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Biometeorological indices explain outside dwelling patterns based on Wi-Fi data in support of sustainable urban planning

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ABSTRACT

This study presents a novel approach to validate the capability of biometeorological indices to predict the likelihood of urban dwellers to be outside during midday. Over a period of ten months three Wi-Fi scanners were used in a public courtyard in Cambridge, MA, to record outside dwelling patterns. Based on encrypted MacIDs courtyard attendees could be divided into 16,000 regulars and 676,000 visitors. Universal Thermal Climate Index (UTCI) predictions based on a combination of measured microclimatic conditions and mean radiant temperature simulations using ENVI-met were shown to strongly correlate with the number of regulars present during lunchtime with coefficients of determination (R^2) of 92% during spring and 70% during summer/fall, respectively. Lunchtime attendance peaked for UTCI values in the *thermal comfort* and *moderate heat stress* ranges. In parallel, the probability for regulars to have lunch outside more than doubled during those UTCI conditions and the median lunchbreak length increased from 8 min to 12 min. These findings suggest that UTCI can be used as a reliable environmental performance metric to support the design and preservation of comfortable outdoor spaces. The reported use of public Wi-Fi data can help city governments to better understand – and potentially improve – the use of outdoor spaces while maintaining the privacy of their constituents.

1. Introduction

As urban populations grow worldwide, city governments are struggling to add sufficient residential and commercial real estate while trying to preserve the character of desirable neighborhoods and/or to create attractive new neighborhoods. Successful densification can reduce the environmental footprint per resident by lowering the mean floor area per person and increasing the use of human powered and public transportation. However, every new structure increases the pressure on the remaining spaces between buildings from public plazas to parks and streets, creating shade, blocking or redirecting wind and contributing to the urban heat island effect. These local and temporal microclimatic effects can decisively impact annual outdoor comfort levels in an urban space affecting adjacent local businesses and public amenities alike. Given that lively outdoor public spaces are the focal point of modern urban life [1–3] and help attracting a competitive workforce and their families, cities pay close attention to protecting these assets. Many cities – including New York City and Boston – are already routinely using direct shading studies to protect their parks and open spaces [4,5]. In Boston, physical models of select neighborhoods have been used for wind tunnel measurements since the 1980s to detect and avoid detrimental microclimatic effects of large new developments [6].

Outdoor thermal comfort is a complex, subjective human sensation that – apart from solar radiation and wind – also depends on activity and clothing level as well as temperatures of surrounding surfaces, evaporative cooling from nearby vegetation and relative humidity levels [7–13]. To quantify the relationship between these diverse outdoor environmental conditions and human comfort, researchers have long worked on so-called biometeorological indices [14,15]. These indices are based on heat budget models of the human body and its environment [11,13–15]. Prominent indices such as Physiological Equivalent Temperature (PET), Perceived Temperature (PT) and Universal Thermal Climate Index (UTCI) are expressed as an equivalent temperature that describes how a human would physiologically react to a given set of environmental conditions. For example, an individual exposed to severe wind or direct sunlight will feel as if being in a colder or warmer environment than in the absence of these effects. While PET and PT are based on two node models of the human body [16,17], UTCI is based on a 187 node model [18,19] and has been shown to be able to detect potential human discomfort under larger sets of microclimatic conditions than other biometeorological indices [16]. In order to use

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UTCI predictions to design more comfortable outdoor environments, computational models of the underlying environmental processes have been developed in recent years [15,20,21].

A remaining, open question is how reliably UTCI calculations predict actual occupancy patterns in public outdoor spaces. Previous studies relied on passerby interviews and presence counting to answer this question [14,22–26]. While interview-based studies [14] have usually been transversal (snapshot in time) with the number of subjects varying from 91 to 2700 [23–27], some longitudinal studies were conducted with in between 8 and 36 subjects [28–31]. The advantage of longitudinal studies is that they provide some insight in the "thermal history" of participants as well as within subject trends. For example, an uncharacteristically warm day in spring tends to lure more people outside than the same day in early fall. A drawback of having to interview the same people repeatedly is that test subjects may over time develop a bias towards the research findings and that the number of participants is limited for practical reasons. Observational studies using presence counting, such as William Whyte's classic 1980 studies in New York City [3], can cover a very large number of people with the caveat that little is known about the observed population. For example, for urban planning purposes it matters whether an observed individual is a visitor, randomly passing by independent of prevailing weather, or a local making the conscious choice to have lunch outside [24]. Any urban intervention aimed at improving outside comfort conditions should therefore have a larger effect on the latter than the former population. Our review of previous studies yielded coefficients of determination (R^2) between the number of people and different biometeorological indices between 0.1% and 74% [23,24].

This study aims to more conclusively test the applicability of biometeorological indices to predict the likelihood of urban dwellers to be outside by combining the benefits of longitudinal and observational studies. To accomplish this goal, we simulated biometeorological comfort indices in a public plaza in Cambridge, MA, over a ten-month period and correlated the simulations with the number of individuals present in the court during lunch time using Wi-Fi signals from portable electronic devices. Following a description of the study site, experimental data collection and simulation procedures we are presenting our results and discuss how they can inform the design of outdoor urban spaces.

2. Methodology

2.1. Site description

The North Court on the campus of the Massachusetts Institute of Technology (MIT) was chosen as the study site since it is an attractive public park with shaded and unshaded tables and benches, adjacent to several cafeterias, cafes and food trucks (Fig. 1(a)). Members of the MIT community as well as local high tech companies frequent the court, especially during lunch hours. We assumed that the seating capacity in the court is generally sufficient to allow individuals to choose between sitting inside or outside under a tree or at an unshaded table. We thus interpret an outside presence of more than 5 min during lunchtime to constitute an active "choice" to be outside, postulating that urban workers have an intrinsic bias towards sitting outside when environmental conditions are favorable.

