Impact of Urbanization on Temperature Variation in Big Cities: Measuring Health Risk While Targeting Vulnerable Population

Maryam E. Karimi

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IMPACT OF URBANIZATION ON TEMPERATURE VARIATION IN BIG CITIES
MEASURING HEALTH RISK WHILE TARGETING VULNERABLE POPULATION

By

MARYAM ELISA KARIMI

A dissertation submitted to the Graduate Faculty in Earth and Environmental Sciences in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2017
Impact of Urbanization on temperature Variation in Big Cities
Measuring Health Risk While Targeting Vulnerable Population

By
Maryam Elisa Karimi

This manuscript has been read and accepted for the Graduate Faculty in Earth and Environmental Sciences in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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THE CITY UNIVERSITY OF NEW YORK

iii
ABSTRACT
Impact of Urbanization on Temperature Variation in Big Cities
Measuring Health Risk While Targeting Vulnerable Population: A Case Study
by
Maryam Elisa Karimi

Advisor: Dr. Reza Khanbilvardi

Densely populated cities are experiencing Urban Heat Island (UHI) effects and localized hotspots. Cities, such as New York can form heat islands all year round. This is primarily due to land surface modifications, radiative trapping in urban canyons and lack of cooling through evapotranspiration caused by displaced trees and vegetation. UHI refers to an increase in air and surface temperature in cities compared to surrounding suburban and rural areas. Large scale environmental forcing can cause subdivisions of UHI throughout a city. The combined of environmental forcing effects lead to the formation of hot pockets within the cities at micro-scale. The adverse effect of UHI in highly dense populated cities ends in a higher number of emergency hospital admissions and heat-related illnesses. Studying UHI phenomenon and temperature variations within cities becomes even more important when global Earth temperature is on the rise. To better understand UHI within Manhattan Island in New York, an exploratory study was done using a three-month field campaign to measure high resolution (3m above the ground) spatial and temporal temperature variations within Manhattan's urban setting. A street-level air temperature and humidity dataset with high resolution spatial and temporal components were created for the island of Manhattan, suitable for use by the urban health and modeling communities. It consists of a set of pedestrian measurements over the course of two summers converted into anomaly maps, and a set of ten light-post mounted installations
measuring air temperature, relative humidity, and illumination at three-minute intervals over three months. These high time resolution temperature measurements and three months of the ‘model weather analysis data’ output of temperature and relative humidity were used to predict temperature variability from weather forecasts. This study shows that regression of weather variables can predict the amplitude of spatial and temporal variation in temperature within a city for different days. The amplitude of spatial variations was dependent on temperature and low-level lapse rate. Temporal variations were dependent on temperature, low level and mid-level lapse rates. This study puts the attention toward high resolution near surface air temperature analysis and offers a new look at surface thermal properties to find the impact effect of weather model data on air surface temperature. The application of this study is most suitable for forecast modelers who are looking to study the impact of weather and micro-scale climate on surface air temperature using weather variables. To further complete this study by looking at the impact of UHI on human health; a quantitative study was completed analyzing satellite imagery of the five boroughs of New York City (NYC). The influence of different surface types on mitigating UHI effect is investigated by looking at consistent physical properties of the urban system through a framework to highlight environmental and social vulnerabilities. The factors of interest include people, the environment, building and infrastructure. The satellite study revealed that increased levels of urbanization, with no methods of heat mitigation, resulted in higher average temperatures. Results show, neighborhoods of Manhattan, Queens and the Bronx are at the greatest risk of vulnerability and should be targeted for policy changes, implementation of green infrastructures and vegetation coverage to counteract the heating effects. Neighborhoods which need to be prioritized for urban planning due to high environmental risk in NYC include Harlem,
Upper Manhattan, East Harlem, Elmhurst, Jamaica, Ridgewood, Bedford, University height and Woodlawn.
PREFACE

Much of this thesis was previously published in conference and journal papers. The papers represent the work and research of Maryam E. Karimi. Earlier designs of chapters two and three were published in different peer review journal publications. Chapter four is currently in press under Elsevier Journal of urban climate. Full citation for each chapter can be found below:


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This thesis is dedicated to my father, mother, sister and husband.

For their endless love, support and encouragement.
ACKNOWLEDGMENTS

The writing of this dissertation was not possible without the personal and practical support of numerous people. Thus, my sincere gratitude goes to my father, aunt, husband, and the rest of my family, and my advisors at the NOAA CREST Institute, The City College of New York and the Professors at The Graduate Center for their support, love, guidance and patience over the years.

First and foremost, I wish to express my sincere appreciation to my advisor, Professor Reza Khanbilvardi, for allowing me to work under his supervision and making my Ph.D. a reality. His guidance and care will not be forgotten. I would like to offer my sincerest gratitude to Professor Harold Connolly for his kind support. He showed me the light when I lost hope and helped me find my path. He would be one of the few people I would never forget. I would also like to thank Dr. Kyle McDonald for his time, attention and help with the walk campaign data collection. Very special thanks to Dr. Peter Romanov for his great contribution and comments on this project.

I am grateful to many people who have helped me through these years, the administrative personnel of NOAA CREST and Earth and Environmental Science Program at The Graduate Center, CUNY and my great friend Ms. Caridad Jenoure who always encouraged me during my difficult times.

I would like to recognize the endless and loving support of my family, most specifically, my father who always gave me unconditional love, support and the strength to reach for the stars and chase my dreams. I owe my hard work, motivation and ambition to my aunt who raised me like a real mother to be the person I am today. Special thanks to my one and only sister who has always been there for me. Many thanks to my beautiful and intelligent Grandmother (RIP) and handsome Grandfather, who took me under their wings and raised me, just likes their own child. Last but not least, these acknowledgments would not be complete without heartfelt thanks to my husband who was my rocking star, who guided me and took every step of this journey with me. I could not have possibly done it without him.

This thesis is only a beginning of my journey.
# TABLE OF CONTENTS

ABSTRACT ............................................................................................................................ iii

PREFACE ................................................................................................................................... vii

ACKNOWLEDGMENTS ............................................................................................................ ix

1  CHAPTER I: INTRODUCTION AND LITERATURE REVIEW ........................................ 1

1.1 Background ........................................................................................................................ 1

1.1.1 Climate and Climate Change ......................................................................................... 1

1.1.2 Climate Change in Northeast U.S. .................................................................................. 4

1.1.3 Climate Change and Impacts in Global Precipitation Patterns ...................................... 5

1.1.4 Understanding the link between Climate Change and Urban Development .......... 7

1.1.5 Urban Heat Island (UHI) and Land Use Effects .............................................................. 8

1.2 THESIS OBJECTIVE ........................................................................................................ 11

1.3 MOTIVATION .................................................................................................................... 11

1.4 APPROACH ....................................................................................................................... 13

1.5 CHALLENGES .................................................................................................................. 13

1.6 CONTRIBUTION ............................................................................................................... 15

1.7 HOW TO READ THIS DISSERTATION ......................................................................... 16

2  CHAPTER II: URBAN HEAT ISLAND ASSESSMENT WITH TEMPERATURE MAPS

USING HIGH-RESOLUTION DATASETS .............................................................................. 17

2.1 Chapter Summary .............................................................................................................. 17

2.2 Chapter Introduction ......................................................................................................... 18

2.3 Study Area ......................................................................................................................... 20

2.4 Mobile Instrument Campaigns .......................................................................................... 23

2.5 Fixed Instrument Campaign .............................................................................................. 28

2.6 Controlled Inter-comparisons ........................................................................................... 29

2.7 Data Processing ................................................................................................................ 29

2.7.1 Mobile Campaigns ....................................................................................................... 30

2.7.2 Fixed Instrument Campaign ........................................................................................... 31

2.8 Measurement Results ....................................................................................................... 32

2.9 Physical Interpretations .................................................................................................... 35

2.10 Comparison of Fixed to Mobile Measurements ................................................................. 41

2.11 Measures and Causes of Variability ................................................................................. 44

2.12 Data Availability ............................................................................................................. 47
2.13 Chapter Conclusions .................................................................................................................. 49

3 CHAPTER III: URBAN HEAT ISLAND ASSESSMENT WITH TEMPERATURE MAPS USING HIGH RESOLUTION DATASETS MEASURED AT STREET LEVEL .......... 51
3.1 Chapter Summary .......................................................................................................................... 51
3.2 Chapter Introduction ...................................................................................................................... 51
3.3 Chapter Literature Review ............................................................................................................ 54
3.4 Chapter Methodology .................................................................................................................... 57
3.5 Classifying Surface Characteristics ............................................................................................... 60
3.6 Chapter Result ................................................................................................................................. 63
3.7 Chapter Conclusion ........................................................................................................................ 64
3.8 Implication and Application ............................................................................................................ 65

4CHAPTER IV: PREDICTING SURFACE TEMPERATURE VARIATION USING REAL-TIME WEATHER FORECASTS .................................................................................................................. 67
4.1 Chapter Summary ............................................................................................................................ 67
4.2 Chapter Introduction ....................................................................................................................... 68
4.3 Methodology .................................................................................................................................. 68
4.4 Chapter Results and Discussion ..................................................................................................... 72
4.5 Chapter Conclusion ........................................................................................................................ 83

5 CHAPTER V: A CONCEPTUAL FRAMEWORK FOR ENVIRONMENTAL RISK AND SOCIAL VULNERABILITY ASSESSMENT IN COMPLEX URBAN SETTINGS .......... 85
5.1 Chapter Summary ............................................................................................................................ 85
5.2 Chapter Introduction ....................................................................................................................... 86
5.2.1 Impacts of UHI on Human Health ............................................................................................... 88
5.2.2 Heat Related Mortality ................................................................................................................. 89
5.2.3 Thermal Indices ............................................................................................................................ 90
5.2.4 UHI Monitoring Methods ......................................................................................................... 91
5.2.5 Mitigation Strategies ................................................................................................................... 92
5.3 Data and Methodology ................................................................................................................... 94
5.4 Landsat Calibration ....................................................................................................................... 95
5.5 Image Correction, Simple dark Object Subtraction Method ............................................................ 95
5.6 NDVI Calculation ........................................................................................................................... 96
5.7 Effect of Albedo on Earth Surface ................................................................................................. 97
5.8 Conversion of at sensor radiance to effective at satellite temperatures ........................................ 98
Lists of Figures

Figure 1-1 Flow Task ................................................................. 13
Figure 1-1 Land and Ocean Temperature Percentiles ......................... 2
Figure 1-2 Average annual global temperatures .................................. 3
Figure 1-3 Land Only Precipitation Percentiles .................................. 6
Figure 1-4 UHI Effect concentrated in urban Center .............................. 9
Figure 2-1 Mobile instrument pedestrian routes and fixed instrument locations 22
Figure 2-2 Instrument mounts ....................................................... 25
Figure 2-3 Cell phone geolocation .................................................. 25
Figure 2-4 The effect of RH lag time on relations between Temperature, RH, and Dew point 27
Figure 2-5 Convective ‘ripple variations’ around diurnal variation .......... 32
Figure 2-6 Street measurements of temperature and dewpoint anomalies 34
Figure 2-7 Temperature and dewpoint anomalies ................................ 37
Figure 2-8 a Temperature Anomalies .............................................. 38
Figure 2-9 Diurnal cycle of spatial and temporal variations for fixed Hobo instruments .... 40
Figure 2-10 Differences between mobile and fixed campaign measurements of temperature .... 42
Figure 2-11 Street level measurements of Temperature .......................... 44
Figure 2-12 Variable temperature anomalies ..................................... 46
Figure 2-13 Variability in mobile temperature measurements ................... 47
Figure 2-14 Pedestrian measurements made one block apart, moving in parallel .......... 47
Figure 2-15 Composite of Building Height ......................................... 49
Figure 3-1 Three-hourly average near-surface air temperature ................. 53
Figure 3-2 Designated street and avenue routes .................................. 58
Figure 3-3 Inputs into the statistical model ....................................... 58
Figure 3-4 Normalized Difference Vegetation Index (NDVI) .................... 61
Figure 3-5 Manhattan’s Supervised Surface Classification ...................... 61
Figure 3-6 Percentages of land cover classes for Manhattan’s supervised surface classification 62
Figure 3-7 Mid-day Temperature Estimations Map .............................. 63
Figure 4-1 Station Locations, Instrument and Instrument Housing .............. 71
Figure 4-2 Weather Variables Regressed against Variability for $\sigma T$ ............ 77
Figure 4-3 Weather Variables Regressed against Variability for $T_{sd}$ ............ 78
Figure 4-4 NYC MetNet Average Normalized Temperatures Compared to Single ........ 81
Figure 4-5 NYC MetNet Average Normalized Temperatures .................... 82
Figure 4-6 Weather Variables Regressed .......................................... 82
Figure 5-1 Exposure-response function ........................................... 89
Figure 5-2 Visual representation of the method workflow ......................... 95
Figure 5-3 Sun radiation pattern geometry ....................................... 96
Figure 5-4 Albedo effect on earth surface ....................................... 97
Figure 5-5 Averaged thermal map of NYC ....................................... 101
Figure 5-6 Summary of the process ............................................... 102
Figure 5-7 Environmental Risk and Social Vulnerability in Manhattan .......... 106
Figure 5-8 NYC’s Environmental Risk and Social Vulnerability ................ 107
List of Tables

Table 1-1 The 1901-2000 average combined land and ocean annual temperature....................... 4
Table 2-1 Instrument specifications......................................................................................... 23
Table 2-2 Instrument Deviations from the Mean........................................................................ 29
Table 2-3 T-values and confidence levels used for figures 2-6b, d.............................................. 34
Table 2-4 Current Surface Data sets ....................................................................................... 49
Table 3-1 Inputs into the statistical model................................................................................ 59
Table 4-1 Physical Description of Areas Surrounding Stations ................................................. 71
Table 4-2 Calculated Correlation Between σT and Weather Variables ................................. 75
Table 4-3 Calculated Correlation between Tsd and Weather Variables...................................... 75
Table 4-4 Correlation between High and Low Elevation Station ............................................. 80
Table 5-1 Current radiometric calibration coefficient for Landsat MSS.................................. 99
Table 5-3 Normalized Vulnerability Variables.......................................................................... 107
CHAPTER I: INTRODUCTION AND LITERATURE REVIEW

1.1 Background

1.1.1 Climate and Climate Change

The Earth's average temperature has been increasing over the past century and is expected to increase even more. The average temperature measure for land and ocean over the past century is "experiencing a long-term warming trend" (Dahlman, 2009). As of January 2016, the reported highest (warm) and lowest (cold) temperature points on the globe are 55°C apart. While some parts of the world could be freezing, other parts are hot, and the temperature can vary from day to night and between seasons. The 2001-2015 global temperatures have been the warmest years on record (Northon, 2016). “Globally-averaged temperatures in 2015 shattered the previous mark set in 2014 by 0.13°C” this has only happened once before in 1988 with the new record being greater than the “old record” by such difference (Northon, 2016). Since the 19th century, the average temperature of the Earth surface has risen by 1°C. Generally speaking, land heats up faster whereas the ocean has a higher thermal inertia. The land temperature has been changing by more than 50 percent in the United States than the oceans; "two to three times greater in Eurasia; and three to four times higher in the Arctic and the Antarctic Peninsula" (Carlowicz, 1894). The coolest years reported for the global temperature was from 1885 to 1945 which tends to grow less cool as we moved towards the 1950s. Even though “sun's irradiance, oscillations of sea surface temperature and changes in the aerosol levels” can cause slight change in the global surface temperature (Dunbar, 2010); the strong warming trend of the recent decade can be explained by the presence of greenhouse gases, anthropogenic heat, and human activities (Carlowicz, 1894). The record warmth over Northern Hemisphere was mostly notable in “the northeastern, equatorial Pacific and a large swath of the western North Atlantic and the Indian
Ocean” for the year 2015 (NOAA National Centers for Environmental Information, 2015). The average temperature over the land surface was reported at 1.33°C for 2015 which surpasses its previous recorded temperature by 0.25°C. Figure 1-1 represents the temperature percentiles over land and ocean for January to December 2015 with dark red showing recorded the warmest location over the globe. Not all states may be affected by the warming of the Earth, but NASA and NOAA have found that “the 2015 annual mean temperature for the contiguous 48 United State was the second warmest on record” (Northon, 2016).

![Figure 1-1 Land and Ocean Temperature Percentiles, Jan-Dec 2015 Blended Land and Sea Surface Temperature Percentiles. NOAA’s National Centers for Environmental Information. Data Source: GHCN-M version 3.3.0. ERSST version 4.0.0](image)

The warm temperature was observed mostly over the continents from parts of South America, Easter U.S. South and East Africa, western Asia and Europe for 2015. Continents have lower heat capacity in compared to oceans and heat up faster. Therefore a higher difference in land surface anomalies can be measured over a continent. This is a serious concern for human populations as higher number of concentration is mostly visible over regions with reported higher land surface temperature (figure 1-1). A monthly average anomaly difference of 0.95oC over land from June to December and difference of 0.28oC from February to October over the
ocean are seen for the year 2015 (NOAA National Centers for Environmental Information, 2015). It must be noted that a “one-degree global change is significant because it takes a vast amount of heat to warm all the oceans, atmosphere, and land by that much” (Carlowicz, 1894).

In fact, a one to two degree drop in temperature was all it would take to put earth into an ice age 20,000 years ago. Figure 1-2 shows the average annual temperature of the global since 1889 to 2000.

![Figure 1-2 Average annual global temperatures. Since "1880 compared to the long-term average (1901-2000) the zero line represents the long-term average temperature for the whole planet; blue and red bars show the difference above or below average for each year" (Trenberth, 2010)](image)

Few impacts of global warming can be changes in the global precipitation, increase in heat waves, UHI effect and impacts on human health (Alcoforado, et al., 2008). Table 1-1 shows the global average temperature for land and ocean for 1901-2015. NASA and NOAA use raw temperature data from incorporating surface temperature from over 6,300 weather stations, satellites, buoy and ship-based observations, airborne and ground-based campaigns (Northon, 2016).
Table 1-1 The 1901-2000 average combined land and ocean annual temperature. "The 1901-2000 average combined land and ocean annual temperature is 13.9°C (56.9°F), the annually averaged land temperature for the same period is 8.5°C (47.3°F), and the long-term annually averaged sea surface temperature is 16.1°C (60.9°F)." (NOAA National Centers for Environmental Information, 2015).

<table>
<thead>
<tr>
<th>JANUARY-DECEMBER</th>
<th>ANOMALY</th>
<th>RANK</th>
<th>RECORDS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>°C</td>
<td>°F</td>
<td></td>
</tr>
<tr>
<td>Global</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land</td>
<td>+1.33 ± 0.18</td>
<td>+2.39 ± 0.32</td>
<td>Warmest 1st</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Coolest 136th</td>
</tr>
<tr>
<td>Ocean</td>
<td>+0.74 ± 0.01</td>
<td>+1.33 ± 0.02</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Coolest 136th</td>
</tr>
<tr>
<td>Land and Ocean</td>
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<td>+1.62 ± 0.14</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Coolest 136th</td>
</tr>
<tr>
<td>Northern Hemisphere</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land</td>
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<tr>
<td></td>
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<td>Coolest 136th</td>
</tr>
<tr>
<td>Ocean</td>
<td>+0.87 ± 0.01</td>
<td>+1.57 ± 0.02</td>
<td>Warmest 1st</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Coolest 136th</td>
</tr>
<tr>
<td>Land and Ocean</td>
<td>+1.09 ± 0.11</td>
<td>+1.96 ± 0.20</td>
<td>Warmest 1st</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Coolest 136th</td>
</tr>
</tbody>
</table>

1.1.2 Climate Change in Northeast U.S.

Northeast is one of the most populated regions in whole U.S. with 64 million in population. It is densely built with a network of infrastructure. It is a mix of urban, suburbs, forest, grasslands, wetlands, and beaches. Northeast's ecosystems and its differently built regions are vulnerable to climate change. Regions of Northeast "depend on aging infrastructure that has already been stressed by climate hazards" including heat waves, coastal and river flooding, storm surge and extreme precipitation (Easterling, et al., 2014).
As of 2015, Eastern North America has experienced its fifth warmest year on the record at 1.3°C (NOAA National Centers for Environmental Information, 2015). Since 1895 the temperature in the Northeast increased by 1.5°C per decade. Northeast on average received an increase of five-inch of rain per decade and a foot of sea level rise since 1900. In compared to other regions in U.S., Northeast received the heaviest events of rainfall between 1958 and 2010 which is more than 70% increase in its precipitation. It has been projected that Northeast will heat up due to greenhouse gas emission by 2.5°C to 5°C by 2080. Many regions of Northeast such as Maryland, Delaware, New Jersey and West Virginia are going to experience many days above 32°C per year which is going to put these states vulnerable population at risk (Easterling, et al, 2014).

