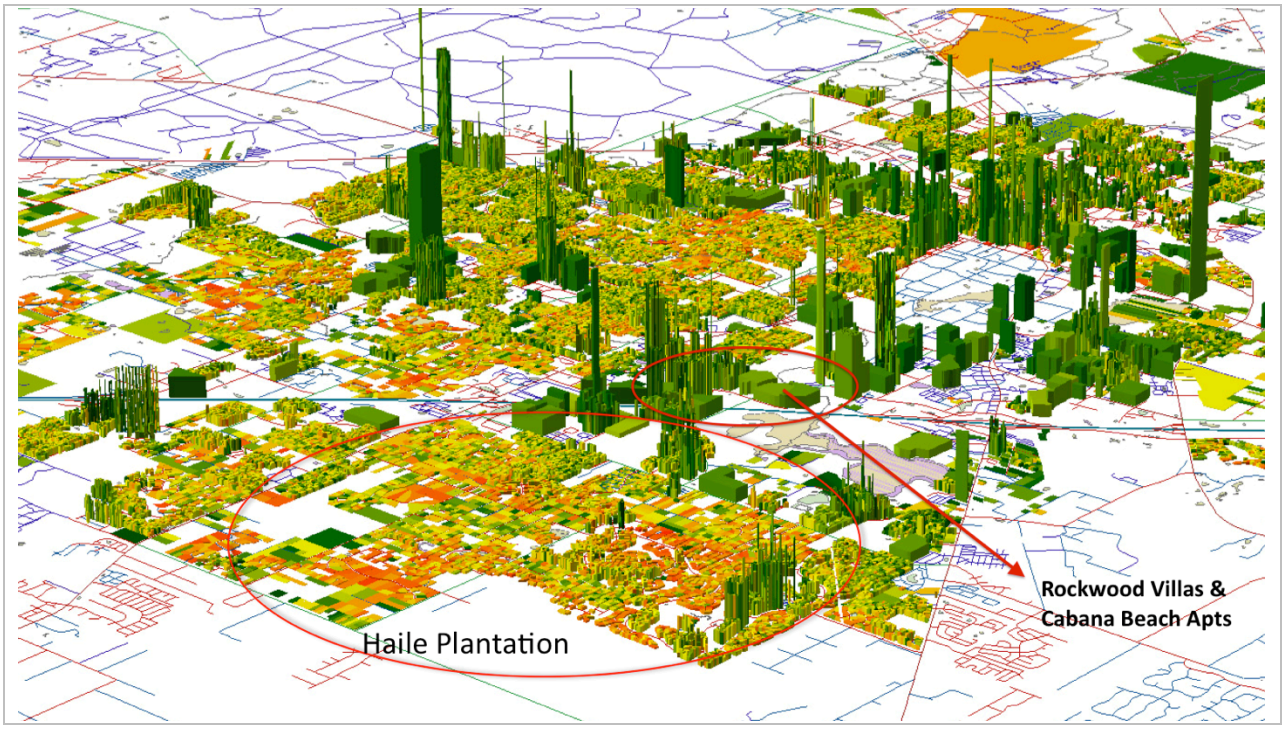


Figure 5-10. The selected areas for case study on the geospatial 3D model.

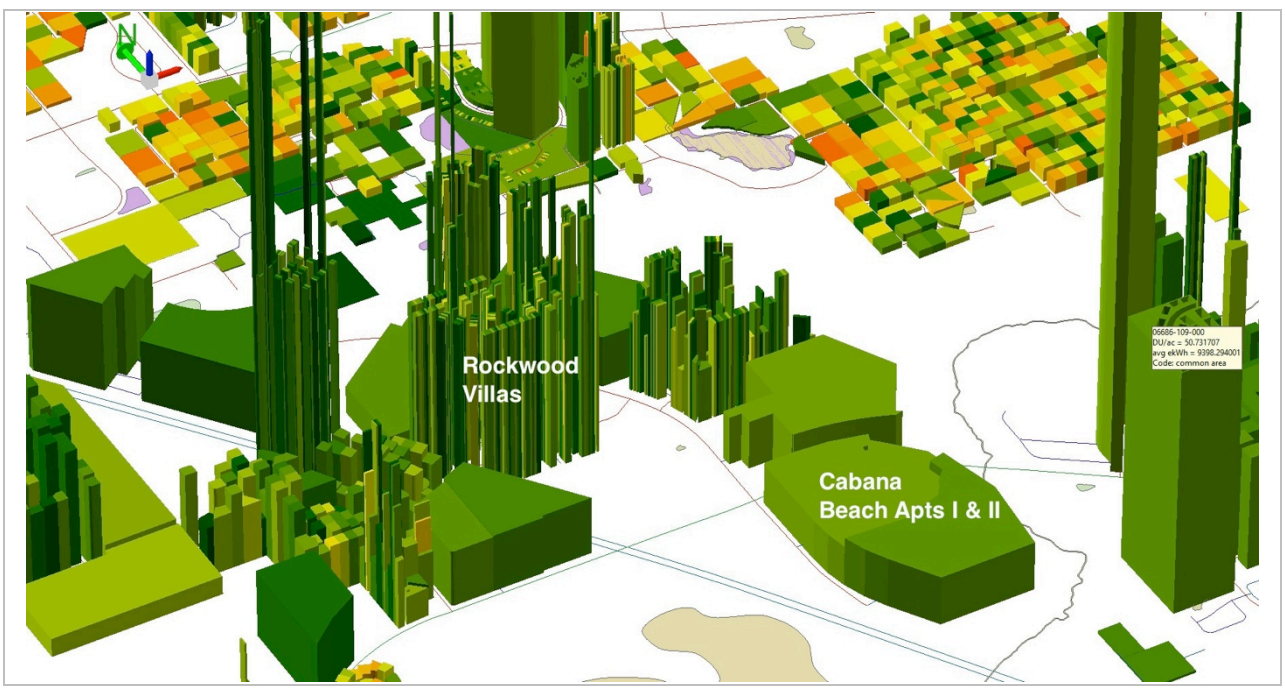


Figure 5-11. Detailed view on selected area of study: Rockwood Villas and Cabana Beach.