2.2. Long-term measurements of people movement in public spaces

To track outside activities, we used encrypted Media Access Control (MAC) numbers or MacIDs from three Wi-Fi scanners located strategically throughout the MIT North Court (Fig. 1(b)). A MacID is a fixed, unique hardware address for a given device such as a smartphone or laptop, provided by the manufacturer that supports the device's communication over a network. When powered on, Wi-Fi-enabled devices such as smartphones, especially when in transit, regularly broadcast

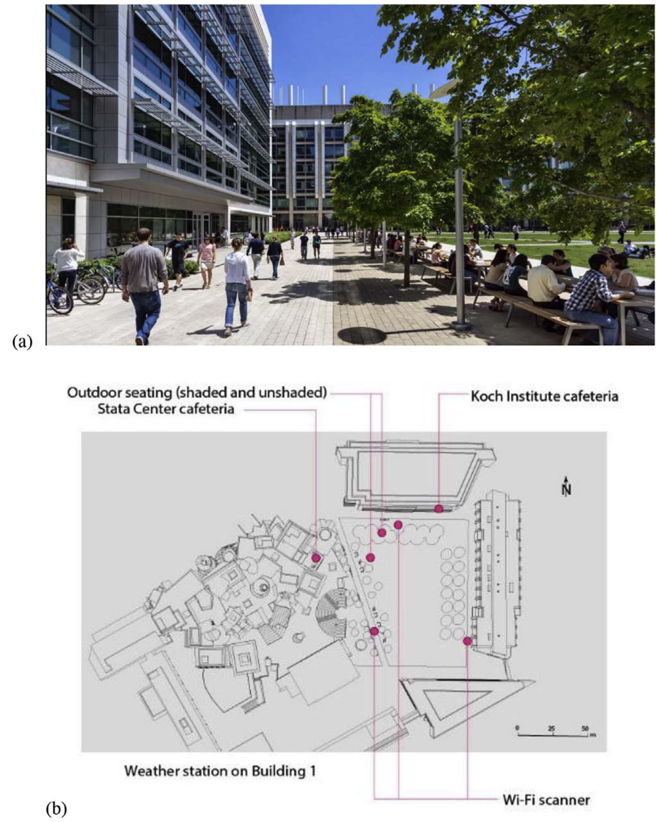

Fig. 1. (a) Photo of the MIT North Court; (b) plan view of the study site.

their presence via "probes" to detect any suitable local networks to connect to [16]. Each probe consists of a date and timestamp as well as the device's MacIDs, the Wi-Fi scanner that detected the probe, the overall signal strength and the name of the network the device was connected to. Given the ubiquitous use of Wi-Fi devices in contemporary urban settings, the number of MacIDs collected at a given place and time strongly correlates with the number of people nearby [32–34]. As described below, using encrypted MacID data further allowed us to distinguish between Wi-Fi signals from different user groups as well as non-personal devices.

Using a range of cell phone types and brands, we conducted a series of spot measurements that confirmed that the Wi-Fi scanners only detected devices located outside and that the rate of probes collected for each device varied with smartphone brand and whether the device is in sleep mode or active. The Wi-Fi scanners were ESP8266 wifi-on-chip modules transmitting in the 2.4 GHz range using an antenna of type SPDA24700/2700 from Pulse Electronics. The scanners were integrated in solar powered benches which offer free charging opportunities for smartphones and comparable electronics to the public. The benches were provided and operated by a local Internet of Things (IOT) company called soofa [35], which centrally collected all probes and replaced all MacIDs with encrypted unique identifier numbers before handing them over to the MIT authors. The encryption was an additional precaution to ensure the privacy of the owners of the monitored Wi-Fi devices.

The three Wi-Fi scanners collected data continuously throughout two study periods which lasted from July 1st to November 30th, 2016 (summer/fall period; 103 workdays) as well as from January 1st to May 21st, 2017 (spring period; 93 workdays). The Wi-Fi scanner generally worked reliably but two of the benches had some downtime during August 2016. In order to account for missed probes during times when one of the benches were down, correction factors were established during July 2016 when all benches were up. These correction factors estimate the amount of missed devices and were used when only one

Table 1
UTCI calculation procedure.

Input variable	Data source	Time resolution	Spatial resolution
Dry bulb temperature	Weather station	Every 5 min	Constant across courtyard
Relative humidity	Weather station	Every 5 min	Constant across courtyard
Wind speed	Correlated data from weather station	Every 5 min	Constant across courtyard
Mean radiant temperature	Validated ENVI-met simulation	Every 60 min	Distribution across a 5 m × 5 m grid

bench was down. When two or more benches were down, all collected data was discarded.

2.3. Biometeorological calculations

Hourly UTCI distributions were calculated across the North Court for all workdays throughout the two study periods except for 18 days during which it rained over lunch according to historic weather data. The UTCI metric depends on a series of meteorological inputs ranging from short and longwave radiation incident on a particular point of interest to local wind speed, dry bulb temperature (DBT) and relative humidity (RH) [7–13]. These different inputs were calculated for every workday between noon and 1pm throughout the study period using a combination of measurements and simulations as described below. The calculation procedure is summarized in Table 1.

DBT, RH, global horizontal solar radiation as well as wind speed and direction were measured and stored every 5 min using a nearby Onset weather station located on the rooftop of MIT Building 1, some 500 m to the Southwest of the study area [36]. For the UTCI calculations, DBT and RH were directly taken from the weather station measurements.

