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Developing HEAT Scores with H-Res Thermal Imagery to Support Urban Energy Efficiency

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by

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Abstract

As part of The Calgary Community GHG Reduction Plan (2009) The City is seeking an implementation strategy to reduce GHGs and promote low-carbon living, with a focus on improving urban energy efficiency. The most cited obstacle to energy efficiency improvements is the lack of interest from consumers (CUI, 2008). However, Darby (2006) has shown that effective feedback significantly reduces energy consumption. To exploit these findings, the HEAT (Heat Energy Assessment Technologies) Geoweb project integrates high-resolution (H-Res) airborne thermal imagery (TABI 1800) to provide unique energy efficiency feedback to Calgary homeowners in the form of interactive HEAT Maps and Hot Spots (Hay et al., 2011). As a part of the HEAT Phase II program, the goal of this research is to *provide enhanced feedback support for urban energy efficiency* by meeting two key objectives: (i) develop an appropriate method to define HEAT Scores using TABI 1800 imagery that allows for the comparison of waste heat of one or more houses with all other mapped houses in the community and city, and (ii) develop a multi-scale interactive Geoweb interface that displays the HEAT Scores at City, Community and Residential scales. To achieve these goals, we describe the evolution of three novel HEAT Score techniques based on: (*i*) a Standardized Score, (*ii*) the WUFI® model and Logistic Regression and (*iii*) a novel criteria weighted method that considers: (*a*) heat transfer through different roofing materials, (*b*) local climatic conditions and (*c*) house age and living area attributes. Furthermore, (*d*) removing or adding houses to analysis based on this 3rd technique, does not affect the HEAT Score of other houses and (*e*) HEAT Scores can be compared within and across different cities. We also describe how HEAT Scores are incorporated within the HEAT Geoweb architecture. It is envisioned that HEAT Scores will promote energy efficiency among homeowners and urban city planners, as they will quantify and visualize invisible waste heat, and provide a public comparison of urban energy efficiency at the scale of homes, communities and cities. Analysis is conducted on 9279 houses in 12 communities over the SW quadrant of The City of Calgary and their results are publically available for comparison at www.saveheat.co.

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List of Abbreviations

CO_2e – Carbon dioxide equivalent

EGR – EnerGuide Rating

ERS – EnerGuide Rating System

GCP – Ground Control Point

GEOBIA – Geographic Object-Based Image Analysis

GHG – Green House Gas

HEAT – Heat Energy Assessment Technologies

JSON – JavaScript Object Notation

NRCAN – Natural Resource Canada

OGC – Open Geospatial Consortium

OLS – Ordinary Least Squares

TABI – Thermal Airborne Broadband Imager

TIR – Thermal Infrared

VGI – Volunteered Geographic Information

WUFI® – Wärme und Feuchte instationär

Chapter 1: Introduction

1.1 The Problem

Canada has the 3rd highest ecological footprint in the world of 7.6 gha (global hectares per person), well beyond the global average of 1.8 gha per person (Footprint, 2008). An ecological footprint measures the amount of resources we consume and compares this to nature's ability to provide these resources and absorb waste. In 2007, Calgary's ecological footprint was estimated to be between 9.5 and 9.9 gha, of which over 50% was from energy use related to carbon dioxide (CO_2) emissions. If everyone on Earth consumed 7.6 gha like the average Canadian, humanity would require 4 ¼ planets to support itself (Footprint, 2008). An important reason for this massive ecological footprint is the Canadian urban energy demand, which has grown by nearly 20% over the last five years and continues to increase with growing population and further urbanization. This rapid urbanization involves the construction of new buildings, which on average emit 35% of green house gasses (GHGs) into the atmosphere, generate 10% of the total airborne particulate matter, consume 50% of Canada's natural resources and account for more than 30% of all energy used in Canada (CUI, 2008). The majority of this energy is used for *space* and *water heating*. Consequently, space heating provides one of the best opportunities for energy savings through improvements in building design and local alternative energy sources.

Along these lines, The City of Calgary has established an ambitious but necessary target to reduce its GHG emissions by 50% at the community level before 2050. To achieve this, the *Calgary Climate Change Accord* (2009), the *Calgary Community Greenhouse Gas (GHG) Reduction Plan* (2011), and *The 2020 Sustainability Direction* (2010) are seeking an

implementation strategy to reduce (GHG) emissions and promote low-carbon living that is cost-effective, actionable and reaches a wide city audience. The city has also developed a multi-stakeholder plan and implementation strategies to reduce community wide GHG emissions in support of *Imagine Calgary's* community goals (Pembina Institute, 2011). One of the actions identified likely to be necessary to meet the city's emission reductions was the *energy labeling* of buildings. These plans also identified that in order to achieve these GHG reduction targets, The City of Calgary has to implement energy efficiency improvements. However the most cited obstacle to energy efficiency improvements is the lack of interest from clients and customers (CUI, 2008). Upon reflection, this comes as little surprise when one considers …*what does energy efficiency look like, where is it located*... and if it cannot be seen, or located… *how can it be managed?*

Darby (2006) has shown that effective *feedback* significantly reduces energy consumption. Furthermore, customer information and behavior programs have explored energy feedback and discovered promising results regarding energy efficiency savings. The following section reviews pertinent behavioral science studies applied to energy efficiency.

1.2 Energy Efficiency and Behavioral Analysis

Cherfas (1991) cautions that if human behavior is not analyzed within the energy efficiency context, lifestyle changes could consume all the energy that is saved through other means. Therefore *behavior changes* play an important role in today's energy efficiency programs. Taking this as a cue, behavioral change theories have been applied within the energy efficiency context, resulting in a number of insights that are increasingly incorporated within the efficiency programs, including: (i) Social norm, (ii) Feedback, (iii) Public commitment and (iv) Goal Setting (Ashby et al., 2010).

Social norm represents how people are influenced by others actions and beliefs even though they seldom admit to being influenced by others (Cialdini, 2007). Research consistently shows that people tend to change their behavior closer to the societal norm (i.e., the standard, model or pattern regarded as 'typical'). *Feedback*, within an energy efficiency context refers to providing individuals with meaningful information on their energy use and related costs. Feedback can be either indirect or direct (Darby, 2006). *Indirect feedback* refers to providing individuals with enhanced billing and estimates of their savings. *Direct* or *real-time feedback* refers to providing individuals with (near) real-time energy consumption information. Smart meters are one such direct feedback device that record detailed consumption information for individual appliances. For example, smart meters such as (i) the eMonitor by Powerhouse Dynamics (www.powerhousedynamics.com), (ii) the ecobee Smart Thermostat by ecobee (www.ecobee.com), and (iii) the Nest Learning Thermostat by Nest (nest.com) allow the user to setup their thermostat control and/or monitor their appliances' energy consumption. This detailed information is then made available to consumers in the form of statistical evaluations such as weekly, monthly and yearly averages, or even second by second maximum energy-use per monitored circuit. These evaluations can be accessed by tools such as personalized web-sites, weekly email summaries, and in-home displays.

An assessment of several recent case studies shows that energy feedback behavior programs conducted in the residential sector prove to be a promising source of energy efficiency savings (Mahone & Haley, 2011). These case studies also noted the following critical findings:

i. Depending on the kind of feedback it is estimated that users will be able to reduce their total energy consumption somewhere between 1 and 7%.
ii. Comparing and focusing on small social groups (i.e., neighborhoods) to achieve certain energy-use goals can be very successful.
iii. *Games* and *contests* are promising areas of further research.
iv. Direct feedback achieves higher savings per participant than indirect feedback; however, indirect feedback has more potential savings opportunity because of its *opt-out* nature and *wider reach*.

Darby (2006) also notes that feedback is a useful self-learning tool that helps consumers understand and adjust their behavior to energy consumption. Abrahamse et al. (2005) reviewed thirty-eight field studies that were aimed at encouraging households to reduce energy consumption. The majority of these studies found feedback to be an effective means of generating energy savings. A similar study was conducted by Mountain (2006) to determine whether a real-time feedback device is sufficient to encourage residential customers to reduce their energy consumption and concluded that feedback is indeed effective in energy conservation. An early study conducted by Burn and Oskamp (1986) also showed that individuals who *publically commit* to change their behavior are more likely to follow through, and that individuals, or households, *setting specific goals* for reducing their energy efficiency are also more likely to carry out the necessary actions to achieve them.

Opower, a company which runs *non-price* energy conservation programs mails *Home Energy Report* letters (HERs) to homeowners. A non-price energy conservation program typically takes carefully crafted psychological cues from behavioral science to influence the energy use behavior of participants (Allcott, 2010). HER letters compare a household's energy use to that of similar neighbors and provide ‘targeted’ energy conservation tips or

recommendations. Opower has also incorporated *social norm theory* from behavioral science to provide neighborhood comparisons of energy consumption[1]. The HER's also feature smiley-face emoticons for the most energy-efficient homes, a feature that Opower added after research showed that some consumers who used less energy than average started using more once they knew the norm was higher (Rahim, 2010). Opower also apply another best practice borrowed from behavioral science, *loss aversion*. That is, people tend to strongly prefer *avoiding losses* than *acquiring gains* (Laskey & Kavazovic, 2010).

While Opower and other mentioned studies provide feedback and comparison in the form of statistics and numbers, projects like the *New York City Building Energy Map* (2012) provide visual feedback in the form of colored maps. That is, they published simple colored maps online to show the estimated energy consumption (i.e, total energy used for space heating, cooling, water heating, and electrical appliances) of buildings in New York city which allows for the comparison of buildings.

Lutzenhiser (1993) has suggested that cooperative research ventures between the academic and private sectors can benefit from integrating the strengths of social and behavioral science, marketing research and building science, in order to motivate a large number of individuals to reduce their energy consumption. It is also clear that consumers must be provided with feedback that is easy to understand, convenient, engaging, meaningful and beneficial; and that the *effectiveness* of this feedback is heavily dependent on consumer's acceptance and participation. Despite these barriers, research consistently recognizes that many consumers are willing to play a vital role in energy management.

[1] It is interesting to note that Opower's chief scientist is Dr Robert Cialdini, Regents' Professor Emeritus of Psychology and Marketing at Arizona State University and the author of "*Influence: The Psychology of Persuasion*," a 1984 book on persuasion that has sold over two million copies and has been translated into 26 languages (sources: http://en.wikipedia.org/wiki/Opower and http://en.wikipedia.org/wiki/Robert_Cialdini).

Furthermore, utility companies can benefit from using this information to better manage their energy demand. While this is still an emerging area, program administrators aiming to leverage human behavior to improve energy efficiency can learn a great deal from the research that has already been conducted in the social sciences. Currently in Canada, the only widely recognized way to 'formally' evaluate the energy efficiency of a home is to obtain an *EnerGuide Rating* from certified energy advisors. The following section introduces the EnerGuide Rating System and discusses its limitations.

1.3 The EnerGuide Rating System

Natural Resources Canada (NRCan) created the EnerGuide Rating System (ERS) to provide a standard measure of a home's energy performance. This rating system allows for comparison of the energy efficiency of comparable homes in neighborhoods across Canada (though we note that such comparison details are not provided by NRCan). An ERS shows a home's present level of energy efficiency and provides recommendations for upgrades that would increase the homes energy efficiency. An ERS can be obtained by a homeowner contacting an *energy advisor* who will assess their home's structural characteristics, such as construction material and building envelope type that will then be used to model the home's energy consumption. The advisor will also perform a blower *door test* and use these results as input into the HOT2000 energy analysis software, which are used to compare a home with a reference house of a similar size in a similar climatic region. A home energy efficiency level is rated on a scale from 0 to 100. A rating of 0 means the home is poorly insulated, has major air leakage and extremely high energy consumption. A rating of 100 means the home is well insulated, airtight and highly energy efficient (Kordjamshidi, 2011).

1.3.1 ERS Limitations

It is important to note that this rating is only an *estimate* of the home energy consumed each year, not the actual amount (which will vary by number of occupants, consumption habits and life style). Furthermore, (i) it can only be provided by a certified energy advisor (thus a typical homeowner cannot conduct it), (ii) it is not easy to calculate and understand, (iii) it requires the calculation of hundreds of variables and two or more home visits (including the noted mechanical blower door test) each taking several hours to complete. It is also (iv) expensive to obtain ($300-$500+), (v) it does not provide the owner with any way to monitor their energy efficiency (i.e., waste heat mapping or energy consumption over time) and (vi) due to privacy restrictions, owners cannot see how their house compares to other houses, unless an owner physically makes their house data available.

Another form of feedback that may aid in improving a building's energy efficiency is to use a thermal sensor to identify temperature anomalies in the building envelope[2] where *waste heat* is leaving the structure, and to correct for them. In this research, waste heat represents expensive heated air that is leaving a house instead of staying inside and keeping the house warm. Additionally, the ***waste heat measured from a building's envelop may be considered a measure of the energy efficiency of the structure itself, rather than the energy consuming devices inside it.*** When appropriately processed, waste heat maps can: (i) be simple to understand, (ii) relatively[3] inexpensive to produce, (iii) facilitate a meaningful comparison of heat loss between different houses, and (iv) through monitoring, provide

[2] The *building envelope* (or building enclosure) is the physical separator between the interior and the exterior environments of a building. It serves as the outer shell to help maintain the indoor environment (source: http://en.wikipedia.org/wiki/Building_envelope)

[3] *Relative* – based on acquiring thermal information for a large number of homes within a single acquisition.

quantitative evidence of heat loss over time. The following section briefly reviews several modern thermal infrared waste heat mapping projects.

1.4 Thermal Infrared Remote Sensing and Heat Loss mapping

Thermal infrared (TIR) remote sensing or *Thermography* is traditionally used in urban environments for (i) roof moisture surveys, (ii) residential heat loss mapping, (iii) urban heat island analysis, (iv) land-cover classifications, and (v) the development of surface atmosphere exchange models (Voogt and Oke, 2003; Allinson, 2007; Weng 2009). When conducting residential heat loss (i.e., waste heat) mapping with TIR imagery, the identification of hot spots is commonly used to quantify the energy efficiency of buildings. To better understand how thermal infrared imagery can be used to map heat loss, five fundamental principles of thermal radiation are introduced in the following section.

1.4.1 Principles of Thermal Remote Sensing

Any object with a temperature above 0 degree Kelvin (absolute zero or -273.15^{o} C) radiates energy (known as *thermal radiation*) in the *infrared* electromagnetic spectrum. This spectrum covers a range of wavelengths from 0.7 to 100 micrometers, which is divided into two types: the *reflected infrared* (ranging from .7 to 3 micrometers) and the *thermal infrared* (ranging from 3 to 100 micrometer). In order to understand the relationship between thermal remote sensing and temperature it is important to understand five key principles of thermal radiation: (i) Planck's law (Rybicki & Lightman, 1979), (ii) Wien's displacement law (Mehra and Rechenberg, 1982), (iii) Stefan-Boltzmann law (Jensen, 2007), (iv) Kirchoff's Radiation law (Kirchhoff 1896), and (v) emissivity (Jacob et al., 2004).

1.4.1.1 Planck's Law

Planck's law defines the radiation intensity of a blackbody[4] as a function of wavelength and temperature. This is given by the following formula:

$$u(\lambda, T) = \frac{2hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda kT}} - 1} \tag{1.1}$$

where u is the radiation intensity, λ is the wavelength, T is the absolute temperature in K, h is the Planck constant (6.626 x 10^{-34} J.s), c is the speed of light (3 x 10^{8}m/s) and k is the Boltzman constant (1.380 $\times 10^{-23}$ J/K). Essentially, Planck's law illustrates that the warmer a body is, the greater its emissions at each wavelength.

1.4.1.2 Wien's Displacement Law

The relationship between the true temperature of a blackbody (T) in degrees Kelvin and its dominant wavelength (λ_{max}) of peak spectral exitance is given by:

$$\lambda_{max} = \frac{k}{T}\ \mu m \tag{1.2}$$

where, k is the Wien's displacement constant (2898 $\mu m\ K$) and T is the temperature in K. This is used to identify the dominant wavelength of an object or material, which can then be used to design the thermal sensor. It should be noted that the above equation gives a discrete value. However, a range of wavelengths (i.e., bandwidths) can also be defined for an object with a corresponding range of associated temperatures.

1.4.1.3 Stefan-Boltzmann Law

The total spectral radiant energy exiting a blackbody per second, per unit area is proportional to the fourth power of the absolute temperature and is given by:

[4] A theoretical body that absorbs all incident electromagnetic radiation (EMR) and reflects none.

$$M = \sigma T^4 \tag{1.3}$$

where, M is the total radiant exitance in W.m^{-2}, σ is the Stefan-Boltzmann constant (5.6697 x 10^{-8} W m^{-2} K^{-4}), T is temperature in K. Consequently, as temperature increases, the total radiant energy increases and the radiant energy peak shifts to shorter wavelengths. This law is used in thermal remote sensing to identify the total amount of radiant energy *'seen' or recorded* by the sensor.

1.4.1.4 Emissivity

Emissivity (ε) is defined as the ratio between the radiance emitted by a real world selective radiating body (Mr) and a blackbody at the same kinetic temperature (Mb).

$$\varepsilon = Mr \,/\, Mb \tag{1.4}$$

By knowing the emissivity[5] of a material, and the amount of energy emitted, the energy (equation 1.3) can be converted into 'true' kinetic temperature values and recorded as an image.

1.4.1.5 Kirchoff's Radiation Law

The spectral emissivity $\epsilon(\lambda)$ of an object generally equals its spectral absorbance $\alpha(\lambda)$:

$$\epsilon(\lambda) = \alpha(\lambda) \tag{1.5}$$

Consequently, "good absorbers are good emitters and good reflectors are poor emitters." This law can be used to determine the emissivity of an object. All selective radiating bodies have emissivity ranging from 0 to 1, depending on the wavelength of the energy being considered. Thus, two different objects could have the same *true* kinetic

[5] Conceptually, emissivity represents a measure between and 0 and 1 that defines a specific materials ability to absorb and emit EMR.

temperature, but different *apparent* temperatures when sensed by a thermal radiometer, due to their differences in emissivity. *True* or *kinetic* temperature can be calculated by knowing the emissivity of each material being sensed, as well as its *apparent* temperature (which is what the sensor 'sees'). This is essential for converting the relative temperature of an object (as viewed by the sensor) to its *true* kinetic temperature. This can then be used for comparing heat loss of a specific building with all other buildings in the study area. The following section briefly introduces a sample of past and present urban heat loss mapping studies.

1.4.2 A brief survey of Urban Heat Loss mapping studies

Over the last 13 years, a number of urban heat loss mapping projects have been conducted around the world. The following list briefly introduces eight of them.

(i) In winter 2000 and 2007 the London Borough of Haringey conducted airborne TIR heat loss surveys to provide residents with an idea of the energy efficiency of their homes (Haringey, 2007).

(ii) In 2001 and 2013 the city of Aberdeen, Scotland conducted a thermal heat loss mapping, in order to identify the least thermally efficient areas and house types, within the city and so target home energy efficiency promotions to those areas (Aberdeen, 2013).

(iii) In 2009, Worcestershire, England conducted the *Warmer Worcestershire* project to encourage residents to improve their building's energy efficiency and save their money (Worcestershire, 2009).

(iv) In 2009 the city of Exeter, England conducted a heat loss survey using airborne thermal imagery with the goal to increase public awareness of energy efficiency and motivate home owners to adequately insulate their houses (Exeter, 2009).

