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Knoxville Microclimates: Spatial and Temporal Variability in Ambient Air Temperature Across Four Urban Neighborhoods

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I am submitting herewith a thesis written by David Andrew Howe entitled "Knoxville Microclimates: Spatial and Temporal Variability in Ambient Air Temperature Across Four Urban Neighborhoods." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Environmental Engineering.

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ABSTRACT

The urban heat island (UHI), has been studied extensively over the past 30 to 40 year, yet questions remain regarding the spatiotemporal variability of the UHI, and what factors influence this variability. More recent studies have emphasized the microclimates within an urban setting, but most do not have the high resolution climate or land cover data necessary to truly understand the interactions taking place at a neighborhood-scale. This study used a network of 10 identical weather stations and high resolution land use data in Knoxville, Tennessee to analyze the microclimates of a medium-sized city with a temperate climate over the course of an entire year. Two stations were installed in each of four urban neighborhoods, in locations with varying localized tree cover, in addition to two additional locations in the center of downtown and in a nearby urban nature center. The goal of the study was to observe the spatial and temporal patterns of temperature in these neighborhoods and analyze what land cover characteristics best explain those patterns. The intra-neighborhood results (Clear vs. Tree) suggest that there is significant temperature variability within a single neighborhood, based on the land use characteristics immediately surrounding a given weather station. However, the inter-neighborhood variability (differences between neighborhoods) was greater in magnitude, which suggests that the overall differences in neighborhood characteristics have a greater effect on climate than more local characteristics. Temperature variability was also found to be greater during the warm seasons (spring and summer) and during days with dry air masses. Land cover at the neighborhood scale (impervious cover and tree canopy percentages at the 500 meter radius) had the highest correlation with the minimum daily temperature (Tmin) during the summer season. Tmax had the highest interaction with the distance of each station from Downtown, but was also significantly related to land use. This work demonstrates the need for high-resolution climate and land cover data to truly understand the interactions of urban characteristics and the microclimates within a city. These data can be used to better inform planning strategies to build resiliency to extreme heat into urban environments.

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1 INTRODUCTION / BACKGROUND

In 1950, only 30 % of the world's population were urban dwellers. Because of increasing urbanization over the past sixty-four years, 54 % of the world's population lived in urban areas (3.9 billion) in 2014. This number is projected to increase to 66 % by 2050, adding 2.5 billion to the world's urban population. North America is the most urbanized region on the world, with 82 % living in urban areas in 2014 [1]. Thus, determining how to live in urban environments in a sustainable manner that promotes public and ecological health is critical.

Urbanization has many documented adverse effects, including an increase in energy consumption, the deterioration of living environment [10], an increase in ozone levels [11], and hotter urban streams [12]; [13]. More extreme heat waves are more likely in city centers due to the UHI and are increasing due to climate change [15]; [16], under which extreme heat events are anticipated to become more recurrent and longer lasting in the next century [17]. Extreme heat waves are considered a human health hazard [18], and have the potential to be life-threatening, even in temperate climates [14]; [19]. In 2007, The Intergovernmental Panel on Climate Change (IPCC) predicted a future increase in heat wave-related deaths worldwide [20].

A well-documented phenomenon that occurs due to urbanization is the urban heat island (UHI) [2]. This effect is recognized by warmer daytime and nighttime temperatures in a city compared to its surrounding areas. It is more pronounced in larger cities with dense urban development and sparse vegetation [57]. The greatest difference in temperature typically takes place overnight, with the urban area producing a higher daily minimum temperature (Tmin) and therefore a lower diurnal temperature range (DTR) [2]; [3], that is, the difference between Tmax and Tmin [Equation 1]. Higher daily maximum temperatures (Tmax) are primarily caused by the low albedo [4]; [5], or low reflected light, and a lack of vegetation which leads to lower evapotranspiration [4]; [6]; [7]. Development patterns, specifically the effects of street canyon geometry and sky view factor, lead to greater heat storage during the day and heat release at night [5]; [8]; [9].

$$DTR = Tmax - Tmin \qquad (1)$$

The surface energy equation combines the roles of surface properties and near-surface climates [Equation 2]. The left-hand side of the equation combines the absorbed solar radiation (1-a * I) and the absorbed long wave radiation (L*) with the anthropogenic heating (Q_f). The right-hand side of the equation represents the sensible (H), latent, and ground heat fluxes, respectively (H, λE, G). Lower albedos in urban areas increases the amount of absorbed solar radiation, and therefore higher temperatures. Impervious surfaces lead to greater runoff and less available surface water for evapotranspiration. Low evapotranspiration (evaporation and transpiration) from soil-vegetation systems in urban areas causes increased latent heat [4].

$$(1-a)I + L^* + Q_f = H + \lambda E + G \qquad (2)$$

Several mitigation measures have proven successful. Increasing albedo can decrease the amount of solar radiation absorbed by impervious surfaces by whitewashing buildings [25], the use of other ‘cool materials’ [24], or with green roofs [58]. Planting and/or protecting existing vegetation, which adds shade and evapotransporative cooling, is a promising technique being considered to reduce urban heat and falls within the increasingly promoted use of green infrastructure in urban environments. Studies have shown that urban parks, or one large greenspace, have a cooling effect on surrounding areas [21]; [22]; [23]. However, the effectiveness of parks may also vary by individual park characteristics [21]. Thus, the interaction between vegetation density with other factors may produce a patchwork of climates, or microclimates within an urban setting [26]. There is a critical need to understand these interactions to truly develop mitigation strategies and support sustainable development using strategically placed green infrastructure.

The study of urban microclimates and their relationship to land use and population characteristics has become more prevalent over the past ten to fifteen years [26]; [27]; [28]; [63]; [64]. Studies have analyzed the correlation between the UHI and other characteristics of an urban environment, including: vegetation [48], population density and night light [34], percentage impermeable surfaces [34], [64], the spatial pattern of greenspace [29]; [30], and various land use/land cover features [28]. Since canopy cover [28] and built/paved surface coverage [30], [34] had the greatest effect on temperature variation, this study analyzed these two land cover characteristics in addition to the distance of an area from the city center.

These smaller-scale analyses require higher resolution climate data. Methodologies used to obtain a higher spatial density of temperature data include remote sensing [29]; [30]; [31], observational transects by car [32]; [28], or a collection of surface observation networks (multiple weather stations) [33]; [34]. Temporally, data is collected on select clear, warm days during the summer [28]; [23], over the course of several months [22]; [23], or long-term [34]; [35]; [36]. Use of higher resolution land cover data is also necessary to truly understand the interaction between land use/land cover and temperature. The National Land Cover Database (NLCD) provides free, easily accessible land cover information, and is used in many fields of study [39]; [40]. However, this 30-meter resolution data may limit smaller-scale studies [41] by underestimating tree canopy and impervious cover percentages. Limitations of previous studies on the UHI include low spatial coverage of temperature data [28]; [32], [48], limited temporal coverage of temperature data [23]; [28], [48], or the use of low-resolution land cover data [26]; [40]. Cities with warmer climates have been the focus of many UHI studies [26]; [27]; [33]; [36]; [40]. Previous studies in Knoxville, TN utilized a surface observation network but primarily focused on the temperature and humidity variability during a few summer months [63]; [64].

The goal of this study was to analyze Knoxville’s microclimates over the course of an entire year, in order to address the question of scale effects on the UHI. This

study utilizes a network of surface observation networks, which provides a greater snapshot of temperature variability within an urban setting, and is necessary to understand this complex issue [37]; [38]. The study area and design are described in greater detail in Sections 3 and 4. To be able to analyze the UHI effect on daytime and nighttime temperature variation, the temperature data was parsed into daily Tmax, Tmin, and DTR for each station. Analyses were run on the temperature data over the course of the entire year, seasonally, and based on specific air mass (Sections 5.1 and 5.2). Finally, the temperature data was compared to high-resolution land use/land cover data (Sections 5.3 and 5.4) from Google Maps. The main focus of this project was to observe spatial and temporal patterns of temperature data collected within an urban setting (Knoxville, TN) to answer two primary questions: (1) how do climates vary within a medium-sized city in the southeast United States, and (2) what land use/land cover characteristics best explain the temperature variability identified.

