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A Study of the Urban Heat Island of Houston, Texas

by

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Abstract

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The magnitude, spatial extent, growth, and seasonal and diurnal behaviors of the urban heat island of Houston, Texas are characterized using both in situ air temperature and remotely sensed surface temperature data. Between 1990 and 2000, the air temperature heat island of Houston had an average magnitude of 1.25 K at night but was largely absent during the day. This behavior is reflected in a survey of extreme temperature events, which reveals a dramatic increase in the number of extremely warm nights relative to the surrounding rural areas. Thermal satellite imagery acquired between 1985 and 2001 demonstrate a surface temperature heat island of approximately 3 K at night and up to 10 K during the day. Climatological analysis reveals an inverse dependence of air temperature heat island magnitude on rural temperature. Conversely, daytime surface temperature heat islands grow with rural temperature, while nighttime surface temperature heat islands show no relationship to rural temperature. Examination of temperature maps reveals an urban heat island area of 1200 km$^2$ at night and 2100 km$^2$ during the day. Comparison of satellite imagery taken twelve years apart exhibits a growth in the nighttime heat island of 0.8 K in magnitude and 650 km$^2$ in area. High-resolution temperature data are also examined and show an urban temperature dependence on population density.
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Chapter 1

Introduction

From the days of prehistory, men and women have gathered about themselves, seeking cooperation with each other in the battle for survival. For humanity, life often depends on aid from others in obtaining food, defense against predators, and raising offspring. From the tribal villages of tens of thousands of years ago to the mega-cities of today, mankind has thrived by living shoulder-to-shoulder.

The benefits of living in these communities are numerous, and as a result man has flourished across the planet. But with those benefits come unforeseen complications. These consequences can be as trivial as a neighbor’s loud music or as dangerous as the fires that swept through London in 1666 and Chicago in 1871. One of the consequences whose impact has yet to be fully ascertained is the effect cities have on the weather and climate around them.

Today, roughly half of the world’s people live in cities. As such, billions are subjected each and every day to various types of these meteorological urban effects,
be they increased pollution, the urban heat island effect, or even altered precipitation and lightning patterns. Only in the last few decades have scientists begun to develop a clear picture of just how great these impacts are, and what they mean for the population of the planet.

The purpose of this thesis is to further that body of knowledge by performing a comprehensive survey of the weather and climate of the urban area of Houston, Texas, using both remote sensing and in situ techniques. The majority of this work will focus on one of the primary effects of urbanization on weather and climate, that of the urban heat island.

The remainder of this chapter explains in general terms how the urban heat island is typically defined, what its causes are, and several of its most important consequences. The introduction also includes some basic principles of remote sensing as well as an overview of the Houston urban area. Chapter 2 continues the discussion of heat island causes with a description of modeling heat transfer in urban materials by both analytical and numerical methods. Chapters 3 and 4 discuss the actual measurement of Houston's urban heat island, chapter 3 using in situ air temperatures and chapter 4 using remotely sensed surface temperatures. The remote sensing measurement techniques presented in chapter 4 are then applied in chapter 5 in an attempt to determine the growth of Houston's urban heat island throughout the last two decades. Chapter 6 extends the heat island analysis to a smaller spatial scale by comparing localized urban heating to the population density throughout the city's neighborhoods. The thesis concludes with chapter 7, which contains final thoughts.
and future areas of inquiry. There are two appendices to this volume: appendix A, in which remote sensing techniques are extended to the subject of the urban land cover, and appendix B, which lists the thermal and radiative properties of various natural and urban materials.

1.1 The Urban Heat Island

The urban heat island (UHI) is one of the most well known forms of localized anthropogenic climate modification. Simply put, an urban heat island occurs when the temperature within a city is greater than the concurrent temperature of the surrounding rural areas and is generally due to alteration of the urban land cover. This effect was first documented in London over 150 years ago by Howard (1833) and has since been studied in many of the largest cities around the world. Heat islands have been documented in most of the major cities in the Western Hemisphere. Recent decades have seen the study of urban heat islands extended to many smaller and more diverse cities around the world. Over the past few years, UHIs have been investigated in cities as diverse as Łódź, Poland (Kłysik and Fortuniak, 1999), Reykjavík, Iceland (Steinecke, 1999), Fairbanks, Alaska (Magee et al., 1999), and Granada, Spain (Montávez et al., 2000).

Figure 1.1 shows a profile of the urban heat island. In general, the temperature rises sharply near the outskirts of the city and plateaus across the suburban, residential, and commercial districts. The maximum temperatures are typically found in the central business district(s) or other areas of high urban density. The heat island
is mitigated somewhat by areas of vegetation and low urban density, such as golf courses, parks, and playing fields.

![Sketch of an Urban Heat-Island Profile](image)

Figure 1.1: A general profile of the urban heat island. Source: Heat Island Group, Lawrence Berkeley National Laboratory

Occasionally the opposite of the heat island effect will occur, when the temperature of the urban area is actually lower than that of the surrounding rural areas. This effect is usually referred to as an urban cool valley (UCV) and seems to occur almost exclusively during the daytime.

### 1.1.1 Significance of the urban heat island

There are numerous reasons to study the urban heat island effect as it involves social, economic, and environmental issues.
Population

In 1950, approximately 30% of the world’s population lived in urban areas. That number is now nearing 50%, with a current urban population estimated at 2.9 billion people (United Nations, 2001). By the year 2030, the global population is predicted to rise by two billion, a growth expected to occur almost entirely in urban areas.

Nearly half of the world’s population is affected, to some extent, by the urban heat island. These numbers will only increase as the world’s urban population is expected to soar during the coming decades. Many of the fastest growing areas are in developing nations, where a lack of urban planning and heat island mitigation techniques only compound the problem.

Morbidity and Mortality

“It’s hot. It’s very hot. We all have our little problems, but let’s not blow it out of proportion . . .” Richard Daley, Mayor of Chicago (USA Today, 19 July 1995)

The statement above was made by Mayor Daley on July 13, 1995, in the middle of a devastating heat wave that killed over 500 people in his city. This apparent lack of concern mirrors the popular underestimation of the dangers of extreme heat. Coupled with the vast urban population discussed in the previous section, urban heat waves pose a major threat to a huge number of people across the United States and around the world.

On average over 1000 people die each year in the United States due to extreme
heat, more than from any other type of weather-related event by nearly an order of magnitude (Changnon et al., 1996). In fact, there are more heat-related mortalities in this country than deaths due to all other weather events combined.

Heat-related deaths most often occur during periods of prolonged high temperatures, commonly referred to as heat waves. Heat waves and the resulting mortalities can be exacerbated within cities by the increased temperature due to the urban heat island. Even though temperatures are highest during the day, the extreme nighttime temperatures resulting from the urban heat island are thought to have a more deleterious effect on mortality. This occurs because inhabitants of urban areas experience heat stresses both day and night, while rural inhabitants are able to obtain some relief during the cooler nights (Clarke, 1972).

Even a small increase in mean temperature can cause significant changes in the likelihood of heat waves. Mearns et al. (1984) use a probabilistic model for several U.S. cities to find that an increase in mean air temperature of 3° F can increase the likelihood of a heat wave (defined as a run of five consecutive daily maximum temperatures at or above 95° F) by a factor of two or more. These higher temperatures usually mean more deaths. Buechley et al. (1972) find that the total mortality rate during a heat wave increases exponentially with maximum daily air temperature. Stronger heat islands are therefore quite likely to increase mortality rates.
Pollution

The increased temperature in urban areas can also accelerate certain atmospheric chemistry cycles leading to an increase in ground-level ozone. This is due in part to Arrhenius' relation, which states that chemical reaction rates generally increase with higher temperature:

\[ k(T) \propto \exp\left(-\frac{1}{T}\right). \]  

(1.1)

In addition to increased reaction rates, higher temperatures can also cause an increase in the emissions of biogenic hydrocarbons as well as higher evaporation rates of man-made volatile organic compounds (VOCs), both of which are linked to the production of tropospheric ozone. Figure 1.2 shows ozone concentration versus air temperature at a TNRCC air-monitoring station in East Houston. The data represent ozone and temperature measurements taken daily at 3 p.m. throughout 1996. The straight dashed line is a linear least-squares fit to the data, while the curved line is a fit to \( \exp(-1/T) \), as suggested by equation (1.1). The positive correlation between ozone level and air temperature is apparent. In fact, there were five days during that year in which the ozone levels exceeded the EPA 1-hour National Ambient Air Quality Standard (NAAQS) of 120 parts per billion (ppb). Four of these five exceedences occurred when the air temperature was over 90° F.

The increased pollution leads to more incidences of respiratory illnesses, another impact of the urban heat island on public health.
Figure 1.2: A plot of afternoon ozone concentration versus temperature in East Houston throughout 1996.

**Economic issues**

The urban heat island effect in some cities has been estimated to cost millions of dollars annually, mostly due to the greater need to cool buildings. Konopacki and Akbari (2002) estimate that Houston alone could save $82M annually (as well as reduce carbon emissions by 59 kilotons) with the implementation of heat island reduction techniques, such as urban reforestation and the use of high-albedo roofing materials.

Of course, urban heating can also have economic benefits in certain circumstances, such as helping to prevent extremely cold nighttime weather during the winter in northern cities.
The climate record

The issue of global warming has received a great deal of attention in recent years. Global temperature measurements seem to indicate that the average surface temperature of the Earth has increased significantly throughout the last century. These temperature measurements, however, are based in part on readings taken at various meteorological stations around the world. Because many of these meteorological stations are located in urban areas, the urban heat island may cause a bias in regional and global temperature estimates. Such a bias must be accounted for and removed in order to accurately determine the global temperature and the extent of global warming. This has been investigated by Karl et al. (1988), who found that throughout the twentieth century urbanization was responsible for a warm bias of 0.06 K in the climate record of the United States.

The urban heat island effect can also be studied as a small-scale version of global warming (Changnon, 1992). Urban heat island magnitudes are typically on the order of a few degrees Celsius, similar to the amount of global warming predicted to occur over the next century. Urban heat islands can thus be used to study how warming affects such things as vegetation growth, atmospheric dynamics and chemistry, and energy exchange between the land and atmosphere.

Meteorological effects

The urban heat island effect is also believed to play a role in altering other meteorological phenomena in and around urban areas. These include the development of
clouds and fog (Sachweh and Koepke, 1995), the frequency of lightning strikes (Orville et al., 2001; Westcott, 1995), the development of thunderstorms, and changes in precipitation rates (Changnon and Huff, 1986).

Many of these effects are due to an urban air circulation that arises in response to the temperature gradient between the urban and rural areas. Warmer urban air rises and can produce cumulus clouds or even air-mass thunderstorms over the city. The rising air leads to a thermal circulation, with the formation of an urban low-pressure area and a "country breeze" from outside the city. This type of circulation is diagrammed in figure 1.3.

Figure 1.3: A diagram showing the air circulation of an urban area. Source: NASA GSFC

1.1.2 Causes of the urban heat island

There are several factors that result in a temperature difference between the urban and rural areas, stemming from changes in the thermal and radiative properties of
surface materials to alterations of the topography.

**Thermal properties of surface materials:** Materials used to build urban structures and cover urban land surfaces often have thermal properties that vary substantially from those of materials found naturally in rural areas. For example, the specific heat capacity (heat capacity per unit mass) of moist soil is approximately 50% greater than that of asphalt and concrete (Oke, 1987). Radiative properties also differ, such as the very low albedo of asphalt relative to that of natural surfaces. The effects of these differences are shown in figure 1.4. Note the large thermal response of rocks and (dry) soils, which are similar in character to urban materials. Damp terrain and vegetation do not react to radiative heating nearly as strongly. The lack of response by metallic objects is presumably due to extremely high reflectivity and thermal conductivity.

![Diagram](image)

Figure 1.4: The temperature fluctuations of different surface materials throughout the day. From Sabins (1997)
One of the thermal properties which are quite important in causing the urban heat island is the thermal admittance, or thermal inertia, of the surface material. The thermal admittance plays a role in determining the amount of thermal flux throughout a substance of a given temperature profile. It is defined as:

\[ \mu = \sqrt{k \rho c}, \]  

(1.2)

where \( k \) is the thermal conductivity of the material, \( \rho \) is the density, and \( c \) is the specific heat capacity. The diurnal temperature fluctuations illustrated in figure 1.4 are dependent upon the thermal admittance of the surface material. In general, temperature variation depends inversely on the thermal admittance, resulting in materials with low thermal admittance, such as those of urban areas, having greater fluctuations than materials of higher thermal admittance, such as moist soils and vegetation. (While the presence of moisture in soils and vegetation alters the overall thermal properties of the materials, the thermal admittance is independent of evaporation or transpiration effects.) The thermal behavior of various types of materials is investigated more fully in chapter 2, which includes discussion of the derivation and use of the thermal admittance, as well as other thermal properties. Appendix B lists thermal and radiative properties of a variety of natural and man-made substances.

**Evapotranspiration:** As urban areas typically replace natural surfaces with artificial ones, there is a marked lack of vegetation in the urban environment. This reduces transpiration as a source of latent heat loss relative to the rural areas. Extensive use of impervious surfaces and improved drainage also act to transport surface
water quickly from the urban area, reducing latent heat loss through evaporation. Evapotranspiration plays a large role in rural energy balance, due to high latent heat of water. For comparison, the latent heat of vaporization of water is $2.3 \times 10^6 \text{ J kg}^{-1}$, while the specific heats of most urban materials is on the order of $10^3 \text{ J kg}^{-1} \text{ K}^{-1}$.

**Canyon effect:** Due to the canyon-like topography of urban areas, especially the urban cores, shortwave radiation is more efficiently absorbed in the urban areas than in rural areas. The canyon topography leads to an increase in the active absorbing surfaces and allows for multiple reflections of solar radiation, resulting in the shortwave radiation being more easily absorbed than in rural areas. The multiple geometries present also allow for better absorption of sunlight during periods of high solar zenith angle, such as during sunrise and sunset. The canyon effect thus lowers the overall albedo of the entire urban area independent of the individual albedos of the surface materials.

**Decreased sky view:** The canyon geometry also decreases the efficiency with which the urban area can radiate longwave radiation into the atmosphere and out into space. The multiple surfaces allow for the reabsorption of longwave radiation, inhibiting the loss of heat through radiative cooling.

**Increased surface roughness:** Urban areas also have an increased surface roughness, which slows down the surface winds. This inhibits sensible heat loss from the urban surface through atmospheric convection.

**Pollution:** The atmosphere of urban areas typically has higher pollution levels than that of surrounding rural areas. Pollution, particularly aerosols, can produce a
pseudo-greenhouse effect, absorbing and reradiating longwave radiation and inhibiting radiative surface cooling.

**Anthropogenic heat generation:** Urban areas produce more heat by anthropogenic means than rural areas, due to the increased population density. Sources of anthropogenic heat include automobiles, construction equipment, air conditioning units, and heat losses from buildings.

### 1.1.3 Different types of urban heat islands

Urban heat islands can be categorized into different types, depending on the type of measurement and the time at which it is made.

**Air and surface temperatures**

Urban heat island studies are generally conducted in one of two ways: measuring the UHI in air temperature through the use of automobile transects and weather station networks, and measuring the UHI in surface (or skin) temperature through the use of airborne or satellite remote sensing. The fundamental difference between these two methods is that they measure two different, though related, quantities. While air temperature and surface temperature are often quite similar, under certain circumstances each can show very distinctive and unique behavior.

There are advantages and disadvantages particular to each type of measurement. *In situ* data have the advantage of high temporal resolution and a long data record, but usually have poor spatial resolution. Conversely, remotely sensed data has higher
spatial distribution but low temporal resolution and a shorter data record. Highly accurate remotely sensed temperature measurements also require the use of concurrent ground truth data and/or radiosonde data in order to correct for infrared absorption and reradiation by various atmospheric components, most notably water vapor (François and Ottilé, 1996).

**Time of day**

Because urban heat islands can vary slightly from hour to hour and significantly from day to night, it is necessary to define at what time the urban heat island is studied. Air temperature urban heat islands are often calculated using the minimum, maximum, or mean daily temperatures of the urban and rural areas. Of these, minimum air temperatures tend to be most useful as they usually show the most apparent heat island signature (Oke, 1982). Maximum air temperatures, on the other hand, are useful as they often determine when urban heating causes the greatest stress on health and the environment. Surface temperatures often exhibit a different behavior, with the daytime heat island usually much greater than the nighttime heat island.

**1.2 The Urban Area of Houston, Texas**

The subject of this survey is the urban area of Houston, Texas, a city of 1.95 million people (U. S. Bureau of Census, 2001). The city of Houston has undergone a period of significant growth in the last decade, including a 20% increase in inhabitants from the 1990 population of 1.63 million (U. S. Bureau of Census, 1996). Geographically,
Figure 1.5: A map of the Houston urban area.
<table>
<thead>
<tr>
<th>Population</th>
<th>1990</th>
<th>2000</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>City of Houston</td>
<td>1.6 M</td>
<td>2.0 M</td>
<td>+0.4 M</td>
</tr>
<tr>
<td>Houston Metro</td>
<td>3.3 M</td>
<td>4.2 M</td>
<td>+0.9 M</td>
</tr>
<tr>
<td>Houston-Galveston-Brazoria Metro</td>
<td>3.7 M</td>
<td>4.7 M</td>
<td>+1.0 M</td>
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<tr>
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<td>+140 km$^2$</td>
</tr>
<tr>
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<tr>
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<tr>
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<td>200 km$^{-2}$</td>
<td>230 km$^{-2}$</td>
<td>+30 km$^{-2}$</td>
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</tbody>
</table>

Table 1.1: The 1990 and 2000 census figures for Houston and the surrounding areas.