(v) In 2010 Paris, France processed information from aerial thermography to show heat loss from buildings on a scale of six colors. This was provided as a web based decision support service to the residents for improving their building's energy efficiency (Paris, 2010).

(vi) In 2011 the inner city of Odense, Municipality of Frederiksberg, and Municipality of Lyngby-Taarbaek in Denmark conducted a similar study. They showed a simple color coded temperature map showing temperature variations on a building's roof (Denmark, 2011).

(vii) In 2011 States of Jersey, Jersey conducted a heat loss map to help residents understand how much heat is being lost from their homes (States of Jersey, 2011).

(viii) In 2012 Portsmouth City Council, England took a thermal image of the whole city to help residents understand the amount of heat lost from their properties (Portsmouth, 2012).

In each of these heat loss mapping projects, the thermal data were published online as very simple temperature class maps, with limited capability for in-depth visual, statistical or location-aware analysis (Hay et al., 2010). Additionally, the 2007 survey conducted in London Borough of Haringey had numerous geometry and radiometric normalization problems with the imagery that were not addressed, leading to limited utility (Hay et al., 2011). Recently the HEAT project is developing a more sophisticated image processing and Geoweb systems to overcome these challenges with heat loss surveys (Hay et al., 2011).

1.5 The HEAT Project – Phase I Limitations

Building on ideas from behavioral science and improving upon airborne TIR heat loss mapping projects, the HEAT (Heat Energy Assessment Technologies) project has evolved.

The HEAT project is a free Geoweb mapping service that is designed to empower the urban energy efficiency movement by allowing homeowners to visualize the amount and location of waste heat leaving their homes and communities as easily as clicking on their house in Google maps (Hay et al., 2010; 2011). The HEAT project provides meaningful visual feedback to residential homeowners in the form of interactive HEAT Maps, HEAT Scores, Hotspots and energy consumption models (see Chapter 2 for details). In 2010, the HEAT Phase I pilot project evaluated 368 residences in the Brentwood community of Calgary, Alberta, Canada. This pilot project used TABI 320 (Thermal Airborne Broadband Imager) data with a 1.0 m spatial resolution, a 0.1^{o}C thermal resolution, and a narrow swath width of 320 pixels. Based on the swath width alone, data acquisition over a large urban area (especially when considering a 20-30% overlap required between each flight line) is impractical in terms of acquisition time and costs. For example, under 'good' weather conditions it is estimated to take approximately 15 days to image the entire (25km x 35km) City of Calgary (Hay et al., 2011), over which time thermal conditions would significantly change due to the weather conditions. Furthermore, the *HEAT Scores* (i.e., waste heat metrics) that were developed in Phase I to provide a relative comparison of building heat loss were only based on the average rooftop temperature of each house (derived from the representative 'roof' pixels within the thermal image). They did not take into account the living area, or any other factors that would influence the energy consumption of a house. Eventually, this simplicity was recognized as a critical drawback, significantly limiting the utility of HEAT scores.

In order to overcome these limitations, HEAT Phase II (2011-2013) was conducted over a larger area using the new TABI 1800 sensor. This sensor has a larger swath width

(1800 pixels vs. 320) enabling faster and less expensive data collection. This study was conducted within HEAT Phase II with the goal to improve upon the earlier HEAT Scores and display them on a multi-scale user interface that is Geoweb enabled. The following section describes these objectives in detail.

1.6 Research Objectives

There are two key objectives of this thesis. The first is to develop an appropriate method to define HEAT Scores. HEAT Scores are ranked numbers that range from 0 to 100 (cold to hot) and represent the amount of waste heat leaving a building. A house with a HEAT Score of 1 represents very low waste heat, consequently it consumes a small amount of energy for space heating. A house with a HEAT Score of 100 represents very high waste heat, consequently it consumes a large amount of energy for space heating. Based on the behavioral science concept of feedback, HEAT Scores need to be developed to allow for a meaningful comparison of waste heat of one or more houses with all other houses in their community and city, and ideally for a comparison between participating communities and cities.

The second objective of this thesis is to develop a multi-scale and interactive user interface to display the developed HEAT Scores on the HEAT Geoweb site (www.saveheat.co). The developed HEAT Scores need to be shown at three different levels namely, (i) City, (ii) Community, and (iii) Residential. At the city level, HEAT Scores will be interpolated and shown as a color coded City HEAT map (blue to red, i.e., low to high waste heat). This will provide the users with an idea of the general trend of the whole city. At the community level the houses will be classified into ten color classes (blue to red)

based on their HEAT Score and showed as Community HEAT maps. At the residential level the HEAT Score value of individual home will be shown.

HEAT Scores developed in this study are made publically available, free of charge on the HEAT Geoweb site (www.saveheat.co). This is intended to indirectly promote users to change their energy use behavior closer to the social norm through several feedback mechanisms.

1.7 Organization of the Thesis

This thesis is organized into 4 chapters. Chapter 1 provides an overview of the problem of increasing urban energy consumption, a review of relevant energy efficiency behavior research, an introduction to waste heat mapping with Thermal Remote Sensing and a description of the thesis objectives. Chapter 2 is organized into four sections. The first section introduces the study area and data required to accomplish the objectives of the thesis. The second section describes three different methods used to develop HEAT Scores. The next section describes the technique used to evaluate the method for defining HEAT Scores. The final section of this chapter describes the HEAT System architecture and multi-scale user interface where the developed HEAT Scores are published. Chapter 3 contains the Results and Discussion. The first two sections of this chapter discuss the results of the HEAT Scores. The final section of this chapter discusses methodological limitations and potential solutions. This is followed by conclusions and future work in chapter 4.

Chapter 2: Data and Methods

This chapter is divided into four sections. The first section introduces the study area and different types of data used in this study. The second section describes three different methods used to calculate HEAT Scores. The following section describes a technique to evaluate the method used for generating HEAT Scores. The final section describes the HEAT Geoweb system architecture and its multi-scale user interface.

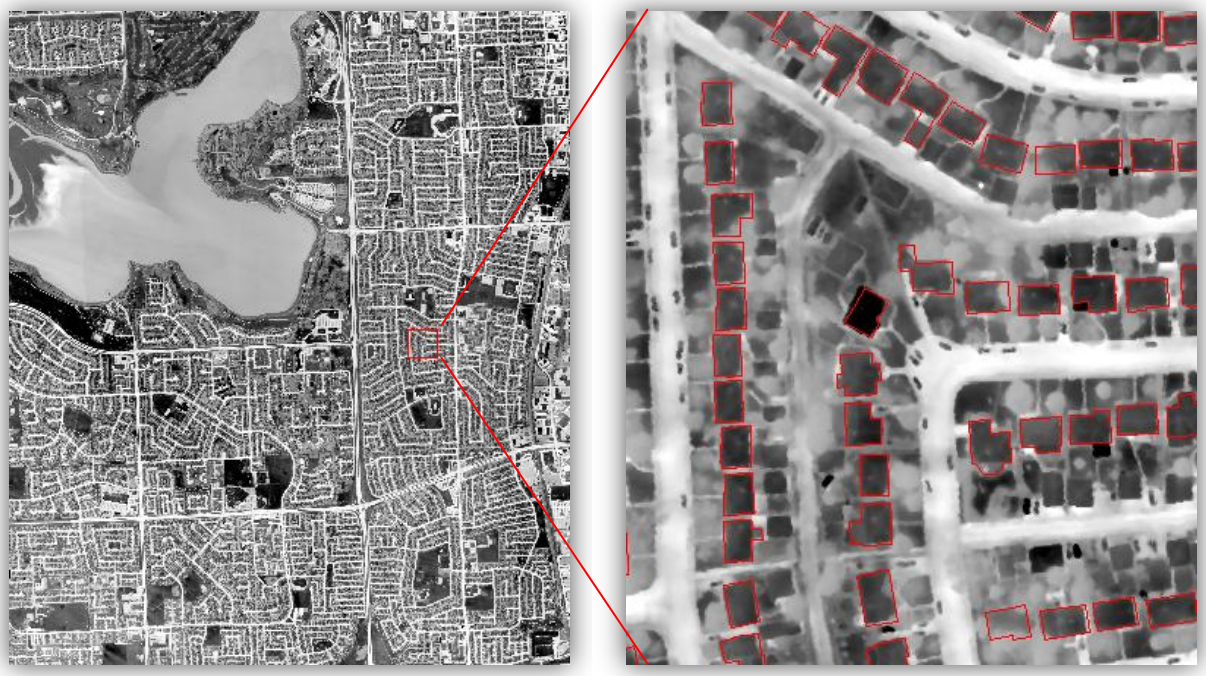
2.1 Study Area and Data

This study is conducted in the SW quadrant of The City of Calgary. It covers an area of approximately 21 km^2 (4.19 x 4.93 km, or 8377 x 9869pixels) that represents 12 established communities and contains 9279 homes. In this study area Kingsland community[6] was established as early as 1957 while Cedarbrae community[7] was established in 1973. Houses in this site were constructed as early as 1900 to as recent as 2011. The living area of houses varies from 65 sq.m to 500+ sq.m (i.e., 700 sq.ft – 5300+ sq.ft). Living area is defined as the living space above and below grade level of a house. The study site also contained a variety of building types including but not limited to, (i) bungalow[8], (ii) garage house[9], and (iii) duplex house[10]. This study site was chosen because of its diversity of building age, type, and living area.

[6] Kingsland community, Calgary, http://en.wikipedia.org/wiki/Kingsland,_Calgary
[7] Cedarbrae community, Calgary, http://en.wikipedia.org/wiki/Cedarbrae,_Calgary
[8] Bungalows are single-level wooden structures, typically less than 1,000 square feet (93 m2), and normally feature a detached garage.
[9] Garage houses have room for one to several cars, including RVs.
[10] A duplex house is a dwelling having apartments with separate entrances for two households.

2.1.1 Thermal Image Acquisition

The thermal infrared (TIR) data for this study were acquired with the TABI 1800 (Thermal Airborne Broadband Imager) sensor flown by ITRES Research Ltd., Calgary (Figure 2.1). The TABI 1800 has a spectral range of 3.7 to 4.8 µm. The sensor was flown at a nominal height of 1000 ft above ground and (16 bit) data were acquired with a 50 cm spatial resolution and a 0.05^{o}C thermal resolution. Imagery were collected on May 14, 2012 in the early morning (between 12:00 am and 4:00 am) when the environment was in *thermal equilibrium*.



(a) (b)

Figure 2.1. An example (a) of the TABI 1800 illustrating a portion of the study site. Grey-toned temperature variations range from white (e.g., hot roads) to black (e.g., cool houses and parks). City of Calgary GIS building outlines are highlighted in red (b).

2.1.2 Climatic considerations

Predawn collection of thermal data is preferred for a number of reasons including but not limited to: (i) at predawn most objects are in thermal equilibrium with the environment (i.e., the influence of sun on the thermal characteristics of the objects will be very minimal); (ii) since most objects are in equilibrium, winds caused by differential heating of the earth's surface would have died down (Jensen, 2007). We note that optimal thermal data acquisition requires a wind speed below 7 km/h (Colcord, 1981). During the period of data collection the wind speed ranged from 13 km/h to 20 km/h[11]. Therefore the influence of wind on the thermal imagery has to be assessed. While this is beyond the scope of this thesis, we note that this limitation is being addressed by Dr. Hay's research team. Once solved the HEAT Scores method developed in this research can be applied to the climate normalized dataset.

Thermal image acquisition poses many challenges including the influence of the atmosphere between the sensor and the surface, the *micro-climate* or the local climatic variability (i.e., wind, humidity, etc), and knowledge of scene objects' emissivity. These challenges make the temperature values recorded in a thermal image prone to error. As a result, houses observed in a thermal image with identical (relative) rooftop temperatures can actually have different kinetic roof temperatures. Each of these challenges has to be carefully accounted for prior to performing any analysis that requires highly accurate temperature values.

[11] Wind speed obtained from http://www.climate.weatheroffice.gc.ca/climateData/hourlydata_e.html?timeframe=1&Prov=XX&StationID=2205&Month=5&Day=14&Year=2012&cmdB1=Go

2.1.2.1 Influence of the Atmosphere

The influence of the atmosphere can be mitigated by applying an atmospheric correction model. Many models have been developed over the years including MODTRAN (Berk et al., 1989) and LOWTRAN (Kneizys et al., 1983); however these require knowledge of specific environmental variables (e.g. humidity, wind speed, dew point etc.) that are typically collected for limited points then applied over very large areas. Fortunately, the thermal data acquired for this project were provided with general atmospheric errors already accounted for by the vendor. However, the data were not corrected for scene/object emissivity, or for local micro-climate variability.

2.1.2.2 Effects of Emissivity in thermal imagery

Research has been conducted to quantify the effects of emissivity in thermal imagery (Nicole, 2009; Stathopoulou et al., 2009; Sugawara and Takamura, 2006; Weng, 2001). By far, the simplest method is to integrate land-use data with the corresponding thermal image. However, each of these studies has been conducted on ASTER or TM data, which have a coarse spatial resolution (90 m and 120 m respectively). In contrast, this study is conducted on a very high spatial resolution image (0.5 m) which additionally brings the challenge of high inter-object variability that can confuse traditional classifiers. For example, in this project, while rooftops are the objects of interest, they will also contain other smaller objects such as chimneys, sun-lights, and vents. Each of these objects are made of different materials such as metals, glass etc., which will have a different emissivity value from that of the dominant roof material. Therefore, correcting for each of these object emissivity values is necessary to calculate the true temperature of the rooftop. However, defining these small objects is a complicated process. So for simplicity, each rooftop is assumed to be of

homogenous materials. Though we note, that objects smaller than the spatial resolution of the sensor will have their signals normalized within the dominant background roof signal.

After carefully studying the TIR dataset and a corresponding 2012 City of Calgary color infrared (R, G, B, NIR) ortho-mosaic (at a 25 cm spatial resolution), it was concluded that 80% of the rooftops in the study area are made of asphalt shingles. The emissivity value of asphalt shingles is 0.91. However, there are other challenges such as the same material (in different locations) having a different surface roughness (from weathering) or differential moisture content, which in turn will result in different emissivity values (Jensen, 2007).

2.1.2.3 Microclimatic variability

Microclimate variability also poses a challenge as there is no simple well-defined procedure to account for its effects. To account for this variability, weather data for May 14, 2012 were collected from 20 weather stations across The City of Calgary. These data were used to generate an interpolated surface of the study site's air temperature using *inverse distance weighting* (Figure 2.2). As seen in Figure 2.2, the SW portion of the study area is relatively warmer (+3 deg.C) compared to other locations in the scene. These climate data were used as one of the inputs to develop HEAT Scores (see section 2.2.2).

2.1.3 City GIS Cadastral Data

Cadastral data (i.e., relating to house/parcel ownership boundaries) containing the vector layers of the building outlines (Figure 2.1, red outlines) were obtained from The City of Calgary. Additional attribute data such as the living area, year of construction and address were also provided by the city.

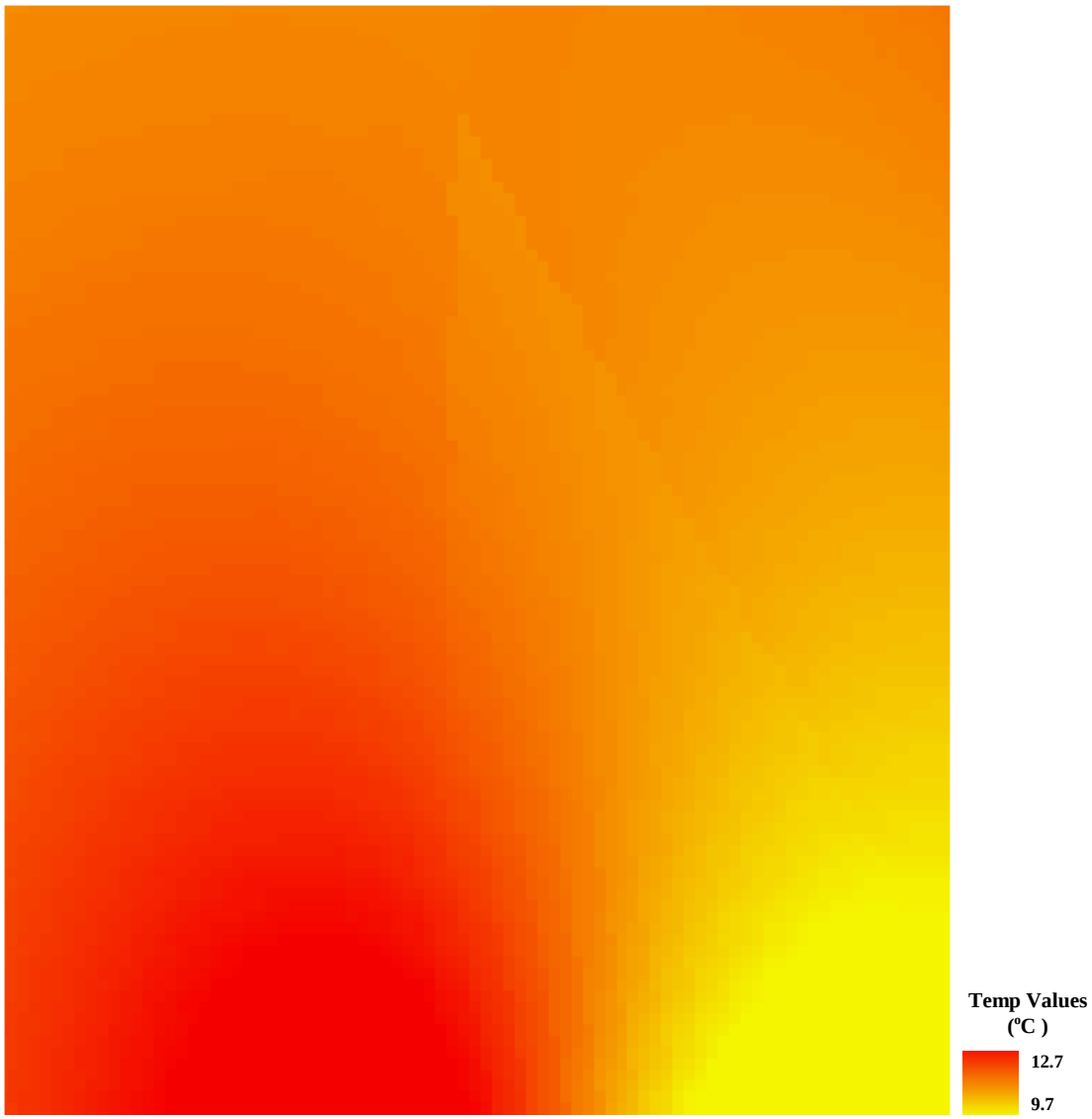
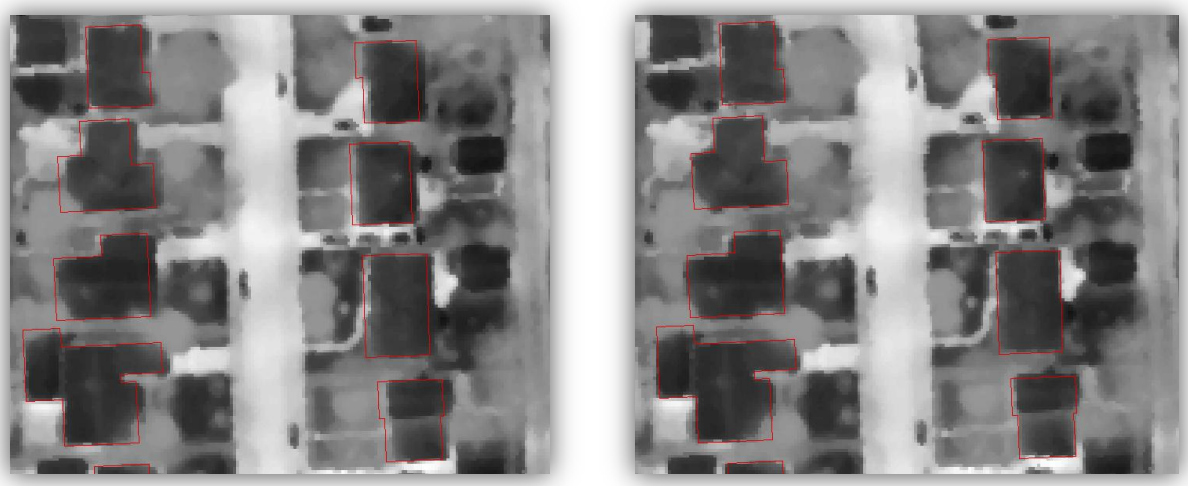


Figure 2.2. Surface air temperature of the study site interpolated using Inverse Distance Weighting from 20 weather stations located across Calgary. Temp' values in °C.