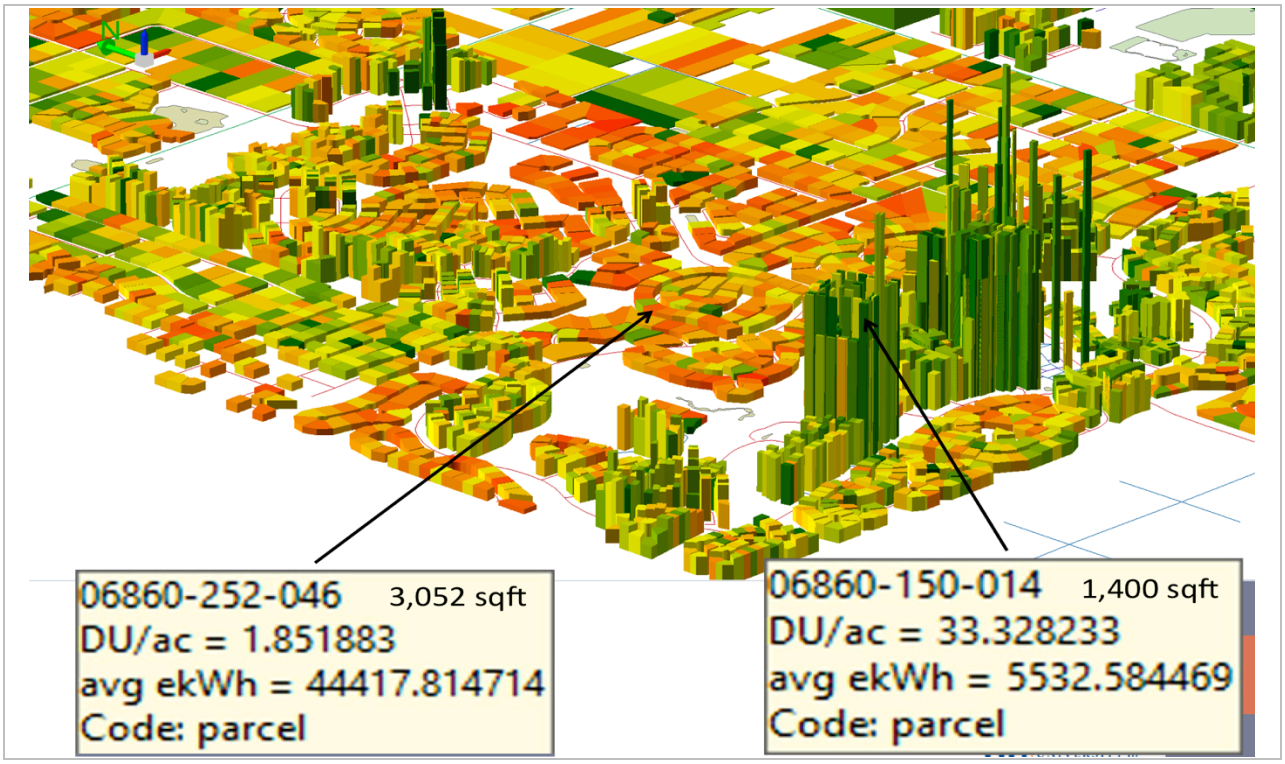


Figure 5-12. Detailed view of selected area of study: Haile Plantation (SFD and SFA)

Rockwood Villas Cabana Beach Apt I & II

Figure 5-13. Aerial views of Rockwood Villas and Cabana Beach Apt areas. [Source: Google Maps.]

Rockwood Villas (typical SFA housing)

Cabana Beach Apt I & II (typical Multi-Family housing)

Figure 5-14. Street-level view of Rockwood Villas and Cabana Beach Apt areas.

Haile Plantation-Unit 15 (SFA housing)

Haile Plantation-Unit 25 Ph. II (SFD housing)

Figure 5-15. Aerial view of Haile Plantation, Unit 15 and Unit 25 Ph. II areas. [Source: Google Maps.]

Haile Plantation-Unit 15 (typical SFA housing)

Haile Plantation-Unit 25 Ph. II (typical SFD housing)

Figure 5-16. Street-level view of Haile Plantation-unit 15 and unit 25/II areas.

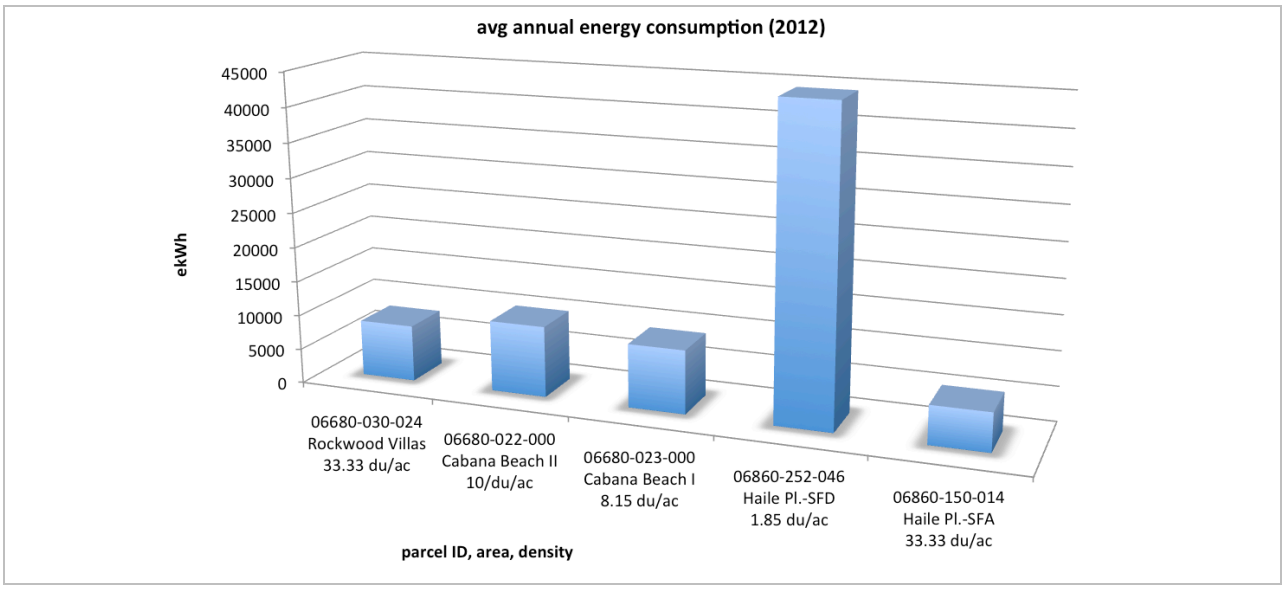


Figure 5-17. Average annual energy consumption per studied residential units.

CHAPTER 6
CONCLUSIONS AND DISCUSSIONS

Key Findings and Conclusions

This thesis study attempts to find the correlation between land-use density and annual energy consumption per residential dwelling unit within the city of Gainesville, Florida. The results provide a quantitative comparison and insights into the residential energy usage pattern based on the dwelling unit density, and house type. The application of statistical inference method helps to confirm the correlation that exists between annual energy consumption per residential unit and development density.

The 3D geospatial model helps to visualize the studied variables by mapping them to their respective geographical locations. The model provides not only a quick visual assessment of the analyzed data on spatial distribution (i.e. the size and location of the land parcels; their average annual energy consumption; and the parcel's land-use density), but also its assessment and analytical insight can be applied to verify those results from the statistical analysis. Moreover, detailed investigation on the differences of the parcels' average annual energy consumptions is feasible through the additional visualization of each parcel's energy usage deviation values.

The results and conclusions presented in this thesis are limited to the use of the 2012 annual GRU residential energy consumption database as source data. The level of accuracy of the model will increase if more historical energy consumption data is added, which may or may not change the overall profiles of the residential energy consumption per land-use density. Based on the analysis result of the distribution of the energy consumption per house type, the study indicates that the overall residential

average energy consumption pattern per land-use density in Gainesville, FL is unlikely to change much if more historical data is added to the model.

In conjunction with other publicly available data, i.e. CAMA 2012 and NAL 2013, it was possible to employ a data-mining algorithm to extract and dissect the data, and to construct the model for statistical analysis purposes as well as for the 3D geospatial modeling.

With the results of this thesis study, it can be concluded that:

1. Based on the statistical inference analysis, it is evident that a correlation exists between land-use density and annual energy consumption per residential dwelling unit within the city of Gainesville, Florida.

2. The statistical regression model shows that there is a non-linear, non-parametric inverse relationship; up to a certain extent (about 15-35 du/ac), with the increasing of land-use density, the level of energy consumption per residential dwelling unit is decreased.

3. Based on the 3D geospatial model, it can be observed that land parcels with the high land-use density tend to have lower energy consumption compared to those parcels with lower land-use density. This characteristic can also be observed and verified in the normal distribution of energy consumption model, as depicted in Figure 4-8 and 4-10.

4. Based on the analysis of the energy consumption per house type, as shown in Figure 5-8 and 5-9, the results suggest that,

    - the SFD has the highest energy consumption per house type. This finding is also in accordance with the SFD's trait, which has a low land-use density value. Its average energy consumption per unit is higher than the overall average energy consumption per unit of all residential housing stock in Gainesville, FL.

    - the SFA average energy consumption is much lower than SFD. Aside from less significant fluctuations up to about 10 du/ac, the SFA values do

not change much as the land-use density increases. However, starting from around 13 du/ac, the SFD values match those from SFA.

- Multi-Family housing has the lowest energy consumption.

5. Based on the median averaged values of energy consumption per house type by land-use density, the calculation yields the following results (in ekWh/[du/ac]): SFD = 17,300; SFA = 9,219; and Multi-Family = 7,401. In other words, on average an SFD unit consumes 2.3 times as much energy as a Multi-Family unit, and 1,88 times as much as an SFA unit. An SFA unit consumes only 1.2 times more energy than a Multi-Family unit.

