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Using Personal Exposure Measurement to Manage Environmental Stressors

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ABSTRACT

Personal exposures to environmental stressors including extreme heat and air pollution vary widely depending on schedules and activities. This paper shares results of a city-scale project to build fixed indoor and outdoor sensor networks while also deploying mobile sensors. The network helps building occupants, building operators, and public officials to safely manage extreme heat and air pollution. The Exposure Duration Curve (EDC) concept is introduced to facilitate comparisons.

INTRODUCTION

Personal exposures to excess heat, cold, and air pollution can lead to adverse health outcomes, especially for vulnerable people experiencing prolonged exposures at high levels. Such health risks justify large-scale government regulation of air pollution, occupational health regulations targeting worker exposures to adverse thermal and air quality conditions, and stipulations that landlords provide habitable spaces for tenants. Designers of building mechanical systems focus much effort on meeting thermal comfort and ventilation standards. Green and healthy building certification systems incentivize better indoor environmental quality. Such protections can be costly, so it is worthwhile to ask how well efforts to improve ambient environmental conditions reduce personal exposures.

People vary in the amounts of time they spend in different indoor and outdoor locations, so personal exposures to environmental stressors may show similar variation. For example, construction workers are likely to have more hours of outdoor exposure than accountants, and retirees may spend more time at home than working people. Knowing human time allocations and measuring conditions in typical locations such as outdoors and indoors, in workplaces, schools, shops, homes, and other frequently visited buildings, are prerequisites for estimating personal exposures.

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This paper shares results of a field study of personal environmental exposures to summer heat stress and local air pollution in Elizabeth, NJ, USA, an environmental justice community surrounded by an international airport, a shipping port, a petrochemical refinery complex, and a major highway. The study employs three data collection systems: (1) a network of fixed outdoor sensors, (2) a network of fixed indoor sensors, and (3) mobile personal exposure monitors with geolocation capabilities carried by residents. The study tracks exposures of people residing in buildings operated by a public housing authority who have different daily schedules: elderly retirees, high-school children, and working-aged people. The three data streams quantify ambient outdoor and indoor conditions and personal exposures over time and allow comparisons of these metrics.

Results confirm that personal exposures differ across people. Their schedules and activities play important roles. Most residents spend more than 90% of the day indoors. Outdoor conditions influence indoor conditions, but the influence is strongly mediated by HVAC system characteristics and by occupant behavior. These findings help occupants, building operators, building designers, and public officials to safely manage extreme heat and air pollution.

LITERATURE REVIEW

Among the most important population-level health concerns are those associated with the environments in which humans live. Thermal extremes and air pollution are known risk factors, the former associated with acute symptoms of heat stress and heat stroke, as well as contributing to mortality due to cardiovascular, respiratory, and cerebrovascular problems in exposed populations (CDC 2024), and the latter associated with asthma and cardiovascular disease, among others (Maji et al 2023). There is substantial evidence of excess morbidity and mortality associated with heat waves (Anderson and Bell 2011, Berko et al 2014) and air pollution episodes (Morawska et al 2021). Human activities are exacerbating these environmental health concerns by creating local urban heat islands and pollution hot spots, as well as global warming (Hayden et al 2023).

Ambient Conditions. There is a substantial literature that uses remote sensing approaches and ground-based sensor networks to characterize urban heat islands and the spatial and temporal extent of heat waves (Cheval et al 2024) and air pollution levels (Tian et al 2023). Satellite imagery has allowed investigation of these phenomena at a global level and confirmed that the environmental stressors are prevalent in locations where people live and work. A sparse network of monitoring stations supports spatial interpolation of ambient stressor levels at intermediate locations and provides ground truthing for models built using various combinations of remote sensing evidence and locations of emissions sources. However, the spatial resolution of these interpolation-based models is limited, with the USEPA AirNow network, for example, providing estimates of temperature and air pollutant levels for 5 km (3.1 mile) grid cells (EPA 2024a).

Local Conditions. Urban planning and landscape architecture research often looks at a finer spatial grain to identify the effects of tree cover, land use, impervious surfaces, and urban design features on local temperature and air pollution levels (Kim and Brown 2021). These studies rely on air temperature and pollution measurement methods that include remote sensing, fixed sensors, and mobile sensors, and often collect field data on urban morphology, building geometries, canopy cover, and street canyons. The level of spatial resolution can be < 0.5 km (0.31 mile). At this scale, it is also possible to ascertain effects of socio-economic and demographic factors on environmental health (Harlan et al 2013).

