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Leveraging an Urban Environmental Sensing Network to Improve Extreme Heat Resilience
(Invited Paper)

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***Abstract*—As the global population continues to urbanize, city residents are increasingly exposed to extreme heat due to the urban heat island phenomenon, which poses a serious threat to human health. Understanding heat exposure in urban areas is challenging due to the heterogeneity of urban form and land uses, which create micro-climates that expose individuals to a wide variation of temperatures in outdoor environments. To address this issue, we have deployed a sensor network throughout the city of Bloomington, Indiana and on the campus of Indiana University. The environmental sensor network includes air temperature, relative humidity, and soil moisture sensors in different urban-forms such as along streets, among densely clustered trees, in parking lots, and in community gardens. The sensor network captures a rich set of data related to local climate, heat exposure, and vegetative heat stress. Local environmental monitoring is an important area of research that enables researchers to more precisely predict and quantify an individuals' exposure to extreme heat in urban environments. In this paper, we describe the application of our environmental sensor network, *the Healthy Cities Sensor Network* (HCSN) and how it can be utilized to increase climate resilience for local communities.**

***Index Terms*—sensor network, extreme heat, urban heat island**

I. Introduction

Extreme heat kills more people annually in the United States than all other extreme weather events combined and these mortality rates are only intensifying with our changing climate [1]–[4]. Cities are particularly vulnerable to extreme heat events because of the urban heat island (UHI) effect. The UHI effect is seen when temperatures in cities are higher than temperatures in their surrounding rural areas [5]–[7]. This amplification in local urban temperatures is due to the displacement of natural landscapes by impervious surfaces such as roads, buildings and parking lots [6]. Additionally, heat wave characteristics, such as frequency, timing, duration and intensity, have been found to be increasing across U.S. cities [8]. The amplification of temperatures due to the urban heat island effect and increase in heat wave frequency, place urban residents in a vulnerable position. Determining an individual's risk of heat stress is challenging as extreme heat exposures vary dramatically throughout a city as do individuals' underlying health conditions, which can compromise a person's ability to regulate internal temperatures [9]. Furthermore, the lack of public awareness regarding risks associated with extreme heat make heat waves a silent killer [9]. The increased frequency of heat waves increases the need for communities to determine how best to prepare and recover from disasters [8].

Understanding the heat exposure of individuals in urban areas is challenging [21]. Meteorological stations for urban regions are typically situated at airports, which are often the only long-term, quality-controlled sources of temperature data available in urban areas. Data from these meteorological stations are commonly used to calculate urban climate trends [22]–[24], but no single monitor location can fully represent the heterogeneity of a region's urban landscape. Temperature data from airport-based meteorological weather stations do not account for variations in temperature caused by differences in land cover and land use [25]. The heterogeneity of urban form and land uses in an urban environment create microclimates exposing individuals to a wide variation of temperatures in outdoor environments [26]. Urban climatologists often use satellite data to illustrate shifting temperatures in the built environment, but satellite data are inherently limited by the spatial and temporal resolutions of any given satellite. Additionally, satellite data represent surface temperatures as opposed to near surface air temperatures (temperatures measured at approximately 2 meters above ground level). Near surface air temperature is the temperature metric used by urban climatologists to unpack the negative health effects that arise from exposure to extreme heat [9]. Aligning local climate data with individual heat exposures and health data can help cities and residents be better prepared to plan for and address challenges of extreme heat.

As such, local environmental monitoring through ubiquitous sensing and Internet of Things (IoT) technologies is an important area of research that has the potential to enable researchers to more precisely quantify individuals' exposure to extreme heat in urban environments [27]. Local sensor networks can be used to improve the understanding of individual and community exposure to high temperatures, quantify performances of climate responsive designs, and validate both urban and regional climate models [27], [28]. Additionally, access to local environmental data may empower individuals and communities to advocate for change [29]. The collection and validation of local environmental data through ubiquitous