In order to correlate rooftop wind speed measurements to wind distributions in the North Court, a second weather station with a wind anemometer was installed for 45 days from June to August 2016 in the North Court. Fig. 2 correlates the resulting rooftop and courtyard wind speeds binned by cardinal wind direction. Using linear correlations with R^2 between 20% and 75% for the different wind directions, courtyard wind speeds at 10 m height were derived from the weather station wind data throughout the study period. The poor correlation for East winds results from more complex urban geometry towards the East of the North Court. Throughout the study period, the wind speed on the roof of MIT Building 1 was 98% of the time below 3 m/s during lunchtime. For each moment in time, it was assumed that the wind speed was constant across the open courtyard including the shaded and unshaded lunch areas.

Mean radiant temperature (MRT) distributions across the courtyard were simulated using ENVI-met (version 4.1), a state-of-the-art CFD based urban microclimate modelling tool [20]. The 3D Model of the North court area was set up in ENVI-met with a grid resolution of a 5 m × 5 m (Fig. 3). Table 2 shows key input parameters for the ENVI-met simulations for each day. Trees were modelled using the Albero module in ENVI-met with the Leaf Area Density set to suggest a dense canopy for the months of July till October, a less dense canopy in November and May and a sparse canopy from January to April for sunlight ingress. The simulations were executed using a simulation time step of 30 min for all study period workdays from 9am to 3pm. ENVI-met version 4.1 only allows to model the solar radiation throughout a day using two factors, "solar radiation adjustment" and "cloud cover". We derived these factors for every day using measured solar radiation

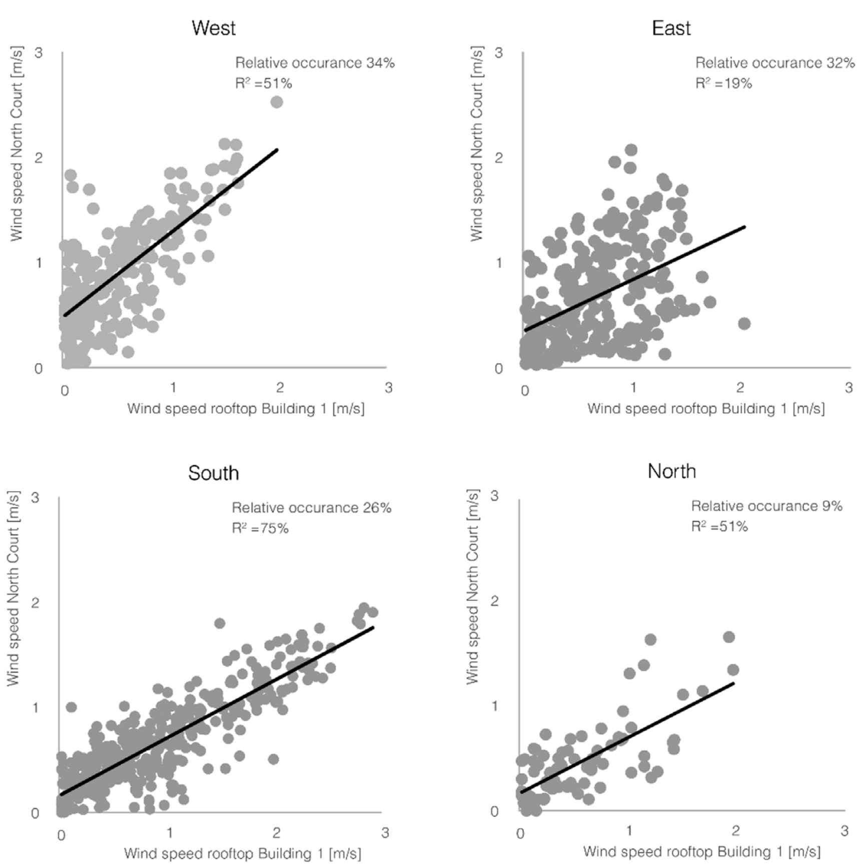

Fig. 2. Correlations between measured wind speeds on the rooftop of MIT Building 1 and the North Court for different wind directions.

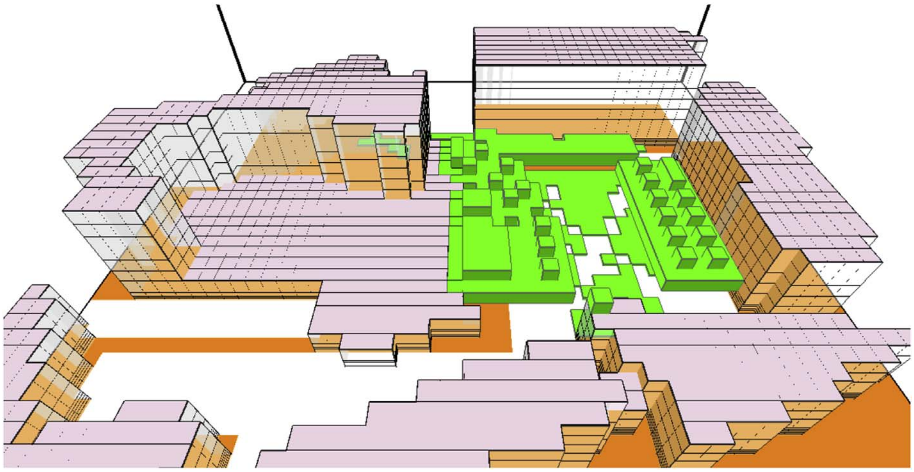

Fig. 3. ENVI-met model of the study area and surrounding buildings.

during lunch time from the weather station. Similarly, only a single pair of wind speed and direction could be provided for a daily ENVI-met run. These values were derived from vector-added wind directions for lunch time from each day as well as correlated courtyard wind speeds as described above. Boundary conditions for dry bulb temperature and the relative humidity could be entered in ENVI-met 4.1 on an hourly basis using weather station data.