Indoor Conditions. ASHRAE has focused intensively on measuring indoor conditions to determine thermal comfort and healthy ventilation levels (ASHRAE 2021) and thereby improve system designs (ASHRAE 2022, ASHRAE 2023). Heating, ventilating, and air-conditioning systems equipped with air filtration technologies can dramatically moderate occupant exposures to temperature extremes and air pollution. Measurement and modeling of conditions and professional design and operating practices have advanced to achieve significant levels of protection in well-resourced buildings, although lower-resourced buildings often lag far behind best practices.

Personal Exposures. Outdoor ambient exposures only modestly correlate with personal exposures to temperature extremes (Bernhard et al 2015) and air pollution (Özkaynak et al 2013) due to variability in factors including personal activities, work schedules, indoor conditions, and local environments. The low correlations carry through to human health effects (Ejike et al 2017). The COVID-19 pandemic also increased interest in personal environmental exposures. It is now possible to fill a knowledge gap in environmental exposure studies by directly measuring personal exposures using low-cost, portable sensors (Bernhard et al 2015, Hass and Ellis 2019, Runkle et al 2019). Metrics for assessing personal exposure data are now emerging, with innovators moving beyond measures of central tendency to highlight the intensity, duration, and frequency of exposure to environmental stressors (Hondula et al 2021, Lin et al 2018).

The present study measures personal exposures in the context of measured indoor conditions, local conditions, and ambient conditions. It offers an exposure duration curve approach, discussed in the Data and Methods section, that unifies several of the personal exposure metrics within a common framework. It considers personal health impacts to be a result of ambient conditions and drivers, local conditions and drivers, indoor conditions and drivers, and personal time allocations, as summarized by us in Figure 1.

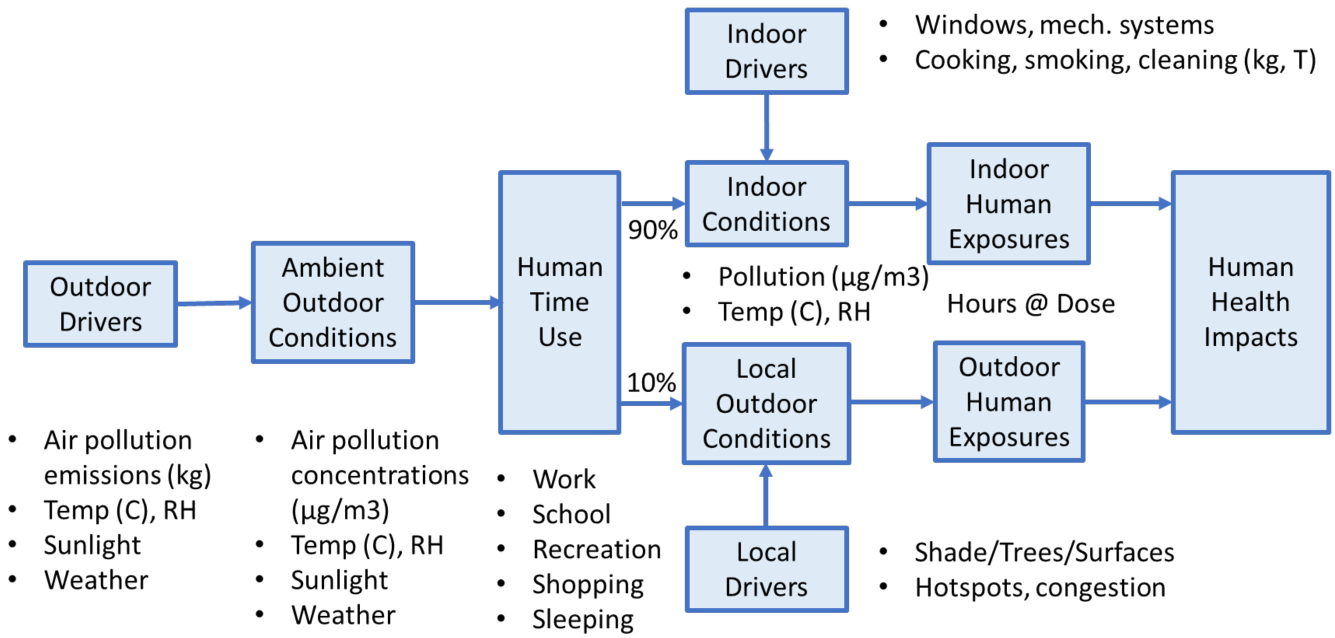

Figure 1 Source, exposure, and outcome continuum for environmental health stressors.