2 STUDY AREA/DESIGN

Knoxville, TN was the location for this project, with an estimated population of 184,281 as of 2014 1 July [Figure 1]. Knoxville is the third largest city in Tennessee [42]. Located in eastern Tennessee, Knoxville lies between The Great Smoky Mountains National Park to the east and the Cumberland Plateau to the west. Its climate is classified by Koppen-Geiger as fully humid war temperate with hot summers (Cfa) [43]. Average yearly precipitation is 1215.64 mm, 165.1 mm of which is in the form of snow. The average maximum temperature of 31.2°C occurs in July and the average minimum temperature occurs in January and is -1.56°C. The average yearly mean temperature for Knoxville is 15.28°C [44].

Ten identical weather stations were installed in July of 2014 in Knoxville. Two weather stations were installed in each of four urban neighborhoods: West Hills, Lonsdale, Burlington, and Vestal. Additionally, two stations were installed at locations in downtown Knoxville and at Ijams Nature Center, a forested park within the Knoxville Urban Wilderness [45]. The four urban neighborhoods were chosen based on their relative proximity to downtown, their differing socioeconomic makeup, and land cover characteristics evidenced by differential tree cover and impervious surface percentages. West Hills had the lowest population density and lowest impervious surface coverage, while Lonsdale had the highest population density and lowest mean income [42]. To minimize confounding factors, locations were chosen that had similar altitude and topographical features. Additional socioeconomic characteristics for each neighborhood as well as their location can be found in [Table 1].

Within each neighborhood, two locations were chosen to provide extremes in terms of the magnitude of localized tree cover. One station was in a location with minimal tree cover (“Clear”), and one was located within denser tree cover (“Tree”). [Figure 2].The differences in tree canopy in Clear and Tree locations were explored, verified, and quantified as described later.

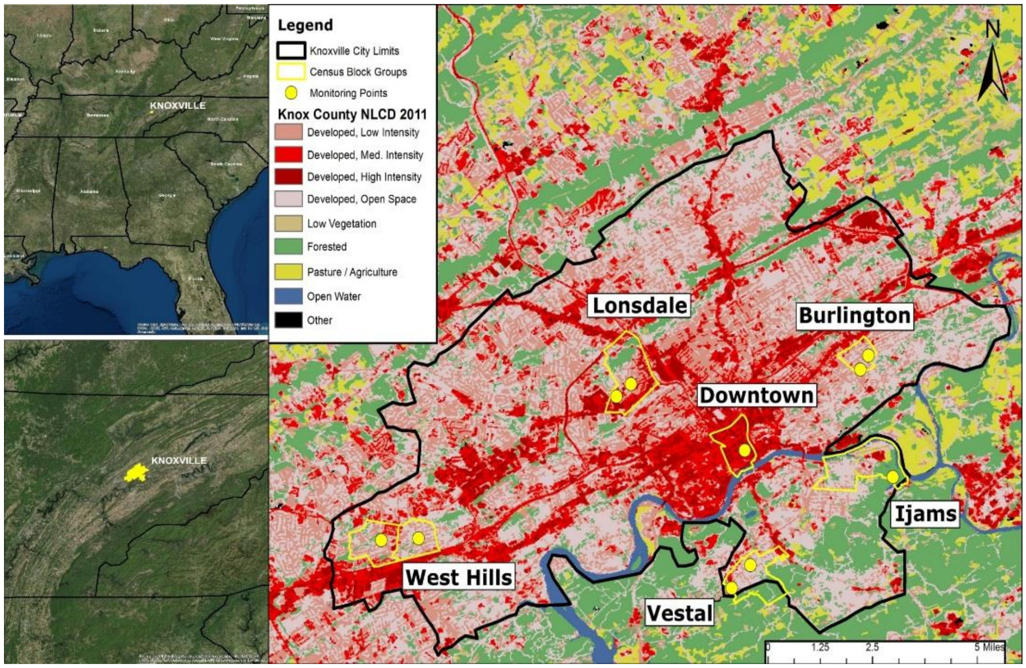

Figure 1. Locations of monitoring stations with 2011 National Land Cover Data.

Table 1. Population density, approximate mean income, elevation, latitude and longitude of 10 weather station locations.

Station	Distance Apart (m)	Population Density (People/sq km)	Approximate Mean Income (USD)	Elevation (m)	Latitude	Longitude
Burlington Tree	540.1	4971	29447	316.1	35.9926	-83.8747
Burlington Clear				335.9	35.9883	-83.8775
Lonsdale Tree	622.1	5941	22950	293.7	35.9839	-83.9569
Lonsdale Clear				290.8	35.9801	-83.9619
Vestal Tree	969.6	3322	24456	280.4	35.9286	-83.9155
Vestal Clear				288.5	35.9217	-83.9220
West Hills Tree	1167.7	2052	42147	312.2	35.9368	-84.0303
West Hills Clear				316.4	35.9363	-84.0432
Ijams	4691.5	N/A	N/A	290.0	35.9555	-83.8663
Downtown		N/A	N/A	286.4	35.9637	-83.9175

Figure 2. West Hills "Clear" and "Tree" stations.

3 METHODS

3.1 Data Collected

Each weather station was assembled by attaching Onset Smart Sensors to a HOBO Micro Station Data Logger (H21-002). The logger was housed within a Cantex Junction Box (20 X 20 X 10 cm), and installed at an average height of 2.25 meters above ground. The Onset 12-bit Temperature/Relative Humidity Smart Sensor (S-THB-M002) measured temperature with a range of -40°C to 75°C, an accuracy of ±0.21°C, and a resolution of 0.02°C. The weather stations were tested prior to installation to ensure consistent readings across all ten units [Appendix].

The temperature data were logged every five minutes and manually collected using the HOBOware Software and a Tripp-Lite Keyspan USB/Serial Adapter (USA-19HS). Data analyzed herein were collected between 2 July 2014 and 1 July 2015. Data were unavailable at several stations for various periods of time due to either vandalism or station malfunction [Table 2]. There were 295 total days available where data were present for all ten stations, and all seasons were well represented.

Table 2. Missing Data.

Station	Dates Missing	Reason
Lonsdale Clear	15—21 August 2014	Vandalism
	30 April—6 May 2015	Malfunction
West Hills Tree	13—20 November 2014	Malfunction
	16 April—6 May 2015	Malfunction
Burlington Tree	15—28 February 2015	Malfunction
	5 April—6 May 2015	Malfunction
Lonsdale Tree	15—28 February 2015	Malfunction

This study focused on the Tmax, Tmin and DTR. After aggregating the data into daily values, it was further broken down by season (summer and winter solstice, fall and spring equinox) as well as air mass type, or Spatial Synoptic Classification (SSC) [46]. The seasonal analysis allows an investigation into the potential changes in the magnitude of temperature data variation during all parts of the year. The SSC was developed to enable synoptic climatological impact analysis by taking into account the source region of the air [47]. This information was used to determine the role of SSC on temperature variation. The daily SSC was collected for the full year of the study with 31

Dec 2014 being the only missing day. Eight air mass types (SSC) were identified during the study period, including: SSC 1 (Dry Moderate), SSC 2 (Dry Polar), SSC 3 (Dry Tropical), SSC 4 (Moist Moderate), SSC 5 (Moist Polar), SSC 6 (Moist Tropical), SSC 66 (Moist Tropical Plus), and SSC 7 (Transition).

3.2 Statistical Tests

Matched-pairs t-tests were run using JMP, a statistical software from SAS. This analysis is used to test whether there is a significant mean difference between two sets of paired data. All dates that had missing data from one or more stations were removed so that all comparisons could be made with the same number of data points and to ensure equitable treatment of all locations. Tests were performed for the full year, comparing temperature variability (Tmax, Tmin, and DTR) within the same neighborhood (intra-neighborhood variability, i.e. Clear vs. Tree) as well as the differences between neighborhoods (inter-neighborhood variability, i.e., Clear vs. Clear and Tree vs Tree). The Downtown and Ijams stations were also analyzed. Additional matched-pairs t-tests were then run to analyze the temperature data across all stations by season as well as by SSC.

3.3 Land Cover Analysis

To examine how neighborhood-scale land use / land cover characteristics play a role in spatial temperature variability, several land cover variables were quantified for each weather station. The amount of impervious surface and the amount of tree cover within various radii from each station (50, 100, 200, and 500 m) were quantified. Previous research has determined that land cover has the greatest influence on air temperature at radii less than 500 m, with the effects diminishing at larger distances [34, 48]. Similarly, Gallo et al. [35] and Li and Roth [36] found 100 m radii were the ideal spatial resolution for visualizing land use effects on DTR and UHI intensity, respectively. Stewart and Oke [49] developed 'local climate zones' (LCZ) to better classify urban microclimates. Each LCZ was characterized by certain geometry and land cover that generates a surface-temperature climate unique to that area. For this classification, a 100—200 m circle of influence was suggested.

