



DTE_x: A dynamic urban thermal exposure index based on human mobility patterns

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ABSTRACT

Background: Extreme heat in light of climate change is increasingly threatening the health and comfort of urban residents. Understanding spatio-temporal patterns of heat exposure is a critical factor in directing mitigation measures. Current heat vulnerability indices provide insight into heat sensitivities within given communities but do not account for the dynamic nature of the human movement as people travel for different activities. Here, we present a new Dynamic urban Thermal Exposure index (DTE_x) that captures the varying heat exposure within urban environments.

Methods: We developed the DTE_x to understand human heat exposure patterns in a mid-sized city. This index incorporates the human movement pattern and the heat hazard pattern obtained via novel and advanced techniques. We generated the human movement pattern from large-scale, anonymized smartphone location data. The heat hazard patterns were extrapolated via machine learning models from air temperature data measured through vehicle-mounted sensors. The exposure index was then developed by combining the two parameters using their standard-deviation-classified indices.

Results: Our exposure index varied between 2 and 12, indicating low to high thermal exposures. Several high-temperature spots associated with a large volume of foot traffic are successfully identified through this DTE_x. We observed the hottest spots at shopping plazas but not specifically in the urban center. During the selected football gameday, the exposure index surged across most places near the football stadium but was reduced considerably further away.

Discussion: The proposed DTE_x is novel because it provides dynamic heat monitoring capability to facilitate heat mitigation strategies at vulnerable locations in urban environments. Combining the mobility data and extensive sensor data generates rich details on the most heat-exposed areas due to human congregation. Such information will be critical for risk communication and urban planning for policymakers. DTE_x could also help smart route planning in sustainable cities to avoid heat hazards risks.

1. Introduction

Heat is the leading weather-related killer in the U.S. It kills more people than hurricanes, tornadoes, and floods (Klinenberg, 1999; NWS, 2007). Taking the example of 2019, the 2nd hottest year for the whole earth, historic highs across the globe exceeded all previous records (NOAA, 2020). Heatwaves pose increasingly severe threats to people as they last longer and become more intense because of climate change

(Della-Marta et al., 2007; Russo et al., 2017). Cities are especially at elevated risk with denser populations and impervious surfaces, which increase air temperatures and enhance the urban heat island (UHI) effects. Nevertheless, urban areas have highly complex land use land cover development that leads to diverse temperature patterns (Coseo and Larsen, 2014; Jenerette et al., 2016).

To help identify at-risk communities, various heat exposure indices and heat vulnerability indices (HVI) have been developed (Reid et al.,

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2009; Wolf and McGregor, 2013). These indices blend the social-economic status (e.g., chronic disease, health insurance, income) (Dolney and Sheridan, 2006; Johnson and Wilson, 2009; O'Neill et al., 2005), and in some cases, physical factors (e.g., land cover type and green space) (Reid et al., 2009) for assessing heat risk. The indices are designed to identify places that need increased mitigation measures in a static sense, usually at the county or census tract level. Several studies have demonstrated the validity of these indices by showing populations at higher exposure locations have greater mortality rates in response to hot days (Maier et al., 2014; Reid et al., 2012). However, the impact of such HVIs is mixed. Some governments and policymakers have adopted these indices to enhance urban resilience by efficient urban heat mitigation planning (Kong et al., 2014; Oliveira et al., 2011). In contrast, some others found a gap between the research and real-world implementations (Grundstein and Williams, 2018; Wolf et al., 2015). Some reasons are the lack of reliability study of HVIs, many uncertain factors of the input datasets, and not incorporating microclimates and other hyperlocal factors.

Heat exposures are highly dynamic along spatial and temporal dimensions due to the changing weather patterns and are affected by human movement and behaviors. People have different time-activity patterns that may lead to vastly different heat exposure degrees (Kuras et al., 2015). For instance, people may congregate in specific locations away from their residence (e.g., retail establishments, sporting events) at certain times that may affect their heat exposure, thus changing a region's heat hazard profile (Kuras et al., 2017). Therefore, human movement data need to be included in identifying where people gather and visit the most. Another key to a dynamic heat exposure index is the use of hyperlocal ambient air temperature (AAT) that an individual experiences over a complex urban environment rather than the use of static land surface temperature (LST) data from satellites or coarse resolution weather station temperature data, which may not represent the spatial variability in AAT (Barnett et al., 2009). Many current heat exposure studies use LST due to insufficient AAT data (Jenerette et al., 2007; Liu and Zhang, 2011; Yuan and Bauer, 2007). However, satellite-derived LST is not strongly correlated with AAT and does not have the high temporal resolution to best capture variations throughout the day or even week (Ho et al., 2016; Kloog et al., 2012; Yin et al., 2020).