DATA AND METHODS

Archival and field data are brought together within a single data frame for this analysis. Ambient, city-average environmental conditions (hourly air temperature, relative humidity, wind direction, wind speed, precifipation) are measured at Newark International Airport (NWS 2024) and permanent monitoring sites in Elizabeth, NJ (hourly PM2.5) and Bayonne, NJ (hourly O_3) (EPA 2024b) and archived by U.S. federal government agencies for public access. Local conditions (one-minute air temperature, relative humidity, O_3, PM2.5, other criteria air pollutants) are measured by us using a newly installed network of 12 community-level (but not regulatory-grade) sensors attached to buildings owned by the local public housing authority and accessed through a portal we have created. Indoor conditions (one-minute air temperature, relative humidity, PM2.5, VOC) are measured by us using newly installed consumer-grade sensors equipped with Wi-Fi or cellphone hotspots located in 16 apartments and 3 offices at 3 sites owned and operated by the housing authority and accessed through a portal we have created. An outdoor model of the consumer grade sensor is located outdoors at each of the 3 buildings and their data are accessed through that same portal. Finally, personal exposure measurement (one-minute air temperature, relative humidity, PM2.5, VOC) is accomplished using two dozen consumer grade mobile sensors that pair via Bluetooth with the cellphone of the person carrying the sensor and periodically upload data and spatial coordinates to the cloud from which we can access and download the data. Technological specifications of the sensors used in this study are available from the authors. The human subjects components of this work were performed following approved Rutgers IRB protocol number Pro2022001227. Subjects were compensated for their participation. The data were assembled into a data frame that coordinates the time stamps and standardizes the time intervals of the observations, and adds variables to allow grouping by date, time, location, person, type of person (youth, senior, working age), and environmental condition level.

This analysis employs some standard data visualization and summarization techniques including time series graphs and summary statistics, and statistical tests of significant difference. It innovates in presenting an Exposure Duration Curve (EDC) that portrays time series observations as a complementary cumulative probability distribution. Figure 2 illustrates the EDC concept, with the vertical axis showing the level of environmental exposure (e.g., air temperature in degrees C, or PM2.5 levels in micrograms/m^3) and the horizontal axis showing the percent of a time period of interest (such as a 24-hour day) that the exposure level is exceeded. Thus, the points on the graph show the percent of the time period during which the exposure to an environmental stressor exceeds a specific level. For example, in Figure 2, the heat index on this late summer day exceeds 60 degrees F-equivalent (15˚ C) for fully 100% of the 24-hour time period, whereas it exceeds 100 F-equivalent (38˚ C) only 14% of the time. Duration curves are widely used in the electric power industry (Booth 1972), especially in renewable energy (Chaiamarit and Nuchprayun 2013) and demand-side management studies (Poulin et al 2008), to represent load thresholds that must be satisfied at different points in time. Their use has been extended to emissions duration curves that relate the timing and duration of energy demand to marginal greenhouse gas emissions (St-Jacques, Bucking and O'Brien 2024) and load and flow duration curves for water quality measurement (EPA 2007). This application to heat stress and air pollution exposure is novel as far as we can ascertain.

Metrics that are derivable from an EDC include, following Hondula et al (2021): Mean Individually Experienced Heat Index (IEHI) and Maximum IEHI, which are intensity measures; Degree Hours Above a Threshhold (DHAT) and Percentage of Hours Above a Threshhold (PHAT), which are frequency and duration measures; and, following Lin et al (2018), Daily Exceedance Concentration Hours (DECH), a frequency and duration measure. Users can also derive otther statistical measures such as the median, minimum, and range from the EDC.