To confirm the validity of the ENVI-met simulations, the earlier mentioned, secondary weather station in the North Court was also equipped with a black globe thermometer to directly measure MRT levels. Fig. 4 shows a comparison between ENVI-met simulations for 27 sensor grid points adjacent to the second weather station (grey area) and the black globe measurements on July 4, 2016, a mostly clear day. The 27 neighboring grid points were used to account for uncertainty due to shading from neighboring buildings and trees. The ENVI-met simulations closely follow the measured data, especially between noon and 1pm, the period based on which the solar radiation in the simulations is based. Differences between measured and simulated MRTs in the morning partially stem from the delayed response of the black globe to solar radiation.

As a final step, UTCI distributions were calculated from the above-mentioned input variables using a grid resolution of 5 m × 5 m across the courtyard. Fig. 5 shows an example distribution on July 4, 2016 at noon. For the preferred UTCI calculations (see Figs. 8–10 below) the unshaded and shaded reference sensors marked in Fig. 5 were used.

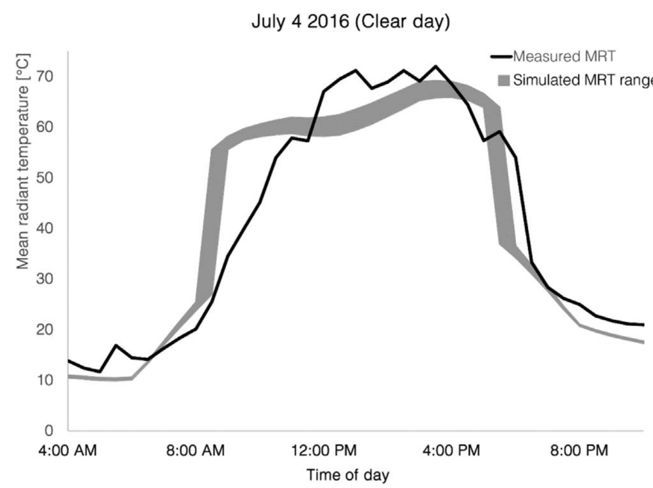

Fig. 4. Comparison between simulated and measured MRT levels in the North court on July 4, 2016.

3. Results

We collected data from July 1st to November 30th, 2016 (summer/fall period; 103 workdays) as well as from January 1st to May 21st, 2017 (spring period; 93 workdays). As shown in Fig. 6, the total number of Wi-Fi probes collected during that time period was 28.7 million. As a

Table 2
ENVI-met input parameters for each day.

Start and duration of the model	
Start time	9:00 a.m.
Total simulation time (h)	6
Meteorological conditions	
Wind speed measured at 10 m height	Correlation used for vector addition of rooftop weather station's wind speed during lunch time
Wind direction	Vector addition of rooftop weather station's wind speed during lunch time
Initial temperature atmosphere	Average temperature for the day from rooftop weather station
Relative humidity at 2 m height (%)	Average relative humidity for the day from rooftop weather station
Factor of shortwave adjustment (0.5–1.5)	Ratio of global horizontal solar radiation during lunch time from the weather station and ENVI-met
Fraction of low clouds	Based on direct solar radiation during lunch time from the weather station
Soil data	
Initial temperature upper layer (0–20 cm)	Monthly ground temperature data from epw file for Cambridge for 0.5 m depth
Initial temperature middle layer (20–50 cm)	Monthly ground temperature data from epw file for Cambridge for 0.5 m depth
Initial temperature deep layer (below 50 cm)	Monthly ground temperature data from epw file for 2 m depth
Geometric data	
Total model volume (in m^3)	250 × 250 × 125
Grid size (in m^3)	5 × 5 × 5 (5 grid points of 1 m size in the z direction near the ground)
No. of grids	50 × 50 × 25
Façade finishes	Heat protection glass
Tree (height × width)	Koch area (10 m × 11 m), Other areas (15 m × 15 m)

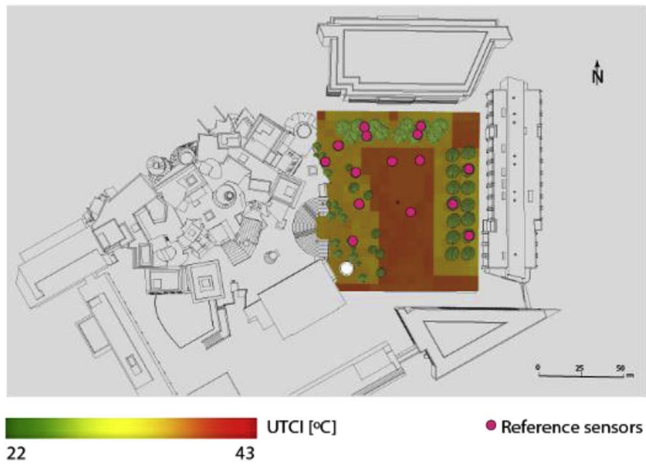

Fig. 5. Simulated UTCI distribution in the North Court on July 4, 2016, at noon.

first step to reduce the resulting, massive data set we only kept one probe by the same Wi-Fi device within the same minute. This reduced the sample size to 14.0 million probes out of which 9.6 million were collected during workdays.