With the development of location-based technology and the proliferation of smartphones, mass population movement can be tracked with reasonable accuracy (Lu et al., 2013). Many studies have implemented the crowdsourced human movement pattern data in identifying neighborhood isolation (Prestby et al., 2020), calibrating business analysis models (Liang et al., 2020), improving disaster response (Bengtsson et al., 2011), and studying human behavior under different circumstance (Gao et al., 2020). Another type of crowdsourced data comes from smart sensors that can gather high-resolution data on environmental parameters to improve weather monitoring and measurements (Anjomshoaa et al., 2018; Eisenman et al., 2006; Honicky et al., 2008). Some studies blend smart sensor data with other biophysical parameters using machine learning techniques, and the generated AAT products can cover a larger area with precise predictions (Hashemi Tonekaboni et al., 2018; Yin et al., 2020). Such data can help identify human movement and exposure risks in heat exposure studies at any point in time. Therefore, the exposure assessment that combines these two dynamic factors can effectively indicate the heat hazard variability between places and communities. Other factors pertaining to people's social-economic status (SES) can also contribute to a more comprehensive index, but currently, due to the privacy issue, such information has not been included.

Our research seeks to build upon the concept of a heat exposure index from a different perspective that accounts for microclimatic thermal conditions and sub-population exposure. To achieve that, we seek to develop a thermal exposure index that can couple the thermal variability in complex urban environments with variable human mobility patterns. The index should have a mechanism to account for the

highly variable temperatures typically experienced in urban environments using a novel high spatial and temporal resolution AAT dataset blended with smartphone extracted location data on human movement. Our overarching objective is to develop and test a Dynamic Thermal Exposure index (DTE_x) that combines hyperlocal AAT with population exposure, which will be useful for both mitigation measures and intervention strategies. Our secondary objective was to demonstrate the index's utility using two highly contrasting foot traffic days in ACC, a regular Saturday vs. an American College Football gameday, Saturday. The novelty of this index lies in the fact that it incorporates two highly granular and dynamic datasets acquired using advanced techniques that prevent large-scale averaging effects prevalent in traditional coarse resolution datasets. We present a case study of this index for a medium-sized county.

2. Methods

We used Athens-Clarke County (ACC), Georgia, U.S. as the study area. ACC is a midsize metropolitan area with a population of approximately 120,000 and is located in a humid subtropical climate in the U.S.'s southeastern region. Several past heat exposure studies have documented that this area has high heat exposure with hot-humid summers and multiple socioeconomic exposure factors such as poorly planned neighborhoods and a high poverty rate (Johnson et al., 2012; Maier et al., 2014; Reid et al., 2009). Here, a poorly planned neighborhood has crowded houses, minimal green space, and little open space within and between blocks (Harlan et al., 2013). Nevertheless, ACC has diverse microclimates (Murdock et al., 2017) represented by highly urbanized locations and those with more green space, and a mobile population that travels for work, school, and shopping, along with extensive social activities like sporting events that bring hundreds of thousands of people to the area. The primary focus of our analysis was to evaluate human mobility as a critical element in identifying heat exposure for ACC. Therefore, we coupled human mobility information with hyperlocal AAT data to analyze heat exposure.

2.1. Exposure data

Foot traffic patterns are identified using data from SafeGraph for September 2019 ("Places Schema," n.d.). This dataset allows us to identify foot traffic patterns to recognize the frequently visited places in a community. SafeGraph collects location data from numerous mobile applications, which covers millions of users to provide insights into businesses and human activities. These data were generated from smartphones with coordinates and corresponding timestamps to annotate the devices' spatio-temporal placement. These data were then aggregated to the counts of foot traffic visits to each location at a specific time range to eliminate private information for increased privacy. Finally, these coordinates were published showing when customers visited a particular establishment and which community contributed the most customers. It worth mentioning that based on the above algorithm, human mobility in residential and rural areas was missed, and people without a smartphone were also not represented in this dataset. However, according to the official document from the vendor (SafeGraph), the original mobility data is a comprehensive sample representing people from all income groups, age groups, residential zip-codes, and education levels (Squire, 2019). Therefore, even though people without cell phones were missed, the dataset is still a representative sample of the population. Furthermore, our study focuses on popular public spaces, so not including residential areas, which are typically low foot traffic areas, will not substantially alter our results.