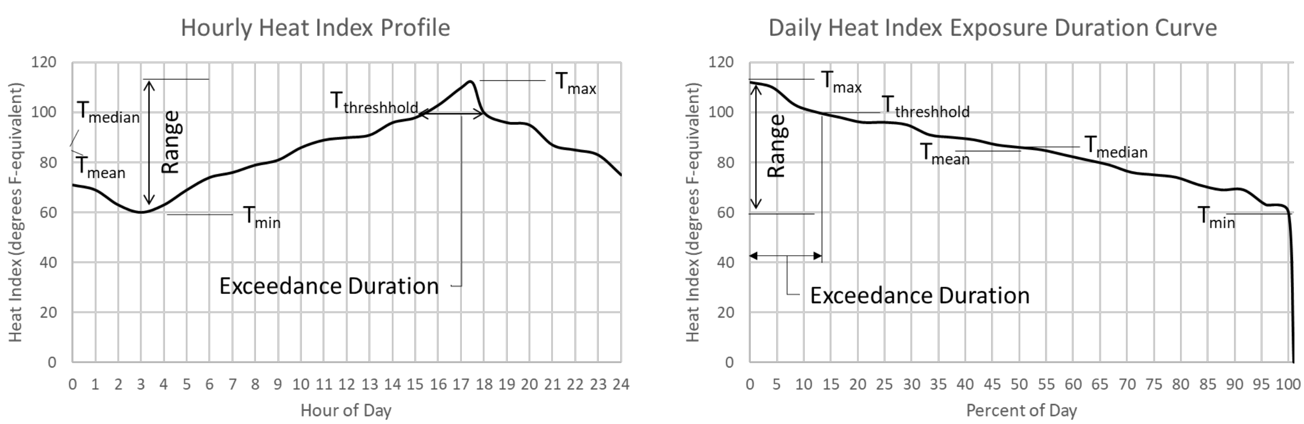

Figure 2 Stylized exposure duration curve shown in relation to temporal exposure profile for Heat Index (degrees F).

RESULTS

Here, we analyze data gathered from the multiple sensor networks to highlight insights available from comparisons of several types. First are contemporaneous interpersonal comparisons, that is, comparisons of EDCs for four community members on the same day. Second are asynchronous intrapersonal comparisons that compare EDCs for the same person on two or more different days. Third are multi-scale comparisons across several levels of measurement (outdoors, indoors, personal). Only thermal comparisons are included due to space constraints.