2.1.4 Geometric Correction between Cadastral data and Thermal imagery

As thermal imagery and cadastral data were collected from different sources at different times and spatial resolution, they do not geometrically match. Therefore, they must be co-registered. This geometric correction step is critical, as the cadastral data will be used in conjunction with thermal imagery to extract building objects. The geometric correction was performed using ENVI© 4.8 software. The cadastral data were created by trained

city photo-interpreters, thus they are assumed to be more accurate than the thermal image. Therefore, they are used as the base map (i.e., the master) for geometric correction. The thermal image (the slave) was corrected to the cadastral data by selecting recognized locations – Ground Control Points (GCPs) - found in both scenes. Corners of houses which were clear of any obstacles such as trees were selected as GCPs. Approximately 800+ GCPs were collected throughout the image. Triangulation (Hosomura, 1994) was selected for geometric correction, after careful visual comparison of results generated using the more conventional least squares method. Nearest Neighborhood interpolation was used for re-projecting the thermal image in order to preserve their original thermal values. Figure 2.3 shows an example of the thermal image before and after geometric correction.



(a) (b)

Figure 2.3. An example of the thermal image (a) before and (b) after geometric corrections was applied. Building outlines are highlighted in red.

2.1.5 EnerGuideRating Data

EnerGuide rating data for 11,940 houses in The City of Calgary were provided by NRCAN (Natural Resource Canada). In order to protect individual's privacy, NRCAN removed any personal information such as the owner's name and address before providing the data. However, the data had other useful information such as the EnerGuide rating, the year of construction, living area, and insulation levels of walls, ceiling and foundation. This information was used to evaluate the method used to develop HEAT Scores (section 2.3).

2.2 HEAT Scores

The primary objective of HEAT Scores is to provide building owners with a simple value that they can use to compare the waste heat leaving their house to other houses. Waste heat typically escapes through poorly insulated doors, windows, walls, ceilings, ductwork and electrical fixtures (i.e., pot lights). This is costly to the homeowner, generates considerably more greenhouse-gas emissions than necessary, and is invisible to the human eye. Waste heat is calculated from the digital numbers in the thermal image (see section 2.2.1). HEAT Scores are ranked numbers between 0 and 100 (representing 'cold' to 'hot'). HEAT Scores are also colored from blue to red. For example, a HEAT Score of 95 is colored *red* indicating that this is a relatively 'hot' house consuming a large amount of energy for space heating. Similarly, a HEAT Score of 10 is colored *blue* indicating that the house is a relatively 'cold' house consuming a small amount of energy for space heating. Figure 2.4 outlines the methodology flow chart of this study. The geometrically corrected thermal image was masked using the building GIS vector data obtained from The City of Calgary. Statistics, such as (i) average temperature, (ii) maximum temperature, (iii) minimum temperature, (iv) standard deviation of temperature, and (v) hotspots location and

its value were calculated after accounting for a general emissivity value of 0.91 (i.e., for asphalt shingles). Along with the GIS house attributes such as age and living area, these statistics are used to calculate HEAT Scores.

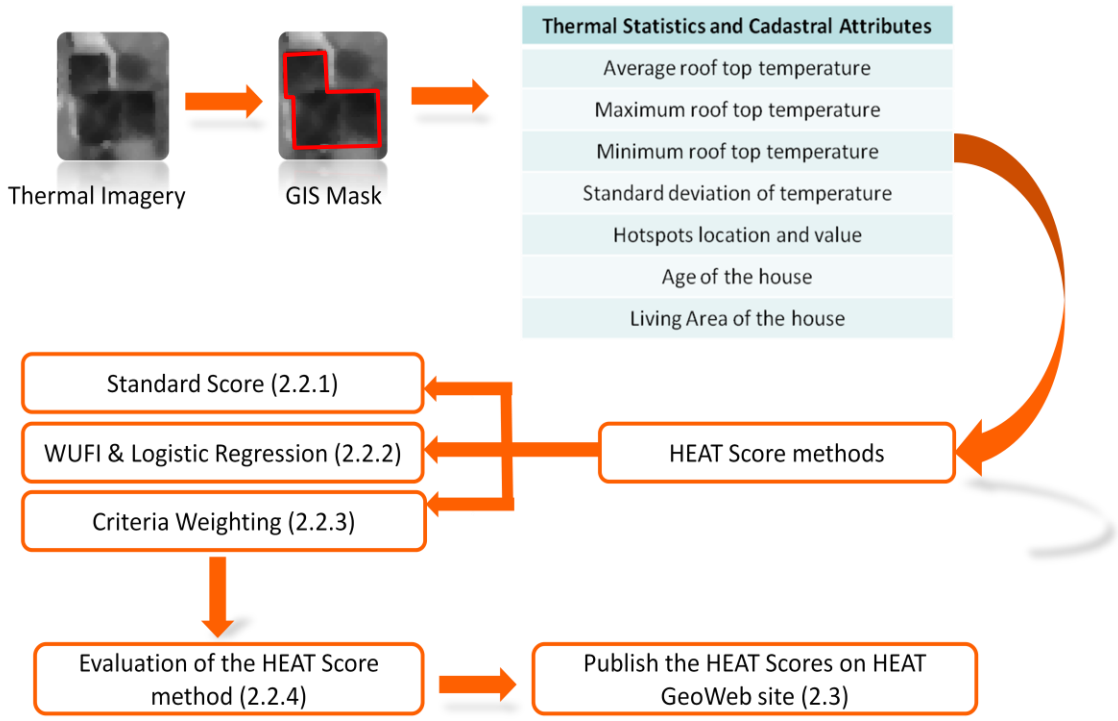


Figure 2.4. Flow chart showing the HEAT Score methodology with related section numbers.

HEAT Scores development has been an evolving process based on identifying three methods and testing their strengths and limitations. Consequently HEAT Scores have evolved from an initial statistical concept standardized score to more complex WUFI models and the inclusion of weather conditions. The final method satisfies HEAT Score requirements by employing a criteria weighting of different thermal and GIS attributes. The conceptual validity of this method is evaluated using the Energuide Rating System data. The following sections describe each step of the flow chart in detail.

2.2.1 HEAT Scores Method 1: The Standardized score

Given that HEAT Scores are between 0 and 100, a simple standardized score was applied to waste heat. A standard score indicates the number of standard deviations an observed value, (in this case the waste heat), is above or below the population mean. For HEAT Scores, the population mean is the average of all the waste heat in the city, or more specifically all the houses in the Calgary SW community dataset.

Waste Heat was calculated as the difference between a house's average rooftop temperature and the minimum of the minimum temperature recorded in the study area multiplied by the living area of the house (Equation 2.1). The assumption made here was that there is a location on some rooftop in the study area that wastes a minimum, or no heat. This was identified using the minimum of the minimum rooftop temperature recorded in the study site and is assumed to be the optimal, or ideal rooftop temperature. Based on this assumption, waste heat for each house has been defined using the following equation:

$$Waste\ Heat\ = (\mu_{Temp} - MIN\ (MIN_{Temp}))\ *\ Area \qquad (2.1)$$

Where μ_{Temp} is the average rooftop temperature of the house; $MIN\ (MIN_{Temp})$ is the minimum of the minimum rooftop temperature recorded in the whole study site, and *Area* is the living area of the house. In order to use standard scores, waste heat has to be tested for normality. Since waste heat was not distributed normally, a natural logarithmic transformation was applied to Equation 2.1. Based on the standard score formula (Equation 2.2), the HEAT Score was calculated as shown in Equations 2.3 and 2.4.

$$z - score\ =\ (x - \mu)/\ \sigma \qquad (2.2)$$

where x is the waste heat of the house to be standardized, μ is the average of all the waste heat in the study site, and σ is the standard deviation of the waste heat in the study site.

$$HEAT\ Score\ =\ z - score\ of\ an\ item\ -\ (-3.49)/(3.49 - (-3.49))\ *\ 100 \qquad (2.3)$$

$$HEAT\ Score\ =\ (z - score + 3.49)/6.98\ *\ 100 \qquad (2.4)$$

Z-scores follow a standard normal distribution; consequently 99.98 percent of the values will lie between -3.49 and 3.49. This z-score is proportionately converted to a scale from 0 to 100 to represent the HEAT Score for every house. Therefore, a HEAT Score of 100 represents the house with a very high waste heat and a HEAT Score of 0 represents the house with a very low waste heat. There is a possibility of outliers that will have a z-score greater than +3.49 or lesser than -3.49. Therefore, outliers have to be accounted for, which can be achieved using *quartiles*. Quartiles are three points that divide the data set into four equal parts. Outliers are calculated using the formula:

$$Lower\ Outer\ Fence\ (LOF)\ =\ Q1\ -\ 3 * IQR \qquad (2.5)$$

$$Upper\ Outer\ Fence\ (UOF) =\ Q3\ +\ 3 * IQR \qquad (2.6)$$

Where *Q1* is lower quartile, *Q3* is upper quartile and *IQR* is inter-quartile range (*Q3-Q1*). Any value below *LOF* (Equation 2.5) or above *UOF* (Equation 2.6) is considered as an *extreme outlier* and a HEAT Score of 100 and 0 is assigned respectively. By using this defined HEAT score, an individual will be able to compare their house with any other house in any part of the city.

2.2.1.1 Limitations of Standardized Score Method

Waste heat was calculated using the assumption that there is a location on some rooftop that wastes minimum, or no heat. Anything above this temperature is considered as waste heat. The problem associated with this assumption is that this minimum temperature might be associated to a metal object on a rooftop. This is important, as metals have a very low emissivity value associated with them and therefore (when uncorrected) appear cold on a thermal image (as they will reflect deep space – which typically records the minimum temperature of the sensor). The result is that waste heat could be miscalculated, thus the corresponding HEAT Score would be in error.

The second limitation of this method is the use of z-scores of the average rooftop temperature. Unfortunately, these scores cannot be compared between different populations (i.e., different cities) without first aggregating all populations – which then dilutes them. Z-Scores are relative, thus adding or removing a data point from the dataset will require recalculation of all other data points. Therefore, every time the study site is extended or new houses are added to the study, HEAT Scores will have to be recalculated for all other houses potentially changing them. This method also doesn't take into account the climate conditions of the study area, which clearly affects the thermal statistics derived from the image.

These new found conditions resulted in the search for other methods with which to define HEAT Scores. Upon reflection, the new method should (i) allow for a comparison of HEAT Scores between cities, (ii) not change the HEAT Score of a house every time new houses are added to the study area, (iii) take into account the weather conditions of the city, and (iv) take into account the heat transfer through building materials. This last condition

will allow for more realistic calculations of waste heat, rather than arbitrarily selecting the optimal, or ideal rooftop temperature based on some untested assumption. The following section describes this new method.

2.2.2 HEAT Scores Method 2: The WUFI® Model and Logistic Regression

In this 'new' method, waste heat is calculated as the difference between the average roof temperature and the modeled roof surface temperature derived from WUFI software. WUFI® (Wärme und Feuchte instationär) is a software family (and modeling environment) that allows realistic calculation of the heat and moisture transport in multi-layer building components exposed to natural weather. This software allows the user to 'construct' models of building roofs/walls for different climatic conditions.

For this project, a vented roof system with asphalt shingles, typical of the most common rooftop in The City of Calgary, is modeled with the following components: (from interior to exterior) 1.25 cm (0.50 in.) interior gypsum wallboard, 19.7 cm (7.75 in.) glass-fiber batt insulation, 19.7 cm (7.75 in.) open-cell polyurethane foam insulation, or 19.7 cm (7.75 in.) closed-cell polyurethane foam insulation between wood rafters, 4 cm (1.50 in.) ventilation space with five air changes per hour, 1.25 cm (0.50 in.) OSB (Oriented Strand Board) sheathing or plywood sheathing, one layer of felt or SRAM, and asphalt shingles (Nelsen, 2009). Figure 2.5 shows the roof assembly modeled using this software. This software also allows the user to input indoor and outdoor climate as parameters for many cities. However, it allows only two options for outdoor climate, (i) a cold year, or (ii) a warm year. These are averages of weather conditions such as outdoor temperature, humidity and due point. Since May 14 2012, the day of the data collection, was relatively warm compared to other years for the same day, a comparable warm year was selected as input for the outdoor climate.

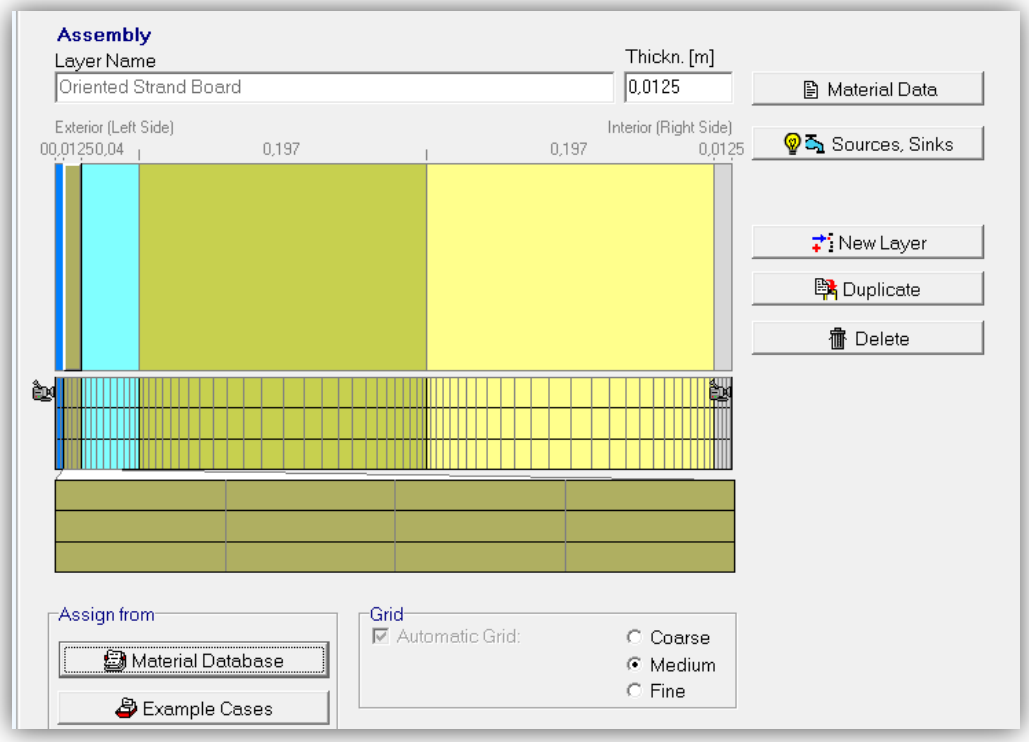


Figure 2.5. Vented Asphalt Shingle Roof Assembly modeled using WUFI®. Different colors represent different layers of a roof. (Blue – Asphalt shingles, Green – Oriented Strand Board, Cyan – Ventilation space, Light Green – Open-cell polyurethane foam insulation, Yellow – fiberglass batt insulation, Grey – Interior gypsum wallboard).

From the graphs plotted for a warm year temperature, it can be seen that on May 14th the minimum outdoor temperature was modeled around 5°C (see Figure 2.6, noted by green arrow); whereas on May 14th 2012, during the data collection period (00:00 am to 4:00 am), the air temperature was actually between 10°C and 14°C. Consequently, a temperature shift of 5°C was added to the outdoor climate. The indoor climate is assumed to be 21°C as this is the most commonly set indoor temperature.

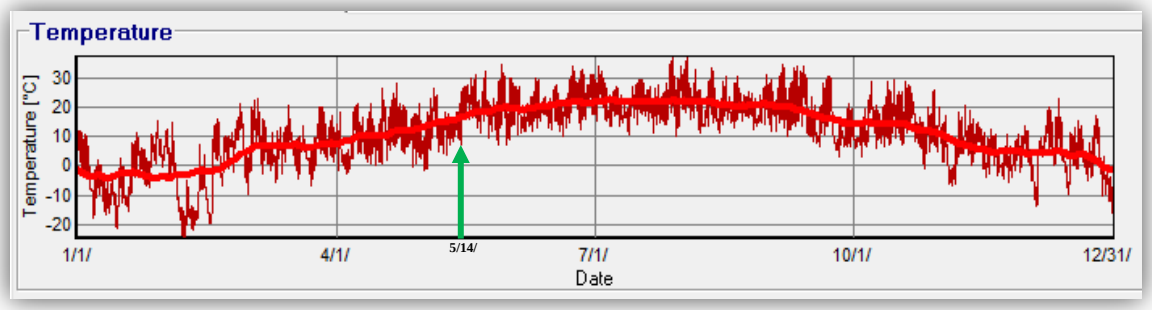


Figure 2.6. Outdoor climate of Calgary for a warm year showing the temperature on May 14th (Noted by the green arrow).

Running this model for an asphalt vented roof assembly produces the exterior surface temperature of the rooftop. This temperature is considered to be the ideal or optimal roof top temperature. Figure 2.7 shows the exterior surface temperature modeled over 3 days. Between 00:00 am and 4:00 am on May 14th the modeled temperature varies between 10.5°C and 11°C (highlighted in the orange transparent box). After correcting for emissivity (0.91) of the roof material, anything above this temperature is considered to be wasting heat.

