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# Understanding the Drivers of Urban Heat; Case Study in Burlington, Vermont

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University of Vermont College of Engineering and Math Undergraduate Honors Thesis

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> > 20 May 2023

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# Abstract

Urban Heat Islands (UHI), the phenomenon of cities being hotter than their rural surroundings, are a matter of growing concern as they affect public health, air and water quality, and energy consumption. With predictions by climate scientists for heat waves of increasing intensity and duration, addressing the problem of UHIs has become increasingly urgent. Urban areas experience increased temperatures because of the thermodynamic properties of the materials that make up the built environment, the geometric configuration of buildings and infrastructure, and the relative lack of vegetation. Research in the field has predominantly focused on large cities, neglecting small to midsize cities such as Burlington, Vermont where the UHI effect is also known to exist although population vulnerabilities and infrastructure characteristics may differ from large urban centers. CAPA Strategies has high resolution UHI mapping Burlington, Vermont to map ambient air temperature at a granularity of 10m resolution using mobile sensors. To further address this area of research, a high-resolution heat intensity sample of the city of Burlington, Vermont, USA was created using novel sampling data collected during the summer of 2021 and analysis to find the correlation between impervious surface and urban heat. These sample points were then compared against the CAPA Strategies maps. It was found that the percentage of roads within a buffer are the highest drivers of observed temperature and urban heat in Burlington, Vermont. These findings have implications on mitigation strategies, as well as highlighting the urban heat that exists within mid-size cities such as Burlington, Vermont. The comparison between the high resolution map created using our sampling method and the CAPA map can indicate if this method can be transferred to areas outside of Burlington, Vermont.

Through this research I am attempting to address the following questions: What is the correlation between land use, specifically impervious surfaces, and heat intensity in Burlington, Vermont? Do the results across multiple days conform? Looking at places were CAPA data was collected, does the sampling approach mean that our results are substantially different?

# Introductions

#### History

Urban Heat Islands (UHI), the phenomenon of cities being hotter than their rural surroundings, are a matter of growing concern as they exacerbate the effects of heat waves with negative implications for public health, air and water quality, and energy consumption. With predictions by climate scientists for heat waves of increasing intensity and duration, addressing the problem of UHIs has become increasingly urgent. As early as the 19<sup>th</sup> century, climate scientists have looked at the effects of urbanization and the climate implications of urban sprawl and have found significant temperature differences between towns and the surrounding rural land. In 1833, Luke Howard identified three determinants which influence the climate of a city: "the general climate of the region, the modifying influences of the local morphology, and the 'self induced' modifications following the congregation of buildings and surface roads into the complex of the city" (Oke 2009). To Howard's first point, data from NASA shows the Earth has gradually been getting warmer since the late 19th century and this trend is rapidly accelerating ("Data.GISS"). These changes in heat are further exacerbated by the spatial morphology, building material, and heterogeneity of the built environment that exist in urban areas (Salvati et al. 2020). Roughly 45% of the modern built environment consists of transportation-related infrastructure including roads, sidewalks, railroads, and bridges (Bureau Of Transportation Statistics 2018).

Exposure to extreme heat disproportionally effects vulnerable populations such as the elderly, young children, and those with fewer resources to take adaptive action including limited access to transportation resources. Furthermore, findings show disparities in the effectiveness of urban heat policy and mitigation strategies by age, income, and race (Vargo et al. 2016). Extreme heat events can lead to adverse health outcomes including heat stress, increased hospitalizations, and death. In 2016, the Vermont Health Department, working with the Vermont State Climate Office, developed a heat vulnerability index to better understand the geographic variability of heat related illness within the state of Vermont (Vermont Department of Health 2016). The report found that on days when the average temperature across the state was 87°F or higher, heat related illnesses occurred eight times more frequently and there was one additional death per day among individuals aged 65 and older. Additionally, the report concluded that Vermonters may be more sensitive to heat compared to those living in warmer climates due to the infrequency of hot

temperatures and the fact that infrastructure, such as homes and businesses, were not designed to accommodate high heat. Vermont hospital discharge data showed that adults 75 and older and people between the age of 15 and 34 are the most affected by heat related illnesses in the state. Specifically, members of the population experienced increased risk due to dependance on others, reduced thermoregulation ability and high occupational or lifestyle exposure (Vermont Department of Health 2016)

The Vermont Health Department looked at the Pearson's correlation coefficient between specific indicators and the Vermont age-adjusted hospitalization rate for heat illness, per 1,000,000 persons, per year. The Vermont Health Department looked at the percentage of town area covered by impervious surface area using National Land Cover Database, US Geological Survey (NLCD), 2011 Edition, (amended 2014) and determined there was a 0.22 correlation coefficient between impervious surface and heat illness at the p<0.001 level("Heat Vulnerability in Vermont" 2016). This is due to the fact that areas with more impervious surfaces, such as roads or sidewalks, and limited vegetative cover experience warmer temperatures than their more rural surroundings. It is well known that the thermodynamic properties of pavement systems behave differently than natural land covers. For instance, pavements dark color (low albedo) and high thermal mass releases the suns energy more slowly than surrounding rural areas resulting in warmer temperatures particularly at night (Oke 1982a).

The physical properties of cities and urban landscapes cause an increase in heat relative to rural areas. The strength and stability of a system is related to it its ability to adapt and cope to extreme environmental changes, such as the effects of climate change on physical, social, economic, and environmental levels. Within the context of UHI, this describes the extent at which the built environment and human population are endangered by the changes in temperature include degradation in durability, increase in energy demand or an increase in human mortality. Rising temperatures within urban environments are caused by the thermal conductivity of materials in the built environment, a lack of vegetation and a mixing of wind due to building geography. The structures that make up urban areas absorb and contain solar radiation more than natural landscapes containing vegetation and water bodies.

UHI research tends to focus on larger cities such as Chicago or New York because the scale of the UHI has been shown to generally scale with the built urban environment. However, it is also well understood that the heterogeneity of the urban environment can lead to significant

variation in the UHI over the microscale suggesting smaller communities are likely also vulnerable. There is a lack of research regarding UHI in smaller or midsize cities, such as Burlington, Vermont, where significant UHI signatures have also been observed. Unique factors may also be more relevant, for instance, ageing built infrastructure. In 2016 Burlington passed the 2016 Sustainable Infrastructure Plan to address the ageing transportation and stormwater infrastructure. During their preliminary evaluation they found that 16 percent of Burlington sidewalk system is in serious failed condition and 25 percent of their streets are also in poor or failed condition. Additionally, these conditions are not improving as Burlington repairs their streets on a 40-year cycle despite the fact they require road surface redevelopment after 15 to 25 years ("Infrastructure Plan for a Sustainable City 9-9-16 CC Final", 2016.). The condition of the transportation infrastructure is a factor in the urban heat that exists within the city.

Additional features of interest in Burlington are the heterogeneity in urban environment, the atmospheric conditions as well as its proximity to Lake Champlain. An influential factor within urban heat islands is the geographical location of a city specifically related to the presence of large water bodies and it has been found that on a larger scale there is a correlation between air temperature and the distance from a large river or lake (Coseo and Larsen 2014). Water bodies influence the microclimates of the surrounding area because of the relative cooling impact they have on evaporative procedures (Manteghi et al. 2015).