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Network Name	Location	Time Period	Sensor Model	No.	Communication Method	Purpose
Fixed Observational Network [10]	Madison, WI	03/12 - 03/19	HOBO U23 Pro v2	146	Manual	Increase confidence of land surface temperature measurements
BUCL UMN [11]	Birmingham, ENG	06/12 - 12/14	Vaisala WXT520 & Aginova Sentinel Micro (ASM)	108	Cellular & Wi-Fi	Create testbed for high quality crowd-sourced and satellite data
Urban Sensor Network	Boston Met. Area, MA [12]	03/14 - 11/15	HOBO U23 Pro v2	25	Manual	Investigate how urban land use affects environmental variables
Greater Los Angeles Network [13]	Los Angeles MSA, CA	06/14 - 09/14	Thermochron iButton	300	Manual	Examine effects of vegetation on urban climate dynamics
Tech Climate Network [14]	Atlanta, GA	2015 - 2017	HOBO U23 Pro v2	37	Manual	Examine effects of land cover, tree canopy and UHI on temperature
Intra-Urban Sensor Network [15]	Bern, SWTZ	05/18 - 09/18	HOBO Temperature Pendant & AWS-Thygan VTP6	82	Manual	Examine performance of Low Cost Devicess for data quality & sources of error
Custom Fixed Sensor Network [16]	Bolzano, ITLY	07/20 - 05/21	Custom	17	LoRaWAN	Analyze tech required for sensor network deployments
Project Eclipse [17]	Chicago, IL	07/21 - Present	Custom	115	Cellular	Develop a low-cost end-to-end method of urban environmental sensing
Array of Things (AoT) [18]	Chicago, IL	08/16 - Present	Custom	130	Cellular	Publicly provide real-time research quality data about different areas in urban spaces
Twin Cities Network [19]	Twin Cities Metropolitan Area	08/11 - 08/14	HOBO U23 Pro v2	200	Manual	Canopy layer UHI monitoring and research
Schools Weather and Air Quality Network [20]	Greater Sydney Area, AU	09/19 - Present	Vaisala WXT536 and Vaisala AQT420	11	Cellular	Encourage citizens to get involved in urban climate and air quality monitoring and metrics

Table I: Table indicating different in-situ environmental sensor networks throughout the world, sensors used, communication channel and objective. Table includes urban scale networks that have been active in the past decade.

low-cost sensor networks can help cities identify heat stress management strategies that increase resilience using sophisticated prediction and adaptive response measures [30].

To better understand the configuration of urban sensor networks and their rationale for deployment, we conducted a literature review of in-situ urban environmental sensor networks. From the literature review, we identified eleven in-situ urban sensor networks deployed in the last decade and highlighted information that characterizes each network (See Table I). Sensor networks vary by sensor type, communication technology, network density, duration, and overall aim/purpose of network. The objectives of a sensor network dictate the resulting spatial coverage and resolution with networks focused on urban phenomena typically being in the Urban/City scale (area of $10^4 - 10^5$m) [31], [32]. Dense city scale networks are vital to understanding the urban heat island (UHI) effect as cities often have heterogeneous land cover making it difficult for a single sensor to effectively characterize a large area [11], [31], [32]. Due to time and high costs associated with maintenance and operation, sensor networks and Urban Meteorological Networks (UMNs) are typically short-term projects not designed for long-term deployment [11], [17], [31]. Barriers to long-term deployment can be exacerbated by sensor network spatial coverage, density, and the types of communication technology used [11], [31]. An example of a more recent urban sensor networks designed for long-term deployments and integrated into the infrastructure of cities is the the Array of Things. The Array of Things (AoT) in Chicago has upwards of 500 planned installations with approximately 130 active sensor modules that have been online since 2016 where each module collects a variety of data such as air quality, climate, video, and sound [18].

This paper describes the deployment and application of the *Healthy Cities Sensor Network*, an environmental sensor network in Bloomington, Indiana designed for monitoring hyperlocal extreme heat and heat wave trends. The network is comprised of an array of in-situ sensing technologies to capture hyperlocal environmental data. We describe how we use these data to create interactive visualizations depicting how temperatures vary within the built environment. We discuss how our sensor network can connect communities with hyperlocal heat exposure data and describe how the data can been used to inform individuals and communities about unhealthy environmental exposures. As cities across the country transition into what are being called "Smart Cities", the collection and validation of local environmental data through ubiquitous low cost sensors is becoming an increasingly important research area.