Waste heat for this 'new' method is defined as the ratio of pixels that are above the modeled temperature to the total number of pixels representing the house (Equation 2.7).

$$Waste\ Heat = \frac{No.\ of\ Pixels\ above\ WUFI\ modeled\ temperature}{Total\ no\ of\ pixels\ on\ the\ roof} \tag{2.7}$$

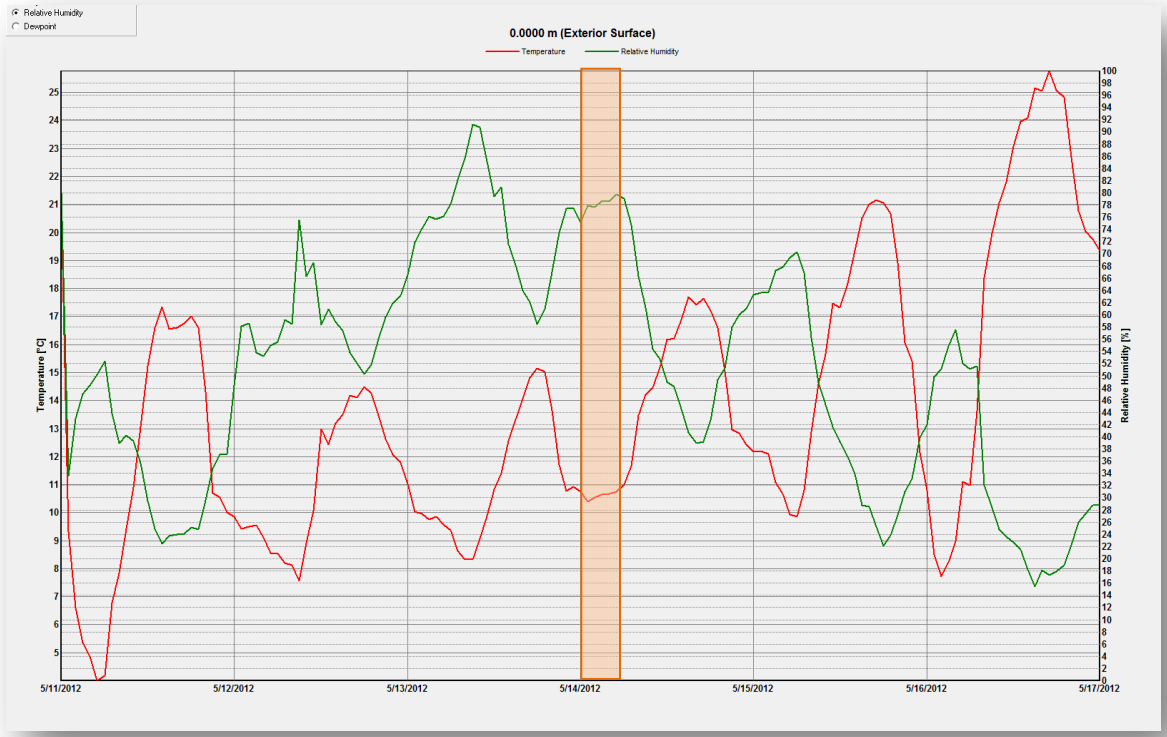


Figure 2.7. Modeled Roof surface temperature for vented asphalt shingle roof system between 00:00 and 4:00 hours on May 14th (highlighted in orange transparent box) using WUFI®.

Consequently, waste heat will have a value between 0 and 1. A waste heat value of 0 means that the house (roof) wastes no heat and 1 represents that the whole roof is wasting heat. Figure 2.8 shows a hypothetical roof with each cell in the table depicting the pixels in a rooftop. Assuming 10°C as the optimal rooftop temperature modeled using WUFI, all the pixels that are *above* this temperature are highlighted in orange and considered as waste heat pixels. Out of the 66 pixels in total, 32 pixels are wasting heat. Therefore waste heat for this hypothetical house is calculated as the ratio of 32/66 which equals 0.49.

From Figure 2.2 (Section 2.1.1), it can be seen that air temperature varied throughout the dataset. Therefore air temperature has to be taken into account while calculating waste heat. The WUFI model was generated for different temperatures and it was concluded that

the variations in air temperature are linearly correlated with rooftop temperature. This was true at least for the temperatures tested from 10°C to 14°C that were recorded on May 14th 2012. Thus, for every one degree rise in air temperature, the modeled rooftop temperature is increased by 1°C.

6	3	4			
7	4	5			
8	2	6			
9	1	7			
10	2	8			
11	3	9			
12	4	10	11	12	13
13	5	11	12	13	14
14	6	12	4	7	3
15	7	13	3	4	
16	8	14	6	11	12
17	9	15	8	10	8
18	10	16	15	9	14
19	11	17	13	6	7

Figure 2.8. Hypothetical rooftop (plan view) and corresponding pixels (rectangles) with numbers representing temperature values. Highlighted pixels (orange) are wasting heat.

2.2.2.1 Rationale Behind the Selection of Independent Variables

After calculating the waste heat adjusted for emissivity and air temperature, it is used as the dependent variable in a logistic regression with the *independent variables*: age, living area, average hotspots and standard deviation of the rooftop temperature. This section describes the rationale behind the selection of these variables.

- ***Age*** - Assuming that 'old' houses are not renovated, older houses are expected to waste more heat through their roofs than new houses. This is also confirmed from the 'Thermal Archetypes' project which concludes that old houses have very poor insulation compared to the newer ones (Parekh and Kirney, 2012).

- ***Living Area*** - As the living area of the house increases, the energy required to heat the house also increases.
- ***Hot Spots*** are geographical representations of unique waste heat locations on the rooftop of a house. In HEAT, hot spots represent an ordered list of (i) the 6 hottest locations around the (1m) roof edge and (ii) the 6 hottest locations covering the remaining rooftop. Within each of these two zones, Hot Spots are located at least 1.5 m away from each other, so that they are not clustered around the same location. This provides a better visual description of the spatial distribution of hot areas over each of the zones. When the hot spots are compared with their location in Google Maps Street View, they visually correspond to heat escaping from specific roof components or the doors, windows, walls and living envelope beneath. The *average* of these 12 hotspots represents the hottest locations on the rooftop. As the average of the 12 hotspots increases, it is also expected that the waste heat will increase.
- *The* ***Standard deviation*** of the rooftop temperature describes the variation of the rooftop temperature. A well insulated roof should show very minimal variation on the thermal image. Therefore, as the variation increases, waste heat is also expected to increase.

2.2.2.2 Logistic regression for HEAT Scores

Logistic regression, an inferential statistical method is adopted to compute HEAT Scores. Regression methods are often used in behavioral science. They attempt to graph the outcome fluctuations to a straight line. Logistic regression is based on the mathematical concept called as *logit* – the natural logarithm of an odds ratio. Logistic regression is generally used for the analysis and prediction of dichotomous outcomes. For example, consider a model to predict the outcome of students being admitted into school based on

their GPA, this can have only two outcomes, either being admitted or rejected. Ordinary Least Squares (OLS) regression has been traditionally applied to this kind of analysis. But OLS has been found to be less ideal for dichotomous outcomes due to its strict statistical assumptions like normality, linearity and continuity (Peng, 2002). Logistic regression was proposed as an alternative for predicting binary responses. The mean response of binary responses is a probability (Walpole et al., 2007), thus it can vary from 0 to 1.

A practical concern with logistic regression is that the number of variable permutations increases with each added variable in a given model. This will increase the number of test cases with low frequency. That is, for each possibility there will be only few cases available in the dataset. When observed frequencies are low, one has three options: (i) accept low power, (ii) collapse factor levels, or (iii) use a goodness of fit test that does not utilize expected frequencies (Tabachnick & Fidell, 2001). However, HEAT Scores developed for this thesis had 9279 observations with only 4 factor levels; consequently this is not a concern to this thesis. Equation 2.8 shows a general equation of the logistic regression.

$$logit(Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ \ldots + \beta_n X_n \tag{2.8}$$

where, π is the dependent variable or the probability of success; α is the intercept; β_1, β_2 and β_n are the coefficients of independent variables X_1, X_2 and X_n respectively. The ratio of pixels that are above optimal rooftop temperature to the total number of pixels is used as the dependent variable (Y) or the binary response in a logistic regression model (Equation 2.8). The predicted value from this model is multiplied by 100 to define the HEAT Score of each house.

Equation 2.9 shows the logistic regression model of HEAT Scores computed with R software. R is a free software environment for statistical computation and graphics.

$$logit(waste\ heat) = -3.84 + 0.02 * Age - 0.001 * LivingArea + 0.03 * Std.Dev + 0.44 * Avg\ Hotspot \quad (2.9)$$

2.2.2.3 Limitations of Logistic Regression Method

The statistical significance of individual regression coefficients (i.e., β in Equation 2.8) is tested using a *t-test*. From Table 2.1 it can be concluded that age, living area and average hotspot temperature are significant predictors of HEAT Score ($p<0.05$). However, standard deviation is not a significant predictor. In addition, living area is negatively related to HEAT Scores, which contradicts the rationale behind the selection of this variable (see Section 2.2.2.1). However, it is *common sense* that as the living area increases, energy consumption will increase (as there is more space to heat). In order to overcome these problems, the following method was developed.

2.2.3 HEAT Scores Method 3: Criteria Weights

This third method assigns weights to the factors contributing to HEAT Score. In order to assign weights to each factor, their effects on waste heat and energy consumption need to be assessed. This section describes the logic behind the selection of weights for different factors.

Table 2.1. Logistic Regression model to calculate HEAT Scores with the p-value for each independent variable.

```
Coefficients:
                                      Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -3.8370611  0.1851019 -20.729  < 2e-16 ***
heatscores_dasbuildings$age          0.0220701  0.0022761   9.697  < 2e-16 ***
heatscores_dasbuildings$livingarea  -0.0006539  0.0002008  -3.257  0.00113 **
heatscores_dasbuildings$stdtemp      0.0331122  0.0488426   0.678  0.49781
heatscores_dasbuildings$avghotspottemp  0.4355672  0.0176539  24.673  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2290.9  on 8250  degrees of freedom
Residual deviance: 1589.5  on 8246  degrees of freedom
AIC: 7088.3

Number of Fisher Scoring iterations: 5
```

Heat leaving a house can be calculated using the Heat Loss rate[12] formula shown in Equation 2.10.

$$Heat\ Loss\ rate\ \left(\frac{Q}{t}\right) = Area\ of\ the\ wall * \frac{T_{inside} - T_{outside}}{Thermal\ Resistance\ of\ Wall} \tag{2.10}$$

Where T_{inside} is the temperature inside the house in K; $T_{outside}$ is the temperature outside the wall in K; and $Thermal\ Resistance\ of\ Wall$ (RSI) is in m^2K/W. The total heat loss of a house is calculated as the sum of the heat loss from all its walls and roofs.

According to the Thermal Archetypes project[13], houses constructed before 1945 have 3 times less insulation than the houses constructed after 2005 (Parekh & Kirney, 2012). A sample calculation shown in Table 2.2 suggests that in Calgary, a house constructed before

[12] Calculating Home Heating Energy, http://hyperphysics.phy-astr.gsu.edu/hbase/thermo/heatloss.html
[13] Thernal Archetypes was developed from a statistical representative data libraries provides default values such as insulation values, furnace efficiency while conducting energy analysis.

1945 with a living area of 81 sq.m consisting of 4 walls and a roof will consume 76 GJ per year at the cost of $ 460 (CAD), whereas a similar house constructed after 2005 will consume only 29 GJ per year at the cost of $ 178 (CAD).

Table 2.2. HEAT loss and cost of heating the houses in Calgary based on different vintage types obtained from the Thermal Archetypes project.

Year of Construction / Living Area	Total Energy consumed Per Year (GJ)	Total Cost to heat home (CAD)
<1945 / 81sq.m	76.87	460.5
>=2005 / 81sq.m	29.87	178.9
<1945 / 225sq.m	184.62	1105.9
>=2005 / 225sq.m	68.06	407.7

To facilitate the calculations shown in Table 2.2, the insulation values of walls, ceilings and foundation were obtained from the Thermal Archetypes project. Heating degree days were obtained from http://www.weatherstats.ca/. Heating degree days is a standard measure used to estimate the amount of energy required to heat a building at a particular location for a given period of time. In simple terms, one heating degree-day is designed to reflect the amount of energy required to heat a house by 1 degree for a day. Generally, temperature inside the house is hotter by 2 to 3 degrees compared to the outside temperature. Therefore, if the house is at 18°C and the outside temperature is 15.5 C it does not have to be heated[14]. Although when it drops below 15.5^{o}C to 14.5^{o}C then the house has to be heated by 1°C. Based on a fixed rate per GJ, a natural gas price for the 11th February 2013 was obtained

[14] Degree days are most commonly calculated with 15.5^{o}C as the base temperature and Weather statistics generally uses 18°C to calculate degree days. http://www.energylens.com/articles/degree-days#hdd

from Enmax® as $5.99. (NB: It can also be seen from the calculations in Table 2.2 that as the living area increases, the corresponding heating cost increases).

From these calculations it can be seen that the older houses cost 2.6 (460.5/178.9) times more than the new houses for space heating, while the living area of large houses costs 2.4 (1105.9/460.5) times more than the small houses. Therefore, age affects the cost a little more than the living area, thus the weight for age has to be more than the weight for living area.

If we assume that there is a hole of size 1m x 1m in the ceiling where insulation is half the original value, it can be easily calculated that this hole will waste twice the energy than if the ceiling was properly insulated (Equation 2.10). Therefore, it is essential to incorporate the average roof hotspots within the HEAT score calculation. It is *hypothesized* that the higher the temperature difference between the average roof hotspots temperature and the optimal rooftop temperature calculated from the WUFI model in Section 2.2.2, the higher the chances of wasting heat. The standard deviation of rooftop temperature is neglected as it was not a significant contributor to waste heat according to the logistic regression (Section 2.2.2.1). In addition to this the average hotspot temperature and the waste heat already take into account the variation of temperature on the roof. Thus, from these assumptions, there are four critical factors namely (i) waste heat, (ii) average hotspots temperature, (iii) age and (iv) living area that need to be considered. Similarly, weights need to be defined, then assigned to each of these factors in order to calculate HEAT Scores.

The absolute *t values* in the logistic regression shows the significance of the factors (Section 2.2.2.2). The higher the absolute t value, the higher its significance on the

dependent variable. As illustrated in Section 2.2.2.2 (Table 2.1, z value), it can be seen that average hotspot temperature is the most significant contributor to HEAT Score while age and living area are the second and third most significant contributor respectively. Since this project is primarily focused on thermal energy leaving a house (and as this attribute – waste heat - represents an information set, unique to HEAT), waste heat is assigned a higher weight compared to other factors. So using this logic, waste heat is assigned a weight of 0.35, average hotspots is assigned a weight of 0.3, age is assigned a weight of 0.2 and living area is assigned a weight of 0.15. The following equation is used to calculate the HEAT Score of each house.

$$HEAT\ Score = [(0.35 * Waste\ HEAT) + (0.3 * Average\ Hotspot) + (0.20 * Age) + (0.15 * Living\ Area)]*100 \quad (2.11)$$

(i) Criteria Weights – Waste Heat: Since waste heat (equation 2.7) is a ratio it will always be less than or equal to 1, consequently, it can be simply multiplied by 0.35.

(ii) Criteria Weights – Average Hotspots: The higher the difference between the hotspot temperature and the WUFI modeled optimal roof temperature, the higher will be the score for the average hotspot temperature. Therefore, the difference between average hotspot temperature and WUFI temperature has to be assessed. Then this assessed value has to be converted to 0.3 (Equation 2.11). For simplicity the difference between average hotspot temperature and optimal roof temperature is divided into five classes. If the difference between the optimal roof temperature and the average hotspot temperature is less than or equal to 0, then it is assigned a score of 0; if it is greater than or equal to 5, then it is

assigned a score of 0.3; between 0.3 and 0 it is scaled linearly for all other classes (Table 2.3).

Table 2.3. Hotspots classes and their weights used to define HEAT Scores.

(Average hotspot temp' – Optimal rooftop temp') ^{o}C	Score
>5	0.3
>4 and <=5	0.25
>3 and <=4	0.20
>2 and <=3	0.15
>1 and <=2	0.10
>0 and <=1	0.05
<=0	0

(iii) Criteria Weights – Age: Based on the Thermal Archetypes project, age is classified into eight vintage groups: group 1 being buildings built before 1945 and group 8 is buildings built after 2005. Therefore, buildings built before 1945 will get a score of 0.2 while buildings built after 2005 will get a score of 0 for age. The groups in between will be scaled accordingly (Table 2.4).

Table 2.4. Age groups and their weights used to define HEAT Scores.

Age Group (Year constructed)	Weight
1 (<=1945)	0.20
2 (>1945 – 1960)	0.17
3 (>1960 – 1977)	0.14
4 (>1977 – 1983)	0.11
5 (>1983 – 1995)	0.08
6 (>1995 – 2000)	0.05
7 (>2000 – 2005)	0.02
8 (>2005)	0

(iv) Criteria Weights – Living Area: Living area is classified into five classes according to the Thermal Archetypes project. Group 1 consists of houses that have a living area greater

than 230 sq.m and group 5 consists of houses with a living area less than 83 sq.m. Therefore, houses in group 1 living area will get a score of 0.15 while houses in group 5 living area will get a score of 0 (Table 2.5). Thus small houses have minimal bias.

Table 2.5. Living Area and their weights used to define HEAT Scores.

Living Area Group (Area in sq.m)	Score
1 (> 231 sq.m)	0.15
2 (>169 – 231 sq.m)	0.11
3 (>121 – 169 sq.m)	0.07
4 (>83 – 121 sq.m)	0.03
5 (<=83sq.m)	0

For each house, waste heat (Equation 2.7) and Tables 2.3-2.5 are used to calculate the corresponding weighted HEAT Scores. This method mitigates the limitations from the other two methods and therefore it is considered to be more reliable.

HEAT Scores can also be calculated for communities and cities. A city HEAT Score is calculated based on the average HEAT Score of all houses in the city, while the community HEAT Scores are calculated based on the average HEAT Score for all homes in each community.

2.2.3.1 Advantages of Criteria Weights Method

Of all methods developed (thus far), this method is considered the most reliable method because it:

i. *considers the temperature transfer through roofing materials,*
ii. *takes into account the local climatic conditions,*
iii. *utilizes the age and living area of the house,*
iv. *Allows for a comparison of HEAT Scores across cities is possible.*

v. *Defines HEAT Scores that are not relative (i.e., changing or removing a house will not affect other houses), and*

Specifically, adding new houses to the study site will not change the HEAT Score of other houses since HEAT Scores for houses are calculated independently without the influence of other houses. Another advantage this method has over the other methods is that comparison of HEAT Scores across cities is valid since this method will take into account the local weather conditions of the city during the data collection as well as the temperature transfer through the roofing materials common in that city. Therefore this method is considered as the best available method yet and is evaluated against the EnerGuide Rating System. The following section describes the technique used to evaluate the conceptual validity of this method.

2.2.4 Evaluation of the HEAT Scores method

In Canada, the energy performance of houses is traditionally rated using the *EnerGuide Rating System (ERS)*. Though service providers increasingly use (hand held) thermal imaging to analyze a house's energy efficiency, to the best of our knowledge, there has been no research carried out using any form of thermal imagery to provide a comparative house-based energy rating system. As a result, HEAT Scores are the first of its kind, which brings with it the challenge of *validation*. A house's energy efficiency is a complex system which is affected by many factors including but not limited to life style of the occupants, outdoor weather conditions, type of the house, insulation of the walls, ceiling and foundation, and the type of doors and windows. This is similar to an open natural complex system where uncertainties are inherently present. Verification and validation of natural systems are impossible (Oreskes et al., 1994; Oreskes, 1998). Therefore HEAT Scores cannot be

validated. However the concept or method used to develop HEAT Scores can be evaluated using ERS data. Energuide Ratings are calculated with a sophisticated (and complicated) piece of software called *HOT 2000*[15], which incorporates many hundreds of parameters, including but not limited to (i) age, (ii) living area, (iii) climatic condition, and (iv) the insulation of ceiling, walls and foundation. In collaboration with the HEAT project, NRCAN provided a total of 11,940 valid Calgary EnerGuide records[16]. Unfortunately, due to privacy restrictions, NRCAN did not provide us with any personal information relating the ratings to the specific house addresses; consequently, EnerGuide Ratings cannot be directly related to HEAT Scores. However, a general linear regression is applied to determine the relationship between the EnerGuide Rating of a house and its age, living area, insulation of ceiling, walls and foundation. It is *hypothesized* that (the amount of) insulation is directly related to the temperature that is observed on the thermal image. This hypothesis is based on the heat loss equation 2.10, which suggests that as the insulation decreases heat loss increases. It must be noted that Allinson (2007) concluded that aerial thermal imagery cannot be used to determine loft insulation thickness. However, the author inferred in her conclusions that there was a small temperature difference recorded on the roof-tops between well insulated and poorly insulated roofs. Therefore based on this hypothesis, if EnerGuide Rating is inversely related to age and living area, but directly related to insulation levels of ceiling, walls and foundations, then the rationale behind the method used to develop HEAT Scores can be accepted as reliable. To test this hypothesis a linear regression model is developed for EnerGuide Ratings.