Using the daily profile of workday probes we further attributed 4.0 million probes to 464 non-personal, "lurking" Wi-Fi devices that were active for over 3 h a day and thus likely caused by non-personal devices such as sprinkler systems and other urban infrastructure. Lurking Wi-Fi devices were excluded from further analysis. The remaining probes were generated by 676,000 visitors (2.1 million probes) and 16,000 regulars (3.5 million probes). We defined a "regular" as a Wi-Fi device that was present during at least 10% of all workdays (20 days) throughout the study period. Among the visitors, 585,000 devices (84%) were only detected once. Analyzing for presence throughout the ten months period, we further split the regulars into around 10,000 staff (present from July to May) and 6000 students (present during the academic year from September to May only). During December 2016 a new firmware was installed on all Wi-Fi scanners to increase the sensitivity of the devices, especially during periods of high traffic. The upgrade likely contributed to the higher number of probes being collected during spring (Fig. 6).

Fig. 7 shows the median occurrence of Wi-Fi probes pertaining to staff, students and visitors on workdays for summer/fall and spring. The North Court lies along a direct route between the MIT main building group and the local subway station and thus shows predictable arrival and departure patterns which ramp up between 8am and 9am, peak around lunchtime and gradually fall between 5pm and 9pm. During summer/fall, visitors tend to arrive later and leave earlier whereas the visitor profile more closely trails staff and student occupancies during

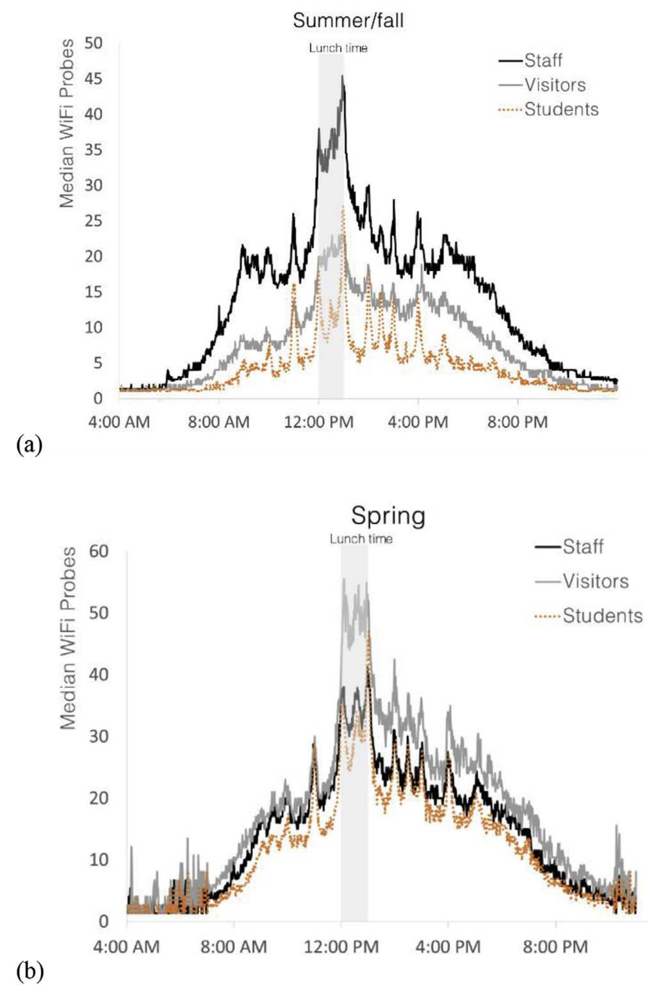

Fig. 7. Median number of Wi-Fi probes on workdays for staff, visitors and students during summer/fall (a) and spring (b).

spring. Students, many of whom live on campus or nearby, tend to pass through the court between classes with distinct peaks at full and half hour marks according to the MIT class schedule. Noon to 1.00 p.m. marks the main lunchtime period in the North Court for all three groups throughout the year, showing that the time for taking lunch is largely dictated by societal conventions and institutional logistics – there tend to be less classes during midday – rather than ambient weather conditions.

To classify a sequence of probes collected from the same Wi-Fi device into a lunch break, we proceeded as follows. During several

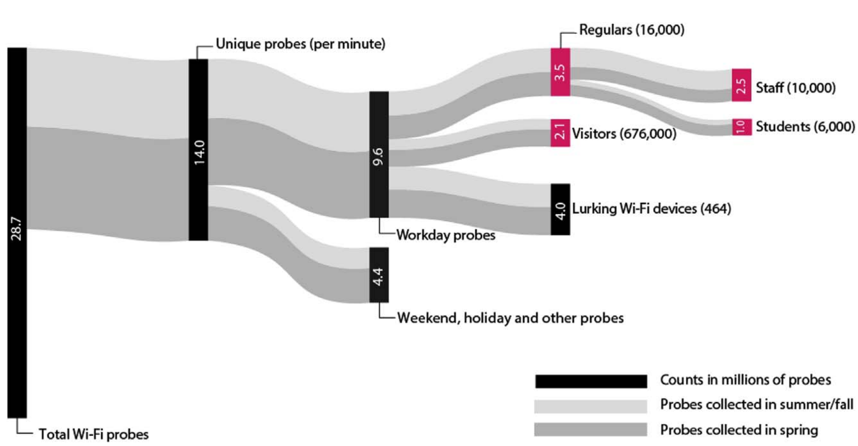

Fig. 6. Sankey diagram of the collected Wi-Fi probes in the MIT North Court throughout the study period.