Lack of vegetation and soil moister which act as natural air conditioners and abundance of dark surfaces, asphalts and concrete causes nights to become few degrees hotter than the day time. Hot days are associated with higher level of pollution at ground level zone. As a result, high risk of vulnerability is posed by people who have asthma and health-related illnesses. Some people might be more vulnerable to heat waves as vulnerability to heat waves is not distributed equally throughout Northeast. Individuals with less social economic opportunity are at higher risk of heat-related illness and mortality. It is projected that heat-related deaths can increase by 50-90% by 2080 from the estimated 600 heat related deaths each year from 2000-2006 (EPA, 2006).

1.1.3 Climate Change and Impacts in Global Precipitation Patterns

Global warming has a direct influence on changes in the precipitation patterns. For every 1°C warming, the "water holding capacity of air" increases by 7%. The increased water holding capacity of air increase the water vapor in the atmosphere which leads to more falling of extreme precipitation events such as thunderstorms, hurricanes, cyclones, flooding and storms (Trenberth, 2010). The increase in the warming can also lead to more evaporation and drought in some areas.
than others. The hydrological cycle is completed by the evaporation of water from land and ocean which is carried back to the Earth after it is moved around by winds and condensed into clouds and precipitated. The intensity and frequency of precipitation can change from time to time depending on changes in climate. The atmospheric circulation patterns can affect the local and regional rainfall. For instance, more warming on ocean surface can lead to stronger hurricanes. A distinct significant change caused by climate change is that higher latitudes are getting more wet while subtropics and tropics are getting drier. NOAA has reported that the land-based rainfall for the year 2015 was below average throughout the globe. Lack of moisture leads to less evaporation and cooling off near surface temperature and cause an increase in local heating. The total land-based precipitation percentiles are shown in figure 1-3 for the year 2015. Lack of precipitation over land caused 98% drought in California and other places.

Figure 1-3 Land Only Precipitation Percentiles, Jan- Dec 2015, NOAA’s National Centers for Environmental Information, Data Source: GHCN-M version 2

Increase in the evaporation of surface moisture is one of the predictable “components of climate change in the future” is associated with human activities which leads to changes in hydrological
cycle (Trenberth, 2010). With the warmer climate in prediction, hotter and more intense and longer lasting heat waves are expected. IPCC Fourth Assessment Report- Climate Change 2007 reported the Atmosphere-Ocean General Circulation Models projection for dryer summers and wetter winter for “most of the northern middle and high latitudes” (IPCC 2007). All climate models assessed greater warming over land “for surface air temperature roughly twice the global average temperatures increase” for 2030 in high northern latitude (IPCC 2007). The near surface air temperature has increased by 0.74°C from 1906 to 2005, which resulted in hot days and warmer nights over Asia and North America (IPCC 2007).

1.1.4 Understanding the link between Climate Change and Urban Development

As our climate is becoming warmer and we are noticing changes in precipitation patterns, cities may get hit harder with such changes. “Developing countries will bear the brunt of the effects if climate change” as these countries are more vulnerable (World Development Report 2010). From other activities that humans affect their climate, is changes in land use and land cover. Cities become warmer than their surrounding due to UHI effect. Paved streets and sidewalks change “how water and energy are exchanged between the land and the atmosphere” (Easterling, et al., 2014). Over the past few years, land development has changed prominent lands in U.S. for the purpose of urban expansion in Northeast, Northwest and Southwest.

U.S. is predominantly a rural country with 81% of its population living in urban areas since 2010. Since 2008, more than 8% of the land in U.S. alone has gone under development with Northeast, Southeast and Midwest being the most developed. Based on land cover statistics for the National Climate Assessment, Northeast had 9.6% of its land developed into an urban land type which is a total of 1.36 percentage change in land cover type from 1973 to 2000. The primary concern with over development and land change is its interaction with climate change
and its effect on humans and ecosystem. Climate change will affect “how and where humans live and use land for various purposes” (Easterling, et al., 2014)

Population growth is expected to continue, and so is land use-land change trend. The projection for the future is that 73 to 98% of urban land development will take place in U.S. by 2050 due to population growth and expansion. Urban areas are covered with impervious surfaces such as concrete and asphalt which have a deep effect on the environment such as modifying the movement of water, absorption of heat, UHI effect, runoff, and flooding. Land use and land change not only plays a role in the interactions of land and atmosphere but also impacts the climate at local, regional and global scale. Few of these impacts are changes in the surface moisture and air temperature, effects on weather and climate as well as shifts in the atmospheric concentration of greenhouse gasses. Temperature change is noticeable in a conversion of grassland to biofuel production lands. The regional maximum temperature has increased in Northeast due to clearing grassland and forests. Land cover changes associated with urbanization have impacts on weather patterns and climate, a formation of convective storms, and concentration of greenhouse gasses (Easterling, et al., 2014).

Nonetheless, land-change decisions may affect the vulnerabilities of individuals, households, communities, businesses, non-profit organizations, and ecosystems to the effects of climate change (Easterling et al., 2014).

### 1.1.5 Urban Heat Island (UHI) and Land Use Effects

The urban structures are mostly made of asphalt; concrete and dark color materials that absorb and store heat during daytime and release at night which cause city's local climate to be warmer than average (figure 1-4). With more population growth and expected urban growth and sprawl, there is going to be a replacement of soil and forests with urban development. Less vegetation
and lack of moisture in combination with a decrease in albedo and increase in anthropogenic heating amplifies the UHI effect. Not only these changes impact an increase in the average temperature of cities but also affect the local and regional energy exchange between land and atmosphere. The Higher temperatures in cities caused by UHI adversely influence the quality of air by an increase in ground-level ozone (Lo, 2003). UHI is indirectly a contributor to respiratory and cardiovascular illnesses and directly cause of heat related mortalities.

![Figure 1-4 UHI Effect concentrated in urban Center](image)

The temperature difference in magnitude for UHI between cities and rural is most felt during dry cool nights that have moderate winds- mostly because man-made materials retrain and re-radiate heat back to the atmosphere at night. Therefore, non-vegetation surfaces have a greater impact on the magnitude of UHI (Voogt, 2002). Studies show that UHI effect has been present in NYC since the 19th century. The mean annual temperature in NYC was higher than "surrounding regions" with the range of 1.2°C to 3.0°C between 1900-1997 (Rosenthal et al., 2003). The mean of NYC’s UHI was 4°C and 3°C respectively in summer and winter from 1997 to 1998 (Gedzelman et al., 2003). The NY Climate & Health Project from Columbia University's Mailman School of Public Health and Columbia Earth Institute projected the impact of climate change on NYC's daily average temperature using greenhouse gas emission scenarios. Based on
high and medium CO₂ emission which is about 30 and 15 gigatons/ year projection, the average annual temperature for 2100 is estimated at 3.0°C to 3.5°C and 2.0°C to 2.5°C respectively (Rosenthal et al., 2004). After the public health researchers predicted over 300 heat-related deaths in NYC between 1964 and 1991; the New York Climate & Health Project indicated that the health of NYC public can worsen due to the impact of climate change By 21st century, “increasing heat related mortalities by more than 55% by the 2050’s” (Rosenthal, et al., 2004).

Few of concerns with NYC’s heat island effect especially during summertime are an increase in energy demand, higher power plant emission for creating energy, air pollutants such as ozone, nitrogen oxide, and VOC and increase in higher urban temperatures (Kinney, 1999; Kalkstein, 2002). Higher urban temperatures increase the risk of heat related mortalities and endanger the well-being and health of elderly and poor citizens in NYC. This study has further completed all studies done on UHI. Not only it develops a simple statistical model to predict urban temperature anomalies and map patches of heat built ups but it also expands the grasp of the research into predicting regressed temperature standard deviation anomalies within the city based on weather model data. It also develops a conceptual model to predict areas that are at highest risk of social and environmental hazard due to increase in temperature and urbanizations.

To better Characterize NYC UHI and better understand its impact on human health and improving current researches, four cross cuttings projects have been pursued in this work:

i) Introducing fine scale, high-resolution data sets to understand UHI in New York,

ii) Using fine scale high-resolution data sets to help map UHI in Manhattan,

iii) Predict Manhattan surface temperature using real-time weather forecast,
iv) Developing a conceptual model to measure environmental risk and social vulnerability in complex urban settings.

1.2 THESIS OBJECTIVE

The primary objectives of this dissertation are the followings:

1. Development of high spatial resolution urban air temperature maps. Characterize the effect of surface characteristics and weather conditions on the urban air temperature distribution.
2. Develop a model to predict hotspots in NYC using physical environment and meteorological variables.
3. Create a conceptual framework to predict environmental risk and social vulnerability in urban population.

This thesis is designed to examine alternative methods of studying the impact of UHI on metropolitan cities with high population density and to create high-resolution data sets to better understand the impact of land cover and land change on UHI in our urban areas. Correspondingly, a surface model has been developed for urban planners to help with designing cooling centers in cities. Furthermore, the final chapter of this thesis focuses on measuring environmental risks associated with urban development and target populations that are at higher risk of vulnerability.

1.3 MOTIVATION

Many UHI studies focus on temperature differences between urban and suburb (Oke, 1982; Grimmond and Oke, 1999) and no information on the local scale temperatures in metropolitan city of New York is available. As many city planners are concerned with temperature increase in
urban areas, there are not much work has been done other than organizing cooling centers during heat waves. Heat-related mortalities increase with temperature. During heat waves, mortality rate becomes even more sensitive to changes in a few degrees (Kinney, et al., 2008). The mortality rate is expected to increase by 50 to 80% by 2080. Therefore there is a need for a better understanding of urban areas' neighborhood, amplifying UHI effects and heat waves within these complex settings. Theoretically speaking, there is enough understanding of the influence of the urban environment on localized temperature at the neighborhood scale (Oke, 1981; Grimmond 1999, 2007). Even though modelers can classify urban systems physically on km scale using satellite data (Rozensweig et al., 2006), the complexity of urban system enables them to measure “all heat transport and storage parameters” at neighborhood scale (Vant-Hull, et al., 2014). Studies lack high resolution datasets. Therefore there are needs to introduce high-resolution data sets to understand the complexity of neighborhood scale block by block and land type. Thus a street-level temperature and humidity dataset with high resolution spatial and temporal components has been created for this study for the island of Manhattan, suitable for use by the urban health and modeling communities. In addition, this study used four basic approaches to gathering high-resolution microclimate data for the urban environment; walk and fix campaign data, temperature profiler, and satellite data. These high-resolution datasets enabled the project to study the impact of UHI on near surface air temperature, understand the impact of land use/ land change on increasing the impact of UHI and establish an understanding of near-surface air profile for land types and conceptualize environmental and social risk associated with the land type and UHI effect. This project is one of the only studies ever done which measure the impact of land cover and urbanizations on temperature variation within NYC while mapping patches of heat islands for targeting vulnerable population within high risk environmental regions.
1.4 **APPROACH**

The summary of the approach taken to complete this dissertation is abridged in figure 1-5.

![Figure 1-5 Flow Task. Tasks Designed and Completed for the purpose of this dissertation](image)

1.5 **CHALLENGES**

1. Weather stations are mostly located above ground in shaded areas and do not represent the actual street temperature. For instance, temperature readings for New York City come from Central Park station which underestimates the actual temperature because of the cooling impacts of its surrounding.

2. Weather station instruments on rooftops represent the larger trends and miss changes occurring near surface.

3. Existing datasets used for studying UHI lack the resolution needed to examine urban microclimate. The existing datasets currently used for studying UHI effects are:
• The National Weather service produces 12km grid resolution (1 grid= Manhattan) used to specify urban weather conditions. Very low in resolution for the purpose of this work. Completely misses changes in entire Island of Manhattan.

• Coupled Oceanic & Atmospheric Mesoscale Prediction System (COAMPS) - model produces 1km resolution region grid for real-time forecasts – Numerical model, used for now cast and forecast-captures regional circulations such as sea-breeze. COAMPS is also very low in resolution for studying UHI in Manhattan. Completely misses changes in block and neighborhood scale.

• Surface station~ 1km (MetNet Station), used for meteorological observations in and around NYC metropolitan area. Surface observations consist, in part, of near real-time atmospheric pressure, relative humidity, temperature, wind direction, wind speed, rain rate, and total rainfall accumulation measurements at building-top sites. Surface stations provide temporal/diurnal information and can capture the range of meteorological conditions. Surface stations represent large-scale environment which does not stand to the limits of this study (Karimi, et al., 2015).

• Landsat with resolutions 30m in the visible and 80m in thermal IR classifies surface type and albedo, and surface temperature. There is no air temperature available using Landsat data.

4. Not being able to extend the labor force to walks at night and city limitations to have fixed campaign shelters’ installation for a three month period only was a major challenge.
5. Satellite data was obtained to help with the surface characterization, except building height. Landsat data is used to find types of ground cover from building density to water, types of vegetation and surface temperature.

6. The urban system is more complicated and hard to be model just using limited observations, and to get better models there is a need for more robust datasets.

7. Accessing hospital data is costly, and not all admissions are being reported.

1.6 CONTRIBUTION

Materials presented in this dissertation helps with both near term and long term benefits in dealing with UHI. The implications of the study are as followings:

Near term – Temperature gradients; health; UHI

- Identify, measure, and model intra-urban temperature gradients in NYC.
- Analyze mortality-temperature relations in metropolitan cities.
- Assess future vulnerability under climate change.
- Add strength to the temperature prediction and heat index calculation within a densely urbanized city.

Longer term - Timescale temperature vulnerability; air quality; decision tools

- Link temperature gradient works with fine-scale health outcome data in NYC.
- Expand to other boroughs and cities, and to air quality.
- Develop future urban decision tools for temperature and air quality risks.
1.7 **HOW TO READ THIS DISSERTATION**

This thesis is organized as following: Chapter 2 outlines the goals of studying UHI using high-resolution street-level temperature and humidity datasets and investigating the relationships between spatial and temporal variability within an urban center. Chapter 3 describes developing a statistical model to map pockets of UHI in Manhattan using the spatial and temporal data sets explained in chapter 2, plus various significant parameters that control temperature in an urban setting such as building height, building density, vegetation, water, elevation, and albedo. Chapter 4 presents an Exploratory model to predict temperature variability from the weather forecast, data sets explained in chapter 2 and three months of model weather analysis data output. Chapter 5 illustrates a conceptual framework to examine the influence of different surface type on mitigation of UHI looking at consistent physical properties of the urban system through a framework to highlight environmental and social vulnerabilities through hotspots. This chapter builds on the understanding of UHI and land cover gathered from chapters 2, 3 and 4 to draw conclusions on the importance of UHI impact and human health. These data are used to calibrate and validate the conceptualized model described in Chapter 5. Chapter 6 describes future work and conclusion.
2 CHAPTER II: URBAN HEAT ISLAND ASSESSMENT WITH TEMPERATURE MAPS USING HIGH-RESOLUTION DATASETS

2.1 Chapter Summary

The definitive urban environment, Manhattan hosts a variety of micro-environments defined by parks, varying building heights, and proximity to water bodies. Fine scale temperature and humidity maps are necessary to characterize how this variation on the neighborhood scale affects variations in microclimate. Backpack mounted data loggers have been deployed in a series of simultaneous parallel walks to measure temperature and humidity at roughly 10 meter intervals, categorized by segments of shade and direct insolation. Roughly 30 such campaigns were completed by the end of the summer of 2013. The measurements have been detrended (calculated) in time against fixed meteorological stations, and then normalized by the daily Manhattan-wide averages and standard deviations. Ten fixed stations have also been located throughout Manhattan measuring temperature and humidity at 3 minute intervals to capture convective and turbulent variations. The data show local temperature anomalies on the scale of several hundred meters that change location from day to day and are ascribed to the convective structure of the atmosphere. Upon averaging multiple days together the convective structure disappears and the remaining signal becomes most strongly correlated to elevation and building height. The resulting temperature and humidity maps have be further used (explained in chapter 3) for multiple variable regressions against local variables of vegetation, building characteristics, albedo, water proximity and elevation to arrive at a formula for predicting micro variations in the urban heat island. Intended applications are predicting and mitigating heat related mortality.
2.2 Chapter Introduction

Nearly all studies of the UHI have focused on the increase of urban over rural temperatures, a difference which peaks at night due primarily to higher heat storage and nocturnal release; and to radiative trapping in urban canyons (Oke, 1982; Grimmond and Oke, 1999). And yet city inhabitants are understandably more concerned with urban daytime temperatures, even if only slightly higher than daytime rural temperatures (Fast et al., 2005; Gedzelman, 2003; Gaffin et al., 2008). The nocturnal heat island prolongs the health risks of a heat wave, but peak daytime temperatures gauge the intensity. Above a certain threshold that varies by city, the heat-related mortality rate increases quasi-exponentially with temperature, so that during heat waves the death rate becomes very sensitive to changes of a few degrees (Kinney et al., 2008a,b).

Variations in building structure, vegetation and albedo within the urban ‘archipelago’ can result in local temperature differences of several degrees (Yamashita, 1996; Weng et al, 2003, 2008; Stewart et al, 2003; Rosensweig et al, 2006; Pena, 2009; Montavez et al, 2000; Grimmond, 2007; Gaffin et al, 2008; Eliasson, 1996a, b; Comrie, 2000; Bottyan and Unger, 2003). The data set described in this paper is a first step towards creating high resolution (~ 10^2 m) neighborhood-scale temperature anomaly maps of a highly urbanized area that may benefit the health community while serving as a test bed for physical modelers.

The influence of the urban environment on localized temperature at the neighborhood scale is well understood theoretically (Oke, 1981; Cleugh and Grimmond, 2001; Grimmond 1999, 2007). Urban systems can be modelled physically at the scale of individual buildings (meter scale) where all boundary values can be measured directly, or at the km scale where averaged properties have been inferred from large-scale atmospheric response and parameterized as part of numerical weather model packages (Rozensweig et al., 2006; Meir et al., 2013). But due to the
complexity of intermediate scales and the inability to directly measure all heat transport and storage parameters, modelers at the multi-building (or neighborhood) scale must resort to case-by-case statistical parameterization based on case study temperature measurements which are typically sparse compared to the scale of neighborhood variability (Bottyán and Unger, 2003; Eliasson, 1996a; Pena, 2009; Weng et al, 2008). The situation is even more complex for daytime versus night time; in addition to heat transport, storage and thermal radiation effects, daytime temperatures are modulated by the shade of buildings and vegetation, and by evaporative cooling that is enhanced by vegetation but inhibited by impervious surfaces (Weng and Schubring, 2003; Steenfeld et al, 2011; Rosenzweig et al, 2006; Pena, 2009).

To verify and to tune all these models, there are three basic approaches to gathering high-resolution climate data for urban environments. The first is to employ fixed stations that for logistical and financial reasons may be widely spaced but can collect data over an extended period of time (Comrie, 2000; Fast et al, 2005; Gedzelman, 2003; Meir et al, 2013; Haeger-Eugensson and Holmer, 1999; Montavez, 2000; Preston-White, 1970; Steeneveld et al, 2011). This approach has the advantage of sampling not only over the diurnal cycle but also over a wide range of weather conditions, allowing for adjustments due to the smoothing effects of wind or clouds (Eliasson, 1996a; Montavez et al, 2000; Oke, 1982) or regional circulations caused by urbanization (Gedzelman, 2003; Meir et al, 2013; Heuger-Eugensson and Holmer, 1999), though caution must be used concerning non-standardized siting of hobby stations (Grimmond, 2010). The second approach is the use of mobile stations deployed across large spatial tracts during a short period (Bottyán and; Comrie, 2000; Eliasson, 1996b; Gaffin et al, 2008; Montavez et al, 2000; Yamashita, 1996). This has the advantage of high resolution in space, but is too
intermittent to capture a full statistical set of weather conditions, and requires a substantial commitment to gather data on a regular basis.