II. Sensor Network Overview

Our environmental sensor network consists of an array of in-situ sensors located across the city of Bloomington, on the Indiana University (IU) campus, and in two urban agricultural locations. The sensor network captures climate and environmental variables such as near surface air temperature and relative humidity (T/RH), dew point, soil moisture, wind speed/wind direction, and solar radiation. Sensors are deployed in differing urban form environments (i.e. along streets, in parking lots, and in community gardens) in order to measure how these environmental data vary across the urban landscape. To support heat resilience planning, in-situ monitoring captures diurnal variations and continuous monitoring of extreme heat events throughout summer months. The sensor network began in 2018. Since 2018 we have maintained and expanded our sensor with the largest growth occurring in 2024 when we added 21 new sensors to our network.

Our urban sensor network consists of a total of 37 sensors. Individual sensors measure temperature/relative humidity/dewpoint (T/RH) (32), soil moisture (SM) (3), solar radiation (SR) (1), and wind speed/wind direction (WSWD) (1). See Table II for a list of sensor technologies deployed in the network. T/RH sensors are widely and evenly distributed across the city and university campus to ensure adequate representation of different urban form conditions. We have installed 13 T/RH sensors on IU's campus and the remaining 19 T/RH sensors are distributed across the city of Bloomington. In addition to our city-level network, we have also established two high density mesh networks at the micro-scale to examine hyperlocal temperature variations and to integrate additional environmental variables. These two high density mesh networks are located along a highly travelled street corridor and in a community orchard (See Fig 1). The dense array of sensors installed along a busy and hot street corridor is used to quantify personal heat exposure for pedestrian and transit riders and to explore opportunities for creating a cool corridor. The sensors located in the community orchard and garden examine the impact of green infrastructure, agriculture land cover, irrigation and evapotranspiration on local temperatures. The solar radiation and wind speed sensors are also installed in the urban agricultural location in order to calculate and monitor evapotranspiration.

A. Sensor Technology

Our sensor network primarily utilizes two sensor configurations from the Onset Computer Corporation; the HOBO MX2302A External Temperature/Relative Humidity Sensor Data Logger and the HOBO RX2106-900 Remote MicroStation which allows for a wireless connection with several different sensor models. The HOBO units are widely used

Model	Variable	No.	Location	LCZ
MX2302A	Temp, RH	22	Campus, City	2, 3, 5, 6, 8, 9, 11, 12, 14, 15
RXW-THC-900	Temp, RH	10	Street, Orchard	2, 3, 5, 14, 9
RXW-SMD-900	Soil Moisture	3	Orchard	9
RXW-WCF-900	Wind Speed & Wind Direction	1	Orchard	9
RXW-LIB-900	Solar Irradiance	1	Orchard	9
RXW-RPTR-900	NA (Repeater)	2	Street.	NA

Table II: Sensor technology utilized in our urban environmental sensor network.

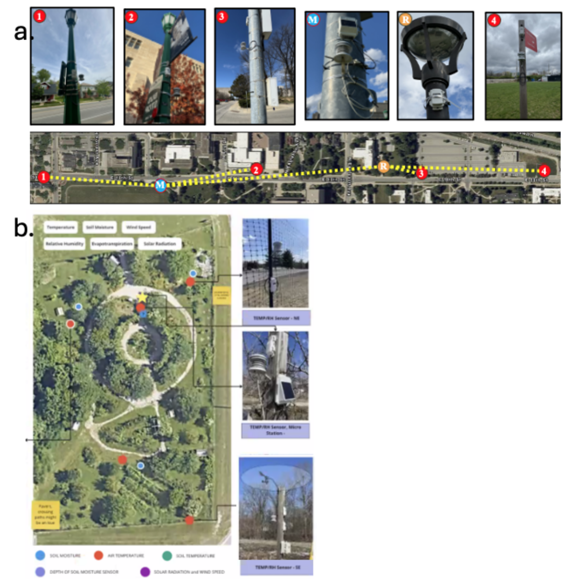

Fig. 1: Maps illustrating two mesh networks and areas of interest targeted for sensor deployment.A: Street Corridor. B: Community Orchard.

and validated in academic research, MicroStations support a variety of sensors, and are robust enough to add additional sensors if the parameters of the sensor network change in the future [14], [33]–[36]. The MX2302A sensors are versatile data loggers designed for measuring temperature, humidity, and calculating dew point. They are battery-powered and bluetooth enabled sensors that can be deployed in remote locations. Data is stored locally on the data logger and collected via bluetooth through the Hobo mobile app, "HOBOconnect", and is uploaded to the HOBOlink cloud server. T/RH sensors are housed within a Solar Radiation Shield (HOBO RS3-B) to improve the accuracy of temperature sensor readings for periods when sensors are exposed to sunlight and to ensure sensors do not overheat.