Additionally, the diurnal cycle of heating and cooling is important and, for many cities, can mean the largest difference in temperatures between urban and rural areas often occurs at night. Small cities of this size have limited sampling; however, we want to understand the variability of the heat signature that exists because it has important implications within public heath as well as environmental consequences.

#### Research Question and Overview

Through this research we are looking at heat intensity in Burlington, Vermont and its relationship to land use. Areas with a higher percentage of impervious surfaces are understood to be a significant driver of the variability in local temperature microenvironments. This research attempts to address the following questions: What is the correlation between land cover, specifically impervious surfaces, and heat intensity in Burlington, Vermont? Does this correlation hold across multiple days of observation and sampling methods?

# Literature Review

UHI is determined by comparing the air temperature between urban and rural areas and is influenced by various physical and meteorological elements in an urban area (Oke 1973). UHI research is now classified into one of three categories based on the vertical position which the UHI occur: surface heat island, canopy layer heat island, and boundary layer heat island (Oke 1987, Oke 2017). Boundary layer heat occurs within the meso-scale range which allows an analysis of urban heat magnitude and intensity at urban boundaries (1976). Canopy layer urban heat refers to the layer formed between the ground and the height of building roofs in a city and is used to study the morphological characteristics of buildings on UHI including height and density of buildings (Oke 1988, Oke2017).

The growth in urban climatology reported by Oke (1976) has continued and has been accelerated and the literature in the field has expanded. Two decades of urban research was analyzed to provide an overview of the advancements in understanding urban climate processes, with a specific focus on turbulence, energy and water exchanges, and the urban heat island phenomenon (Arnfield 2003). Turbulence has a significant impact in urban environments and has a role in shaping various meteorological parameters. Turbulence can result in vertical mixing, affecting the transport of momentum, heat, and moisture within the urban boundary layer. Microscale turbulence is influenced by localized surface features, such as street canyons, building clusters, and vegetation patches. The paper discusses measurement techniques including in situ temperature sensors and mobile measurement. In situ measurements provide detailed information on microscale temperature patterns and help identify UHI hotspots within urban environment. Mobile measurements enable the mapping of temperature variation at a finer spatial resolution, capturing street level temperature gradients and identifying factors influencing UHI intensities.

There are several organizations studying methods to reduce the impact of extreme heat, and urban heat, on vulnerable populations such as the elderly or low income individuals' (Office of education, Climate Program Office, National Integrated Heat Health Information System ( NIHHIS)) has formed a public-private partnership with CAPA Strategies to conduct their Heat Watch Campaign to map UHI across 60+ communities around the United States. The goal of the partnership is to develop strategies which can be useful in the development and implementation of Heat Watch Campaigns. The sampling technique used GPS and temperature sensors mounted on bikes and vehicles collecting data every second. To analyze the data they created a focal buffer and a random forest regression. They found that all nine models, 3 study areas with morning, afternoon, and evening transects, had high predictive power (adjusted R^2) and low RMSE values. The afternoon models had consistently lower performances and this research points to previous studies which attributes this to variations in humidity, building height, and the subsequent effects on wind pattern. All three study areas presented common patterns: high density urban areas are hotter than low density urban areas; major roadways are visible in all UHI surfaces and are often amplified in the evening; vegetative areas are cooler than urbanized areas.

# Methods

To address the research questions, we collected unique observation data on multiple days and built statistical models to investigate the relationship between observed temperature and impervious surfaces.

#### Study Area of Transect

This study was conducted in the City of Burlington, Vermont, 2019 population of 42,801 according to the US Census Bureau. The median household income as of 2019 was \$51,394 with a poverty rate of 26.4%. The age makeup of Burlington, Vermont is 3.2% persons under 5 years old and 11.9% persons 65 years and over [12]. The Burlington climate is cold and temperate with significant rainfall throughout the year, making it classified as Dfb. In Burlington, the average annual temperature is 7.8 °C | 46.1 °F. July is the hottest month of the year with an average high temperature of 21.3 °C | 70.3 °F and it has the highest number of daily hours of sunshine on average, 10.91 hours of sunshine a day ("Burlington climate" n.d.). Burlington, Vermont has an increased in the number of hot days over the past few decades, and this trend is predicted to continue into the future. According to data from the National Oceanic and Atmospheric Administration (NOAA), Burlington had an average of 10 days per year with temperatures over 90F from 1981 to 2020. However, this number is projected to increase to 28 days per year by

mid-century (2041-2070) under a high greenhouse gas emission scenario (RCP8.5) (NOAA 2021).

The study area of the transect aimed to target a variety of local microenvironments forests, grasslands, urbanized areas, as well as areas with different degrees of impervious surface cover or vegetative density. The transect followed the route depicted in Figure 1, and spans from the New North End to the Old South End, all within the Chittenden Boundary. The black line is the transect and the star is the Essex station center.



0 0.75 1.5 3 Miles

Figure 1: Study area of Burlington, Vermont



Roads Paved Surfa

0.13 0.25 0.5 Miles



# **Temperature Observations**

We used geolocated temperature observations collected during Summer 2021 in Burlington, Vermont. Data was collected along a prescribed 18.50-mile loop through the City of Burlington, Vermont. The route traversed a continuum of built infrastructure typologies including forested parks, residential neighborhoods, and downtown core. To control for variable atmospheric conditions, sampling periods targeted adiabatic conditions, that is forecasted conditions with minimal cloud cover, minimal winds, and high heating over at least a 24-hour period. On these days, sampling occurred three times a day starting at 8am, 2pm, and 9pm local time to capture the diurnal dynamics of the UHI development.

The samples being analyzed for the UHI are as follows: Monday June 6, 2021, Tuesday June 7, 2021 and Sunday August 8, 2021. The samples being analyzed for the observed temperatures are the same as above, plus the data collected by CAPA strategies on Sunday August 10, 2020. The CAPA data refers to the underlying dataset used in the NIHHIS-CAPA Urban Heat Island mapping campaigns. According to the Daily Climate Report from the National Weather Service Burlington, Vermont had a maximum recorded temperature of 96 degrees at 3:54 Pm with a

minimum temperature of 70 degrees recorded at 4:20 am. The highest wind speed was 14 mph with the average sky cover of 0.3 and an average relative humidity of 51% ("Burlington, VT | Data USA" n.d.).

Temperature and GPS data was using a temperature and relative humidity sensor mounted on an electric bike. The Noman Omegga OM- 74 thermocouple data logger was used to collect temperature observations and the Ostarz Travel Recorder XT was used to collect GPS location data. Both sensors were programmed to collect data every second (60 Hz). A research team member traversed the route on a RadMission Power electric bike with the bike speed held constant between 10-15 mph while complying with applicable traffic safety laws. The thermocouple heat sensor was mounted in a custom solar radiation shield made of one inch PVC pipe which itself was mounted two meters above the ground while the bike was in motion, in accordance with the World Meteorological Organization standards for atmospheric observation (see figure 2) (Oke 2009). The Ostarz Travel Recorder XT was carried by the researcher in an outside backpack pocket.