The third approach to collecting climate data is via satellite—most notably high resolution thermal-IR capable satellites such as Landsat and ASTER (Pena, 2009; Rosenzweig et al., 2006; Weng and Schubring, 2003; Weng et al., 2008; Weng, 2009). The main advantage of satellite data is the ease of collection. But like mobile measurements, satellite datasets also suffer from the intermittent nature of overpasses under clear conditions that make them unsuitable for most weather analysis. Moreover, surface temperatures retrieved by satellite should not be confused with air temperatures measured by most probes. The surface typically interacts more strongly with the radiative environment and mainly serves as an intermediary between radiation and the air near the surface, often creating steep vertical air temperature gradients (Clough and Grimmond, 2008; Eliasson, 1996b; Grimmond and Oke, 1999; Oke 1982; Gaffin, 2013). Satellite observation of highly built up areas such as Manhattan also samples a mix of rooftop and street-level surface temperatures, which for high buildings can introduce significant deviations from the surface level.

2.3 Study Area

The island of Manhattan in NYC is of interest both as an exemplar of the urban environment and for its high population density of nearly 27 thousand per km². It features a range of elevations, building heights, and street widths (with and without trees); and parkland, commercial and residential sectors of apartments or row houses. The island of Manhattan consists of different elevations, 20m elevation in the center and 35m in the heights of the island. The mean UHI effect in NYC during summer was estimated at 2.5ºC and 3.5ºC during winter and spring. The average annual temperature for 2050 is projected to increase by 1ºC to 4.6ºC (Knowlton, et al.,
2007). The diverse population of Manhattan has millions of residents who are 65 years old and older, many of which have respiratory illnesses and other risk factors. Heat waves and UHI effect can increase their vulnerability during summer time.

With these strengths and weaknesses in mind, the dataset presented in this chapter consists of a mix of well characterized fixed and mobile measurements at street level. The measurements consist of pedestrian mounted temperature and relative humidity surveys in simultaneous parallel transects near the hottest part of the day during two summers, and a set of light-post mounted instruments, collecting data continuously during the summer of 2013. For ease of future study, the field campaign data is co-located with data from the US Geological Survey (USGS), the National Building Statistics Database (NBSD), and retrievals of surface properties from the MODIS and Landsat satellites. This data set serves as a complement to the ongoing, but coarser resolution NYC MetNet collection of government and hobby weather station data plus wind profilers and radiometric instruments curated at http://nycmetnet.ccny.cuny.edu/.

The remainder of this chapter describes data collection and processing, with a discussion of data quality and the unique attributes of a data set of this kind. An important part of the data processing is an averaging procedure based on the position of each measurement within each day's statistical distribution rather than the explicit value, which the authors feel is a more robust approach to calculating anomalies. An outline is included in future plans to use this data for short-term and climatic forecasts.

Figure 2-1a is a Landsat Google Earth image of Manhattan, with pedestrian routes marked in yellow and fixed instrument locations marked with orange boxes. This RGB image portrays a sense of the variation in vegetation, building size and density, and albedo on the island. The axis of Manhattan is tilted at approximately 27° East of North, with streets running roughly East-
West (with the street names of the various routes labeled in white) and avenues running roughly North-South, bounded by the Hudson River and the East River. There are approximately 16 streets per km if traveling along an avenue. Due to the inclination, at the time of the walks (between and 2 and 3 PM) the sun would be shining directly down the avenues, while pedestrians on the south side of the streets would be in the shade.

![Map of New York City](image)

**Figure 2-1 Mobile instrument pedestrian routes and fixed instrument locations (a, left). Elevations and neighborhoods (b, right)**

Elevation also affects temperature, and Figure 2-1b indicates the elevation in grayscale, with the main neighborhoods and Central Park marked. Elevations range from 1 to 2 meters above mean sea level (MSLE) near the rivers to up to 20 meters in the center of the island, and up to 35 meters MSLE in the Heights. The skyscrapers are concentrated in Downtown and Midtown where the bedrock is close to the surface, giving way to buildings of a few stories high in the villages and Lower East Side (LES, which includes Chinatown) due to a much deeper soil layer. Central Park runs from 59th street to 110th street, with buildings becoming increasingly residential and lower in height while traveling northwards up the Upper West Side and Upper
East Side (UWS and UES) into Harlem, with occasional government sponsored residential buildings that are 20 to 30 stories high but spaced apart in islands of greenery. Harlem and the Heights are mainly composed of tightly packed apartments of 4 to 7 stories high, row homes of 2 to 3 stories, and the occasional government project buildings described above.

2.4 **Mobile Instrument Campaigns**

The primary intent was to collect high-resolution data rapidly, necessitating a temperature sensor with a fast response time. The Vernier Corporation surface temperature sensor is a plastic coated thermocouple at the end of a wire, and our tests found a response time on the order of 10 seconds, in agreement with the manufacturer’s quoted values (Table 2-1). This was matched with the Vernier RH sensor and Light Probe; all recorded on a Vernier Labquest 1 data logger.

<table>
<thead>
<tr>
<th>Table 2-1 Instrument specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Instruments</strong></td>
</tr>
<tr>
<td>Vernier <em>(mobile)</em></td>
</tr>
<tr>
<td>Temperature</td>
</tr>
<tr>
<td>Relative Humidity</td>
</tr>
<tr>
<td>Hobo <em>(fixed)</em></td>
</tr>
<tr>
<td>Temperature</td>
</tr>
<tr>
<td>Relative Humidity</td>
</tr>
</tbody>
</table>

Though these instruments are intended for educational rather than research purposes, the specifications for the temperature probe were close to the research grade instruments used in the mounted installations, and the combination of low heat capacity and continuous graphical readout made them ideal for field campaign purposes. Dewpoint was calculated from temperature and relative humidity via the Magnus formula (Aldukov and Eskridge, 1996).
The instruments were mounted on white cardboard, with the ends of the RH and temperature probes protected from sunlight by a Styrofoam cup (Figure 2-2). The thermocouple was positioned to be in free air in the middle of the cup. A light sensor was positioned looking roughly upwards, to be used not for quantitative analysis but to distinguish between direct sunlight and shadow during the walks. The instrument trays were affixed to backpacks filled with clothing to insulate the instruments from body heat, at a uniform 1.5 +/- 0.1 meters above the ground. The color and size of backpacks were not standardized. Based on our experiences we recommend that the instrument trays for future campaigns be improved by shielding the entire body of the RH meter from sunlight (the large horizontal cylinder shown in Figure 2-2) and aspirating the cup with a small fan.

Eight field workers were deployed at a time on either the street or the avenue routes shown in Figure 2-1. Each walk started with several minutes for instrument acclimation after leaving public transport, then a simultaneous start at 2 pm, proceeding from West to East (streets) or North to South (avenues) for roughly 40 minutes - the time to walk across Manhattan. Field workers were instructed to walk at a constant pace from starting to stopping point, staying in the shade when possible. Individual collection times were, therefore, dependent on walking speed, but measurements were detrended from regional, temporal variations as described in the data processing section. Data was recorded every 10 seconds across the length of the route and binned into equal time segments during post processing. Typical walking speeds are between 1 and 2 m/s, yielding measurements every 10 to 20 meters that were averaged into larger segments.
Given the high buildings of Manhattan, GPS geolocation was not feasible. When data collection began in the summer of 2012, very few of the participants had smartphones capable of geolocation using cell tower triangulation, but by the summer of 2013 surveys could be made of walk timings and locations. As shown in Figure 2-3 the normal dithering of cell phone geolocation results in a wandering path that only approximates the actual path taken, so we resorted to timing straight line segments and interpolating between these measured points. The interpolation was done by the fractional time of the entire walk rather than absolute time: fast and slow walkers would spend the same percentage of the walk in each segment. Separation into
segments also allowed correction to walking speed due to changes in elevation and street traffic. Crossings at intersections introduced a random element due to traffic, but these stops were found to be rarely more than 30 seconds, with an average stop every 3rd intersection of about 10 seconds due to the pedestrian tendency to cross as soon as traffic clears rather than wait for the cross signal. The random element was more common on the avenue walks because of shorter blocks, though east-west traffic tends to be lighter and the stops shorter. The estimated variation due to traffic was ~30 meters, which influenced the bin size selected for post-processing.

In 2012, eight street campaigns and two avenue campaigns were performed from late June through August, and nine street campaigns and eleven Avenue campaigns were conducted from mid-July through early October of 2013. Weather conditions were noted on each day. Route data from each day were inspected by eye and compared with others from the same day: those with obviously spurious data were rejected (missing data; more than 5 degrees or 10% RH difference). Bad data were attributed to bad batteries, operator error or insufficient wait time after exiting public transit.

Table 2-1 shows the accuracy, resolution, and response times of all instruments used. The slower response time of the mobile RH meter is primarily due to thermal inertia. So long as the mobile instruments do not pass near any sources of water vapor such as vegetation or large bodies of water, water vapor density should reflect the slowly changing air mass. In such cases, we would physically expect the relative humidity to drop as the temperature increases (raising the saturation point), while dew point remains constant to reflect the unchanged water content of the air. In cases where the air temperature changes quickly as the walker passes into new surroundings, the temperature of the RH meter will lag the actual air temperature. So if the air temperature increases suddenly the RH meter will not register the expected drop in RH, reading
higher than the true value, which would result in a higher calculated dew point. The reverse is true if the temperature drops suddenly. In the case of rapid changes in temperature, the effects of a temperature lag in the RH meter are therefore twofold. First, the physically expected anti-correlation between temperature and RH is muted by the lagged response. Second, the failure of RH to change produces a spurious positive correlation between temperature and dew point. This is seen in the raw data of Figure 2-4.

![Figure 2-4](image)

**Figure 2-4** The effect of RH lag time on relations between Temperature, RH, and Dew point. Note that RH has been divided in half to fit all variables on the same scale. a) (Left) raw data. b) (Right) data smoothed with a 2-minute average as used for the field campaigns.

The strong anti-correlation expected between temperature and relative humidity is not apparent in the raw data, while a strong correspondence is seen between the high-frequency noise in the temperature and dew point. The correlations between temperature and (RH, DP) are (-0.52,
0.27). After averaging is applied the high-frequency responses are muted, and the correlations between T and (RH, DP) become (-0.75, -0.17). It should be noted that if the temperature were not trending up while dew point was trending down, the correlation between DP and T in the raw data would have been more strongly positive, and in some datasets, the correlations were as high as 0.85. For this particular instrument bias, averaging over a suitable time interval brings the numbers closer to physical reality for both RH and DP. The 2-minute average chosen for the mobile campaign is a balance between how quickly the physical surroundings are expected to change at typical walking speed, and the instrumental time lag.

2.5 Fixed Instrument Campaign

Ten Onset Corporation Hobo micro station data loggers were mounted inside white painted pine thermometer shelters (Ben Meadows, Figure 2-2), with a combination temperature and relative humidity probe suspended inside, and a solar pyranometer mounted outside facing upwards. The New York City Department of Transportation granted three months consent to mount the shelters on light posts from mid-June through mid-September. All were mounted from 3.1 to 3.7 meters above the ground (depending on signage) on the south side of streets so that they would primarily be in shade (there were periods of direct sun in the mid-morning and late afternoon). They were set to collect data every three minutes to capture temporal variability due to convection. Where possible most stations were mounted directly above the street routes, with locations selected to capture the range of variability noted in the walking campaigns of 2012. As for the walking campaigns, dew point was calculated from T and RH.
Table 2-2 Instrument Deviations from the Mean

<table>
<thead>
<tr>
<th></th>
<th>Vernier T (C)</th>
<th>Hobo T (C)</th>
<th>Vernier RH %</th>
<th>Hobo RH %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average deviation from mean</td>
<td>0.2</td>
<td>0.04</td>
<td>1.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Max deviation from mean</td>
<td>0.35</td>
<td>0.05</td>
<td>3.6</td>
<td>0.74</td>
</tr>
<tr>
<td>Max10 min variability</td>
<td>0.03</td>
<td>0.03</td>
<td>0.33</td>
<td>0.6</td>
</tr>
</tbody>
</table>

2.6 Controlled Inter-comparisons

Instruments were compared by placing the probes close together on a table in a large room, covered with a cardboard box to reduce convective and radiative gradients. After collecting data for 10 minutes, the table was rotated 180 degrees and the process repeated. A comparison was done to the group average rather than to an absolute standard, which conforms to the data processing done for the field data. When both Vernier and Hobo instruments were on the table together, the averages for the two types of temperature measurements were within $0.05^\circ C$ of each other, and the RH meter averages were within 2% of each other, with the Vernier showing the largest variation between instruments.

Based on the above procedure, measures of stability for the two types of instrument appear in Table 2-2. The deviations from the average were used to correct each instrument readings towards the ensemble average. The variability shows the standard deviations of measurements during a 10 minute period. The drift of these deviations in the last row shows how much these corrections changed in a six month period. Note that the Hobo drift values were too small to be significant so are omitted.

2.7 Data Processing

Average anomalies were calculated for both campaigns, but the mobile campaigns required detrending so that all measurements on a day could be treated as though made at one time.
2.7.1 **Mobile Campaigns**

The purpose of the dataset was to estimate a relative temperature and moisture differences between locations in Manhattan. To this end the walking campaign data set was processed in three steps:

1. Detrending data from temporal changes during the 40 minute measurement period
2. Binning detrended data from each route into line segments and averaging
3. Differencing each bin average from the Manhattan-wide average (forming anomalies) and normalizing by the standard deviation.

Detrending is done by taking spatially fixed reference data (mean values from a set of station data in the NYC MetNet system, including Central Park), and performing a linear fit between the 2 pm and 3 pm reference data to arrive at reference values \( V_{\text{ref}}(t) \) for each point in time during the measurement period (‘V’ stands for temperature, relative humidity, or dew point values). A measurement value \( V \) made at time \( t \) and position \( x \) will be converted into detrended data \( V_{\text{dt}} \) by

\[
V_{\text{dt}}(x) = V(x,t) - V_{\text{ref}}(t) \quad \text{(data detrending)}
\]  

Note that this is based on a single reference trend rather than local trends, which could be expected to vary from location to location depending on radiative and evaporative effects. The result may be an imperfect correction for temporal changes during the measurement period. The use of multiple stations averaged together for the reference trend reduces the chance that the detrending will be strongly affected by outlier stations. Each route was divided into 20 equal segments by time (roughly 2 minutes or 12 measurements per segment) with averages taken over each segment. Fast walkers would thus have fewer points per segment, but cover the same geographical distance of roughly 150 meters (2 street crossings or about \( \frac{1}{2} \) a block from the
avenue to avenue). This distance corresponds to the surface temperature correlation length for urban settings found by satellite survey (Weng et al., 2003).

After the data is detrended and averaged over route segments, Manhattan-wide averages, and standard deviations are calculated. From these are derived the ‘differences' and ‘deviations' from the average at each location x, which are calculated as follows:

\[ V_{\text{diff}}(x) = V_{\text{dt}}(x) - \langle V_{\text{dt}} \rangle \]  
\[ \text{“differences”} \]  
\[ V_{\text{dev}}(x) = \frac{V_{\text{diff}}(x)}{\text{SD}} \]  
\[ \text{“deviations”} \]  

(2-2)  
(2-3)

The deviations represent how many standard deviations each measurement is from the average, which effectively normalizes the measurements each day to the unit Gaussian distribution centered on zero. For each variable (temperature, relative humidity, dew point) the differences and deviations are averaged over all days for the street and avenue campaigns separately.

2.7.2 Fixed Instrument Campaign

Beyond spatial anomalies, data reduction for the fixed instruments was focused on short-term temporal variability (ripples in the data set), assumed to be due to primarily to convection. The convective cycle for cloud systems is roughly 30 minutes, so an hour (20 data points) is taken as the smoothing window to average out all variability on shorter time frames. Pairs of hourly data sets are formed from the raw data; hourly averages and hourly standard deviation of temporal variability. Averages are formed with an hour-long averaging window centered on each hour. The temporal variability is calculated in two steps: a 21 point running average is subtracted from the raw data to form a set of ‘ripple differences' (Figure 2-5); then the hourly standard deviation is calculated from the set of differences in the one hour period bracketing each hour (30 minutes on either side of the hour mark).
Figure 2-5 Convective ‘ripple variations’ around diurnal variation. The differences between the ripple and diurnal cycle for each hour are used to calculate the temporal standard deviations.

Note that the hourly averages for the ten instruments can be used to calculate stable spatial anomalies free of temporal variation. This is the equivalent of applying equations 2 and 3 as used for the mobile campaigns, but for hourly average data rather than detrended data.

2.8 Measurement Results

Figure 2-6 shows average temperature and dew point anomalies for the street campaigns, represented as the mean number of standard deviations each location varies from the Manhattan average each day (referred to as "deviations" - see Data Collection and Instrumentation). On most days the Manhattan-wide temperature standard deviation was roughly 1-degree Centigrade. Dew point (DP) is shown rather than relative humidity (RH) because as a representation of the water vapor density, DP should be largely independent of temperature. The statistical significance of the difference between the average of two data sets can be calculated using the Student T-test, which takes into account the standard deviations and sizes of both data sets. We wish to establish the statistical significance of the anomalies, differing from the average value of zero. These anomalies at each location are composed of the measurements made at that location each day of the field campaign, converted into deviations. There is no single data set to compare
these anomalies to. An average data set is constructed with a mean value of zero - a standard deviation equal to the mean standard deviation of all the measured points in Manhattan, and a size slightly less than the total number of days in the field campaign (not all routes were measured each day, reducing the average number of measurements per location). The T values appear in Figure 2-6b and 2-6d. To aid in interpretation, the approximate statistical significance of the T values appear in Table 2-3. For example, if an anomaly in Figures 2-6a, b has an associated T value of between 0.75 and 1.25 (red in Figure 2-6c, d) the difference from the average is significant with the confidence of 77% to 89%.

Figure 2-7 shows the equivalent of Figure 2-5 for avenues. The measurements made along the avenues were generally in full sunlight, which is likely responsible for the patchwork pattern seen in Figures 2-7a, b due to heating of the instruments. This is discussed in more detail in the interpretations section below, along with the method used to correct partially for differential heating by matching endpoints, marked with white bars. The result of endpoint balancing is shown in Figures 2-7c, d. This corrective procedure invalidates T-test calculations, which are therefore not shown. The fixed instrument data can be treated the same way as the walking data: except done hourly instead of daily. Each instrument is averaged over an hour period to reduce noise, and then the average and standard deviation of the 10 instruments are calculated for that hour. Differences from the average are converted into deviations as in equations 2-2 and 2-3. Figure 2-8 shows average anomalies of temperature and dew point for 2 am, 8 am, 2 pm, and 8 pm so that the afternoon measurement coincides with the starting time of the walking campaigns. The color scheme for deviations is the same as for Figures 2-6 and 2-7.
Figure 2-6 Street measurements of temperature and dewpoint anomalies. (a, c) Each colored square in ‘a’ and 'c' represents the mean number of standard deviations from which the measurement varies from the Manhattan average on the day each measurement was taken. (B, D) The Student T values in B and D are calculated using the mean and standard deviation of the measurements at that point compared to an “average sample” with a mean of 0, a standard deviation equal to the average standard deviation, and a number of points equal to the number of days measurements were done.

Table 2-3 T-values and confidence levels used for figures 2-6b, d

<table>
<thead>
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<th>Colors (negative)</th>
<th>T value</th>
<th>Confidence level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>+/- 0.25</td>
<td>60%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>+/- 0.75</td>
<td>77%</td>
</tr>
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<td></td>
<td></td>
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</tr>
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<tr>
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<td></td>
<td>+/- 2.25</td>
<td>99%</td>
</tr>
</tbody>
</table>

The deviations shown in figure 2-8 represent spatial variability between locations, with the temporal variation averaged out. A comparison of the spatial and temporal variability for this set of instruments appears in Figure 2-9. Spatial variability represents the differences between instruments, calculated as the standard deviation of the hourly averages of all 10 instruments. Temporal variability is the standard deviation of the ripple amplitudes indicated in Figure 2-5, averaged over all instruments. The plots shown in Figure 2-9 are averages at each hour taken.
over the three month period the instruments were mounted in order to find the diurnal cycle of variability. This variability is crucial to interpretation of the deviation maps of Figures 2-6:8.

The average diurnal cycle of differences between the Hobo instruments can be calculated by multiplying the spatial standard deviations in Figure 2-9 by the deviations in the maps of Figure 2-8. Interpreting the maps of Figure 2-6 and 2-7 requires translation of the spatial and temporal deviations of the fixed instruments into those of the walking campaigns, and is discussed in the next section.