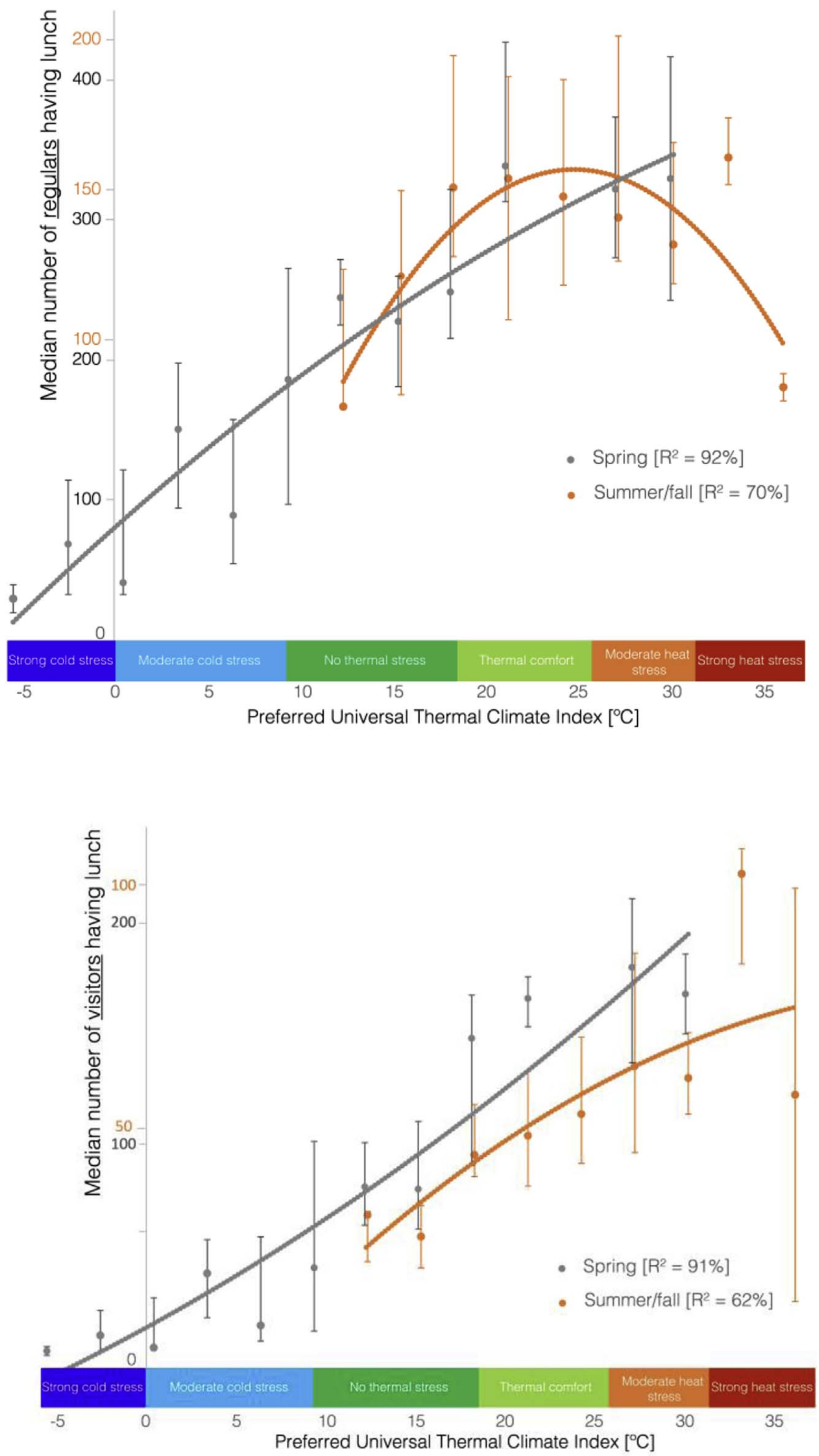

Fig. 8. Preferred UTCI levels versus the median number of regulars (top) and visitors (bottom) during lunchtime during summer/fall and spring.

instances we compared the total number of Wi-Fi devices connected to the MIT network (public and internal) in the North Court to the number of devices according to our Wi-Fi scanners. Trying several inter-probe times, i.e. the time interval within which successive probes by the same Wi-Fi device can be interpreted as constant presence, we found that for 10 min the two quantities aligned best. Going forward, we then interpreted a device to be constantly present in the North Court when successive probes were less than 10 min apart and a presence to have ended when no probe was detected for a period of 10 min or more. Any presence for more than 5 min between noon and 1PM was considered a lunch break. Based on this lunchtime interval, Fig. 8 relates preferred UTCI predictions to the median number of courtyard occupants during lunchtime for regulars and visitors during summer/fall and spring, respectively. The UTCI ranges marked in Fig. 8 from *strong cold stress* to *strong heat stress* were originally established by the International Society of Biometeorology Commission 6 for individuals “walking lightly” [37]. The subinterval from 18 °C to 26 °C constitutes the “thermal comfort zone” according to the Commission for Thermal Physiology of the

