Urban Climate 32 (2020) 100640

Contents lists available at ScienceDirect

Urban Climate

journal homepage: www.elsevier.com/locate/uclim

Thermal impacts of built and vegetated environments on local microclimates in an Urban University campus

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ABSTRACT

Extreme urban temperatures pose a significant threat to human health, and are expected to worsen in a warming climate. While many heat island studies use land surface temperature to estimate exposure, air temperatures are more relevant to human health and comfort. The Tech Climate Network (TCN) was established to monitor 37 sites across the campus of the Georgia Institute of Technology and surrounding neighborhoods in various built and vegetated environments. This study seeks to answer: What is the distribution and intensity of the urban heat island on campus, and what impacts do surface-level land cover and surrounding tree canopy have on average summer air temperatures? Using multiple regression models, we examine the relationship between land cover parameters and minimum, maximum, and average air temperatures in the summer of 2017. We found that vegetated sites had lower temperatures than predominantly impervious environments, with differences in maximum temperatures up to 3.77 °C. UHI intensities were significantly correlated with tree canopy and landscaping. By characterizing the thermal properties of built and natural environments in such a diverse campus as Georgia Tech, this method allows for the estimation of local air temperatures without deploying a dense network of sensors.

1. Introduction

Extreme temperatures pose a significant threat to human health, including clinical syndromes of heat stroke, heat exhaustion, heat syncope, heat cramps, or even death (Bouchama and Knochel, 2002; Kovats and Hajat, 2008; Luber and McGeehin, 2008). The observed positive trend of extreme heat exposure is projected to accelerate in the coming decades with increased intensity, duration, and frequency of heat waves, further elevating the risk of heat-related morbidity and mortality in urban areas (Battisti and Naylor, 2009; Diffenbaugh and Scherer, 2011; Habeeb et al., 2015; Knowlton et al., 2007). The urban environment can be significantly warmer than surrounding rural areas, a phenomenon known as the urban heat island (UHI) effect. The UHI is in part driven by built materials absorbing incoming solar radiation and storing it as heat. Lack of vegetation can also elevate temperatures due to reduced shading and cooling from evapotranspiration (Oke, 1987). In many cases, heat-related illness is preventable through both personal behavioral adaptations and long-term investment in land cover change using vegetative strategies to passively reduce outdoor temperatures (Davis et al., 2003; Stone et al., 2014). To effectively plan capital improvements in long-term passive heat mitigation strategies, urban planners must be able to identify areas of highest UHI intensity and the impact of land conversion driving their formation.

Like many urban areas, the physical context of the Georgia Institute of Technology campus is changing. In response to both global

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https://doi.org/10.1016/j.uclim.2020.100640
Received 1 May 2019; Received in revised form 8 March 2020; Accepted 26 April 2020
2212-0955/

and local scale climate change, temperatures in the Atlanta region have been rising more rapidly than in previous decades. An analysis of urban and proximate rural temperature trends in major US cities finds Atlanta to be the third most rapidly warming metropolitan region in the country (Habeeb et al., 2015). With an increase in the incidence of extreme heat during the warm season, and higher temperatures generally throughout the year, the Georgia Tech campus and population is increasingly vulnerable to a growing range of health, thermal comfort, and infrastructure-related impacts. More effective monitoring of climate trends on campus, in concert with climate-responsive design strategies, can lessen both the human impacts and infrastructure costs of rising temperatures. Heat island analysis commonly uses remotely sensed data such as land surface temperature (LST) to compute a comprehensive temperature dataset (Jenerette et al., 2007; Liu and Zhang, 2011; Yuan and Bauer, 2007). However, air temperatures are more relevant to human health and comfort, so it is critical to obtain or model air temperature data to identify the location and intensity of extreme heat exposure. Studies have not found a strong correlation between LST and air temperature, with R-square values less than 0.5 (Ho et al., 2016; Kloog et al., 2012). Using a high-density array of temperature sensors in the Tech Climate Network, this study explores the distribution of the urban heat island at Georgia Tech, and the influence of the built and vegetated environments on local microclimates.

1.1. High-density temperature sensor networks

Technological advancements and decreased monetary costs have enabled researchers to create urban meteorological and climate networks. But there are still a limited number of networks that are dense enough to provide a high quality dataset for use in comprehensively monitoring air temperatures across an urban area (Muller et al., 2013). Here we detail some of the emerging climate and meteorological networks around the world, each created to suit individual research needs.