2.9 Physical Interpretations

Some general trends are evident in the street data maps of Figure 2-6. Temperature is lower in the Heights on the west ends of 145th and 120th streets, and higher in the low lying east sides of 120th and 14th streets. The cooling effects of vegetation can be seen while traversing parks on 120th street and 79th street, and while near water on 57th, Houston, and Warren streets. Lower buildings allowing greater street insolation may also be responsible for warmer areas on 34th, Houston and 120th streets. The dew point generally increases near water and vegetation, and decreases with elevation. These observations have been paired with albedo, NDVI, building parameters and proximity to water, but a full statistical analysis of the correlations and cross correlations between these variables is beyond the scope of this paper. Preliminary results show that for the street data the strongest temperature correlation is to altitude, followed by vegetation (NDVI), building parameters and proximity to water.

The avenue data suffered a patchwork biasing effect between routes (Figures 2-7a, b) almost certainly due to full insolation as compared to the shade of the street routes. The tendency was for dew point to drop as temperature increased. This is not due to the temperature lag between instruments; for if the temperature probe warmed more than the RH meter, the calculated dew
points would be higher, not lower (this spurious correlation between temperature and dew point was discussed in the instrumentation section). The most likely explanation is that the RH meter is black and only the tip was shielded from solar insolation, so would warm more than the temperature probe, yielding lower RH and hence lower dew points calculated based on the cooler temperature probe. The temperature probe was within a few cm of the RH meter inside an open Styrofoam cup, so likely would have been warmed, but less than the RH meter – explaining the opposite trends of temperature and dew point under insolation. Since the fieldworkers were consistently assigned to the same routes, individual route insolation biases may occur. All instrument packs were mounted at 1.5 meters; for short people this meant the instruments were near the tops of their backpacks, less likely to block the sun with backpacks or upper body. Tall people would have the instruments mounted halfway down their backs and were likely to be in shade.
Figure 2-7 Temperature and dewpoint anomalies measured along avenues with meanings for ‘a’ and ‘b’ as explained in figure 6. Boundaries between measurement routes are marked with white lines. The patchwork effect seen in A and B is likely due to solar heating of the relative humidity instrument, so endpoint matching is done in ‘b’, ‘c’. The procedure is described in the next section, but invalidates T-test calculations which are not shown.

These trends can be partially mitigated (‘corrected’ is too strong a term) based on two assumptions. The first is that the instruments are close to a steady state thermal balance, so that the correction for slow temporal trends based on the fixed MetNet instruments will apply to the mobile instruments despite insolation. The second assumption is that temperatures and dew points change slowly in space, so that adjacent measurements on the scale of the field campaigns are nearly the same. Though both assumptions violate the intended purpose of studying local differences in temperature and dew point, they allow us to address the patchwork pattern by requiring that the endpoints of adjacent routes be adjusted to the same values, and that this adjustment can be applied uniformly to the entire route. The West and East sides are
independent, so after the individual route adjustments were applied both sides were adjusted uniformly to an average deviation of zero. All adjustments were constant across each route so that differences between adjacent points within each route were preserved.

Figure 2-8 a Temperature Anomalies
Figure 2-8 Fixed instrument average anomalies for selected hours of the day. a) Temperature (top), b) Dew point (bottom)

The results of the patchwork mitigation appear in Figure 2-7c, d. In general the temperatures are lowest and dew points are highest near water, and with the exception of warm temperatures seen on the Upper West Side the trend of temperature and dew points dropping with elevation is also seen. The weakness of the patchwork mitigation scheme is most apparent in the warmer temperatures on the West versus the East sides in the upper 2/3 of Manhattan. For this reason this data is useful mainly for comparison within routes, and should only be trusted between routes where uniform values are seen for some distance on either side of the route junctions, as seen for temperature in the boundary between the bottom two routes on the West side, and the top three routes on the East side.
With these cautions in mind, preliminary statistical analysis shows that the temperatures in the insolated avenues correlate most strongly to albedo, closely followed by vegetation and building height. The effects of building height in avenues are opposite to the shaded street data: in the streets higher buildings have a cooling effect, while in the sunny avenues higher buildings have a warmer effect, likely due to increased reflection. Further numerical statements are being reserved for future publication.

The fixed instruments shown in Figure 2-8 show the largest temperature variation between locations in the morning, most likely because the sun shines down the streets before returning to shade (Note the 10 am peak in Figure 2-9). The station mounted on 81st street along Central Park is cooler throughout the diurnal cycle, most likely due to transpiration and shade during the day, and not being in proximity to buildings which produce the signature night time UHI effect (Oke, 1982). In contrast, the dew point is far more stable, exhibiting slightly lower values in the northern heights and higher values at the southern tip, surrounded by water.
2.10 Comparison of Fixed to Mobile Measurements

The fixed Hobo stations were set primarily along street routes of the mobile campaigns. When comparing the maps of Figure 2-8 to Figure 2-6 it is important to recognize that the deviations are calculated from a much larger array of points for the mobile versus the fixed campaign. Given the geographical variability, it is not expected that the statistics of large and small samples will match, thereby shifting the deviations. Though absolute values may not be the same, relative differences between the same geographic points should have similar trends for the large (mobile) and small (fixed) data sets. Relative comparisons between the data sets exhibit a few points of obvious discrepancy: the east end of 120th street is warmer in the mobile campaign but cooler for the fixed instruments. Other points are less obvious when looking at a map: on 57th street to the east and west of Central Park the mobile data looks very similar, but the east appears much warmer in the fixed data set. This discrepancy is due to the standard deviations being much smaller among the fixed instruments (0.5°C on average versus 1.1°C on average in mobile instruments, which includes temporal variability), so that a small difference that would not cause a color change in the map of the mobile data set causes a change of two bins as seen in the fixed campaign map. With this in mind the similarity between the west side of 57th street and 81st street Central Park West (CPW) in the fixed data must be marked as a discrepancy with the mobile data, which shows a cooler CPW at coarser resolution. Though the fixed and mobile routes are not co-located at 81st street CPW, the fixed instrument was shaded by trees while much of the mobile route at this point was exposed to sunlight, and should be warmer, not cooler. A better understanding of these differences can be found by making comparisons day by day and location by location. This is done in Figure 2-10, which compares the spread of temperature differences between mobile and fixed instruments. On each day temperatures are extracted from a two minute period of the mobile instrument that should correspond to closest
proximity to the Hobo station. There were 8 days of mobile campaigns that overlapped with the fixed campaign, and for each location the temperature differences each day between the 2 minute average (12 measurements) of the mobile instruments were compared to the nearest fixed instrument (3 minute intervals). In Figure 2-10 the average difference for each site is enveloped by thick lines representing one standard deviation on either side of the average, and thin lines representing the minimum and maximum difference.

![Figure 2-10 Differences between mobile and fixed campaign measurements of temperature. Differences shown for when mobile instruments pass by fixed locations. Green locations are co-located with mobile routes; red locations are generally 1 block north or south of the routes. Thick lines show 1 standard deviation on either side of the average (8 separate days), and thin lines show the maximum and minimum.](image)

We see from this comparison that the fixed instrument temperatures are generally about 1°C cooler than the mobile temperatures, despite the fact that in carefully controlled inter-comparisons they are identical. This is likely due to the difference in elevation: 1.5 meters above ground versus 3.5 meters for the fixed instruments. Such steep temperature gradients (5 times the adiabatic lapse rate - the theoretical limit for a stable atmosphere) are expected in the layer adjacent to solar heated surfaces, commonly seen in the afternoon (Cleugh and Grimmond, 2001). Though the shaded sides of streets where the measurements are made do not receive
direct insolation, mixing within the streets would produce a similar temperature profile. The large variation in these differences at each location indicates the magnitude of local variability. The two largest variabilities between instruments occur in stations one block away from the mobile routes, shown in red. The one degree difference between street level measurements and fixed station measurements is also seen in comparisons to the NYC MetNet data, which includes a collection of surface stations, many of them hobby stations mounted on rooftop. The diurnal cycle of variations between street level and fixed station data is of interest, and for this purpose a 24 hour campaign was built around a MetNet station on the Upper West Side near the Museum of Natural History. Six sets of measurements were made at fixed locations within two blocks of the station. For each measurement location the field worker would stand facing the sun (so the instruments on the back were in shadow), and collect data continuously for a 10 second average on either side of the street. Data was collected every two hours, a process of approximately 30 minutes. The winds were moderate, on the order of 3 to 5 m/s, with partially cloudy skies. The results are shown in Figure 2-11, with temperature and humidity used to calculate dew point. Station data for every 15 minutes is shown with a solid line, street measurements are crosses. The measurements began at 14:00 local time, with the hours wrapping around so that times above 24 hours are the next day. A warm front moved through at sundown (17:00 hours) on November 19, 2012, raising the dew point and holding nighttime temperatures steady until sunrise at hour 32 (8 am) the next morning. The street level data is generally a bit less than 1 degree warmer than the station data, with the greatest differences seen during rapid temperature changes, presumably due to the time it took to make the street level measurements. The dew points did not create such a consistent pattern between instruments, though at any given time the street measurements were nearly all either above or below the station data. The diurnal
consistency of the cooler elevated station suggests that the nocturnal temperature inversion common in rural areas may not hold for urban environments due to heat storage and nocturnal emission (Oke, 1982).

![NHM_19Nov2011 Station versus Street: Dewpoint](image)

**Figure 2-11** Street level measurements of Temperature, (a, top) and Dewpoint (b, bottom) compared to a station in the NYC MetNet system on Nov 19-20, 2011. Street measurements shown with crosses, station measurements by solid line. Data collected for 24 hours starting at 2 pm local time.

2.11 Measures and Causes of Variability

In Figure 2-9 we see that the difference between fixed stations (spatial variability) is several times larger than the temporal variability seen at each station. The attribution of these temporal variations to convection is supported by a diurnal variation that matches solar heating. The sun also affects spatial variability in temperature, which peaks when the sun briefly shines directly down the streets around 10 am in the morning (the instruments are normally in shadow); a corresponding afternoon peak is not seen perhaps because the air is well mixed by then. The temperature differences between mobile and fixed instruments in Figures 2-10 and 2-11 exhibit day to day variation that is related to that seen in Figure 2-9. The nature of this variability is evident when comparing mobile measurements on two days with similar meteorology. Figure 2-12 shows temperature deviations on 57th and 34th street on June 8 and June 29, 2012. Both days
had clear skies with WNW winds of about 3 m/s, and though June 29 was 8 degrees warmer we are only interested in the deviations from the average as shown. The most evident difference is the relative coolness of 57th street on June 29. We also see that the west end of 34th street is warmest on June 8, while the east end is warmest on June 29th. Since the surface environment has not changed (and there were no clouds), the only source of variation is the atmosphere. These moving hotspots most likely correspond to the convective structure of the atmosphere, and the distance between them of roughly 1 km corresponds to the typical scale of large convective eddies in the atmosphere that produce cumulus clouds. The idea that convective variation is captured in the mobile measurements is supported by comparison between variability seen in the mobile and fixed instrument data sets. The mobile dataset for each day contains variability caused by spatial variations in the surface environment, and by temporal variations in the atmosphere. The standard deviation calculated from the mobile measurements each day can be related to the spatial and temporal variations captured in the fixed instruments by assuming a linear combination of the variances:

$$(SD_{mobile})^2 = \sigma \cdot (SD_{spatial})^2 + \tau \cdot (SD_{temporal})^2$$ (2-4)

The coefficients $\sigma$ and $\tau$ are found by regression, which shows a correlation to spatial variability of 0.63 and to temporal variability of 0.35. Figure 2-13 shows that this vector combination of the two types of variability results in a better match to the mobile observations than either one alone. It should be noted that if the fixed Hobo instrument variability completely reflects the mobile instrument variability, the intercept must go to zero. This only happens when the two types of variability are combined. With temporal correlations nearly twice as large as spatial correlations, it’s reasonable to question whether local measurements are valid for wider regions. Before the field campaigns were launched, a test was made of the assumption that local measurements were
representative of conditions within at least a block radius. Most of Manhattan is on a grid with parallel streets a uniform 80 meters apart. The Vernier instrument pack described above was deployed simultaneously on 146th and 147th streets, which are similar residential tree-lined streets that descend from a park on a cliff overlooking the Hudson, traversing a gentle hill of 10 m altitude above the starting and stopping points. The results are shown in Figure 2-14, with a correlation between temperature datasets of 0.68 and correlation between RH datasets of 0.92. The rise in RH at the end may be due to an increase in tree cover on both streets. The sudden jumps in temperature in one dataset remain unaccounted for and may due to such things as proximity to pedestrians or other anthropogenic heat sources. Despite such irregularities, the correlations observed under the conditions of a one block separation were sufficient to justify a field campaign based on the techniques described in this paper.

![Figure 2-12 Variable temperature anomalies on two days with similar meteorology.](image)

*Figure 2-12 Variable temperature anomalies on two days with similar meteorology.* The color scale is the same as found in Figs. 2-6: 2-8.
Figure 2-13 Variability in mobile temperature measurements versus spatial and temporal variability in fixed Hobo instrumentation for 8 different days. Standard Deviations of the mobile instrument measurements are plotted versus: (Top) Hobo spatial variations. (Middle) Hobo temporal variations. (Bottom) Vector combination of Hobo spatial and temporal variations.

Figure 2-14 Pedestrian measurements made one block apart, moving in parallel

2.12 Data Availability

The data sets described in this paper are available online at http://glasslab.engr.ccny.cuny.edu/u/brianvh/UHI. The fixed Hobo instrument data sets are
available in their entirety, plus hourly averages and hourly calculations of temporal variability. Due to the large amount of quality control and the confounding effects of convective variability, the mobile Vernier data set is only available as average anomalies calculated over the two summers. This set should reflect persistent spatial features due to surface characteristics, so a collection of surface feature data is available in two forms: co-located with the anomaly data, and as separate gridded data sets. The data has been re-gridded to square latitude-longitude grids, and are described in Table 2-4. The surface cover data sets will continue to evolve, with the MODIS vegetation and albedo data being replaced by LandSat, and the NBSD data set being replaced by New York City building level data. Up to date and more detailed descriptions of how the surface feature data sets are being created will be found on the website. To get a feeling for the content of the data sets, the RGB Google Earth images of Figures 2-1 and 2-15 provides a visual estimate of albedo, and the elevation is shown beside it. The variation of surface cover is indicated in Figure 2-15, in which vegetation (NDVI) is shown in green, building area fraction is shown in blue, and building height is shown in red; all at 0.025 degree resolution (approximately 250 m). The mixtures of colors show variations in surface characteristics that will affect the persistent spatial anomalies of temperature.

The coarse resolution seen in Figure 2-15 will degrade correlations between surface features and temperature-humidity measurements. For this reason a higher resolution Landsat data set is being prepared for albedo and NDVI, and with improved building data is posted to the website.
Table 2-4 Current Surface Data sets

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<th>Resolution</th>
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<td>0.025 deg</td>
<td>MODIS satellite</td>
<td>Narrow to broadband conversion from visible and NIR</td>
</tr>
<tr>
<td>Vegetation</td>
<td>0.025 deg</td>
<td>MODIS satellite</td>
<td>NDVI: standard index calculated from red and NIR</td>
</tr>
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<td>Building Fraction</td>
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<td>National Building Statistics Database</td>
<td>Database of all major cities in USA, 250 m resolution</td>
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<tr>
<td>Building Height</td>
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<td>NBSD</td>
<td>See above</td>
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<tr>
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<td>USGS</td>
<td>US geological survey</td>
</tr>
<tr>
<td>Water Proximity</td>
<td>0.005 deg</td>
<td>Based on USGS</td>
<td>Fraction of water within 1 km2 centered on point. Water detected by elevations &lt; 0.2 m above sea level.</td>
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</table>

Figure 2-15 Composite of Building Height (Red), Building Area Fraction (Blue) and Vegetation index NDVI (Green) compared to a Landsat image of Manhattan. Low buildings with trees will thus appear blue-green; high buildings with vegetation will appear yellow.

2.13 Chapter Conclusions

The temperature and humidity dataset described in this paper is perhaps the highest resolution measurement of the street level structure of the UHI made to date. Nineteen sets of mobile
pedestrian measurements along Manhattan streets and thirteen along avenues over two summers were augmented by ten light-post mounted instruments recording every 3 minutes for 3 months. The novel approach of scaling anomalies by the standard deviation of the day each measurement was made tends to weight the effects of all meteorological conditions equally rather than favoring the extremes. Variability in the daily mobile street level temperature measurements can be separated into persistent local anomalies induced by surface characteristics and moving patterns attributed to convection. The contributions of each to the total variability can be estimated from the high temporal resolution measurements of the set of fixed instruments, separated into spatial and temporal variability. Statistical relationships between surface characteristics and temperature and humidity anomalies are explained in chapter 3 and 4, with the goal of relating the size of the anomalies to present and predicted meteorological conditions. Such a model is useful for predicting the fine structure of heat waves in the urban environment.
3  CHAPTER III: URBAN HEAT ISLAND ASSESSMENT WITH TEMPERATURE MAPS USING HIGH RESOLUTION DATASETS MEASURED AT STREET LEVEL

3.1  Chapter Summary

The impact of heat on human health has been subject of many studies showing that during extreme weather events, mortality increases in urban areas. Cities, such as New York, form heat islands all year round. Large scale environmental forcing can cause subdivisions of UHI throughout a city. The combined effects leads to the formation of hot pockets within the cities at micro-scale and it is difficult to pick out these physically defined regions using satellite remote sensing which has traditionally focused on regional and global scale. The highest spatial resolution available on an environmental satellite is 30 meters in visible and 60-100 meters in thermal infrared bands. The main challenge in using satellite data to study UHI in urban environment is the complexity of the system and lack of information on near surface air temperature in fine scale. This work consists of high resolution data sets measured at the street level in Manhattan, New York to produce temperature maps showing smallest hotspots which could not be identified using high resolution satellite. Data from two consecutive years of field campaigns at street level, plus various significant parameters that control temperature in an urban setting such as building height, building density, vegetation, water, elevation and albedo were used to create temperature maps using statistical model to locate hot spots in the system.

3.2  Chapter Introduction

The average global air temperature has increased by about 0.15°C per decade since 1970. More frequent and longer lasting heat waves are resulting from warmer climate. Some parts of the world are going to experience a larger increase in temperature than the global average in other places. The projected temperature increase by 2100 in the United States is about 4-11°C (IPCC,
2009) and it is projected to be 1°C to 4.6°C in 2050 (Knowlton, et al, 2007). Therefore, many states and especially metropolitan areas may expect to have more frequent and extreme heat events. The northeast has been witnessing climate-related changes such as more frequent days with higher temperature and rising sea surface temperature due to global warming. The northeast is projected to witness more warming and change in climate patterns which can easily alter the quality of life. These warming and increase in the frequency of heat waves can increase the intensity of UHI effect in NYC metropolitan area (IPCC, 2009; Horton et al, 2010). NYC is one of the most densely populated cities in the United States. Studies show that heat related deaths in NYC has been increasing over the past century and is expected to raise even higher (Kinney, et al 2008). The numbers of days with temperature exceeding 32-35°C are expected to increase which means 74 additional yearly heat related fatalities in Manhattan based on the 370 heat related deaths since 1980s (Knowlton, et al, 2007).

The urban climatic factors in Manhattan such as increase in temperature, humidity, wind and precipitation are caused by retain of heat in its buildings and pavements and lack of sufficient vegetation coverage. The typical surfaces of urban areas such as brick, concrete, asphalt and stone absorb a greater portion of short wave solar radiation than trees, grass and vegetation. The modification of land surface in New York metropolitan area causes radiative trapping in canyons and reduces the evapotranspirative cooling. Higher temperature at nights exists due to gradual release of heat from urban infrastructures. Therefore understanding urban microclimate, and finding ways to redesign cities and buildings is an important task in order to minimize the effect of a changing climate and reducing the UHI (Solecki, 2005). New York City is at particular risk from extreme weather conditions and heat waves because of UHI and an increase in regional temperature. Studies have shown that temperatures within Manhattan can vary by several
degrees centigrade from one area to next and patches of UHI exists throughout the city (Figure 3-1).