In our research, we first applied data filtering to extract the visits to different points of interest (POIs), which are all the commercial and public areas in ACC, from the original SafeGraph database. Then we created a 10-meter buffer around the polygons of all POIs to indicate the possible scopes of human movement. Specifically, we selected the

counts of noontime foot traffic visits (11 am–1 pm) during September, the third warmest September on record in ACC (NOAA and N.W.S., 2020). The selected counts show how many people visited each location in ACC between 11 am and 1 pm during September 2019. We also compared our index on different days, where we selected the counts of foot traffic visits for two days: an American football home game day on Sep 21st, 2019, and a typical Saturday, Sep 28th, 2019. The above two days had close temperature range (Sep 21st: 61–84°F/16–29 °C, Sep 28th: 72–82°F/22–28 °C).

2.2. Heat hazard data

We used high-resolution AAT data to represent community-level heat hazards. The AAT product was generated from a machine learning framework presented in Yin et al. (2020) that blends bus-borne temperature data, satellite LST products, and surface biophysical parameters such as canopy shading, solar radiation, and weather station temperature. In brief, we equipped 40 city and UGA campus buses with Arduino microprocessors operated fast-response (every 5 s) air temperature sensors. Each sensor included an AdFruit M0 Feather microprocessor, a real-time clock, a GPS unit, a DS18B20 waterproof temperature sensor, a battery set, a micro SD card, boards and wires that connect the components, and the parts above are all sealed in an IP67 waterproof box (Yin et al., 2020). Using these bus sensors, we repeatedly measured daytime and nighttime AAT over 2 years during summer and fall seasons for every bus route within Athens, GA, and collected more than 10 million data points. AAT is the key parameter to illustrate human thermal exposure, whose distribution is highly correlated with land cover, solar radiation, canopy shading, and other biophysical parameters (Makido et al., 2016; Voelkel and Shandas, 2017). Therefore, we applied the Random Forest model to expand our collected AAT data along bus routes to create AAT maps covering the entire Athens, GA area. These AAT maps have a resolution of 30-meter and can capture variability within urban environments (Yin et al., 2020). The model output expands the original temperature data coverage to different land types across ACC yet still possesses a high accuracy with less than 1 °C mean absolute error (MAE). Because the business foot traffic counts were aggregated to the whole month of September for each hour of a day, we also averaged all the output noontime (11 am–1 pm) AAT maps of September 2019 (see Fig. 1).

The map on the left is the September noontime foot traffic map for ACC. We can identify several known popular POIs, for example, the UGA campus in the center, several shopping plazas between road sections,

State botanical garden beneath the UGA campus, the Athens Country Club with a light-green color right outside the northern perimeter, the Sandy Creek Natural Center with a blue color east to the Country Club, and many small POIs along the roads. The map on the right is the AAT temperature map, with blue color indicating colder temperatures and red color indicating warmer temperatures. Most red areas are located at the ACC downtown, the UGA campus, and along the roads because these are places with the most impervious surface and least greenspace. Coupling these two maps together, we can assume the ACC downtown, the UGA campus, and POIs along roads might have higher heat exposure. However, the only way to get the exact result is to calculate the index using our proposed method.

2.3. Dynamic thermal exposure index (DTE_x)

We developed DTE_x using two novel datasets, the machine learning model derived AAT, and the cellular phones derived population exposure data. In developing the index, we followed a similar procedure to Reid et al. (2009). Reid's index and other traditional indices were all constructed with many not normally distributed data. However, these indices do not require an accurate discretizing of the original data but a clear separation between extremes and normal. Therefore, Z score, which is the number of standard deviations a data value lies from the mean in the dataset it comes from, becomes our choice (Larson et al., 2009). First, we standardized the AAT and movement data using a z-score and then assigned an ordinal value from 1 to 6, where 1 corresponds to the smallest value and 6 to the highest value (Table 1). Z scores with an absolute value greater than 2, which is 1 and 6 in our index value, are considered unusual have been previously used in vulnerability and exposure index calculations (Pauline et al., 2020). This was done to minimize the impact of possible outliers and to foster ease of interpretation. We also assumed that the two variables carried the same

Table 1
Categories created by observed distributions.