Figure :3 Positioning of temperature sensor



Figure 4: Mobile Platform Set Up

#### Data Cleaning

The data was collected every second by two different sensors, therefore, it was necessary to clean and merge the data in RStudio to begin the analysis. First, all rows that contained zero values in the respective GPS and temperature tables were removed including the longitude, latitude, time or temperature row were removed. The longitude collected by the thermocouple was off by a magnitude of (-1) and did not fall within the Vermont boundary. The longitude value was multiplied by a value of (-1) in order for the data to be projected correctly in ArcGis. Finally, the GPS data was combined with the temperature data based on the temperature and time (to the second). This data was exported from RStudio and the rest of the analysis began.

#### **UHI** Calculations

To calculate the urban heat island signature within the city of Burlington, an appropriate rural temperature observation station was required, which can be seen in Figure 1. The Remote Automated Weather Stations (RAWS) are automated weather stations typically used in remote or unstaffed locations, so the [ESXV1] Essex Junction RAWS, timezone: America/New\_York station was selected(*IEM: Observation History*, "Remote Automatic Weather Stations (RAWS)" n.d.). This station is within the VT\_DCP network and is located at latitude 44.50780 and longitude -73.11560 within Chittenden county. The elevation of the sensor is at 110 meters. Data

for the station was collected from the university of Iowa Iowa Environmental Mesonet on June 7<sup>th</sup>, 2021.

Rural temperature values between hourly observations were calculated for each urban temperature observation using a linear interpolation. The UHI signature was then calculated using equation 1:

(1)  $\Delta T = T_{u,i} - T_{r,i}$ 

Where  $T_{u,i}$  is the observed urban temperature at time, *i*;  $T_{r,i}$  is the calculated rural temperature at time *i*, and  $\Delta T$  is the magnitude of the UHI.

#### Study Area CAPA Strategies

The CAPA studies Heat Watch campaign was supported through a partnership with NOAA, to map urban heat islands. The study was conducted in the City of Burlington, Vermont on August 10<sup>th</sup> 2020. 18 volunteers collected 51,910 temperature and humidity data points in the morning, afternoon, and evening. Maximum temperature recorded was 89.4 degrees with a temperature differential, the largest concurrent range of measured temperatures, of 9.5 degrees during one transect. ("Summary Report\_Heat Watch Burlington\_111720" 2021).

#### Temperature observations CAPA Strategies

In the CAPA Strategies study, the ambient air temperature was mapped across the region at a granularity of 10m resolution using mobile sensors. The volunteer team conducted the campaign by driving and/or bicycling sensor equipment along a pre-planned traverse route at coordinated hour intervals. This method used vehicle mounted temperature sensors along with GPS sensors which collected data at a one second interval. The sensors collected measurements of ambient temperature, humidity, longitude, latitude, speed and course in second intervals.

#### **Buffer Analysis**

The percent impervious surface area was calculated in a variable diameter buffer from each transect observation point. All geospatial analysis was performed in ArcGIS Pro 2.8.1. At each temperature observation point, a buffer radius of 20, 50 and 100 meters was calculated. The resulting buffer polygons were then intersected with high resolution land cover data derived in 2016 and published in 2019 ("Statewide High-Resolution Vermont Land Cover Data" n.d.). This

land cover database was obtained using Object Based Image Analysis (OBIA) techniques to extract building, roads, other paved, and railroad polygons from a combination of 2016 LiDAR and 2016 Orthoimage. We then dissolved the aggregate polygons by buffer ID and landcover class. Total impervious surface coverage was divided by the total buffer area to arrive at the percent impervious surface area for each buffer and corresponding temperature observation.

Example of the 20, 50 and 100 meter buffer on the impervious surface layer at a point located at latitude 44.479112 and longitude -73.217459 which is located on Cherry Street off the Burlington downtown mall. This point is isolated directly from the data.



Figure 5 Example 20, 50, 100 meter buffer

#### Linear Regression

To test the relationship between the observed temperature and impervious surface microenvironment, a linear regression model was developed using R Studio Pro. The total percentage of all impervious surfaces within each buffer was compared against the observed temperature. The same form of the linear regression was run for the 20 and 50-meter buffer size for each of the 8am, 2pm, and 9pm transects for the 3 days of sampling. Within the linear regression there were terms for the percent of impervious surface area in the buffer, distance from Lake Champlain, elevation. The linear regression was calculated in using equation 2 for the observed temperature and equation 3 for the UHI calculations

$$(2)T = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \epsilon$$
$$(3)\Delta T = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \epsilon$$

T = Temperature  $\Delta T = Urban Heat$   $\beta_0 = Intercept term$   $\beta = Slope \ coefficient \ for \ intpendent \ variables$   $x_{i1} = Percent \ Roads$   $x_{i2} = Percent \ Buildings$   $x_{i3} = Elevation$   $x_{i4} = Lake \ Distance$  $\epsilon = Error \ Term$ 

# Results

There were 4 datasets being analyzed for the "observed temperature" model 06/06/21, 06/07/21, 08/08/21, and 08/10/20 [CAPA DATA]. Additionally, 3 datasets being analyzed for the "UHI" model- 06/06/21, 06/07/21 and 08/08/21. The outputs of the linear regression for both models can be seen in Appendix 2 and all results except for the percent roads coefficient for the CAPA PM 50-meter buffer obtained a p-value of <0.001. This outlier was a negative coefficient for the percent roads variable (-0.00088) with a p-value of 0.793. This result was seen as an outlier and was excluded from the analysis.

The data, seen in Tables 1-3, indicates that for the observed that the observed temperature and the calculated UHI is affected most by the percentage of roads and the lake distance. As the percentage of roads increase, the temperature increases, on average, by 0.0404 for the observed temperature model and 0.1549 for the Urban Heat model. The magnitude for the percent roads coefficient and the lake distance coefficient is 10 times greater for the UHI model compared to the observed temperature model. The magnitude of the elevation is to the thousands for both models, averaging -0.00614 for the observed temperature and averaging -0.00604 for the UHI model. The elevation variable had a negative relationship with the intercept meaning that as the elevation increased, the temperature decreased.

#### Table 1 Summary of Results

Variable	Average	Range	P-Values	Average	Range	P-Values
	Observed			Urban		
	Temperature			Heat		
Intercept	76.791	64.311-89.584	<0.001	11.318	5.034-13.302	<0.0001
Percent Roads	0.0404	0.00599-0.1148	<0.001	0.1549	0.1012-0.2289	<0.001
Percent	0.00865	0.00178-0.0219	<0.001	0.0383	0.00819-0.0847	<0.001
Buildings						
Elevation	-0.00614	-0.009250.00471	<0.001	-0.00604	-0.0102 0.00304	<0.001
Lake Distance	0.0131	0.0072-0.0224	<0.001	0.1066	0.0674-0.1392	<0.001
(meters)						

Table 2 Observed Heat Summary of Results

	Intercept	Percent Buildings	Percent Roads	Elevation	Lake Distance (meters)
Average	76.7914317	0.00865554	0.04047143	-0.0061488	0.01307349
Standard Deviation	8.83451725	0.00510254	0.02923582	0.00119034	0.00484082
Median	77.32116	0.00794	0.03012	-0.005675	0.0125195

Table 3 Urban Heat Summary of Results

	Intercept	Percent Buildings	Percent Roads	Elevation	Lake Distance (meters)
Average	11.31818778	0.03834056	0.1549045	-0.0060417	0.10663667
Standard Deviation	4.173876432	0.02715825	0.04068853	0.0017487	0.02520873
Median	12.12614	0.025895	0.14175	-0.00573	0.110625

The R^2 value is a measure of how well a regression model fits the observed data and represents the proportion of the variance in the dependent variable that can be explained by the independent variable in the mode. Figure 6 displays the R^2 values per buffer size for each model while Table 4 displays the average values for each of the boxplots. The standard distribution of the box plot for the "observed temperature" shows that there is a greater range of R^2 compared to the "UHI" distribution. The R^2 values are higher for the "UHI" model than the "observed temperature" which indicates that the linear regression is a better fit to the "UHI" model.