![Figure 3-1 Three-hourly average near-surface air temperature, June 8. Source: Meir, et al., 2013](image)

New York City's diverse population has millions of residents who are 65 years and older, many of which have respiratory illnesses and other risk factors that can increase their vulnerability during heat waves in summer time. New York City is used as case study in this research to develop a statistical model of UHI build up. This model is used to generate temperature maps for New York and other cities to prepare for extreme weather conditions and related fatalities. This study is an extension of a previous study (refer to Chapter 2) which explains the collection and processing of a dataset gathered for the purpose of studying the impact of UHI in an urban setting (Vant-Hull, 2014). The purpose of this study is to find the smallest (size and magnitude) UHI effect and map out hot spots in a densely populated city. In addition to categorize different land surface types and classes that can increase or decrease the impact of UHI, we aim to produce fine scale mapping of Manhattan to show temperature variation on underlying temperature of urban area considering local surface characteristics and UHI.
3.3 Chapter Literature Review

Even though UHI is portrayed in different ways, studies commonly focus on comparing urban air temperatures with rural temperatures (Oke, 1987). This comparison can be done by showing radiometric surface temperatures using remote sensing to reveal high temperature produced by urban environment impervious surfaces versus rural vegetated areas. In addition the comparison of urban vs. non-urban temperature differences can be shown by changes in spatial and time scales variations in New York City’s UHI intensity over time and space (Gaffin, et al, 2008).

Land surface temperature retrieval from satellite data has been widely adopted by researchers specializing in climatology since remotely sensed data became available on a regular basis. Even though remote sensing data is cheaper to get, it is not possible to get fine resolution data. The highest resolution available with remote sensing is 30 meters from Landsat satellite. Satellite imagery covers larger areas rather than detailed area which are needed for this study. A series of satellite and air borne sensors have been developed to collect the Thermal Infrared (TIR) data from the earth surface. It includes Landsat TM/ETM+, Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER), Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Along-Track Scanning Radiometer (AATSR). Satellite thermal data should be used with caution because it measures surface temperature, not air temperature. The two may come into equilibrium at night, but rarely during the daytime as the sun heats the surface (but not the air) directly. In the recent years remote sensing investigations of UHI have developed. The advent of satellite remote sensing technology has made it possible to study UHI both remotely and on continental or global scales (Streutker, 2002). Surface temperature (radiometric) maps produced using remote sensing can reveal the highs and lows of temperature caused by impervious urban surfaces and rural (vegetated) areas. Mapping impervious surfaces can relate to understanding the impact of UHI in metropolitan areas. The impact of impervious
surface such as commercial, residential, rural areas can be studied by acquiring satellite images of different seasons. MODIS satellite captures the land surface temperature and variations in surface heat island (Cheval, et al, 1997). MODIS produces instantaneous views at 1-KM resolution of Land Surface Temperature (LST). The surface temperature derived from MODIS can be used in investigating the spatial extension and the magnitude of the UHI in any urban/rural agglomeration (Cheval, et al, 1997). In images created with MODIS, some maps can generate a slightly better estimation and images of the impervious surfaces than other. For instance self-organizing maps (SOM) can cope with mixed pixel better and show accurate result in residential area than the multi-layer perceptron maps (MLP) (Hu and Weng, 2009). However, there is a limitation in the MODIS thermal data. In comparing UHI in urban versus rural, Pena examined the land surface temperature response of Santiago city between 1998 and 2005 using seven Landsat and ASTER images. Images produced by Landsat and ASTER where correlated with albedo, soil moister and vegetation cover for the region of study. Clearly, well vegetated land cover (rural) showed colder condition where as poorly vegetated urban area showed warming condition in satellite images (Pena, 2009). Landsat has the longest “continuous global record of Earth’s observations from space” since its launch in 1972 (Landsat Science, 2014). Its spatial resolution is detailed enough to characterize urban growth (Landsat Science, 2014). An inverse correlation between rural temperature and UHI magnitude was also found in remote sensing study of the UHI of Houston, Texas. With the purpose of characterizing the magnitude of UHI and determining the correlation between UHI magnitude and rural temperature, the radiative surface temperature maps were derived from satellite sensor. The result of the study found that the magnitude of UHI to be “inversely correlated with rural temperature” (Streutker, 2002). Weng examined land surface temperature patterns and their relationship with land cover
in Guangzhou, China and in the urban clusters in the Zhujiang (Pearl River) Delta, China (Weng, 2003). Recently, Weng et al utilized a Landsat ETM+ image (60 meters thermal infrared data) to examine the Land Surface Temperature (LST) vegetation abundance relationship in India-Napoli’s (Weng, et al, 2004). The results of his studies indicate that in estimating the impervious surface, vegetation phenology has a fundamental impact which can lead to less accurate estimation of impervious surfaces (Weng, et al, 2004). In cases where ground based and weather stations are not able to record the characteristics of urban/rural climate, satellite images can produce information on the geometry, magnitude and Land Surface Temperature (LST) of each and any location (Hu, 2009). In an attempt to reduce the impact of urban temperatures by dampening the UHI effect, a study was done in Beijing, China to find the relation between impervious surface and land surface temperature. In examining the effect of impervious surfaces spatial patterns on land surface temperature, the TM-thematic mapper images from Landsat for land surface temperature were retrieved to estimate the relationship between impervious surface and land surface temperature. A correlation coefficient of 0.94 was found between impervious surface fraction and the land surface temperature for the region of study using Landsat images (Xio, et al, 2007). Other studies used Landsat for examining the characteristics of land cover and land use in urban environment. Lu and Weng used Landsat ETM images to develop a model for characterizing urban land cover/land use in Indianapolis. The result of this study shows that classifying urban landscapes are very complex and often difficult due to the fact that typical compositions of urban landscapes are smaller than the spatial resolution of Landsat sensor. As result of that, a mixed pixel is created from different land cover types are contained in one pixel for an urban setting. This fact becomes a problem when dealing with the “effective use of remotely sensed data” (Lu and Weng, 2004). In another study remote sensing has been used for
soil classification and land use in sub-tropical region of Nanjing, China. The main purpose of the study was to survey the conditions of soil and use of land using remote sensing data. The classification of the soil type and land use was done on the Landsat data based on earth surface materials reflectance. Using maximum classifier, the surface materials were classified into seven classes. However, classification and training data is complicated and “it has been proved, that, within limitations, classification algorithms and threshold parameters have an important influence on the classification result and should be selected carefully based on the training area” (Ming et al, 1993). Remote sensing data are useful in classifying land surfaces; however these data must be combined with GIS data and land survey data/maps for best results.

3.4 Chapter Methodology

The walk campaign data collection was done during the summer of 2012 ad 2013 to measure temperature and relative humidity at the street level throughout Manhattan. The measurements were done using Vernier handheld devises with relative and temperature sensors. The sensors were deployed by foot simultaneously for measuring street level environmental conditions. The walks began at 2 pm each day and lasted 40-45 minutes. These measurements are high in spatial resolution and contain data from the hottest part of the day (datasets are explained in more details in chapter 2). Figure 3-2 shows the designated (Street vs. Avenue) routes and devices used for data collection. Detailed information on the duration/ design of the routes and data processing is available through the scientific paper “Fine Structure in Manhattan’s daytime UHI: a New Dataset” published by researchers at NOAA-CREST Institute, City University of New York (Vant-Hull, et al, 2014).
Figure 3-2 Designated street and avenue routes (Left). Schematic of handheld device and instruments attached (Bottom Right). (Top Right) Student carry instrument on bag pack (Top Right)

Figure 3-3 Inputs into the statistical model. Top left-right: Albedo (250m), elevation (50m), water (50m). Bottom left-right: building area (250m), NDVI (250m), building height (250m). Source: MODIS images
The parameters included in this analysis are albedo, building height, building area, Normalized Difference Vegetation Index (NDVI), elevation, and water. These parameters are chosen to see whether they have any impact on increasing or decreasing the UHI effect in different neighborhoods. NDVI is used to find the impact of vegetation in decreasing temperature as it is expected to feel lower temperature in/around vegetated area. The building height and density has been used to study the impact of built environment on surface temperature. The walk campaign data is correlated against the noted surface parameters to measure anomalies (calculated using the walk campaign data) to develop a surface atmospheric model. The data from walk campaign is analyzed and compared to Landsat data and available MetNet surface stations. This is to determine how measurement from walk campaign may differ due to their geographic location and land cover. A regression coefficient model is used to find the correlation between land surface parameter (figure 3-3) and temperature data measured by walk campaign instruments. Table 3-1 shows the results of calculated correlation and coefficient for surface variables and measured surface temperature for this model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation (Avenue Route)</th>
<th>Coefficient (Avenue Route)</th>
<th>Correlation (Street Route)</th>
<th>Coefficient (Street Route)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>-0.1870</td>
<td>-2.0931</td>
<td>-0.2695</td>
<td>-0.7810</td>
</tr>
<tr>
<td>Albedo</td>
<td>-0.2055</td>
<td>-7.3566</td>
<td>0.0940</td>
<td>3.0136</td>
</tr>
<tr>
<td>Area</td>
<td>-0.012</td>
<td>1.0699</td>
<td>-0.1297</td>
<td>-1.0938</td>
</tr>
<tr>
<td>Height</td>
<td>-0.1361</td>
<td>0.0074</td>
<td>-0.1386</td>
<td>-0.0048</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.0433</td>
<td>0.0046</td>
<td>-0.4760</td>
<td>-0.0234</td>
</tr>
<tr>
<td>Water</td>
<td>-0.1616</td>
<td>-1.4083</td>
<td>0.0991</td>
<td>-0.6704</td>
</tr>
<tr>
<td>Volume</td>
<td>-0.1412</td>
<td>-0.0611</td>
<td>-0.1114</td>
<td>0.0158</td>
</tr>
</tbody>
</table>

The impact of albedo and large water bodies in avenue routes and NDVI and elevation in street routes are important variables in reducing the surface and near ground temperature. The variables were scaled by standard deviations, but 1 standard deviation is approximately 1 degree
Centigrade, though it varies by day. By this the cooling effect of elevation works out to about 30 degrees per km, which is super-adiabatic. This is likely due to the fact that the surface is always warmer than the air during mid-afternoon, and higher elevations experience more wind.

3.5 **Classifying Surface Characteristics**

Understanding the different land surface type is important in understanding the impact of UHI since different land classes such as vegetation and large water bodies can reduce the surface and near ground temperature. Pena also proved that there is a strong correlation coefficient between land cover and UHI (Pena, 2009). To better understand the different land surface classes in Manhattan, a NDVI image is produced using Landsat 5 temperature map of May 1, 2010 to classify the surface at 30 meters resolution. This map is a simple indicator or green vegetation observed in Manhattan (figure 3-4). Then K-Means classification was applied to the unsupervised classification of the NDVI image to cluster the pixels into their nearest classes. Eventually the data are trained using supervised classification to cluster pixels into similar classes. A Supervised classification of this image shows the amount of urban, vegetation, barren land, and water body in figure 3-5 and total percentage of each class (figure 3-6).
Figure 3-4 Normalized Difference Vegetation Index (NDVI) image Source: LandSat 5TM. May 1, 2010

Figure 3-5 Manhattan’s Supervised Surface Classification (Red) Urban, (Blue) Water, (Yellow) barren Land, and (Green) vegetation, Source: LandSat 5TM. May 1, 2010
Most of Manhattan land surface is developed as urban. The total percentage of land cover classes in Manhattan simply explains why this city heat ups during summer and is affected by UHI all year around.
### 3.6 Chapter Result

Using the walking campaign data and surface characteristics, temperature estimation maps are produced. The avenue walks were in full sun while the street routes were shadowed during the time of the walks. The results and production of this work are temperature estimation maps for both sunny and shadowed sides of streets in Manhattan. These plots are based on regressions between average measured temperatures at street level and local surface characteristics such as albedo, elevation, NDVI, water fraction, building height, and building area fraction. A further improvement to the plots has been made through introduction of three modifications of building height, water fraction and NDVI. The building height modification was calculated as $H = 1 - \exp(-H/H_0)$. This was done so that the effect of height saturates with a scale factor of 10m. The water

![Figure 3-7 Mid-day Temperature Estimations Map](image)
fraction was done by calculating $W = W \times \exp \left( -\frac{E}{E_0} \right)$ where $E$ is elevation. The modification to water fraction was done to reduce its impact on higher elevations. The scale shows the number of standard deviations from the average, where the standard deviation is calculated from the temperatures measured throughout Manhattan for each day data was collected. In this figure yellow represents an average temperature; the red end is warmer and the blue end is cooler.

Figure 3-7 shows the temperature estimation maps based on walk campaign data. The left hand side figure show expected spatial temperature variations on the shady side of the streets. The right hand side figure shows expected spatial temperature variations along the avenue, which were generally in full sun. For both cases the scale shows the number/fraction of standard deviations from the average. In the shady side of the street walks shown in the left figure, the map captures some hot spots in east Harlem, west and east side of Manhattan in which the sunny avenues in the right map fail to do so. On the other hand the avenues side image captures the cooler temperature of central park and at the piers. Scatter hot spots are captured throughout Manhattan in mid-town and lower east side. In addition, warmer spots are shown around the piers and villages in the street map of Manhattan.

3.7 Chapter Conclusion

Clearly, the high resolution datasets of this study enables us to find subdivisions of UHI throughout Manhattan. Bigger hotspots are seen on the street side map while smaller and more scatter hotspots are shown in the avenue side map. Elevation seems to have a great impact on reducing the UHI. As seen in the two maps of figure 3-7 much cooling exists in the heights and central park with higher elevations in compared to the rest of the city. Sea breeze can explain the poorly modelled cooling in the downtown area. The model clearly predicts warm spots in the west side. The warming in the village is mostly caused by low buildings. The anomaly maps in
normalized amplitude use a weather forecast to predict the average and the amplitude of the anomalies. Even though past studies may have found the UHI in different cities, no study has been able to pinpoint subdivisions of UHI within an urban setting.

The intended end users for this research are the increasing population in the cities, officials in the city management, urban developers. The result of this work can be used to aid in both the improvement and development of current and new urban environments. Business and communities can also benefit from the result of this study by understanding the effects of urban structures on the UHI, strategic implementation of methods of heat mitigation which can be used in locations that are deemed to be at risk for high UHI effect in order to reduce the overall heating effect of cities. This will reduce the energy demands of buildings because occupants will no longer feel an extreme heat stress due to the urban setting, and will therefore require less air conditioning to keep them at comfortable temperatures. This in turn will allow both businesses and those living in the community to save money on electricity and reduce the strain of cooling urban environments on city power grids.

In addition reducing the additional heat gathered within urban centers will reduce the stresses felt by surrounding wildlife. One such stress is one experienced by surrounding aquatic wildlife. The excess heat within the urban environments can cause storm runoff to also be at increased temperatures. These waters then enter the aquatic environment and cause changes in temperature that negatively impact the wildlife. As such, mitigating UHI not only improves quality of life for those living within a city but also for its surrounding areas.

3.8 Implication and Application

The intended end users for this research are the increasing population in the cities, officials in the city management, urban developers as well as UHI modelers to factor in the surface temperature
fluctuations. The result of this work can be used to aid in both the improvement and development of current and new urban environments. Business and communities can also benefit from the result of this study by understanding the effects of urban structures on the UHI, strategic implementation of methods of heat mitigation which can be used in locations that are deemed to be at risk for high UHI effect in order to reduce the overall heating effect of cities. This will reduce the energy demands of buildings because occupants will no longer feel an extreme heat stress due to the urban setting, and will therefore require less air conditioning to keep them at comfortable temperatures. This in turn will allow both businesses and those living in the community to save money on electricity and reduce the strain of cooling urban environments on city power grids. In addition reducing the additional heat gathered within urban centers will reduce the stresses felt by surrounding wildlife. One such stress is one experienced by surrounding aquatic wildlife. The excess heat within the urban environments can cause storm runoff to also be at increased temperatures. These waters then enter the aquatic environment and cause changes in temperature that negatively impact the wildlife. As such, mitigating UHI not only improves quality of life for those living within a city but also for its surrounding areas.

The next chapter presents an Exploratory model to predict temperature variability from the weather forecast, using field campaign measurements explained in chapter 2 and three months of model weather analysis data output.
CHAPTER IV: PREDICTING SURFACE TEMPERATURE VARIATION USING REAL-TIME WEATHER FORECASTS

4.1 Chapter Summary

High densely populated cities are experiencing Urban Heat Island (UHI) effects and localized hotspots. The inverse effect of UHI in big cities ends is higher number of emergency hospital admissions and heat related illnesses. Studying UHI effect and temperature variations within cities becomes even more important when global earth temperature is on the rise. To better understand UHI within Manhattan island in New York, an exploratory study was done using three months of a field campaign study data to measure high resolution (3m above the ground) spatial and temporal temperature variations within Manhattan’s urban setting. These high time resolution temperature measurements and three months of weather model analysis data output of temperature and relative humidity were used to predict temperature variability from weather forecasts. The main goal of this work was to find correlation between independent weather variables and near surface air temperature. Results show that the amplitude of spatial and temporal variation in temperature within a city for each day can be predicted by regression of weather variables.

The amplitude of spatial variations was most dependent on temperature with calculated correlation r of 0.4, and low level lapse rate with correlation of 0.258. Temporal variations were most dependent on low level lapse rates (r of 0.36) and mid-level lapse rate (r of -0.32). This study puts the attention toward high resolution near surface air temperature analysis and offers a new look at surface thermal properties. The application of this study is most suitable for forecast modelers studying the impact of weather and microscale climate on near surface air temperature using weather variable.
4.2 Chapter Introduction

UHI effects or local hotspots are common phenomenon experienced in urban settings. These concentrated areas of elevated temperature “represent one of the most significant human–induced changes to Earth’s surface climate” (Zhao, et al., 2014). UHI is caused by lack of evapotranspiration, waste heat produced by air conditioning, industries and vehicles, air pollution and radiative trapping due to land surface modification in cities (Oke, 1982). This phenomenon leads to increase in air and surface temperature in urban centers and convection of heat from surface temperatures into the lower atmosphere. Local climate can impact UHI, which can alter convection patterns, and so statistical models of local climate/weather may help create forecast models for predating temperature variations at surface level (Zhao, et al., 2014). A number of heat transfer mechanisms that vary throughout a city, can cause variations in air temperature. For instance, absorption of sunlight will vary by albedo and shading due to building materials and geometry. Infrared radiation is absorbed and re-radiated by surrounding structures, so that variations in exposure to the sky (sky view fraction) will cause variations in radiation cooling. These factors affect surface temperature, which is transferred to the air depending on wind flow. More exposed areas will have both more radiation cooling as well as faster wind flow, so that the heat transfer per volume of air is less, leading to cooler air temperatures. Note that weather variables may have dual effects: higher wind may result in greater air temperature contrasts between exposed and sheltered areas while mixing air between areas. Cloud cover will produce less variation due to solar heating, yet less variation due to infrared cooling.

The U.S. EPA Climate Change Indicators report released its’ extreme heat section statement of May 2014 specifying that “the number of increased heat-related deaths in the future is going to be greater than the number of reduced cold-related deaths” (2014). “Heat is the number one
weather-related killer in the U.S. alone” (EPA, 2014). Profound impacts of UHI are seen on the lives of those who reside in cities (Zhao, 2014). Hotter days are associated with serious health impacts, heart attacks and respiratory and cardiovascular diseases (Kenward, et al., 2014). In studying UHI effect understanding inner city temperature variations are important because health impacts are a sensitive function of temperature (Kinney, et al., 2008), so temperature variability within a densely populated area can have large effects. Extreme climate events are predicted to increase in number, duration, and frequency with on-going climate change (Astrom, et al., 2011). In recent decades, several devastating heat waves have caused large health consequences across the globe. For example, the 1987 heat wave caused around 2000 deaths in Athens; the 1995 Chicago heat wave caused around 700 deaths; and the 2003 heat wave in Europe was estimated to have caused 70 000 deaths (Katsouyanni, et al., 1988; Semenza, et al., 1996).

Densely populated cities like Manhattan can be affected by the impact of UHI much more than less populated cities. Urbanization increases “the diurnal minima and the daily means in all seasons” (Karl, et al., 1988). Manhattan lacks evaporative cooling from vegetation and moist soil and retains heat with its buildings and pavements which causes radiative trapping in canyons. The typical physical features of Manhattan’s land surface and its mixture of land cover reacts differently with UHI and causes smaller islands of urban heat throughout the city (Grimmond, 2007). As the impact of UHI increases so does the health risks of heat wave. Even though many studies have been focused on the impact of UHI and temperature changes between urban and rural air temperature, not many look at the temperature variations within a city. These studies mostly use remote sensing data such as MODIS, Landsat and Aster or typical measurements collected by local meteorological station networks. Satellite data only register daytime surface temperature and are low in resolution in compared to local measurements data. Satellite imagery
mostly covers larger ranges of study area and cannot be used for smaller regions like Manhattan which is only about 60 km2 in size.