Category	Assigned Value
≥ 2 SD below mean	1
1–2 SD below mean	2
< 1 SD below mean	3
< 1 SD above mean	4
1–2 SD above mean	5
≥ 2 SD above mean	6

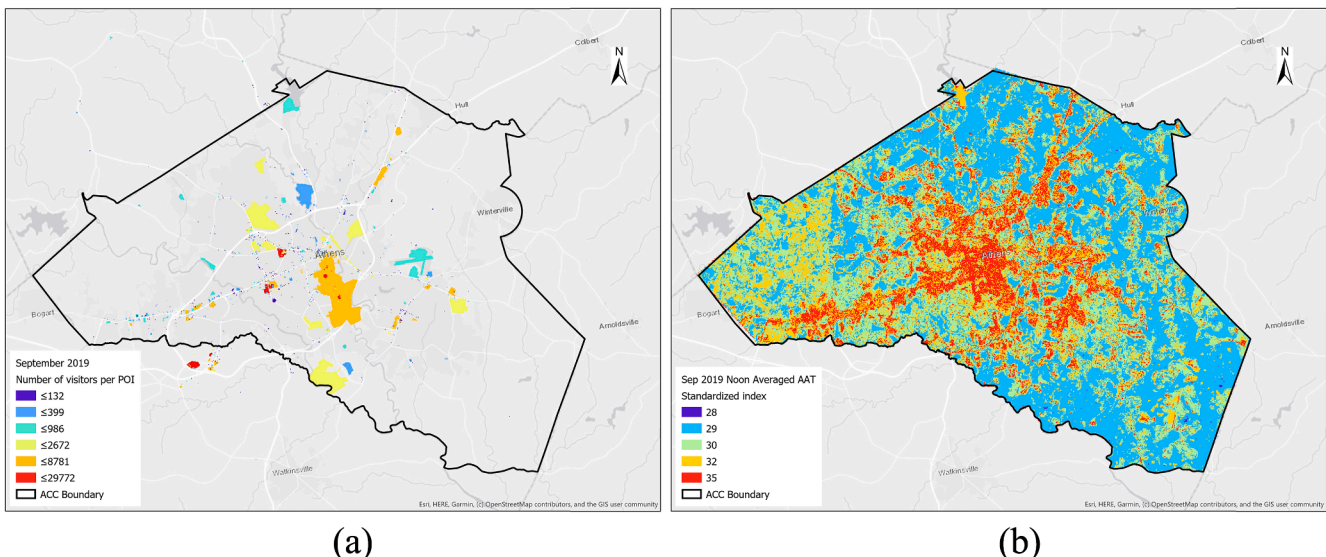


Fig. 1. Noontime exposure and heat hazard map of ACC for September 2019, (a) Exposure map (places with ≤1 visit are not colored); (b) AAT Heat hazard map.

weight in quantifying total heat exposure for any given location. In the end, the heat exposure index had a scale from 2 to 12, with 12 representing the worst possible heat exposure within the community.

3. Results

3.1. Comparison between constructed DTE_x maps vs. AAT and foot traffic maps

The DTE_x map for September 2019 is shown in Fig. 2c. To elaborate on how this index precisely considers the human foot traffic and its utility, we examined several different communities in the ACC area in zoomed-in views and circled with black outlines (Fig. 3 a-c). Area 3a, downtown Athens, hotter than the non-urbanized areas but had moderate foot traffic, leading to its slightly above average DTE_x 6.5. Area 3b, Sandy Creek Park, is a popular destination for recreational activities but had lower temperatures because of the ample green space. Therefore, most of the parks had low DTE_x. Area 3c, the UGA Health Science Campus, where many people walk around during noontime and is a typical urbanized area with higher temperatures, resulting in a high DTE_x.

3.2. Comparison between DTE_x on a high foot traffic day vs. A regular day

Existing heat vulnerability maps are static because of the nature of the input datasets and, therefore, do not represent the variations in heat hazards and heat exposure over frequent time intervals and with different population exposures. To demonstrate DTE_x's potential to capture temporal variations as frequently as every 1-hr interval, we present DTE_x maps for two different scenarios with the same AATs but different foot traffic: a typical Saturday and an American college football game day. On this game day, it was reported that up to 150,000 visitors visited the town, with more than 93,000 people sitting in the stadium (Grady NewsSource, n.d.). This is also clearly shown in the foot traffic maps below, where downtown and the UGA Campus received much more visits than a regular Saturday (Fig. 4a). Simultaneously, suburban and rural businesses and parks experienced significantly lower visits (Fig. 4b). We combined these two foot traffic maps (Fig. 4a and b) with the same heat hazard map to generate the game day DTE_x map (Fig. 4c and d) because two days have a close maximum temperature (Sep 21st: 84°F/29 °C, Sep 28th: 82°F/28 °C).