Suggestions for Further Studies

There are several areas in this study, which could be improved or extended in the future research. In particular:

- To increase sample size by adding more historical energy consumption data to the model to improve accuracy.

- To study in a more detailed manner the possible effect caused by the implementation of building codes and standards in the past on the residential energy consumption by comparing house energy consumption across building vintage.

- To further break down the seasonal residential energy consumption analysis into more sub-dimensions, such as house type (to investigate whether there is any significant relationship exists between seasonal energy usage and house type) and seasonal energy usage per house vintage (to investigate whether there is any improvement in home energy efficiency, due to new building codes etc.)

- To study the residential energy consumption related to Urban Heat Island effect.

- To study the residential energy consumption analysis based on Floor Area Ratio (FAR).

- To study the microclimatic effects, such as tree shades and canopy benefits on residential energy efficiency.

- To study the residential water consumption and its correlation with land-use density.

- To study the potential GHG emissions related to Gainesville land-use density.

Discussions

This thesis study provides empirical and quantitative analyses on the correlation between net land-use density and annual energy consumption per residential dwelling unit within the city of Gainesville, Florida. Based on the key findings and conclusions in this study, additional analyses can be derived from the available datasets, these include the analysis of residential energy consumption by building vintage, seasonal residential energy consumption and also future projected energy demand and forecasts in different scenarios could be developed. Although these supplementary analyses are formally not a part of the main objectives of this thesis, however they are interesting and can provide a further insight into various dimensions of the correlation between net land-use density and annual energy consumption for further discussions and recommendations.

Residential Energy Consumption by Building Vintage

The graph in Figure 6-1 shows the residential avg ekWh 2012 consumption plotted against the density (DU/ac). It also shows the comparison of residential buildings energy consumptions for buildings built before 1990 (orange line) and those built in year 1990 and thereafter (blue line).

The prevailing wisdom suggests that buildings built in the 1990s and thereafter should consume less energy due to their energy-efficiency requirements imposed by building codes, such as better insulation, window glazing, Energy Star rated equipment, etc. However, surprisingly the graph above shows that this assumption is reversed. The assumption to respond to this deviation is that the average residential unit size (sq ft) has gradually increased since 1980s, as shown in Figure 6-2.

Since the energy consumption is only related to the heated area, the average heated area (htd area) is used in the calculation instead of average total floor area (heated area + non-heated area). The pre-1930 buildings are not included since their numbers are sparse and therefore less representative.

Seasonal Residential Energy Consumption

Based on the GRU residential energy consumption 2012 data, further insight into the energy consumption patterns can be obtained. Figure 6-3 shows the seasonal residential energy consumption plotted against the land-use density (DU/ac). Prior to aggregating the usage values of the residential units (premises) to determine the average usage per land parcel, the energy usage value in each record must be split and assigned proportionally or pro-rated to its respective usage months (monthly binning method) based on its meter reading date.

For example, a premise has a usage value = 1,250 kWh, meter reading duration is equal 30 days and meter reading date of May 20, 2012 ($read\ date = 20$), and let monthly ekWh usage bins = u_m where $\mathrm{m} = 1 \text{ to } 12$ denoting the month number. This is calculated as:

1. Calculate the normalized daily usage:

   $$\bar{u}_i = \frac{usage_i}{duration_i} = \frac{1{,}250}{30} = 41.667\ kWh\ /day$$

2. If read date < duration: Add May 2012 pro-rated usage to current month's bin (m=5):

   $$u_{5_i} = \bar{u}_i \times read\ date_i = 41.667\ kWh \times 20 = 833.33\ kWh$$

3. If read date < duration: Then add the remaining pro-rated usage to (m-1)'s bin:

   $$u_{4_i} = \bar{u}_i \times (duration_i - read\ date_i) = 41.667\ kWh \times 10 = 416.67\ kWh$$

4. In special cases, if read date > duration (e.g. for month May):

$$u_{5_i} = usage_i$$

Note that the index i above indicates the premise index of a parcel (refer to equation 3-1). The subsequent step is to sum all the pro-rated monthly usage bins of respective premise together. The final seasonal usage value of each premise is obtained by aggregating the monthly values based on following rule:

- Spring months = March, April, May
- Summer months = June, July, Aug
- Fall months = Sep, Oct, Nov
- Winter months = Dec, Jan, Feb

Finally, the density of each parcel is calculated based on equation 3-4 and its premise seasonal usage is aggregated based on the sample median method.

The result in Figure 6-3 shows that the highest seasonal residential energy consumption in 2012 occurred during the summer months. On the other hand, in the winter months, the energy consumption is the lowest compared to the rest of the seasons. This seasonal energy consumption pattern is expected, where the energy consumption profile matches that of the City of Gainesville and Florida's seasonal energy consumption profiles. In Florida generally and in Gainesville specifically, the summer electricity peak demand is usually higher compared to winter peak demand.

Energy load analysis for additional residential units in various scenarios

Assuming that there are 1,000 to 2,000 new residential units to be added to Gainesville's housing stock, these units will add additional GWh of Net Energy Load (NEL) to the original GRU's forecasted energy demand. The potential energy

consumption profiles of the new built residential units will depend on their land-use density.

Table 6-1 shows history and forecast of NEL and Seasonal Peak Demands, and was compiled from the GRU's 2013-Ten-Year Site Plan (GRU, 2013). Based on the data, the GRU predicted NEL for the year of 2014 up to 2022 graph can be plotted (see Figure 6-4). The NEL forecast line has a linear function: $y = 7.33x – 12838$, and using this function, the total NEL in various additional residential units scenarios can be extrapolated.

Based on the previous calculation of the Seasonal Residential Energy Consumption vs. land-use density above, as shown in Figure 6-3 and Figure 6-5, the maximum median ekWh of both summer and winter consumption for density 0-15 du/ac and >15-50 du/ac can be determined. From the previous assumption above, a new development project will add a few thousand new residential units to Gainesville's housing stock, and thus the additional energy loads as shown in various scenarios, including summer energy load and winter energy load for the additional housing units, as shown in Table 6-2 and 6-3.

Note that, to simplify the calculation, the density values are grouped to "0-15" and ">15-50" respectively. Table 6-4 shows the additional energy loads of 1K-2K residential units, added to the GRU's forecast NEL, and based on the calculated numbers, the additional energy loads to GRU's previous forecasted NEL can be added.

The graph in Figure 6-6 shows NEL in various scenarios: original NEL; NEL of 1K additional res units with 0-5 du/ac; NEL of 2K additional res units with 0-5 du/ac; NEL of 1K additional res units with >15-50 du/ac and NEL of 2K additional res units with

>15-50 du/ac. Based on these different scenarios, a maximum of NEL that will add to the original GRU's forecasted energy demand is approximately 37.84 GWh.

Table 6-1. GRU's Historical and Projected Net Energy Load (NEL) and Summer/Winter Peak Demands (MW)

Year	Total installed capacity	Capacity Available Summer	Summer Peak Demand	Capacity available Winter	Winter Peak Demand
2003	610	607	417	628	350
2004	611	608	432	629	377
2005	611	608	465	629	386
2006	611	608	464	632	362
2007	611	611	481	631	361
2008	610	659	457	711	421
2009	608	709	465	705	464
2010	608	710	470	681	409
2011	608	664	445	683	371
2012	610	667	415	672	338
2013	598	657	441	724	342
2014	598	710	416	724	343
2015	598	711	417	701	345
2016	575	690	419	702	347
2017	575	690	421	702	348
2018	561	676	422	672	350
2019	533	648	424	657	351
2020	533	648	425	657	353
2021	533	648	427	657	355
2022	458	573	428	582	357

Data compiled from GRU's 2013-Ten-Year Site Plan (GRU, 2013).