Houston is well suited to an analysis by remote sensing means. A lack of city zoning laws has led to an abundance of urban sprawl, resulting in a city of large area and relatively low population density. The city of Houston has an area of approximately 1400 km$^2$ and is centered at 95.4° W and 29.7° N on the upper Texas Gulf Coast, an area lacking significant orographic features. A map of the city of Houston and the surrounding area is shown in figure 1.5, while table 1.1 lists the 1990 and 2000 census figures for the city and the area.

The climate of Houston is classified as humid subtropical. Houston’s proximity to the Gulf of Mexico causes its winters to be quite mild, while the summers are rather hot with high levels of humidity. Winter air temperatures average 63° F (17° C) during the day and 43° F (6° C) at night, while the corresponding summer temperatures are 92° F (33° C) and 76° F (24° C). Houston averages 50 inches of rainfall each year,
with the majority of it falling between May and September.

1.3 Principles of Remote Sensing

The most general definition of remote sensing is the detection and study of any object or phenomenon from a distance via some carrier of information, such as electromagnetic radiation (e.g. photography, radar), soundwaves (sonar, seismic surveys), atomic particles (positron emission tomography), or even gravitational waves (Laser Interferometer Gravitational Wave Observatory). In the geophysical sciences community, this definition is usually restricted to the use of electromagnetic radiation with the employment airborne- and spacecraft-based sensors. Remote sensing devices can be both active and passive.

This study will make use of satellite remote sensing in the visible, near infrared, and thermal infrared regions of the spectrum, at wavelengths from 400 nm to 15 µm. The sensors utilized are the Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA Polar-orbiting Observational Environmental Satellite (POES) system, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) on board the NASA Terra satellite, and the Multispectral Scanner (MSS) on board the NASA Landsat satellites.

Figure 1.6 shows the blackbody radiation curves resulting from various temperature sources. The topmost curve corresponds to a source temperature of 6000 K, approximately equal to that of the sun. This curve peaks in the visible part of the spectrum, and as a result the majority of the sun's energy output is in the form of
Figure 1.6: A comparison of the blackbody spectra from different temperature sources. From Lillesand and Kiefer (2000)
visible light. The surface temperature of the Earth, on the other hand, is approximately 300 K. The corresponding blackbody curve peaks in the infrared, at roughly 10 μm. Hence one must look in the thermal infrared in order to determine Earth-like temperatures.

1.3.1 Atmospheric transmission

While the atmosphere is usually thought of as transparent, this is not truly the case. The atmosphere is of course almost completely transparent in the visible part of the spectrum, where the human eye functions. There are however many parts of spectrum, such as the ultraviolet and several regions in the infrared, where the atmosphere is almost totally opaque.

![Atmospheric transmission diagram](image)

Figure 1.7: The atmospheric transmission at various visible and thermal wavelengths. From Sabins (1997)

Figure 1.7 shows the fractional transmission through the atmosphere in the ultraviolet, visible, and infrared parts of the spectrum. The transmission is nearly 100% throughout the visible wavelengths, but it drops to zero in many areas of the infrared
spectrum. The infrared transmission bands that are used in satellite remote sensing and thus in this study are those located in the 700–1100 nm and 8–14 μm ranges.

1.3.2 Remote sensing of urban areas

In recent years, the field of remote sensing has lent itself well to the study of urban areas and urban heat islands. As early as two decades ago, Welch (1980) was using Landsat and Defense Meteorological Satellite Program (DMSP) data to study the relationship between population, urban area, and energy utilization in China. Since then, remote sensing has become vital in the field of urban studies, including the study of urban climate and the urban heat island.

Roth et al. (1989) and Gallo and Tarpley (1996) used AVHRR data to compare the urban heat island effect to vegetation index for cities along the west coast of North America. Lee (1993) also used AVHRR data to study the urban heat island of cities in South Korea, while Kim (1992) used higher-resolution Landsat data to study the urban heat island of Washington, D.C. Fractional vegetation cover and surface moisture availability were used by Owen et al. (1998) to study the impact of urbanization on climate in and around State College, Pennsylvania. Lo et al. (1997) studied the urban heat island by combining high-resolution thermal infrared data and Geographic Information System (GIS) techniques. Kawashima et al. (2000) used Landsat data to study the relationship between surface temperature and air temperature during winter nights in Japan and found that the effect of the surface temperature on air temperature was related to the mean lapse rate of the atmospheric
boundary layer.
Chapter 2

Modeling the Heat Island

2.1 Average Surface Temperature

Simple estimates of the average surface temperature resulting from solar heating can be made by balancing the incoming and outgoing energy flux at the surface and in the atmosphere. The flux of solar energy at the Earth’s orbit is given by the solar constant, $F_0 = 1370 \text{ W m}^{-2}$. A fraction of this flux, dependent on the total albedo and the amount of atmospheric transmission, is absorbed by the Earth’s surface. The total flux intercepted by the Earth is given by:

$$E_{\text{sfc}}^{\text{in}} = (1 - \alpha - a_{\text{vis}})F_0 \times \pi R_E^2,$$  \hspace{1cm} (2.1)

where $\alpha$ is the combined albedo of the Earth’s surface and atmosphere, $a_{\text{vis}}$ is the effective atmospheric absorption coefficient in the visible wavelengths, and $\pi R_E^2$ is the planet’s cross-sectional area. This energy is then reradiated from the surface as
infrared flux:

\[ E_{\text{sfc}}^{\text{out}} = \varepsilon \sigma T_{\text{sfc}}^4 \times 4 \pi R_E^2, \]  

(2.2)

where \( \varepsilon \) is the emissivity of the Earth’s surface and \( \sigma = 5.67 \times 10^{-8} \text{ W m}^{-2} \text{K}^{-4} \) is the Stefan-Boltzmann constant. The atmosphere absorbs a fraction of this energy, along with the absorbed solar energy:

\[ E_{\text{atm}}^{\text{in}} = a_{\text{vis}} F_0 \times \pi R_E^2 + a_{\text{IR}} \varepsilon \sigma T_{\text{sfc}}^4 \times 4 \pi R_E^2, \]  

(2.3)

where \( a_{\text{IR}} \) is the infrared absorption coefficient of the atmosphere. (This analysis treats the atmosphere as a single layer, with constant absorption coefficients and temperature. Thus \( T_{\text{atm}} \) represents an average temperature of the entire atmosphere and should not be confused in later discussions with the air temperature near the surface. While these assumptions are not entirely physical, they can still provide insightful results.) The atmosphere also reradiates this energy:

\[ E_{\text{atm}}^{\text{out}} = 2 a_{\text{IR}} \sigma T_{\text{atm}}^4 \times 4 \pi R_E^2. \]  

(2.4)

The factor of two is due to the fact that the atmosphere radiates both upwards and downwards. By Kirchhoff’s Law, the atmosphere’s infrared radiation coefficient must be equal to its infrared absorption coefficient, \( a_{\text{IR}} \). The flux that is radiated downward is then re-absorbed by the surface, requiring that equation (2.1) be amended:
\[ E_{\text{sfc}}^{\text{in}} = (1 - \alpha - a_{\text{vis}}) F_0 \times \pi R_E^2 + \varepsilon a_{\text{IR}} \sigma T_{\text{atm}}^4 \times 4 \pi R_E^2. \quad (2.5) \]

Again, by Kirchoff's Law, the surface infrared absorption coefficient must be equal to its (infrared) emissivity. These four equations can be combined such that the incoming and outgoing energies balance both at the surface and in the atmosphere.

\begin{align*}
\text{Surface} & : \varepsilon \sigma T_{\text{sfc}}^4 = a_{\text{IR}} \varepsilon \sigma T_{\text{atm}}^4 + \frac{(1 - \alpha - a_{\text{vis}}) F_0}{4} \quad (2.6) \\
\text{Atmosphere} & : 2 a_{\text{IR}} \sigma T_{\text{atm}}^4 = a_{\text{IR}} \varepsilon \sigma T_{\text{sfc}}^4 + \frac{a_{\text{vis}} F_0}{4} \quad (2.7)
\end{align*}

(The common factors of \(4 \pi R_E^2\) are cancelled throughout.) These equations can be solved for the surface and atmospheric temperatures.

\begin{align*}
T_{\text{atm}} &= \sqrt[4]{\frac{F_0}{8 a_{\text{IR}} \sigma} \times \frac{a_{\text{IR}}(1 - \alpha - a_{\text{vis}}) + a_{\text{vis}}}{1 - 0.5 a_{\text{IR}} \varepsilon}} \quad (2.8) \\
T_{\text{sfc}} &= \sqrt[4]{\frac{F_0}{4 \varepsilon \sigma} \times \frac{1 - \alpha - a_{\text{vis}}(1 - 0.5 \varepsilon)}{1 - 0.5 a_{\text{IR}} \varepsilon}} \quad (2.9)
\end{align*}

Assuming an albedo of \(\alpha = 0.3\), a surface emissivity of \(\varepsilon = 0.9\), and atmospheric absorption coefficients of \(a_{\text{IR}} = 0.75\) and \(a_{\text{vis}} = 0.15\), the resulting surface and atmospheric temperatures are approximately \(T_{\text{sfc}} = 281\) K and \(T_{\text{atm}} = 242\) K. While these figures are not completely accurate, they are fairly good estimates for such a simple calculation. Equation (2.9) demonstrates explicitly the dependence of surface tem-
perature on both the albedo and the emissivity of the surface material. As a result urban areas have higher average surface temperatures than rural areas, due to the lower urban albedos and emissivities.

This is an adequate treatment for the average surface temperature, but a time-dependent analysis requires employing the heat equation.

### 2.2 Solving the Heat Equation Analytically

A basic model can be created to approximate the variation in surface temperature throughout the day due to the influence of solar radiation. The basis of such a model is the equation of heat transmission:

\[
\frac{\partial T}{\partial t} = -\frac{1}{c \rho} \nabla \cdot \mathbf{f}, \tag{2.10}
\]

where \( T \) is the temperature, \( \mathbf{f} \) is the heat flux, \( c \) is the specific heat, and \( \rho \) is the density.

This can be combined with Fourier’s law:

\[
\mathbf{f} = -k \nabla T, \tag{2.11}
\]

where \( k \) is the thermal conductivity. Equations (2.10) and (2.11) can be combined as:

\[
\frac{\partial T}{\partial t} = \kappa \nabla^2 T. \tag{2.12}
\]
This is the common form of the heat equation, assuming there are no internal heat sources. $\kappa$ is the thermal diffusivity and is defined as:

$$\kappa = \frac{k}{c \rho}.$$  \hspace{1cm} (2.13)

The thermal diffusivity can be interpreted as the ratio of how rapidly a substance transfers heat to the amount of heat it can store. Reducing to one spatial dimension, in this case depth, equation (2.12) becomes:

$$\frac{\partial T(z, t)}{\partial t} = \kappa \frac{\partial^2 T(z, t)}{\partial z^2}.$$ \hspace{1cm} (2.14)

Solving equation (2.14) by the method of separated solutions, one obtains solutions of travelling waves that decay exponentially with depth.

$$\Phi_1(z, t) = e^{-\sqrt{\omega \kappa} z} \sin \left( \omega t - \sqrt{\frac{\omega}{2 \kappa}} z \right)$$ \hspace{1cm} (2.15)

$$\Phi_2(z, t) = e^{-\sqrt{\omega \kappa} z} \cos \left( \omega t - \sqrt{\frac{\omega}{2 \kappa}} z \right)$$ \hspace{1cm} (2.16)

Assuming a time-periodic boundary condition which can be represented as a Fourier series:

$$T(0, t) = T_0 + \sum_{n=1}^{\infty} [A_n \cos(n \omega t) + B_n \sin(n \omega t)],$$ \hspace{1cm} (2.17)

where $T_0$ is the average surface temperature and, in the case of diurnal solar forcing,
\[ \omega = \frac{2\pi}{24\text{ hours}} = 7.27 \times 10^{-5} \text{ s}^{-1}. \] The solution becomes:

\[ T(z, t) = T_0 + \sum_{n=1}^{\infty} e^{-\frac{n \omega}{2 \kappa} z} \left[ A_n \cos \left( n \omega t - \sqrt{\frac{n \omega}{2 \kappa}} z \right) + B_n \sin \left( n \omega t - \sqrt{\frac{n \omega}{2 \kappa}} z \right) \right] . \] (2.18)

These waves have a characteristic dampening length of:

\[ z_{\text{damp}} = \sqrt{\frac{2 \kappa}{n \omega}} . \] (2.19)

For typical urban materials, the dampening length is on the order of ten centimeters or less. For moderately turbulent air, it can be tens of meters.

The thermal flux can be determined by applying Fourier's law to equation (2.18), resulting in:

\[ f(z, t) = \mu \sum_{n=1}^{\infty} \sqrt{n \omega} e^{-\frac{n \omega}{2 \kappa} z} \left[ A_n \cos \left( n \omega t - \sqrt{\frac{n \omega}{2 \kappa}} z + \frac{\pi}{4} \right) 
+ B_n \sin \left( n \omega t - \sqrt{\frac{n \omega}{2 \kappa}} z + \frac{\pi}{4} \right) \right] , \] (2.20)

where \( \mu = \sqrt{k \rho c} \) is the thermal admittance or thermal inertia. Thus the flux traveling across any arbitrary surface or boundary is linearly proportional to the thermal admittance of the material. The thermal flux in materials of low thermal admittance will be less than the flux in materials with higher thermal admittance.

The flux from the surface is found by setting \( z = 0 \) in (2.20):
\[ f(0, t) = \mu \sum_{n=1}^{\infty} \sqrt{n \omega} \left[ A_n \cos \left(n \omega t + \frac{\pi}{4}\right) + B_n \sin \left(n \omega t + \frac{\pi}{4}\right) \right]. \] (2.21)

Equation (2.21) shows that the surface temperature lags the flux by approximately one eighth of a cycle, or three hours in the diurnal case. One can also see how the flux depends on temperature variability by comparing equation (2.21) to equation (2.17), where the time-dependent terms differ only by a factor of \( \mu \sqrt{n \omega} \). To illuminate this point, the surface temperature is assumed to be a pure sinusoid. The equations for the temperature and flux are then:

\[ T(0, t) = T_0 + \Delta T \sin (\omega t) \] (2.22)
\[ f(0, t) = \mu \sqrt{\omega} \Delta T \sin \left(\omega t + \frac{\pi}{4}\right) \] (2.23)

where \( \Delta T \) is the diurnal surface temperature variability. Assuming the flux at the surface peaks at local noon \( (\omega t = \pi) \), then the equations must be phase-shifted by \( \pi/4 \) and become:

\[ T(0, t) = T_0 + \Delta T \sin \left(\omega t - \frac{\pi}{4}\right) \] (2.24)
\[ f(0, t) = \mu \sqrt{\omega} \Delta T \sin (\omega t) \] (2.25)
Thus the temperature will lag approximately three hours behind the flux, peaking in midafternoon. Similarly, the minimum temperature will occur a few hours after midnight. One can also see that for a given flux, the temperature variability is inversely proportional to the thermal admittance. Materials with a low thermal admittance, such as asphalt and brick, will have greater temperature variability than materials with high thermal admittance, such as damp soils and water. This is why thermal admittance is also known as thermal inertia; materials with a higher thermal inertia "resist" temperature change.

The temperature variability can be found by substituting for the maximum flux.

\[
(1 - \alpha - a_{vis}) F_0 = \mu \sqrt{\omega} \Delta T
\]  

\[
\Delta T = \frac{(1 - \alpha - a_{vis}) F_0}{\mu \sqrt{\omega}}
\]  

For typical thermal admittance values, the diurnal temperature variability can be as large as many tens of degrees.

The surface flux and temperature have up to this point been assumed to be purely sinusoidal. This is obviously not truly the case. A more accurate representation of solar forcing is the following:

\[
f_{\text{Solar}}(t) = \begin{cases} 
0 & \omega t < \pi/2 \\
\zeta F_0 \cos(\omega t) & \pi/2 < \omega t < 3\pi/2 \\
0 & \omega t > 3\pi/2 
\end{cases}
\]
where $\zeta = 1 - \alpha - a_{\text{vis}}$ is the absorptivity of the surface. This is still somewhat idealized in that it assumes an equatorial location and no axial tilt of the planet. Such a forcing is equal to the following Fourier series:

$$f_{\text{solar}}(t) = \frac{\zeta F_0}{\pi} \left[ 1 + \frac{\pi}{2} \cos(\omega t) + \sum_{n=1}^{\infty} \frac{2}{4n^2 - 1} (-1)^{n+1} \cos(2n\omega t) \right]. \quad (2.29)$$

The surface boundary condition must also include the outgoing thermal flux radiated by the surface:

$$f_{\text{IR}}(t) = -\varepsilon \sigma T^4(0, t). \quad (2.30)$$

According to Kirchoff's Law, emissivity and absorptivity are equal at individual wavelengths, i.e. $\varepsilon_\lambda = \zeta_\lambda$. In this analysis, however, $\zeta$ and $\varepsilon$ are not necessarily equal, as $\zeta$ is the absorptivity averaged primarily over visible and near-infrared wavelengths, while $\varepsilon$ is the emissivity averaged over thermal infrared wavelengths.