The Birmingham Urban Climate Laboratory established a series of 29 weather stations distributed at about one per 10 km^2 over the entire city of Birmingham, England, that has been utilized to examine urban heat advection as well as other climatological phenomena (Bassett et al., 2016; Chapman et al., 2015). In the United States, the City of Oklahoma City created the Oklahoma City Micronet (OKCNET) in 2008 to examine atmospheric data in the Oklahoma City area. OKCNET deployed 40 weather stations at a height of nine meters across the city with sites 3.3 km apart on average (Basara et al., 2011). These sensors are mounted on traffic signals and record air temperature, wind, relative humidity, rainfall, pressure, solar radiation, soil temperature, and soil moisture. Prior to this network, the city was the site of a U.S. Department of Defense and U.S. Department of Homeland Security study that tested the accuracy of outdoor dispersion models. The study utilized 100 different sensors logging continuously over the course of 10 days for 8 h each day.

In Helsinki, Finland, researchers built a network of 40 sensors at a height of 120 m, and another at 300 m in conjunction with several weather stations and instruments that record the activities of sizeable weather systems (Koskinen et al., 2011). The Novi Sad Urban Network is composed of 28 sensors that monitor "climate peculiarities" and provide an early warning system for the city of Novi Sad, Serbia (Šećerov et al., 2019). Tokyo, Japan, is also the site of an urban climate network that consists of 20 rooftop sensors and 100 additional sensors located at schools throughout the city. This allowed the researchers to examine the effect that urban heat islands have on land and sea breezes (Takahashi et al., 2009).

In addition to urban climatological and meteorological phenomena, urban air temperature sensor networks can be used to measure the effect that land cover and green infrastructure have on urban heat islands. In Rosario, Argentina, researchers used eight U23 HOBO outdoor temperature sensors and data loggers set to record every hour for a full year from 2013 to 2014 in order to measure the effects of different land cover types on air temperature (Coronel et al., 2015). Similarly, a large park in London was utilized to analyze the range of influence of green space on temperatures. A total of 17 sensors over the course of five months measured the temperature in the park and at distances of 70 m to 340 m away from the park (Doick et al., 2014). Different vegetative placements were analyzed in a study in downtown Toronto, Canada, using 13 temperature sensors over six months to determine what kind of vegetation strategies were most efficient at reducing summer temperatures (Millward et al., 2014). Unique sites provide researchers with the ability to capture high quality data. The agricultural research center at University of California Riverside was used to measure the effect of urban vegetation on air temperature by utilizing carefully planted citrus trees spaced 1.5 m apart. Three hundred air temperature sensors recorded data over four months, finding temperature reductions from the tall citrus canopy of up to 6 °C compared to the bare ground (Shiflett et al., 2017).

1.2. The Tech Climate Network

In response to Atlanta's warming trends, the Georgia Institute of Technology's Urban Climate Lab established a dense network of temperature and relative humidity sensors throughout the campus to identify the location of hot spots, measure the impact of ongoing development on micro-climatic conditions, and assess how the use of vegetation and cool materials around campus can moderate warming trends. Established in 2015 and expanded in 2016, the network consists of 37 HOBO U23 Pro v2 external temperature/relative humidity data loggers with RS3 radiation shields from Onset Computer Corporation. The sensors are deployed across Georgia Tech's campus and the Atlanta metropolitan region, representing many micro-climatic conditions including both 2-meter and rooftop locations. Of the 37 sensors, 29 are within Georgia Tech's campus, an area of roughly one square mile (2.6 km^2), and 25 of those are at 2-m height. The sensors collect temperature and relative humidity readings every 5 min. The sensors are collected and calibrated in an environmental chamber once per year, and sensors are replaced if drift is detected in exceedance of the 0.21 °C sensor accuracy, as determined by the manufacturer. The network is funded by the Georgia Institute of Technology's office of Capital Planning and Space Management, and a grant from the U.S. Forest Service. This network lays the groundwork for the establishment of a more extensive

Percentile	Daily T_{max} (°C)
85	31.7
90	32.8
95	33.9
99	35.6

Fig. 1. Top percentile daily maximum temperature normals (1987–2016) for Atlanta, GA (Hartsfield-Jackson International Airport Station, NOAA).

network across the greater Atlanta metropolitan region or other campuses worldwide.