Table 6-2. Summer energy load forecasts of seasonal residential energy load based on 0-15 and >15-50 du/ac

du/ac	max. med ekWh	x 1,000 new residential units	x 2,000 new residential units
0-15	5,468.23	5,468,230 ekWh	10,936,469.55 ekWh
>15-50	2,072.99	2,072,990 ekWh	4,141,973.06 ekWh

Table 6-3. Winter energy load forecasts of seasonal residential energy load based on 0-15 and >15-50 du/ac

du/ac	max. med ekWh	x 1,000 new residential units	x 2,000 new residential units
0-15	4,899.61	4,899,610 ekWh	9,797,211.95 ekWh
>15-50	1,494.22	1,494,220 ekWh	2,988,434.19 ekWh

Table 6-4. NEL calculation table with 1K and 2K extra residential units added.

year	NEL	NEL+1K =0-15	NEL+1K >15-50	NEL+2K =0-15	NEL+2K >15-50
2014	1,932	1,949.72	1,939.08	1,968.18	1,946.89
2015	1,938	1,957.06	1,946.41	1,975.51	1,954.22
2016	1,946	1,964.39	1,953.74	1,982.84	1,961.55
2017	1,953	1,971.72	1,961.08	1,990.18	1,968.89
2018	1,960	1,979.06	1,968.41	1,997.51	1,976.22
2019	1,967	1,986.39	1,975.74	2,004.84	1,983.55
2020	1,975	1,993.72	1,983.08	2,012.18	1,990.89
2021	1,982	2,001.06	1,990.41	2,019.51	1,998.22
2022	1,991	2,008.39	1,997.74	2,026.84	2,005.55

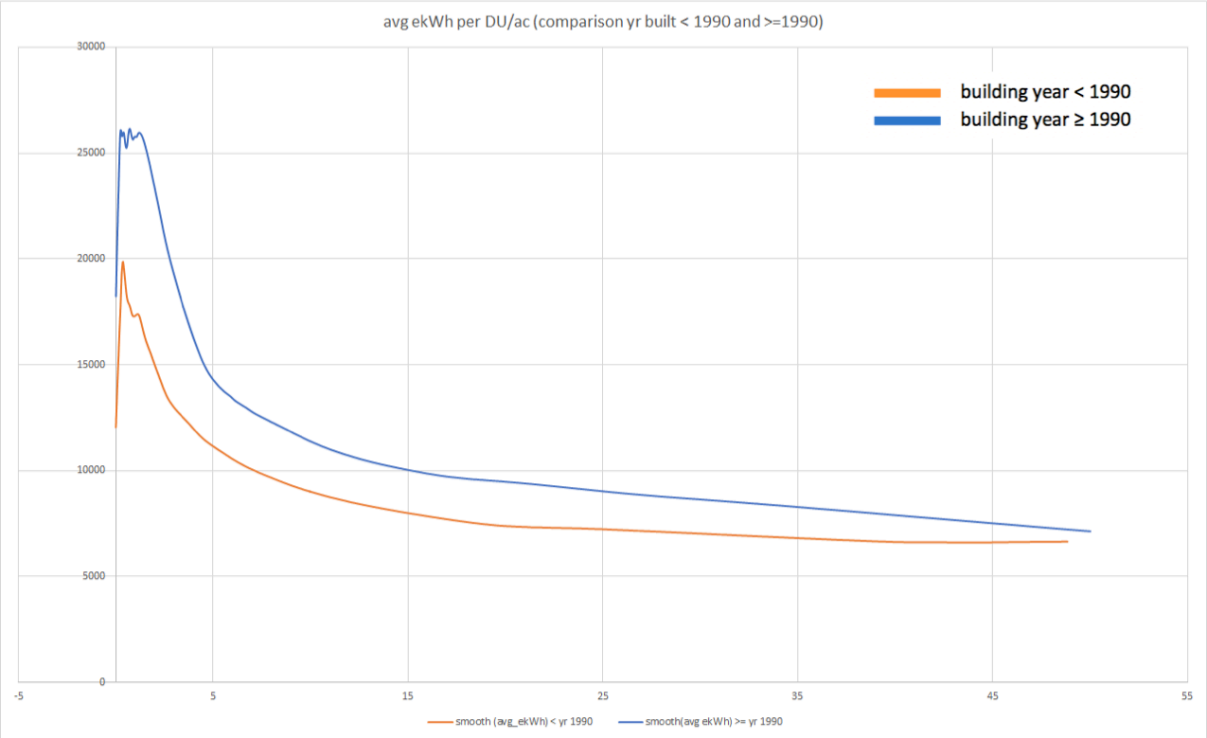


Figure 6-1. Residential energy consumption (2012) by land-use density, split by built-year

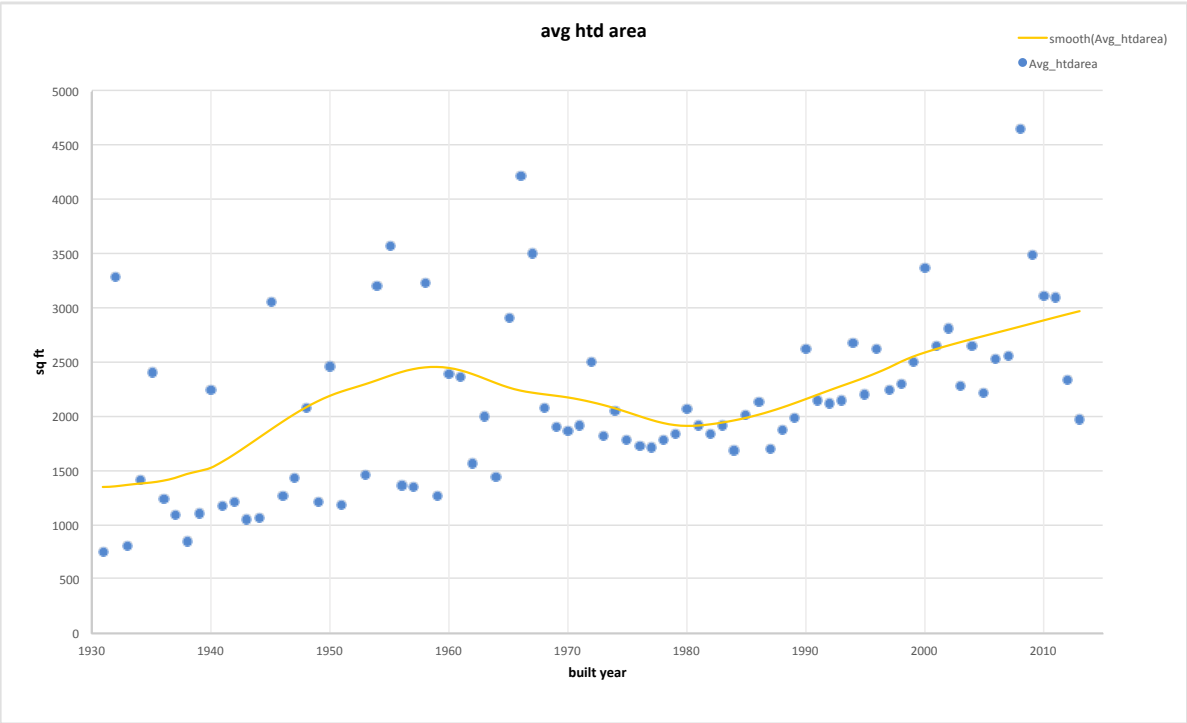


Figure 6-2. Average floor area (heated area) by built-year.