It is assumed that the interior of the Earth has an average temperature $T_0$, approximated by equation (2.9), about which the surface temperature fluctuates. This implies that the average heat energy density does not change and that, when averaged over an entire day, the net heat flux in any direction is zero. This can be seen in equation (2.20), which averages to zero over full cycle and also goes to zero at large depths. As such, the net flux across the surface must also be zero when integrated over an entire day. The solar radiation absorbed during any 24-hour period must be
balanced by the thermal radiation emitted throughout that period.

Thus a full solution for the time-dependent heat flux, and therefore the temperature, can be found by setting equation (2.21) equal to the sum of equations (2.29) and (2.30) and solving for the Fourier coefficients $A_n$ and $B_n$.

\[
\mu \sum_{n=1}^{\infty} \sqrt{n \omega} \left[ A_n \cos \left( n \omega t + \frac{\pi}{4} \right) + B_n \sin \left( n \omega t + \frac{\pi}{4} \right) \right]
= \frac{\zeta F_0}{\pi} \left[ 1 + \frac{\pi}{2} \cos(\omega t) + \sum_{n=1}^{\infty} \frac{2}{4n^2 - 1} (-1)^{n+1} \cos(2n \omega t) \right]
- \varepsilon \sigma \left[ T_0 + \sum_{n=1}^{\infty} [A_n \cos(n \omega t) + B_n \sin(n \omega t)] \right]^4
\]  

(2.31)

Unfortunately, because the outgoing thermal flux depends on $T^4(0,t)$, the equation becomes nonlinear and an analytic solution is not easily determined.

### 2.3 Solving the Heat Equation Numerically

With no analytical solution forthcoming, the solution must be found by employing numerical modeling. Equation (2.14) can be solved by using the following numerical derivatives.

\[
\frac{\partial T(z,t)}{\partial t} \Rightarrow \frac{T(z,t + \Delta t) - T(z,t)}{\Delta t}
\]  

(2.32)

\[
\frac{\partial^2 T(z,t)}{\partial z^2} \Rightarrow \frac{T(z - \Delta z,t) - 2T(z,t) + T(z + \Delta z,t)}{\Delta z^2}
\]  

(2.33)
Substituting these equations into (2.14) and solving for $T(z, t + \Delta t)$, one gets:

$$T(z, t + \Delta t) = \frac{\kappa \Delta t}{\Delta x^2} [T(z - \Delta z, t) + T(z + \Delta z, t)] + \left[ 1 - \frac{2 \kappa \Delta t}{\Delta x^2} \right] T(z, t). \quad (2.34)$$

The sum of the coefficients on the right-hand side of equation (2.34) is equal to one only if $2\kappa \Delta t/\Delta x^2 \leq 1$. This represents conservation of energy in the equation and serves as a stability requirement governing the sizes of $\Delta t$ and $\Delta z$.

The surface boundary condition governing the incoming solar radiation and outgoing infrared radiation is represented by:

$$T(0, t + \Delta t) = T(0, t) + \frac{f_{\text{solar}}(t) - \varepsilon \sigma T^4(0, t)}{c \rho} \times \frac{\Delta t}{\Delta z}. \quad (2.35)$$

By creating a model based on the equations listed above, and using the thermal and radiative properties listed in appendix B, approximate time-dependent surface temperatures are calculated. (The model also includes a single layer atmosphere, similar to that employed in section 2.1.) Figure 2.1 shows the results of such a model, a plot of the surface temperature versus time. The solid line is the temperature of a vegetated surface, the dashed line a concrete surface, and the dotted line an asphalt surface.

The asphalt surface has a very high thermal variability compared to the vegetated and concrete surfaces, due to its low thermal admittance. The asphalt surface also has the highest average temperature due to its very low albedo and emissivity, while
Figure 2.1: A plot of surface temperature versus time. The solid line is a vegetated surface, the dashed line a concrete surface, and the dotted line an asphalt surface.

The vegetated surface has the lowest average temperature due to its relatively high albedo and emissivity. As both concrete and asphalt are major components of the urban land cover, urban surface temperatures are usually higher and more variable than rural surface temperatures. This allows the surface temperature heat island to be very strong during the day, as much as 10 K or more. At night, in the absence of solar forcing, the heat island typically has a magnitude of no more than a few degrees. In reality, the temperature variability displayed by natural surfaces is quite a bit lower than is indicated by the model. This results from natural factors not contained within the model that tend to inhibit temperature variability. The factors that are most notably absent include the sensible and latent heat transfer from the surface to the atmosphere.
To this point the discussion has focussed almost entirely on surface temperature. The behavior of the air temperature is, of course, related to the analysis conducted above. But it can vary a great deal from that of the surface temperature. Due to air's low thermal admittance, especially during calm conditions, the thermal coupling between the air and surface is rather weak. This can also be seen in equation (2.8), which demonstrates the lack of dependence of $T_{atm}$ on surface emissivity.

Nighttime air temperature heat islands tend to be strongest on clear, calm nights. Clear skies allow the surface to cool most efficiently as it radiates heat into space. As was noted earlier, urban surfaces tend to have lower emissivities than rural surfaces. Because of this, rural surfaces cool faster than the urban surfaces, enhancing the urban-rural surface temperature difference. When the air is calm, the layer of air closest to the ground is in thermal contact with the surface throughout the night, allowing it to cool by conducting heat to the surface, which is then radiated away. This process brings about a temperature inversion in the boundary layer, where the air near the ground is cooler than the air atop it, forming a very stable condition. As the ground-level air stays in thermal contact with the surface throughout the night, the air temperature tracks the surface temperature quite well. Thus the surface temperature heat island is mirrored in the air temperature heat island throughout the night.

During the day, conditions are markedly different. Solar radiation rapidly heats the ground, which in turn heats the air in contact with it. As the low-level air heats, any remaining nocturnal temperature inversion vanishes and the air eventually
Figure 2.2: (a) The potential temperature as a function of height throughout the surface boundary layer during the day. (b) The nighttime potential temperature profile. From Oke (1987)

becomes unstable. This produces convection and mixing in the surface boundary layer, often extending up to a kilometer in height. Due to the turbulence of the boundary layer, ground-level air does not remain long in contact with the surface and is not heated efficiently. (Though the turbulence increases the thermal admittance of the air, this effect is more than compensated for by the enlargement of the active volume of air.) As a result, the urban air temperature does not rise appreciably above the rural air temperature, and the air temperature urban heat island is often quite weak. These effects are illustrated in figure 2.2, which shows the potential temperature as a function of height throughout the surface boundary layer during both the day and the night. (The potential temperature of a parcel of air is the temperature it would have if lowered adiabatically to the surface.)

Figure 2.2(a) shows the potential temperature structure of the boundary layer during the day. Notice that for both the urban and rural areas, there is a slight warming
of the air near the surface, with the temperature remaining constant throughout the boundary layer. The urban and rural temperatures are quite similar, resulting in little or no air temperature heat island.

This is contrasted in figure 2.2(b), which shows the nighttime temperature structure. In this case there is a significant cooling of the air near the surface in the rural area. The air near the surface in the urban area does not cool nearly as quickly, and the urban-rural temperature difference is large, resulting in a heat island.
Chapter 3

The Air Temperature UHI

The basic criteria regarding the data collection for the measurement of an air temperature heat island is that enough measurements be taken to distinguish between the rural temperature and the urban temperature. Though the sample can be as small as a single measurement each for the urban and rural areas, it is typically large enough to provide some amount of spatial distribution. Temperature measurements are most often obtained in one of two ways. The first method is to perform one or more transects of the city, usually by automobile, taking measurements at numerous points along the way. One advantage of this method is that the resulting measurements can have a fairly dense spatial coverage, depending on how much of the city is covered during the transect. A second advantage is that the transects can be performed at any time of day, whenever is best suited to the research needs.

There are also several disadvantages to the transect method. The most significant disadvantage is that the transects, if performed with an automobile, are limited to
existing city roads. This can result in an uneven spatial coverage of the city. It may also cause the temperature measurements to be biased due to the close proximity of the road and automobile traffic, each of which are sources of urban heating.

The other method of air temperature measurement is the use of a network of meteorological stations. This method is quite advantageous in that many such stations already exist, meaning no active data collection is necessary. These stations also provide a record of data taken at the same location and at the same time of day throughout the operational history of the station. A disadvantage of using a network of stations is that the spatial coverage throughout the city can be sparse or insufficient for some investigations.

In light of the advantages and disadvantages of each method listed above, automobile transects are favored when one requires a single "snapshot" of urban temperatures, while station networks are preferred when one desires to study temporal variations.

In order to characterize the air temperature heat island of Houston, data are taken from several meteorological stations in and around the city operated by the National Weather Service. As a rule, these stations measure the air temperature at a height of approximately 2 m (6.5 ft) above the ground. The Houston area stations and their temperature records are listed in table 3.1. (Though some of these stations may be better defined as suburban, they are considered rural for the purposes of this study.)

A map showing the stations in and around Houston is presented in figure 3.1. Figure 3.2 shows the array of stations throughout southeastern Texas. Both maps
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<thead>
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<th>Station</th>
<th>Type</th>
<th>Data Record</th>
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<td>Baytown</td>
<td>Rural</td>
<td>1946–1971, 1982–present</td>
</tr>
<tr>
<td>Bush Intercontinental Airport</td>
<td>Rural</td>
<td>1969–present</td>
</tr>
<tr>
<td>Cypress</td>
<td>Rural</td>
<td>1963–1965</td>
</tr>
<tr>
<td>Hobby Airport</td>
<td>Urban</td>
<td>1941–present</td>
</tr>
<tr>
<td>Houston Port</td>
<td>Urban</td>
<td>1991–present</td>
</tr>
<tr>
<td>Houston National Weather Service Office (League City)</td>
<td>Rural</td>
<td>1990–present</td>
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<td>Houston Weather Bureau Office</td>
<td>Urban</td>
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<td>San Jacinto Dam</td>
<td>Rural</td>
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<td>Sugarland</td>
<td>Rural</td>
<td>1946–present</td>
</tr>
<tr>
<td>Thompsons</td>
<td>Rural</td>
<td>1942–present</td>
</tr>
</tbody>
</table>

Table 3.1: A list of the temperature records of meteorological stations in and around Houston.

include an outline of the city of Houston.

### 3.1 Minimum Temperature UHI

The data record from each of the stations shown in figure 3.2 contains the daily minimum and maximum temperatures recorded at that station. (It is assumed throughout the following analyses that the minimum temperatures occur during the night and the maximum temperatures occur during the day.) These records are used to produce a number of air temperature heat island analyses, many of which involve calculating and comparing mean temperatures. The data records, however, are in general not entirely complete. Some records are missing data from a few solitary days, while others have gaps of weeks, months, or even years. This leads to concern that interruptions in the data record could produce biases in the calculation of monthly
and annual temperature means. For instance, an average annual temperature would be artificially low if several weeks of summer temperatures are not included. In order to prevent this possible bias, the existing data for each station are fit to a sine function with a period of exactly one year. Thus even if part of a year’s data is missing, the fit not be affected. In order to guarantee an accurate fit to the available data, only records that are at least 75% complete are used.

Figure 3.3 shows a contour plot of the average minimum temperature at the stations throughout southeastern Texas between the years of 1990 and 1999. The stations used in this plot are the same as those in figure 3.2 and are indicated with a “+”. Stations that are shown in figure 3.2 but not in figure 3.3 are not used due to an insufficient data record. Also included in the figure are outlines of the city of Houston,
Figure 3.2: The locations of weather stations throughout southeastern Texas.
the Gulf of Mexico, and the Texas-Louisiana border. The contour plot is produced by fitting a minimum curvature surface to the average minimum temperature measurements from each station. As with any such fit, the behavior of the contour surface near the edges of the data sample is highly suspect.

![Average Minimum Temperature 1990–1999](image)

Figure 3.3: A contour plot of the average minimum temperature for southeastern Texas from 1990 to 1999.

The dominant feature of figure 3.3 is the gradual warming in the direction of the coast. This is expected, as bodies of water generally have a more temperate climate than the land, due to the very high thermal admittance of moving water. In addition to the coastal warming, the Houston area does display an urban heat island, with an average minimum temperature more than two degrees higher than that of the surrounding area. This is borne out in the data from the individual stations. For example, the Port of Houston has a mean minimum temperature of 62.1° F, while
the average at Bush Intercontinental Airport is 59.3°F. (Throughout this thesis, the error in measurement will be stated explicitly only if it is greater than the precision of the declared value. In this case, the error is therefore less than 0.1°F.)

To investigate the distribution of heat island magnitudes, it is helpful to view them as a histogram. Figure 3.4 shows a histogram of the daily minimum temperature heat islands of Houston. Individual (nightly) heat island magnitudes are calculated by subtracting the average minimum temperature of the rural stations listed in table 3.1 from the average minimum temperature of the urban stations. The histogram displays all such measurements from 1990 through 1999.

Figure 3.4: A histogram of the minimum temperature heat islands of Houston.

The inference from the contour map is borne out; the histogram shows that Houston does indeed possess a minimum temperature urban heat island a majority of the
time. The mean UHI for the decade is $2.25 \pm 0.04^\circ$ F, with a median of $2.17^\circ$ F and a standard deviation of $2.69^\circ$ F. Of a total of 3650 daily measurements, 3217 (88%) show a positive heat island while 433 (12%) show a negative heat island (cool valley). There are 716 days (20%) with a UHI greater than $3.0^\circ$ F and 241 days (7%) over $5.0^\circ$ F. The mean rural temperature throughout the decade is $59.8 \pm 0.2^\circ$ F.

### 3.2 Maximum Temperature UHI

Figure 3.5 shows the contour plot of the average maximum temperature between the years 1990 and 1999. As in the minimum temperature map, the stations with a satisfactory data record are indicated with a “+”.

**Figure 3.5:** A contour plot of the average maximum temperature for southeastern Texas from 1990 to 1999.
Like the minimum temperature contour plot, figure 3.5 shows a temperature trend in the direction of the coast. Though in this case the temperature instead drops with proximity to the Gulf of Mexico. Also in contrast to the minimum temperature case, the figure indicates that the Houston area does not possess a significant maximum temperature heat island.

Lack of an average temperature heat island does not mean, however, that a heat island never exists during the daytime. This is evident from figure 3.6, which shows a histogram of the maximum temperature heat islands.

![Maximum Temperature UHI Histogram 1990–1999](image)

Figure 3.6: A histogram of the maximum temperature heat islands between 1990 and 1999.

As the histogram demonstrates, Houston vacillates between a heat island and a cool valley. On average, there is effectively no heat island for this period, with a mean value of $0.01 \pm 0.05^\circ$ F and a median of $0.14^\circ$ F. The standard deviation is $2.89^\circ$ F,
slightly greater than that of the minimum temperature measurements. Out of a total of 3648 measurements, 1980 (54%) are greater than zero, and 1668 (46%) are less than zero. The average rural temperature for this time is $79.3 \pm 0.2^\circ F$.

3.3 Seasonal Variations

The air temperature heat island of Houston also displays seasonal variations. Figures 3.7 and 3.8 show the mean minimum and maximum temperature heat islands, with standard errors, for each month of the year.

![Minimum Temperature UHI](image)

Figure 3.7: A plot of the monthly average minimum temperature heat island measurements. The dotted lines represent the standard errors of the means.

Figure 3.7 reveals that the largest minimum temperature heat islands occur in the colder months, from October to February. During these months the nighttime heat
islands grow to 3\textdegree \ F or more. The heat islands are weakest during May and June, falling to around 2\textdegree \ F.

![Maximum Temperature UHI](image)

Figure 3.8: A plot of the average maximum temperature heat island measurements for each month. The dotted lines represent the standard errors of the means.

Figure 3.8 indicates that there is no time during the year when Houston possesses a significant average maximum temperature heat island. During the cold months of December and January, there may be a slight heat island of approximately half of a degree, though the uncertainty is high. Throughout the rest of the year, there is no apparent heat island.

There are two interesting features present in both figures 3.7 and 3.8. The first is that the winter heat islands are approximately one-half to one degree greater than the summer heat islands during both the day and the night. The second feature is the increased standard error in the heat island measurements during the cooler months,
indicating a greater variability in the heat island magnitudes during these times. This shift in behavior, depending on time of year, demonstrates the need for an analysis based on the ambient background, rural temperature.

3.4 Dependence on Rural Temperature

The previous analysis leads to speculation that the heat island magnitude depends somewhat on the rural temperature itself. Figures 3.9 and 3.10 show scatter plots of the daily heat island magnitude versus rural temperature for both the minimum and maximum temperature measurements.

These figures reveal no obvious relationship between heat island magnitude and rural temperature in either case. Why then does there seem to be such a relationship in the plots of monthly dependence (figures 3.7 and 3.8)?

In order better to search for any evident relationship, the average heat island magnitude is calculated as a function of rural temperature, using bins of four degrees in rural temperature. Figures 3.11 and 3.12 display the mean UHI magnitude versus rural temperature for both the minimum and maximum temperatures. The figures reveal a dependence of the heat island magnitude on rural temperature in both the minimum and maximum temperature cases. The minimum temperature UHI shows an inverse dependence on rural temperatures, falling quickly to zero once the rural temperatures become quite high. The maximum temperature UHI, on the other hand, is present only at very low rural temperatures and falls quickly to zero as the rural temperature rises into the high 60s. At very high rural temperatures, a slight cool
Figure 3.9: A scatter plot of the minimum temperature heat island magnitude versus rural temperature.