In local meteorological study, mobile traverses measured temperature variations within a town in Hungary four hours after the sunset to find the impact of UHI. In regression of its measured temperature against building fraction, water fraction, and sky view fraction correlations of 0.8 to 0.9 were calculated based on the season. Ho, et al (2014) used 60 weather stations in the Vancouver area to develop a model for air temperature given sky view fraction, vegetation, elevation and solar radiation. Comrie (2000) mapped the heat island of Tucson Arizona using mobile instruments, and attributed most inner city temperature variability to cool air drainage from the mountains. Eliasson (1996) was able to predict the differences in temperature between two urban locations (open and urban canyon) based on regression of weather variables. A study using a combination of mobile and fixed instruments in Granada mapped the structure of the heat island and noted how the amplitude decreased with wind speed and cloudiness (Montavez, et al., 2000).

Whereas all previous studies of the evaluation of UHI variability have only focused on urban and rural air temperature, the current study will uniquely look at spatial and temporal variation in temperature within a city using weather forecast. Eventually this work will lead to a model that could predict the air temperature and variability within a city based on the weather factors.

4.3 **Methodology**

HOBO Micro-Station Data Loggers (Onset Product #: H21-002) which consist of relative humidity and temperature sensors were installed inside white instrument shelter boxes and mounted 3-4 meters above ground on lampposts at ten different predetermined stations throughout the island of Manhattan. Data was taken, starting June 23, 2013, in three minute
intervals for the entire period of the study, ending September 20, 2013. Figure 4-1 show the maps locations of all ten stations (left), sensors (center), and the equipment mounted on a lamppost (right).

![Figure 4-1 Station Locations, Instrument and Instrument Housing](image)

The locations of the shelters were picked based on street routes from a previous study “with locations selected to capture the range of variability noted in the walking campaigns of 2012” (Vant-Hull, et al., 2014). The first station located at 63A Reade Street (South side of the street), the second located at 118 Prince Street (North side), the third station located at 140 E. 14th Street (South side), the fourth located at 146 E. 35th Street (South side), the fifth located at 114 E. 57th Street (South side), the sixth located at 348 W. 57th Street (South side), the seventh located at 211 Central Park West (East side), the eighth located at 346 E. 120th Street (South side), the ninth located at 150 W. 120th Street (South side), and the tenth located at 300 W 145th Street
(South side). Further information regarding descriptions of the areas of which each station was located is available in Table 4-1.

Table 4-1 Physical Description of Areas Surrounding Stations

<table>
<thead>
<tr>
<th>Station #</th>
<th>Street Description</th>
<th>Latitude (N)</th>
<th>Longitude (W)</th>
<th>MSL (m)</th>
<th>AGL (m)</th>
<th>B-Avg. Fraction</th>
<th>B-Avg. Height (m)</th>
<th>Sky View</th>
<th>NDVI Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17 m wide, no trees</td>
<td>40.71497</td>
<td>74.00659</td>
<td>9</td>
<td>3.7</td>
<td>0.94</td>
<td>46</td>
<td>0.06</td>
<td>0.12</td>
</tr>
<tr>
<td>2</td>
<td>13.5 m wide, no trees</td>
<td>40.72513</td>
<td>73.99974</td>
<td>7</td>
<td>3.4</td>
<td>0.74</td>
<td>28</td>
<td>0.28</td>
<td>0.11</td>
</tr>
<tr>
<td>3</td>
<td>27 m wide, few trees</td>
<td>40.73353</td>
<td>73.98815</td>
<td>11</td>
<td>3.9</td>
<td>0.65</td>
<td>42</td>
<td>0.35</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>18 m wide, some trees</td>
<td>40.74618</td>
<td>73.97871</td>
<td>14</td>
<td>3.1</td>
<td>0.66</td>
<td>40</td>
<td>0.34</td>
<td>0.02</td>
</tr>
<tr>
<td>5</td>
<td>33 m wide, some trees</td>
<td>40.76123</td>
<td>73.96993</td>
<td>14</td>
<td>3.4</td>
<td>0.59</td>
<td>71</td>
<td>0.41</td>
<td>0.20</td>
</tr>
<tr>
<td>6</td>
<td>32 m wide, many trees</td>
<td>40.76747</td>
<td>73.98488</td>
<td>25</td>
<td>3.5</td>
<td>0.57</td>
<td>70</td>
<td>0.42</td>
<td>0.13</td>
</tr>
<tr>
<td>7</td>
<td>15 m wide, in trees</td>
<td>40.78233</td>
<td>73.97137</td>
<td>30</td>
<td>3.3</td>
<td>0.66</td>
<td>51</td>
<td>0.34</td>
<td>0.25</td>
</tr>
<tr>
<td>8</td>
<td>31 m wide, many trees</td>
<td>40.79877</td>
<td>73.93413</td>
<td>3</td>
<td>3.5</td>
<td>0.10</td>
<td>4</td>
<td>0.96</td>
<td>0.04</td>
</tr>
<tr>
<td>9</td>
<td>21 m wide, many trees</td>
<td>40.80534</td>
<td>73.94968</td>
<td>8</td>
<td>3.1</td>
<td>0.70</td>
<td>25</td>
<td>0.33</td>
<td>0.34</td>
</tr>
<tr>
<td>10</td>
<td>28.5 m wide, some trees</td>
<td>40.82298</td>
<td>73.94274</td>
<td>9</td>
<td>3.3</td>
<td>0.63</td>
<td>22</td>
<td>0.40</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Table above: Descriptions include the side of the street, width from building to building, and trees: “few”=unlikely to affect temperature, “some”=may affect if wind blowing through, “trees”=wind will always blow through, but instrument has some sky fraction, “in trees” = no sky view through trees. “B avg Frac” = average building fraction in 100 m square in which instrument is located. “B avg height”= average building height in meters in which instrument is located, empty space excluded. The sky view fraction is estimated from the building parameters.

The sky view fraction is estimated from the building parameters and was calculated using Gladt and Bednar’s new method (2013). NDVI is the average of 3x3 Landsat pixels centered on the instrument, with negative values set to zero. The zero vegetation offset is near 0.1 but varies with background, hence the NDVI is not adjusted by the offset. NDVI is calculated using two
satellite bands and is measured as NIR-RED divided by NIR+ RED. The values drop between -1 to +1 by taking a ration of two bands (Zhang, et al., 2006; Voogt, et al., 2003). The zero vegetation offset is near 0.1, but varies with background, so the NDVI is not adjusted by the offset. Due to high near infrared and low visible reflectance, vegetation areas yield positive values while water and clouds yield negative index values with soil resulting in near zero values.

This study focused on midafternoon temperatures of 1500 LT and considered the spatial and temporal variabilities that could affect weather predictions (July 7 and 15 data were removed from the datasets due to wet ground caused by rain during 1400-1500 LT (= 2000 GMT)). The spatial variability represents differences in temperature due to surface features alone. The temporal variability represents local changes in temperature caused by convection and perhaps mechanical turbulence plus temporal variability of large scale weather patterns.

The related field campaigns with portable instruments recorded spatial variability across all axes which was attributed mainly to changes in elevation and vegetation (Karimi et al, 2015). Any regional gradient in temperature is not immediately apparent on this scale (10 km). Manhattan is small compared to large scale weather patterns, so we assume all instruments are exposed to the same weather variables. The diurnal patterns of variability in temperature were reported in Vant-Hull et al, 2014. These large- slower changes in temperature were filtered out of the calculation of temporal variability by use of a running average to define fluctuations in temperature. In an exploration of how weather is related to the diurnal cycle of inner city, temperature variability was left for a later and much longer study.

In processing the campaign datasets, the spatial temperature standard deviation ($\sigma_s$) was calculated by averaging the data for each hour at every location to eliminate the convection variation. The $\sigma$ of all 10 stations’ hourly averages was calculated to get $\sigma_s$. The temporal
variation for each hour was calculated by first finding the difference between the temperature at each three minute interval and one hour running average then calculating the temporal standard deviation ($\sigma_T$) of these differences over a one hour period.

The NYC MetNet website from the Optical Remote Sensing Laboratory of the City University of New York contains National Digital Forecast Database (NDFD) data and National Oceanic and Atmospheric Administration (NOAA) forecast for many stations throughout NYC. Weather variables that relate to the amplitude of fine scale temperature anomalies include temperature ($T$) Celsius, relative humidity (RH%), Eastward wind speed ($v$), Northward wind speed ($u$), and lapse rate (LR) from the North American Model Reanalysis data set archived by the National Climatic Data Center (available every three hours with a 40 km resolution and a vertical resolution of 25 millibar near the surface (roughly 250 meters)). Low-Level LR (LLLR) is the slope of change in temperature with sea level height ($dT/dH$) at atmospheric pressures between 975 and 950 millibar grams (mbg) and temperature differences between 975 and 950 mbg. Mid-Level LR (MLLR) is the slope of change in temperature with sea level height ($dT/dH$) at atmospheric pressures between 950 and 925 mbg and temperature differences between 950 and 925 mbg. Other variables affecting temperature include cloud fraction (CF), $V$-total ($V$), which is the vector magnitude of $u$ and $v$, and evaporation rate (ER) calculated as $(V)(1-RH/100)$. ER does not include soil moisture or other transpiration factors such as light.

The same weather variables were correlated with the $T\sigma$. In comparing the correlation of the weather variables to the $\sigma_S$ and $\sigma_T$, it can be determined which variables can have more effect on spatial and temporal variability.
4.4 Chapter Results and Discussion

Coefficients were first calculated using linear regression equation (1) for each variable.

Calculated coefficients from first equation were used to regress spatial and temporal values with weather station data using equation 2.

The statistical quantities in table 4-2, 4-3 and 4-4 were calculated using the data from all sites and the two formulas below:

\[\text{Coefficient} = \text{Regress}(X, Y, yfit=yreg, \text{Const}=T0, \text{Corelation}=\text{Correlation}, Ftest=fvalue) \quad (1)\]

\[\text{Temp regress} = \text{const} + a0x0, i + a1x1, i + \ldots + aNterms\cdot xNterms\cdot i, I \quad (2)\]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (f)</th>
<th>Correlation (r)</th>
<th>Correlation (r^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.014</td>
<td>0.400</td>
<td>0.16</td>
</tr>
<tr>
<td>RH</td>
<td>0.002</td>
<td>-0.163</td>
<td>0.026569</td>
</tr>
<tr>
<td>v</td>
<td>-0.017</td>
<td>-0.165</td>
<td>0.027225</td>
</tr>
<tr>
<td>u</td>
<td>0.000</td>
<td>0.145</td>
<td>0.021025</td>
</tr>
<tr>
<td>CF</td>
<td>0.000</td>
<td>0.110</td>
<td>0.0121</td>
</tr>
<tr>
<td>Mid-Level LR</td>
<td>6.085</td>
<td>-0.156</td>
<td>0.024336</td>
</tr>
<tr>
<td>Low level LR</td>
<td>-11.068</td>
<td>-0.258</td>
<td>0.066564</td>
</tr>
<tr>
<td>V</td>
<td>-0.009</td>
<td>-0.038</td>
<td>0.001444</td>
</tr>
<tr>
<td>ER</td>
<td>0.024</td>
<td>0.069</td>
<td>0.004761</td>
</tr>
</tbody>
</table>

The result of Calculated Correlation Between \(\sigma_S\) and weather variables show the highest correspondence with T \((r=0.400)\) followed by LLLR \((r=-0.258)\). All other variables have values below 0.100 and show very low significance in predicting \(\sigma_S\) using weather forecast. However they are included in the regression since a variable negatively correlated with another variable
can cancel out variations that do not affect the first variable. The results of the correlation between $\sigma_T$ and the weather variables can be seen in Table 4-2.

**Table 4-3 Calculated Correlation between $\sigma_T$ and Weather Variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (f)</th>
<th>Correlation (r)</th>
<th>Correlation ($r^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.003</td>
<td>0.398</td>
<td>0.158404</td>
</tr>
<tr>
<td>RH</td>
<td>-0.000</td>
<td>-0.309</td>
<td>0.095481</td>
</tr>
<tr>
<td>$v$</td>
<td>0.004</td>
<td>0.154</td>
<td>0.023716</td>
</tr>
<tr>
<td>$u$</td>
<td>-0.001</td>
<td>0.019</td>
<td>0.000361</td>
</tr>
<tr>
<td>CF</td>
<td>-0.000</td>
<td>-0.120</td>
<td>0.0144</td>
</tr>
<tr>
<td>Mid-Level LR</td>
<td>-3.753</td>
<td>-0.320</td>
<td>0.1024</td>
</tr>
<tr>
<td>Low level LR</td>
<td>-2.845</td>
<td>-0.361</td>
<td>0.130321</td>
</tr>
<tr>
<td>V</td>
<td>0.001</td>
<td>-0.119</td>
<td>0.014161</td>
</tr>
<tr>
<td>ER</td>
<td>-0.003</td>
<td>-0.031</td>
<td>0.000961</td>
</tr>
</tbody>
</table>

From the weather variables in table 4-3; T, LLLR, MLLR, and RH show the highest correlation calculated with $r$= 0.398, -0.361, -0.320 and -0.309, respectively. With T, LR, and RH having high single-variable correlations to the T variation, strong effects on temporal variability can be assumed. LRs have a large effect on the temporal variability probably because it represents convection, and more negative lapse rates should result in greater convection. Winds can lead to more cooling in high elevations. It can be speculated that the reason the winds increase the $\sigma$ rather than decrease it by mixing is due to elevation effects: higher elevations were more exposed to wind. Since this study was done in the afternoons, the surface temperatures were higher than the air temperature so areas with more wind exposure were cooler than sheltered areas in which the air temperature came closer to equilibrium with the surface temperature.

The correlations calculated in table 4-2 and 4-3 are not necessarily the same sign as the linear regression coefficients. This is mostly caused by cross correlations, such as an increase in cloud fraction with relative humidity. The $v$, with a much higher correlation value has a larger
influence than u on spatial temperature variability which might be due to the eastern component being larger than the northern component. It is not clear why RH has a strong negative effect on temporal variability. It would seem higher RH would stimulate clouds and convection with higher variability, but the effect was opposite of the expected. This may be due to evaporative cooling, but then it was expected it to have similar impacts on both spatial and temporal variability. The variable $\sigma_{T0}$ is the expected standard deviation in temperature when all weather variables were set to zero. Calculated $\sigma_{T0}$ for spatial variable is -4.038 and for temporal is calculated at -0.935 which may reflect the larger dependence of the spatial variability on temperature, which always has a high value in the summer.

To further see the patterns between the weather variables and spatial and temporal variability, the regressed relationships were graphed (Figs 4-2 and 4-3).

![Figure 4-2 Weather Variables Regressed against Variability for $\sigma_S$. Each circle represents the standard deviation of observed temperature values vs. simulated values.](image-url)
In fig 4-2 and 4-3, each circle represents the σ of observed temperature values vs. simulated values. Deviation from the trend line represents the points where there is less agreement between observed values of temperature and simulated values. It can be noted that there is a great difference in slope between the temporal and spatial graphs. The multiple-variable regression coefficients for σ₅ and σ₇ were calculated as 0.541 and 0.501 and can be seen in the graphs as the range of predictability that the model can have for a given weather conditions. It is also noted that the spatial variability at a level of three or four meters above the ground is as much as ¼ the variability at a typical human trunk height of one and half meters (Vant-Hull et al, 2014), due to the steep temperature gradient in air temperature near the surface. The temperature variations shown in the plots above therefore underestimate the temperature variability seen by pedestrians. This shows that the weather forecasts exhibit moderate skill in predicting spatial and temporal temperature variability within cities.

To further analyze the relationship, the correlations and coefficients of the weather variables to temperature differences between the high and low stations were calculated (table 4-4). This was
done to study the impact of winds on the variation of temperature between the lowest (57St West) and highest (120St West) streets stations. The trend line in fig 4-4 shows a moderate correlation between the values. In testing for the importance of wind and impact of variation in temperature between the two stations, elevation plays an important role in the cooling effect of the area.

Figure 4-4. Weather Variables Regressed Against Variability in Differences between Highest and Lowest Elevation Stations. Each circle represents the standard deviation of observed temperature values vs. simulated values

To further analyze the relationship, the correlations and coefficients of the weather variables to temperature differences between the high and low stations can be seen in Table 4-4.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (f)</th>
<th>Correlation (r)</th>
<th>Correlation (r²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>0.067</td>
<td>0.471</td>
<td>0.221841</td>
</tr>
<tr>
<td>RH</td>
<td>0.011</td>
<td>-0.134</td>
<td>0.017956</td>
</tr>
<tr>
<td>v</td>
<td>0.012</td>
<td>0.186</td>
<td>0.034596</td>
</tr>
<tr>
<td>u</td>
<td>0.025</td>
<td>0.278</td>
<td>0.077284</td>
</tr>
<tr>
<td>CF</td>
<td>-0.003</td>
<td>-0.047</td>
<td>0.002209</td>
</tr>
<tr>
<td>Mid-Level LR</td>
<td>-15.315</td>
<td>-0.106</td>
<td>0.011236</td>
</tr>
<tr>
<td>Low level LR</td>
<td>-41.859</td>
<td>-0.216</td>
<td>0.046656</td>
</tr>
<tr>
<td>V</td>
<td>-0.001</td>
<td>0.018</td>
<td>0.000324</td>
</tr>
<tr>
<td>ER</td>
<td>0.024</td>
<td>0.076</td>
<td>0.005776</td>
</tr>
</tbody>
</table>

There is a clear correlation to T. The magnitude of u and v, and the lapse rates are elevation dependent. The calculated r for each one of these variables are 0.471, 0.278, 0.187 and -0.216, respectively. This indicates that the winds play an important role in causing changing temperatures within Manhattan, with more cooling at higher elevations. It’s not clear why the total wind has such a low correlation to the temperature differences with elevation; it may be due to topographical effects producing large changes with direction, as seen in the factor of two difference between linear coefficients of the north and east winds.

Other factors that can change temperature gradient within the island of Manhattan are winds. The island is mostly affected with low winds of northwest and southeast direction. To better understand the impact of winds or no winds on temperature gradient in Manhattan, summer images of temperature distribution affected by winds are shown in figs 4-5 and 4-6. The images were taken from NYC Metnet network.
Figure 4-5 NYC MetNet Average Normalized Temperatures Compared to Single Blue (-2 to -1), green (-1 to 0), orange (0 to 1), and red (1 to 2). (Top left) shows a single day with no wind and a clear temperature gradient, (top right) shows Summer temperature averages with no wind, (bottom left) shows Summer temperature averages with wind coming from the North-Northwest direction, and (bottom right) shows Summer temperature averages with wind coming from the South-Southeast direction.

In fig 4-5, four different images are showing temperature trend impacted by local wind patterns. The points highlighted in green shows cooling effect and red shows warming effect. A clear temperature gradient can be seen on days with no wind for top right and left images. The bottom two left and right images with summer temperature averages and winds show less temperature gradient throughout Manhattan. The winds help reduce the temperature gradient inland. Similar to the previous image, fig 4-6 shows NYC MetNet images of temperature gradients impacted with winds. Low winds help reduce the temperature gradient and more of a unified temperature can be seen in top left figure. On days with no wind temperature gradient is noticeable in top right and two bottom images.
The analysis clearly shows that Manhattan is mostly affected by low winds of less than 1 m/s, and winds that blow from either north or south of the island. Manhattan is small compared to large scale weather patterns, so we assume all instruments are exposed to the same, if not extremely similar weather variables. The diurnal patterns of variability in temperature were reported in Vant-Hull, et al., 2014. These larger, slower changes in temperature were filtered out of the calculation of temporal variability by use of a running average to define fluctuations in temperature. An exploration of how weather is related to the diurnal cycle of inner city temperature variability is left for a later and much longer study.
4.5 Chapter Conclusion

There are a number of heat transfer mechanisms that will vary throughout a city, causing variations in air temperature. Absorption of sunlight will vary by albedo and shading due to building materials and geometry. Infrared radiation is absorbed and re-radiated by surrounding structures, so that variations in exposure to the sky (sky view fraction) will cause variations in radiation cooling. These factors affect surface temperature, which is transferred to the air depending on wind flow. More exposed areas will have both more radiation cooling as well as faster wind flow, so that the heat transfer per volume of air is less, leading to cooler air temperatures. Note that weather variables may have dual effects: higher wind may result in greater air temperature contrasts between exposed and sheltered areas while mixing air between areas. Cloud cover will produce less variation due to solar heating, yet less variation due to infrared cooling. The regressed relationships between weather variables and the spatial and temporal variabilities can be used to predict variability in given conditions and model the effects that specific variables can have on the variability.