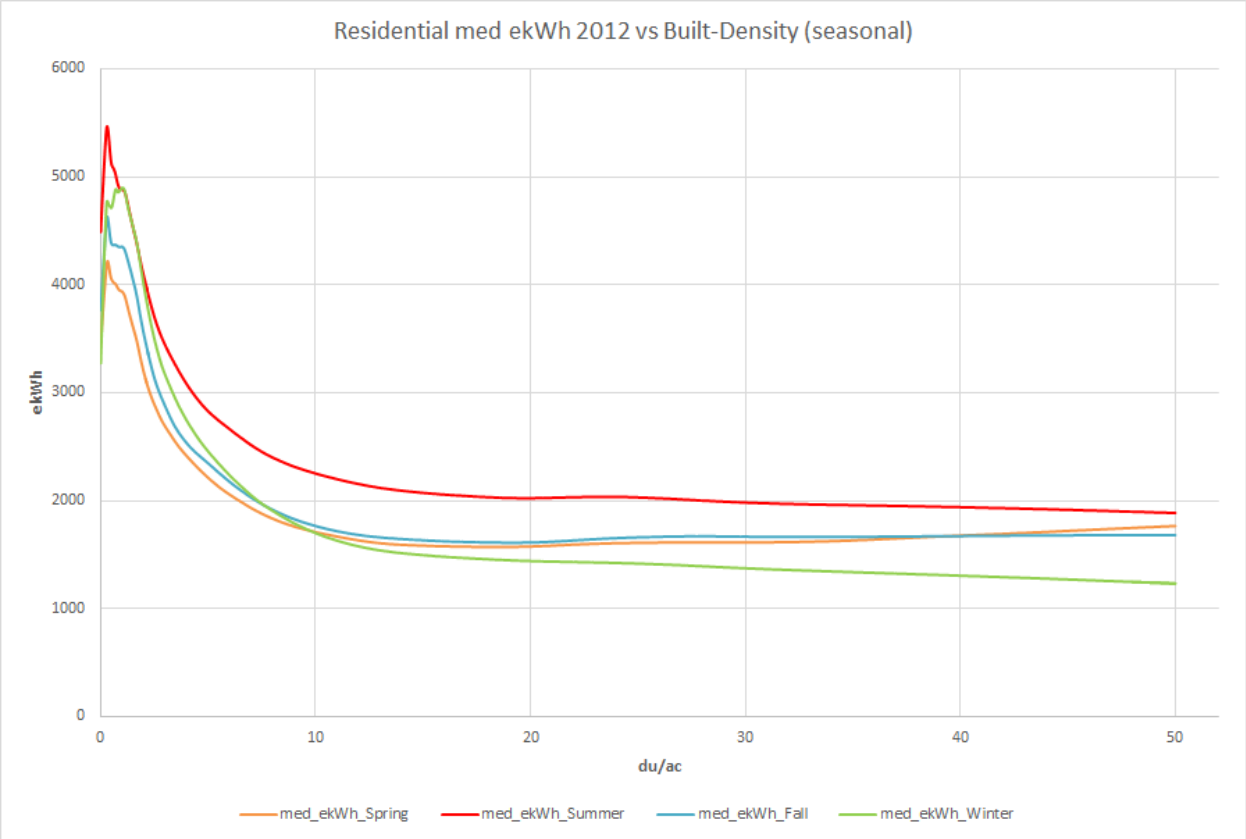


Figure 6-3. Residential energy consumption (2012) by seasons.

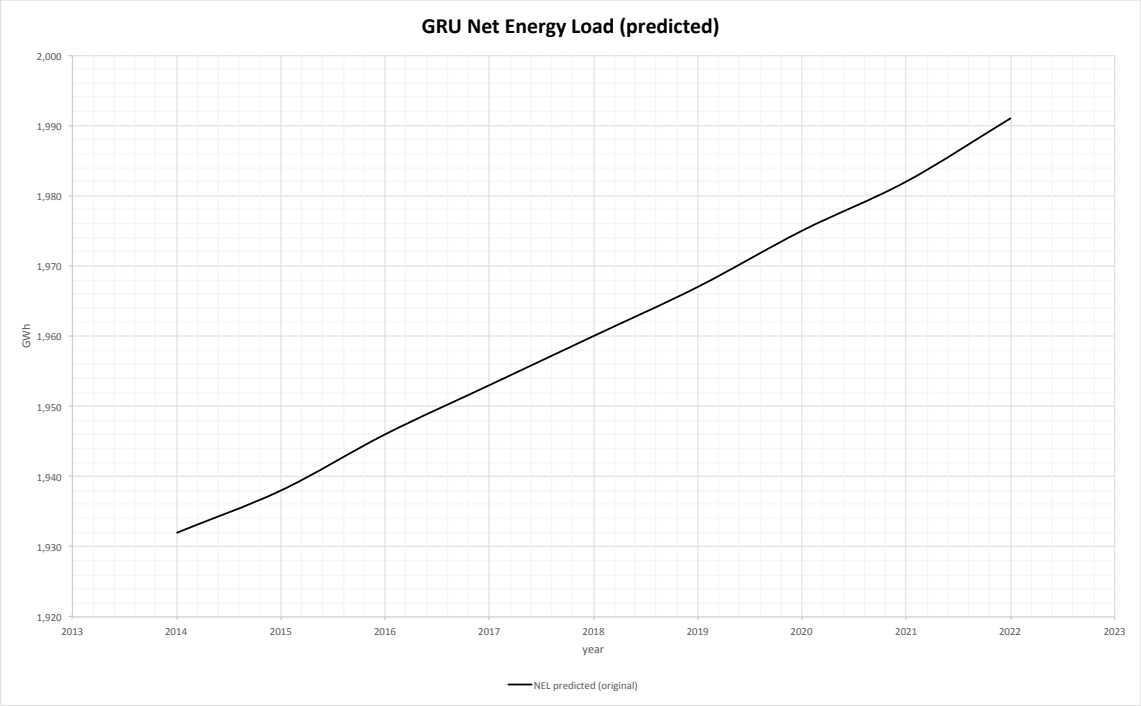


Figure 6-4. GRU's Historical and Projected Net Energy Load (NEL)