Figure 3.10: A scatter plot of the maximum temperature heat island magnitude versus rural temperature.
valley develops.

This type of relationship had been noted previously by Camilloni and Barros (1997). They were able to show that for several cities in Argentina, Australia, and the United States (not including Houston), UHI magnitudes are almost always negatively correlated with rural temperature.

![Minimum Temperature UHI Magnitude vs Rural Temperature](image)

Figure 3.11: A plot of the average minimum temperature heat island magnitude versus rural temperature.

### 3.5 Extreme Temperatures

As was discussed in section 1.1.1, heat-related morbidity and mortality are directly related to high temperature heat waves. It may therefore be useful to investigate the urban heat island of Houston in terms of extreme temperatures. For example, between
Figure 3.12: A plot of the average maximum temperature heat island magnitude versus rural temperature.

1990 and 1999, the Port of Houston meteorological station experienced an average of 41 days per year where the minimum daily (nighttime) temperature was equal to or greater than 78° F. Over the same period, Bush Intercontinental Airport only experienced an average of ten such days. (While there may be some concern that the Port of Houston weather station is biased due to its proximity to the water, this is likely not the case. It is located within the Interstate 610 loop, far from Galveston Bay. While it is near the Houston Ship Channel, the station should not be influenced by this waterway any more than the numerous other stations located near bayous and rivers.)

Figure 3.13 shows a contour plot of the average number of nights per year for which minimum temperature is equal to or greater than 78° F. As can be clearly
seen in the figure, the Houston urban area experiences far more nights when the
temperature stays at or above 78° F than do the surrounding rural areas. In fact,
many rural areas appear to experience less than a half a dozen such hot nights each
year. This factor alone may significantly increase the risk of heat-related morbidity
and mortality within the city of Houston.

Similarly, the Port of Houston experienced an average of only eight nights per
year when the temperature fell to or below 34° F, while Bush Intercontinental Airport
experienced an average of 18 such nights. Figure 3.14 shows a contour plot of the
average number of nights per year for which the minimum temperature is equal to or
less than 34° F. The figure seems to reveal a small urban influence during extremely
cold nights, under which the city experiences slightly fewer very cold nights than do
the surrounding rural areas, at least those to the north and west.

Generally speaking, the city appears to be significantly warmer during the ex-
tremely hot nights and slightly warmer during the extremely cold nights.

There is very little difference between the urban and rural areas in terms of ex-
tremely high daytime temperatures. The average number of days per year when the
temperature equaled 96° F or more was 26 for the Port of Houston and 17 for Hobby
Airport. Farther from the city center, Bush Intercontinental Airport had 35 such
days, Baytown only 15, and Thompsons 34. Figure 3.15 shows the contour plot of
the average number of days per year for which maximum temperature is equal to or
greater than 96° F.

There does seem to be a slight, though widespread urban influence on the lowest
Figure 3.13: A contour plot of the average number of nights per year for which the minimum temperature is equal to or greater than 78° F.

Figure 3.14: A contour plot of the average number of nights per year for which the minimum temperature is less than or equal to 34° F.
daytime high temperatures. The average number of days per year where the temperature equaled 56° F or less was 19 for the Port of Houston and Hobby Airport, 20 for Bush Intercontinental Airport, and 23 for Baytown. Farther from Houston, Sugarland had 25, Conroe and Anahuac had 27, and Cleveland had 30. Figure 3.16 shows a contour plot of the average number of days per year for which maximum temperature is equal to or less than 56° F. One can see from the plot that there appear to be more cold days per year to the west, north, and east of the city than in and around the city itself.

Figures 3.15 and 3.16 also show an example of a possibly biased station record. The station at Groveton (located near 31° N, 95° W, c.f. figure 3.2) appears to be abnormally warm on both the hot and cold days. This bias is also apparent in figure 3.6, the map of average maximum temperature. A likely explanation is that the station thermometer is improperly positioned or is not adequately shaded from direct sunlight. This would also account for the fact that the minimum temperatures from the station do not appear to be similarly biased.

Overall, daily maximum temperatures do not appear to be influenced by the urban heat island nearly as much as daily minimum temperatures. This reinforces the conclusion presented in section 3.2 that Houston displays a significant nighttime heat island, but a rather weak, if any, daytime heat island.
Figure 3.15: A contour plot of the average number of days per year for which the maximum temperature is greater than or equal to 96° F.

Figure 3.16: A contour plot of the average number of days per year for which the maximum temperature is less than or equal to 56° F.
Chapter 4

The Surface Temperature UHI

With the completion of the previous chapter’s overview of the air temperature heat island, the focus of this thesis now turns to Houston’s surface temperature heat island and the use of remote sensing in its investigation. The surface temperature of Houston and the surrounding areas is measured using infrared radiance data from satellite-based radiometers. This data is available from any of a number of satellites currently in orbit. It was also desired, however, that upon development of a UHI measurement technique it be applied to a time-series of images to study long term change in the urban heat island. This requires a satellite or satellite series with a long operational history—the longer, the better. Such a requirement narrowed the list of candidates to two: the Landsat satellite series and the NOAA polar-orbiting satellite series. The final determining factor was cost and availability of the satellite data. While data from both satellites can be easily obtained via the internet, a sizable cost is associated with Landsat data. This is not true of the NOAA data, which was thus
<table>
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<th>Channel</th>
<th>Wavelength</th>
<th>Spectral Region</th>
<th>Primary Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>580–680 nm</td>
<td>Red</td>
<td>Daytime Cloud and Surface Mapping</td>
</tr>
<tr>
<td>2</td>
<td>730–1100 nm</td>
<td>Reflected IR</td>
<td>Surface Water Delineation</td>
</tr>
<tr>
<td>3</td>
<td>3.55–3.93 μm</td>
<td>Near IR</td>
<td>Sea Surface Temperature, Nighttime Cloud Mapping</td>
</tr>
<tr>
<td>4</td>
<td>10.3–11.3 μm</td>
<td>Thermal IR</td>
<td>Sea Surface Temperature, Cloud Mapping</td>
</tr>
<tr>
<td>5</td>
<td>11.5–12.5 μm</td>
<td>Thermal IR</td>
<td>Sea Surface Temperature</td>
</tr>
</tbody>
</table>

Table 4.1: The wavelengths and primary uses of the AVHRR channels.

chosen for use in this study.

4.1 Advanced Very High Resolution Radiometer

The history of the Advanced Very High Resolution Radiometer (AVHRR) goes back to 1978, when it was first launched aboard the TIROS-N satellite. Since then, the AVHRR has been included on nearly every satellite of the NOAA POES system. As the name implies, these satellites are in a low-Earth polar orbit, circling the planet 14.1 times each day at an altitude of approximately 830 km and providing global coverage almost daily. The orbits are nearly sun-synchronous, meaning that each and every passage of the satellite above a given location occurs at approximately the same local time. The orbits are usually devised such that the daytime equatorial crossings occur during the local mid-morning or mid-afternoon.

Current versions of the AVHRR have five spectral channels ranging from the visible to the thermal infrared regions of the electromagnetic spectrum. The wavelengths and primary uses of each channel are listed in table 4.1.
The method by which the AVHRR scans the surface is demonstrated in figure 4.1. The scan direction is cross-track, perpendicular to the travel of the satellite. The instrument's angular field of view is over 110°, resulting in a swath width of up to 3000 km. Each scan line contains 2048 pixels, with a spatial resolution in all channels from $1.1 \times 1.1$ km at nadir to $2.3 \times 6.4$ km at the maximum scan angle.

Figure 4.1: A figure showing the scanning method of the AVHRR instrument. From Sabins (1997)

4.1.1 Timing of the satellite overpass

As the NOAA satellites are in sun-synchronous orbits, individual satellites will pass directly over the Houston area at nearly the same time each day, with the ascending and descending passes separated by approximately twelve hours. If only nadir views are used, all images would be taken at nearly the same local time, varying
only due to a small amount of drift resulting from the orbital precession of the satellite. Using only nadir views is advantageous, as it is the case of shortest atmospheric path length, ensuring the least possible amount of atmospheric absorption. The path lengths, and therefore the atmospheric absorption, would also be the similar for each image, making them easier to compare.

Unfortunately, nadir views of any single location only occur approximately once every two weeks, the time it takes the satellite to revisit the same spot. Combined with the frequency of cloud cover, this would produce a minimal amount of data, too little for a statistical study. On account of this, the use of off-nadir images is also required. By using images with satellite zenith angles of up to 20°, images can be acquired on a nearly daily basis. Images with zenith angles greater than 20° are rejected as they may be subject to larger and unacceptable uncertainties due to the lengthened atmospheric path (Prata, 1993).

The imagery used throughout this study was acquired by the NOAA-9 and NOAA-14 satellites. These satellites are chosen because they have similar orbits with the descending pass occurring at approximately 0400 LST. This is fortunate in that each image was obtained at a time when the local temperature was likely near the daily minimum. The air temperature urban heat island is known to be strongest during the night (Oke, 1982), as demonstrated in the previous chapter, and typically reaches its maximum value when the rural air temperature is at a daily minimum (Karl et al., 1988). Consequently, the nighttime surface temperature UHI is also likely to be strongest at this time.
4.2 Obtaining Temperature Maps

Temperature maps for the city of Houston are obtained from AVHRR Level 1b High Resolution Picture Transmission (HRPT) data. These data are freely obtained from the NOAA Satellite Active Archive. The analysis area encompasses a $2^\circ \times 2^\circ$ box centered about the city. Radiance values are calculated for channels 4 (10.3–11.3 $\mu$m) and 5 (11.5–12.5 $\mu$m) using the calibration coefficients contained within the ephemeris data. (Channels 4 and 5 are often referred to as the "split window" channels as they occupy neighboring wavelengths and effectively split the atmospheric window between 10 and 13 $\mu$m.) These radiance values are then corrected for the non-linearity of AVHRR channels 4 and 5 using radiance correction coefficients (Kidwell, 1998). The corrected radiance values ($R_i$) are then converted to brightness temperatures by using the inverse of Planck's equation of radiation.

$$T(R_i) = \frac{C_2 \nu_j}{\ln(1 + \frac{C_1 \nu_j^2}{R_i})} \quad (4.1)$$

The constants in equation (4.1) are $C_1 = 1.1910659 \times 10^{-5}$ mW m$^{-2}$ sr$^{-1}$ cm$^4$ and $C_2 = 1.438833$ cm K, with $\nu_j$ the central wave number of each channel. The brightness temperature data from the split window channels are then used to calculate the surface temperatures using the technique of Price (1984):

$$T_{\text{surface}} = T_4 + R(T_4 - T_5), \quad (4.2)$$

where $T_4$ and $T_5$ are the brightness temperatures of channels 4 and 5 and
\( R = \frac{1}{\beta_4 - 1} = 3.33 \). (\( \beta_4 \) and \( \beta_5 \) are atmospheric absorption coefficients for channels 4 and 5.) This step is necessary, as the brightness temperature data are inaccurate due to the atmospheric absorption in each channel. Equation (4.2) is an attempt to correct for the atmospheric absorption and represents essentially a first-order correction to the surface temperature. An example of the resulting surface temperature is the temperature map shown in figure 4.2, a scene from September 9, 1999.

![Temperature Map](image)

Figure 4.2: A temperature map of the Houston, Texas area for September 9, 1999.

Several features in figure 4.2 are immediately noticeable. The first is that the surface temperature of the water is much greater than that of the land. This is due to lower temperature variability and was remarked upon in previous chapters. The second conspicuous feature is the temperature difference between the urban area and its surroundings—the urban heat island itself. The dark stripe immediately south
of the city and extending out over the Gulf of Mexico is a cloud, identified as such by its extremely low temperature. Areas of localized heating are also visible on the northern shore of Galveston Bay and southwest of the city. These are likely the heat signatures of power generation plants.

4.3 Characterizing the Urban Heat Island

4.3.1 Cloud and water rejection

In order to isolate the heat island in each image, it is necessary to mask the water and cloud components. The first to be eliminated are the bodies of water in the analysis area. This is accomplished with the use of a land cover characterization made available from the USGS Earth Resources Observation System (EROS) Data Center (Sellers et al., 1996). It is necessary to transform the land cover characterization map to unprojected geographical coordinates in order to combine it with each surface temperature map.

The presence of clouds in each image would also have contaminated the heat island signature. Cloud pixels are removed by virtue of their low temperature relative to the surface. After the water pixels are removed, a temperature histogram of the remaining pixels is created. The dominant feature of the temperature histogram is a peak composed primarily of the land pixels. This peak is then fit to a Gaussian curve. Any pixels with a temperature less than two standard deviations below the peak are assumed to be located in the cores of clouds. These cloud cores are then removed,
as well as the pixels neighboring them. Figure 4.3 shows the temperature histogram of the September 9, 1999 image. The dashed line represents the Gaussian fit to the histogram. Note the large population of pixels below 15° C. It is these pixels which are assumed to be clouds.

![Temperature histogram](image)

Figure 4.3: A temperature histogram of the land pixels in the September 9, 1999 image. The dashed line is the Gaussian fit to the histogram.

### 4.3.2 Fitting the UHI to a surface

As was mentioned in section 1.3.2, many urban heat island studies have been performed using AVHRR thermal infrared measurements. Of the UHI measurement techniques presented, several appear to be inadequate in that they are rather subjective. A number of the studies cited determine UHI magnitude based on a sample
of relatively few pixels from the urban area, pixels that are not necessarily representative of the urban area as a whole. Additionally, none of these studies attempt to make any type of direct measurement of the heat island’s spatial extent. The investigation presented here will endeavor to remedy both of these shortcomings by fitting temperature data of the entire heat island to a mathematical surface.

Individual UHI measurements are determined from the surface temperature maps of each scene by making a least-squares fit of the entire heat island to a Gaussian surface. This surface can be broken into two components, the rural “background” and the urban heat island itself.

\[
T(x, y) = T_{\text{Rural}}(x, y) + T_{\text{UHI}}(x, y)
\] (4.3)

The rural component of the fitting surface takes the form of planar background.

\[
T_{\text{Rural}}(x, y) = T_o + a_1 x + a_2 y
\] (4.4)

This component determines the mean rural temperature \((T_o)\) and the overall spatial temperature gradients \((a_1\) and \(a_2\)) of the surface. The spatial gradients are included primarily to remove effects due to the proximity to the coast.

The UHI component contains the Gaussian surface that represents the urban heat island.
\[ T_{\text{UHI}}(x, y) = a_0 \exp \left[ - \frac{(x - x_0) \cos \phi + (y - y_0) \sin \phi)^2}{0.5 a_x^2} - \frac{(y - y_0) \cos \phi - (x - x_0) \sin \phi)^2}{0.5 a_y^2} \right] \] (4.5)

This method provides not only a measure of the urban heat island magnitude representative of the entire city \((a_0)\), but also the spatial extent \((a_x \text{ and } a_y)\), orientation \((\phi)\), and central location \((x_0 \text{ and } y_0)\) of the heat island as well. Figure 4.4 shows an example of the complete Gaussian surface represented by the above equations.

![Gaussian Surface](image)

**Figure 4.4:** An example of the Gaussian surface defined in equations (4.3), (4.4), and (4.5).

In order to perform the fit, a land temperature image is created by masking out all areas of clouds and open water. As the general location of the urban area is known
a priori, the region of the land temperature image that contains the urban area is temporarily masked out, producing an image consisting entirely of rural pixels. Since the exact spatial extent of the urban heat island is unknown prior to measurement, the mask of the urban area must be large enough that it completely covers the urban pixels. It is inevitable, then, that some rural pixels near the urban area are masked out as well. This urban mask does not change from image to image, resulting in all cloud-free rural images having the same number of rural pixels.

This rural temperature image is then fit to the planar surface of equation (4.4), resulting in the determination of $T_o$, $a_1$, and $a_2$. The rural temperature components are then subtracted from the land temperature image, effectively producing a “flattened” image with only the heat island remaining. An example of such an image is shown in figure 4.5, again for the September 9, 1999 scene.

The temperature image of the UHI is then fit to the pure Gaussian surface of equation (4.5). This is done by fitting the natural logarithm of the image to equation (4.6) using the method of least-squares. This determines the UHI measurements. The UHI magnitude is the height of the Gaussian ($a_o$), and the longitudinal and latitudinal extents of the UHI are the Gaussian width parameters ($a_x$ and $a_y$). The orientation ($\phi$) and central location ($x_o$ and $y_o$) of the UHI are also calculated in this step.

\[
\ln[T_{UHI}(x, y)] = \ln(a_o) - \frac{(x - x_o) \cos \phi + (y - y_o) \sin \phi)^2}{0.5 a_x^2}
\]
Figure 4.5: Image of the isolated urban heat island for the September 9, 1999 scene.

\[
-(y - y_0) \cos \phi - (x - x_0) \sin \phi \over 0.5 a_\phi^2
\]  \hspace{1cm} (4.6)

Figures 4.6 and 4.7 show the cross-sections of the temperature data (solid line) and the resulting Gaussian surface (dashed line) along lines of constant longitude and latitude for the September 9, 1999 image. The cross-sections correspond roughly to the major and minor axes of the Gaussian surface.