Our sensor network also utilizes wireless sensors for the creation of our two high density mesh networks, one of which is deployed along a street corridor with major pedestrian activity and the other which is deployed in a local community orchard. To create our high density mesh networks, a series of wireless sensors connect to a HOBO RX2106-900 MicroRX Monitoring System (MicroStation). The MicroStation has a built-in solar panel with a rechargeable battery and acts as a central data logger where environmental data is collected and transmitted over the cellular network to HOBO's cloud servers. Each wireless sensor has a built-in antennae for radio communication across the mesh network with a 450-600 meter wireless range (line of sight) and is equipped with a built-in solar panel and a rechargeable battery. The mesh networks includes 10 T/RH wireless sensors (RXW-THC-900), 3 wireless soil moisture sensors (RXW-SMD-900), 1 windspeed/wind direction wireless sensor (RXW-WCF-900) and 1 solar radiation wireless sensor(RXW-LIB-900). Two wireless repeaters were needed along the street corridor in order to effectively connect sensors wirelessly. Buildings, buses, trees, other urban infrastructure and elevation changes can create physical barriers that inhibit the connection of wireless sensors to the central MicroStation. Wireless repeaters help to bridge these communication gaps and can be installed at higher elevations compared to the T/RH sensors to facilitate connection.

The sensors collect data at regular intervals of 5 minutes, store the data locally and transmits the data wirelessly to our university server. All collected data are stored on HOBOlink, a cloud storage solution designed to store, manage, and export collected data from all MX and RX series sensors. Sensors connected to a Microstation broadcast data to the HOBOlink website and to our servers every hour, whereas MX sensors can store data up to 3 months locally. Data is pushed for these sensors weekly during summer months.

B. Location

When determining where to locate T/RH sensors, we take into account several factors including the height above ground level, local land cover and built environment characteristics, socioeconomic characteristics, and areas of interest to the community. The T/RH sensors are mounted to structures approximately 2 meters above ground, which is the optimal height for capturing temperature metrics that impact human health [9]. In-situ sensors are mounted on street posts, trees, and other vertical structures. Soil Moisture (SM) sensors are deployed at either 6 inches or 12 inches below grade depending on the location. All sensor heights as well as mounting type (post, tree,etc) are recorded in our database. The in-situ T/RH sensors are strategically placed throughout the city and campus to ensure that they are spatially evenly distributed across our region of interest [6], [37]. The overall average distance between a sensor and its nearest three neighbors across the city is 0.42 km. Sensor locations are also selected to ensure representation across different urban forms.

When selecting a sensor location we take into account the characteristics of the local built environment. City design and local urban morphological conditions cause hyperlocal temperatures to vary dramatically throughout cities. For example, near surface air temperatures over dark-paved impervious surfaces, such as parking lots, can be more than 22°F hotter than near surface air temperatures in forested areas and greenspaces [6], [38]. To identify potential sensor location, we collect land cover and urban form data to classify our region of interest into distinct urban form typologies known as local climate zones [26]. Local Climate Zones (LCZ), are predefined typology classes used by urban climatologists to more accurately describe the surrounding physical landscape into micro climates [26]. LCZs were originally established in order to standardize urban sensor network installations and have been used to predict near surface air temperatures in relation to other LCZs [26]. To classify the city into LCZs, we use a random forest (RF) machine learning classifier in Google Earth Engine, training data and a combination of input features such as multi-temporal Landsat 8 data. The LCZ