The map illustrates the variations in heat exposure between the two scenarios, even with the same heat hazard. There were large increases in DTE_x, ranging from 2 to 5 in standardized indices throughout the near-campus community and downtown businesses because of the increased foot traffic on game days in particular locations in the city. Fig. 4e, a regular Saturday, a golf course on the top left of the map, a botanical garden on the bottom center, several shopping plazas, and business on

the left/west side are popular destinations with a total DTE_x of 9–12 (within the purple polygons). Simultaneously, the airport on the east side has few visitors, which results in a DTE_x of 6–8, and most of the campus is between 8 and 10 in heat exposure (within the red polygons). On the contrary, during a home football game day such as on Sep 21st, only a few dozens of people went to the golf course or the botanical garden, which is clearly shown in Fig. 4f with a DTE_x of 7 or less. The airport shows an increase of 2–3 in the index, and the majority of the campus has 11–12 DTE_x because hundreds of people flew into the town, and the phone location data recorded more than 20,000 visits to the campus and the football stadium. Therefore, constructing this DTE_x index can produce high-frequency DTE_x maps for different scenarios throughout a year, either a regular weekday or a special day with sports or carnival events. Such an approach can simulate exposure under different circumstances for planning purposes and help planners choose mitigation measures between increasing green space and building temporal cooling stations more strategically to the targeted areas.

4. Discussion and limitations

While built upon concepts from previous heat vulnerability indices, our index is different in its focus on human thermal exposure rather than on adverse health outcomes. We identify the dynamic heat exposure patterns (both spatially and temporally) via human mobility data and extensive mobile sensor-network temperature data. These data are increasingly adopted in business analysis, contact-tracing (Gao et al., 2020), environmental applications such as water quality analysis (Mishra et al., 2020), and high-resolution weather monitoring studies (Yin et al., 2020). Coupling these two aspects together, we identified this novel objective to construct an exposure index from dynamic human mobility and mobile-sensed temperature. Our index can provide knowledge about which places have constant high heat exposure and high exposure locations at specific days or times. Therefore, policy-makers and urban planning teams can choose different strategies for different scenarios. Greenspace and less impervious surfaces work better to alleviate permanent hot spots, while emergency/temporal cooling stations like a misting station will work better for occasional hot spots (Vanos et al., 2020). This study also features a 30-m AAT product. These index maps outperform the traditional maps at census block or county levels in identifying the at-risk places and communities within a complex urban environment. The contrast exposure observed between a regular day and a game-day illustrates high variability in these 30-meter maps.

Another novelty is that most prior heat hazard studies do not account for human mobility; thus, AAT or LST maps solely contribute to identifying the places vulnerable to high heat hazards. But now, the above DTE_x maps, Figs. 3 and 4, allow us to identify locations with various heat exposures. Such information is useful for urban planners and other decision-makers to guide mitigation approaches. For instance, the UGA