Tree cover and impervious surface percentages for each station were calculated at the four radii using i-Tree Canopy, an online analysis tool by the US Forest Service [52]. I-Tree Canopy uses aerial images available in Google Maps to allow an estimate of land cover. Project boundaries (4 radii, all 10 stations) were loaded into the program after being created in ArcMap 10.2. Random sample points were generated by i-Tree and classified by the user as "Tree", "Impervious", or "Tree+Impervious". The "Tree" classification was chosen for any point covered by tree canopy that did not overhang an impervious surface. The "Impervious" classification was chosen for any impervious

surface (building, sidewalk, pavement) not covered by canopy. The third category, “Tree+Impervious” was any impervious surface covered by tree canopy. This category was created to investigate if those areas acted more like an impervious surface or tree canopy. For the classification of an entire city, i-Tree suggests using between 500 and 10000 survey points. Two hundred survey points were classified for the 50 m radius, with 300 (100 m), 400 (200 m), and 800 (500 m) points classified for the larger areas. These analyses were completed three times per area and the average result was used. The distance from each station to downtown was calculated in Google Earth.

For comparison purposes, the impervious cover percentages were also quantified using the 2011 National Land Cover Dataset [50] as well as a 1-m resolution raster provided by Knoxville Geographic Information Systems (KGIS) [51], a Geographic Information System collaboration between the city of Knoxville, Knox County, and Knoxville Utilities. For the NLCD, shape files were created for each of the radii around each station (50 m, 100 m, 200 m, and 500 m) in ArcMap10.2. With a 30-m resolution, zonal statistics were used to process the input data to provide an output of the average coverage for that particular zone (impervious %). For the 1 m-resolution KGIS data, each cell was represented by a 1 or a 0 (impervious, pervious), so that the total percentage of impervious surface for each station could be calculated by dividing the total number of impervious cells by the total area.

3.4 Least Squares Regression

Once all temperature and land use data were organized, several regression analyses were run in JMP. The mean yearly Tmax, Tmin, and DTR data for all 10 stations were compared to the land use data using simple least squares regression analyses. The following were used as independent variables in the analyses: distance from downtown, elevation difference from downtown, as well as impervious and tree canopy percentages for all four radii. After the yearly tests were completed, the temperature data were then broken down by season and by SSC and the same analyses were repeated.

4 RESULTS AND DISCUSSION

4.1 Intra-Neighborhood

4.1.i Full Year

The mean differences between Tmax, Tmin, and DTR within each neighborhood (Tree vs. Clear) over the course of the study period were analyzed, and all of the clear stations reported a higher Tmax average over the course of the year [Table 3]. Burlington Clear had a yearly Tmax 0.8 °C greater than Burlington Tree, while Lonsdale Clear's Tmax was negligibly greater than the Tmax for Lonsdale Tree. The clear areas had more impervious areas as well as less tree canopy cover for each neighborhood, which results in a lack of evapotranspiration and shading, lower albedo, and higher daytime temperatures [4]; [6].

More developed areas store more heat during the day, which they then release at night, resulting in a higher Tmin [8]; [9]. This expected pattern was less consistent for our study. The Burlington and West Hills Clear stations had a lower Tmin than their tree station counterparts, while Lonsdale and Vestal showed the opposite pattern. Because of this inconsistency with Tmin, the DTR pattern is also unclear. In three out of the four neighborhoods, the Clear station had a greater DTR than its Tree station counterpart. In an area experiencing a UHI, the greatest difference typically occurs at night. Urban areas typically experience lower DTRs because of a high Tmin, which more than compensates for its higher Tmax [8]; [35]. The lower Tmin for the West Hills and Burlington Clear stations resulted in a greater DTR. In Vestal, the greatest difference between the stations occurred during the daytime (Tmax, 0.7°C), producing a greater DTR for the Clear station. These observations may also be influenced by season or air mass, which are explored below.

Table 3. Full year intra-neighborhood comparisons (°C). Positive numbers indicate Clear station is greater. A bold number indicates a statistically significant difference ($p<0.05$)

Neighborhood	Tmax	Tmin	DTR
West Hills	**0.6**	**-0.2**	**0.8**
Burlington	**0.8**	**-0.1**	**0.9**
Lonsdale	0.0	**0.3**	**-0.2**
Vestal	**0.7**	**0.5**	**0.2**

Matched-pairs t-tests were conducted to determine if the differences between Tree and Clear stations within each neighborhood were significant ($p<0.05$). The only neighborhood comparison that was not statistically significant was the Lonsdale Tmax analysis. The remainder of the t-tests showed that the temperature differences between the two stations within each neighborhood were significant.

4.1.ii Seasonal

The temperature data were parsed by season and the same comparisons discussed above were performed for each station. The summer 2014 season (2014 2 July – 1 Oct) showed a much greater intra-neighborhood variability than any other season. The Tmax for the clear stations in Burlington (+1.2°C), Vestal (+1.1°C), and West Hills (+0.7°C), were all significantly hotter than their Tree station counterpart during this time period. The Lonsdale Clear station was only 0.09°C greater than the tree station, and this difference was not statistically significant. While the differences in Tmin and DTR within each neighborhood were greatest in the summer, an observable pattern was unclear [Table 4]. Regardless, all Tmin and DTR differences were statistically significant ($p<0.05$). The summer results were the same as reported by Ellis et al in 2015 [63].

As a contrast to the summer season, the winter 2015 season (2015 2 Jan – 1 April) showed much less intra-neighborhood variability than any other season. While the clear stations had the same relationship to the Tree stations as in the summer season, the mean difference between the stations was much less [Table 4]. The mean differences for Burlington Tmin, West Hills Tmax, Vestal DTR, and Lonsdale Tmax were not statistically significant. The data from the spring and fall seasons can be found in the [Appendix]. A greater variability between weather stations during the summer season was expected, because the UHI is most prevalent during the warm season [53]; [54]. This is likely due to the variations in vegetative cover, as well as the seasonality of weather controls, such as air mass [2].

Table 4. Intra-Neighborhood comparisons by season (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference ($p<0.05$). Summer season is 2014 2 July – 1 October, excluding 15 – 22 August. Winter season is 2015 2 Jan – 1 April, excluding 15-28 February and 30 March – 1 April.

Summer				Winter			
Neighborhood	**Tmax**	**Tmin**	**DTR**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
West Hills	**1.0**	**-0.3**	**1.2**	West Hills	0.0	**-0.1**	**0.1**
Burlington	**1.2**	**-0.2**	**1.4**	Burlington	**0.4**	-0.1	**0.4**
Lonsdale	0.1	**0.3**	**-0.3**	Lonsdale	-0.1	**0.1**	**-0.2**
Vestal	**1.1**	**0.6**	**0.5**	Vestal	**0.6**	**0.5**	0.1

4.1.iii Air Masses

To determine if the intra-neighborhood variability was greater during a specific air mass type, the temperature data was divided by spatial synoptic classification (SSC). For the study period, there were eight different classifications, including: SSC 1 (Dry Moderate), SSC 2 (Dry Polar), SSC 3 (Dry Tropical), SSC 4 (Moist Moderate), SSC 5 (Moist Polar), SSC 6 (Moist Tropical), SSC 66 (Moist Tropical Plus), and SSC 7 (Transition). It should be noted that the number of study days for each classification was not equal. The matched-pairs t-tests were run the same way for all eight SSC, but the low number of study days for several may have skewed the results.

After comparing the raw temperature data as well as the t-tests, it appears that the greatest intra-neighborhood temperature variability occurred during Dry Moderate, Dry Polar, and Moist Tropical days. On Dry Polar days, the Vestal Clear station had a Tmax (+1.7°C) and Tmin (+0.6°C) greater than the Vestal Tree station, and during Moist Tropical days, the Burlington Clear station had a Tmax (+1.3°C) greater than the Burlington tree station. For these three classifications, only the Burlington Tmin (Dry Moderate) and the Lonsdale Tmax comparisons (Moist Tropical) did not show statistically significant intra-neighborhood temperature differences [Table 5]. The remainder of the SSC comparisons can be found in the [Appendix].