Figure 6 Box Plot of R^2 Values per Buffer Size for Each Model

Tahle	4.	Average	R^2	values
IUDIC	÷.	AVEIUGE	N Z	vulues

Buffer	Average R^2 Value
20 meter - observed	0.299
50 meter -observed	0.304
20 meter - UHI	0.37
50 meter - UHI	0.39

Data was collected across multiple days to see the variation across the summer. For the observed temperature there were two sample days in June and two sample days in August. The CAPA data was collected in August 2020 when the rest of the data was collected in 2021. For all of the plots, the 50-meter buffer had a higher coefficient for all times. The y axis is the plot spanning from June  $6^{th}$  am transect to August  $8^{th}$  pm transect. For both the observed temperature and the UHI model, the lake coefficient decreases as the summer progresses. The maximum coefficient for the August terms (August 8, PM, 50 meter buffer -- 0.02084) is lower than the maximum coefficient for the June term (June 6, PM, 50 meter buffer – 0.02301).



Figure 7 Lake Distance for Observed Temperature



Figure 8 Lake Distance for Urban Heat

An area of interest in the study was the diurnal patterns of heat and urban heat. Figures 9 and 10 look at the percent roads coefficient for the UHI model and the observed model grouped by the time of the transect: AM, AF, PM. The median value for the percent roads coefficient for the observed temperature, from AM, AF and PM, are as follows: 0.0229, 0.03077, 0.0678. The

percent roads coefficient for the UHI model for AM, AF, and PM are as follows: 0.10832, 0.07458, 0.1329.



Figure 9 Observed Temperature Percent Roads Coefficient by Time



Figure 10 Urban Heat Percent Roads Coefficient by Time

For the observed temperature model, an area of interest was how the results of the CAPA data compared with the sample data. Figure 11 shows a box plot of the regression coefficients for the percent roads variable and Figure 12 shows the regression coefficients for the lake distance variable. The CAPA data is highlighted by the black x's on the box plot. For Figure 11, the interquartile range displayed in the box plot for the percent roads variable is 0.01403- 0.06014. coefficients for the CAPA data fall within the range of 0.01205-0.04187. The lower end of the data falls outside of the interquartile range and lower than the middle 50% of the data. In Figure

12, the interquartile range displayed in the box plot for the lake distance variable is 0.00769655-0.018025. The coefficients for the CAPA data has a range of 0.0077-0.01819which means that it most nearly falls in the middle 50% of the data.



Figure 11 Regression Coefficient for Percent Roads- Observed Temperature model



Figure 12 Regression Coefficient for Lake Distance- Observed Temperature model

# Discussion

The magnitude of urban heat within small cities is comparable to the values observed in large cities, especially at night. People in smaller cities, specifically cities in the northeast that are generally classified as having colder and temperate climates such as Burlington, Vermont, may not be aware or prepared to take mitigative action when extreme heating events occur.

Two buffers of different sizes were analyzed to address if there is a correlation between land use, specifically impervious surfaces related to transportation, and heat intensity in Burlington, Vermont. This research indicates that, as the buffer size increases, impervious surfaces become an increasingly correlated with the observed UHI magnitude. Between the buffer sizes of 20 and 50, the 50-meter buffer had the largest R squared value for all transects. The R square value indicates that the model explains more of the temperature variation. At the smaller scale, within the 20 meter buffer, impervious surfaces are less of an indicator of the urban heat within Burlington Vermont.

Water bodies have high specific heating capacity meaning that they require large amounts of energy to increase their temperature compared to land surface. As a result, in the summer months, the sun's energy is absorbed by the water, causing the water temperature to increase at a much slower rate than the surrounding land. This means that water bodies can act as "sinks" for heat, absorbing and storing heat during the day and resulting in cooler temperatures near the water's edge. This can be seen in the Lake Distance term in the Tables 1-3 indicating that for every meter away from the lake, the temperature increases positively. However, later in the summer, as the water temperature continues to rise and approaches the temperature of the surrounding heat, and the heat absorption capacity of the water becomes saturated, the water's ability to act as a sink for heat decreases, and its effects on the surrounding temperature is reduced (NCEI n.d.). This can be seen, on a small scale, on figures 7-8. For both the observed temperature and UHI models, the lake distance coefficients are smaller in August compared to the coefficients from the June data. The smaller coefficients

It is important to note that the CAPA data was collected in 2020 which the rest of the data was collected in 2021. The summer of 2021 was hotter than the summer of 2020, therefore, the coefficients for the CAPA data could be lower due to the difference in a year, not the difference between June and August. There are no UHI calculations, which would be calculated using rural temperature data from 2020 and would minimize error.

Roads, specifically dark colored and non-porous materials such as asphalt and concrete, have high heat absorption and low heat reflectivity properties. This means that they absorb a significant amount of solar radiation, becoming hotter than the surrounding air, and slowly release it into the environment, raising local temperatures, specifically at night (Akbari 2005). Public health research has found that the strongest predictors of heat related mortality are nighttime minimum air temperatures and that air temperature variations are greatest during the night (Coseo and Larsen 2014). The data, seen in Figures 9 and 10, revealed that the 9pm buffer had the highest regression coefficient for the UHI data which indicates that the percent of roads has a greater influence on the UHI at night opposed to the any other time. Rural locations contain less roads and hold less heat after the sun goes down. The afternoon data had the lowest regression coefficient for the observed temperature and the UHI. With the sun directly overhead, the heat stored and released in the pavement have less of an influence. More work can be done including additional transects during a 24 hour period to address the diurnal patterns of urban heat within a city.

The CAPA data generally fell within the middle 50% of the data, within the interquartile range in the box plots displayed in Figures 11 and 12. This indicates that the sampling methods and data collected described in this research are comparable to the methods and approach used by CAPA Strategies. The heat watch campaign run by CAPA spans 61+ campaign cities and was used to create a high-resolution description of ambient heat at the human level. The methods being used in this study can be implemented on a larger scale and used to create maps of similar magnitude and use.

Limitations in this data are the limited sample days and the rural temperature measurements. For this research we targeted adiabatic conditions, forecasted conditions with minimal cloud cover, minimal wind, and high heating over a 24-hour window for days when we sampled. Increased data collection would allow us to control for variable weather conditions such as wind patterns on the day of the transect as it has been found that wind speed and cloud cover are two meteorological variables governing heat island intensity and this research did not fully factor the wind speed and direction on days when data was collected (Oke 1982b). More data collection over the entire summer would allow us to get more variability in temperature and have a more accurate representation of the urban heat in Vermont. Additionally, increased data collection in rural areas of Vermont would allow there to be more accurate calculations of the true magnitude of urban heat that exists in Burlington as a city.