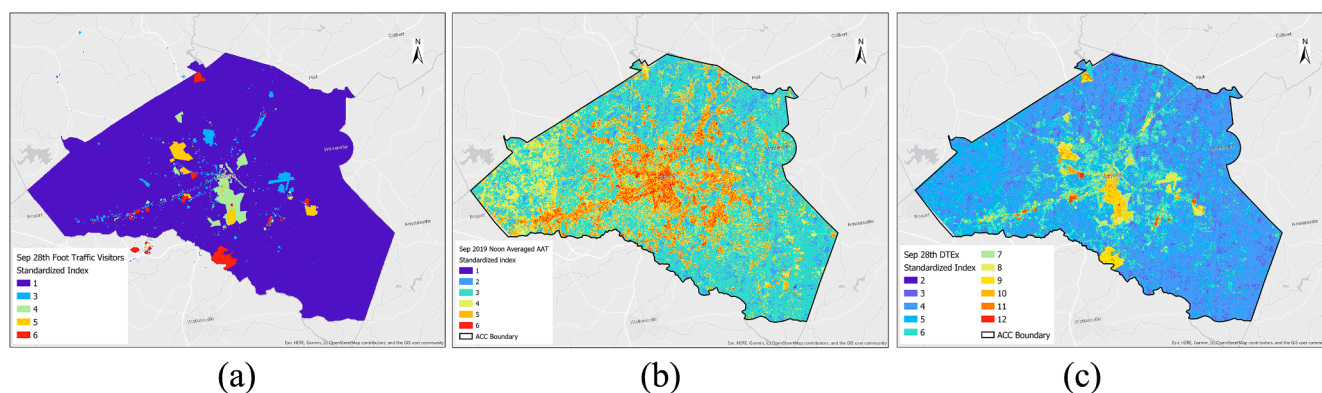


Fig. 2. Maps showing the construction of DTE_x with (a) foot traffic standardized index, (b) AAT standardized index, and (c) the final DTE_x result.

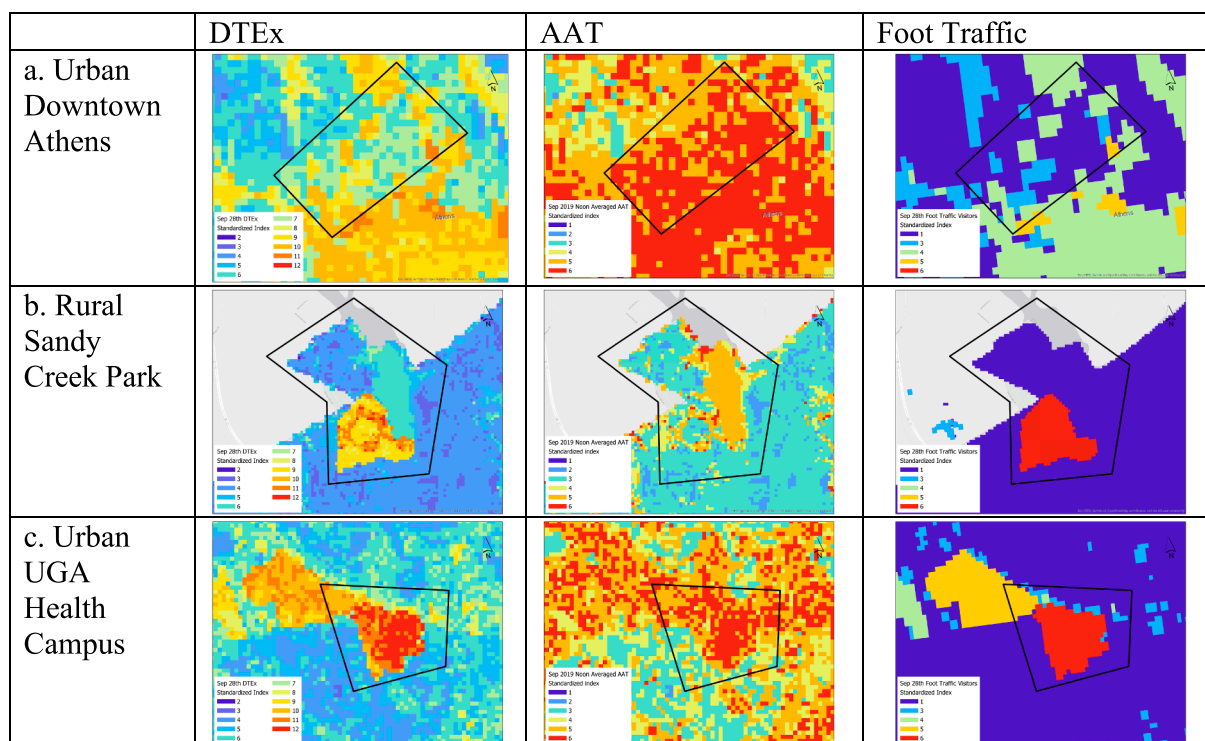


Fig. 3. Specific communities that demonstrate the differences between DTEEx, AAT, and Foot traffic map (a) Downtown Athens, (b) Sandy Creek Park, (c) Health Campus.