This study showed the greatest intra-neighborhood variability during days with an SSC of Dry Moderate, Dry Polar, and Moist Tropical. The magnitude of intra-neighborhood temperature variability, as well as inter-neighborhood variability (discussed in Section 5.2), is impacted by the prevailing weather pattern, or air mass type (characterized by SSC). More humid air masses mask the land use or maritime impacts on temperature, while dry air masses intensify those effects [55]; [56]. In other words, greater temperature variability due to the UHI is expected during dry (less humid) days. The variability during the Moist Tropical days could be explained by the higher percentage of days in the summer and spring (warm) seasons.

Table 5. Intra-Neighborhood comparisons by SSC (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference ($p<0.05$). Dry Moderate included 85 total days (21 summer, 31 fall, 19 winter, and 14 spring). Dry Polar included 31 total days (5 summer, 10 fall, 13 winter, and 3 spring). Moist Tropical included 58 total days (27 summer, 9 fall, 2 winter, and 20 spring).

	Duration	Neighborhood	Tmax	Tmin	DTR
SSC 1	85 Total Days 21 summer, 31 fall, 19 winter, and 14 spring	West Hills	0.6	-0.3	0.9
		Burlington	0.7	-0.1	0.7
		Lonsdale	-0.1	0.2	-0.3
		Vestal	1.2	0.7	0.5
SSC 2	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	31 total days 5 summer, 10 fall, 13 winter, and 3 spring	West Hills	0.4	-0.5	0.9
		Burlington	0.5	-0.4	0.8
		Lonsdale	-0.5	0.2	-0.7
		Vestal	1.7	0.6	1.2
SSC 6	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	58 total days 27 summer, 9 fall, 2 winter, and 20 spring	West Hills	0.7	-0.1	0.8
		Burlington	1.3	-0.1	1.3
		Lonsdale	0.1	0.3	-0.2
		Vestal	0.6	0.6	0.0

4.2 Inter-Neighborhood

4.2.i Full Year

Daily Tmax, Tmin, and DTR values were compared between neighborhoods and to the Downtown and Ijams stations to determine the larger-scale differences in temperature [Table 6]. Because of the differences observed in the intra-neighborhood analyses, we did not average Tree and Clear stations for each neighborhood. Vestal was consistently warmer during the day than the other neighborhoods, with the Vestal Clear station recording a mean Tmax (22.3°C) close to that of the Downtown station (22.3°C).

Lonsdale was the warmest neighborhood at night (10.7°C, 10.4°C mean Tmin) followed closely by Burlington. Conversely, Vestal was the coolest neighborhood at night (9.4°C, 10.0°C mean Tmin) even though it was the warmest during the day. This indicates that the UHI strength may not be the only factor contributing to inter-neighborhood variability. Mean DTRs ranged from 10.5°C (Burlington Tree) to 12.3°C (Vestal Clear).

Table 6. Full year mean Tmax, Tmin, and DTR (°C) for all stations.

Station	Tmax	Tmin	DTR
West Hills Tree	20.7	10.1	10.6
West Hills Clear	21.3	9.9	11.4
Burlington Tree	21.0	10.4	10.5
Burlington Clear	21.7	10.3	11.4
Lonsdale Tree	21.6	10.4	11.2
Lonsdale Clear	21.7	10.7	11.0
Vestal Tree	21.6	9.4	12.2
Vestal Clear	22.3	10.0	12.3
Ijams	21.9	9.6	12.4
Downtown	22.3	11.6	10.7
Range (clear only)	1.0	0.7	1.3
Range (tree only)	0.9	1.0	1.6
Range (all stations)	1.6	2.2	1.6

The ranges (difference in greatest mean value and lowest mean value) of Tmax, Tmin, and DTR (1.6°C, 2.2°C, 1.6°C) for the entire network (all 10 stations) were slightly less than a study completed in Mainz, Germany between 2011 and 2013. The climate of Mainz, Germany, classified by Koppen and Geiger as Cfb (warm temperate climate, fully humid, warm summer) [43], is similar to Knoxville (Cfa, warm temperate climate, fully humid, hot summer). Their Tmax/Tmin/DTR ranges for 10 stations (842 total days) were 2.2°C/1.8°C/2.1°C, respectively [34].

Matched-pairs t-tests were used to determine the significance of the inter-neighborhood differences in Tmax, Tmin, and DTR. Clear stations were compared to Clear stations in other neighborhoods, while Tree stations were compared to other Tree stations. Differences between clear stations were significant except for Lonsdale-Burlington (Tmax), Vestal-West Hills (Tmin), and Burlington-West Hills (DTR). Differences between tree stations were significant except for Burlington-Lonsdale (Tmin), and Lonsdale-Vestal (Tmax). The inter-neighborhood differences were greater in magnitude than the intra-neighborhood differences, suggesting that neighborhood scale characteristics may be more critical to the observed trends than local scale conditions within each neighborhood [Table 3].

The yearly mean Downtown Tmin (11.6°C) was the highest of any station and 2.0°C greater than the Ijams Tmin (9.6°C). The Downtown Tmax (22.3°C) was also the highest of any station, but was only 0.4°C greater than the Ijams Tmax (21.9°C). The

small difference in Tmax between these two stations is a surprising because of the high density canopy cover in Ijams. The closest neighborhood to the Ijams station was Vestal. Vestal and Ijams were both relatively cooler at night (low Tmin) and warmer during the day (high Tmax). Increasing the spatial dataset (greater station density) in this area may be beneficial in future research to further examine this area. All of the neighborhood comparisons with the Downtown and Ijams stations were significantly different except for Vestal clear-Downtown (Tmax), Vestal clear-Ijams (DTR), and West Hills tree-Downtown (DTR). Box plots of all temperature data are found in [Figure 3].

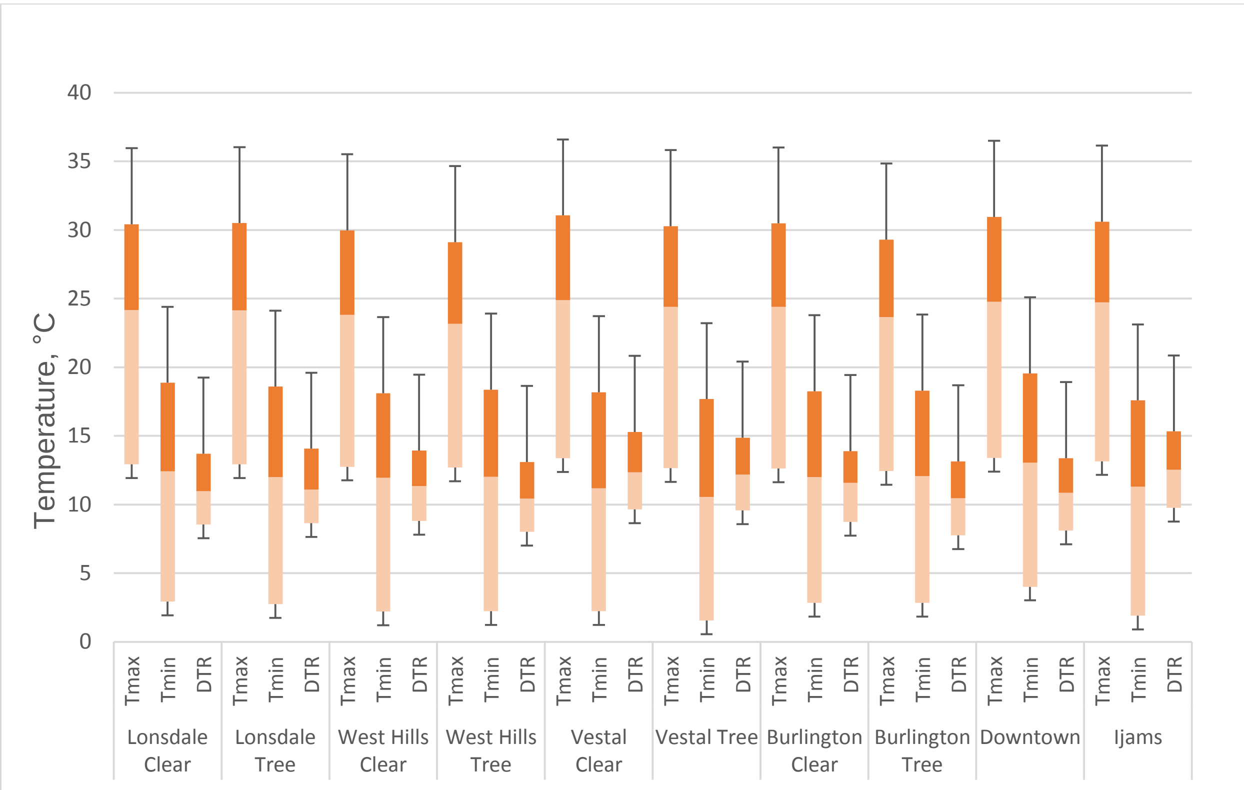

Figure 3. Full year temperature data box plots for all 10 weather stations.