Georgia Tech's campus provides an ideal location for exploring microclimatic activity both spatially and temporally. Tech's campus consists of a variety of microclimates at the surface level, such as parking lots, green space, and urban forests, all within a relatively small area. Such microclimate variety is uncommon in a large city like Atlanta. In this study, we utilize the diversity of microclimates and data collected from the Tech Climate Network to answer two research questions: 1) What is the distribution and intensity of the urban heat island within a single campus; and 2) What is the impact of surface-level land cover and surrounding tree canopy on minimum, average, and maximum daily air temperatures on campus? In accordance with the literature, we hypothesize that the variety of microclimates on campus will result in a wide range of UHI intensities, and that built environment land cover types (e.g. streets, sidewalks, and buildings) will be significantly associated with higher temperatures for all temperature metrics (Oke, 1987). A significant relationship between these land cover types and UHI intensity will help urban planners understand the thermal impacts of development even without deploying a sensor network of their own.

2. Methods

Temperature data were collected during the summer of 2017 (June, July, and August) using only the 25 Tech Climate Network sites at 2-meter height across campus. 2017 was a particularly warm year, with an average daily maximum temperature of 34.4 °C, between the 95th and 99th percentile warmest daily maximum temperatures in Atlanta's previous 30-year climatological normal (see Fig. 1 below). These data were processed using a script in the statistics software package R, that first cleans data outliers attributable to sensor noise with a 1% trim of high and low readings, thus removing the noise and providing a conservative estimate of extremes. The script then identifies minimum (T_{min}), average (T_{avg}), and maximum (T_{max}) temperatures for each day, then averages the 92 days for a seasonal average. Additionally, we monitored the number of hot days at each site, defined as a day that exceeds a maximum temperature of 32.8 °C, which is the 90th percentile of maximum temperature for Atlanta's 30-year annual climatology. A percentile approach ensures that this temperature constitutes a hot day even by Atlanta standards. We present our temperature measurements in both absolute averages, as well as UHI intensities defined by the deviation from a rural control site in Austell, GA, roughly 14 miles west of Atlanta. This metric portrays UHI intensity in Atlanta relative to a predominantly forested rural site representative of the native land cover of the American Southeast region. UHI intensity mapping was conducted in ArcGIS 10.5 using the Spatial Analyst extension to conduct a second-order inverse distance weighted function to illustrate the temperature distribution visually across the various microclimates of campus.

To analyze the influence of land cover, we utilize two layers of environmental data: a high resolution base map land cover dataset and tree inventory maintained by Georgia Tech's department of Capital Planning and Space Management and the Center for Spatial Planning Analytics and Visualization. The base map dataset contains land cover classes including buildings, landscaping, streets, and sidewalks. This dataset was generated and maintained manually using aerial photography by campus planners and landscape architects. Additionally, we analyze the surrounding tree canopy with a tree inventory that records the location and canopy diameter of each tree on campus. This dataset is generated using field measurements of tree coordinates and canopy diameter and is updated on a regular basis. In cases of coincident tree canopy, the largest overlapping canopy is recorded as the two-dimensional vertical projection of the canopy layer.

Using both datasets provides information on what is above and below each sensor. We record the percentage of each land cover type within a Euclidean buffer of 100 ft. (30.48 m) around each sensor to characterize the built and vegetated environment at each site. This buffer size was chosen to be of sufficient size to capture a variety of land cover types around each site. Further research will be necessary to analyze the relationship between this buffer size and temperature to characterize the size of microclimate effects. Additionally, a dummy variable indicates whether a sensor is directly under tree canopy (1) or outside tree canopy (0) using a vertical projection in ArcGIS. An example of the land cover datasets used in this regression is illustrated in Fig. 2 below. Finally, we correlated these land cover variables with the full-summer average daily minimum, mean, and maximum temperatures, as well as the number of hot days over the summer using a set of multiple regressions in R. As percentages, the surface land cover types are mutually exclusive and exhaustive and therefore at risk of multicollinearity. To remove this threat, the buildings land cover variable was omitted from the regression model.