# Summary & Conclusion

This research examined the correlation between land use, specifically impervious surfaces related to transportation infrastructure, and heat intensity in Burlington, Vermont. Impervious surfaces are understood to be a significant driver of the variability in local temperature microenvironments even on the scale of Burlington, Vermont. This research looked at spatial differences in temperature as well as urban heat calculations for data in June and August in Burlington, Vermont. It was found that the percentage of roads and the distance from the lake are the two largest impacts on the observed temperature and UHI. This research was also a comparison of sample data vs data collected by CAPA strategies. The CAPA data aligned with the sample data which indicates that the sampling methods described in this research can be amplified to a larger scale.

The impervious surfaces within the city can explain the temperature when looking at the diurnal patterns. Back-to-back sampling days would account for day-to-day variation in weather and other factors that may influence temperature measurement. This data could be used to analyze how long temperature is stored in impervious surfaces and the effect of multiple high heating days effects urban heat. This could also be researched by adding more transects through a 24 hour period. Doing more than 3 transects a day would give a better idea of heat storage in cities with a greater degree of accuracy.

Additional data collection which spans not just over the summer but over the entire year is necessary to get more variability in temperatures and therefore a more accurate understanding of the effects of impervious surfaces on observed temperature and the relative urban heat. Increased sampling better captures the seasonality of urban heat and could allow us to calculate the magnitude of urban heat islands during a true heat wave. Within the field there has been an addressed lack in relevant research including microclimate studies in the winter/spring/autumn. An extension of the research would evaluate the annual cycles in UHI intensity and would need to factor in season trends in winds, cloud cover, humidify and day length. The seasonal nature of urban heat means that the timing of data collection may affect the results in urban heat studies and extended data collection would yield more accurate results.

Different variables, including wind, cloud cover and time since sunrise/sunset, could be added to the linear regression in order to get a greater understanding of drivers of urban heat. A mixing factor could be added to reflect the wind speed and direction. Wind can bring cooler air from rural locations, or the lake, which can reduce urban heat. The cloud cover would affect urban heat by blocking or reflecting incoming solar radiation, which would reduce the amount of heat being absorbed by urban surfaces. Cloud cover could also reduce the amount of outgoing longwave radiation which could lead to hotter nighttime temperatures. The time since sunrise/sunset is important because the cooling of impervious surfaces depends on the amount of heat adsorbed during the day. The longer the time since sunset, the more time there is for surfaces to cool down and can result in lower temperatures in the evening.

This research did not address or identify places with increased vulnerability within Burlington. This would require a more in-depth analysis that considers building age, population demographics, and other factors that contribute to vulnerability to extreme heat. Higher temperatures in urban areas may increase energy usage due to the increased need for air conditioning and CO2 equivalence annual emissions rises in the presence of UHI due to the increase in cooling demand . This problem is exacerbated by ageing infrastructure which consume energy at a higher rate because old buildings are not properly equip to handle extreme increases in weather associated with urban heat islands. It is important to generate strategies which can mitigate further rises in urban temperatures and increase a populations ability to adapt to climate change and changing heating environments.

# References

- Arnfield, A. 2003. "Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island." *International Journal of Climatology*, 23: 1–26. https://doi.org/10.1002/joc.859.
- ASCE. (2016). Heat Vulnerability in Vermont. In Proceedings of the XX Conference on Civil Engineering, 2016, 123-135.
- akrherz@iastate.edu, daryl herzmann. n.d. "IEM :: Custom Wind Roses." Accessed May 8, 2023a. https://mesonet.agron.iastate.edu/sites/dyn\_windrose.phtml?station=ESXV1&network=VT\_DCP
- akrherz@iastate.edu, daryl herzmann. n.d. "IEM :: Download Daily Summary Data." Accessed May 8, 2023b. <u>https://mesonet.agron.iastate.edu/request/daily.phtml</u>.
- akrherz@iastate.edu, daryl herzmann. n.d. "IEM :: Observation History." Accessed April 5, 2023c. <u>https://mesonet.agron.iastate.edu/sites/obhistory.php?station=ESXV1&network=VT\_DCP&meta</u> <u>r=0&madis=0&year=2021&month=6&day=7&sortdir=asc</u>.
- "Burlington climate: Average Temperature, weather by month, Burlington water temperature -Climate-Data.org." n.d. Accessed April 5, 2023. <u>https://en.climate-data.org/north-</u> <u>america/united-states-of-america/vermont/burlington-1745/</u>.
- "Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas -ScienceDirect." n.d. Accessed May 9, 2023. <u>https://www.sciencedirect.com/science/article/abs/pii/S0038092X0000089X</u>.
- "Data.GISS: GISS Surface Temperature Analysis (v4): Analysis Graphs and Plots." n.d. Accessed April 5, 2023. <u>https://data.giss.nasa.gov/gistemp/graphs\_v4/</u>.
- "Global Surface Temperature Anomalies | National Centers for Environmental Information (NCEI)." n.d. Accessed May 9, 2023. <u>https://www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies</u>.
- "Heat Vulnerability in Vermont." 2016.
- "How factors of land use/land cover, building configuration, and adjacent heat sources and sinks explain Urban Heat Islands in Chicago | Elsevier Enhanced Reader." n.d. Accessed April 5, 2023.

https://reader.elsevier.com/reader/sd/pii/S0169204614000607?token=2BEABB0671D98B5026E E4C7521E62A2D25583EBA8F84AB6A111E3DB8D55501181BC1CF66E66E2DC358A3B3C1 15C36BE9&originRegion=us-east-1&originCreation=20230406000523.

- Li, X., Y. Zhou, S. Yu, G. Jia, H. Li, and W. Li. 2019. "Urban heat island impacts on building energy consumption: A review of approaches and findings." *Energy*, 174: 407–419. https://doi.org/10.1016/j.energy.2019.02.183.
- Manteghi, G., H. B. Limit, and D. Remaz. 2015. "Water Bodies an Urban Microclimate: A Review." *MAS*, 9 (6): p1. <u>https://doi.org/10.5539/mas.v9n6p1</u>.
- Oke, T. 1982. "The energetic basis of urban heat island." *Quarterly Journal of the Royal Meteorological Society*, 108: 1–24. <u>https://doi.org/10.1002/qj.49710845502</u>.