Simply defining a station as Tree or Clear does not describe the extent to which a station is surrounded by tree canopy or impervious surfaces. Essentially, what constitutes “Tree” in one neighborhood may not be the same as what constitutes “Tree” in another. Further, explanatory variables such as air mass and distance from the downtown urban core may also explain the variability noted herein. Thus, additional analyses were performed to move beyond characterizing these data and begin to understand what variables influence these trends (Sections 5.2.ii, 5.2.iii, 5.3, and 5.4).

4.2.ii Seasonal

The temperature data, parsed by season, were compared across all 10 weather stations [Table 7]. Unlike the intra-neighborhood comparisons, the greatest inter-neighborhood temperature variability occurred during the spring 2015 season (2015 2 April – 1 July). The ranges (difference between greatest mean value and lowest mean value) of the Tmax, Tmin, and DTR (2.0°C/2.4°C/2.5°C) in the spring season surpassed those of the full year range (1.6°C/2.2°C/1.6°C). While the greatest overall variability occurred in the spring, the largest Tmax range across all stations (2.2°C) occurred during the summer season (2014 2 July – 1 October). The data from the summer and fall seasons can be found in the [Appendix]. For comparison, Harlen et al (2006) found a 4°C variability (in average temperature differences; they did not calculate Tmax and Tmin) in Phoenix, Arizona during the summer of 2003 [27]. The ranges during the summer 2014 season were the same as reported by Ellis et al in 2015 [63]. While the Harlen et al. (2006) study showed greater temperature variability, Phoenix (Koppen climate classification of Bwh) is warmer and more densely populated (1,537,058 people as of 2014 1 July) than Knoxville (Koppen climate classification of Cfa; 184,281 people as of 2014 1 July) [42]; [43]. Similar to the intra-neighborhood comparisons, the lowest inter-neighborhood variability occurred during the winter 2015 season (2015 2 Jan- 1 April). The ranges of Tmax, Tmin, and DTR (0.9°C/2.0°C /1.5°C) in the winter season were less than the full year range (1.6°C/2.2°C/1.6°C).

Matched-pairs t-tests were used to determine the significance of the inter-neighborhood differences in Tmax, Tmin, and DTR during the spring and winter seasons. As with the full year comparisons, Clear stations were compared to Clear stations in other neighborhoods, while the Tree stations were compared to other Tree stations. During the spring season, differences between Tree stations were all significant, while differences between Clear stations were significant ($p<0.05$) except for Lonsdale-Downtown (DTR) and Vestal-West Hills (Tmin). During the winter, differences between Clear stations were significant ($p<0.05$) except for Lonsdale-Burlington (Tmax, Tmin, and DTR), Vestal-West Hills (Tmin), and Burlington-West Hills (DTR). Differences between Tree stations were all significant except Lonsdale-Vestal (Tmax) and Lonsdale-West Hills (DTR). Although significant differences were observed under all seasons, the magnitude of temperature differences was higher during the warmest time of year.

Table 7. Inter-Neighborhood spring and winter temperature data (°C). Spring season is 2015 2 April – 1 July, excluding 2 April – 6 May. Winter season is 2015 2 Jan – 1 April, excluding 15-28 February as well as 30 March – 1 April.

Spring				Winter			
Station	**Tmax**	**Tmin**	**DTR**	**Station**	**Tmax**	**Tmin**	**DTR**
West Hills Tree	29.6	18.1	11.6	West Hills Tree	11.8	0.5	11.4
West Hills Clear	30.2	18.0	12.2	West Hills Clear	11.9	0.4	11.5
Burlington Tree	29.9	18.2	11.7	Burlington Tree	11.7	0.9	10.8
Burlington Clear	31.0	18.1	12.9	Burlington Clear	12.1	0.8	11.3
Lonsdale Tree	30.7	18.5	12.2	Lonsdale Tree	12.0	0.7	11.4
Lonsdale Clear	30.7	18.8	11.9	Lonsdale Clear	12.0	0.8	11.2
Vestal Tree	31.4	17.4	14.0	Vestal Tree	12.0	-0.1	12.1
Vestal Clear	31.2	17.9	13.3	Vestal Clear	12.6	0.4	12.2
Ijams	31.2	17.2	14.0	Ijams	12.2	0.1	12.2
Downtown	31.6	19.6	12.0	Downtown	12.6	1.9	10.7
Range (Clear only)	1.0	0.9	1.3	Range (Clear only)	0.7	0.5	1.0
Range (Tree only)	1.8	1.1	2.5	Range (Tree only)	0.3	0.9	1.2
Range (All stations)	2.0	2.4	2.5	Range (All stations)	0.9	2.0	1.5

4.2.iii Air Masses

The temperature data, parsed by spatial synoptic classification (SSC), were compared across all 10 weather stations. Of the 8 classifications during the study period, the three classifications with the greatest inter-neighborhood temperature variability were Dry Moderate, Dry Polar [Table 8], and Moist Tropical [Appendix]. The ranges (difference between greatest mean value and lowest mean value) of Tmax, Tmin, and DTR for all three classifications were greater than the full year ranges (1.6°C/2.2°C/1.6°C).

Matched-pairs t-tests were run to compare all temperature variables within each classification. Out of the 29 total comparisons for Dry Moderate, Dry Polar and Moist Tropical, 22, 19, and 22 were statistically significant, respectively ($p<0.05$). The degree of inter-neighborhood variability, like the intra-neighborhood variability, is affected by the prevailing weather pattern (SSC). Prior research has shown that drier air masses intensify the UHI, while more humid air masses mask it [55]; [56]. Dry Moderate and Dry Polar are dry air masses, while the variability in SSC 6 may be explained by the disproportionate number of days during the spring and summer seasons (47 out of 58 days in spring or summer).

The results from sections 5.1 and 5.2 show that there are significant temperature differences across the entire station network. Both season and air mass affect the

intensity of the UHI, with the greatest temperature variability occurring during the spring and summer seasons, as well as the drier air masses (Dry Moderate and Dry Polar). Additional analyses were performed (Sections 5.3 and 5.4) to determine if certain land cover characteristics (tree canopy and impervious surface percentages along with distance from downtown) influence the temperature variability as well.

Table 8. Inter-Neighborhood comparisons by SSC (°C). Dry Moderate: 85 total days (21 summer, 31 fall, 19 winter, and 14 spring). Dry Polar: 31 total days (5 summer, 10 fall, 13 winter, and 3 spring).

Dry Moderate				Dry Polar			
Station	**Tmax**	**Tmin**	**DTR**	**Station**	**Tmax**	**Tmin**	**DTR**
West Hills Tree	21.3	8.4	12.8	West Hills Tree	12.3	-0.1	12.3
West Hills Clear	21.9	8.1	13.7	West Hills Clear	12.6	-0.6	13.2
Burlington Tree	21.7	8.9	12.8	Burlington Tree	12.7	0.4	12.4
Burlington Clear	22.4	8.9	13.5	Burlington Clear	13.2	0.0	13.2
Lonsdale Tree	22.4	8.7	13.7	Lonsdale Tree	13.3	0.1	13.2
Lonsdale Clear	22.3	8.9	13.3	Lonsdale Clear	12.9	0.3	12.5
Vestal Tree	22.0	7.3	14.7	Vestal Tree	12.5	-1.0	13.6
Vestal Clear	23.2	7.9	15.2	Vestal Clear	14.3	-0.5	14.8
Ijams	22.7	7.7	15.0	Ijams	13.6	-0.5	14.1
Downtown	23.1	10.3	12.8	Downtown	13.9	1.8	12.1
Range (Clear only)	1.3	1.0	1.9	Range (clear only)	1.6	0.9	2.2
Range (Tree only)	1.1	1.7	2.5	Range (tree only)	1.0	1.4	1.2
Range (All stations)	1.9	3.1	2.5	Range (all stations)	2.0	2.4	2.6

4.3 Land Cover

Percentage of canopy cover and impervious surfaces were calculated in i-Tree for four radii (50 m, 100 m, 200 m, and 500 m) around all 10 weather stations [Figure 4]. The percentages vary by the size of the area studied, but as expected, the Tree stations had higher tree canopy percentages and lower impervious surface coverage while the reverse was true for the Clear stations. The Downtown control station had the highest percentage of impervious cover and lowest tree canopy cover at all radii, while Ijams had the highest tree canopy and lowest impervious cover numbers. A third category of land cover classification, “Tree+ Impervious” (any impervious surface covered by tree canopy), was also calculated for all stations. This category was added to each of the other two categories separately during the correlation analyses to examine if it acted more like an impervious surface or an area covered by tree canopy.