International Union of Physiological Sciences [38]. When faced with the decision to sit under a tree or at an unshaded table, we assume that test subjects always choose the more comfortable condition out of the two UTCI predictions. For example, if at any moment in time the unshaded and shaded UTCIs are 30 °C (moderate heat stress) and 23 °C (no thermal stress), respectively, the "preferred" UTCI would be 23 °C. If both UTCIs are in the same comfort range, we assume that individuals prefer to sit under a tree, in accordance with anecdotal observations of actual behavior in the North Court. The collected Wi-Fi scanner data did not allow us to exactly determine where individual devices were located within the study area. Previous studies conducted meteorological measurements right near the location at which human subjects were interviewed which allowed them to organize UTCI data in one degree bins and correlate them to interview responses [24]. However, given that we could not exactly track human subject positions, we selected a three degree binning size for UTCI predictions instead which accommodates an uncertainty in MRT predictions of around 10 K [19]. Fig. 8 shows parabolic regression fits ($N > 1$) for regulars and visitors assuming that occupancy rates should peak for a certain UTCI range. The corresponding R^2 values from 70% to 92% for regulars and 62%–91% for visitors correspond to and exceed earlier reported correlations for considerably smaller sample sizes. It is interesting to see that during summer/fall the attendance for regulars peaks at around 25 °C or at the higher end of the comfort zone. Seasonal differences in behavior are difficult to extract from Fig. 8 since the sensitivity of the Wi-Fi scanners was different during summer/fall and spring. This question is further explored below. While the total number of visitors detected during the study period is 40 times larger than the number of regulars, the median number of visitors having lunch was only half of that of the regulars. The visitor data exhibits no distinct peak, suggesting that the group tended to more randomly pass through the court. Fig. 8 reveals the benefit of being able to distinguish between regulars and visitors for identifying local behavior patterns.

In order to compare attendance rates between summer/fall and spring, Fig. 9 shows the probabilities for regulars to have lunch in the North Court depending on preferred UTCI levels throughout the year. These probabilities were calculated by binning all regular probes by days with a certain UTCI range during lunchtime and dividing the total number of lunch breaks taken by regulars on these days by the sum of all regulars in attendance on these days. This analysis was done separately for summer/fall and spring. Fig. 9 shows that the probability to visit the North Court for lunch outside rose from 5% up to 14% during spring compared to 5%–10% during summers/fall revealing a seasonal preference for individuals to be outside following an extended period of colder weather. This behavior is consistent with adaptive thermal comfort theory for indoor spaces [13]. Attempts to locally improve outside comfort conditions should therefore have clear benefits for restaurants and other commercial entities.

Fig. 10 further links preferred UTCI levels to the median lunch break length for regulars. During both study periods the median dwell time rose from around eight to 12 min for more attractive outside conditions. During fall/summer, the 75th percentile group exhibited lunch break increases from 15 to 23 min on days in the moderate to strong heat stress range. Compared to other cultural settings, a 20 min lunch break might not seem extravagant and we would expect this effect to be larger for a different user group. It might seem surprising that any regular would be outside for several minutes during times of "strong cold stress". However, one should note, that the number of dwell times for the strong cold stress range in Fig. 10 are based on an order of magnitude less observations than for the higher ranges.

4. Discussion

Given the enormous number of subjects observed over a ten month period, the above described results show that preferred UTCI predictions are a strong predictor of both, the amount of locals frequenting an outside space as well as their dwell time. As a direct consequence, outdoor planners should aim to design flexible and thermally diverse outdoor environments – including combinations of shaded and unshaded as well wind exposed and sheltered areas – that allow visitors to remain within their thermal comfort range for extended periods of time in the year. While this recommendation seems intuitive, if not obvious, our results show that UTCI calculations can be used to quantify this design goal in meaningful ways such as by predicting the additional

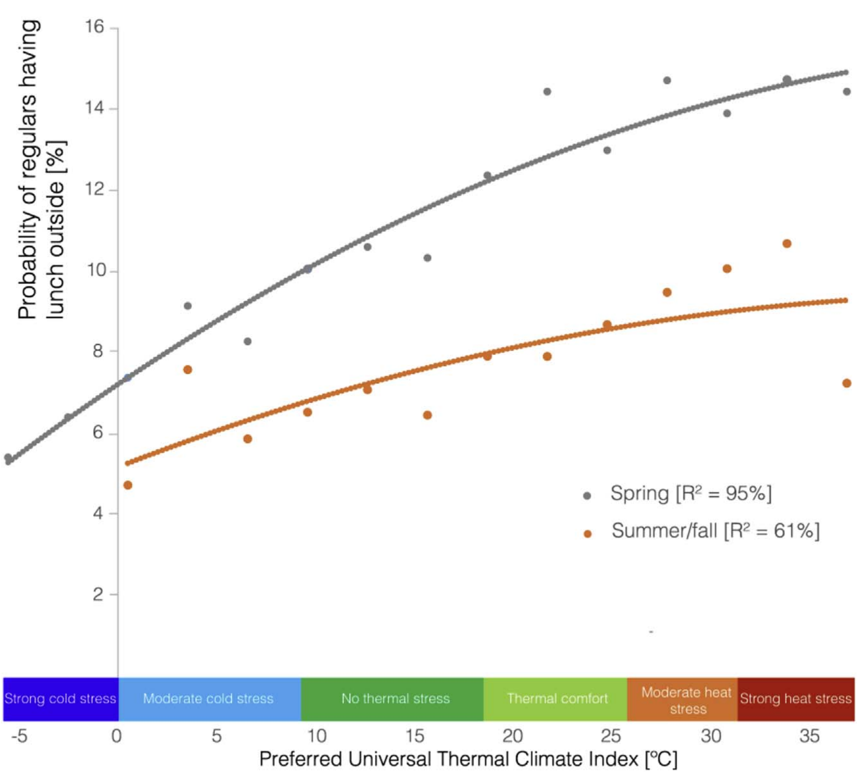

Fig. 9. Probability for regulars to have lunch in the North Court for days with varying lunchtime UTCI levels.