4.4 Discussion of Error

Price (1984) cites three sources of error in the measurement of land surface temperature: radiometric calibration errors of less than 1 K, dependence of \( R \) on atmospheric
Figure 4.6: Longitudinal cross-section of the September 9, 1999 heat island.

Figure 4.7: Latitudinal cross-section of the September 9, 1999 heat island.
absorption which can result in changes of temperature retrievals of 2 K, and variations in surface emissivity which can result in changes in retrieved temperatures of order 1 K. These factors combine to produce an rms error of 2–3 K.

The split window method of land surface temperature derivation can also be affected by emissivity differences between channels 4 and 5 as well as emissivities not equal to one. Becker (1987) uses radiative transfer theory to derive an error due to differences in emissivity of order:

$$
\Delta T \approx \frac{1-\bar{\varepsilon}}{\bar{\varepsilon}} \times 50 \text{K} - \frac{\varepsilon_4 - \varepsilon_5}{\bar{\varepsilon}} \times 300 \text{K},
$$

(4.7)

where $\varepsilon_4$ and $\varepsilon_5$ are the surface emissivities in channels 4 and 5, and $\bar{\varepsilon}$ is the average of the two. One should note that the error due to differences in emissivity is six times greater than the error due to nonunity emissivities, and that if $\varepsilon_4$ is greater than $\varepsilon_5$, the errors will partially cancel. In their UHI analysis, Henry et al. (1989) assume emissivity values of $\varepsilon_4 = \varepsilon_5 = 0.97$, which result in a temperature bias of +1.5 K. Vidal (1991) finds $\varepsilon_4 - \varepsilon_5 = -0.011$ for agricultural surfaces, resulting in a temperature bias of −3.1 K. Unfortunately, there is little available information concerning the comparable emissivities of urban surfaces.

A major advantage of studying the urban heat island is that the quantity of interest is not the absolute urban temperature, but the difference in temperature between the urban and rural areas. The sources of error listed above are systematic and are thus partially removed in the differencing procedure. However, a significant source of error in this study may in fact be due to spatial differences in emissivity.
between the urban area and the surrounding rural area. Urban surfaces tend to have slightly lower emissivities than rural, vegetative ones. A difference in emissivity of at least 0.01 is quite likely and would thus cause the urban heat island magnitudes to be underestimated by a degree or more (Oke, 1987; Rees, 1990).

4.5 Energy Flux

Before this chapter ends, it may be of use to consider the urban heat island in terms of energy. The total excess energy radiated by a heat island of the form presented in equation (4.3) is given by the following approximation.

\[
E = \iint \sigma T^4(x, y) \, dx \, dy - \iint \sigma T^4_{\text{Rural}}(x, y) \, dx \, dy \\
\approx 2\pi \sigma a_o a_x a_y T_o^3
\]

For nominal values of \( T_o = 300 \) K, \( a_o = 3 \) K and \( a_x = a_y = 30 \) km, the total excess energy emitted is approximately \( 2.6 \times 10^{10} \) W. This is equivalent to an annual energy output of \( 2.3 \times 10^5 \) GWh. Distributed over an area of 900 km\(^2\), this represents an energy density of 250 kWh m\(^{-2}\).

By comparison, in 2000 Reliant HL&P provided \( 7 \times 10^4 \) GWh to its 1.7 million customers (Public Utility Commission of Texas, 2000). The power consumption was split relatively evenly between the residential, commercial, and industrial sectors. The 1.7 million customers likely represent at least twice as many end users, translating to
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<tr>
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</tr>
<tr>
<td>Solar Insolation, Globally Averaged</td>
<td>343</td>
</tr>
<tr>
<td>300 K Blackbody Radiation</td>
<td>460</td>
</tr>
<tr>
<td>Power Required to Evaporate Water</td>
<td>640</td>
</tr>
<tr>
<td>at a Rate of 1 mm hr⁻¹</td>
<td></td>
</tr>
<tr>
<td>Power Required to Melt Snow</td>
<td>190</td>
</tr>
<tr>
<td>at a Rate of 1 cm hr⁻¹</td>
<td></td>
</tr>
<tr>
<td>Power Required to Raise 2 cm</td>
<td>23</td>
</tr>
<tr>
<td>Deep Water 1 K hr⁻¹</td>
<td></td>
</tr>
<tr>
<td>Power Required to Raise 2 cm</td>
<td>12</td>
</tr>
<tr>
<td>Thick Concrete Slab 1 K hr⁻¹</td>
<td></td>
</tr>
<tr>
<td>Power Required to Raise 10 m</td>
<td>3.4</td>
</tr>
<tr>
<td>Air Column 1 K hr⁻¹</td>
<td></td>
</tr>
<tr>
<td>Excess Heat Radiated by a 3 K Urban Heat Island</td>
<td>19</td>
</tr>
<tr>
<td>Heat Radiated by a Person</td>
<td>~ 100</td>
</tr>
</tbody>
</table>

Table 4.2: The energy flux of various phenomena.

A power usage of roughly 20 MWh per capita. Multiplied by the city of Houston’s population density of 1300 km⁻², this is equivalent to 26 kWh m⁻², roughly one tenth of the heat island energy excess.

Similarly, the 560,000 Houston customers of natural gas average an annual consumption of approximately 50,000 cubic feet each (Railroad Commission of Texas, 2000). Proceeding by the same method used above, and with 1,000 cubic feet of natural gas equivalent to an energy of 290 kWh, this represents an equivalent energy usage of 10 kWh m⁻².

Table 4.2 shows the energy flux corresponding to different types of natural phenomena.
Chapter 5

Urban Heat Island Growth

To date the vast majority of UHI climatological studies have been performed using in situ data, due in large part to the brevity of the remotely sensed data record. An example of such a study is by Wang et al. (1990), who find an increase of 0.1 K per decade in the UHIs throughout China since the late 1970s. The purpose of the analysis presented in this chapter is to use the remote sensing techniques developed in Chapter 4 to measure the change in the surface temperature UHI of Houston over the course of a twelve-year period, from 1987 to 1999.

The urban heat island measurements are determined from surface temperature maps of the Houston region derived from radiance data acquired by the AVHRR instruments on board the NOAA-9 and NOAA-14 satellites. Data are obtained for 1946 individual scenes over two discrete time intervals. Of these, one hundred and fifty-seven relatively cloud-free images are obtained for the two-year interval of March 1985 through February 1987 ("interval 1") by the NOAA-9 instrument. An addi-
Figure 5.1: The monthly distribution of the nighttime UHI measurements. The dashed line shows the interval 1 distribution and the solid line shows the interval 2 distribution.

A total of one hundred and seventy-three relatively cloud-free images are obtained for the two-year interval of July 1999 through June 2001 ("interval 2") by the NOAA-14 instrument. The nighttime images were acquired during the descending pass of the satellite, between the hours of 0200 and 0530 LST (0800–1130 GMT), while the daytime images were acquired during the ascending pass between the hours of 1230 and 1730 LST (1830–2330 GMT). Of the interval 1 images, 82 are nighttime and 75 are daytime. Of the interval 2 images, 125 are nighttime and 48 are daytime. The monthly distributions of the images within the two intervals are shown in figures 5.1 and 5.2.
Figure 5.2: The monthly distribution of the daytime UHI measurements. The dashed line shows the interval 1 distribution and the solid line shows the interval 2 distribution.

5.1 Nighttime UHI Measurement

5.1.1 UHI magnitude

The mean rural temperature of the area surrounding the city of Houston is $17.2 \pm 0.7^\circ \text{C}$ for all of the images in interval 1. The mean rural temperature of the same area for interval 2 is $17.1 \pm 0.8^\circ \text{C}$, virtually identical to the earlier interval. Temperature histograms of both of these sets of data are shown in figure 5.3. Due to the differing number of measurements in the two intervals, each histogram is normalized according to the sample size of the interval. As can be seen in this figure, a large fraction of the rural temperatures from both intervals lie in the range of 20–25$^\circ \text{C}$, with the rest of the measurements spread evenly between 0$^\circ \text{C}$ and 20$^\circ \text{C}$.
C. This distribution is due to the images being acquired throughout the year and during a variety of temperatures. As can be seen in figure 5.1, the majority of the measurements were taken during the summer and early fall months, resulting in the high-temperature peaks in figure 5.3. The fact that the mean rural temperature and its uncertainty for these two periods are so similar serves to indicate that there were no significant climatic differences in the region between the two intervals, and that the individual AVHRR instruments are well calibrated with respect to each other.

![Rural Temperature Histogram](image)

**Figure 5.3:** A normalized histogram of nighttime rural temperatures. The dashed line shows the rural temperatures from interval 1, while the solid line shows the rural temperatures from interval 2.

The mean nighttime UHI magnitude ($a_0$ from equation (4.5)) for the 82 images in interval 1 is found to be $2.37 \pm 0.07$ K. The mean UHI magnitude for the 125 images in interval 2 is $3.19 \pm 0.08$ K, an increase of $0.82 \pm 0.10$ K. Figure 5.4 shows histograms of the UHI magnitudes of both of these periods, normalized as in figure
5.3. The interval 1 data (dashed line) peak at a lower temperature than the interval 2 data (solid line). The interval 1 data show a standard deviation of 0.60 K, while the standard deviation of the interval 2 data is slightly higher, at 0.86 K. As can be seen in figure 5.3, the data from both intervals appear to be quite well-behaved, forming near-normal distributions. This confirms the premise that the mean UHI magnitude is a significant characteristic of the heat island and that any departure from the mean follows a "natural" deviation or variability.

![UHI Magnitude Histogram](image)

Figure 5.4: A normalized histogram of the nighttime UHI magnitudes. The dashed line shows the UHI magnitudes from interval 1, while the solid line shows the UHI magnitudes from interval 2.

Seasonal considerations

As is apparent from figure 5.1, the UHI measurements are not distributed evenly throughout the year in either of the two intervals, likely due to increased cloud cover.
<table>
<thead>
<tr>
<th>Season</th>
<th>Interval 1</th>
<th>Interval 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>January–March</td>
<td>$2.77 \pm 0.21$ K (13)</td>
<td>$3.45 \pm 0.28$ K (10)</td>
</tr>
<tr>
<td>April–June</td>
<td>$2.19 \pm 0.10$ K (24)</td>
<td>$2.51 \pm 0.23$ K (14)</td>
</tr>
<tr>
<td>July–September</td>
<td>$2.42 \pm 0.09$ K (37)</td>
<td>$3.36 \pm 0.10$ K (62)</td>
</tr>
<tr>
<td>October–December</td>
<td>$2.01 \pm 0.18$ K (8)</td>
<td>$3.11 \pm 0.13$ K (39)</td>
</tr>
<tr>
<td>Seasonal Mean</td>
<td>$2.32 \pm 0.06$ K</td>
<td>$3.20 \pm 0.07$ K</td>
</tr>
</tbody>
</table>

Table 5.1: The mean UHI magnitudes for each season. The numbers in parentheses are the total number of measurements in each season.

during the cooler months. This leads to concern that monthly differences in the UHI measurements could influence the statistical analysis. A bias could be introduced because a larger fraction of the interval 2 images were acquired during the summer months than were the images in interval 1. In order to determine whether such a bias exists, a seasonal analysis is conducted.

Table 5.1 shows the mean UHI magnitude for the individual seasons. In each season the mean UHI magnitude is greater in interval 2 than interval 1. The interval 1 seasonal mean (the weighted mean of the four individual season means) is $2.32 \pm 0.06$ K, while the interval 2 seasonal mean is $3.20 \pm 0.07$ K. These values are in very good agreement with the results of the more general analysis conducted above—a difference in the means of $0.88 \pm 0.10$ K, compared with the $0.82 \pm 0.10$ K difference found previously.

The UHI magnitudes do, however, appear to demonstrate some seasonal variability. The mean magnitudes are greatest during the winter and summer months, while the mean growth in magnitude is greatest during summer and fall.
Diurnal considerations

Due to differences in the orbital characteristics of the two satellites, the interval 2 data was taken an average of ninety minutes later in local time than the interval 1 data, as can be seen in figure 5.5. The interval 1 data, shown as diamonds, were collected between 0230 and 0400 LST. The interval 2 data, shown as asterisks, were collected between 0330 and 0530 LST. This led to concern that the difference in mean UHI magnitude was due, at least in part, to diurnal temperature variations and possibly the onset of solar insolation in the interval 2 data. Figure 5.6 shows a plot of the average diurnal variations in air temperature during the year 2000 at the William P. Hobby Airport, located in the southeastern part of the city (solid line). Also plotted are the average diurnal air temperatures for the months of January (dashed line) and July (dotted line). As can be seen from the graph, diurnal heating does not begin until at least 0500 LST, or after nearly all of the data was acquired. A comparison of image collection times with sunrise times indicates that one or two of the images in interval 2 may have been taken as the sun rose.

If the UHI magnitudes are influenced by diurnal temperature variations (i.e. if the falling temperature during the night causes the UHI magnitudes to increase), then the magnitudes would be expected to show a correlation with the surface temperature, either rural or urban. This, however, does not seem to be the case. In fact, neither the interval 1 data nor the interval 2 data show any significant correlation with either rural temperature or local time. When correlated against rural temperature, the data show correlation coefficients of 0.1 and -0.2 for the two intervals. It is thus unlikely
Figure 5.5: A plot of nighttime UHI magnitudes versus local time. The diamonds represent the UHI magnitudes from interval 1, while the asterisks represent the UHI magnitudes from interval 2.

that any of the data are affected by diurnal variations. Figure 5.7 shows a plot of UHI magnitudes versus rural temperatures.

5.1.2 Orientation

The mean orientation ($\phi$) of the nighttime urban heat island is $4.3 \pm 1.1^\circ$, with a median of $1.9^\circ$. A rotation of $0^\circ$ indicates the major axis of the heat island footprint is parallel to a line of constant latitude. Thus the Houston heat island tends to be oriented very nearly east-west. Because of this, the major and minor axes are referred to as the “longitudinal” and “latitudinal” axes throughout this study. There is no significant difference between the mean rotations of interval 1 and interval 2.
Figure 5.6: A plot of the average air temperature versus local time for the year 2000, as calculated from daily measurements at the William P. Hobby International Airport in Houston. The solid line represents the average temperature throughout the entire year. The dashed and dotted lines represent the average temperatures throughout the months of January and July, respectively.
Figure 5.7: A plot of nighttime UHI magnitudes versus rural temperature. The diamonds represent the UHI magnitudes from interval 1, while the asterisks represent the interval 2 magnitudes.

5.1.3 Spatial extent

The mean spatial extents ($a_x$ and $a_y$) for the interval 1 UHI data are found to be $33.0 \pm 1.3$ km in longitude and $17.3 \pm 0.5$ km in latitude. The mean spatial extents for the interval 2 UHI data are found to be $40.5 \pm 0.9$ km in longitude and $19.6 \pm 0.3$ km in latitude. These values represent increases in extent of 23% in longitude and 13% in latitude. Figure 5.8 shows a scatter plot of the spatial extents of the heat islands. Due to the increase, the interval 2 data, shown as asterisks are on average above and to the right of the interval 1 data, which are shown as diamonds.

The two spatial extent parameters for each UHI measurement can be combined to determine the overall area or footprint of the UHI. The footprint itself has the
Figure 5.8: A plot of UHI latitudinal and longitudinal extents. These spatial extents are determined using the Gaussian parameters $a_x$ and $a_y$ from equation (4.5). The diamonds represent the spatial extents from interval 1, while the asterisks represent the spatial extents from interval 2.
form of an ellipse with the major and minor axes equivalent to the latitudinal and longitudinal extent parameters. (This could be demonstrated by taking a horizontal cross-section through the surface in figure 4.4.) The area of each UHI can then be calculated as:

\[
\text{Area} = \frac{\pi a_x a_y}{4}. \tag{5.1}
\]

Using equation (5.1), the mean area of the interval 1 UHI data is found to be 450 ± 20 km². The mean area for the interval 2 UHI data is found to be 620 ± 20 km², an increase of 38%. A normalized histogram of individual area measurements is shown in figure 5.9, with the interval 1 data shown as the dashed line and the interval 2 data shown as the solid line.

These UHI areas are significantly smaller than the geopolitical areas of the city given in table 1.1. While it is not surprising that the extents of a natural phenomenon do not correspond exactly to political boundaries, this does provide evidence that the urban heating is likely limited to within the city proper.

By solving equation (4.5) for \( x = a_x \) and \( y = a_y \), one finds that the temperature is given by \( T(a_x, a_y) = T_o + a_o e^{-1/2} \). Thus the spatial extents are defined as the point at which the heat island falls to a level of \( e^{-1/2} \), or 61%, of its maximum value. It may be that spatial extents could be better understood if they represent the area of the UHI for which the temperature is greater than some absolute value, instead of a fraction of the maximum value. By using a constant threshold, in this case of 1.0 K, the spatial extent is no longer dependent on the heat island magnitude and may more
Figure 5.9: A normalized histogram showing the area of the UHIs. The dashed line represents the interval 1 data, and the solid line shows the interval 2 data. The interval 2 UHIs have, in general, larger areas than the interval 1 UHIs.

accurately represent the entire footprint of the heat island. The relationship between the 1 K spatial extents ($a_{x,y}^{1K}$) and the previous Gaussian extents ($a_{x,y}^{Gauss}$) is

$$a_{x,y}^{1K} = a_{x,y}^{Gauss} \times \sqrt{\frac{\ln a_o}{2}}. \quad (5.2)$$

Figure 5.10 further illustrates the relationship between $a_{x}^{Gauss}$ and $a_{x}^{1K}$.