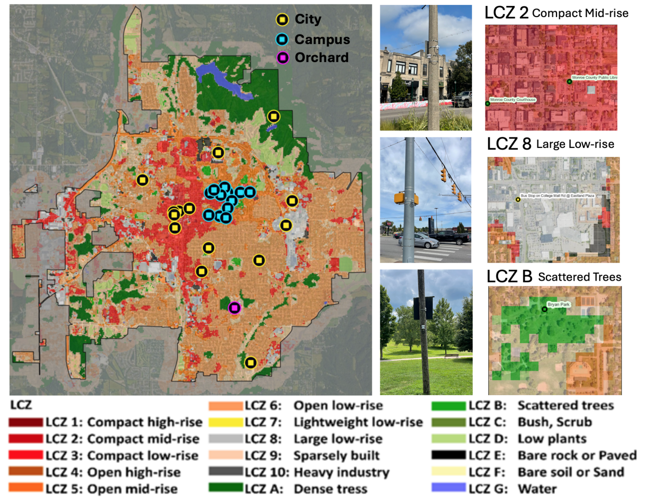

Fig. 2: T/RH sensor locations overlaid on top of 30 meter resolution LCZ map. Sensors are color coded by location. LCZ categories are represented below the image. Urban classes are from 1-10 and natural class are from A-G.

classification scheme includes 17 different class, where 10 represent developed classes and 7 represent natural land cover classes (see Fig 2). We try to ensure consistent representation of sensors across LCZs which are present in the city. We document the LCZ of each sensor location in our back-end database. Figure 2 illustrates a LCZ map with sensor locations and examples of different LCZs for the in-situ sensors.

We also worked extensively with local stakeholders to determine optimal locations for our sensors across the three sites (campus, city, and community orchard). For IU's campus, we worked directly with a representative from landscape services in order to ensure sensor deployments were deployed in accordance with campus protocols. For the city of Bloomington, we worked with their Economic and Sustainability department to identify both areas of high heat vulnerability as well as places of interest to the community. Specifically, we targeted busy bus stops which did not have shelters, housing authority apartment complexes, mobile home parks, and Title I schools. We also identified locations based on community impact and outreach such as the local public library, a children's science museum, and the downtown courthouse which is located in a high density mixed use commercial development which serves as a central location for community gatherings. For the community orchard, we held two public engagement workshops for orchard leadership and volunteers. The workshops introduced stakeholders to the dangers of heat, the potential application of sensing technology, and explored areas of interests and concern for the community orchard members. Designing sensor networks with communities allows for more meaningful application and outcomes for IoT deployments.

C. Data Flow

Data generated from the in-situ sensor network is consolidated and integrated into a robust back-end database system, where we implement consistent quality control measures and

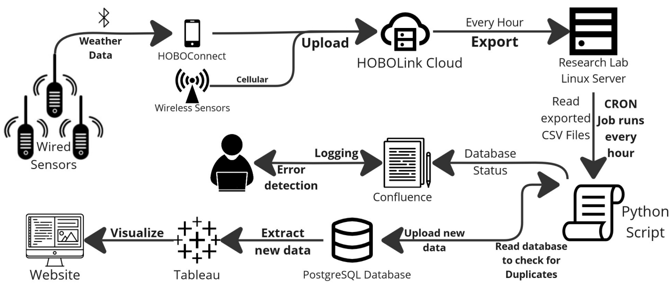

Fig. 3: Diagram depicting data flow from individual in-situ sensor to final data visualization output

produce real-time continuous heat monitoring visualizations. Figure 3 illustrates the data flow from in-situ sensors to online visualizations. The collected sensor data from HOBOlink is exported to a university-hosted linux server every hour as CSV files. The Linux server hosts a PostgreSQL database and a website. An hourly CRON job runs Python scripts that process the incoming data, remove duplicates (if any), and inserts it into the PostgreSQL database. The database is the main storage for all collected sensor data, which is backed up periodically into CSV files. A website hosts Tableau visualizations that are frequently updated to provide real-time insights into environmental conditions over the sensor network. The Tableau dashboards are directly connected to the PostgreSQL database, and whenever new data is added by the CRON job, the visualizations are refreshed automatically.