This exploratory study helps to better understand UHIs effect within NYC using a field campaign temperature measurements. The high resolution temporal and spatial temperature measurements calculated using field campaign data was correlated with weather model data to predict temperature variability within NYC. The amplitude of spatial variations was most dependent on temperature (r= 0.400) and low level lapse rate (r= -0.258) while temporal variations were most dependent on temperature (r= 0.398), RH (r=-0.309) low level lapse rates (r=-0.361), and mid-level lapse rate (r= -0.320). Regression of weather variables can be used to predict the amplitude of spatial and temporal variation in temperature within a city for each day. Based on the finding is this study it can be noted that temperature, wind, and elevation dependent
lapse rate had the most influence on the variability predictions. Winds can increase spatial variations in temperature, and our evidence links this to elevation differences. Lapse rates have a large effect on the temporal variability probably because it represents convection, and higher lapse rates should result in greater convection.

This study puts the attention toward high resolution near surface air temperature analysis and offers a new look at surface thermal properties. This study shows that near surface air temperature is highly variability and new datasets are needed to address this in future modeling and applications. Urban developers and modelers can use this study to factor in the impact of local weather and microclimate on variation of temperature in highly dense populated cities in both improving current infrastructure and future projects for reducing energy consumption and cooler cities.
5 CHAPTER V: A CONCEPTUAL FRAMEWORK FOR ENVIRONMENTAL RISK AND SOCIAL VULNERABILITY ASSESSMENT IN COMPLEX URBAN SETTINGS

5.1 Chapter Summary

High numbers of weather-related mortalities are associated with extreme heat events in the United States. Heat island pockets are linked to higher risks of heat related illnesses and heat stroke. Satellite data confirms that the increased urbanization leads to increased temperatures within microclimates. The goal of this study was to examine the influence of different surface types on the impact of UHI by looking at consistent physical properties of the urban system through a framework to highlight environmental and social vulnerabilities. Therefore, a quantitative study was completed analyzing satellite imagery of the five boroughs of New York NYC. A conceptual model was developed using LST Landsat data, data from department of building, sociodemographic census data and physical aspects of built cities. The factors of interest include people, environment, and building/infrastructure.

The aim of this study was not only to map vulnerable population based on their socioeconomic status and age but also to identify primary land surface characteristics that play a stronger role in developing UHI effect in cities for intervention guide of heat mitigation. This model quantifies risk as a function of temperature and other variables discussed in this dissertation.

Results show, neighborhoods of Manhattan, Queens and Bronx are at the highest risk of social and environmental vulnerability and should be targeted for policy changes, implementation of green infrastructures and vegetation coverage to counteract the heating effects. Neighborhoods which need to be targeted for urban planning due to high environmental risk are Harlem, Upper Manhattan, East Harlem, Elmhurst, Jamaica, Ridgewood, Flatbush, University height and Woodlawn.
5.2 **Chapter Introduction**

UHI reflects an elevated temperature in cities as compared with nearby rural areas which is due to landscapes changing from permeable moist surfaces to impermeable and dry surfaces (EPA, 2015). This phenomenon is most prevalent in large cities like NYC in which the surface type is mainly impermeable concrete. UHI is most predominant in metropolitan cities, which consist of dense buildings, sidewalks and mix use neighborhoods (commercial and residential). The preliminary statistical analysis of a study done to measure the impact of UHI in Manhattan using high resolution data sets indicates that “higher buildings have a cooling effect in streets, while in the sunny avenues higher buildings have a warming effect”(Vant-Hull, et al, 2014). Another study also helped predict subdivisions of UHI throughout Manhattan using weather campaign data to “find the smallest UHI effect and map out hot spots in a densely populated city, by understanding different land surface types and classes” which can increase or decrease the impact of UHI (Karimi, et al, 2015). Human thermal comfort is at risk when higher levels of ambient temperature are felt. In this study and many studies Land surface Temperature (LST) measurements from Landsat are used to measure the impact of UHI on urban environment and human health. Even though LST is not “directly equivalent to ambient air temperature”, it gives information on “thermal inertia of surface characteristics” by tracking changes of LST in the morning and the afternoon in cities (Johnson, et al, 2009). Even though the exact relationship between LST and ambient air temperature is not certainly clear; Johnson, D, et al (2009) and Tomlinson, C, et al (2011) suggested that LST can also contribute to human discomfort while heat waves occur and as result remote sensing data are useful for such studies (Johnson, et al, 2009; Tomlinson, et al, 2011).
Manik et al (2015) found “land use patterns and land use cover” as the strongest drivers of urban temperature. From few of the land surface characteristics; building height and building density can also add to increasing ambient air as they reradiate the heat back to air. Wolf et al (2013), Tomlinson et al (2011), Loughn et al (2012) find building height to be the most important factor behind UHI effect. Higher building heights with high building density causes a greater insulation effect than if there was a low building density with high building heights. Building density provides the proximity of buildings within a region which when related to building height and population greatly influences risk. Similarly, a greater negative effect can be expected with high building density and high population. Income and socioeconomically status can as well affect the health and wellbeing of people. Johnson et al (2009).

Few factures can amplify human vulnerability to heat such as the environment, infrastructure, social and economic status, age and exposure and sensitivity level. Rosenthal (2010) evaluated the “impact of the urban heat island on public health” as a “spatial and social determinants of heat-related mortality in New York City”. Highest numbers of mortality were among neighborhoods that had lived in “poor housing conditions, poverty and impervious land cover” (Rosenthal, 2010). Other studies touched on social, biophysical and environmental factors than influences human comfort (Cutter, et al 2003; Few, 2007; Reid et al, 2009; Stafoggia et al, 2008 and Vescovi et al, 2005). For the purpose of this study, New York was investigated for a relationship between building and infrastructure, nature, and people. The hope is to correlate these factors so regulations will change accordingly for the health of people in urban areas. The optimum locations of study are the areas where people who are most susceptible to heat-related mortality live. A conceptualized model has been designed to find common heat pockets that form over the city of New York while it targets populations that are at higher risks of susceptibility by
analyzing 11 years of Landsat satellite data and combined socioeconomic and environmental variable such as: build height, building density, vegetation index and temperature. The model is used to map and project population vulnerability to heat in NYC.

The goal of this study is not only to map vulnerable population based on their socioeconomic status and age but also to identify primary land surface characteristics that play a stronger role in developing UHI effect in cities for intervention guide of heat mitigation.

5.2.1 Impacts of UHI on Human Health

Warmer days can contribute to heat related problems such as heat stroke and heat cramps as well as heat related mortality. Health related responses of populations to heat are commonly assessed using regression analysis of long records of daily observations of health events (most commonly, deaths) vs. temperature measured at a single urban monitoring site. A citywide exposure-response function is estimated to quantify the excess mortality or morbidity that occurs above a temperature threshold. Figure 5-1 shows the response of daily deaths in Manhattan, New York to daily max temperature measured at Central Park (Li et al, 2013). Heat-related mortality is quantified above a reference temperature based on a statistical analysis of deaths from all causes in relation to daily temperatures, as illustrated in the Figure 5-1. However, to date, this and all similar analysis in the literature rely on central site temperature data to characterize the exposure of persons at risk of adverse health impacts.
This study shows that mortality increases in NY’s Heat-related mortality is a function of temperature and a population’s sensitivity to temperature. Both vary on the neighborhood scale: temperature varies due to physical characteristics of surface cover; temperature sensitivity varies mainly due to socio-economic factors (Li et al, 2013). A factor that could be a large contributor to the slope difference between cold and heat mortalities is the requirements for providing heat versus cool air in urban northeast. While heating is required at a certain temperature threshold, air conditioning is not required. In New York City, fire hydrants are opened for people to cool themselves off but there will be hotspots that either may not get their hydrants opened or it is already 10 degrees hotter than the average temperature and possibly too late. Older age, obesity and diabetes are among the major risk factors for heat-related mortality (Basu, 2009, Basu et al, 2002, Huang et al, 2008). As temperature increases above the heat threshold (Figure 5-1), mortality is seen to become increasingly sensitive to small changes in temperature.

### 5.2.2 Heat Related Mortality

Research has shown that increased rates of heat mortality are a result of areas being vulnerable. Differences in vulnerability exist depending on climate, culture, infrastructure, and other factors.
(Kovats et al, 2008). Climate differences affect vulnerability; first, the initial increased temperature causes the heat-related mortality issues. Then, regions have different temperatures, which underestimates some areas’ vulnerability to the climate effects. Within the culture factor lays the main issue of age; very young and older aged people do not have as strong of a thermoregulatory system, therefore extreme temperatures affect them worse than the average person. Infrastructure may also be a factor in vulnerability since brick houses have a high thermal mass and apartments that have little ventilation will be more susceptible (Kovats et al, 2008). Colleen Reid et al. mapped and analyzed 10 vulnerability factors for heat-related mortality within the United States (age, poverty, education, living alone, race/ethnicity, 2 household air conditioning variables, vegetation cover, and diabetes prevalence) and found that urban areas showed the highest vulnerability to heat (Reid et al, 2009). This vulnerability to heat then leads to extremes of temperature that are associated with short-term increases in daily mortality (Medina-Ramón et al, 2006).

5.2.3 Thermal Indices

Thermal indices have been developed in order to describe the effect humans feel on their body based on the environment. This is used to attempt to quantify the exact effects that are felt on humans due to excess heat in urban environments. Ágnes Gulyás et al. conducted two field-surveys in Szeged, a South-Hungarian city. The studies placed special emphasis to the human-biometeorological assessment of the microclimate of complex urban environments through the application of the thermal index Physiological Equivalent Temperature (PET). The studies resulted in differences in the PET index as high as 15-20 °C due to the different irradiation and that the different modelled environments (only buildings, buildings and trees) revealed significant alterations in the human comfort sensations between the situations (Gulyás et al,
Taleghani et al. modeled different thermal environments to understand how PET can change based on the layout of an urban environment. It was found that the duration of direct sun and mean radiant temperature (influenced by urban form) play the most important role in thermal comfort (Taleghani et al, 2015). Panagiotis Nastos et al. analyzed the region of Athens, Greece by comparing the daily mortality with the daily values of PET and Universal Thermal Climate Index (UTCI). The comparison was completed by applying Pearson’s χ² test to find the probability of mortality relating to the thermal indices and it was concluded that the air temperature and PET/UTCI exceedances over specific thresholds depending on the distribution reveal that, the extreme heat condition is a risk factor for the daily mortality (Nastos et al, 2012).

### 5.2.4 UHI Monitoring Methods

Satellites have been utilized to monitor and assess the increase in surface temperature caused by urban environments. Streutker in 2003 monitored the growth of the surface temperature UHI of Houston, TX. Two sets of heat island measurements that were taken 12 years apart were compared by calculating the individual heat island characteristics from radiative temperature maps obtained using the split-window infrared channels of the Advanced Very High Resolution Radiometer (AVHRR) on National Oceanic and Atmospheric Administration (NOAA) polar-orbiting satellites. This comparison revealed a mean growth in UHI characteristics with a magnitude of 0.8 K, or 35% (Streutker, 2003). The surface temperature was also monitored in Tel Aviv by Orit Rotem-Mindali et al. and the goal of this study was to assess the cooling effect of residential areas with high vegetation cover compared to that of small to medium size public parks. Satellite data of Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) were combined to produce 10-year average LST and NDVI maps. Industrial areas were found to have the highest LST due to the lowest ratio of vegetation while green areas
displayed the lowest LST. It was found that small-medium public parks displayed higher LST than expected, likely due to the low vegetation to free space ratio (Rotem-Mindali et al, 2015). Yongming Xu and Yonghong Liu derived the near-surface air temperature of Beijing by using Landsat/TM satellite imagery. A statistical model was established to estimate the air temperature, using LST, NDVI, altitude, and surface albedo. The Mean Absolute Error (MAE) of the model was 0.87 °C and the $R^2$ was 0.66, indicating that it can be used to effectively estimate the air temperature. It was found that the UHI effects in Beijing are significant and that the air temperature increased with increasing impervious surface coverage (Xu et al, 2014). A study performed with respect to heat in the urban environment was the study performed by Karimi et al. on infrared imagery collected using satellite imaging. The highest resolution available for this study was 60-100 meters in thermal infrared bands. The main challenge in using satellite data to study UHI in urban environment is the complexity of the system and lack of information on near surface air temperature in fine scale. This work consists of high resolution data sets measured at the street level in Manhattan, New York to produce temperature maps showing the smallest hotspots that could not be identified using high-resolution satellite. Data from two consecutive years of field campaigns at street level, plus various significant parameters that control temperature in an urban setting such as building height, building density, vegetation, water, elevation and albedo were used to create temperature maps using statistical model to locate hot spots in the system (Karimi et al, 2015).

5.2.5 Mitigation Strategies

Heat mitigation strategies are being developed in order to lessen the impact of UHI on human health. In Portland, Oregon, Taleghani investigated the possibility of using courtyard vegetation, high albedo surfaces, and courtyard ponds to mitigate heat. Field measurements and simulations
on a university campus environment were used and it was found that park had a cooling effect on
the entire campus, vegetation and water showed reductions in air temperature (1.6 °C and 1.1 °C
respectively), and changing the albedo of the pavement from black (0.37) to white (0.91) led to
2.9 °C increase of mean radiant temperature and 1.3 °C decrease of air temperature (Taleghani et
al, 2014). In other researches, it was found that courtyards were the most comfortable form of
urban layout within the Netherland’s climate (Taleghani et al, 2015). Rotem-Mindali’s research
suggests adding more vegetation to areas with the free space to better cool the area and to add
small-medium parks in metropolitan areas that lack the sufficient free space for larger parks
(Rotem-Mindali et al, 2015). The heat mitigation strategies can only be confirmed once
monitored over long periods of time. Proper monitoring methods have yet to be developed. J.a
Voogt and T.r Oke performed a review on thermal remote sensing of urban areas and found that
is mainly a qualitative description of thermal patterns and simple correlations. Improvements in
the spatial and spectral resolution of current and next generation satellite-based sensors and high
resolution portable thermal scanners will allow for the progress in the application of urban
thermal remote sensing to study the climate of urban areas (Voogt et al, 2003). A new method
was introduced by Bo Huang et al. in which a spatiotemporal image fusion model is used to
produce high spatiotemporal resolution LST data. This is done by combining the high spatial
resolution of Landsat images the frequent coverage of Moderate Resolution Imaging
Spectroradiometer (MODIS) images. This method accounts for the warming and cooling effect
of ground objects in urban areas and establishes a new weight function to account for the effect
of neighboring pixels (Huang et al, 2013).
5.3 **Data and Methodology**

Specific boroughs within NYC were analyzed utilizing Landsat 5 imagery. Also, multiple data sets were obtained and applied to find the most vulnerable regions. These data sets include income, population density, susceptibility, temperature, vegetation, building height, and building density. The income, population density, and susceptibility data was obtained from the U.S. Census Bureau. The susceptibility data is the sum of those below the age of 5, aged 65 and over, and those living alone in each ZIP code (20 block radius). The social and historical dataset for this study was chosen based on author’s understanding of urban land cover and dynamics of cities (mentioned in previous chapters) and also based on the literature review for heat wave vulnerability index and urban heat/health risks. Many studies have found that specific number of population can be more vulnerable to the impact of UHI and heat events. Chow et al (2012) found elderlies to be at higher risk of vulnerability as they are more susceptible to heat waves. Therefore, susceptibility data from U.S. census was used.

To find hotspots within neighborhood, Landsat data was used to find temperature trends within city environment. Landsat 5, 7 and 8 comprising Enhanced Thematic Mapper Plus (ETM+) satellite images from U.S. Geological Survey (USGS) database were collected from 2000 to 2011. To obtain land surface temperature using visible (0.45-0.52μm), near infrared (0.77-0.90 μm) and thermal infrared (10.40-12.50 μm) bands, images were corrected for clouds, cloud shadows, upward emission, downward irradiances, albedo and other physical phenomena. A comparative performance analysis of cloud removal algorithms and tools was conducted with ENVI and Matlab and the implementation of new strategies and algorithms was investigated to reduce both effects of clouds and their shadows from multispectral satellite sensor images. Calculation of at-surface radiance from cell values was performed. This last value is then
converted to land surface temperature in Kelvin. The summary of the process is represented by the flow chart in Figure 5-2. In order to obtain a thermal representation and thus calculate the land surface temperature of every pixel contained in the images, an in-house code was developed. This code processed all the images and converted the values into thermal maps.

![Flowchart](image)

**Figure 5-2 Visual representation of the method workflow**

### 5.4 Landsat Calibration

Before using Landsat data as input, it was necessary to calibrate the images. Landsat data are typically delivered as pictures where each pixel is a single byte, possessing a value from 0-255. During the radiometric calibration of pixel values from raw, unprocessed image data are converted to units of absolute spectral radiance. The data provided by USGS is in GEOTIFF format. Data were imported as Landsat GeoTIFF with Metadata, in preparation of the calibration step (The Yale Center of Earth Observation, 2013).

### 5.5 Image Correction, Simple dark Object Subtraction Method

Image correction is performed following the Dark Object Subtraction (DOS) technique. Several factors are considered when estimating the land surface temperature from satellite observations.
This includes the effect of the atmosphere, vegetation, and the land surface emissivity. DOS techniques are atmospheric correction technique for optical bands and it is calculated by simple dark object subtraction method, which can be seen in Equation (5-1). The DOS model assumes that within each satellite image there are scenes with negligibly small surface reflectance where the observed top of the atmosphere reflectance (TOA) is explained solely by the atmospheric contribution. A graphical representation of the sun radiation geometry pattern used by Equation (5-1) can be found in Figure 5-3. In this equation, \( \rho \) is the TOA reflectance, \( L \) is the sensor radiance, \( T \) is atmospheric transmissivity, \( x \) is the zenithal solar angle, \( d \) is the distance from the earth to the sun and \( L_p \) is radiance:

\[
\rho = \frac{\pi (L_{sat} - L_p) d^2}{E \cos (x) \cdot T}
\] (5-1)

This atmospheric correction processes every pixel in the images to obtain TOA reflectance values (Chander et al 2007).

5.6 NDVI Calculation

For accurate land surface temperature estimation it is critical to know the land surface emissivity in the infrared. The implemented approach uses the links between the land surface emissivity and the state of the vegetation cover expressed in the form of the Normalized Difference Vegetation Index (NDVI). The equation for NDVI can be seen below in equation (5-2). The TMs in this
equation represent bands of the Landsat bands with numbers referring to a specific band. In the equation below, the TM4 band represents the near-infrared band and the TM3 represents the visible band (Zhang et al, 2006, Voogt et al, 2003).

\[
NDV1 = \frac{(TM4 - TM3)}{(TM4 + TM3)}
\]  

(5-2)

5.7 Effect of Albedo on Earth Surface

Due to complexity of urban systems, it is important to take into account the last correction which is the albedo effects. Albedo is the property of the land surface characterizing its potential to reflect shortwave solar radiation (Figure 5-4). The albedo correction for satellites is calculated by multiplying the reflectance of all points of an image by the energy fraction. When light interacts with objects, we have absorption, reflection and transmission. On Earth only reflection and absorption takes place, there is no transmission.

![Figure 5-4 Albedo effect on earth surface](image)

On Earth 30% of light is reflected back. This is known as albedo (nsidc.org, 2016). Albedo is the ratio of the outgoing reflected flux to the incoming flux. Flux is the energy that passes through a physically defined surface that may not be aligned in the direction of propagation. Reflectance data and the top of the atmosphere (TOA) given by the satellite do not account for the albedo effect from the atmosphere, so we have to estimate the albedo integrated across all wavelengths and directions. Calculation of albedo plays a vital role in determining the reflectivity. In running the LST model to correct for possible back scattering in the urban areas and complexity of urban
systems, the albedo correction was done to detect for any possible extreme anomalies in urban area. The reflectivity expected is expressed as reflection coefficient

\[ R = \frac{I_{\text{reflected}}}{I_{\text{surface}}} \] \hspace{1cm} (5-3)

Where \( I_{\text{surface}} \) is the solar radiation that has passed through the atmosphere. But the satellite data provides equation 5-4 given equations 5-5.

\[ R_{f} = \frac{I_{\text{satellite}}}{I_{\text{sun}}} \] \hspace{1cm} (5-4)

Albedo = \( \Sigma (\text{reflectance})(\text{energy fraction}) \) \hspace{1cm} (5-5)

Emissivity and albedo are the two main parameters in calculation of Land Surface Temperature (LST).