When this method is used, the mean spatial extents for the interval 1 UHI data are found to be $42.4 \pm 1.9$ km in longitude and $22.2 \pm 0.8$ km in latitude, resulting in an area of $740 \pm 40$ km$^2$. The mean spatial extents for the interval 2 UHI data are found to be $60.4 \pm 1.6$ km in longitude and $29.2 \pm 0.7$ km in latitude for an area of $1390 \pm 50$ km$^2$. The increases in extent are 42% in longitude and 32% in latitude,
Figure 5.10: A diagram showing the spatial extents based on the Gaussian and 1 K threshold methods of determination.

resulting in a change in overall area of 88%. Figure 5.11 shows a scatter plot of the spatial extents when the 1 K threshold is used. As with the Gaussian-based measurements, the interval 2 data are above and to the right of the interval 1 data. A normalized histogram of UHI areas calculated from these spatial extents is shown in figure 5.12, with the interval 1 data shown using the dashed line and the interval 2 data with the solid line.

While the interval 1 area given by this method is quite a bit smaller than the 1990 geopolitical area of the city of Houston (1400 km$^2$), the interval 2 area corresponds well to the 2000 area of 1540 km$^2$.

The hypothesis that the 1 K threshold extents are more meaningful than the Gaussian extents is supported by correlating the UHI magnitudes with the UHI ar-
Figure 5.11: A plot of UHI latitudinal and longitudinal extents. These spatial extents are determined using 1 K threshold method. The diamonds represent the spatial extents from interval 1, while the asterisks represent the spatial extents from interval 2. (Note the axes are different than those of figure 5.8.)
Figure 5.12: A normalized histogram showing the area of the UHIs, using the 1 K threshold method of determining the spatial extent. The dashed line represents the interval 1 data, and the solid line shows the interval 2 data. The interval 2 UHIs have, in general, larger areas than the interval 1 UHIs.
<table>
<thead>
<tr>
<th></th>
<th>Interval 1</th>
<th>Interval 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>January–March</td>
<td>410 ± 70 km² (13)</td>
<td>460 ± 70 km² (10)</td>
</tr>
<tr>
<td>April–June</td>
<td>400 ± 30 km² (24)</td>
<td>670 ± 70 km² (14)</td>
</tr>
<tr>
<td>July–September</td>
<td>560 ± 40 km² (37)</td>
<td>710 ± 30 km² (62)</td>
</tr>
<tr>
<td>October–December</td>
<td>310 ± 40 km² (8)</td>
<td>550 ± 30 km² (39)</td>
</tr>
<tr>
<td>Seasonal Mean</td>
<td>410 ± 20 km²</td>
<td>620 ± 20 km²</td>
</tr>
</tbody>
</table>

Table 5.2: The mean UHI areas for each season, as determined with the Gaussian extents. The numbers in parentheses are the total number of measurements in each season.

eas. When UHI magnitude is correlated against the Gaussian-derived UHI area, the correlation is very poor, with a correlation coefficient of less than 0.3. It is reasonably expected, however, that the two would be correlated—a stronger heat island should mean a larger heat island. The correlation is seen, however, when the UHI magnitude is compared to the 1 K threshold-derived UHI area, with a correlation coefficient of 0.7.

**Seasonal analysis**

As with the UHI magnitudes, the UHI areas are analyzed by season. Table 5.2 gives the season means for the areas calculated using the Gaussian spatial extents, while table 5.3 gives the means for the areas calculated using the 1 K threshold spatial extents.

In each season, the area of the urban heat island increases between interval 1 and interval 2. As with the UHI magnitudes, the seasonal means (the weighted means of the individual season means) agree quite well with the overall mean areas given in section 5.1.3. Like the mean UHI magnitudes, the mean areas also show seasonal
<table>
<thead>
<tr>
<th>Season</th>
<th>Interval 1</th>
<th>Interval 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>January–March</td>
<td>880 ± 170 km$^2$ (13)</td>
<td>1140 ± 210 km$^2$ (10)</td>
</tr>
<tr>
<td>April–June</td>
<td>600 ± 60 km$^2$ (24)</td>
<td>1170 ± 170 km$^2$ (14)</td>
</tr>
<tr>
<td>July–September</td>
<td>970 ± 90 km$^2$ (37)</td>
<td>1700 ± 90 km$^2$ (62)</td>
</tr>
<tr>
<td>October–December</td>
<td>450 ± 100 km$^2$ (8)</td>
<td>1230 ± 80 km$^2$ (39)</td>
</tr>
<tr>
<td>Seasonal Mean</td>
<td>680 ± 40 km$^2$</td>
<td>1410 ± 50 km$^2$</td>
</tr>
</tbody>
</table>

Table 5.3: The mean UHI areas for each season, as determined with the 1 K threshold extents. The numbers in parentheses are the total number of measurements in each season.

variability. Using the Gaussian extents, the mean area is greatest during the spring and summer months, with the greatest growth occurring in the spring. Using the 1 K threshold extents, the largest areas are in the summer, and the most growth is in the summer and fall.
5.2 Daytime UHI Measurement

5.2.1 UHI magnitude

For interval 1 the mean rural temperature of the area surrounding the city of Houston is 27.9 ± 0.8°C. The mean rural temperature of the same area for interval 2 is 27.1 ± 1.5°C. Normalized temperature histograms of both of these sets of data are shown in figure 5.13.

![Rural Temperature Histogram](image)

Figure 5.13: A normalized histogram of daytime rural temperatures. The dashed line shows the rural temperatures from interval 1, while the solid line shows the rural temperatures from interval 2.

The mean UHI magnitude for the 75 daytime images in interval 1 is found to be 5.4 ± 0.3 K. The mean UHI magnitude for the 48 images in interval 2 is 3.8 ± 0.3 K, a decrease of 1.6 ± 0.4 K. Figure 5.14 shows histograms of the UHI magnitudes of both of these periods, normalized as in the nighttime histogram. The interval 1 data
show a standard deviation of 2.2 K, while the standard deviation of the interval 2 data is 1.8 K.

![UHI Magnitude Histogram](image)

Figure 5.14: A normalized histogram of the daytime UHI magnitudes. The dashed line shows the UHI magnitudes from interval 1, while the solid line shows the UHI magnitudes from interval 2.

In light of the findings stated in the previous section, it is unusual that the mean daytime UHI magnitude is smaller in interval 2 than it is in interval 1. Also of note is the fact that the mean rural temperature is also lower in interval 2 than in interval 1 by nearly a degree. Both of these features may in fact be due not to a decline of the heat island but to diurnal variations. The daytime UHI magnitudes versus local time are shown in figure 5.15.

As is evident from this figure, the daytime UHI magnitudes appear to decrease with local time, especially the interval 2 magnitudes. This dependence on local time makes any comparison of the two intervals quite difficult and would potentially result
Figure 5.15: A plot of daytime UHI magnitudes versus local time. The diamonds represent the UHI magnitudes from interval 1, while the asterisks represent the UHI magnitudes from interval 2.

in a high uncertainty if such an analysis is conducted. In light of this, no attempt at a comparison is made in this study.

5.2.2 Rural temperature dependence

Unlike the nighttime values, the daytime UHI magnitudes are highly correlated with the daytime rural temperatures. Figure 5.16 shows the UHI magnitudes plotted versus rural temperature, with the interval 1 data as diamonds and the interval 2 data as asterisks.

The rural temperatures and UHI magnitudes have a correlation coefficient of 0.74. A least-squares linear fit of the data in figure 5.16 is:
Figure 5.16: A plot of daytime UHI magnitudes versus rural temperatures. The diamonds represent the UHI magnitudes from interval 1, while the asterisks represent the UHI magnitudes from interval 2.

\[ \text{UHI} = (0.19 \pm 0.02) \times T_{rural} - (0.39 \pm 0.44) ^\circ C. \]  

(5.3)

Thus the average daytime surface temperature UHI ranges from being absent at a rural temperature of 0° C to a magnitude of approximately 8 K at a rural temperature of 40° C.

5.2.3 Spatial extent

Figures 5.17 and 5.18 display the areas of the maximum temperature urban heat islands. Figure 5.17 shows the areas calculated using the Gaussian method of determining spatial extent, while figure 5.18 shows the areas calculated using the 1 K
threshold method. As previously, the dashed line represents the interval 1 data and the solid line represents the interval 2 data.

![UHI Area Histogram](image)

Figure 5.17: A normalized histogram showing the area of the UHIs, using the Gaussian method of determining spatial extent. The dashed line represents the interval 1 data, and the solid line shows the interval 2 data.

As was seen with the nighttime UHIs, the daytime UHI magnitudes are highly correlated with the 1 K threshold-derived UHI areas (correlation coefficient of 0.7), though not with the Gaussian-derived areas (correlation coefficient of 0.02).

**Seasonal analysis**

As with the nighttime UHI areas, the daytime UHI areas are also analyzed by season. Table 5.4 gives the season means for the areas calculated using the Gaussian spatial extents, while table 5.5 gives the means for the areas calculated using the 1 K threshold spatial extents. As with the overall mean, nearly all of the seasonal means
Figure 5.18: A normalized histogram showing the area of the UHIs, using the 1 K threshold method of determining spatial extent. The dashed line represents the interval 1 data, and the solid line shows the interval 2 data.

decrease from interval 1 to interval 2.

5.2.4 Orientation

The mean orientation (φ) of the daytime urban heat island is $6.1 \pm 2.3^\circ$, with a median of $3.6^\circ$. As with the nighttime UHIs, the daytime UHIs also tend to be oriented very nearly east-west, as well as showing no significant difference between interval 1 and interval 2.
<table>
<thead>
<tr>
<th>Seasonal Period</th>
<th>Interval 1</th>
<th>Interval 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>January–March</td>
<td>$820 \pm 60$ km$^2$ (24)</td>
<td>$630 \pm 50$ km$^2$ (17)</td>
</tr>
<tr>
<td>April–June</td>
<td>$820 \pm 40$ km$^2$ (30)</td>
<td>$670 \pm 50$ km$^2$ (5)</td>
</tr>
<tr>
<td>July–September</td>
<td>$580 \pm 40$ km$^2$ (8)</td>
<td>$630 \pm 60$ km$^2$ (12)</td>
</tr>
<tr>
<td>October–December</td>
<td>$690 \pm 50$ km$^2$ (13)</td>
<td>$690 \pm 60$ km$^2$ (14)</td>
</tr>
<tr>
<td>Seasonal Mean</td>
<td>$710 \pm 20$ km$^2$</td>
<td>$660 \pm 30$ km$^2$</td>
</tr>
</tbody>
</table>

Table 5.4: The mean UHI areas for each season, as determined with the Gaussian extents. The numbers in parentheses are the total number of measurements in each season.

<table>
<thead>
<tr>
<th>Seasonal Period</th>
<th>Interval 1</th>
<th>Interval 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>January–March</td>
<td>$2020 \pm 140$ km$^2$ (24)</td>
<td>$1350 \pm 130$ km$^2$ (17)</td>
</tr>
<tr>
<td>April–June</td>
<td>$3170 \pm 170$ km$^2$ (30)</td>
<td>$2340 \pm 220$ km$^2$ (5)</td>
</tr>
<tr>
<td>July–September</td>
<td>$2390 \pm 190$ km$^2$ (8)</td>
<td>$2190 \pm 230$ km$^2$ (12)</td>
</tr>
<tr>
<td>October–December</td>
<td>$1620 \pm 230$ km$^2$ (13)</td>
<td>$1120 \pm 170$ km$^2$ (14)</td>
</tr>
<tr>
<td>Seasonal Mean</td>
<td>$2350 \pm 90$ km$^2$</td>
<td>$1560 \pm 90$ km$^2$</td>
</tr>
</tbody>
</table>

Table 5.5: The mean UHI areas for each season, as determined with the 1 K threshold extents. The numbers in parentheses are the total number of measurements in each season.
5.3 Comparison with Air Temperatures

The radiative temperature measurements are also compared to the corresponding air temperatures measured at the meteorological stations discussed in Chapter 3. Figure 5.19 shows a comparison of concurrent air and surface rural temperatures, while figure 5.20 compares the air and surface temperature UHI magnitudes. (The rural and urban air temperatures are determined by the method described in Chapter 3.) These figures include data from both intervals. In the figures, plus-signs indicate nighttime temperatures and triangles indicate daytime temperatures.

![Rural Temperature Diagram](image)

Figure 5.19: A figure comparing the concurrent air and surface rural temperatures. The dashed line represents a one-to-one relationship.

The mean rural air temperatures correspond quite well to the mean rural surface temperatures. The comparison is shown in table 5.6. Except for the interval 1 daytime mean, the air and surface temperatures are equal to within the uncertainty.
Figure 5.20: A figure comparing the concurrent air and surface UHI magnitudes. The dashed line represents a one-to-one relationship.

<table>
<thead>
<tr>
<th>Interval</th>
<th>Surface Rural Temperature</th>
<th>Air Rural Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval 1 Nighttime</td>
<td>17.2 ± 0.7°C</td>
<td>18.3 ± 0.6°C</td>
</tr>
<tr>
<td>Interval 2 Nighttime</td>
<td>17.1 ± 0.8°C</td>
<td>17.6 ± 0.6°C</td>
</tr>
<tr>
<td>Interval 1 Daytime</td>
<td>27.9 ± 0.8°C</td>
<td>26.2 ± 0.7°C</td>
</tr>
<tr>
<td>Interval 2 Daytime</td>
<td>27.1 ± 1.5°C</td>
<td>25.6 ± 1.1°C</td>
</tr>
<tr>
<td>Overall</td>
<td>21.1 ± 0.5°C</td>
<td>20.9 ± 0.4°C</td>
</tr>
</tbody>
</table>

Table 5.6: A comparison of mean rural air and surface temperatures.
<table>
<thead>
<tr>
<th></th>
<th>Surface UHI Magnitude</th>
<th>Air UHI Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval 1 Nighttime</td>
<td>2.4 ± 0.1 K</td>
<td>1.7 ± 0.2 K</td>
</tr>
<tr>
<td>Interval 2 Nighttime</td>
<td>3.2 ± 0.1 K</td>
<td>1.7 ± 0.1 K</td>
</tr>
<tr>
<td>Interval 1 Daytime</td>
<td>5.4 ± 0.3 K</td>
<td>-0.7 ± 0.3 K</td>
</tr>
<tr>
<td>Interval 2 Daytime</td>
<td>3.8 ± 0.3 K</td>
<td>0.2 ± 0.1 K</td>
</tr>
<tr>
<td>Overall</td>
<td>3.6 ± 0.1 K</td>
<td>0.9 ± 0.1 K</td>
</tr>
</tbody>
</table>

Table 5.7: A comparison of mean air and surface temperature UHI magnitudes.

The nighttime air and surface temperature UHI magnitudes correspond fairly well also, with the surface measurements somewhat higher than the air measurements. The daytime air and surface UHI magnitudes show no similarity whatsoever. The surface measurements are quite large, while the air measurements are predominately less than zero.

It is interesting to note that the rural air and surface temperatures seem to be strongly coupled, while the air and surface UHI magnitudes do not. The UHI magnitudes are shown in table 5.7. This supports the assertion of Chapter 3 that while Houston possesses an air temperature UHI at night, it does not possess one during the day.

There appears to be no increase in the air temperature UHI between interval 1 and interval 2. In fact, a thorough analysis of the historical air temperature data reveals no significant growth in the air temperature heat island over the last several decades, for either minimum or maximum temperatures. Several methods of detection are employed, including performing linear fits of temperature versus time, comparing UHI histograms from different years, and comparing contour plots from different years.
and decades.

Figures 5.21 and 5.22 show contour plots of the annual change in minimum and maximum temperatures throughout southeastern Texas from 1990 to 1999. The temperature changes are determined by the same method used to calculate the mean temperatures in sections 3.1 and 3.2, with the addition of a linear term to the constant and sinusoidal terms.

If there had been appreciable growth in the urban heat island of this period, one would expect it to be manifested in a temperature increase in the urban area. But as can be seen in the figures, there is no significant growth in the urban area for either the minimum or maximum temperatures. In addition, any temperature growth in the urban area would be of questionable significance due to the highly variable growth rates exhibited throughout the region.
Annual Minimum Temperature Growth
1990–1999

Figure 5.21: A contour plot of the average annual change of the minimum air temperature from 1990 to 2000.

Annual Maximum Temperature Growth
1990–1999

Figure 5.22: A contour plot of the average annual change of the maximum air temperature from 1990 to 2000.
Chapter 6

Urban Temperature and Population Density

The previous chapters have all dealt with the urban heat island as a uniform, monolithic phenomenon. This is of course a vast oversimplification. The urban heat island is the composite effect of a tapestry of surface types and configurations, each of which has unique properties and behavior. These diverse components of the urban fabric are frequently combined in a seemingly random fashion, particularly in Houston. This chapter describes an effort to reduce the complexity of this issue by comparing the level of urban heating throughout the city to the regional population densities.