[15] HOT2000 is a building energy simulation tool that is considered North America's top-of-the-line energy analysis and design software for low-rise residential buildings (source: http://canmetenergy.nrcan.gc.ca/software-tools/hot2000/84).
[16] Though we note, there were some records which had a rating below 0.

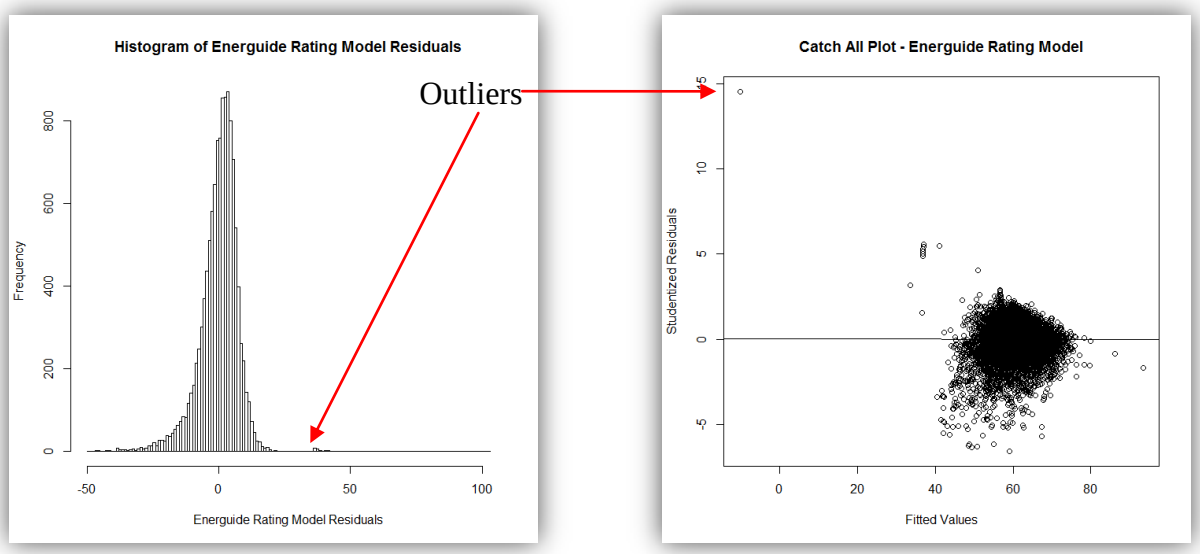
Table 2.6. Linear Regression model defining the relationship between the EnerGuide House rating and age, living area and insulation of the house.

```
Call:
lm(formula = eghrating$eghrating ~ age + floorarea + ceilins +
    mainwallins + fndwallins, subset = eghrating$eghrating >
    0)

Residuals:
    Min      1Q  Median      3Q     Max
-49.143  -3.424   1.035   4.504 102.197

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 56.2932579  0.5548025  101.47   <2e-16 ***
age         -0.1115372  0.0051759  -21.55   <2e-16 ***
floorarea   -0.0199596  0.0006694  -29.82   <2e-16 ***
ceilins      1.1135490  0.0479067   23.24   <2e-16 ***
mainwallins  2.5105601  0.1990184   12.62   <2e-16 ***
fndwallins   2.8794770  0.0930716   30.94   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.458 on 11934 degrees of freedom
Multiple R-squared: 0.3131,     Adjusted R-squared: 0.3129
F-statistic:  1088 on 5 and 11934 DF,  p-value: < 2.2e-16
```

Results from the regression model (Table 2.6) show that all the independent variables (i.e., age, floor area etc) were statistically significant at $p < 0.001$. Even though the R-squared is only 0.31, the F statistic [17]shows that the overall model is significant at $p < 0.001$ level. Since the model proves to be statistically significant it needs further assessment to determine if it meets the assumptions of linear regression or ordinary least squares (OLS). One of the assumptions in OLS is that the residuals are normally distributed. Figure 2.9a shows that except for very few outliers (noted by the red arrow) the residuals from the

[17] Generally F Statistic is used to test the significance of a model. The p value for this model is less than 0.001 which means that this model is significant at 99.9% confidence level.

model are normally distributed. Furthermore, Figure 2.9b illustrates that the resulting residual plot clearly shows no clear pattern, confirming the assumptions of linear regression. Therefore this linear regression model can be regarded as a significant model, supporting the validity of the (tested) HEAT Score method.



(a) (b)

Figure 2.9. Testing the assumption of the linear regression model for the EnerGuide Rating: (a) This histogram shows that the residuals are normally distributed except for very few outliers (noted by the red arrow) and (b) The residual plot shows no pattern confirming the assumptions.

It can further be deduced from the model (Table 2.6) that:

i. *as age increases, the EGR decreases*

ii. *as the living area increases, the EGR decreases*

iii. *as the insulation of the walls ceiling and foundation increases, the EGR also increases.*

We suggest that these findings indirectly evaluate the HEAT Scores method. It also needs to be *noted* that while higher EnerGuide Rating numbers are considered as a sign of

increasing home energy efficiency, lower HEAT Score values represent more energy efficient houses (or at least, homes wasting less heat). Therefore, as age and living area increases, HEAT Scores will also increase. Insulation values are inversely related to thermal values. Thus, as insulation values decrease, the thermal values recorded in the thermal image will increase. Consequently HEAT Scores will increase as insulation levels decrease.

The second objective of this study is to publish the newly generated HEAT Scores on HEAT Geoweb site. This objective is achieved by integrating the HEAT Scores into the HEAT System architecture and developing a multi-scale interactive user interface. The following section describes the HEAT System Architecture and user interface.

2.3 HEAT System Architecture and Multi-Scale User Interface

2.3.1 HEAT System Architecture

The HEAT System architecture was developed in-house and is based on Open Geospatial Consortium (OGC) standards and includes: (i) an image processing pipeline, (ii) a geospatial database, (iii) a web server platform capable of running server side scripts and web frameworks, and (iv) an AJAX supported web browser (Figure 2.10).

HEAT Scores developed in this study are uploaded into the geospatial database and integrated into the HEAT system. To access the HEAT Scores and the interface (www.saveheat.co), a user clicks on the Google map in the HEAT Scores page using a web browser to request information from the server. Python scripts were developed on the server to process these requests. These scripts query the PostgreSQL database which holds the information such as the HEAT Scores, energy models and thermal statistics in a relational

geospatial database. Depending on the spatial scale at which the user requested information, either a specific HEAT map (i.e., City, Community, or House), or a -

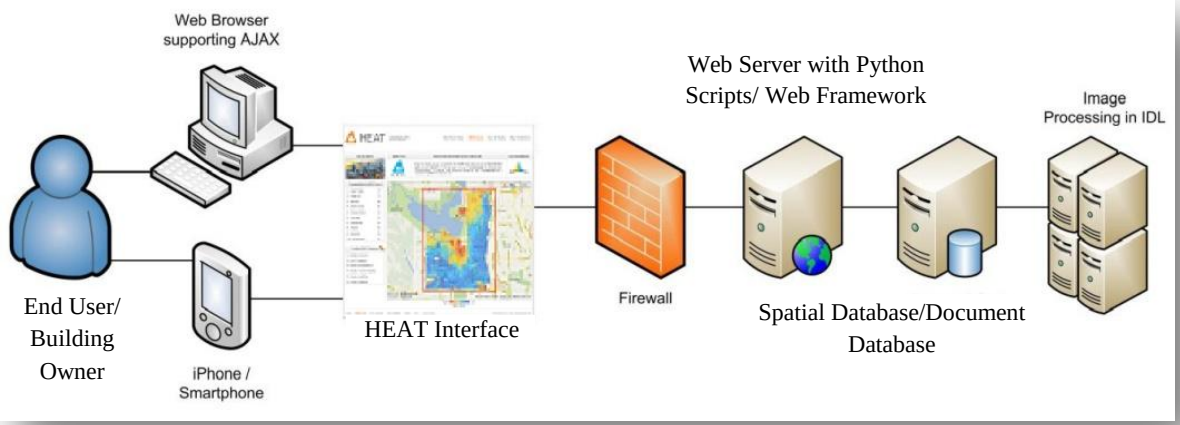


Figure 2.10. HEAT System Architecture.

JSON (JavaScript Object Notation) response is sent back to the user's browser. These maps are served to the client in OGC standard KML[18] format. When the user requests information at the finest scale for a house, a JSON response is sent back to the client's browser with the information pertaining to this house. JavaScripts were developed to interpret the KML and JSON response. These JavaScripts enable the user to visualize HEAT Scores on a multi-scale interface and attractive user interface. HTML5 standards are followed to enable tablets and mobile devices to display the Google maps Street View component. The following section illustrates this attractive multi-scale user interface.

[18] KML (Keyhole Markup Language) is an OGC notation for expressing geographic annotation and visualization within Internet-based, two-dimensional maps and three-dimensional Earth browsers (source: http://en.wikipedia.org/wiki/.kml)

2.3.2 Multi-scale user Interface of HEAT Scores

2.3.2.1 City Level

HEAT Scores are visualized on a multi-scale interface in the HEAT Geoweb site (Figure 2.11). When users log into the HEAT Scores page[19], they experience the *City*[20] *HEAT Map* (Figure 2.11a) as a smoothly gradated image - with colors varying from red (hot or high waste heat) to blue (cold or low waste heat). This map is actually an interpolated image of HEAT Scores using the inverse distance weighting algorithm. It is created to allow users to quickly scan over the city and find the hottest locations. That is, they will be able to quickly see which communities in the city are wasting more heat and consequently consuming more energy. A City HEAT Score is also provided to the user which is a simple average of all the HEAT Scores in the city (Figure 2.11b). The users will also see a statistical summary of the city such as the total number of homes, total estimated financial cost and GHG emissions, and estimated savings and GHG reductions for a specific fuel source (Figure 2.11b). They will also see the distribution of HEAT Scores in the city as a histogram, (Figure 2.11d) as well as the list of all communities in the city (Figure 2.11e).

[19] HEAT Scores http://www.saveheat.co/heat-scores.php
[20] Until the entire City of Calgary is completely assessed, this Map represents the *pseudo*-city study area.

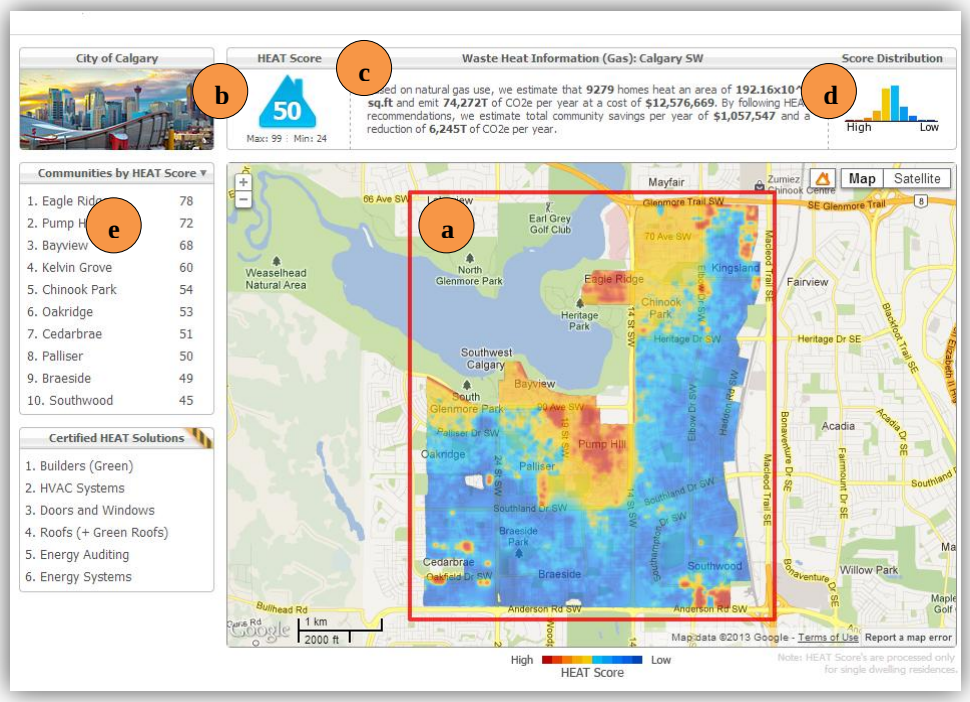


Figure 2.11. The HEAT Score web page showing (a) the interpolated City HEAT map with hot (red) and cold (blue) locations, (b) the selected city/community's HEAT Score, (c) the associated statistics for estimated total consumption cost, total savings, GHG emissions and GHG reductions for space heating - per fuel type i.e., Natural Gas, (d) the distribution of HEAT Scores - within the assessed area, (e) the list of communities in the city ordered by HEAT Score**.**

2.3.2.2 Community Level

When a user zooms into the next level, they will see a *Community HEAT map* (Figure 2.12). In this map, HEAT Scores are divided into 10 simple equi-interval classes ranging from 0 to 100. These are shown as house polygons colored from blue to red: blue represents 0, (i.e., a cold house) while red represents 100, (i.e., a hot house). Figure 2.12 shows the houses in the Calgary community of Cedarbrae. Community HEAT maps provide an additional level of detail allowing a user to quickly scan over individual hot and cold houses within the study area. Similar to the City HEAT Map, each community is also provided with a HEAT Score and statistical summary (Figure 2.12 a-c).

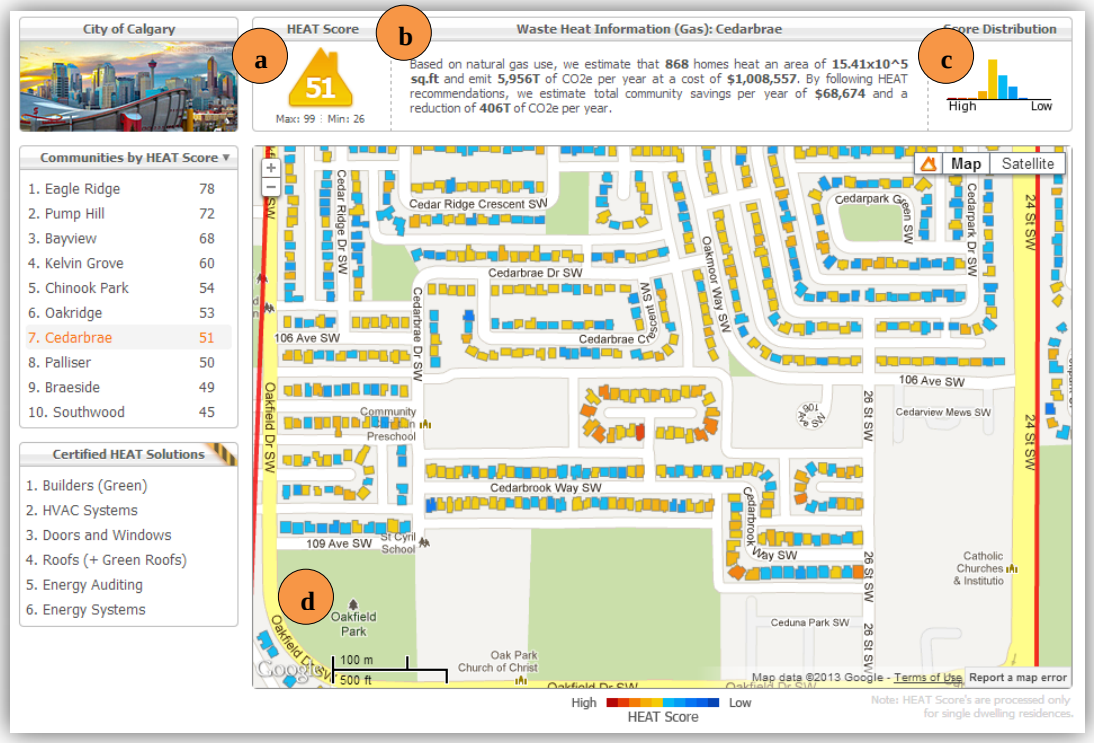
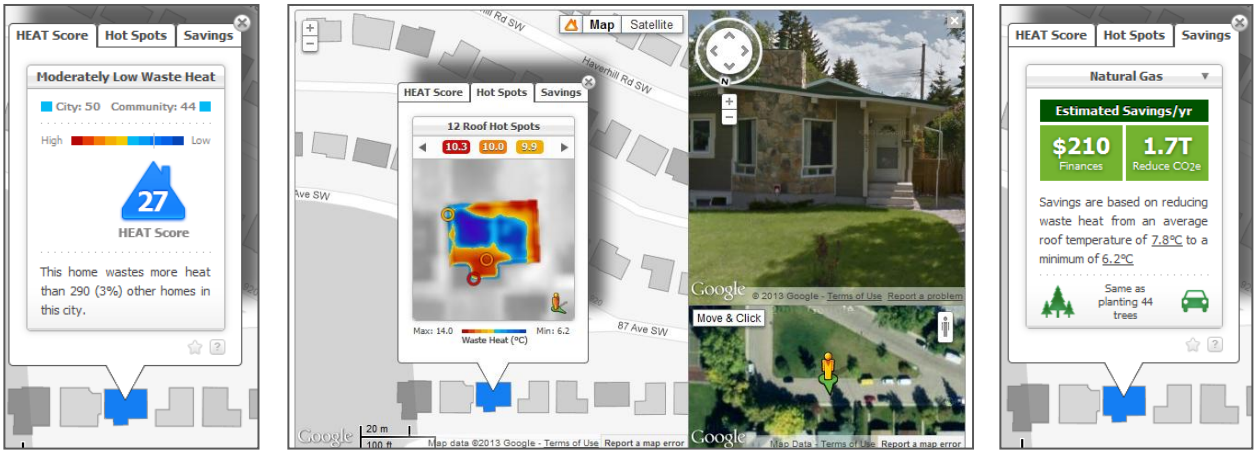


Figure 2.12. The HEAT Score web page showing (a) the Cedarbrae community's HEAT Score, (b) Community statistics for estimated total cost, savings, GHG emissions and GHG reductions for space heating - per fuel type i.e., Natural Gas, (c) the community distribution of HEAT Scores, (d) the Community HEAT map showing houses colored from red to blue representing high - low waste heat per house.

2.3.2.3 Residential Level

At the finest scale, when a user clicks on a house, a *pop-up gui (Graphical User Interface)* is shown with three tabs (Figure 2.13). The first tab shows the *HEAT Score* of the selected house, with a comparison with the City and Community HEAT Scores. It also provides a relative descriptor and detailed comparative city information related to this ranking. For example, the house in - Figure 2.13a has a HEAT Score of 27, which is described as "Moderately Low Waste Heat". It is also noted that "This house wastes more heat than 290 (3%) other homes in this city".