3. Results

3.1. UHI intensity and distribution

In Fig. 3 below, we summarize the average temperatures and UHI intensities measured over the 92 days of the study period, and the range between the lowest and highest average temperatures across the Tech Climate Network. The mean daily maximum

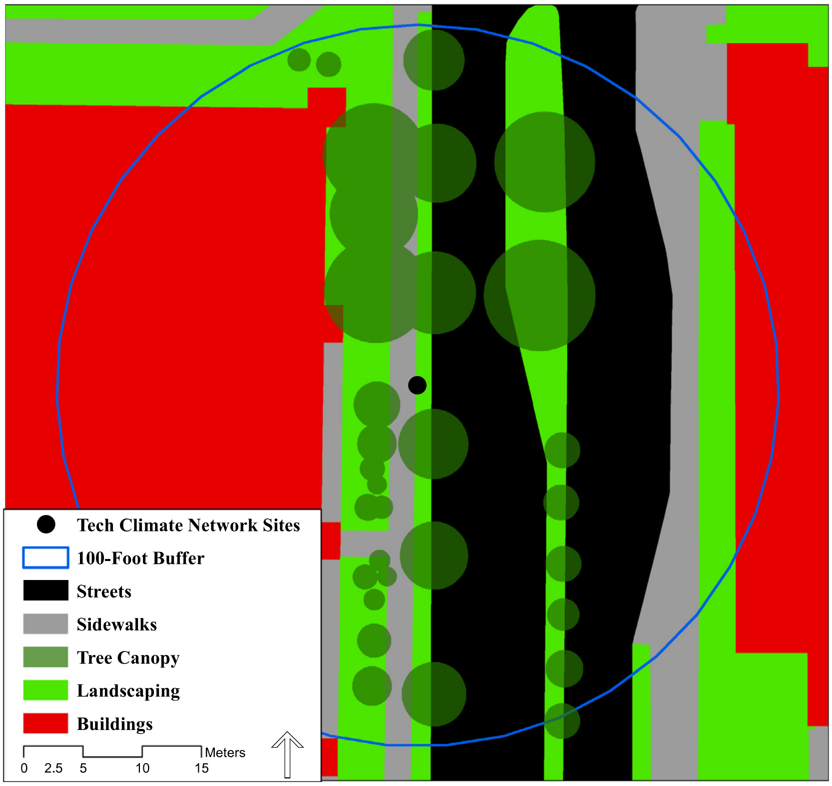

Fig. 2. Surface land cover and canopy within 100 ft of a Tech Climate Network site.

	Min	Max	Range
T_{min}	21.24	22.37	1.13
T_{min} UHI	1.13	2.26	
T_{avg}	25.13	26.63	1.50
T_{avg} UHI	1.18	2.68	
T_{max}	29.98	32.97	2.99
T_{max} UHI	0.79	3.77	
Hot Days	7	56	49

Fig. 3. Average daily temperatures (°C) measured as absolute and UHI intensity across the 25 TCN sites used in this analysis.

temperature displays the greatest UHI intensity, with intensities up to 3.77 °C above the rural reference. T_{max} also displays the greatest range between the warmest and coolest site, with a range of 2.99 °C. Minimum and average temperatures are less extreme, ranging from roughly 1.13 °C to 2.26 °C warmer than the rural control for T_{min}, and 1.18 °C to 2.68 °C warmer for T_{avg}. The number of hot days across campus varied greatly, ranging between 7 days in the coolest site to 56 days at the warmest site, or a range of 49 days across the network for the 92-day summer. To highlight the urban-rural difference in thermal exposure, the rural reference site showed no exceedances of this temperature threshold during the summer.

The map in Fig. 4 shows the UHI intensity for the summer average daily maximum temperature. This illustrates that the UHI on campus is not one large hot spot across the campus, but rather a collection of distinct microclimates. The images surrounding the map illustrate sites of the diversity of microclimates, with cooler areas much more heavily vegetated, and warmer areas characterized by more impervious surface cover.

3.2. Land cover regression

In Fig. 5, we show the results of the land cover regressions with land cover variables and UHI intensity. The slope (B) represents °C change per 1% increase in a given land cover type within 100 ft of a sensor site. "Direct Overhead Canopy" is used as a dummy variable to indicate whether the site is located directly beneath tree canopy with a value of 1 if the site intersects the vertical projection of tree canopy, and 0 otherwise. "Tree Canopy Area" indicates any tree canopy within 100 ft (30.48 m). The R-Squared is also reported to show the predictive power of each model. Coefficients highlighted in red indicate a warming effect, while blue