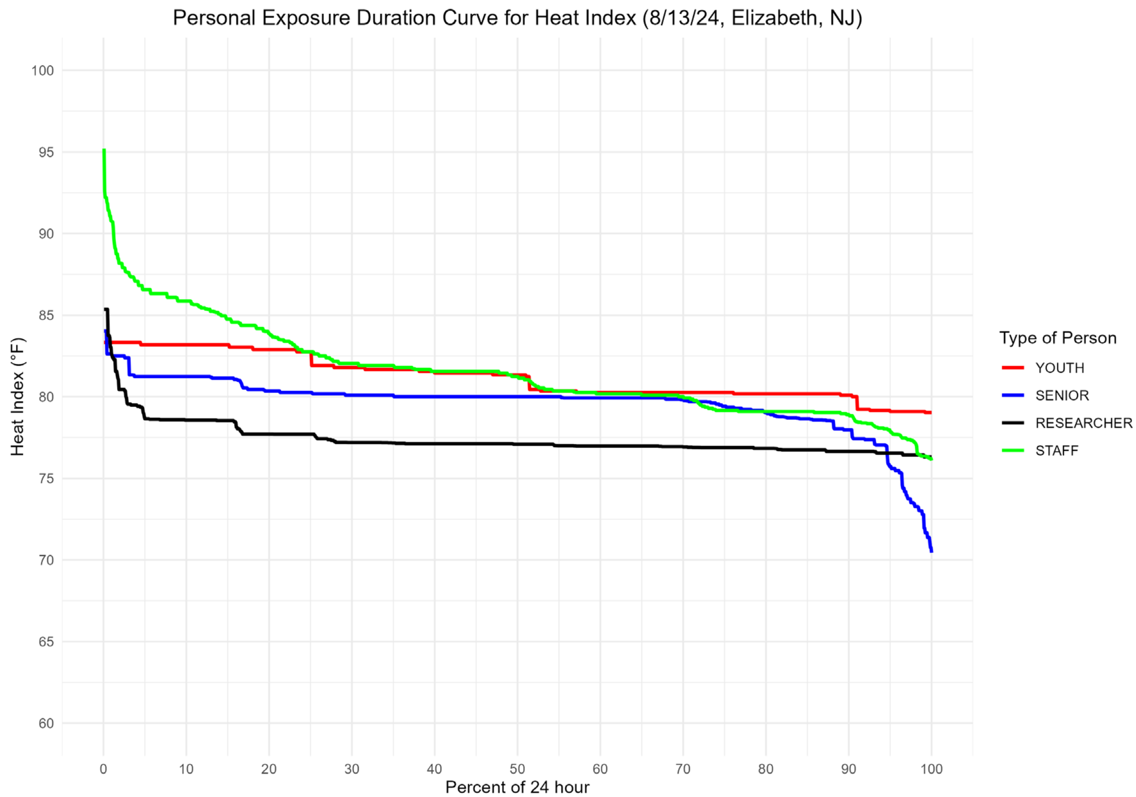

Figure 3 Contempraneous interpersonal comparisons of Heat Index EDCs for four community members.

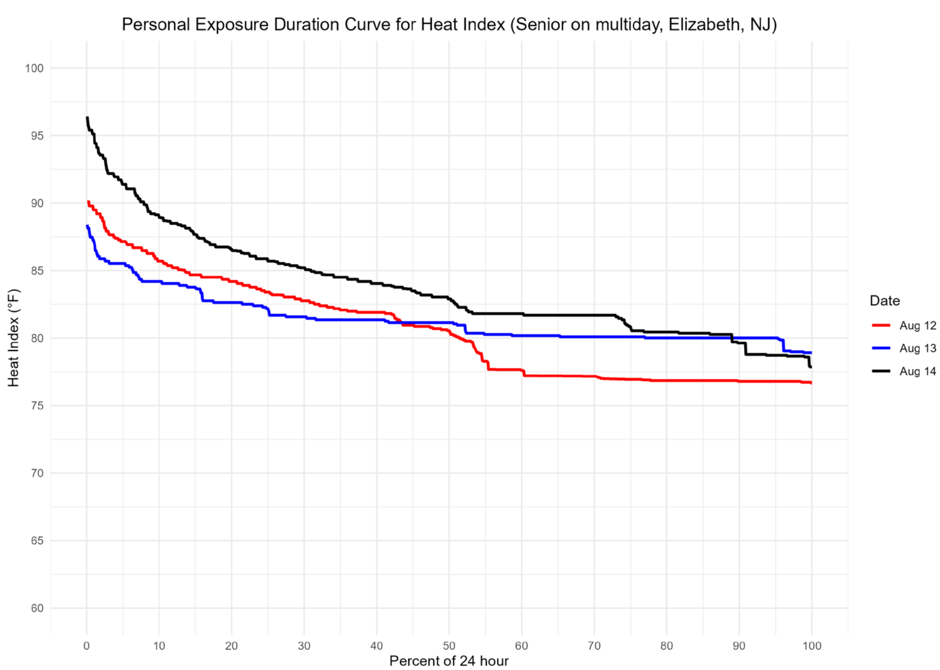

Figure 4 Asynchronous intrapersonal comparisons of EDCs for one community member (a Senior).