(a) (b) (c)

Figure 2.13. This figure shows (a) the HEAT Score tab which allows users to compare their house HEAT Score to their city and community scores. (b) The Hotspots tab shows the hottest roof locations on the selected house, which can be linked to Google Street View to identify potential problem areas. For example, the warmest Hot Spot (10.3°C) corresponds to the front door and chimney area. (c) The Savings tab shows house specific energy model estimates for savings and GHG reductions – along with environmental equivalents (i.e., *Same as planting 44 trees*).

Table 2.7 shows the HEAT Scores and their corresponding waste heat descriptions. As illustrated in Figure 2.13, the second tab (*Hot Spots*) shows the actual thermal image of the house of interest [colorized from red (hot) to cold (blue)] with the 12 hottest locations, shown three at a time (and the ability to scroll through them). Users are also able to see their house with an integrated Google Street view to verify the location of their hotspots. For example, in the Street View image (Figure 2.13b), the corresponding thermal location shows two hotspots and a red colored area over the front door (and around the chimney) suggesting that these areas are leaking heat and may benefit from further evaluation.

The third tab (Figure 2.13c) shows the estimated *Savings* and GHG reductions ($210 CAD per year and 1.7 metric tonnes) if the owner is able to take action that will reduce their heat loss from the average roof (waste heat) temperature (7.8°C), to the minimum roof temperature (6.2°C) shown on either side of the colored waste heat legend in Figure 2.13b.

This information is derived from a house specific energy model and specific fuel source (i.e., natural gas).

Table 2.7. HEAT Scores and their relative waste heat descriptions.

HEAT Score	Relative Waste Heat Description
90-100	Very High
75-89	High
50-74	Moderately High
25-49	Moderately Low
10-24	Low
0-9	Very Low

Chapter 3: Results and Discussion

The first section in this chapter discusses the results of the HEAT Scores developed using three methods. The second section discusses the statistical and spatial distribution of HEAT Scores over the entire study site. The final section discusses six challenges faced by this study and their potential solutions.

3.1 Comparison of Different HEAT Scores

Figure 3.1 shows different HEAT Score for the same house resulting from the three different methods described in Chapter 2. This house was constructed in 1910 and has a living area of 330 m^2.

(a) (b) (c)

Figure 3.1. Different HEAT Scores for the same house developed using (a) Standard Score (z-score), (b) Logistic regression and (c) weights assigned to different factors contributing to the HEAT Score (see Chapter 2 for method details).

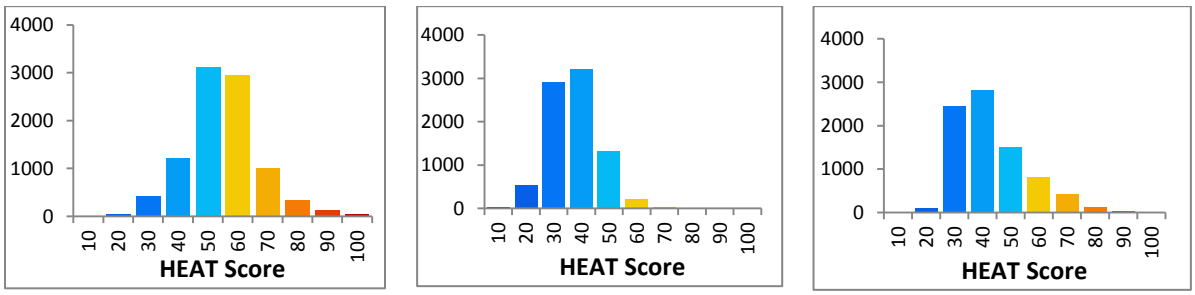
The HEAT Scores developed from the standardized score and logistic regression are very similar, 75 and 76 respectively. However the HEAT Score developed by assigning

weights has rated the house at 89. This is one of the oldest and largest houses in the city (in the absence of information regarding energy efficiency renovations). Therefore according to the rationale developed in section 2.2.3, this house will consume very large amount of energy, thus it should have a high HEAT Score.

3.2 Distribution of HEAT Scores from three different methods

3.2.1 Statistical Distribution of HEAT Scores

Figure 3.2 shows the statistical distribution of HEAT Scores developed from three different methods. HEAT Scores developed using the standardized score vary from 1 to 99 and are normally distributed throughout the city (Figure 3.2a). This comes as no surprise as z-scores are normalized scores. The HEAT Scores developed using logistic regression varies from 1 to 76 (Figure 3.2b) and their distribution are skewed to the left – the 'cooler' more 'energy efficient' portion of the HEAT Score spectrum. The HEAT Scores developed by assigning weights to individual factors varies from 12 to 89 (Figure 3.2c). This distribution is also skewed to the left but it shows more variation than the HEAT Scores developed using the logistic regression. A well distributed HEAT Scores is preferred as the study site contains a broad range of house ages, living area and construction types.



(a) (b) (c)

Figure 3.2. HEAT Score statistical distributions representing the entire study site derived from (a) Standard Score or z-score, (b) Logistic regression and (c) weights assigned to different factors.

From Table 3.1 it can be seen that the Community HEAT Scores developed using the *standard score* widely range from 42 to 78, with the community of Eagle Ridge being the 'hottest' (i.e., high waste heat). HEAT Scores developed using *logistic regression* range from 31 to 46, with the community of Cedarbrae being the 'hottest'. We also note that Pump Hill, which is one of the hottest communities based on *standard scores*, ties for the coldest community according to logistic regression. This is because Pump Hill contains some of the largest houses in the study area and HEAT Scores derived from the standard score were directly related to living area, while HEAT Scores derived from logistic regression are inversely related to living area. HEAT Scores derived from *weighted attributes* range from 31 to 52, resulting in a slightly wider distribution than logistic regression. According to this method, Cedarbrae is the hottest community with a value of 52, which is very close to the value of 51 from the Standard Score, and ties for the hottest community with a value of 46 from logistic regression

Table 3.1. Community HEAT Scores developed using different methods – Ranked from hottest to the coldest based on the standard scores.

Community	No. of Homes	Average HEAT Score using		
		Standard Score	Logistic Regression	Factors Weights
Eagle Ridge	96	78	39	47
Pump Hill	405	72	31	41
Bayview	212	68	35	39
Kelvin Grove	379	60	36	42
Chinook Park	465	54	37	42
Palliser	474	50	31	31
Oakridge	896	53	39	41
Kingsland	753	42	31	32
Haysboro	1868	44	33	37
Braeside	1408	49	38	34
Southwood	1455	45	36	47
Cedarbrae	868	51	46	52

Based on the HEAT Scores developed from *weights* and from *logistic regression*, Palliser is the coldest community. However, Palliser was not the coldest according to the HEAT Scores developed from standard scores. On further examination it was revealed that this occurred due to the influence of the hotspots. This is because average hotspot temperatures in this community are closer to the WUFI modeled optimal rooftop temperature which resulted in a low score for hotspots and waste heat, and consequently a low HEAT Score. This could mean that either the WUFI modeled rooftop temperatures for this portion of the study area are in error or that the roofs in this community are not made of asphalt shingles (as assumed) – thus, their related emissivity values and (resulting 'true') temperature are incorrectly modeled. By evaluating the roof-tops of this community in Google Street view, it is apparent that there are a number of roofs made of cedar; however, there are also many rooftops composed of asphalt shingles. As a result, this issue can only be solved after carefully modeling rooftop temperatures for different kinds of roof systems found in this site and applying an emissivity correction for the corresponding roof materials. Though beyond the scope of this thesis, and as previously noted in the data and methods, this will require developing a detailed and accurate land-cover map (composed of roof-top material classes) and assigning corresponding emissivity's to correct *relative* rooftop temperatures to *true* kinetic temperatures.

Table (3.1) also suggests that there is no clear pattern or trend between the HEAT Scores developed from these methods. This is due to the fact that all these methods are very different from each other. For example, a house that has a very large living area will get a high HEAT Score based on standard score, a low HEAT Score based on logistic regression while HEAT Score based on criteria weights assign only 15% of the weights

for living area. Also age is not considered in HEAT Score based on standard score while the other two methods give age a considerable weight. Therefore an old house with a large living area is more likely to get a high HEAT Score based on criteria weights than the other two methods.

3.2.2 Spatial Distribution of HEAT Scores

Figure 3.3 shows the City HEAT Map developed using *standard scores*. This map represents a smooth interpolated image of HEAT Scores using inverse distance weighting and illustrates the general trend of the hottest houses in the study area ranging from red to blue (high – low waste heat). Figure 3.4 shows the Community HEAT Map using the same standard scores. These maps show the highest variation compared to the other two methods for generating HEAT Scores. As noted earlier this is due to the fact that standard scores are based on a normal distribution and these data were transformed to be normally distributed. As a general trend in both these maps, it can be seen that Pump Hill, Eagle Ridge and Bay View communities waste more heat. The reason for this is that they are composed of very large houses and *living area* is an important factor for calculating HEAT Scores with this method.

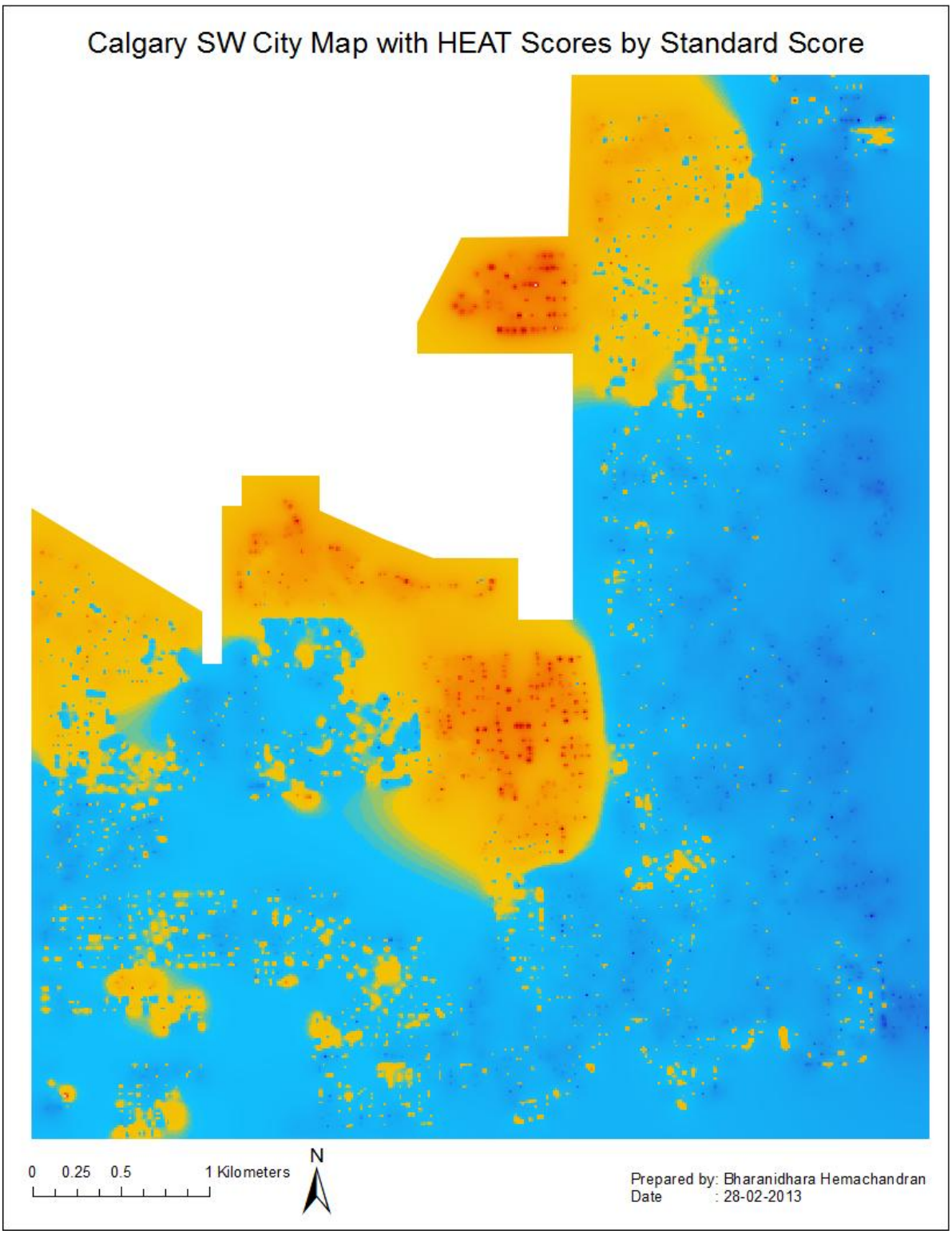


Figure 3.3. The interpolated City HEAT map developed using the standard score method, showing HEAT Score variations for the entire study site, ranging from red to blue (high - low).

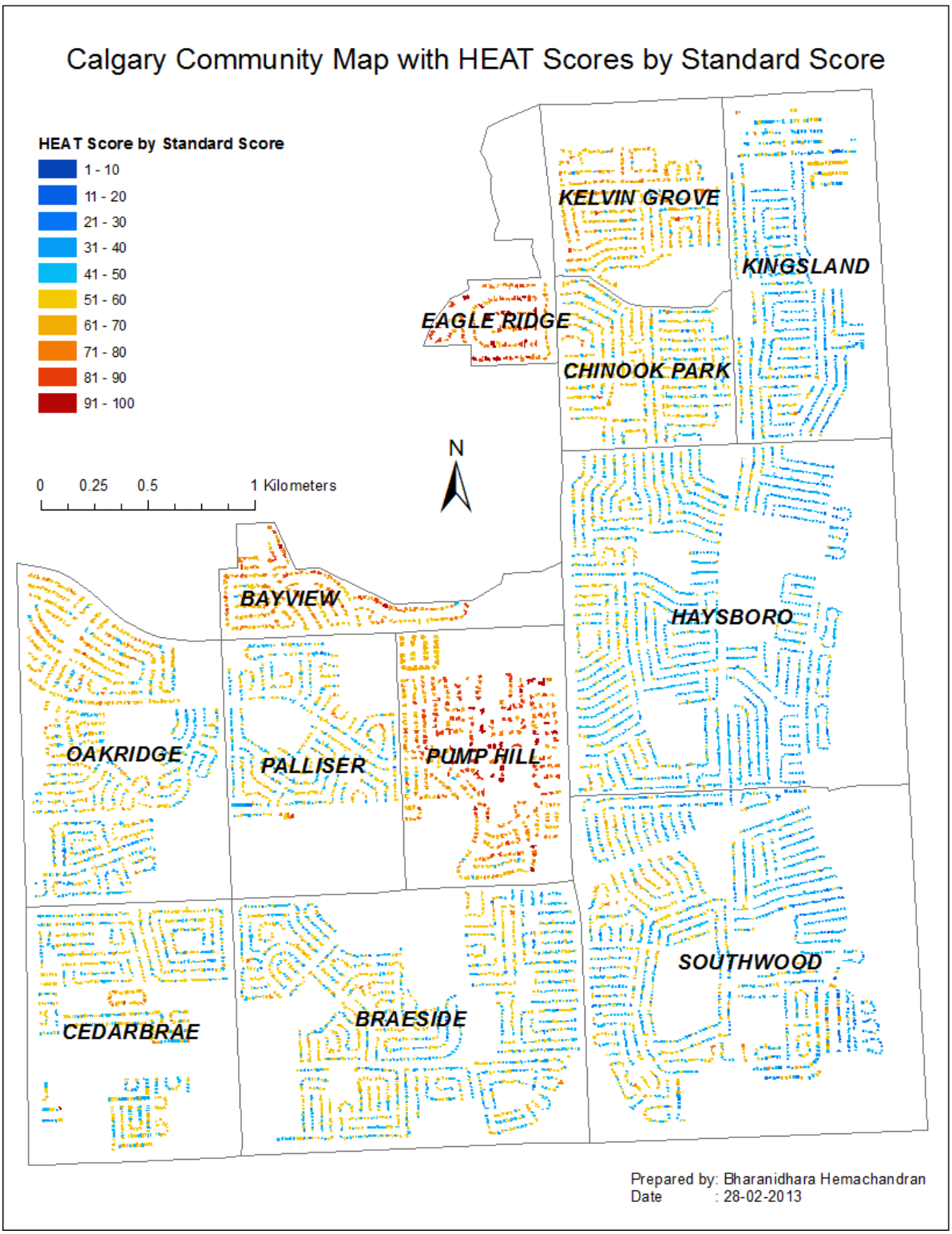


Figure 3.4. The Community HEAT Map showing the spatial distribution of HEAT Scores for each house in the entire study site derived from standard score.

Figure 3.5 shows the City HEAT Map and Figure 3.6 shows the Community HEAT Map developed using *logistic regression*. These maps show very little variation and most of the places are cool (blue), indicating that they waste minimal heat. It can also be seen that Cedarbrae (bottom left) is the hottest community. This is due to the fact that the houses in this area have the largest difference between the WUFI modeled roof temperature and their average hotspot temperature. Pump Hill, which was one of the hottest communities in the HEAT Map generated with the standard score method is shown as a cold community with this method. This is primarily due to the fact that *living area* was negatively related to HEAT Scores using logistic regression and Pump Hill had some of the largest houses in the entire study site.

Figure 3.7 shows the City HEAT Map and Figure 3.8 shows the Community HEAT Map resulting from *criteria weights*. These maps show better variation compared to the logistic regression results but less variation compared to standard scores method. Similar to the logistic regression method Cedarbrae is again the hottest community. This is due to the fact that these houses have the highest differences between the WUFI modeled rooftop and average hotspots temperature. Pump Hill, which was the coldest community according to logistic regression, has a HEAT Score of 47 (tied for 2nd hottest) based on HEAT Scores by weights. This is reasonable considering the fact that this community contains very large houses. Thus, as the living area increases the energy consumption and waste heat also increases.