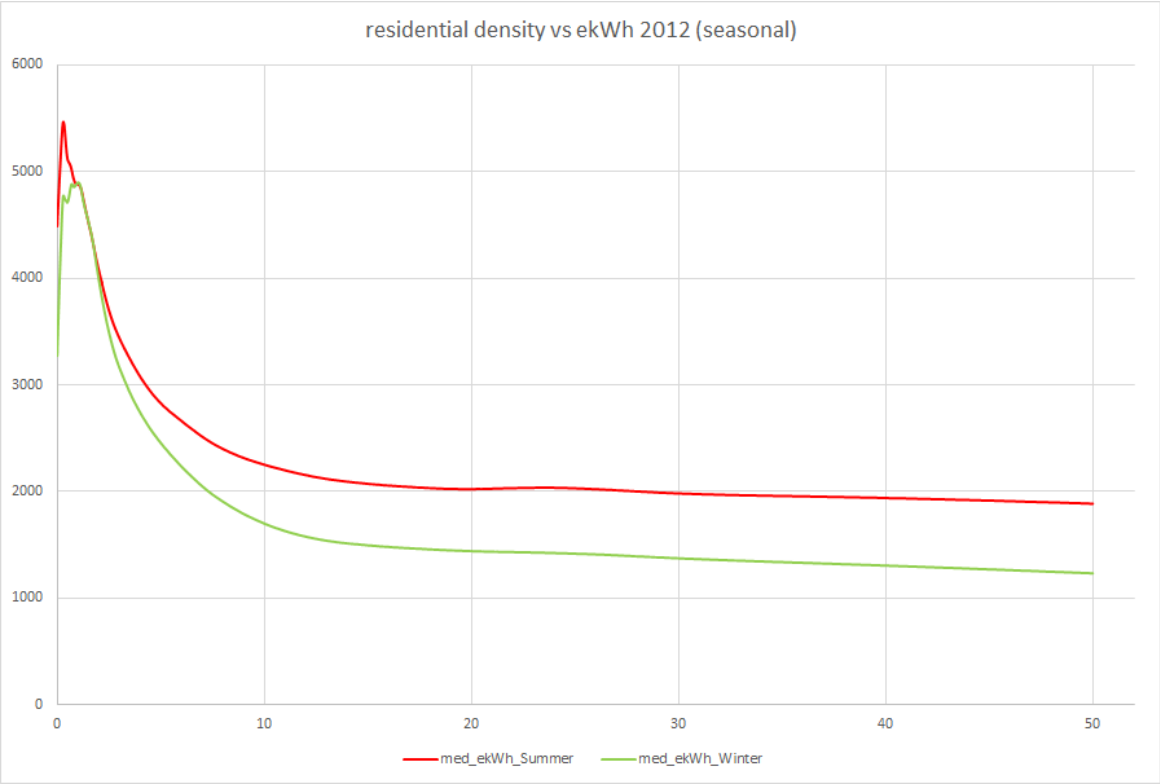


Figure 6-5. Summer/Winter residential energy consumption in ekWh vs. du/ac

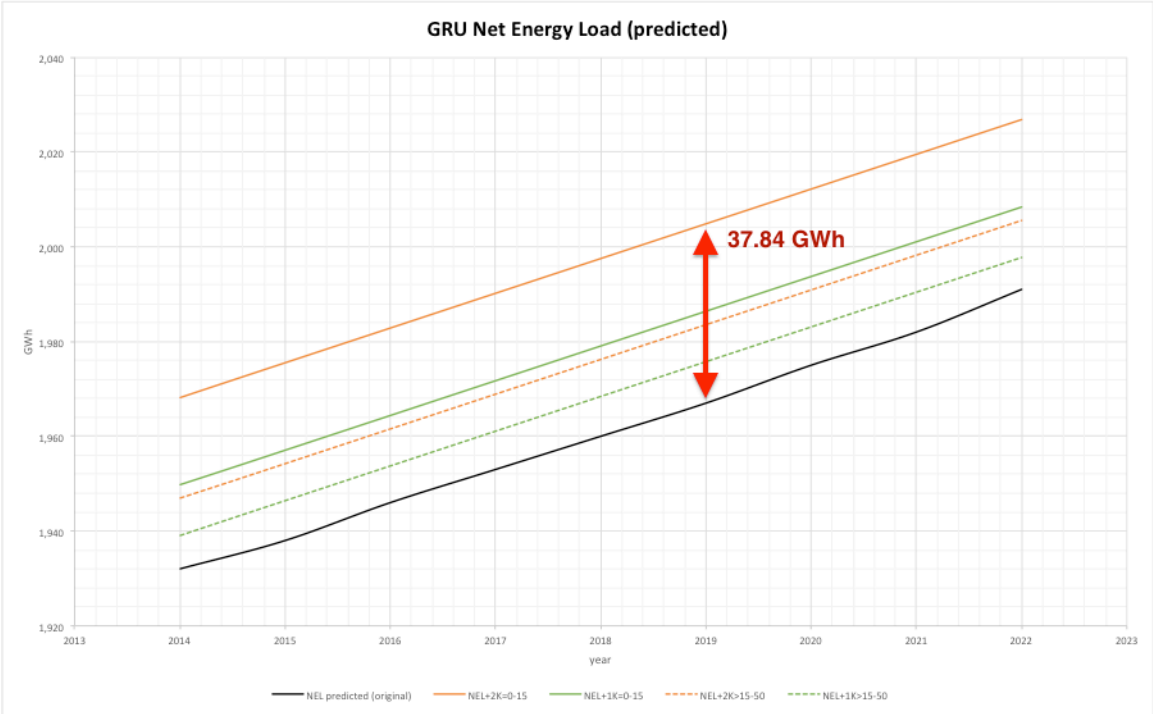


Figure 6-6. Additional NEL in various scenarios.

APPENDIX A
LIST OF DATABASES, TABLES AND FIELDS

	Tables (Database)	Fields
1.	GRU_CY2012	customer_id, premise_id, premise_parcelid, read_cycle, rate_code, service_point_id, meter_type, meter_units, usage_value, duration, is_estimate, is_cancellation, BELNR, date_to
2.	GRU_PREMISES (PREC)	premise_id, premise_house_number, premise_street_name, premise_unit, premise_city, premise_state, premise_zip_code, premise_parcelid, premise_type
3.	NAL11P201302	ID, CO_NO, PARCEL_ID, FILE_T, ASMNT_YR, BAS_STRT, ATV_STRT, GRP_NO, DOR_UC, PA_UC, SPASS_CD, JV, JV_CHNG, JV_CHNG_CD, AV_SD, AV_NSD, TV_SD, TV_NSD, JV_HMSTD, AV_HMSTD, JV_NON_HMSTD_RESD, AV_NON_HMSTD_RESD, JV_RESD_NON_RESD, AV_RESD_NON_RESD, JV_CLASS_USE, AV_CLASS_USE, JV_H2O_RECHRGE, AV_H2O_RECHRGE, JV_CONSRV_LND, AV_CONSRV_LND, JV_HIST_COM_PROP, AV_HIST_COM_PROP, JV_HIST_SIGNF, AV_HIST_SIGNF, JV_WRKNG_WTRFNT, AV_WRKNG_WTRFNT, NCONST_VAL, DEL_VAL, PAR_SPLT, DISTR_CD, DISTR_YR, LND_VAL, LND_UNTS_CD, NO_LND_UNTS, LND_SQFOOT, DT_LAST_INSPT, IMP_QUAL, CONST_CLASS, EFF_YR_BLT, ACT_YR_BLT, TOT_LVG_AREA, NO_BULDNG, NO_RES_UNTS, SPEC_FEAT_VAL, MULTI_PAR_SAL1, QUAL_CD1, VI_CD1, SALE_PRC1, SALE_YR1, SALE_MO1, OR_BOOK1, OR_PAGE1, CLERK_NO1, SAL_CHNG_CD1, MULTI_PAR_SAL2, QUAL_CD2, VI_CD2, SALE_PRC2, SALE_YR2, SALE_MO2, OR_BOOK2, OR_PAGE2, CLERK_NO2, SAL_CHNG_CD2, OWN_NAME, OWN_ADDR1, OWN_ADDR2, OWN_CITY, OWN_STATE, OWN_ZIPCD, OWN_STATE_DOM, FIDU_NAME, FIDU_ADDR1, FIDU_ADDR2, FIDU_CITY, FIDU_STATE,

		FIDU_ZIPCD, FIDU_CD, S_LEGAL, APP_STAT, CO_APP_STAT, MKT_AR, NBRHD_CD, PUBLIC_LND, TAX_AUTH_CD, TWN, RNG, SEC, CENSUS_BK, PHY_ADDR1, PHY_ADDR2, PHY_CITY, PHY_ZIPCD, ALT_KEY, ASS_TRNSFR_FG, PREV_HMSTD_OWN, ASS_DIF_TRNS, CONO_PRV_HM, PARCEL_ID_PRV_HMSTD, YR_VAL_TRNSF, EXMPT_01, EXMPT_02, EXMPT_03, EXMPT_04, EXMPT_05, EXMPT_06, EXMPT_07, EXMPT_08, EXMPT_09, EXMPT_10, EXMPT_11, EXMPT_12, EXMPT_13, EXMPT_14, EXMPT_15, EXMPT_16, EXMPT_17, EXMPT_18, EXMPT_19, EXMPT_20, EXMPT_21, EXMPT_22, EXMPT_23, EXMPT_24, EXMPT_25, EXMPT_26, EXMPT_27, EXMPT_28, EXMPT_29, EXMPT_30, EXMPT_31, EXMPT_32, EXMPT_33, EXMPT_34, EXMPT_35, EXMPT_36, EXMPT_37, EXMPT_38, EXMPT_39, EXMPT_40, EXMPT_80, EXMPT_81, SEQ_NO, RS_ID, MP_ID, STATE_PAR_ID, SPC_CIR_CD, SPC_CIR_YR, SPC_CIR_TXT
4.	Address (CAMA 2012)	OBJECTID, SHAPE, ADDRESSID, PARCEL, FULLADDR, ADDRNUM, ROADPREDIR, ROADNAME, ROADTYPE, UNIT, CITY, STATE, ZIP, ESN, MSAGCOMM, LANDMARK, E911TYPE, APR_NO, ADDRCOMMENTS, ISSUED_DATE, STATUS, LRSIDE, EDITOR_NAME, EDIT_DATE, ADDRFLAG, CAPTUREMETH, MAPSAG_EXC, OLDADDRESSID, USNGCOORD, NO_MSAG, C1_EXCEPTION, LASTUPDATE, LASTEDITOR, Field0
5.	Parcel (CAMA 2012)	OBJECTID, SHAPE, CODE, PIN, REDEVELOPMENT, X, Y, LOT, LINK_ACPA, ACCURACY, SOURCE, ACRES_CALC, ACRES_CAMA, EDITOR_NAME, EDIT_DATE, LASTUPDATE, LASTEDITOR, SRCREF, OWNTYPE, Vincent_ACPA_parcel_AREA, SHAPE_Length, SHAPE_Area
6.	Building (CAMA 2012)	OBJECTID, parcel, seq, style, effyr, beds, baths, buse, qual, extw1, extw2, actyr, cond, roof, ac, heat, fuel, stories, floor1, floor2, intw1, intw2, totarea, htdarea
7.	Code01 (CAMA 2012)	OBJECTID, type, code, description