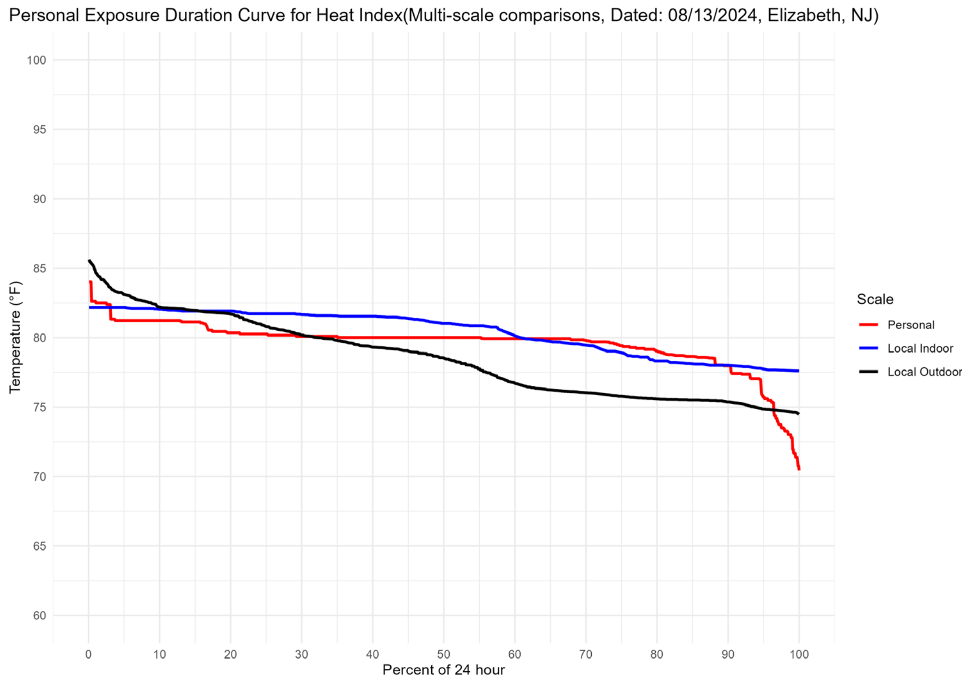

Figure 5 Comparing EDCs for one community member (a senior) using outdoor, indoor, and personal mobile temperature/humidity sensors.

DISCUSSION

Figure 3 shows that different people based in the same housing complex on the same date have very different personal exposures to summer heat. Representative study participants, designated Researcher, Senior, Youth, and Staff, illustrate the range of results for one 24-hour summer day. The Researcher, who works in a mechanically cooled office and lives in a mechanically cooled house has the lowest exposure, with <5% of the day spent outdoors. The Senior also spends little time outdoors (10%) but their home has a higher cooling setpoint than that of the Researcher. The Youth experiences high but steady heat index levels reflecting relatively short trips outdoors while living and going to summer activities in rooms with high cooling setpoints. Staff of the housing complex have the most extreme heat exposures due to work tasks outdoors that represent much of the working day (>30% of the 24 hours). Figure 4 illustrates that any one person's heat exposure can vary widely by date, as weather conditions and personal activities vary, even within one 3-day period. The person shown is an active Senior who gardens every day. Figure 5 shows that personal exposures lie mostly within an envelope established by indoor and outdoor conditions at a specific date and location. Outdoor thermal conditions vary substantially, as expected. Indoor conditions vary the least, as expected. Personal exposure reflects the relative amounts of time spent indoors and outdoors, although this person also visited a colder location (for shopping) that was neither home nor outside. The community member shown (a Senior who takes morning walks) spends about 10% of the day outdoors (mostly in early morning when it is cooler than indoors and more briefly in the afternoon when outdoors is warmer than indoors).

This research is limited because it includes only data that are collected in one city for one summer for a small number of people. Additionally, the instruments have inherently different levels of accuracy and reliability, which limits their comparability. Hence, the paper relies on probabilistic data representations. Future research includes (1) testing the extent to which the personal exposure patterns of people cluster in systematic ways such as by occupation, age, income, building type, or location; (2) developing a "difference between EDCs" metric to quantify comparisons; and (3) comparing and possibly integrating EDCs that represent exposures to heat and air pollution.

There are several implications of this research for engineering practice: system design and sizing criteria, building energy modeling, indoor air quality and ventilation standards, control system logics, public health protection, and occupant behavior considerations. An important threshold value for HVAC designers is the Cooling Design Condition that informs equipment sizing calculations. ASHRAE (2021, Ch. 14) specifies three threshold values for consideration: 0.4%, 1.0%, and 2.0% annual probability of exceedance for the Dry Bulb and Mean Coincident Wet Bulb temperatures. ASHRAE (2021, Ch. 14, Table 1) derives these values from long-term hourly weather data spanning the period 1994 to 2019. These thresholds can be approximated in Heat Index terms for Elizabeth, NJ, as follows, using methods in Rothfusz (1990) and Miers (1991): 0.4% condition is 97 degrees F-equivalent (36˚ C); 1.0% condition is 93 degrees F-equivalent (34˚ C); and the 2.0% condition is 90 degrees F-equivalent (32˚ C). These design conditions are exceeded in the microclimate data collected during the current study. The EDC method can also inform building energy performance modeling by providing an empirical link to modeled Unmet Load hours during which systems fail to satisfy comfort conditions ASHRAE (2021, Ch. 19).

CONCLUSION

Personal exposure measurement reveals different aspects of the environmental exposure story than do indoor, local, or ambient measurements. The differences among them help explain why ambient environmental data often only weakly predict human health outcomes. EDCs, introduced here, provide a succinct way to consider intensity, frequency, and duration of environmental exposures. The current application to summer thermal conditions could be generalized to include air pollutant exposures (such as O_3, $PM_{2.5}$).

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