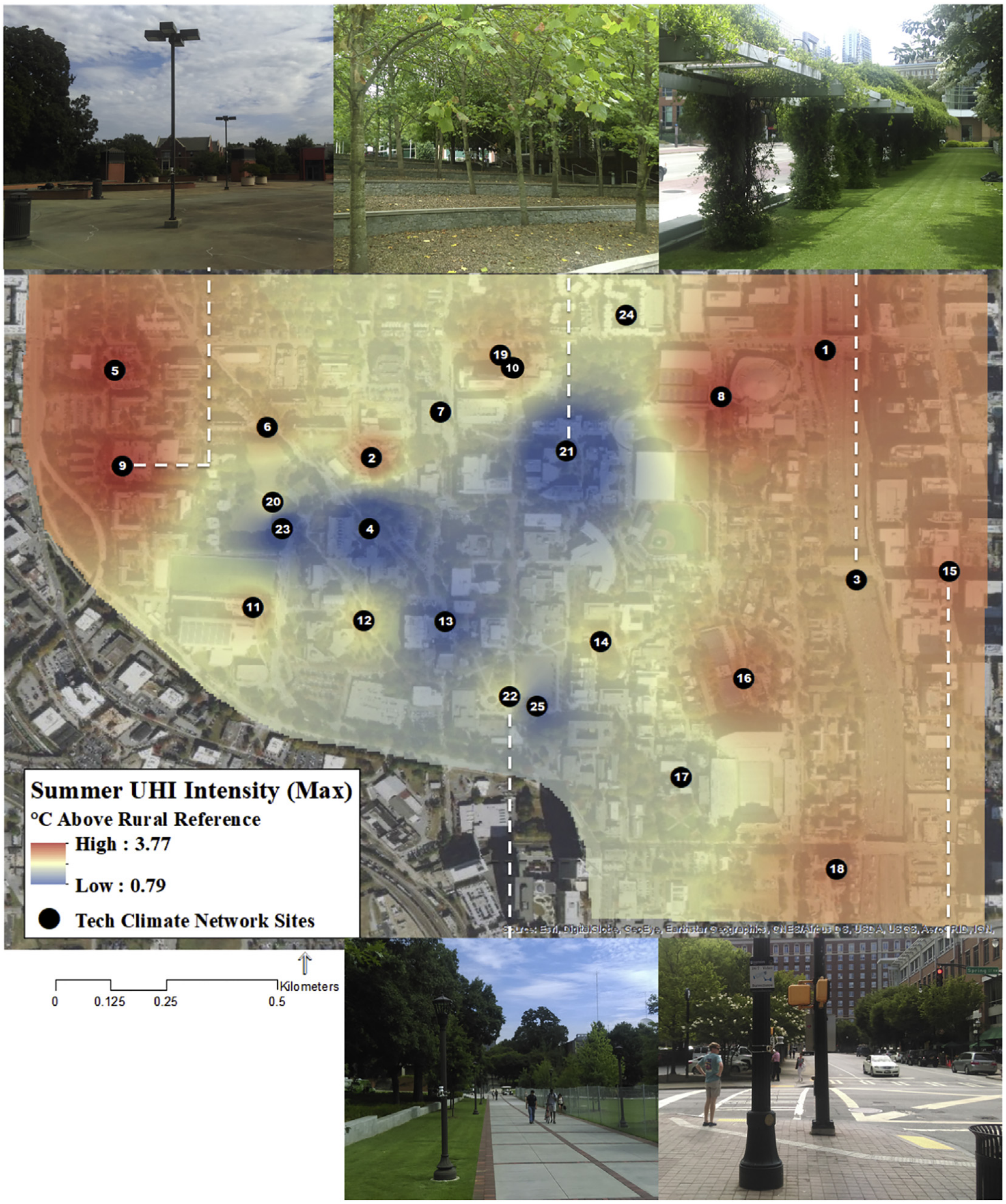

Fig. 4. Average daily maximum urban heat island intensity with images of select Tech Climate Network sites representing a variety of campus microclimates. Temperature visualization uses interpolated second-order inverse distance weighted function in ArcGIS.

indicates a cooling effect.