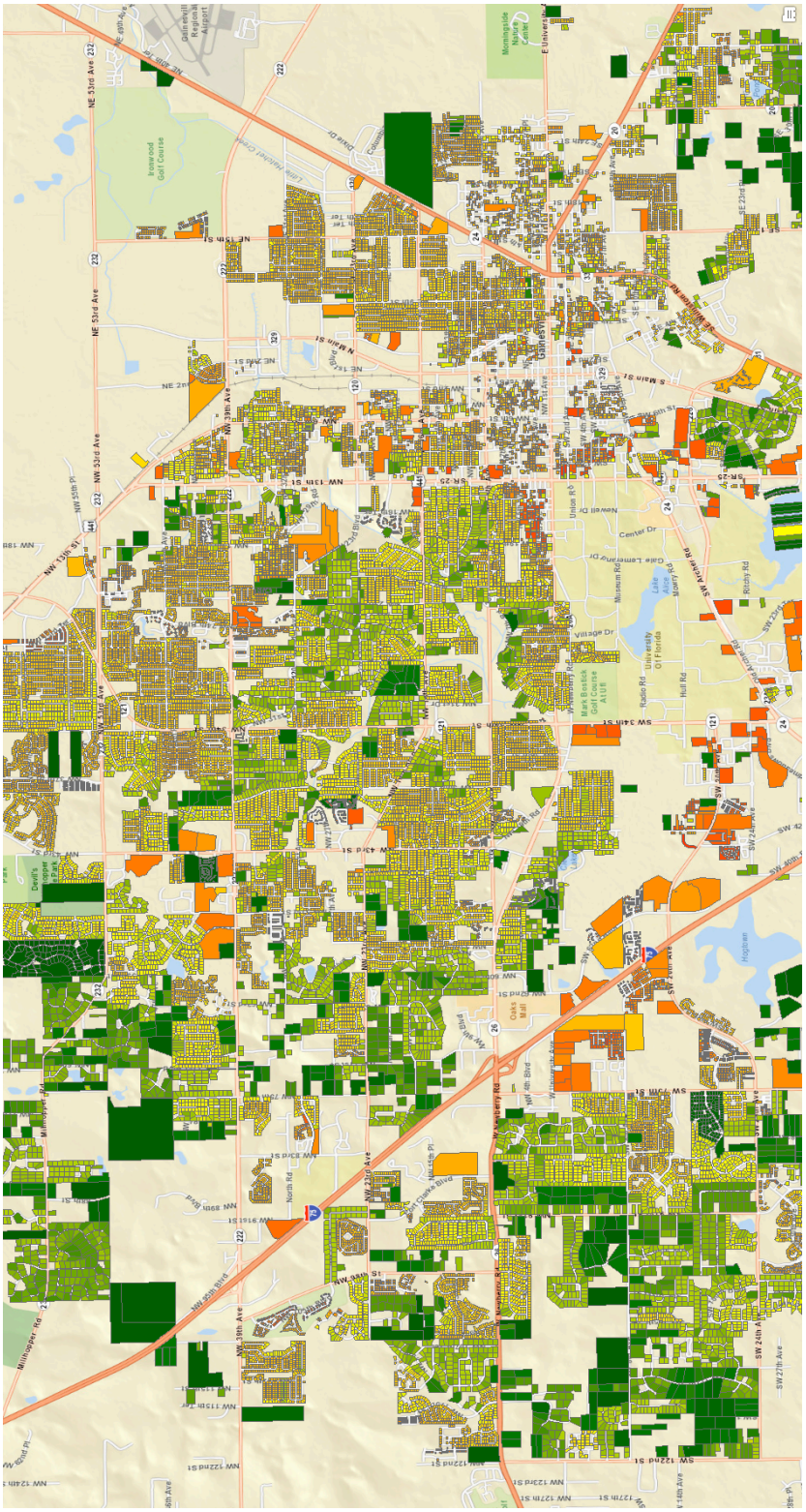
APPENDIX B
CAMA 2012 TABLE METADATA: BUILDING

#	Name	Alias	Description
1	parcel	Parcel Number	Parcel Identification Number
2	seq	Sequence	Sequence Number Used To Indicate Number Of Buildings
3	style	Style	Building Style
4	effyr	Effective Year	Year Improvement Was Built As Indicated By Its Condition. May Not Be The Actual Year Built.
5	beds	Bedrooms	Number of Bedrooms
6	baths	Bathrooms	Number of Bathrooms
7	buse	Building Use	Building Use. See BUSE Fields In GIScode01 Table For Details.
8	qual	Quality	Quality Level Of Building 1=Lowest, 3=Average, 6=Highest
9	extw1	Exterior Wall 1	Primary Material Used In Exterior walls. See EXTW Fields in GIScode 01 Table For Details.
10	extw2	Exterior Wall 2	Secondary Material Used In Exterior Walls. See EXTW Fields in GIScode 01 Table For Details.
11	actyr	Actual Year	Actual Year Improvement Was Built
12	Cond	Condition	Code To Indicate If Additional Depreciation Is Warranted Due To Special Condition. See OBSCC Fields In Code01 Table For Details.
13	roof	Roof	Type of Roof Covering. See RFCVR Fields In Code02 Table.
14	ac	AC	Type of Air Conditioning System. See AC Fields In Code01 Table
15	heat	Heat	Type of Heating System. See HTG Fields In Code01 Table.
16	fuel	Fuel	Type of Heating Fuel. See HTFL Fields In Code01 Table.
17	stories	Stories	Number of Building Stories.