Health Campus's high exposure might prioritize mitigating heat at that location compared with Sandy Creek Park. Also, this method can be easily replicated in other cities using similar crowdsourced smartphone data. AAT can be calculated by incorporating the required biophysical parameters into an easy-to-train machine learning model (Yin et al., 2020). However, we recognize several limitations to our work. First, due to the limitation of the raw mobility dataset, we cannot determine if the visitors were indoor or outdoor. If any of these visitors were indoors, then the AAT may not represent their thermal environment during the indoor time. This is not a critical issue for our DTEEx, which represents heat exposure variation. Firstly, for the case studies we presented in the manuscript, we knew that the discussed high DTEEx places had many people congregated at outdoor spaces. Secondly, some POIs have many indoor visitors, for example, hotels, hospitals, and shopping malls. However, those people will experience outdoor heat exposure on their way to indoor locations, such as at the parking lot. Therefore, there will be a certain degree of correlation between outdoor AAT and exposure levels at those locations. Nevertheless, as a precaution, those high foot traffic indoor locations should be flagged in our DTEEx maps and filtered as highly vulnerable locations. In this study, we presented case studies in which we can clearly contrast high DTEEx places with highly congregated locations and relatively high temperature with low DTEEx places with minimum human mobility events and relatively lower temperature. Overall, DTEEx is responsive to the spatial-temporal dynamic of people and shows varying population heat exposure. If human outdoor mobility data become available in the future, we can easily extend and incorporate such data in DTEEx to explicitly describe outdoor human exposure variations.

Second, our index accounts for conditions only in public spaces. Thus, this index would not be useful for individuals who do not travel to public places or businesses. Also, this index excludes people who take walks in their residential neighborhoods or rural areas. Another drawback is the index is dependent on cell phone location, so areas with poor cell phone connectivity will be misrepresented. Although the sampled human mobility pattern is proven to be representative of the total

population (Squire, 2019), there is still a small portion of people not included in the data and study.

Third, we directly combine the two parameters in identifying heat exposure and assume equal significance between them. Previous studies have different formulas and algorithms to identify how much exposure was observed at a particular place, including multiplying the exposure time by exposure intensity (Int Panis et al., 2010; Morawska et al., 2013), defining a threshold for heat hazard instead of using raw temperature to indicate heat hazard (Gabriel and Endlicher, 2011; Zhou and Shepherd, 2010). In our study, the same foot traffic visit might have significantly different thermal exposure, affecting thermal comfort and possibly health outcomes. For the exact foot traffic count, some people might only stay outside for a few seconds, while some workers might spend hours working outside. The most recent foot traffic data from SafeGraph now provides additional information such as dwell time for each POIs. In the next step, we will calculate the average dwell time for each POIs and then multiply the time with the visitor counts to get the cumulative exposure.

Another limitation is that we have not assessed or validated our index via other established datasets. One possible solution is working with social scientists to survey people on thermal comfort in different areas. Another possible approach is to validate with a study of individual time-activity patterns to see how people behave at different places if more people linger or more people just directly go from cars to buildings.

5. Conclusion

We present a novel dynamic thermal exposure index (DTEEx) that accounts for high-resolution heat hazards and heat exposure. This index uses crowdsourced foot traffic data and ambient air temperature data from a drive-by sensing and modeling framework to quantify and visualize spatio-temporal variations in community heat exposure. Our research demonstrates the capability of mobile environmental sensing and crowdsourced location data in heat exposure analysis at the