Such an analysis will require the fusion of two very different types of data sets: remotely sensed thermal information and census population figures.
<table>
<thead>
<tr>
<th>Channel</th>
<th>Wavelength (μm)</th>
<th>Spectral Region</th>
<th>Resolution (m)</th>
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<td>0.52–0.60</td>
<td>Green</td>
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<tr>
<td>2</td>
<td>0.63–0.69</td>
<td>Red</td>
<td>15</td>
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<tr>
<td>3</td>
<td>0.76–0.86</td>
<td>Reflected IR</td>
<td>15</td>
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<tr>
<td>4</td>
<td>1.600–1.700</td>
<td>Shortwave IR</td>
<td>30</td>
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<tr>
<td>5</td>
<td>2.145–2.185</td>
<td>Shortwave IR</td>
<td>30</td>
</tr>
<tr>
<td>6</td>
<td>2.185–2.225</td>
<td>Shortwave IR</td>
<td>30</td>
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<td>7</td>
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<td>30</td>
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<td>30</td>
</tr>
<tr>
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<td>30</td>
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</tr>
<tr>
<td>14</td>
<td>10.95–11.65</td>
<td>Thermal IR</td>
<td>90</td>
</tr>
</tbody>
</table>

Table 6.1: The wavelengths and resolutions of the ASTER channels.

6.1 Advanced Spaceborne Thermal Emission and Reflection Radiometer

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) was launched on the NASA Terra satellite in December 1999. Like the NOAA POES satellites, Terra is in a low, sun-synchronous orbit, with daytime equatorial crossings occurring at approximately 1030 LST.

In many ways, the ASTER is intended to replace the AVHRR. It too has channels ranging from the visible to the thermal infrared, though many more than the AVHRR. Advances in sensor technology have also allowed the resolution to be dramatically increased. Table 6.1 lists the fourteen ASTER channels and their respective spatial resolutions.
6.2 Surface Temperature

The surface temperatures are calculated from an image acquired by the ASTER on November 8, 2001, at a time of 0900 LST. Since the ASTER has been operating for only a few years, there are not yet any generally acceptable multichannel algorithms for determining accurate surface temperature, as there are for the AVHRR. The only option is calculating the temperature from a single channel using equation (4.1). Channel 13 was chosen as its spectral domain of 10.25–10.95 μm is nearest the peak of the blackbody spectrum radiated by the ~ 300 K Houston urban surface. Figures 6.1 and 6.2 show two ASTER images of Houston. Figure 6.1 is a false color temperature image derived from the channel 13 thermal data, while figure 6.2 is a pseudo-color image combining the visible and reflected infrared bands 1, 2, and 3.

As with previous maps, the outlines of the city of Houston and of the Gulf Coast are included. The temperatures in figure 6.1 range from 18 to 28°C. The uncertainties in temperature described in section 4.4 are valid for the ASTER data as well as for the AVHRR data, resulting in an rms error of 2–3 K in the ASTER temperature determination. But just as with the AVHRR-based analyses, the property of interest here is not the absolute temperature, but the temperature variability throughout the urban area.
Figure 6.1: A false color temperature image of Houston from the ASTER channel 13.
Figure 6.2: A pseudo-color image of Houston from the ASTER bands 1, 2, and 3. In this image, red is band 3, green is band 2, and blue is band 1.
6.3 Population Density

Population density information is derived from the 2000 U.S. Census data for Harris county. The smallest unit of the census data are census blocks, of which there are 649 in Harris County, ranging in size from 0.51 km$^2$ to 152 km$^2$, with an average size of 7.1 km$^2$.

Figure 6.3 shows the population density throughout Harris County. For the year 2000, Harris county had a total population of 3.40 million in an area of 4610 km$^2$, an average population density of 740 km$^{-2}$. The population density of the individual census blocks ranges from 0.24 km$^{-2}$ to 12,600 km$^{-2}$. The mean population density of the census blocks is 1840 km$^{-2}$. 

Figure 6.3: The population density of Harris County, from the 2000 Census.
6.4 Comparing the Population Density and the Temperature

Figure 6.4 shows the overlap of the ASTER temperature data with Harris county. Only the areas contained within both data sets are used in the analysis. The population statistics are distributed by the U.S. Census Bureau in a GIS vector format, in which population data is associated with individual geographical regions. As such, it is necessary to convert the data to a raster format that matches the 90 m resolution of the surface temperature data.

Once the population density data and the surface temperature data are in compatible formats, a comparison can be made between the two in an attempt to detect any relationship or correlation.

Figure 6.5 shows a scatterplot of the surface temperature versus population density. The density of data points is plotted on a logarithmic scale. As can be seen in the figure, there does appear to be a relationship between the surface temperature and population density. The dashed line shows a least-squares fit of the temperature to the population density. The fit has a slope of 1.22 K per 1000 people per square kilometer. The solid line is the average surface temperature as a function of the population density. This temperature function corresponds very well to the fit, increasing almost linearly with the population density.

The previous chapters documented the well-known fact that sparsely populated (rural) areas tend to be cooler than densely populated (urban) areas. While Harris
Figure 6.4: The outlines of the ASTER data set and the Harris county border, showing the overlap of the data sets.
Figure 6.5: A scatterplot of the surface temperature versus population density for Harris county.

County has a relatively dense population on the whole, there are some parts which can still be considered rural. Does figure 6.5 then just show another example of the urban heat island effect, where the rural areas of the county are cooler than the urban areas?

The goal of this chapter is to study variations in surface temperatures within an urban area, exclusive of the difference from the rural temperature. To make certain this goal is achieved, the area of interest is restricted to the city of Houston itself. Figure 6.6 shows the population densities throughout the city of Houston, while figure 6.7 shows the outline of the city inside the extent of the ASTER coverage.

Within the city of Houston, there are 513 census blocks ranging in area from 0.51 km² to 54.6 km². The population density of the census blocks within the city of
Houston have the same range as for all of Harris County, from 0.24 km$^{-2}$ to 12,560 km$^{-2}$. As was done for Harris county, the temperature is plotted versus population density for the city of Houston. The resulting scatterplot is shown in figure 6.8.

Within the city boundaries, the relationship between temperature and average population density is quite linear. The dashed line in figure 6.8 again shows the least-squares fit, which has a slope of 0.71 K per 1000 people per square kilometer. This is less than the value found for the entire county by more than 40%. The decrease is to be expected, however, as the influence of the rural areas has been removed. The average temperature as a function of population density, shown as the solid line, is again quite linear, even more so than in figure 6.5.

Throughout Harris County, the average surface temperature increases by 1.22 K for every additional 1000 people per square kilometer. In the city of Houston itself, this value falls to 0.71 K per 1000 people per square kilometer. Both of these results
Figure 6.7: The outlines of the ASTER data set and the Houston city limits, showing the overlap of the data sets.
Figure 6.8: A scatterplot of the surface temperature versus population density for the city of Houston.

indicate that surface temperature does indeed increase with population density, even within the urban area itself. It should also be noted that the thermal data was acquired at a fairly early local time during the second week of November. As such, the temperatures are quite mild compared to what they would be during the height of summer. It would be of considerable interest and value to repeat this investigation using images acquired in the pre-dawn and afternoon hours, both during the summer and winter months. This type of analysis would reveal which parts of the city are most susceptible to heat waves and heat-related stresses and are thus candidates for heat island mitigation strategies.
Chapter 7

Conclusions

The goal of this thesis is to perform a comprehensive survey of the urban heat island of Houston, Texas. In support of this, the heat island is investigated using both air and surface temperatures measured day and night. Techniques are developed to make use of both in situ and remotely sensed temperature data. Diurnal and seasonal behaviors are documented, as well as growth of the urban heat island over recent decades. Localized variations within the urban heat island are also examined and found to be linked with population density.

7.1 Summary of Results

There are many different traits of the urban heat island that deserve attention, including the overall magnitude, area, growth, and variability. The following sections highlight significant results from the various analyses presented throughout this thesis and attempt to provide a detailed and comprehensive picture of the phenomenon in
its entirety.

Rural temperatures

In order to study the heat island of an urban area, it is necessary to document the behavior of the surrounding regions with which the heat island is held in comparison. Based on measurements throughout the last decade, the rural area around Houston possesses an average air temperature of $59.8 \pm 0.2^\circ F$ ($15.4 \pm 0.1^\circ C$) at night and $79.3 \pm 0.2^\circ F$ ($26.3 \pm 0.1^\circ C$) during the day. When compared with the surface temperature values, the concurrent air temperatures are equal to within the uncertainties of the measurements. The only substantial deviation between the two temperatures occurs at the temperature extremes. Overall, rural air and surface temperatures appear to be well coupled to each other.

UHI magnitudes

The surface temperature urban heat island behaves largely as expected. During the day the heat island has a mean value of $4.8 \pm 0.2 K$, though it can range as high as $10 K$. The surface temperature UHI tends to be milder at night than during the day, with a mean value of $2.87 \pm 0.06 K$. The nighttime UHI also fluctuates, ranging between 1 and 5 K.

The air temperature UHI, on the other hand, does not behave quite as one might expect. The average nighttime heat island is $2.25 \pm 0.04^\circ F$ ($1.25 \pm 0.02 K$), with a positive UHI present nearly 90% of the time. The nighttime heat island occasionally reaches magnitudes of $9^\circ F$ ($5 K$) or higher. During the day, there does not seem to be
a consistent air temperature UHI present. The days on which a positive heat island exists are matched by a similar number of days with a negative heat island. That being said, the daytime heat island can frequently reach several degrees in magnitude, as can the daytime cool valley.

When comparing air temperature UHIs and surface temperature UHIs, one must be cognizant of selection effects resulting from the use of satellite data for the measurement of surface temperatures. The ability to collect satellite data depends on the local weather conditions, specifically on cloud coverage. As such, the surface temperatures are determined only on days and nights when the weather is predominantly clear. These conditions are known to be favorable for extreme temperatures and strong heat islands. It is therefore inappropriate to assume that the set of satellite-derived measurements are representative of the average environment throughout all types of weather. Consequently, surface temperatures should be compared only to air temperatures measured concurrently, and not to the entire set of air temperature data.

The air and surface temperature UHIs are similar during the night. As mentioned above, the mean nighttime surface temperature UHI is $2.87 \pm 0.06$ K, while during the same nights the mean air temperature UHI is somewhat less, at $1.70 \pm 0.09$ K. This suggests that the urban air and surface temperatures are moderately coupled at night, at least more so than during the day.

The mean daytime surface temperature UHI is $4.8 \pm 0.2$ K, while the mean air temperature UHI on the same days is $-0.3 \pm 0.2$ K. This suggests that the urban air
and surface temperatures are not coupled very strongly at all during the day.

The low thermal admittance of air, especially still air, weakens the dynamic thermal coupling of air with the ground surface. At night, the air and surface remain partially coupled when the conditions are reasonably calm. On the other hand, such coupling almost completely severed during the day due to the turbulent boundary layer, as was explained in chapter 2.

Another reason for the disparate behaviors of the air and surface temperatures stem from the various UHI causes. As was noted in section 1.1.2, there are several different factors that contribute to the urban heat island. Each of these factors is likely to contribute differently to the air temperature and surface temperature heat islands. For example, anthropogenic heat generation certainly contributes to the air temperature heat island in the form of heat exhausted from automobiles and air conditioners. This heat probably contributes very little, however, to the surface temperature heat island, as it is discharged directly into the air.

The urban heat island also has a notable influence on the extreme air temperatures in the urban area. Most profoundly affected are the nighttime temperatures, which show a significant increase in the number of extremely hot nights and a decrease in the number of extremely cold nights throughout the year. There appears to be little or no influence on the number of extremely hot and extremely cold days in the urban area during the year.
UHI area

The technique used to measure the surface temperature heat island also allows for the measurement of the heat island area. The area is measured using two different methods, one using a Gaussian parameter and one measuring the total area for which the heat island is greater than 1.0 K. Using the Gaussian method, the mean heat island area is $720 \pm 20 \text{ km}^2$ during the day and $570 \pm 20 \text{ km}^2$ during the night. Using the 1 K threshold method, the daytime area is $2120 \pm 90 \text{ km}^2$, while the nighttime area is $1190 \pm 50 \text{ km}^2$.

The 1 K threshold method in determining spatial extents seems to be the preferred of the two choices, as it is shown to better relate to the UHI magnitude as well as making a better estimate of the total area affected by the heat island. When the 1 K threshold extents are used, the resulting areas compare well to the geopolitical area of the city. This is one indication that the urban heat island seems to be limited to the urban area and does not extend far into the suburban or nearby rural areas, especially during the night.

Accurate estimates of the area of the air temperature UHI could not be made independent of the surface temperature measurements. This is due primarily to the relatively low density of meteorological stations throughout the urban and suburban areas of the city.
UHI growth

Between 1990 and 2000, the city of Houston grew in population by over 300,000 residents, an increase of nearly 20%. The Houston metropolitan area grew from 3.3 million to 4.2 million persons, an addition of nearly one million residents. One manifestation of this considerable growth is a change in the heat island signature of the city.

Over the course of twelve years, between 1987 and 1999, the mean nighttime surface temperature heat island of Houston increased $0.82 \pm 0.10$ K in magnitude. It increased in area $170 \pm 30$ km$^2$ using the Gaussian method of area determination, and $650 \pm 60$ km$^2$ using the 1 K threshold method. It is interesting to note that the growth of urban heat island in magnitude scales roughly with the increase in population (extrapolated to 1987 levels), at approximately 30%.

A similar analysis of growth in the daytime surface temperature UHI was not possible. This is due to an inability to remove the diurnal time dependence from the temperature measurements. Whatever growth of the heat island that may have occurred appears to be eclipsed by the diurnal temperature variations.

No apparent growth is detected in the air temperature urban heat island, for either the minimum or maximum temperatures.

UHI climatology

Also of interest is the large amount of variation displayed by the UHI measurements, particularly in the UHI spatial extents. The UHI magnitudes varied over
several degrees K, while the spatial extents varied over nearly an order of magnitude in area. It is well known that UHI magnitude depends on environmental variables such as wind speed, cloud cover, and atmospheric aerosol and water vapor content. The UHI spatial extent likely also depends on many spatial variables, such as surface moisture and vegetation cover, in addition to those listed above. This seems to be an indication that the urban heat island should be viewed as a dynamic meteorological phenomenon and not as a constant, uniform feature.

There is a considerable amount of evidence that the heat island magnitude depends on the ambient rural temperature, and as such displays seasonal variation. The daytime surface temperature UHI magnitude scales with rural temperature, as both are likely dependent on solar flux. For every increase of 5° C in rural temperature, the heat island increases by approximately 1 K. As a result, the greatest surface temperature heat islands occur during the summer months. The nighttime surface temperature UHI, on the other hand, does not seem to have any dependence on rural temperature or time of the year.

As has been seen for other cities, the Houston air temperature UHI magnitudes show an inverse dependence on rural temperatures. Correspondingly, both day and night UHIs seem to be greater during the cooler months, with daytime UHIs turning into UCVs during the hot months. Differences of 1.0° F (0.6 K) between the winter and summer values occur both in the average day and night UHI magnitudes. A possible explanation for the inverse dependence on temperature is similar to that of the difference between the night and day UHIs. When the overall temperature is
low, the atmosphere is more stable and the air temperature heat island can form. As the temperature increases, the boundary layer becomes more turbulent and inhibits the formation of the heat island. Just as the air temperature heat island is stronger during the (cooler) nights than the (warmer) days, so it is stronger on the cooler days than the warmer ones.

The area of the heat island also displays some seasonal behavior, although it is quite erratic. In both intervals and using both methods to determine the area, the greatest UHI area occurs during the summer months. In most cases, the smallest areas occur during the fall and winter months. The amount of variation throughout the year is on the order of 35–50%.

Another possible cause of the seasonal dependence of both the UHI magnitude and area is due to emissivity changes in the rural land cover. It is entirely possible that seasonal growth in the vegetation can alter the emissivity of the vegetation and thus of the rural surface. This change in the emissivity results in differences in the temperature retrieval from the radiance data.

**Population density**

Analysis of high-resolution temperature imagery shows that urban heating is somewhat dependent on the population density. Throughout Harris County, the surface temperature increases by 1.22 K for every additional 1000 persons per square kilometer. Within the city of Houston itself, this number falls to 0.71 K.

While this effect probably contributed to the overall increase of the heat island
documented in chapter 5, it does not appear to be large enough to account for all of the growth, as the average population density of Houston grew only by 100–200 people per square kilometer. Based on the analysis, this population change would result in a UHI increase of only one or two tenths of a degree.

7.2 Implications

There are a number of implications from the results presented here. The first is that the heat island of Houston is most severe at night. While the surface temperature heat island can be quite strong during the day, it is the air temperature heat island which has a more direct effect on human comfort and health. It is also the nighttime air temperature which may be the most important factor in determining the severity and lethality of heat waves. This effect is demonstrated most vividly by the extreme temperature data, which shows that the number of extremely warm nights is three or more times greater in the city than in the rural area.

The dependence of urban heating on population density is also significant. It may be of interest to urban planners that the temperature is likely to rise with increased density. If nothing else, this fact may cause urban planners to place more emphasis on heat island mitigation strategies in order to counter any expected rise in temperature due to development.

A third impact is further evidence that the explosive growth experienced by the city of Houston is not without environmental consequences. The massive influx of people into the city during the last two decades has resulted in a heat island that is
both a stronger and larger than before. Urban growth on this scale is expected to be commonplace around the world in the coming decades, with repercussions that could dwarf the effects seen here.

7.3 Other Meteorological Effects

This thesis has dealt almost entirely with a single aspect of the urbanization influences on weather and climate, that being the urban heat island. Urbanization, however, has many other effects on weather and climate, as remarked upon in section 1.1.1. While some of these effects have already been studied for the Houston area, all deserve attention.