5.8 Conversion of at sensor radiance to effective at satellite temperatures

Once DNs are converted to spectral radiance and influence of external factors to be corrected are taken into account, surface temperature can be calculated. The values retrieved are also called effective at-satellite temperatures. The thermal band data (Band 6) can be converted from at sensor spectral radiance to effective at sensor brightness temperature. Here we assume that Earth's surface is the black body and consider emissivity as one. The conversion formula from the at sensor's spectral radiance to at sensor brightness temperature is

\[ T_{b} = K_{2}[ \ln ( \frac{K_{1}}{L_{\lambda}} ) + 1] \] \hspace{1cm} [NASA, 2009] (5-6)

Where \( T_{b} \) is the effective at sensor brightness temperature in Kelvin; \( K_{2} \) is calibration constant 2; \( K_{1} \) is calibration constant 1; and \( L_{\lambda} \) corresponds to the spectral radiance at the sensors aperture calculated with Equation (1). The constants \( K_{1} \) and \( K_{2} \) vary depending on the satellite used. The following table 1 shows the respective values.
Table 5-1 Current radiometric calibration coefficient for Landsat MSS

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<td>L7 ETM</td>
<td>666.09</td>
<td>1282.71</td>
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</table>

5.9 Calculation of Land Surface Temperature

Finally, the LST can be calculated as shown below in equation (5-7). In this equation, Tb is the reference body black temperature, $\lambda$ is the wavelength of emitted radiance, $p$ is Planck’s constant ($6.26 \times 10^{-34}$ J*s) multiplied by the velocity of light ($3 \times 10^8$ m/s), divided by is the Boltzmann constant, $b$ ($1.38 \times 10^{-23}$ J/4), and $e$ is the land surface emissivity (Weng et al, 2003).

$$St = \frac{Tb}{1 + (\frac{\lambda \times Tb}{p}) \times \ln e}$$  \quad (5-7)

Emissivity is the quantification of the intrinsic ability of a surface in converting heat energy into above surface radiation. It depends on the physical properties of the surface and observed conditions. To determine the land surface temperature, land surface emissivity (LSE) plays a vital role. Land surface emissivity was calculated sing equation (5-8).

$$\varepsilon_{TM6} = 0.004 P_v + 0.986$$  \quad (5-8)

Where, $\varepsilon$ (TM6) is land surface emissivity and $P_v$ is vegetation proportion. (Sobrino et. al, 2004).

At this point the initial satellite data is completely converted into a color coded thermal map. The following results demonstrate the applicability and advantages of the above-mentioned process as a tool for vulnerable neighborhood identification.
5.10 Chapter Results

The analysis focused on finding the average year round surface temperatures of each borough within NYC based on collected images. Landsat images are delivered as images with pixel of single byte possessing values of 0-255. Using radiometric calibration, Landsat raw data are converted into units of absolute spectral radiance (USR). Over 11 years of Landsat satellite images were collected from the year 2000 to 2011 to sum up to a total of 150 images. Images with less than 10% cloud coverage were selected and processed to develop average year round surface temperatures on a normalized scale. Landsat overpasses NYC around 3pm in the afternoon and that is roughly the same time for all images collected. All images from the same year were average based on pixel by pixel average values after calculation land surface temperature using the NASA model. Images of Landsat LST retrieval results can be found in appendix.

These images were compared to building densities and NDVI to determine if a correlation could be made between urbanization and increased LST. Figures 5-5 show the results of the analysis of five boroughs of NY and Roosevelt Island. The images are generated with atmospheric correction on satellite images. Figure 5-5a shows the temperature across all five boroughs of New York City. Impacts of UHI are seen in all boroughs of NYC which increases higher risks of heat related illnesses and heat stroke. It should be noted that John F. Kennedy Airport is in the jurisdiction of Queens and so the average temperature of this entire neighborhood increases due to the large area covered by black top asphalt that absorbs and maintains heat. Figure 5-5 provides a snapshot of the datasets collected and processed for this research. Figure 5-5a shows image composite data of Landsat surface temperature calculated from over 150 year round images over 11 years. Figure 5-5b shows the building density for all boroughs of New York City.
Highest building density is observed in Manhattan. Although its building density is the highest, has surprisingly low average temperature compared to the rest of the areas which can primarily be associated to the green/ white roof presents in this area. Detailed NDVI for each borough is shown in figure 5-5c with Manhattan and Brooklyn having the least amount of vegetation.

Finally, detailed building heights for all five boroughs are shown in figure 5-5d. Manhattan has the highest rate of building height in compare to all other boroughs.

5.11 Conceptual Framework

Specific boroughs within New York City were analyzed utilizing Landsat imagery. The results of the imagery take place in the following four steps illustrated in figure 5-6; step1; Identification
of environmental risks which includes land surface temperature, vegetation coverage (NDVI), building height, and building density data. In the next step, social data including income, population, and susceptibility were obtained from the U.S. Census Bureau. These data sets were then downsized into ZIP codes in order to separate the five boroughs of New York City into smaller sections during step 2.

Figure 5-6 shows the process from when data is obtained to identifying the areas that need to apply heat mitigation strategies. Steps 3 and 4 used the data from the previous two steps and calculated both risk and vulnerability, respectively, which are explained in more detail in the following subsection.

5.12 Development of Environmental Risk and Social Vulnerability Indices

Environmental vulnerability can be calculated using different methods. One study implied IPCC 2007 formula as a base to calculate susceptibility as a function of exposure, sensitivity and adaptive capacity (Manik, et al, 2015). Tomlin et al (2011) highlighted the potential heat health
risk areas in UK by combining MODIS LST data as hazard layer with exposed layer (demographic and lifestyle) and vulnerable layer (age, illness and density) as equal weight. A few available articles have described social economic and environmental factors that influence population’s exposure to heat. Of the many studies that used sociodemographic as “indications of the spatial variation in vulnerability”, many studies do not account for physical parameters that increase the environmental risk associated with heat events (Smoyer, 1980, 1995, 1998, 2000, Harlan et al, 2006, and Conti et al, 2005).

However, Johnson et al, (2009) accounts for physical environment variable found to be associated with increase in UHI effects. The socioeconomic indictors and land surface temperature are used to integrate sociodemographic risks simply by adding all variables used; Landsat TM5 LST, Age, poverty, education, and race. Even though Johnson et al (2009) approach used LST as an import variable in its logistic model but does not account for physical and environmental parameters associated with heat events and like many other UHI studies, population vulnerability to heat is not mapped.

This paper’s conceptual model is built around Johnson et al’s study and the understanding of the impact of land cover on land surface and ambient air temperature (chapters 2 and 3 of this dissertation). Addition variables are used to calculate total environmental risk and social vulnerability within the five boroughs of NYC. This model considers all the important parameters that are (T-test) statically significant (chapter 2). A conceptual model was developed using LST Landsat data, data from department of building, sociodemographic census data and physical aspects of built cities. The factors of interest include people, environment and building/infrastructure. The aim of this study was not only to map vulnerable population based on their socioeconomic status and age but also to identify primary land surface characteristics.
that play a stronger role in developing UHI effect in cities for intervention guide of heat mitigation.

High densely populated cities consist of tall and wide buildings that can impact the ambient air temperature. Building density which provides the proximity of buildings within a region showed to cause a greater insulation (chapter 2). The building density adds to increasing ambient air by reradiating the absorbed heat back to air leading to more social and environmental risk (chapter 2). The second most important factors in social vulnerability are lack of vegetation and people’s social wellbeing (income). Vegetation and trees help in reducing the surface and air temperature by providing shades and through evapotranspiration. Vegetation can help reduce the air temperature by 2-8°C and surface temperature by 15-20°C (Doick et al, 2013). Income and socioeconomic status can as well affect the health and wellbeing of people (Johnson et al 2009). People with higher income can buy air conditioner and afford to run it all day long.

Based on the factors mentioned above, variables were closely chosen to help calculate environmental risk and social vulnerability. Variables were divided into four layers; Hazard layer: temperature, NDVI, building height and density, Exposed layer: Population density, Vulnerable layer: population age and Sensitivity layer: income.

The total risk due to the heat can be estimated as a function of building density, building height, temperature, population density, age, and vegetation. Building density provides the proximity of buildings within a region which when related to building height and population greatly influences risk. Higher building heights with high building density causes a greater insulation effect than if there was a low building density with high building heights. Similarly, it can expect a greater negative effect with high building density and high population. When there are more people below the age of 5 and above 65, they are more susceptible to heat related mortality.
Vegetation is one of the factors, which counters the risk of heat related illness so that value is subtracted from the sum of the negative factors. All of these variables are used to calculate the total risk using equation (5-8). The risk assessment model is a linear fit to help estimate the risk within the system. Whereas making an absolutely correct estimate is a lot more complicated, this model puts the risk at the concept of a value by introducing a qualification of risk and vulnerability within a system.

Because some of the variables were recorded as standard deviations, the data had to be normalized instead of a basic calculation of the variable value divided by the maximum variable value. From all of these, the total risk was calculated. Chow et al (2012) used an equally weighted index in developing a vulnerability index for the two time study of Pheonix Arizona.

\[
%\text{TR} = (aD + bH + cT + dP + eA - fV)
\] (5-8)

Where \( T_R \) is Total environmental risk, \( D \) is Building density, \( H \) is Building height, \( T \) is Temperature, \( P \) is Population density, \( A \) is population Age and \( V \) is Vegetation which is represented by NDVI value and \( a, b, c, d, e, f \) and \( g \) in both equations were coefficients derived from modeling of the local parameters. The social vulnerability is then calculated (equation 5-9) from the total risk by including the population’s income which is one of the most important factors because money can negate many of the negative factors.

\[
%\text{Vu} = (aD + bH + cT + dP + eA - fV - gIp)
\] (5-9)

Where \( Vu \) is social Vulnerability and \( Ip \) is Population’s income. The values are presented as numerical summation of the risk for each important factor presented as a total sum in percentage for the total risk and vulnerability. Numerical risk values are normalized and calculated in percentile. Higher percentile indicates environmental risk and social vulnerability.
The island of Manhattan was used as a control study and mapped for only selected zip code (figure 5-7) of which the socioeconomic, environment and physical neighborhood is most known to the research team.

Based on the results shown in figure 5-7 East Village, followed by Harlem, Upper Manhattan are at highest risk of vulnerability in compared to other zip codes. Since the result of the control study matched with physical condition of the selected neighborhoods, the model was applied to the rest of the boroughs.

![Image](image.png)

**Figure 5-7 Environmental Risk and Social Vulnerability in Manhattan**

Normalized values that were used to analyze postal code areas to determine the neighborhoods in New York City are shown in Table 5- 2. The most vulnerable neighborhoods are color coded from dark to light for high to low risk.
Finally, the risk and vulnerability calculated were all plotted by the ZIP code for those with available information in Figure 5-8.

The model predicting heat and environmental related risk-model was found to be significant for the purpose of this study. The model was calculated using higher value coefficient for temperature, NDVI, building density, and income (figure 5-8). Based on the model, the areas to approach are the darker reds and black being the most important location to try and improve living conditions.
Environmental risk map shows Manhattan, Brooklyn, Staten Island followed by Queens at high risk. High risk neighborhoods are incorporated with lack of vegetation, high building density and low income individuals. Based on the results shown in vulnerability map; the residence living in Manhattan from Washington Heights down to West Village on the West Side and from East Harlem down to East Village are at highest risk of vulnerability. Those living in Sunset Park, Borough Park, Midwood and Flatbush, and in South and Central Brooklyn are at high risk of vulnerability as also seen in with residence living in Elmhurst, Jamaica, Woodhaven, Ridgewood, Kew Gardens, Jackson Height, Sunny Side in Queens. Most part of Staten Island and Bedford, University Heights and Woodlawn in Bronx have high social vulnerability among its population and are in need for either policy changes or new green infrastructure and vegetation to counteract the heating effects.

5.13 Chapter Discussion and Conclusion

Environmental risk and social vulnerability should be studied carefully in the context of urban systems. They may carry a similar connotation but can have very different applications. One simply states the risk caused by environmental factors but the other one shows the population at risk and areas where the citizens do not have the means to combat such risks. By taking into account the age and income of residents, the target areas can change. Higher income allows money to be spent on air conditioning and health concerns; younger and older residents are more susceptible to health problems related to heat. According to the City of New York, it is mandated that heat is supplied at outside temperatures 13°C or lower during the day. Other specifications for night temperatures and inside temperatures are allocated as well (Heat and Hot Water, 2015). The same should be taken into account for summer heat. The installation of air conditioning in American homes is the reason why the chances of dying on an extremely hot day fell 80 percent
over the past half-century (Eilperin, 2012). There are more measures to prevent heat related mortality and a greater awareness of heat related health problems because of outreach to those that are vulnerable in Chicago (Franklin, 2015) but these measures need to be stressed and spread in other urban areas. With the changing climate and heat waves becoming more common during the summer, there needs to be a change in policy to protect residents of large cities, like New York City. Whether the change is requiring air conditioning or requiring green roofs and more vegetation in urban area design, action needs to be taken to mitigate heat in urban centers. The areas of interest vary based on a number of factors. The factors specifically studied in this research involved the effect people have, the effect nature has, as well as buildings’ and infrastructures’ effects. Based on the results, several sections of New York City must make a change in policy or include new green infrastructure and vegetation to counteract the heating effects and protect citizens.

Suggestions for reducing the impact of UHI within a microclimate include increasing vegetation in an area, using reflective materials for roof tops, and using pavements that are modified to not absorb as much heat (USEPA).

Satellite analysis has also confirmed that LST increases in areas with increased urbanization and decreased vegetation except the areas with very tall buildings which can be associated with higher wind speed at higher elevations. This will aid in better understanding of urban microclimates and their temperature patterns.
CHAPTER VII: CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

This dissertation can help broaden the understanding of UHI using fine-scale mapping to show temperature variation in urban areas considering local surface characteristics and basic weather condition to predict hotspots in metropolitan cities using weather variables, and create a conceptual model to predict environmental risk and vulnerable population. In pursuing the impact of UHI on human health and improving the current researches the following work has been done: 1) First high resolution data sets ever used in NYC, identified the location and impact of heat buildup, 2) Predicting temperature anomalies within urban systems, 3) Fine-scale mapping of New York underlying temperature, 4) Predicting air temperature and variability within a city based on weather forecast and surface properties, 5) Obtained and analyzed more than 11 years of satellite data to identify and find hotspots within a city and use that information to produce heat maps, 6) For the first time, connected independent physical variables (build height, build density, NDVI & etc) with social indicators (pop density, income & etc) in the context of quantifiable indices (envir. risk & social vul), and 7) Adding strength to the temperature prediction and vulnerability calculation within a densely populated cities.

This thesis was designed to not only look into other methods of studying the impact of UHI on densely populated metropolitan cities but also to create high-resolution data sets to better understand the impact of land cover and land change in our urban areas. In addition, the surface model that has been developed can be used for urban planners and city managers in designing cooling centers and heat resilient cities. Furthermore, this dissertation looks into environmental risks associated with urban development but also to target population that is at higher risk of social vulnerability.
The areas of interest vary based on many factors. The factors specifically studied in this research involved on the effect people have, and the effect nature has, as well as buildings and infrastructures’ effects. Based on the results, several sections of New York City must make policy changes to include new green infrastructure and vegetation in their building and neighborhood designs to counteract the heating effects of UHI to protect citizens.

Suggestions for reducing the impact of urban heat island within a microclimate include increasing vegetation coverage, using reflective materials for rooftops, and using pavements that are modified not to absorb significant amount of radiative and latent heat.

This study can be used to add strength to the temperature prediction and heat index calculation within a densely urbanized city like Manhattan, which up until this work has not been done. It is quite important to consider the physical and societal properties of a neighborhood when reporting heat index to issue a warning. The two new models developed by this research, environmental risk and social vulnerability framework, can open new doors into issuing targeted warnings in complex urban settings, helping the population in need and minimizing the chaos caused by issuing mass warnings. The few limitation of the conceptual models are: 1) The terrain is assumed to be flat, 2) Wind speed is even throughout the system, 3) Cloud fraction and wind direction is not considered, Building density and height data needs to be gridded and processed for the purpose of this study, and 5) Transition of the developed model to other cities depends on availability of data.

The other benefit of this research is ease of replication. Other cities with similar datasets can easily reproduce this work to apply to their location. Urban developers and modelers can use this study to factor in the impact of local weather and microclimate on the variation of temperature in
highly densely populated cities in both improving current infrastructure and future projects for reducing energy consumption and cooler cities.

Furthermore, it is necessary to understand the relative importance of temperature variation and UHI in creating greater risk on not only the environment but also demographic and socioeconomic status that may influence the heat mortality and hospital admission rates during heat events.

6.2 **FUTURE WORK**

- Incorporating more comprehensive hospital admission datasets for improved calibration and validation of the proposed models
- Detecting mega cities' temperature anomalies by downscaling various satellite temperature data that are currently unable to detect temperature extremes in urban areas
- Incorporating climate data for future projection of UHI impact on human health in the face of climate change
- Predicting the impact of different land surfaces on urban microclimate
- Develop a surface temperature profile model using temperature profile data and surface type
- Correlating the LIDAR and Landsat data to variables in Surface Temperature Profile and Atmospheric Surface Temperature Profile model for land surface classification at high resolution.
In addition to the above mention work, as a part of this dissertation, we have started expansion of the conceptual model and the calibration and validation of the model which is presented in the following section:

6.3 Extension of Conceptual Model Using Hospital Admission Data- Future Project

In an extension to the conceptual model explained in chapter 5, hospital admission data from Healthcare Cost and Utilization Project (HCUP) can be used to confirm the accuracy of framework. HCUP data contains information from state date organizations, hospital associations, private data organizations and the federal government to create a national information resource of encounter-level healthcare data. HCUP Inpatient Databases (SID) are hospital databases that contain the universe of the inpatient discharge abstracts from participating States that are translated into a uniform format to facilitate multistate comparisons and analyses. The SID encompasses almost 90 percent of all U.S. hospital discharges. The SID contain a core set of clinical and nonclinical information on all patients, regardless of payer, including those covered by Medicare, Medicaid, private insurance, and the uninsured. Patient information such as age in years at admission, admission month, diagnosis, patient sex, hospital state postal code, median household income, patient zip code, and heat related diagnosis are available. These data can be used to calibrate and valid the conceptual.

A small test was done to find correlations between result of the conceptual model and number of people who were admitted to hospitals heat exposure. Two years of patient discharge record from hospitals in New York City were used to identify the number of people who were affected by high temperatures during summers of 2012 and 2013. For year 2012; 242 records for heat related diagnosis for New York City was found and 336 records for year 2013. By calculating number of patients belonging to each zip code the highest number of patient heat wave hospital
admissions belongs to following zip codes for year 2012 and 2013: Year 2012: zip code 10452, in the borough of Bronx with neighborhoods of Claremont Village, Concourse, Concourse Village, High Bridge, Morris Heights, Mount Eden and Mount Hope. Zip code 11212, in the borough of Brooklyn with neighborhoods of Brownsville, Canarsie Crown Heights, East Flatbush and East New York. For the year 2013: zip code 10452, in the borough of Bronx with neighborhoods of Claremont Village Concourse, Concourse Village, High Bridge, Morris Heights, Mount Eden and Mount Hope. The NYC Vulnerability Map for heat-related Illnesses shows the count of patients per zip code for five borough of New York for both summers combined (figure 6-1).

Figure 6-1 Heat related vulnerability map and patients count. Vulnerability (left) and Patient Hospital Admission data for Zip codes (right) throughout New York City

In comparing neighborhoods with highest social vulnerability and number of patient heat related admission for years 2012 and 2013 (figure 6-2), areas with high social vulnerability are matching with areas that are showing most hospital admissions for heat related diagnosis.
Comparison of vulnerability and hospital data map showed that areas with a high number of people admitted to hospitals of NYC with heat related diagnosis can relate zip codes that have high vulnerability risk.

The results of the preliminary work are quiet promising and are going to be a topic to be persuaded by the author in the future. This future project can further be expanded by having access to more years of hospital admission data. Once this project is completed it can help with the validation of the conceptual model.
7 APPENDICES

7.1 Appendix

The probe reading for each day at different elevations compared to the Landsat 8 temperature extracted for the same latitude and longitude.

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Landsat LST retrieval image - March 2011
Landsat LST retrieval image - April 2011


Solecki, W. Rosenzweig, C. Parshall, L. Pope, G. Clark, M. Cox, J. Wiencke, M. Mitigation of the Heat Island Effect in Urban New Jersey. Environmental Hazards, 2005