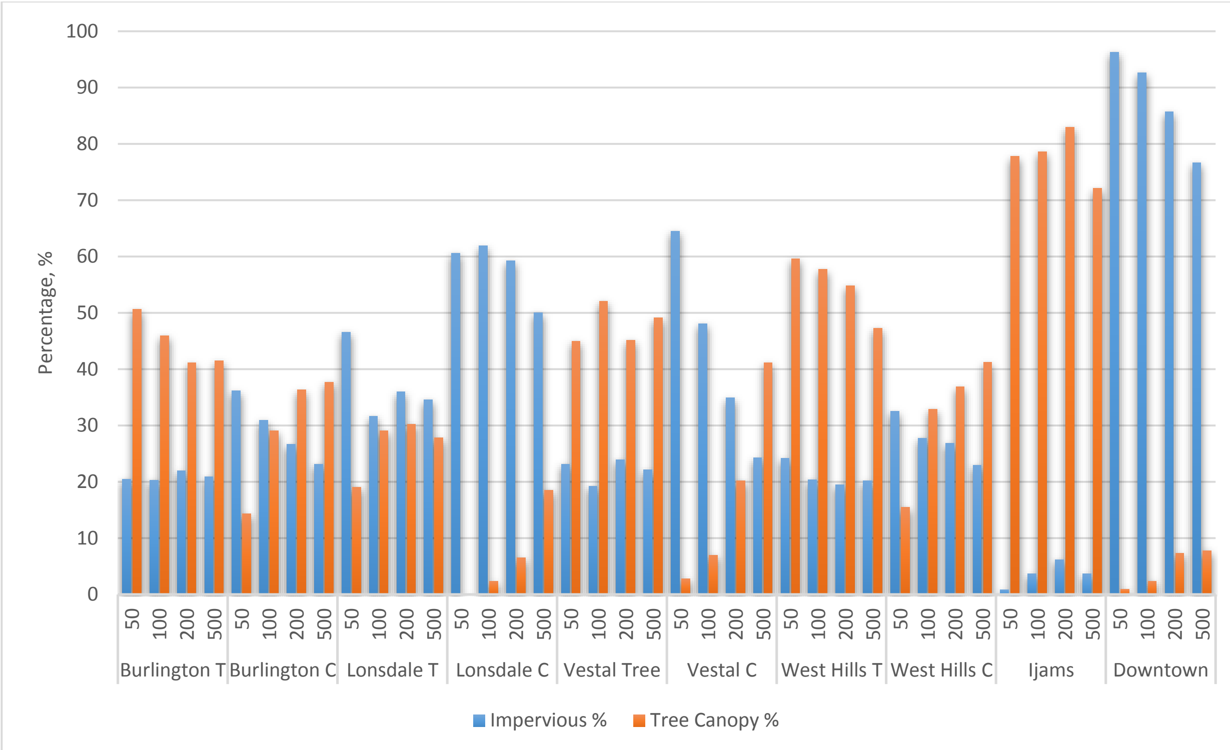

Figure 4. Impervious surface and tree canopy cover percentages for all stations at all four radii (50 m, 100 m, 200 m, and 500 m), as calculated with i-Tree.

The impervious surface results from i-Tree were then compared with the results from the 2011 National Land Cover Dataset (NLCD) [50], as well as the 1-m resolution raster from KGIS [51]; [Table 9]. The impervious percentages calculated in i-Tree were higher than those from the NLCD and KGIS at all radii. While evaluating the 2001 NLCD, Nowak and Greenfield (2010) found that impervious cover was underestimated by 1.4%, with a 5.7% underestimation in places (e.g., cities and towns) [41]. Another study found that the 2001 NLCD-derived impervious cover estimates in Baltimore, MD, were 7% lower than higher resolution estimates. The variations were primarily due to the NLCD not detecting smaller buildings and noncontiguous pavement [59]. In this study, even the higher resolution KGIS dataset did not detect smaller buildings, driveways, and sidewalks, leading to an underestimation of impervious cover.

The tree canopy and impervious cover categories are not mutually exclusive designations in the NLCD and KGIS data. In other words, areas with tree cover over impervious cover ("Tree + Impervious") are included in both categories even though those areas may have characteristics more akin to one than the other or act like a hybrid of the two. I-Tree estimations for Tree canopy were also much greater than those from the NLCD [Table 10]. Nowak and Greenfield (2010), as well as Smith et al (2010), found that the NLCD underestimated tree canopy cover by 9.7% and 10%,

respectively [41]; [59]. These significant underestimations emphasize the importance of using higher resolution land cover data, especially at smaller scales.

Table 9. Differences (average percentage) between impervious cover estimations from i-Tree and NLCD/KGIS. Positive numbers indicate i-Tree was greater. The "Tree+Impervious" designation was included (not-included) in the i-Tree estimation for the w/ "T+I" (w/o "T+I") column.

Radius Around Weather Station	Average Difference From NLCD 2011		Average Difference from KGIS	
	w/o "T+I"	w/ "T+I"	w/o "T+I"	w/ "T+I"
50 m	8.88%	11.66%	5.68%	8.46%
100 m	6.38%	8.73%	5.68%	8.03%
200 m	5.86%	8.70%	3.95%	6.80%
500 m	0.54%	3.13%	5.41%	7.99%

Table 10. Differences (average percentage) between tree canopy cover estimations from i-Tree and 2011 NLCD Positive numbers indicate i-Tree was greater. The "Tree+Impervious" designation was included (not-included) in the i-Tree estimation for the w/ "T+I" (w/o "T+I") column.

Radius Around Weather Station	Average Difference From NLCD	
	w/o "T+I"	w/ "T+I"
50 m	-2.33%	0.45%
100 m	2.67%	5.03%
200 m	2.80%	5.64%
500 m	6.11%	8.70%

The i-Tree Canopy analysis tool uses aerial images available in Google Maps. Google Earth imagery is used in many applications to supplement other data or when other data sources are incomplete on nonexistent [60]; [61]. However, there are limitations of photo-interpretation methods. One limitation is the date of the data used. The NLCD maps were based in 2011, while the Google Maps imagery used in i-Tree were from 2014-2015. Development over time usually results in increasing impervious

cover and decreasing canopy cover in urban environments. However, Wickham et al. [60] found that time lags have little effect on the difference between reference and map data. Another possible limitation is photo-interpretation error, thus each analysis was completed three times for quality control, as described in the methods. Both of these limitations were believed to be minor, allowing the conclusion that the data collected from i-Tree were valid and could be utilized further for analysis with the temperature data to determine which land cover characteristics correlate the most with inter-neighborhood temperature variability.

4.4 Regression Analyses

The mean yearly Tmax, Tmin, and DTR data for all 10 stations were compared to the land use data, and the distance of each station from the Downtown location, using a simple least squares regression analysis in JMP. Downtown portions of cities are typically the areas of highest UHI due to thermal storage in urban infrastructure, thus, proximity to this region was theorized as possibly affecting neighborhood microclimates.

The results with the highest coefficient of determination (R^2) can be found in Table 11, with the significant ($p<0.05$) results bolded. The importance of scale is evident. Land cover had the most significant interaction with Tmax at a radius of 50 m, while the 500 m radius was significantly related to Tmin and DTR. Analyses were run with the “Tree+Impervious” category included in both the Impervious and Tree Canopy categories and also with it omitted entirely. These two methods did not produce significantly different results.