The regression analysis shows that land cover performs fairly well in predicting minimum and average urban heat island intensities, and less well in predicting maximum intensities and hot days. The regression also shows that few land cover types significantly predict urban heat island intensity, with only landscaping, tree canopy area, and direct overhead canopy found to be statistically significant. Landscaping significantly reduced minimum UHI intensity, with a predicted cooling of 0.116 °C (± 0.028 °C) for every 10% increase in landscaped area. Direct overhead canopy reduced average UHI intensity by 0.351 °C (± 0.155 °C) for a site directly below tree canopy as compared to a comparable site not directly below tree canopy. Tree canopy area was significantly associated with a reduction in maximum UHI intensity by 0.289 (± 0.125 °C) and a reduction in the number of hot days by 2.509 (± 1.04 °C) for every 10% increase in tree canopy area. While not significant, it is interesting to note that minimum UHI intensity was slightly elevated by tree canopy, potentially due to the effect of canopy limiting ventilation and retaining warm air beneath the canopy.

	T_{min} UHI			T_{avg} UHI		
	B	Std. Error	P-Value	B	Std. Error	P-Value
(Intercept)	2.3724	0.2948	***	2.5596	0.3802	***
Streets	-0.0036	0.0032		0.0012	0.0041	
Sidewalks	-0.0037	0.0039		-0.0014	0.0050	
Tree Canopy Area	0.0029	0.0039		-0.0075	0.0050	
Landscaping	-0.0116	0.0028	***	-0.0061	0.0036	
Direct Overhead Canopy	-0.1384	0.1199		-0.3506	0.1546	*
R-Squared	0.6689			0.6999		
	T_{max} UHI			Hot Days		
	B	Std. Error	P-Value	B	Std. Error	P-Value
(Intercept)	3.6313	0.9564	**	32.9876	7.9362	***
Streets	0.0011	0.0103		-0.0194	0.0852	
Sidewalks	-0.0029	0.0125		-0.0745	0.1040	
Tree Canopy Area	-0.0289	0.0125	*	-0.2509	0.1040	*
Landscaping	-0.0037	0.0090		-0.0726	0.0747	
Direct Overhead Canopy	-0.5328	0.3888		-3.8331	3.2265	
R-Squared	0.5633			0.5813		

Fig. 5. Urban heat island intensity and cover regression results. Significance levels: *** $p < .001$; ** $p < .01$; * $p < .05$. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

4. Discussion

This study has demonstrated the utility of a dense temperature sensor network to characterize microclimates and the impacts of their built and vegetated environments across a U.S. university campus. The land cover data are entirely derived from sources that are increasingly available to urban planners or other practitioners and analysists, and can be used to further understand the seasonal thermal characteristics of diverse neighborhoods. With similarly classified land cover and tree inventory datasets, urban planners can gain a deeper understanding of the thermal characteristics of existing or proposed site developments without deploying a sensor network of their own. This regression analysis can help quantify air temperatures and UHI intensities on a microclimatic scale. With similar land cover inputs, our findings can also be used in a GIS kriging analysis to model air temperatures on a neighborhood or city-wide scale. Further research will be necessary to analyze the broader utility of these findings and their validity outside the campus context.

But it is important to note that this analysis was conducted from a seasonal average perspective, and that individual daily or hourly measurements may show more extreme UHI intensity. Given the temporal limitations in the land cover data, we have assumed that land cover remains constant through the summer, when the tree canopy has reached its full extent and remains stable through the study period. As this study uses a full-season average UHI intensity, it does not account for changes in shading over the course of the day for either buildings or tree canopy. Shading would influence the observed temperature for any sensor within the daily shading pattern of nearby buildings and trees even when the sensor is not located directly beneath them. This analysis includes two sensors located on the north side of buildings that fall into such a shading pattern. A higher temporal resolution analysis, such as hourly averages, would need to take these effects into account. Additionally, the cooling potential of tree canopy has been found to depend on the prevailing weather conditions (Wang et al., 2019). For example, cooling potential may change during a heat wave, or on sunny days compared to cloudy days. While these results are useful from a long-term planning perspective, further research will be necessary to analyze these short-term and weather-dependent effects.