Precipitation

Studies have also shown that urbanization can have an influence on precipitation patterns, due in large part to the urban convection cycle described in section 1.1.1. One of the first major studies to investigate this phenomenon was the METROMEX study conducted for St. Louis, Missouri, which found increased precipitation rates downwind of the city (Huff and Changnon, 1986). This effect has been documented for other cities, and recently with the use of remote sensing. Shepherd et al. (2002) used the precipitation radar instrument on board the Tropical Rainfall Measuring Mission (TRMM) to detect increased rainfall rates for several cities in the southern United States. The rainfall anomalies were generally downwind of the cities, within 30–60 km.
Figure 7.1: A contour plot of average daily precipitation in southeastern Texas between 1990 and 1999.

This may also be the case in the Houston area. Figure 7.1 shows a contour plot of the average daily precipitation in southeastern Texas between 1990 and 1999. At first glance, this figure does not appear to reveal any urban anomaly. There may, however, be a precipitation deficit to the northwest of the city. The city of Waller, for example, has an average of 0.107 inches per day, while the stations within the city of Houston (Hobby Airport, the Port of Houston, Houston Heights, Clodine, Sugarland, Deer Park) average between 0.14 and 0.16 inches per day. Whether or not this apparent deficit is significant and related to urbanization has yet to be determined.
Lightning

Recent studies have also shown that lightning rates are increased above and downwind of many cities, including Houston. Orville et al. (2001) studied the flash density of cloud-to-ground lightning in the Houston area between 1989 and 2000 and found that the flash density is greater over the urban area than over nearby rural areas. The authors speculate that this may be due at least in part to Houston’s urban heat island.

7.4 Further Work

The emissivity question

One of the largest sources of uncertainty in this study is the lack of data concerning the emissivity of various materials, especially those found in urban areas. Without accurate emissivity values at a variety of infrared wavelengths, remotely sensed radiance temperatures cannot be determined to a high precision. This dearth of knowledge also affects the local and mesoscale meteorological models, as the emissivity determines thermal energy flux throughout the system.

Application to other cities

While most urban areas share many features, each city is unique. As such, it would be quite informative to apply the techniques discussed here to other cities throughout the nation and around the world. By sampling cities of various sizes, climates, and
topographies, one can learn a great deal about how urban influences are affected by different urban properties. Houston is a subtropical city, with high average humidity. Studying the urban heat islands of cities in more moderate and arid climates would provide insight into how atmospheric water vapor content affects urban temperature. Similarly, Houston has a relatively low population density. The results of Chapter 6 seem to indicate that population density plays a role in heat island magnitude—do the heat islands of other cities depend on their respective population densities?

Application to climate models

The data presented here might also have an application to local and mesoscale climate modeling. It may give a better estimate of the anomalous energy flux and flux density in the urban areas, and whether this needs to be taken into account in the models. It would also provide the climate modelers with better information concerning the dependence of the heat island on the time of year and on the rural temperature.

Dependence on population density

The analysis presented in chapter 6 merely scratches the surface of this topic. As was remarked upon at the end of that chapter, a more balanced analysis would include thermal imagery from different seasons, both day and night. The inclusion of demographic and/or land cover information would also be of interest. For example, are the hottest parts of the city during the day also the hottest at night? What is the heat island of the residential areas during the night, where the majority of the
people are? What neighborhoods are most at risk during a heat wave? These and other questions can be answered with extension of this research.
Appendix A

Characterizing Urban Land Cover

The main body of this thesis dealt almost entirely with the thermal properties of the urban area. There are, of course, other viable ways of using satellite remote sensing to study the urban area. One of the most common techniques is to observe the land cover in and around a city and monitor how it changes over time.

A.1 Landsat Multispectral Scanner

The Landsat program was the first high-resolution land cover observing system to be launched. The inaugural Landsat satellite was launched in 1972. Since then, Landsat satellites have continuously been in orbit. As with the satellites previously mentioned, the Landsat satellites are in a sun-synchronous orbit, with a daytime equatorial crossing time in the mid-morning. The Landsat satellites carried the Multispectral Scanner (MSS) until 1992, when it was replaced by the Thematic Mapper (TM).
<table>
<thead>
<tr>
<th>Channel</th>
<th>Wavelength (µm)</th>
<th>Spectral Region</th>
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</thead>
<tbody>
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<td>0.5–0.6</td>
<td>Green</td>
</tr>
<tr>
<td>2</td>
<td>0.6–0.7</td>
<td>Red</td>
</tr>
<tr>
<td>3</td>
<td>0.7–0.8</td>
<td>Reflected IR</td>
</tr>
<tr>
<td>4</td>
<td>0.8–1.1</td>
<td>Shortwave IR</td>
</tr>
</tbody>
</table>

Table A.1: The wavelengths of the Landsat MSS channels.

The Landsat MSS has a spatial resolution of 80 m. Table A.1 lists the individual channels of the Multispectral Scanner.

The simplest way to view land cover is through the use of true-color or pseudo-color images. True color images are similar to what an observer would actually see and are made with sensors that have channels in the red, green, and blue visible wavelengths. Often, as is the case with the MSS as well as the ASTER, there is no blue channel included. In this case the reflected infrared channel is substituted, creating a pseudo-color image.

Figure A.1 is a pseudo-color image of the Houston area, taken by the MSS in the summer of 1992. In this case, the red component of the image is the infrared sensor channel, the green image component is the green sensor channel, and the blue image component is the red sensor channel. In this type of image, vegetation appears dark red, while urban areas tend to be a grayish-blue.

These images are part of the North American Landscape Classification (NALC) data set, created and distributed by the USGS. Each data set contains three MSS images of the same region, one image from each of the last three decades. The Houston area data set contains images from 1974, 1985, and 1992. All of the images
Figure A.1: A pseudo-color image of Houston from 1992.
were acquired between June 26 and July 6.

Often a land cover index is calculated in order to quantify different types of land cover. The most well known of these are vegetation indices, of which the most widely used is the Normalized Difference Vegetation Index, or NDVI.

A.2 The Normalized Difference Vegetation Index

In general, vegetation is highly reflective in the near infrared, while chlorophyll absorbs strongly in the red part of the spectrum. This is why the vegetation in figure A.1 appears quite red, which represents the near infrared sensor channel. This combination of traits can be taken advantage of to calculate a vegetation index. The NDVI combines the red and near infrared channels in the following manner:

\[
NDVI = \frac{\text{IR} - \text{Red}}{\text{IR} + \text{Red}}
\]  

(A.1)

As it is normalized, the NDVI of a surface will have a value between -1.0 and 1.0. Vegetation has a relatively high NDVI compared to most other surfaces. Differences in plant vigor can also be detected with the NDVI, with healthier plants having higher values. Table A.2 lists the approximate NDVI values for different types of land cover found in the urban area.
<table>
<thead>
<tr>
<th>Class</th>
<th>NDVI Range</th>
</tr>
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<tbody>
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<td>-0.40 - -0.20</td>
</tr>
<tr>
<td>High Urban</td>
<td>-0.15 - 0.00</td>
</tr>
<tr>
<td>Low Urban</td>
<td>0.00 - 0.20</td>
</tr>
<tr>
<td>Dense Residential</td>
<td>0.20 - 0.30</td>
</tr>
<tr>
<td>Sparse Residential</td>
<td>0.30 - 0.40</td>
</tr>
<tr>
<td>Vegetation</td>
<td>0.40 - 0.65</td>
</tr>
</tbody>
</table>

Table A.2: The individual classes based on NDVI level.

A.2.1 The NDVI of Houston

NDVI values for the Houston area are derived using the Landsat MSS imagery. The NDVI maps are calculated using MSS channels 2 and 4 in accordance with equation (A.1). Figure A.2 shows the NDVI values for the Houston area as calculated from the 1992 MSS image shown in figure A.1.

As expected, the areas of high vegetation around the city have a correspondingly high NDVI value. The urban areas, on the other hand, have a relatively low NDVI value, as do water surfaces.

A.3 Land Cover Classification

There are several ways of detecting change using a land cover index. The most basic of these is simply to subtract one image from another, resulting in a difference image. A disadvantage of this, however, is that the result contains no information other than the difference. A moderately urbanized area growing into a densely urbanized area may be indistinguishable from an area of sparse vegetation growing into a residential area. In each case, the change in NDVI may be the same, though the
Figure A.2: NDVI values for the city of Houston in 1992.
initial and final conditions are quite different.

Another method that can be used in this case is to combine the individual NDVI images from each decade into a single composite RGB images. This is done in figure A.3.

![RGB Composite](image)

Figure A.3: An image made by combining the NDVI images from each decade.

In the composite image, the red component is the 1992 NDVI image, the green
component is the 1985 NDVI image, and the blue component is the 1974 NDVI image. In the figure, the overall color is determined by the relative NDVI values in each decade. For instance, if the NDVI of an area remained unchanged throughout the three decades, then the image of the area would have equal levels of red, green, and blue color and would appear as gray. If the area were highly vegetated, the area would appear a light gray due to the high NDVI values, and if the area had very little vegetation, it would appear a dark gray due to the low NDVI values.

Similarly, NDVI changes produce colored areas. If an area were highly vegetated in 1974, but less vegetated in 1985 and 1992, it would have a blue tint. If it were vegetated in both 1974 and 1985, but less vegetated in 1992, it would have a yellowish tint instead.

While this method includes information about relative NDVI levels, it still is somewhat subjective, based on the image interpretation skills of the observer and on what color various areas “look”. It is also limited to data sets of three images.

An alternative technique that avoids the problems mentioned above is image classification. This method involves assigning individual pixels to classes or groups which all show similar spectral characteristics. This can be demonstrated by figure A.4, which shows a scatter plot comparing the 1974 NDVI value with the 1985 NDVI value for each pixel.

(The remainder of this analysis will compare the 1974 and 1985 images and will not refer to the 1992 image. This is done for two reasons. The first is that the eleven-year period between the 1974 and 1985 images will provide more contrasting land cover
Figure A.4: A scattergram comparing pixel values in the 1974 and 1985 NDVI images.

data than the seven-year period between the 1985 and 1992 images. The second and more important reason is that upon closer inspection the 1992 image appears to have unreliable data, or at least data that is not suitable for comparison to the other images. This may be due to any number of effects, most likely an atmospheric or environmental anomaly when the image was acquired.)

The dashed line in figure A.4 shows the line of one-to-one correspondence. Pixels that fall near this line have an NDVI that is relatively unchanged between 1974 and 1985. Much of the data does indeed fall quite near to this line. The solid line represents the average 1985 NDVI as a function of the 1974 NDVI.

It is immediately evident that the large majority of pixels fall into one of several groups. This cluster of pixels located near an NDVI of -0.25 in both images is primar-
ily composed of water pixels. The dominant cluster located at 0.2–0.6 is composed of the suburban and urban pixels. The most interesting group, however, is located below the dashed line, with an 1974 NDVI of approximately 0.4 and a 1985 NDVI ranging from 0.1 to 0.3. These pixels are of areas that decreased in NDVI between the times the two images were acquired, and are thus candidates of urban growth during that interval.

This effect of identifying pixel groupings in data-space is the basis of the classification scheme. One can perform a supervised classification in which the classes are set before the analysis, or an unsupervised classification, in which the analysis procedure determines the class parameters that best suit the data. The classification can be performed using only two sources of data, as is done here, or for as many dimensions as one has data.

Figure A.5 shows the results of a classification performed on the 1974 and 1985 images. The classification is unsupervised, with 10 individual classes. As can be seen from table A.3, classes 1–6 are static, with little or no change between 1974 and 1985, while classes 7–10 show significant change. The table also lists the total combined area of each class. Areas that experienced land cover change make up a large fraction of the total, more than one-third of the county. This includes over 800 km$^2$ of lost or significantly decreased vegetation.
Figure A.5: A classification image made using the 1974 and 1985 NDVI images, with the ten classes.
<table>
<thead>
<tr>
<th>Class</th>
<th>Color</th>
<th>1974 NDVI</th>
<th>1985 NDVI</th>
<th>Area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Water</td>
<td>Blue</td>
<td>-0.50</td>
<td>-0.61</td>
<td>107</td>
</tr>
<tr>
<td>2 High Urban</td>
<td>Dark Gray</td>
<td>-0.03</td>
<td>-0.04</td>
<td>313</td>
</tr>
<tr>
<td>3 Low Urban</td>
<td>Light Gray</td>
<td>0.17</td>
<td>0.17</td>
<td>443</td>
</tr>
<tr>
<td>4 Dense Residential</td>
<td>Brown</td>
<td>0.24</td>
<td>0.31</td>
<td>546</td>
</tr>
<tr>
<td>5 Sparse Residential</td>
<td>Orange</td>
<td>0.36</td>
<td>0.38</td>
<td>778</td>
</tr>
<tr>
<td>6 Vegetation</td>
<td>Green</td>
<td>0.54</td>
<td>0.59</td>
<td>494</td>
</tr>
<tr>
<td>7 Vegetation to Low Urban</td>
<td>Purple</td>
<td>0.42</td>
<td>0.20</td>
<td>483</td>
</tr>
<tr>
<td>8 Vegetation to Residential</td>
<td>Pink</td>
<td>0.49</td>
<td>0.39</td>
<td>365</td>
</tr>
<tr>
<td>9 Residential to High Urban</td>
<td>Red</td>
<td>0.38</td>
<td>-0.01</td>
<td>341</td>
</tr>
<tr>
<td>10 Increasing Vegetation</td>
<td>Dark Green</td>
<td>0.41</td>
<td>0.52</td>
<td>518</td>
</tr>
</tbody>
</table>

Table A.3: The classes of figure A.5 and their corresponding NDVI levels.
Appendix B

Thermal and Radiative Properties

Listed below are the main thermal and radiative properties of various types of urban land cover.

<table>
<thead>
<tr>
<th>Material</th>
<th>density</th>
<th>specific heat capacity</th>
<th>thermal conductivity</th>
<th>thermal diffusivity</th>
<th>thermal admittance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(kg m$^{-3}$)</td>
<td>(J kg$^{-1}$ K$^{-1}$)</td>
<td>(W m$^{-1}$ K$^{-1}$)</td>
<td>(m$^2$ s$^{-1}$ × 10$^{-6}$)</td>
<td>(J m$^{-2}$ s$^{-1/2}$ K$^{-1}$)</td>
</tr>
<tr>
<td>Asphalt</td>
<td>2110</td>
<td>920</td>
<td>0.06</td>
<td>0.031</td>
<td>340</td>
</tr>
<tr>
<td>Brick</td>
<td>1830</td>
<td>750</td>
<td>0.83</td>
<td>0.61</td>
<td>1070</td>
</tr>
<tr>
<td>Concrete</td>
<td>2300</td>
<td>880</td>
<td>1.4</td>
<td>0.69</td>
<td>1790</td>
</tr>
<tr>
<td>Glass</td>
<td>2480</td>
<td>670</td>
<td>0.74</td>
<td>0.44</td>
<td>1110</td>
</tr>
<tr>
<td>Moist Soil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sandy loam</td>
<td>1670</td>
<td>1680</td>
<td>0.93</td>
<td>0.33</td>
<td>1620</td>
</tr>
<tr>
<td>Clay soil</td>
<td>1700</td>
<td>1470</td>
<td>1.3</td>
<td>0.52</td>
<td>1800</td>
</tr>
<tr>
<td>Water, Still</td>
<td>1000</td>
<td>4180</td>
<td>0.57</td>
<td>0.14</td>
<td>1550</td>
</tr>
<tr>
<td>Air</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Still</td>
<td>1.2</td>
<td>1010</td>
<td>0.025</td>
<td>20.5</td>
<td>5</td>
</tr>
<tr>
<td>Turbulent</td>
<td>1.2</td>
<td>1010</td>
<td>$\sim$ 125</td>
<td>$10^7$</td>
<td>390</td>
</tr>
</tbody>
</table>

Table B.1: A list of thermal properties of common surface materials. Sources: Incropera and DeWitt (1990), Oke (1987), Sabins (1997), and Welty (1974)
<table>
<thead>
<tr>
<th>Material</th>
<th>albedo</th>
<th>emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asphalt</td>
<td>0.05–0.20</td>
<td>0.85–0.96</td>
</tr>
<tr>
<td>Brick</td>
<td>0.20–0.40</td>
<td>0.90–0.94</td>
</tr>
<tr>
<td>Concrete</td>
<td>0.10–0.40</td>
<td>0.70–0.95</td>
</tr>
<tr>
<td>Glass, zenith angle &gt; 40°</td>
<td>n/a</td>
<td>0.80–0.95</td>
</tr>
<tr>
<td>Roofing, tar and gravel</td>
<td>0.08–0.18</td>
<td>0.92</td>
</tr>
<tr>
<td>Soil, sandy loam, 4 % water</td>
<td>0.05–0.40</td>
<td>0.90–0.98</td>
</tr>
<tr>
<td>Water</td>
<td>0.03–0.10</td>
<td>0.92–0.99</td>
</tr>
<tr>
<td>Vegetation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grass</td>
<td>0.16–0.26</td>
<td>0.90–0.95</td>
</tr>
<tr>
<td>Forest</td>
<td>0.05–0.20</td>
<td>0.97–0.99</td>
</tr>
</tbody>
</table>

Bibliography