We utilize a Confluence wiki for project documentation, knowledge management, and metadata documentation and representing our internal knowledgebase for our sensor network. We utilize the Confluence wiki to monitor the status of our database. For each sensor in our network, a table is auto-updated in Confluence recording sensor location and the last available timestamp of the sensor observation. This allows for monitoring and verification of the data, ensuring that each sensor data is timely, and that sensors are not malfunctioning. Additional, we use the wiki for on-boarding new researchers. We create how-to tutorials that describe installation protocols for each sensor type, training documentation for data acquisition, and documentation of our database structure. We use the wiki to document the history of the sensor network, which include routine maintenance (i.e. battery replacements), sensors removals/additions, and network problems/failures.

III. Data Analysis and Visualizations

Utilizing this database system, we create interactive visualizations of near surface air temperature and heat index data. We calculate apparent temperature to represent the heat index (the "feels like" temperature) using similar methods as the National Weather Service (NWS). We include separate visualizations that depict hourly average temperature and heat index graphs as well as daily min/max temperature graphs for partnering stakeholder groups. These visualizations can help community members identify when they are experiencing unhealthy heat days. The Heat Index (HI) is calculated based on temperature (T) and relative humidity (RH). Corrections are applied if the relative humidity (RH) is less than 13% and the temperature (T) is between 80°F and 112°F, or if the relative humidity (RH) is greater than 85% and the temperature (T) is between 80°F and 87°F [39].

We identify Extreme Heat Events (EHEs) and Heat Waves (HWs) for every sensor in our network and illustrate how communities exhibit various levels of heat exposures and heat waves trends. Extreme heat thresholds are based on the long-term average for each community and HW calculations are based on our previous HW methodology [8]. To identify EHEs and HWs, we calculate threshold markers for both minimum and maximum apparent temperature. To determine the local threshold for EHEs, we use the 85^{th} percentile for the long-term average (July and August temperatures from 1981-2010). The maximum and minimum apparent temperature thresholds for our location is $92.84°F$ and $74.79°F$ respectively and these thresholds are included in the online temperature and heat index graphs. Figure 4 illustrates the temperature variation for the hottest week of 2023 across three sensor locations. Temperatures peaked on August 25, 2023 with the highest temperatures occurring in a parking lot with a heat index of 118°F. However a nearby forested area exhibited the coolest temperatures of 107°F representing an 11-degree difference between these two sensor location and their representative local climate zone. The urban form data for these locations provides additional insights into this temperature disparity. The forested location has a pervious surface fraction of 100%, meaning the entire area is permeable (grass, trees, dirt, etc). Conversely, the parking lot is highly impervious with only a 10% pervious surface fraction with the majority of the land cover dedicated to buildings, parking lot or roads. This difference in land cover directly impacts the 11-degree temperature variation, as the parking lot's heat-retaining surfaces and limited vegetation create a more intense urban heat island effect compared to the forested area. Using data from our sensor network we can also analyze which areas of a city are experiencing more frequent and intense heat waves. Table III lists the number of HW days in 2024 per LCZ. Sensors located in built environments classified as Open Midrise (LCZ

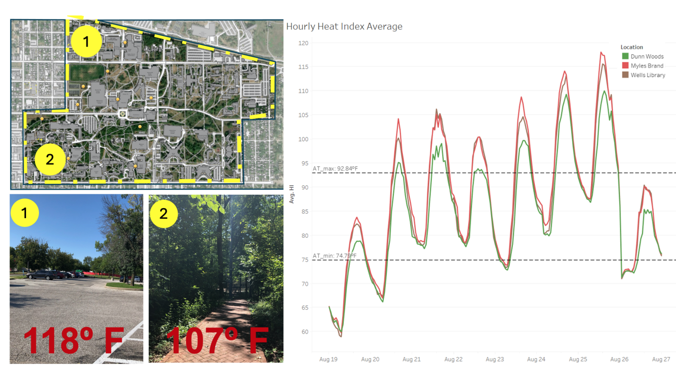

Fig. 4: Real time hourly temperature data visualization

LCZ	No. of heatwave days
5 - Open Midrise	29
15 - Bare rock or paved	15
14 - Low Plants	15
2 - Compact Midrise	14
11 - Dense Trees	7
12 - Scattered Trees	6

Table III: No. of heatwave days per local climate zone (LCZ) based on the daily maximum apparent temperature

5) experienced 29 HW days compared to LCZs classified as Scattered Trees (LCZ 12) which has only experienced 6 HW days. This illustrates that different locations across one city can experience a wide variations of unhealthy hot days exposing residents to different levels of extreme heat.