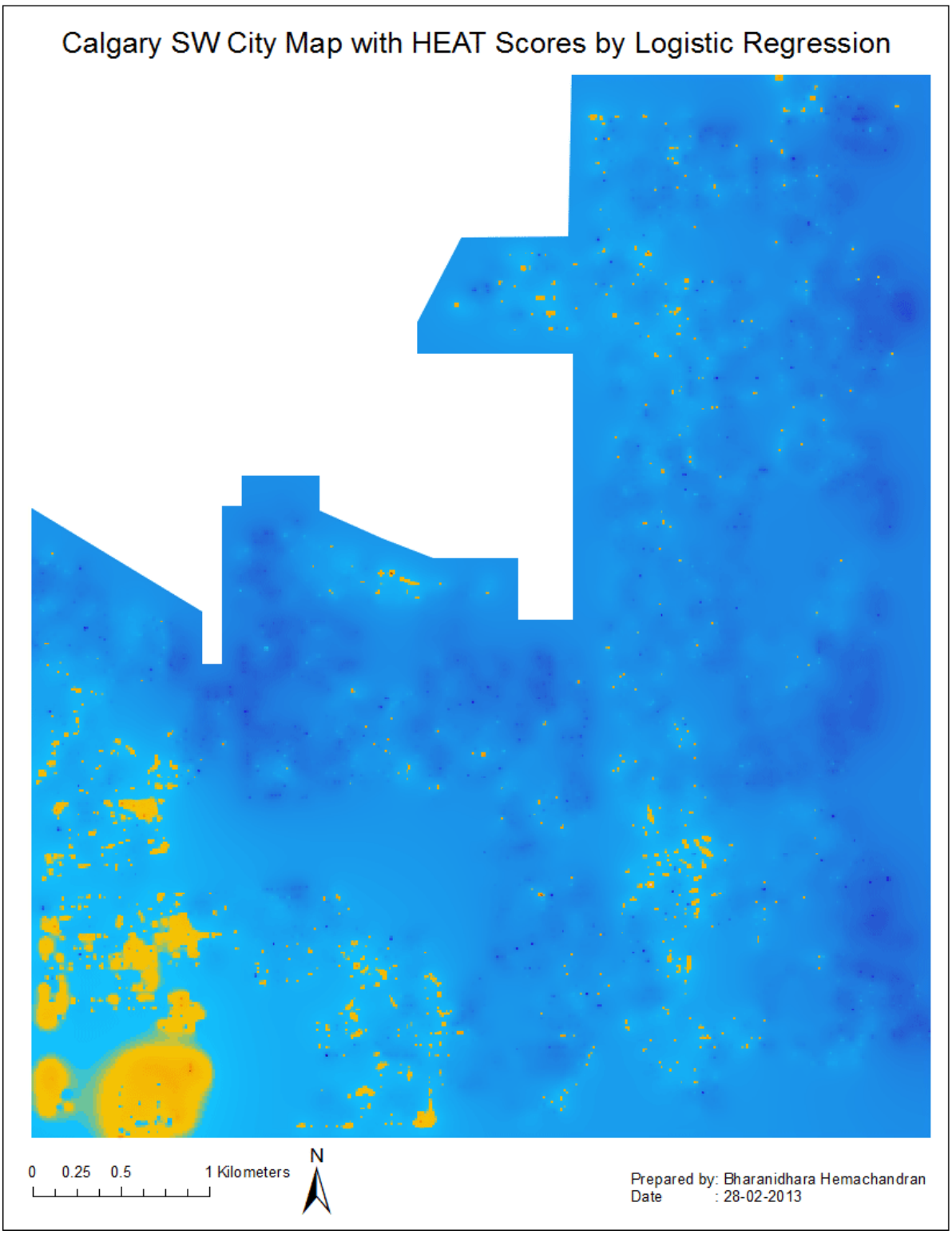


Figure 3.5. The interpolated City HEAT map developed using logistic regression, showing HEAT Score variations for the entire study site, ranging from red to blue (high - low).

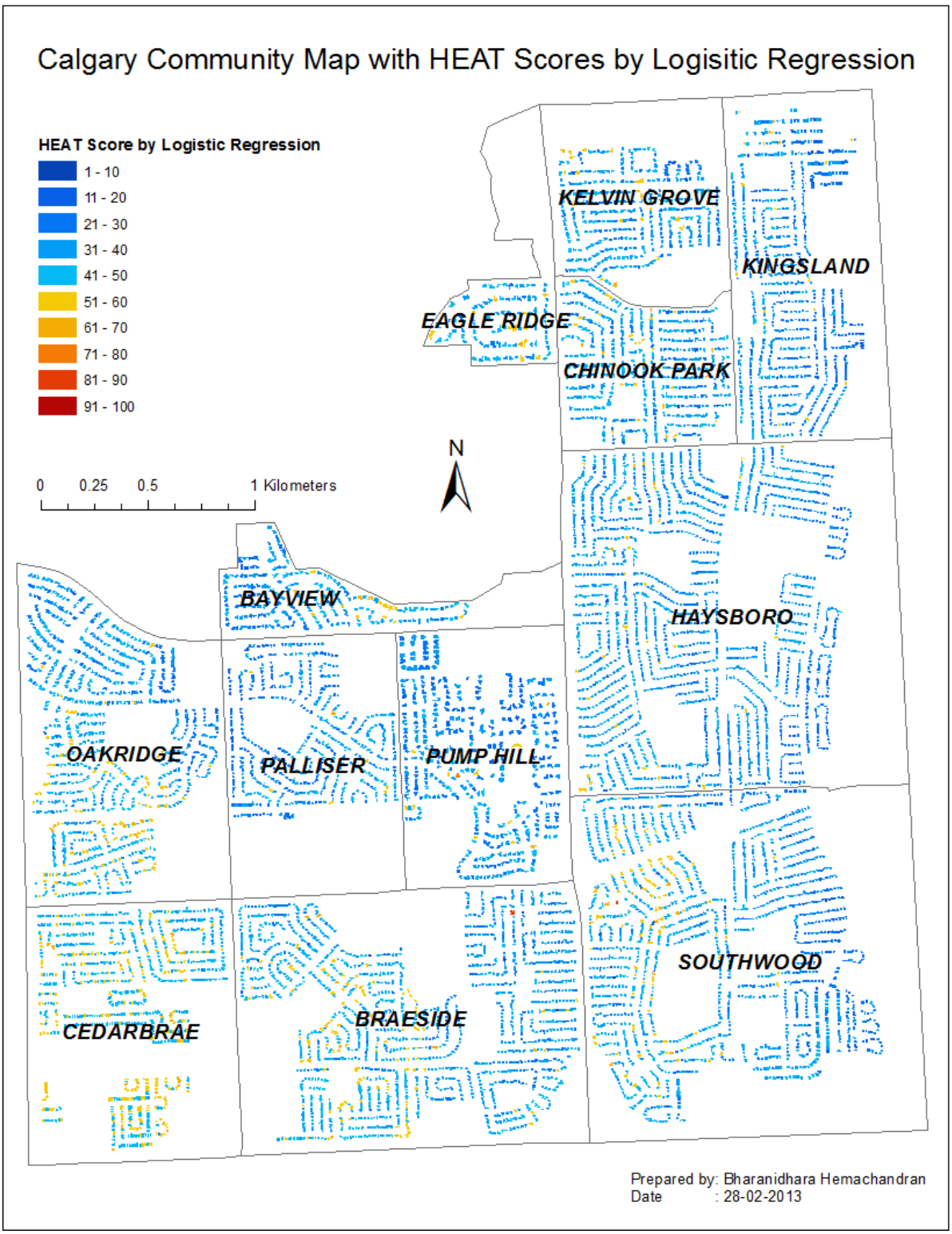


Figure 3.6. The Community HEAT Map showing the spatial distribution of HEAT Scores for each house in the entire study site derived from logistic regression.

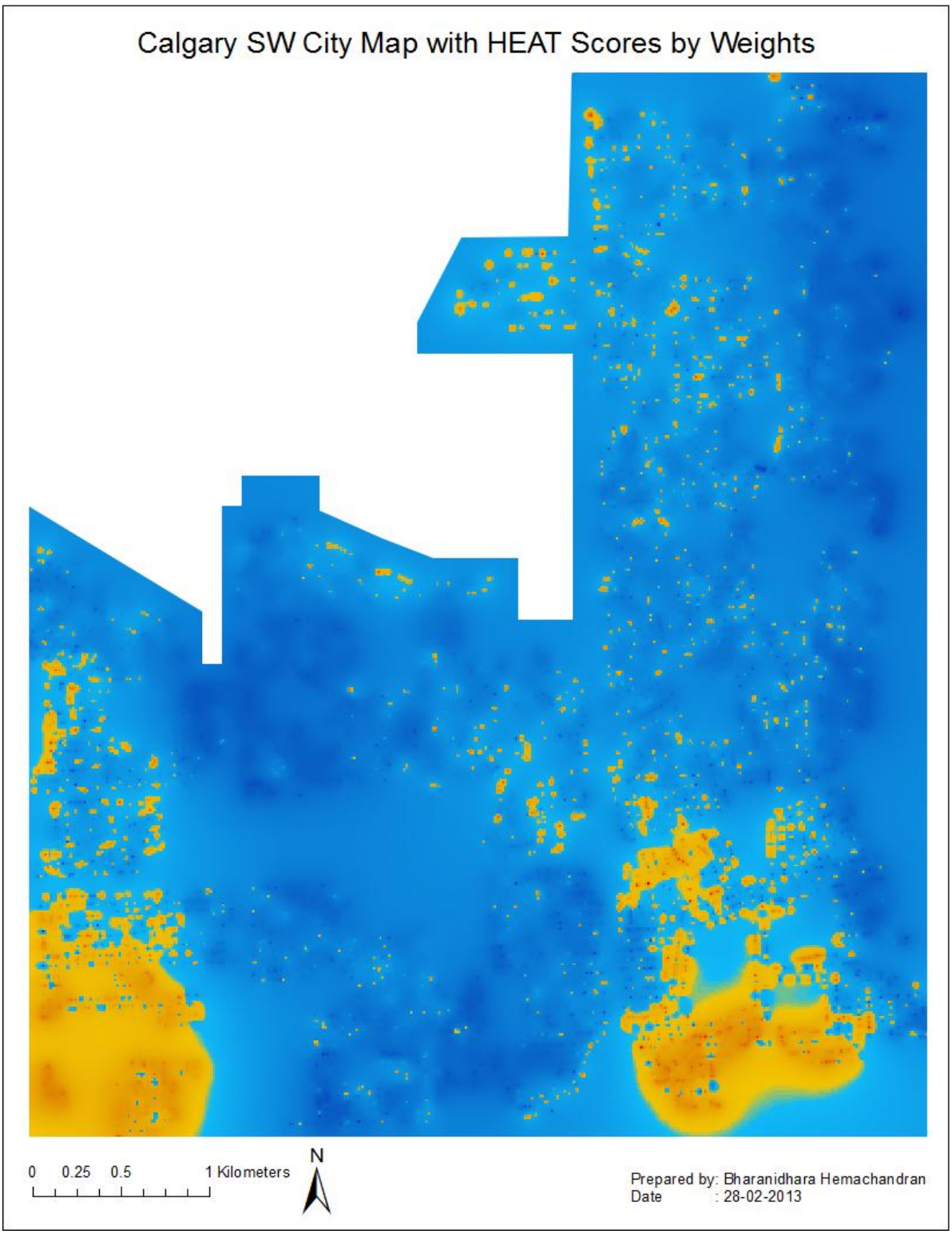


Figure 3.7. The interpolated City HEAT map developed using the weighted method, showing HEAT Score variations for the entire study site, ranging from red to blue (high - low).

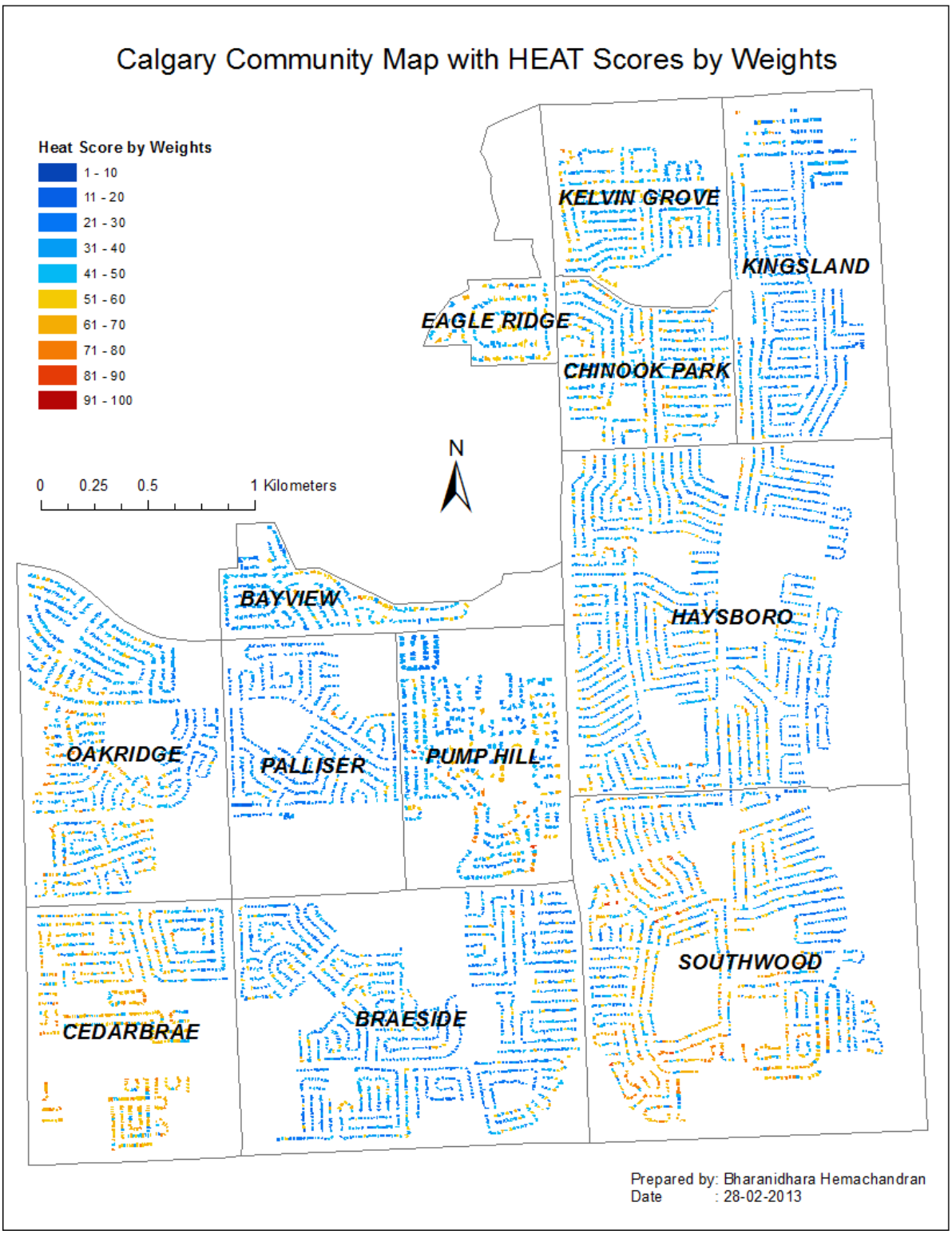


Figure 3.8. The Community HEAT Map showing the spatial distribution of HEAT Scores for each house in the entire study site derived from criteria weights.

3.3 Challenges

This project faces a number of challenges. In the following sections, we will briefly discuss the effects of (i) geometric correction, (ii) vegetation covering homes, (iii) defining correct emissivity values, (iv) microclimatic variability, (v) defining rooftop temperature and (vi) the relationship between hotspots and energy consumption. Though it is beyond the scope of this thesis to solve each of these challenges, it is important to recognize the limitations inherent in this research. Furthermore, while the HEAT Score methods and Energy Models (Figure 2.13c) described in this thesis are intended as improvements over the initial Phase I HEAT proof-of-concept, their potential for operationalization over larger areas will only be fully realized, as solutions to these challenges are implemented.

3.3.1 Effects of Geometric Correction on HEAT Scores

The first challenge that this project faced was the accuracy of the geometric correction between the thermal and City GIS datasets. As described earlier, the thermal data and the cadastral data come from different sources at different times and therefore these had to be geometrically corrected to each other. Even though both datasets were painstakingly geometrically corrected to each other (with 800+ GCPs), there are places where the geometric accuracy is questionable. For example, in Figure 3.9, it can be seen that the overlap between the cadastral dataset (red) and the thermal image (grey tones), while reasonable, is not perfect. These kinds of errors may result in defining hotspots on *the ground* (i.e., the lighter grey ‘warmer’ pixels located within the red polygon) instead of being located on *the rooftop* (the darker grey ‘cooler’ within the red polygon). This will

affect the thermal metrics such as the average hot spot temperatures, which in turn will affect the calculation of waste heat and HEAT Scores over the entire image.

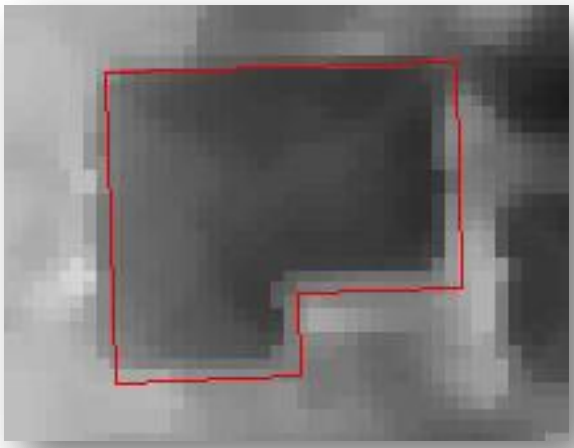
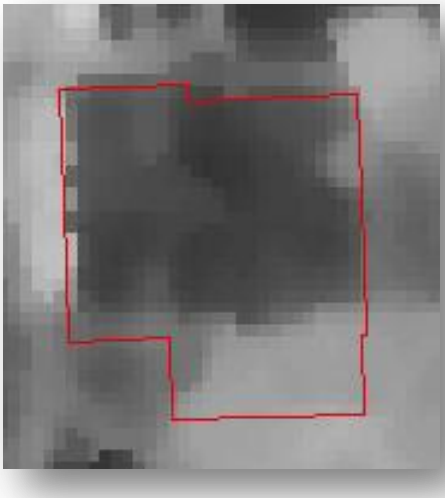


Figure 3.9. Errors in geometric correction between the thermal image and cadastral GIS data.

3.3.2 Effects of Vegetation on HEAT Scores

The next challenge is the vegetation overlapping many rooftops, thus obscuring the TIR house signal (Figure 3.10a). In our TIR image, vegetation appears to be hotter than the rooftops (see Figure 3.10b - note the light grey tones of the vegetation located at the bottom of the red polygon). This is due to the high emissivity values of vegetation compared to the rooftops (Brunsell & Gillies, 2003). As a result, vegetation covering the roof (and within the GIS polygon) will appear hot, resulting in misidentified hotspots and higher HEAT scores for these houses. The solution to this problem is to first remove the trees from the analysis. This could be achieved either by using a NDVI (Normalized Difference Vegetation Index) image created from complimentary data to classify the vegetation (such as the 2012 City of Calgary R, G, B, NIR ortho-photo), or by using GEOBIA ‘feature detection’ methodologies to define house-objects instead of using the GIS cadastral data. GEOBIA is the acronym for

(a)



(b)

Figure 3.10. A view of trees (bottom right) obscuring part of the (same) rooftop (a) as seen in Google Maps and (b) the thermal image (images not to scale).

Geographic Object-Based Image Analysis. "*GEOBIA is a sub-discipline of Geographic Information Science (GIScience) devoted to developing automated methods to partition remote sensing imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scales, so as to generate new geographic information in GIS-ready format.*" (Hay and Castilla 2008). Using GEOBIA methods in combination with vegetation indices and GIS polygons (to automatically define the relative area/object of interest) holds great promise to define house objects and solve the issues with overlapping vegetation (as well as with the geometric correction), and is an active area of research in Dr. Hay's research team.

3.3.3 Effects of Emissivity on HEAT Scores

Based on visual analysis, approximately 80% of all roofs in the study area are estimated to be composed of asphalt shingles. Therefore a general emissivity value of 0.91 is used for

calculating the true temperature of roofs. However there are some houses with rooftops constructed of metal, cedar shingles, rubber and cement. The metal rooftops appear very cold on the image and result in a very low HEAT Score (which is relatively easy to define and confirm in Google Street view). However, it is non-trivial to define a single generic emissivity value for metals, rubber or cement, especially with the variation in building types and the many coatings that exists for these roofing classes. In order to solve this problem, a rooftop classification needs to be carried out to define different types/classes of roof materials. Then each classified roof can be allocated with a more accurate emissivity value. Though beyond the scope of this thesis, this is also an active area of research by Dr. Hay's research team.