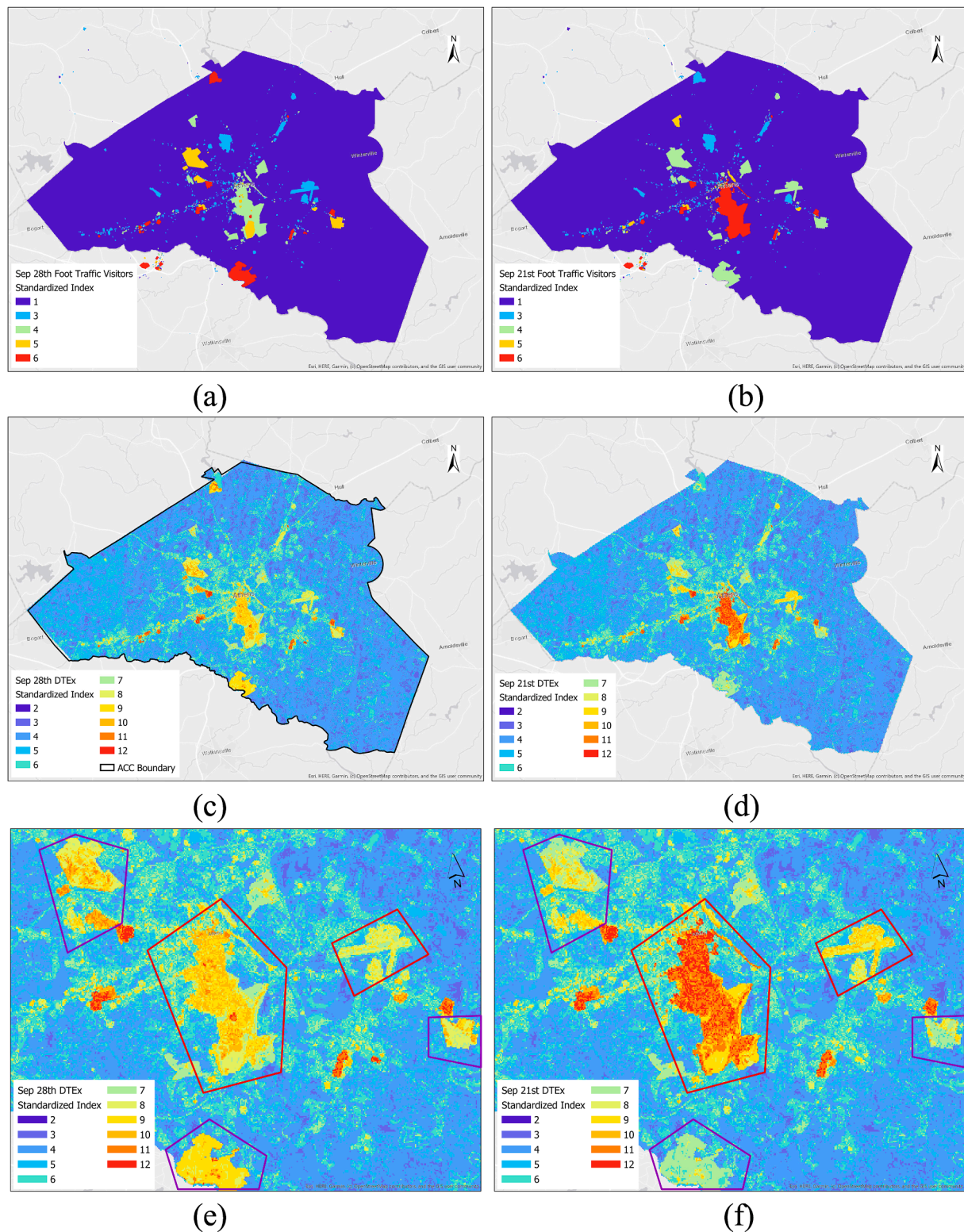


Fig. 4. Foot traffic map and DTEx maps for UGA Campus and surrounding areas at (a) regular day foot traffic, (b) a game-day foot traffic, (c) regular day DTEx, (d) a game-day DTEx, (e) zoomed-in regular day DTEx, (f) a game-day DTEx, (regular Saturday: Sep 28th, 2019 the home game Saturday: Sep 21st, 2019).

hyperlocal level under different scenarios. We shared two examples of how differently people experience heat hazards and how this is a scalable and dynamic framework to be adopted in other cities. Furthermore, examining how neighborhood disparities of social-economic backgrounds affect mobility behavior and include social-economic information in exposure study can promote new findings.

Once finetuned, in the future, if DTEx score can be distributed via an opt-in alert system such as a smartphone-based warning system, a health and age-related warning message or vulnerability alert can be sent to users with a few suggestions about “actions to take.” The users can then decide which suggestion they will follow based on their ages, health conditions, and preferences. If such location-based exposure warning

can be issued to people's phones, it will have a broader societal impact by generating critical community interests to create momentum for heat hazard policies at the local and state level. Including this index score in the alert system might also convince people to trust and follow the suggestions. We call on policymakers to facilitate scientific monitoring and research and explore possible low-cost but accurate monitoring and warning systems like what we have proposed in this study.

CRediT authorship contribution statement

Yanzhe Yin: Conceptualization, Software, Data curation, Formal analysis, Investigation, Writing - original draft. **Andrew Grundstein:** Conceptualization, Methodology, Writing - review & editing. **Deepak R. Mishra:** Conceptualization, Methodology, Writing - review & editing. **Lakshmish Ramaswamy:** Conceptualization, Methodology, Writing - review & editing. **Navid Hashemi Tonekaboni:** Data curation, Visualization, Validation. **John Dowd:** Software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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