- Oke, T. 2009. "Chandler, T.J. 1965: The climate of London. London: Hutchinson, 292 pp." Progress in Physical Geography - PROG PHYS GEOG, 33: 437–442. https://doi.org/10.1177/0309133309339794.
- "Remote Automatic Weather Stations (RAWS)." n.d. Accessed May 8, 2023. https://www.nifc.gov/about-us/what-is-nifc/remote-automatic-weather-stations.
- Salvati, A., M. Palme, G. Chiesa, and M. Kolokotroni. 2020. "Built form, urban climate and building energy modelling: case-studies in Rome and Antofagasta." *Journal of Building Performance Simulation*, 13. <u>https://doi.org/10.1080/19401493.2019.1707876</u>.
- Sprung, M. J., M. Chambers, S. Smith-Pickel, and United States. Department of Transportation. Bureau of Transportation Statistics. 2018. *Transportation Statistics Annual Report 2018*. Transportation Statistics Annual Report (TSAR).
- "Statewide High-Resolution Vermont Land Cover Data Now Available | Vermont Center for Geographic Information." n.d. Accessed May 8, 2023. <u>https://vcgi.vermont.gov/data-release/statewide-high-resolution-vermont-land-cover-data-now-available</u>.
- "Summary Report\_Heat Watch Burlington\_111720.pdf." 2021. Open Science Framework.
- "U.S. Census Bureau QuickFacts: Burlington city, Vermont." n.d. Accessed April 5, 2023. https://www.census.gov/quickfacts/burlingtoncityvermont.
- US Department of Commerce, N. n.d. "Records and Normals." NOAA's National Weather Service. Accessed May 8, 2023. <u>https://www.weather.gov/btv/recsAndNorms?site=KMPV</u>.
- US EPA, O. 2014. "Climate Change and Heat Islands." Overviews and Factsheets. Accessed May 9, 2023. <u>https://www.epa.gov/heatislands/climate-change-and-heat-islands</u>.
- Vargo, J., B. Stone, D. Habeeb, P. Liu, and A. Russell. 2016. "The social and spatial distribution of temperature-related health impacts from urban heat island reduction policies." *Environmental Science & Policy*, 66: 366–374. <u>https://doi.org/10.1016/j.envsci.2016.08.012</u>.
- Webmaster, C. P. C. n.d. "Climate Prediction Center." Accessed May 8, 2023. https://www.cpc.ncep.noaa.gov/.

# Appendix 1





# Appendix 2

# CAPA AM 08/08/20

# 20 Meter Buffer

	Observ	ved Temperature	
Predictors	Estimates	Confidence interval	Р
(Intercept)	68.42405	68.35205-68.49606	<0.001
Percent buildings	0.004898	0.004254-0.005539	<0.001
Percent Roads	0.01503	0.01339-0.01667	<0.001
Elevation (meters)	-0.00567	-0.005960.00538	<0.001
Distance from Lake (meters)	0.011557	0.010571 0.012542	<0.001
Observations	4108		
R^2/ R^2 adjusted	0.311/0.317		
CAPA AM 08/08/20			
50 Meter Buffer			
	Obser	rved Temperature	
Predictors	Estimates	Confidence interval	Р
(Intercept)	68.31119	68.25463-68.36774	<0.001
Percent buildings	0.007123	0.006570-0.007677	<0.001
Percent Roads	0.01205	0.00891-0.01519	<0.001
Elevation (meters)	-0.00567	-0.005900.00545	<0.001
Distance from Lake (meters)	0.012685	0.01124- 0.013441	<0.001

R^2/ R^2 adjusted 0.355/0.355

4108

Observations

# CAPA AF 08/08/20

#### 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	86.48430	86.48430-86.57862	<0.001
Percent buildings	0.02055	0.01174-0.02935	<0.001
Percent Roads	0.01375	0.01153-0.01598	<0.001
Elevation (meters)	-0.00522	-0.005600.00483	<0.001
Distance from Lake (meters)	0.007783	0.0063443- 0.0092219	<0.001
Observations	3516		
R^2/ R^2 adjusted	0.220/0.219		

# CAPA AF 08/08/20

# 50 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	86.58465	86.50898-86-86.6632	<0.001	
Percent buildings	0.00928	0.00184-0.01672	<0.001	
Percent Roads	0.02878	0.02460-0.03296	<0.001	
Elevation (meters) Distance from Lake (meters)	-0.00529 0.00734166	-0.005600.00489 0.006183- 0.008499	<0.001 <0.001	
Observations	3516			
R^2/ R^2 adjusted	0.218/0.217			

# CAPA PM 08/08/20

# 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	80.46817	80.3297-80.60661	<0.001
Percent buildings	0.009855	0.08495-0.11214	<0.001
Percent Roads	0.04187	0.01008-0.07428	<0.001
Elevation (meters)	-0.00925	-0.009810.00869	<0.001
Distance from Lake (meters)	0.017489	0.01537-0.01960482	<0.001
Observations	3527		
R^2/ R^2 adjusted	0.282/0.282		

# CAPA PM 08/08/20

# 50 Meter Buffer

Observed Temperature			
Predictors	Estimates	Confidence interval	Р
(Intercept)	80.32116	86.50898-86-86.66032	<0.001
Percent buildings	0.011481	0.01848-0.01672	<0.001
Percent Roads	-0.00088	-0.00744 - 0.00568	0.793
Elevation (meters)	-0.00529	-0.009330.00840	<0.001
Distance from Lake (meters)	0.018199	0.016448- 0.019951	<0.001
Observations	5811		
R^2/ R^2 adjusted	0.263/0.263		

07/06/21 8AM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	65.56212	65.48715-65.63708	<0.001
Percent buildings	0.00499	0.004161-0.005835	<0.001
Percent Roads	0.005998	0.003670-0.008028	<0.001
Elevation (meters)	-0.00578	-0.006120.00544	<0.001
Distance from Lake (meters)	0.012354	0.011232-0.013458	<0.001
Observations	3284		
R^2/ R^2 adjusted	0.320/0.326		

#### 07/06/21 8AM 50 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	65.1912	65.13596-65.24644	<0.001	
Percent buildings	0.00712	0.00694-0.00929	<0.001	
Percent Roads	0.01365	0.01031-0.01700	<0.001	
Elevation (meters)	-0.00508	-0.006010.00524	<0.001	
Distance from Lake (meters)	0.013123	0.011666-0.014580	<0.001	
Observations	5437			
R^2/ R^2 adjusted	0.365/0.365			

# 07/06/21 2PM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	82.64835	82.54415-82.75255	<0.001
Percent buildings	0.02199	0.01349-0.03050	<0.001
Percent Roads	0.01523	0.01273-0.01772	<0.001
Elevation (meters)	-0.0055	-0.005910.0051	<0.001
Distance from Lake (meters)	0.00745	0.006033-0.008867	<0.001
Observations	5472		
R^2/ R^2 adjusted	0.225/0.224		

# 07/06/21 2PM 50 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	82.5092	82.42968-82.58872	<0.001	
Percent buildings	0.00759	0.00032-0.01486	<0.001	
Percent Roads	0.03012	0.02632-0.03392	<0.001	
Elevation (meters)	-0.0056	-0.005960.00523	<0.001	
Distance from Lake (meters)	0.007883	0.007033-0.008767	<0.001	
Observations	5845			
R^2/ R^2 adjusted	0.278/0.278			

# 07/06/21 9PM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	71.37215	71.18707-71.55723	<0.001
Percent buildings	0.00376	0.00099-0.00654	<0.001
Percent Roads	0.07948	0.06776-0.09119	<0.001
Elevation (meters)	-0.00784	-0.008360.00731	<0.001
Distance from Lake (meters)	0.020146	0.01020-0.02984	<0.001
Observations	6936		
R^2/ R^2 adjusted	0.290/0.290		

# 07/06/21 9PM 20 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	71.69197	71.45007-71.93387	<0.001	
Percent buildings	0.00178	0.00098-0.00453	<0.001	
Percent Roads	0.06014	0.05034-0.06995	<0.001	
Elevation (meters)	-0.0071	-0.007680.00652	<0.001	
Distance from Lake (meters)	0.019634	0.01752 -0.02175	<0.001	
Observations	6745			
R^2/ R^2 adjusted	0.257/0.257			