3.3.4 Effects of Microclimate on HEAT Scores

Another challenge that this project encounters is micro-climate variability. Places closer to the valleys and rivers/streams appear colder (especially at night). These places will also have a different amount of humidity compared to other places in the study area. Ji et al. (2012) noted that the effect of an urban river on decreasing local temperatures is high. Therefore these microclimate conditions need to be mitigated in order to obtain the true kinetic temperature. For HEAT Scores, this has been partially mitigated by interpolating the air temperature obtained from twenty weather stations. While twenty stations for the whole city are not ideal, currently it represents the best available estimate.

3.3.5 Defining optimal rooftop temperature for HEAT Scores

Estimates of optimal rooftop temperature for asphalt roof assemblies are modeled using WUFI® (see Section 2.2.2.2). Ideally these temperatures have to be validated using field measures. Currently this method produces the best estimates available for this project. In the

future a number of sample field measurements (at least one measurement for each different type of roof material in The City) have to be collected using a thermal infrared camera, ideally while the airborne thermal image is being collected. These measurements need to be observed on new houses where the waste heat is known to be minimal. While taking these measurements, the roof type materials need to be recorded, so that they can be accurately corrected for emissivity. The WUFI modeled temperatures for different roof assemblies could then be validated with these field measurements.

3.3.6 Hotspots and their relation to energy consumption

The next challenge is that some of the hotspots defined on the rooftops might be due to chimneys or vents whose main purpose is to provide ventilation for hot gases or smoke. In order to minimize their effects, the average of the first 12 hotspots on the rooftop is used. This smoothes out any high temperatures generated from chimneys/vents.

Though it is common sense to know that the hotter the (night time) rooftop temperature, the higher the energy consumed by the house, there is no clear relationship between the temperature recorded by the sensor and the energy consumed *inside* the house. In order to overcome this challenge, a thermal infrared camera should observe the rooftop temperatures of two ‘control’ houses over a period of time. The first ‘control’ house should be an old house which wastes more heat and the second one a newly constructed house wasting minimal heat. Thermal data recorded over the period of time could then be used in conjunction with the energy consumption data to discover the relationships between them.

Chapter 4: Conclusion

On the world scale, Canada is a massive energy consumer (Ménard, 2005) and is environmentally ranked 24th (1 being the best and 25 being the worst) among the 25 OECD (Organization for Economic Co-operation and Development) countries reviewed in a study conducted by the David Suzuki Foundation (Gunton 2005). Buildings consume 30% of all the energy produced; consequently they are a major candidate for energy conservation. The majority of this energy is consumed for space and water heating. As a result, space heating provides significant opportunities to conserve energy. Behavioral science theories applied to energy analysis suggest that incorporating feedback, the social norm and public commitment into energy efficiency programs is highly effective. Research conducted on energy consumption feedback has consistently shown that people tend to reduce their energy consumption if they know how much they consume and how much money they can save. By building on these concepts, this thesis has focused on providing relevant feedback to support urban energy efficiency in the form of HEAT Scores derived (in part) from thermal imagery.

The first objective of this research was to develop an appropriate method for HEAT Scores that allow for a comparison of waste heat of one or more houses with all other houses in a community and city. The HEAT Scores were developed using three different methods namely (i) the Standard Score or Z-Score, (ii) WUFI and Logistic regression, and iii) criteria weighting. The first two methods had their limitations which led to the development of third method. HEAT Scores developed by assigning weights to attributes was evaluated against the EnerGuide Rating System, which is traditionally used to analyze the performance of houses in Canada. The results of HEAT Scores from different methods were also compared with each other. Statistical and Spatial distribution of HEAT Scores

from three methods were also discussed. The effects of (i) discrepancy in geometric correction, (ii) vegetation on rooftops, (iii) emissivity of roof materials, (iv) microclimate variability, (v) defining optimal rooftop temperature, and (v) relationship between hotspots and energy consumption on HEAT Scores were also noted as limitations that require solutions prior to accepting HEAT Scores as valid descriptors of waste heat.

The second objective was to develop a multi-scale and interactive user interface for accessing HEAT Scores on the HEAT Geoweb site. HEAT Scores and HEAT maps were integrated into the HEAT system architecture which were then displayed to the users at three different levels namely (i) City, (ii) Community, and (iii) Residential.

This study developed a novel method to support urban energy efficiency by providing feedback to residents in the form of HEAT Scores that are defined from thermal imagery. Specifically the criteria weights method satisfies five important considerations of HEAT Scores. It allows for:

i. *Incorporating heat transfer through different roofing materials,*
ii. *Consideration of local climatic conditions,*
iii. *Including house age and living area attributes in its calculation,*
iv. *Removing or adding new houses to the analysis without affecting the HEAT Scores of other houses.*
v. *Comparison of HEAT Scores across and within cities.*

Other similar studies around the world that provide building energy efficiency feedback to the users based on thermal imagery displayed heat loss maps as simple colored maps without any in-depth visual or statistical analysis. However this thesis focused on providing a detailed multi-scale visual and statistical analysis of urban energy efficiency by defining HEAT Scores that allow for a comparison of houses across communities and city.

This thesis has contributed to the HEAT Geoweb Project by developing a multi-scale user interface and a new robust method for defining HEAT Scores that builds upon and provides solutions to the HEAT Phase I pilot project limitations. Within a free Geoweb environment it is also envisioned that these HEAT Scores will incorporate the behavior theory concepts of *(i) indirect feedback, (ii) social norm, and (iii) public commitment.* Specifically, the HEAT Scores will provide meaningful indirect visual feedback to the users in the form of colored maps and simple ranked values (between 0 and 100 representing low and high waste heat respectively). As a result individuals will be able to compare their house with all other houses in the city. Since the results are freely available on a public web site, we envision individuals will follow the social norms of the community/city and encourage healthy competition to reduce their energy consumption. Furthermore, it is expected that people will commit to reduce their energy consumption as nobody wants to be seen wasting energy. City planners may also benefit from using Community HEAT scores to identify high waste heat communities and target their energy retrofit programs. HEAT Scores may also be used to promote web-based 'urban energy efficiency' monitoring/competitions between Canadian home-owners, communities and cities.

4.1 Future Work

As future work, the weighted criteria HEAT Scores method will be applied to and evaluated over the entire City of Calgary (300,000+ houses). In this thesis this conceptual method was evaluated against ERS data. In the future the HEAT Scores themselves needs to be evaluated against ERS data. This may be accomplished either by collecting Volunteered Geographic Information (VGI) from the users, or by obtaining access to ERS data with address information. In addition to evaluating HEAT Scores, the optimal roof top

temperature defined using WUFI® needs to be evaluated using field measurements. These field measurements need to be sampled over a variety of house types including those composed of different age groups and roof materials. This study assumed that a majority of the roof materials were asphalt shingles. In the future, a detailed emissivity classification of roof materials needs to be performed in order to generate more accurate estimates of true roof-top kinetic temperature. This will further improve the validity of HEAT Scores which are based on these temperature values.

References

Aberdeen. (2013). Thermal images of city recorded during flyovers, Aberdeen City Council, England, http://www.aberdeencity.gov.uk/CouncilNews/ci_cns/pr_thermalimages_260213.asp, last accessed 15-04-2013.

Abrahamse, W., Steg L., Vlek C., Rothengatter T. (2005) "A review of intervention studies aimed at household energy conservation", Journal of Environmental Psychology 25, pp 273–291.

Allcott, H. (2011), Social norms and energy conservation, Journal of Public Economics. Volume 95, Issues 9-10, pp 1082. http://dx.doi.org/10.1016/j.jpubeco.2011.03.003.

Allinson, D. (2007). Evaluation of Aerial Thermography to Discriminate Loft Insulation in Residential Housing. Ph.D. Thesis, University of Nottingham, Nottingham, UK, Available online: http://etheses.nottingham.ac.uk/284/, pp 166.

Ashby, K. V., M. Nevius, M. Walton, and B. Ceniceros. (2010), "Behaving Ourselves: How Behavior Change Insights Are Being Applied to Energy Efficiency Programs." American Council for an Energy-Efficient Economy (ACEEE) 2010 Summer Study on Energy Efficiency in Buildings, pp 7-16.

Berk, A.; Bernstein, L. S.; Robertson, D. C. (1989). MODTRAN A Moderate Resolution Model for LOWTRA7N, AFGL-TR-89-0122, U.S. Air Force Geophysics Laboratory, Hanscom Air orce Base, Mass.

Brunsell, N.A. and Gillies, R.R. (2003). Length scale analysis of surface energy fluxes derived from remote sensing. Journal of Hydrometeorology, 4: pp 1212–1219.

Burn, S.M., and S. Oskamp. (1986). "Increasing Community Recycling with Persuasive Communication and Public Commitment." Journal of Applied Social Psychology 16: pp 29-41.

Calgary Climate Change Accord. (2009). http://www.calgary.ca/UEP/ESM/Pages/Climate-change/Calgary-Climate-Change-Accord.aspx, last accessed 12-01-2013.

Calgary Community Greenhouse Gas (GHG) Reduction Plan. (2011). http://www.calgary.ca/UEP/ESM/Documents/ESM-Documents/Calgary_GHG_Plan_Nov_2011.pdf, last accessed 12-02-2013.

Carroll, E., Hatton E., Brown M. (2009). Residential Energy Use Behavior Change Pilot, Report presented to Joe Plummer, Minnesota Department of Commerce, Office of Energy Security.

Cherfas, J. (1991). Skeptics and visionaries examine energy savings. Science 25 1 : 1 54-56.

Cialdini, R.B. (2007). "Descriptive Social Norms as Underappreciated Sources of Social Control." Psychometrika 72: 263-268.

Colcord, J. (1981). Thermal Imagery Energy Surveys. Photogrammetric Engineering and Remote Sensing , 47 (2), 237-240.

CUI, (2008). Energy Mapping Study. Prepared by the Canadian Urban Institute. December 19, 2008. pp, 92.

Darby, S. (2006). The Effectiveness of Feedback on Energy Consumption. Report published by Environmental Change Institute. University of Oxford, pp 21.

Denmark. (2011). Thermal Mapping of HEAT-Loss from Buildings, Denmark, http://blomasa.com/news/thermal-mapping-of-heat-loss-from-buildings-denmark.html, last accessed 15-04-2013.

Ecobee, www.ecobee.com, last accessed 28-03-2013.

Exeter. (2009). Exeter heat loss survey, Exeter, England, http://www.exeter.gov.uk/index.aspx?articleid=10560, last accessed 15-04-2013.

Footprint, (2008). Towards a preferred Future. Understanding Calgary's Ecological Footprint, pp 24 Downloaded from, http://www.footprintnetwork.org/images/uploads/Calgary_Ecological_Footprint_Report.pdf - last accessed 03-03-2013.

Gunton, T. et al. (2005). The Maple Leaf in the OECD, Comparing Progress toward Sustainability. Vancouver: David Suzuki Foundation.

Hay, G.J., and G. Castilla, (2008). Geographic Object-Based Image Analysis (GEOBIA): A new name for a new discipline, *Object-Based Image Analysis–Spatial Concepts for Knowledge-driven Remote Sensing Applications* (T. Blaschke, S. Lang, and G.J. Hay, editors),Springer-Verlag.

Hay G.J., Hemachandran B., and Kyle C.D. (2010). HEAT (Home Energy Assessment Technologies): Residential Waste Heat Monitoring, Google Maps and Airborne

Thermal Imagery. Alberta, Canada. GIM International. Issue 03, Vol 24, March, pp 13-15.

Hay G.J., Kyle C., Hemachandran B., Chen G., Rahman M.M., Fung T.S., and Arvai J.L. (2011). "Geospatial Technologies to Improve Urban Energy Efficiency." Remote Sens. 3, no. 7: 1380-1405, http://www.saveheat.co.

Haringey. (2007). Home Heat Loss, http://www.haringey.gov.uk/index/housing_and_planning/housing/housingadvice/homeheatloss.htm, last accessed 15-04-2013.

Hosomura T. (1994). Geometric correction of NOAA images by triangulation. Proc. SPIE 2357, ISPRS Commission III Symposium: Spatial Information from Digital Photogrammetry and Computer Vision, 387 (August 17, 1994); doi:10.1117/12.182885.

Jacob, F.; Francois, P.; Schmugge, T.; Vermote, E.; French, A.; Ogawa, K. (2004). Comparison of Land Surface Emissivity and Radiomatric Temperature Derived from MODIS and ASTER. Remote Sensing of Environment, 90, pp 137-152.

Jensen, J. R. (2007). Remote Sensing of the Environment: An Earth Resource Perspective 2nd edition. Upper Saddle River: Pearson Prentice Hall.

JI, P., ZHU, C., & LI, S. (2012). Effects of urban river width on the temperature and humidity of nearby green belts in summer. Yingyong Shengtai Xuebao, 23(3), 679-684. http://www.ncbi.nlm.nih.gov/pubmed/22720611 last accessed 14-02-2013.

Kirchhoff, G. (1896). On the relation between the Radiating and Absorbing Powers of different Bodies for Light and Heat, translated by F. Guthrie in Phil. Mag. 4-20: 130, 1-21.

Kneizys, F.X.; Shettle, E.P.; Gallery, W.O.; Chetwynd, J.H.; Abreu, L.W.; Selby, J.E.A.; Clough, S.A.; Fenn, R.W. (1983). Atmospheric transmittance/ radiance: computer code LOWTRAN 6. Air Force Geophysics Laboratory, Environmental Research Paper 846, Hanscom AFB, MA.

Kordjamshidi, M. (2011). House Rating Schemes, Green Energy and Technology, DOI 10.1007/978-3-642-15790-5_2, Springer-Verlag Berlin Heidelberg, pp 9-10.

Laskey, L., Kavazovic O. (2011). Energy Efficiency through behavioral science and technology, OPOWER, XRDS, Summer 2010, Vol 17, No 4, pp 48 – 49.

Lutzenhiser L. (1993). SOCIAL AND BEHAVIORAL ASPECTS OF ENERGY USE, Annual Reviews Energy Environment, pp 281

Mahone, A., Haley B. (2011). Overview of Residential Energy Feedback and Behavior based Energy Efficiency, Report Prepared for the Customer Information and Behavior Working Group of the State and Local Energy Efficiency Action Network, Energy and Environmental Economics, Inc., San Francisco, pp 41-42.

Mountain D. (2006). The impact of real-time feedback on residential electricity consumption: the Hydro One pilot. Mountain Economic Consulting and Associates Inc., Ontario.

Mehra, J.; Rechenberg H. (1982). The Historical Development of Quantum Theory. 1. New York: Springer-Verlag. ISBN 0-387-90642-8

Ménard, M. (2005). Canada, A Big Energy Consumer, A Regional Perspective. Ottawa, Ont.: Statistics Canada. Available From: http://www.statcan.gc.ca/pub/11-621- m/11-621-m2005023-eng.htm#5 last accessed, 14-02-2013.

Nelson, P. E. and Ananian, J. S. D. (2009) Compact Asphalt Shingle Roof Systems: Should They be Vented?, Journal of ASTM International, Vol. 6, No. 4, pp 6.

Nest, www.nest.com, last accessed 28-03-2013.

New York City Building Energy Map. (2012). http://modi.mech.columbia.edu/nycenergy/about.html last accessed, 15-04-2013.

Nicole, J.E. (2009). An Emissivity Modulation Method for Spatial Enhancement of Thermal Satellite Images in Urban Heat Island Analysis. Photgrammetric Engineering & Remote Sensing. vol. 75, No. 5.

Oreskes, N. (1998). "Evaluation (not validation) of quantitative models." Environmental Health Perspectives Supplements 106(S6): 1453-1460.

Oreskes, N., K. Shrader-Frechette, K. Belitz. (1994). "Verification, validation, and confirmation of numerical models in the Earth Sciences." Science 263: 641-646.

Parekh, A. Kirney, C. (2012). Thermal and Mechanical Systems Descriptors For Simplified Energy Use Evaluation of Canadian Houses, SimBuild Conference Aug 1-3, Madison, Wisconsin, pp 1-8, http://www.ibpsa.us/simbuild2012/Papers/SB12_TS05a_2_Parekh.pdf, last accessed 13-02-2013.

Paris. (2010). Thermal Mapping, Paris, France, http://thermographie-gpso.webgeoservices.com/viewer/index.php, last accessed 15-04-2013.

Pembina Insititue. (2011). Options to reduce GHG emission in Calgary, Research report.

Peng, C. Y., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. The Journal of Educational Research, 96, pp 1-14.

Portsmouth. (2012). Is your home leaking heat and money?, Portsmouth City Council, England, http://portsmouththermalmap.bluesky-world.com/, last accessed 15-04-2013.

Powerhouse Dynamics, www.powerhousedynamics.com, last accessed 28-03-2013.

Rahim, Saqib. (2010). Finding the 'Weapons' of Persuasion to Save Energy. http://www.nytimes.com/cwire/2010/06/21/21climatewire-finding-the-weapons-of-persuasion-to-save-ene-8137.html?pagewanted=1;title last accessed 29-3-2013.

Rybicki, G.B.; Lightman, A.P. (1979). Radiative Process in Astrophysics. New York: John Wiley and Sons., ISBN - 0-471- 82759-2

States of Jersey. (2011). Heat Loss Map of Jersey, States of Jersey, http://www.gov.je/Environment/GenerateEnergy/Energyefficiency/Pages/JerseyHeatLossMap.aspx, last accessed 15-04-2013.

Stathopoulou, M., Synnefa, A., Cartalis, C., Santamouris, M., Karlessi, T., & Akbari, H. (2009). A surface heat island study of Athens using high-resolution satellite imagery and measurements of the optical and thermal properties of commonly used building and paving materials. International Journal of Sustainable Energy, v 28, pp 59-76.

Sugawara, H., & Takamura, T. (2006). Longwave radiation flux from an urban canopy: Evaluation via measurements of directional radiometric temperature. Remote Sensing of Environment, vol 104, pp 226-237.

Tabachnick, B. G., & Fidell, L.S. (2001). Using multivariate statistics (4th ed). Needham Heights, MA: Allyn & Bacon, pp 522, 537.

TABI 1800, http://www.itres.com/products/imagers/tabi1800, – last accessed 13-02-2013

The 2020 Sustainability Direction. (2010). http://www.calgary.ca/CA/cmo/Pages/The-2020-Sustainability-Direction.aspx, last accessed 12-02-2013.

The Urban Archetypes Project. (2007). Community Case Study: The City of Calgary; Canmet ENERGY Cat. No. M154-15/3-2009 E-PDF; CanmetENERGY: Ottawa, ON, Canada, pp 10.

Voogt J.A., Oke T.R., (2003). Thermal remote sensing for urban climates, Remote Sensing of Environment 86, pp 370–384.

Walpole, R.E., Myers H. R. Myers S. H., Ye K. (2007). Probability and Statistics for Engineers & Scientists, Eighth Edition, Pearson Perntice Hall, pp 500-503

Weiss, M., Helfenstein, A., Mattern, F., and Staake, T. (2012) "Leveraging smart meter data to recognize home appliances," in Proceedings of the IEEE International Conference on Pervasive Computing and Communications (PerCom 2012), Lugano, Switzerland, Mar. 2012, pp 190–197.

Weng, Q. (2001). A remote sensing-GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. International Journal of Remote Sensing, 22, pp 1999−2014.

Weng, Q. (2009). Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. ISPRS J. Photogramm. Remote Sens. 64, pp 335-344.

Worcestershire. (2009). Warmer Worcestershire, Worcestershire Council, England, http://www.warmerworcestershire.com/, last accessed 15-04-2013.

WUFI, http://www.wufi-pro.com/ , last accessed on 21-09-2012.