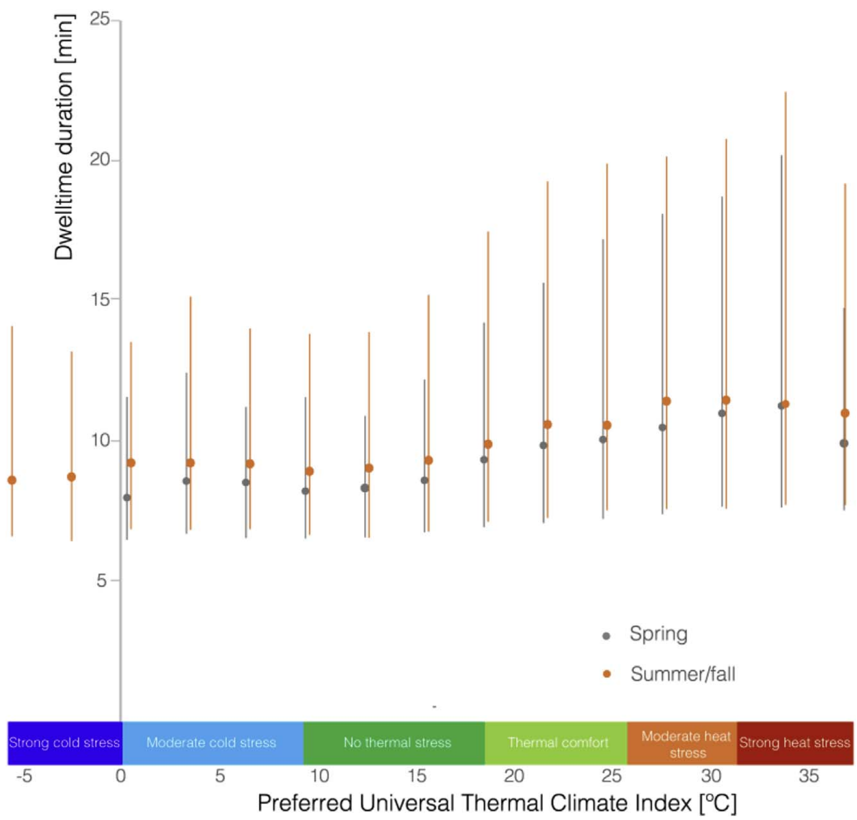

Fig. 10. Distribution of dwell times over lunch for regulars for different UTCI levels.

number of hours that a certain intervention may help to improve UTCI levels and thus booster regulars' occupancy rate. This type of analysis may help municipalities to quantify the spatiotemporal impact of a potential new development on a park. Businesses depending on local foot traffic may use the metric to identify preferred locations within an urban setting.

In Fig. 10, the dwell time over lunch for the 75th percentile peaked around the moderate to severe heat stress ranges. A possible explanation for this finding is that regulars around the MIT North Court tend to spend their days in air-conditioned spaces and may thus enjoy experiencing somewhat warm variants to their otherwise thermally homogeneous workday. Given the length of most lunch breaks, regulars were typically not long enough outside to fully adjust to the warm ambient conditions. Since the reference activity for the UTCI ranges in Figs. 8–10 is "walking lightly", individuals sitting down for lunch should have a lower metabolic rate and thus higher tolerance towards warmer outside conditions. For climates comparable to Boston with cold winters and hot summers, the authors therefore recommend for urban planners to design outside seating arrangements in the *thermally comfortable* to *moderate heat stress* UTCI ranges.

Taking a more global perspective, this study demonstrates considerable potential for using Wi-Fi data from public hotspots to increase confidence in environmental analysis methods and to confirm the success of an urban planning intervention through comparative pre/post occupancy studies. Given that the number of hotspots worldwide crossed the 50 million mark in 2015 with another sevenfold increase expected by 2018 [39], the hardware costs for collecting the resulting data are low to non-existing. The more pressing question is under what legal framework this data should be collected and accessed as well as how privacy infringements may be avoided. For the present study, MIT's Committee on the Use of Humans as Experimental Subjects (COUHES) granted us permission to keep all probe data for a year to develop the data analysis methods described above. Going forward, others could adopt our method while keeping individual probes for only four weeks going back in order to filter out lurking Wi-Fi devices and divide the remaining probes into regulars and visitors (assuming that regulars have to be present at least 2 to 3 times within a 4 week window to keep that status). Beyond the four weeks, in order to generate Figs. 8 and 10, lunchbreak date and timestamps as well as break lengths would need to be kept for individual regulars. To create Fig. 9, all occupancy days for regulars would be required as well. To capture seasonal effects, this reduced data set would need to be kept for a year and could be deleted afterwards. The resulting, completely anonymized data (Figs. 8–10) could be shared with the general public. Arguments against adopting such a stringent data policy are that it would slow down innovations in urban data analytics as new data sets would have to be collected repeatedly to explore new ideas and that encrypted MacIDs already make it impossible to track individuals in busy public spaces. However the reader may feel about the subject of data privacy, we hope that this manuscript will serve as a case study for legislators and the general public to understand the potential benefits (validated urban metrics to design more sustainable cities) versus the risk of potential data privacy infringements resulting from the use of Wi-Fi data in public outdoor spaces.

5. Conclusion

This manuscript presents a novel, low-cost measurement technique based on Wi-Fi data from public hotspots that facilitates presence-detection of thousands of individuals in public outdoor spaces. Using encrypted MacIDs, urban dwellers were further divided into regulars and visitors. It was shown that the former group exhibits a strong preference for being outside when UTCI conditions are in the *thermal comfort* to *moderate heat stress* regions. The dwell time of regulars was also shown to increase significantly for these UTCI range. These results suggest that UTCI calculations may serve as a meaningful environmental performance metric to support the design and preservation of thermally comfortable outdoor spaces. Large urban data sets such as the one collected for this study have the potential to provide city governments with valuable insight in the use of their outdoor spaces without infringing on the privacy of their constituents.

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