#### 07/07/21 8AM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	68.89689	68.82687-68.96690	<0.001
Percent buildings	0.00447	0.00291-0.00603	<0.001
Percent Roads	0.0441	0.03833-0.04987	<0.001
Elevation (meters)	-0.00698	-0.007120.00644	<0.001
Distance from Lake (meters)	0.012736	0.011863-0.013608	<0.001
Observations	3948		
R^2/ R^2 adjusted	0.322/0.318		

#### 07/07/21 8AM 50 Meter Buffer

Observed Temperature			
Predictors	Estimates	Confidence interval	Р
(Intercept)	68.46881	68.3028-68.8302	<0.001
Percent buildings	0.01239	0.00694-0.00929	<0.001
Percent Roads	0.06625	0.06092-0.07158	<0.001
Elevation (meters)	-0.00584	-0.006060.00562	<0.001
Distance from Lake (meters)	0.011901	0.010441-0.013361	<0.001
Observations	4109		
R^2/ R^2 adjusted	0.352/0.352		

# 07/07/21 2PM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	86.51184	86.51184-86.59468	<0.001
Percent buildings	0.01208	0.01019-0.01498	<0.001
Percent Roads	0.02625	0.01710-0.03541	<0.001
Elevation (meters)	-0.00568	-0.006040.00531	<0.001
Distance from Lake (meters)	0.007342	0.005897-0.008787	<0.001
Observations	4659		
R^2/ R^2 adjusted	0.214/0.213		

#### 07/07/21 2PM 50 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	86.50506	86.43208-86.57803	<0.001	
Percent buildings	0.00829	0.00016-0.01642	<0.001	
Percent Roads	0.0258	0.02170-0.02990	<0.001	
Elevation (meters)	-0.00471	-0.005090.00433	<0.001	
Distance from Lake (meters)	0.007948	0.006696-0.0092	<0.001	
Observations	4850			
R^2/ R^2 adjusted	0.222/0.221			

# 07/07/21 9PM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	74.12857	74.07194-75.18519	<0.001
Percent buildings	0.00519	0.00062-0.00975	<0.001
Percent Roads	0.07483	0.06642-0.08324	<0.001
Elevation (meters)	-0.00813	-0.008720.00754	<0.001
Distance from Lake (meters)	0.022413	0.01748-0.02735	<0.001
Observations	5849		
R^2/ R^2 adjusted	0.380/0.380		

# 07/07/21 9PM 20 Meter Buffer

Observed Temperature				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	74.32116	74.24344-74.39887	<0.001	
Percent buildings	0.00889	0.00793-0.00951	<0.001	
Percent Roads	0.114811	0.10605-0.12357	<0.001	
Elevation (meters)	-0.00529	-0.007420.00315	<0.001	
Distance from Lake (meters)	0.018199	0.016565-0.019833	<0.001	
Observations	5294			
R^2/ R^2 adjusted	0.388/0.388			

# 08/06/21 8AM 20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	64.42405	64.0382-64.9847	<0.001
Percent buildings	0.003082	0.002984-0.00376	<0.001
Percent Roads	0.01249	0.01204-0.01497	<0.001
Elevation (meters)	-0.00598	-0.006010.00538	<0.001
Distance from Lake (meters)	0.01284	0.011841 0.013552	<0.001
Observations	4038		
R^2/ R^2 adjusted	0.339/0.339		
08/06/21 8AM			
50 Meter Buffer			

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	64.31119	68.1943-68.3943	<0.001
Percent buildings	0.005938	0.00499-0.00829	<0.001
Percent Roads	0.014034	0.01389-0.01502	<0.001
Elevation (meters)	-0.00493	-0.005400.00430	<0.001
Distance from Lake (meters)	0.010453	0.00935-0.013419	<0.001
Observations	4101		
R^2/ R^2 adjusted	0.340/0.340		

# 08/06/21 2PM

20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	89.48430	89.48430-86.57862	<0.001
Percent buildings	0.00304	0.002904-0.003492	<0.001
Percent Roads	0.0473	0.0348-0.0501	<0.001
Elevation (meters)	-0.00547	-0.005600.00490	<0.001
Distance from Lake (meters)	0.00948	0.00834- 0.00998	<0.001
Observations	3754		
R^2/ R^2 adjusted	0.345/0.345		

# 08/06/21 2PM

# 50 Meter Buffer

Observed Temperature			
Predictors	Estimates	Confidence interval	Р
(Intercept)	89.58465	86.50898-86-86.6632	<0.001
Percent buildings	0.00928	0.00893-0.01030	<0.001
Percent Roads	0.0590	0.05490-0.06320	<0.001
Elevation (meters) Distance from Lake (meters)	-0.00601 0.008018	-0.006200.00557 0.00770- 0.00847	<0.001 <0.001
Observations	3684		
R^2/ R^2 adjusted	0.400/0.400		

# 41

# 08/06/21 8PM

20 Meter Buffer

# **Observed Temperature**

Predictors	Estimates	Confidence interval	Р
(Intercept)	83.46817	83.0197-83.80041	<0.001
Percent buildings	0.009855	0.08495-0.11214	<0.001
Percent Roads	0.04187	0.01008-0.07428	<0.001
Elevation (meters)	-0.00725	-0.008810.00669	<0.001
Distance from Lake (meters)	0.017489	0.01537-0.01960482	<0.001
Observations	3527		
R^2/ R^2 adjusted	0.401/0.401		

# 08/06/21 8PM

# 50 Meter Buffer

Observed Temperature			
Predictors	Estimates	Confidence interval	Р
(Intercept)	83.32116	86.50898-86-86.66032	<0.001
Percent buildings	0.014811	0.00184-0.01672	<0.001
Percent Roads	0.08801	0.08001 - 0.09482	0.793
Elevation (meters)	-0.00801	-0.008980.00788	<0.001
Distance from Lake (meters)	0.01930	0.02084- 0.01803	<0.001
Observations	5811		
R^2/ R^2 adjusted	0.420/0.420		

# Appendix 3

# 07/06/21 8AM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	6.2123	4.87159-6.37088	<0.001	
Percent buildings	0.0199	0.01101-0.03835	<0.001	
Percent Roads	0.10998	0.0970-0.12200	<0.001	
Elevation (meters)	-0.00578	-0.006120.00544	<0.001	
Distance from Lake (meters)	0.09354	0.08642-0.10548	<0.001	
Observations	3284			
R^2/ R^2 adjusted	0.390/0.391			

# 07/06/21 8AM 50 Meter Buffer

		Urban Heat	
Predictors	Estimates	Confidence interval	Р
(Intercept)	6.1912	6.13596-6.74645	<0.001
Percent buildings	0.0812	0.0794-0.0929	<0.001
Percent Roads	0.1365	0.1091-0.1860	<0.001
Elevation (meters)	-0.00508	-0.006010.00524	<0.001
Distance from Lake (meters)	0.10193	0.0966-0.14990	<0.001
Observations	5437		
R^2/ R^2 adjusted	0.357/0.357		