Diurnal variations allow us to see the difference between maximum and minimum temperatures throughout a day. When visualizing temperature trends, it is important to analyze diurnal variations across different land cover patterns. Minimum temperatures, also known as high nighttime temperatures, have been shown to be a better predictor of negative health effect to extreme heat [9] and as such are often prioritized in analyzing trends in EHEs and heat waves [8]. Various types of green infrastructure such as urban forests, parks, and urban agriculture play a role in lowering temperatures in the built environment and do so to varying degrees. Increasing tree coverage can significantly reduce maximum temperatures compared to other land cover strategies, as can be seen in Figure 4 and Figure 5. On the the other hand, open green space and urban agricultural locations are better at reducing minimum temperatures due to their high skyview factor (percentage of sky that is visible) which allows for long-wave radiation to be more efficiently released into the atmosphere [6]. Figure 5 illustrates average hourly temperature for three distinct location in our sensor network: a parking lot, a forested area (Dunn Woods) and an urban agriculture site (Willie Streeter). The parking lot exhibits the highest maximum and minimum temperatures, and the forested area exhibits the lowest maximum temperature, approximately 10°F less than the parking lot. Though the urban agricultural site moderately reduces maximum temperatures as compared to the parking lot, we see at night, temperatures are the coolest in the agricultural site – outperforming the forested location in reducing minimum temperatures. Green infrastructure also modulates temperature and heat index values due to the process of evapotranspiration and due to irrigation practices. Evapotranspiration reduces near surface air temperatures in the built environment but the combine process of irrigation and evapotranspiration also increases local humidity levels thereby elevating the heat index (apparent temperatures)

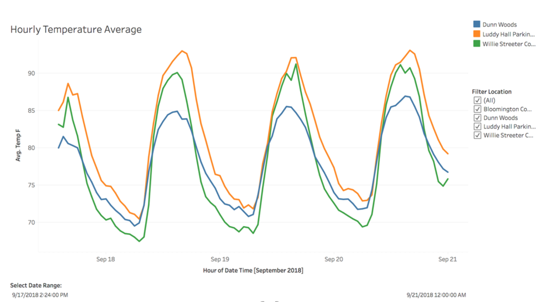

Fig. 5: Average hourly temperature for three distinct locations- forested, urban agriculture, and parking lot.

IV. Discussion - Challenges & Broader Impacts

A. Challenges

Creating urban environmental sensor networks is a complex task with various challenges, from the design of the sensor network to deployment and maintenance of the network. Community and civic partnerships are essential to establish and sustain effective long-term deployments. In order to design and deploy our network, we worked extensively with campus leadership (landscape services), the local government (the office of sustainability, the parks department, the department of public works, and the local utility company), and community leaders for the community garden and orchard. When designing the sensor network we needed to ensure sensors were evenly distributed across different LCZs and finding suitable locations could be difficult. Land ownership influenced potential installation sites thus limiting site options. As a result, identifying potential installation sites required flexibility as we needed to identify multiple substitute locations which took consistent outreach and coordination. This process can be time consuming and requires careful planning. Installation challenges were exacerbated when sensors utilizing radio frequency for data communication were deployed and required line of sight between devices to ensure complete and efficient data transfer. To accommodate the line of sight requirement, we situated our data loggers above our sensors to avoid any interruptions from intermittent sources (i.e. vehicular traffic) and used repeaters to extend the communication signal.

Working with local stakeholders is key when designing and installing a sensor network which can ensure sensor technology is incorporated into the infrastructure of campuses and cities allowing for long-term monitoring, maintenance, support and engagement. For long-term deployments, sensors should be viewed as public infrastructure. Introducing sensors as a type of public infrastructure helps to facilitate the essential collaboration needed to successfully integrate sensors into the current infrastructure. For example, repeaters needed for wireless mesh networks would have benefited with higher elevation locations to better support line of sight and avoid structural interference but this placement would require more coordination for both installation and maintenance.