The UHI analysis indicates that the UHI intensity is lower for minimum temperatures than maximum. Though smaller, the minimum temperature is a critical metric for public health. Areas that remain warm throughout the night can present a greater risk than extreme temperatures if residents are unable to get any cooling relief over long periods of time (Robinson, 2001). Being a whole-summer average, this analysis shows that many areas of campus and the Midtown neighborhood routinely experience these kinds of sustained elevated temperatures. This finding corroborates previous studies that found daytime (maximum) UHI intensities in excess of overnight (minimum) UHI intensities. In a study of 491 global cities, Peng et al. (2011) found annual average remotely sensed surface urban heat island (SUHI) intensity to be higher in the daytime (1.5 ± 1.2 °C) than the annual average nighttime SUHII (1.1 ± 0.5 °C). In a study of Birmingham, UK, Azevedo et al. (2016) found SUHI intensities to be greater during the day at the time of peak solar irradiance, ranging 1 °C to 8.7 °C, while overnight SUHI ranged 1 °C to 3 °C. However, regarding air temperature our findings contrast with studies finding nighttime minimum UHI intensities to exceed daytime maximum UHI intensities. Using Weather Research and Forecasting (WRF) models of Louisville, KY, USA, Stone et al. (2019) found warm season average overnight minimum UHI intensities of 7.22 °C and average daytime maximum UHI intensities of only 2.78 °C In a study of Greater Manchester, UK, Smith et al. (2011) found average daytime maximum UHI intensities of 3 °C and nighttime minimum UHI intensities of 5 °C. As these studies show, measures of UHI intensity are sensitive to temporal and spatial averaging, changing in magnitude with the local context. Our research indicates that the UHI of Georgia Tech's campus exacerbates daytime maximum temperatures even in excess of the sustained overnight minimum temperatures. Further research will be needed to analyze the SUHI of Georgia Tech's campus and relationship between LST and air temperature in the Tech Climate Network. The incorporation of LST into the regression model may help improve the predictive potential off campus using comprehensive remote-sensed datasets.

Similarly, the wide range of hot days between the cooler and warmer areas of campus, ranging from 7 to 56 days, illustrate the great disparities in thermal exposure even within a relatively small area of Atlanta. This means people living in hot areas such as Midtown experienced almost two more months of extreme temperatures in the summer of 2017 than those in cooler areas. From a public health perspective, this disparity makes a significant difference: several studies have observed that heat event duration may have a greater impact than intensity on human health because sustained elevated temperatures exacerbate the risks of heat exposure over time as heat accumulates in the body (Kalkstein and Davis, 1989; Kleerekoper et al., 2012).

Heat wave intensity is also a significant risk for elderly populations (Kalkstein and Davis, 1989). This study has shown that the campus UHI is most intense for daily maximum temperatures, but can be significantly mitigated using tree canopy, in both tree canopy area and direct overhead canopy. Several studies have shown that tree canopy is a highly effective UHI mitigation strategy (Bowler et al., 2010; Harlan et al., 2006; Kuras et al., 2015; Shashua-Bar et al., 2009). Wang et al. (2018) similarly found that the size of tree canopy providing shade played a critical role in reducing urban temperatures in a model of the contiguous United States, as larger tree crowns prevent more incoming solar radiation from reaching the surface. Future research should take the size of the overhead canopy into account when measuring cooling potential. The regression analysis also confirms the influence of landscaping on minimum temperatures, potentially aided by irrigation and its resultant evapotranspiration. Gober et al. (2010) found a similar effect in using watered landscapes to reduce UHI intensity. Urban planners can use this information to plan cooler spaces using greening strategies for passive cooling, particularly in areas with vulnerable populations who may not be able to afford air conditioning.

5. Conclusions

In a warming climate, it is increasingly important for cities to adopt strategic plans to mitigate the urban heat island and protect our most vulnerable populations from heat-related morbidity and mortality. Cities must begin to monitor local temperatures now as a first step toward creating a resilient urban environment and population. This study is the first of its kind to use a dense network of air temperature sensors all within a single campus. All Tech Climate Network sensors are within the same context of the greater regional UHI of the Atlanta metropolitan area, allowing for direct intercomparison without the influence regional temperature differences. This information can help urban planners and public health officials improve their emergency response plans and communication strategies for heat mitigation in urban areas by specifically targeting short and long-term responses where temperatures are most extreme. By characterizing the thermal properties of built and natural environments, this method allows urban planners to estimate local air temperatures without deploying a dense network of sensors across the entire city. This method utilizes common GIS techniques with which planners are becoming increasingly familiar, thereby allowing planners to estimate air temperatures within their budget and technical capability. Understanding which urban areas are at greatest risk of extreme summer temperatures can help planners shape the policies necessary to combat the impacts of climate change tailored to their local context, and could substantially advance the policies cities use to adapt to a warming climate.

Declaration of Competing Interest

There are no conflicts of interest to report for this study.

Funding

This work was supported in part by the USDA Forest Service, Grant #16-CS-11330144-055.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2020.100640.

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