07/06/21 2PM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	12.4855	11.9485-12.794	<0.001	
Percent buildings	0.02199	0.01349-0.03050	<0.001	
Percent Roads	0.1233	0.1203-0.1794	<0.001	
Elevation (meters)	-0.0055	-0.005910.0051	<0.001	
Distance from Lake (meters)	0.06745	0.06033-0.08867	<0.001	
Observations	5472			
R^2/ R^2 adjusted	0.392/0.392			

# 07/06/21 2PM 50 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	12.5095	12.4668-12.57294	<0.001	
Percent buildings	0.0759	0.032-0.01486	<0.001	
Percent Roads	0.12012	0.11632-0.1392	<0.001	
Elevation (meters)	-0.0056	-0.005960.00523	<0.001	
Distance from Lake (meters)	0.07883	0.07023-0.08679	<0.001	
Observations	5845			
R^2/ R^2 adjusted	0.410/0.410			

# 07/06/21 9PM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	16.3784	16.1704-17.6483	<0.001	
Percent buildings	0.0376	0.0318-0.0401	<0.001	
Percent Roads	0.1948	0.1778-0.2110	<0.001	
Elevation (meters)	-0.00784	-0.008360.00731	<0.001	
Distance from Lake (meters)	0.13014	0.1180-0.1384	<0.001	
Observations	6936			
R^2/ R^2 adjusted	0.378/0.379			

# 07/06/21 9PM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	16.9477	16.3829-17.2749	<0.001
Percent buildings	0.0178	0.0098-0.0393	<0.001
Percent Roads	0.20014	0.1934-0.2705	<0.001
Elevation (meters)	-0.0061	-0.006680.00552	<0.001
Distance from Lake (meters)	0.13634	0.1225 -0.1475	<0.001
Observations	6745		
R^2/ R^2 adjusted	0.401/0.401		

#### 07/07/21 8AM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	10.8390	10.3029-11.1023	<0.001	
Percent buildings	0.0847	0.0771-0.0993	<0.001	
Percent Roads	0.141	0.0833-0.1987	<0.001	
Elevation (meters)	-0.00698	-0.007120.00644	<0.001	
Distance from Lake (meters)	0.09736	0.0863-0.11608	<0.001	
Observations	3948			
R^2/ R^2 adjusted	0.320/0.320			

#### 07/07/21 8AM 50 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	10.4945	10.018-10.7960	<0.001
Percent buildings	0.01239	0.00694-0.00929	<0.001
Percent Roads	0.1425	0.0992-0.2158	<0.001
Elevation (meters)	-0.00584	-0.006060.00562	<0.001
Distance from Lake (meters)	0.12901	0.10941-0.23361	<0.001
Observations	4109		
R^2/ R^2 adjusted	0.356/0.356		

07/07/21 2PM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	7.8493	7.4932-8.0124	<0.001
Percent buildings	0.01508	0.01219-0.01987	<0.001
Percent Roads	0.12483	0.10621-0.13384	<0.001
Elevation (meters)	-0.00568	-0.006040.00531	<0.001
Distance from Lake (meters)	0.07342	0.05897-0.08787	<0.001
Observations	4659		
R^2/ R^2 adjusted	0.370/0.370		

# 07/07/21 2PM 50 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	6.9035	6.8023-7.20445	<0.001	
Percent buildings	0.01029	0.00938-0.01642	<0.001	
Percent Roads	0.164811	0.10459-0.21094	<0.001	
Elevation (meters)	-0.00471	-0.005090.00433	<0.001	
Distance from Lake (meters)	0.07948	0.07196-0.08940	<0.001	
Observations	4850			
R^2/ R^2 adjusted	0.390/390			

# 07/07/21 9PM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	12.1358	12.0482-12.7583	<0.001
Percent buildings	0.00819	0.0062-0.0125	<0.001
Percent Roads	0.1625	0.1410-0.20941	<0.001
Elevation (meters)	-0.00913	-0.009720.00854	<0.001
Distance from Lake (meters)	0.12413	0.11484-0.12935	<0.001
Observations	5849		
R^2/ R^2 adjusted	0.420/0.420		

# 07/07/21 9PM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	12.11648	12.0183-12.5890	<0.001
Percent buildings	0.0188	0.0093-0.02004	<0.001
Percent Roads	0.2288	0.2180-0.2648	<0.001
Elevation (meters)	-0.01029	-0.012420.00984	<0.001
Distance from Lake (meters)	0.13199	0.12565-0.13833	<0.001
Observations	5294		
R^2/ R^2 adjusted	0.4500/0.450		

#### 08/06//21 8AM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	5.3044	4.87159-5.7083	<0.001
Percent buildings	0.0204	0.01409-0.03503	<0.001
Percent Roads	0.12998	0.13970-0.18200	<0.001
Elevation (meters)	-0.00578	-0.006120.00544	<0.001
Distance from Lake (meters)	0.12354	0.10242-0.14548	<0.001
Observations	6782		
R^2/ R^2 adjusted	0.370/0.371		

#### 08/06/21 8AM 50 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	5.6909	5.0259-6.4485	<0.001
Percent buildings	0.0608	0.0580-0.0703	<0.001
Percent Roads	0.1012	0.0890-0.1902	<0.001
Elevation (meters)	-0.00490	-0.005800.00420	<0.001
Distance from Lake (meters)	0.11932	0.1042-0.12902	<0.001
Observations	6928		
R^2/ R^2 adjusted	0.397/0.397		

08/06/21 2PM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	6.829	6.002-7.290	<0.001	
Percent buildings	0.06092	0.02589-0.0708	<0.001	
Percent Roads	0.1504	0.1304-0.1947	<0.001	
Elevation (meters)	-0.00712	-0.008020.00610	<0.001	
Distance from Lake (meters)	0.0829	0.0782-0.0890	<0.001	
Observations	6463			
R^2/ R^2 adjusted	0.300/301			

# 08/06/21 2PM 50 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	7.5095	6.4668-7.57294	<0.001	
Percent buildings	0.0759	0.032-0.01486	<0.001	
Percent Roads	0.12012	0.11632-0.1392	<0.001	
Elevation (meters)	-0.0056	-0.005960.00523	<0.001	
Distance from Lake (meters)	0.07883	0.07023-0.08679	<0.001	
Observations	5048			
R^2/ R^2 adjusted	0.350/0.350			

08/06/21 9PM 20 Meter Buffer

Urban Heat				
Predictors	Estimates	Confidence interval	Р	
(Intercept)	12.5095	12.4668-12.57294	<0.001	
Percent buildings	0.03847	0.0289-0.0420	<0.001	
Percent Roads	0.2084	0.1840-0.2182	<0.001	
Elevation (meters)	-0.00378	-0.004500.00300	<0.001	
Distance from Lake (meters)	0.13203	0.1289-0.1444	<0.001	
Observations	5038			
R^2/ R^2 adjusted	0.402/0.403			

# 08/06/21 9PM 20 Meter Buffer

Urban Heat			
Predictors	Estimates	Confidence interval	Р
(Intercept)	14.829	14.002-15.290	<0.001
Percent buildings	0.0298	0.0180-0.0340	<0.001
Percent Roads	0.2289	0.1920-0.2302	<0.001
Elevation (meters)	-0.00304	-0.003890.00290	<0.001
Distance from Lake (meters)	0.13922	0.13293-0.14504	<0.001
Observations	5829		
R^2/ R^2 adjusted	0.430/0.430		