Tmin was related most closely with land cover, while Tmax interacted the most with the distance from Downtown, and these those three relations were statistically significant ($p<0.05$). None of the comparisons with DTR were significant. In a related study, Linden and Esper [34] found that Tmax versus built/paved surfaces had an R^2 of approximately 0.28 at a 100 m radius, while Tmin versus built/paved surfaces had an R^2 of 0.22 at 300 m (they did not analyze a 500 m radius). Linden [48] found that Tmin vs. green vegetation had an R^2 of 0.74 at a 400 m radius, but Tmax versus paved surfaces or green vegetation cover produced low R^2 (0.02 and 0.01, respectively). Yokobori and Ohta [32] found that comparing vegetated area to daytime (nighttime) temperatures resulted in an R^2 of 0.77 (0.92). These studies confirm the observations herein, that max temperatures appear to be best explained by impervious land cover in close proximity to a given weather station, while minimum temperatures are better explained by the green space in the larger surrounding area.

Table 11. Full year regression results for all 10 stations. Bold numbers indicate $p<0.05$. The Tree+Impervious category is included in both the impervious surface and tree canopy percentages.

	Significant Explanatory Variables	R^2	p
Tmax	**Distance from DT**	**0.5**	**0.02**
	50 m Imp	0.32	0.09
	50 m Tree	0.25	0.14
Tmin	Distance from DT	0.22	0.17
	500 m Imp	**0.79**	**<0.01**
	500 m Tree	**0.76**	**<0.01**
DTR	Distance from DT	0.01	0.76
	500 m Imp	0.24	0.15
	500 m Tree	0.31	0.09

Next, the temperature data were parsed by season and air mass, and the regression analyses were run again. The summer 2014 season and Moist Moderate air mass produced the greatest increase in R^2 values across the board [Table 12]. The summer results reinforces the findings of the previous analyses. Just as temperature variability was greatest during the warm seasons (spring and summer), land cover most significantly explains that variability during the summer season. Linden and Esper [34] also found that the correlation between built/paved surfaces and temperature increased during the spring and summer season. While the Moist Moderate air mass classification was not highlighted in the earlier sections, the matched-pairs t-tests showed that inter-neighborhood variability was nearly as significant during Moist Moderate days as it was during Dry Moderate and Dry Polar days. Therefore, the fact that the relationship between temperature and land cover was the greatest during Moist Moderate days wasn't totally unexpected. These results showed that land cover at a neighborhood-scale may have the greatest effect on nighttime temperatures (Tmin) during the summer.

A previous Knoxville study [63] showed significant interaction between tree cover/SSC with Tmax at a 100 m radius during summer 2014 but did not show a significant interaction between tree cover/SSC with Tmin. This study showed significance between tree cover and Tmin at all radii, including 100 m, while Tmax and tree cover interactions were not significant at any radii. The differences between the two studies could be explained by differing methodology (Three-Way Analysis of Variance versus a simple linear regression) or by different land cover data (NLCD 2011 versus i-Tree). That Ellis et al [63] study showed significant interactions between Tmin and Tmax with the neighborhood designation, while this study showed significant

interaction between Tmax and the distance from the downtown station. These results show that location within a city may be just as important as localized land cover.

Table 12. Summer and Moist Moderate regression results. Bold numbers indicate p<0.05. Summer season is 2014 2 July – 1 October, excluding 15 – 22 August. Moist Moderate: 54 total days (21 summer, 15 fall, 14 winter, and 5 spring). The Tree+Impervious category is included in both the impervious surface and tree canopy percentages.

	Significant Explanatory Variables	**Summer**		**Moist Moderate**	
		R^2	**p**	**R^2**	**p**
Tmax	**Distance from DT**	**0.41**	**0.05**	**0.43**	**0.04**
	50 m Imp	0.34	0.08	**0.39**	**0.05**
	50 m Tree	0.38	0.06	**0.4**	**0.05**
Tmin	Distance from DT	0.21	0.18	0.23	0.16
	500 m Imp	**0.87**	**<0.01**	**0.93**	**<0.01**
	500 m Tree	**0.86**	**<0.01**	**0.88**	**<0.01**
DTR	Distance from DT	0.03	0.6	0.06	0.46
	500 m Imp	0.14	0.29	0.1	0.38
	500 m Tree	0.19	0.21	0.18	0.23

5 CONCLUSION

The urban heat island, which leads to warmer daytime and nighttime temperatures in a city relative to its surroundings, has been studied in great detail over the past 30 to 40 years [2]; [6]. In recent studies, it has been observed that varying land use characteristics within an urban setting can produce a patchwork of climates, or microclimates within a given city. However, many of those studies had one or more limitations, including: low spatial [28]; [32]; or temporal coverage [23]; [48]; of temperature data, or the use of low-resolution land cover data [26]; [40]. Additionally, studies have primarily focused on larger cities in warm climates [27]; [33].

This study utilized a network of 10 identical weather stations across four urban neighborhoods in Knoxville, Tennessee to analyze the microclimates of a medium-sized city with a temperate climate over the course of an entire year. Two stations were installed in each neighborhood to analyze intra-neighborhood temperature variability in addition to inter-neighborhood variability. One location was chosen to have minimal localized tree cover (Clear), with the other having denser tree cover (Tree). The study aimed to observe the spatial and temporal patterns of this data to determine how climates vary within the city and what land cover characteristics best explain that variability. Specifically, this study builds on previous research by: Linden and Esper (2014) [34], Stabler et al (2005) [26], Harlan et al (2006) [27], Ellis et al (2015) [63], and Hass et al (2016) [64], [among others.

The daily (Tmax), (Tmin), and DTR were analyzed for the full year. The Clear stations in all neighborhoods registered higher Tmax values than their Tree station counterparts, while the pattern for Tmin and DTR was less clear. The intra-neighborhood differences for all three variables was significant except for the Tmax analysis in Lonsdale, where tree cover was relatively lower than the other locations, even at the Tree location. The ranges of yearly mean Tmax, Tmin, and DTR between all locations were 1.6°C, 2.2°C, and 1.6°C, respectively, which is a result similar to a study of microclimates in Mainz, Germany (another city with a temperate climate) [34]. The inter-neighborhood variability was greater in magnitude than the intra-neighborhood differences, which suggests that the overall differences in neighborhood characteristics may be more critical than the local (within neighborhood) scale characteristics.

The temperature data was then parsed by season and air mass (SSC). Both season and air-mass had a noticeable effect on temperature variability. In the intra and inter-neighborhood analyses, the warmer seasons (spring and summer) and drier air masses (SSC 1 – Dry Moderate, SSC 2 – Dry Polar) showed the greatest temperature differences. As the UHI is most prevalent during the warm season [53]; [54] and during days with dry air masses [55]; [56], these results were expected.

Finally, land cover characteristics (percentage of canopy and impervious surface cover surrounding a given climate station) were quantified in i-Tree, an online analysis tool supported by the U.S. Forestry Service that uses Google Maps imagery. Previous

studies have shown the importance of scale [34], and the use of higher resolution land cover data [41] to more accurately identify trends between land cover and temperature variation. Land cover, along with distance from downtown, were compared with the average daily Tmax, Tmin, and DTR data for all 10 stations. The results showed that Tmin related with land cover at the 500 m radius around each station, while Tmax related with the distance of each station from the Downtown location, although more local land (50 m radius) cover was a significant factor. The correlations were even higher during the summer season and on days with Moist Moderate air masses (SSC 4). The results also showed that land cover at a neighborhood-scale relates the most with Tmin during the summer season. However, a greater density of data within a single neighborhood is necessary to better understand this relationship.

Temperature is correlated to a wide range of sustainability concerns in the urban environment, from accurately determining evapotranspiration rates to inform water balances, to differences in energy use based on exterior conditions. Thus, these initial attempts to understand temperature variability can be a springboard for future studies to understand a range of urban dynamics. Future studies should focus on a greater spatial density of temperature data to truly understand how urban microclimates are influenced by green infrastructure. Such data are critical to better understanding how resiliency to extreme heat can be built into cities through better planning and land use management. Further, data such as these can be used to provide more localized climate data to citizens, ultimately allowing them to make more informed decisions regarding their own health.