B. Tools for Researchers

Maintaining a sensor network over time has a set of unique challenges which require a significant amount of time, effort, an array of tools, and constant tracking and observation. Interactive tools developed to support sensor networks can help to increase efficiency, cost, and reduce system failures. Metadata documentation is needed to sufficiently describe the evolution of a sensor network such as documenting new/decommissioned sensors, battery changes, sensor failures, hose clamp readjustments to prevent tree girdling, etc. Tools that allow user to seamlessly enter metadata in the field as well as receive push notifications to alert researchers of potential systems failures or when a network node is reaching its carrying capacity (full data loggers, batteries not charging, etc) can support the overall function of the network. New tools are needed to better enable researchers to understand the state of their networks and to anticipate and manage potential equipment challenges before they become problematic.

C. Data to Knowledge

The Healthy Cities Sensor Network generates a large volume of environmental data that can be used by a wide variety of stakeholders to better understand their local climate. However, translating these data into actionable knowledge for use by a lay audience is no trivial task. Interactive technologies such as dashboards, mobile apps, or dedicated tools designed for professionals can help bridge this gap by visualizing these environmental data and educating stakeholders on how to engage with and better understand their local climate. Effectively translating environmental data into knowledge with the goal of supporting decision making and community action can be challenging as how we measure heat stress is not always straightforward. Therefore, it is important to educate stakeholders about the different metrics that are commonly used. For example, minimum temperatures are often overlooked by residents and local stakeholders as an important measure of heat even though minimum temperatures play a significant role in impacting heat-related mortality. Explaining the differences between surface temperature and near surface air temperatures, or describing why local thresholds are used to define EHEs can be be complicated as is educating individuals on the difference between using apparent temperature (the combination of temperature and humidity) as compared to Wet Bulb Globe Temperature (which includes wind speed, solar radiation, temperature and humidity) as a measure of heat stress. Unpacking environmental data is complicated and new approaches are needed to help accomplish this need so that the full impact of deploying a local sensor network to collect hyperlocal environmental data can be realized.

D. Broader Impacts

The long-term deployment of urban sensor networks has the potential to make significant multidisciplinary contributions to a community's climate resilience by enabling comprehensive monitoring of environmental parameters across cities while delivering real time data to support decision-making for various applications. Sensor networks can help campuses and cities achieve sustainability goals by enabling city sustainability officers, as well as campus facilities, to better understand how their built environment is contributing to extreme heat, how vegetation strategies may reduce near surface air temperatures and how smart watering systems may be incorporated in order to efficiently monitor and manage vegetation on campus

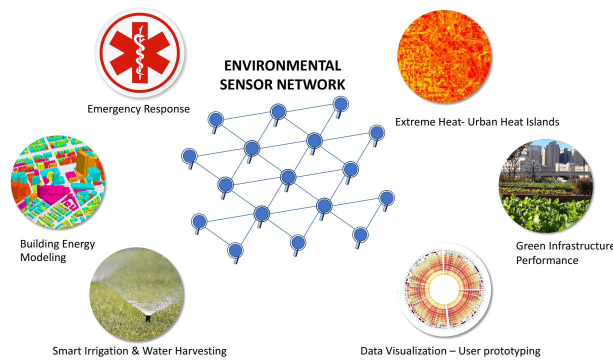

Fig. 6: The long-term outcomes and synergies from an environmental sensor network.

and throughout a city (See Figure 6). Urban environmental sensor networks can play a role in establishing meaningful community engagement and can be leveraged to support citizen science, environmental stewardship, and can also enhance climate education. Data collected from urban sensor network can be used to monitor and document the local responses to the changing climate, can help cities identify and target sustainable design measures to improve efficiency and performance of various operations and can be used to create a healthier climate for local communities.

V. Conclusion

In this paper, we describe the deployment and application of an environmental sensor network in Bloomington, Indiana, and its applications in monitoring hyperlocal extreme heat exposures and trends. We discuss the overall design and construction of our sensor network, including sensor technology, sensor installation and locations, data flow and management, and data analysis. We also discuss the purpose and of utility of our sensor network for connecting communities with hyperlocal heat exposure data through the deployment of sensor technologies for heat observations. This paper can act as blueprint for communities across the United States to establish local heat monitoring networks and how they leverage hyperlocal environmental data to increase heat resilience in their local community.

VI. Acknowledgments

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