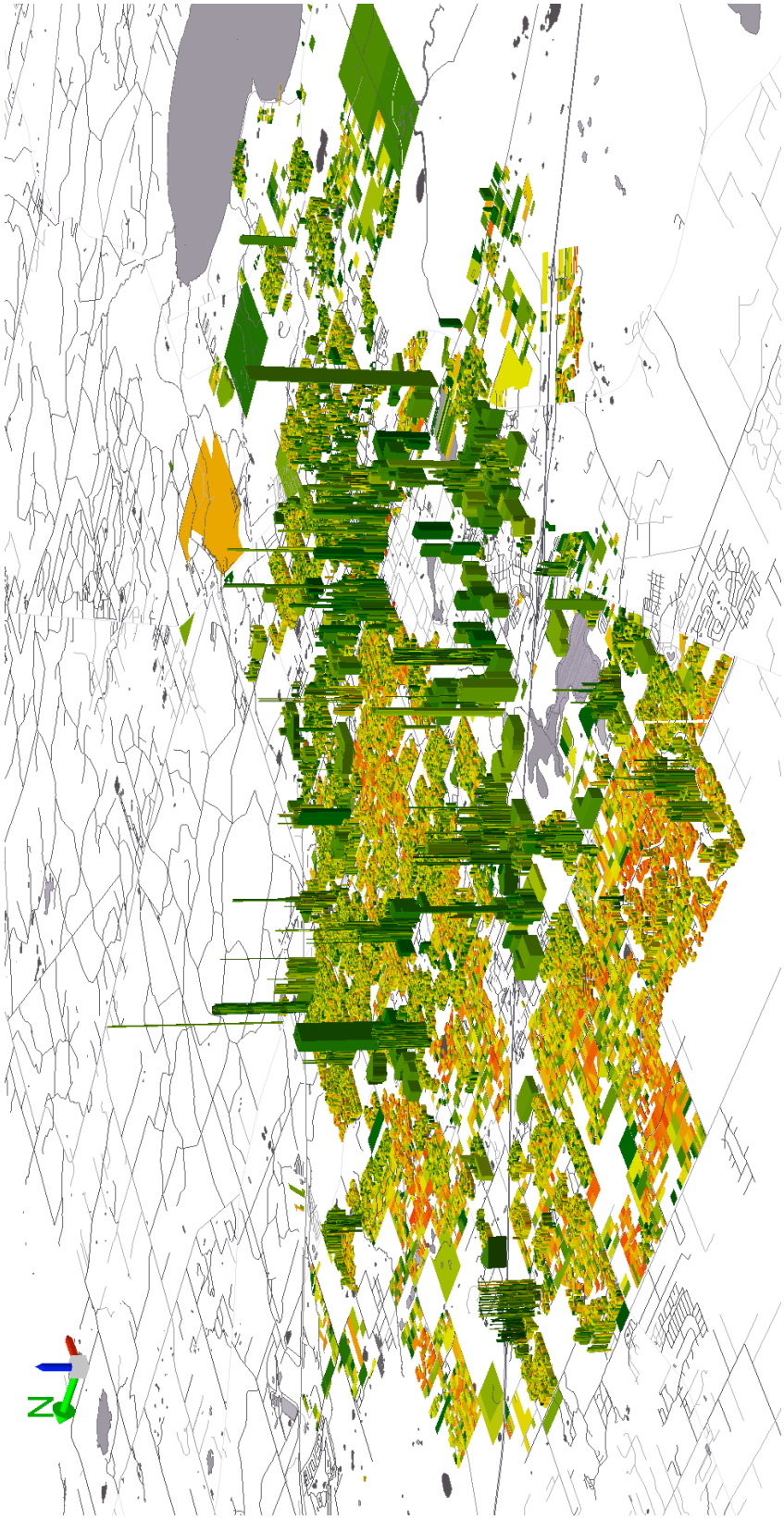
18	floor1	Floor 1	Primary Type of Flooring Material. See FLR Fields In Code01 Table.
19	floor2	Floor 2	Secondary Type of Flooring Material. See FLR Fields In Code01 Table.
20	intw1	Interior Wall 1	Primary Type of Material Used in Interior Walls. See INTW Fields In Code01 Table.
21	intw2	Interior Wall 2	Secondary Type of Material Used in Interior Walls. See INTW Fields In Code01 Table.
22	totarea	Total Area	Total Area (Heated + Sub Areas) of Building in Square Feet.
23	htdarea	Heated Area	Area of Building in Square Feet Considered To Be Enclosed And Subject To Heating And Cooling

APPENDIX C
LIST OF IMAGES

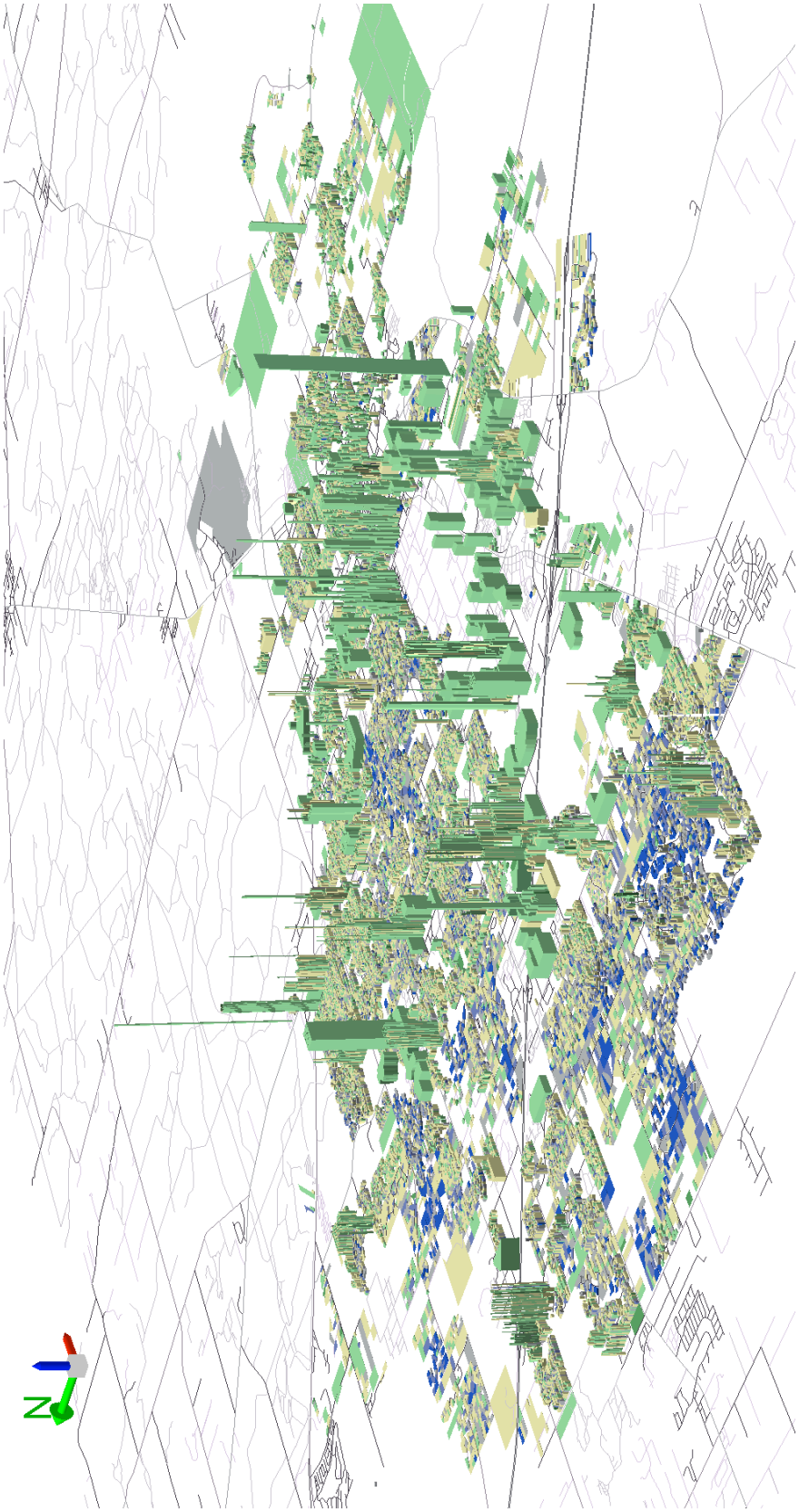
Gainesville Land-Use Density Map



3D Geospatial Model of Average ekWh per Land-Use Density



3D Geospatial Normal Distribution of the Energy Consumption



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BIOGRAPHICAL SKETCH

Djundi Tjindra received his Diplom-Ingenieur Elektrotechnik-Automatisierungs-technik degree from Märkische FH, Hagen, Germany (currently FH Südwestfalen). Professionally, he has 20+ years of experience in both information technology and creative fields. Djundi has lived and work in Europe, Asia and the United States. He speaks fluently several languages, including Indonesian, German, English and Chinese.

Djundi is interested in how information technology can contribute to the sustainable design study in the built environment. In 2012, he pursued this interest by enrolling in the Master's in Sustainable Design program - College of Design, Construction and Planning at University of Florida. He hopes that the research of this thesis can unfold into further studies. He is a photographer in his free time.