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APPENDIX

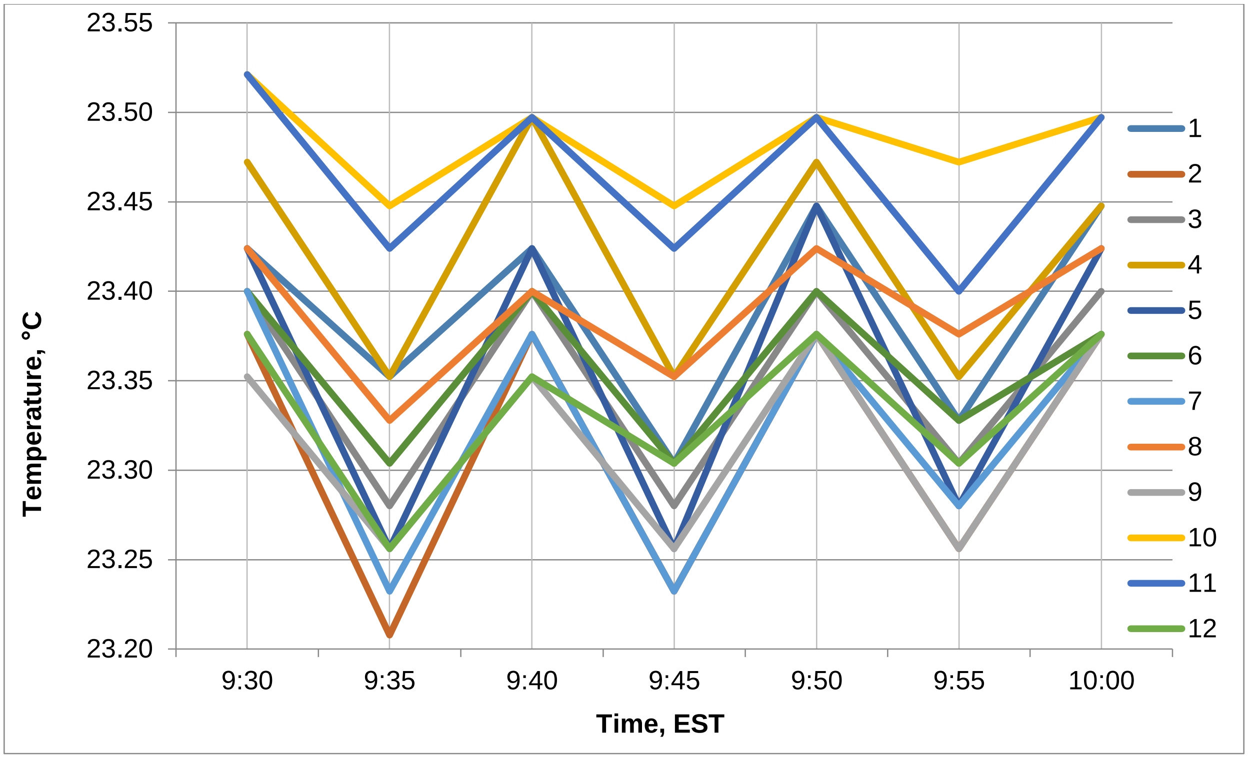

Figure 5. Air temperature trial results performed on 2014 23 June. Largest variability between all stations during trial was 0.144°C.

Table 13. Intra-Neighborhood Comparisons by season (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference (P<0.05). Fall is 2014 2 October—2015 1 January, excluding 2014 13 – 20 November. Spring is 2015 2 Jan – 1 April, excluding 15–28 February as well as 30 March – 1 April.

Fall				Spring			
Neighborhood	**Tmax**	**Tmin**	**DTR**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
West Hills	**0.7**	**-0.3**	**0.9**	West Hills	**0.6**	**-0.2**	**0.8**
Burlington	**0.4**	**-0.1**	**0.6**	Burlington	**1.1**	**-0.1**	**1.1**
Lonsdale	0.0	**0.2**	**-0.2**	Lonsdale	0.1	**0.3**	**-0.3**
Vestal	**1.1**	**0.5**	**0.6**	Vestal	-0.2	**0.5**	**-0.8**

Table 14. Intra-Neighborhood comparisons by SSC (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference ($P<0.05$).

	Duration	Neighborhood	Tmax	Tmin	DTR
Dry Tropical	9 Total Days 2 fall, 4 winter, and 3 spring	West Hills	0.4	0.0	0.5
		Burlington	0.2	**0.3**	0.0
		Lonsdale	-0.1	0.1	-0.1
		Vestal	**0.7**	**0.7**	**-1.8**
Moist Moderate	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	55 Total Days 21 summer, 15 fall, 14 winter, and 5 spring	West Hills	**0.7**	0.0	**0.7**
		Burlington	**0.8**	**-0.1**	**0.9**
		Lonsdale	**0.3**	**0.2**	0.1
		Vestal	**0.3**	**0.4**	0.0
Moist Polar	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	22 Total Days 2 summer, 10 fall, 9 winter, 1 spring	West Hills	**0.3**	**-0.1**	**0.4**
		Burlington	**0.6**	**-0.2**	**0.8**
		Lonsdale	**0.3**	**0.2**	0.0
		Vestal	0.0	**0.3**	**-0.3**
Moist Tropical Plus	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	12 Total Days 4 Summer, 1 Winter, and 7 Spring	West Hills	**0.4**	0.0	**0.4**
		Burlington	**0.9**	-0.1	**1.0**
		Lonsdale	0.0	**0.4**	**-0.4**
		Vestal	0.0	**0.5**	-0.5
Transition	**Duration**	**Neighborhood**	**Tmax**	**Tmin**	**DTR**
	22 Total Days 4 Summer, 4 Fall, 12 Winter, and 2 Spring	West Hills	**-0.2**	**-0.9**	**0.7**
		Burlington	**0.4**	**-0.2**	**0.6**
		Lonsdale	0.1	**0.2**	-0.1
		Vestal	0.0	**0.5**	**-0.4**

Table 15. Inter-Neighborhood Comparisons by season (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference (P<0.05). Fall is 2014 2 October—2015 1 January, excluding 2014 13 – 20 November. Summer season is 2014 2 July – 1 October, excluding 15 – 22 August.

Summer				**Fall**			
Station	**Tmax**	**Tmin**	**DTR**	**Station**	**Tmax**	**Tmin**	**DTR**
West Hills Tree	28.6	18.4	10.3	West Hills Tree	14.6	5.0	9.6
West Hills Clear	29.6	18.1	11.5	West Hills Clear	15.2	4.7	10.5
Burlington Tree	28.9	18.6	10.3	Burlington Tree	15.1	5.4	9.7
Burlington Clear	30.1	18.4	11.7	Burlington Clear	15.5	5.3	10.2
Lonsdale Tree	30.0	18.7	11.4	Lonsdale Tree	15.6	5.2	10.4
Lonsdale Clear	30.1	19.0	11.1	Lonsdale Clear	15.6	5.4	10.2
Vestal Tree	29.8	17.7	12.1	Vestal Tree	15.2	4.1	11.1
Vestal Clear	30.8	18.3	12.5	Vestal Clear	16.3	4.7	11.7
Ijams	30.3	17.7	12.6	Ijams	15.9	4.8	11.1
Downtown	30.7	19.9	10.8	Downtown	16.4	6.6	9.8
Range (clear only)	1.3	0.9	1.4	Range (clear only)	1.1	0.8	1.6
Range (tree only)	1.4	1.0	1.8	Range (tree only)	1.0	1.3	1.5
Range (all stations)	2.2	2.2	2.3	Range (all stations)	1.8	2.5	2.1

Table 16. Inter-Neighborhood comparisons for SSC 6, Moist Tropical (°C). Positive numbers indicate clear station is greater. A bold number indicates a statistically significant difference (P<0.05). 58 total days: 27 summer, 9 fall, 2 winter, and 20 spring.

Moist Tropical			
Station	**Tmax**	**Tmin**	**DTR**
West Hills Tree	28.70	18.15	10.55
West Hills Clear	29.42	18.07	11.35
Burlington Tree	28.81	18.35	10.46
Burlington Clear	30.07	18.27	11.79
Lonsdale Tree	29.75	18.49	11.27
Lonsdale Clear	29.85	18.83	11.02
Vestal Tree	29.94	17.53	12.42
Vestal Clear	30.50	18.10	12.40
Ijams	30.28	17.56	12.72
Downtown	30.52	19.54	10.98
Range (clear only)	1.08	0.76	1.94
Range (tree only)	1.25	0.96	1.96
Range (all stations)	1.82	2.01	2.26

VITA

David Andrew Howe was born on November 4, 1985. He graduated from Boyd-Buchanan High School in Chattanooga, Tennessee in May of 2004. Mr. Howe graduated from the University of Tennessee at Knoxville in May 2009 with a Bachelor's of Science in Civil Engineering. Upon graduation, Mr. Howe worked in the construction management field for five years before returning to the University of Tennessee to work as a graduate research assistant under Dr. Jon Hathaway in August of 2014. Mr. Howe will receive his Masters of Science in Environmental Engineering in May of 2016.