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Climate change and health: Indoor heat exposure in vulnerable populations☆

Jalonne L. White-Newsome[a,*], **Brisa N. Sánchez**[b,1], **Olivier Jolliet**[c,2], **Zhenzhen Zhang**[b], **Edith A. Parker**[d,3], **J. Timothy Dvonch**[e,4], and **Marie S. O'Neill**[f,4]

[a] University of Michigan School of Public Health, Environmental Health Sciences Department, 109 S. Observatory, SPH II, Rm. M6314, Ann Arbor, MI 48109, USA

[b] University of Michigan School of Public Health, Biostatistics Department, M4164 SPH II, 1415 Washington Heights, Ann Arbor, MI 48109-2029, USA

[c] University of Michigan School of Public Health, Environmental Health Sciences Department, 6622 SPH tower, 1415 Washington Heights, Ann Arbor, MI 48109-2029, USA

[d] University of Michigan School of Public Health, Health Behavior and Health Education Department, 1415 Washington Heights, Ann Arbor, MI 48109-2029, USA

[e] University of Michigan School of Public Health, Environmental Health Sciences Department, 1415 Washington Heights, 6642 SPH Tower, Ann Arbor, MI 48109, USA

[f] University of Michigan School of Public Health, Environmental Health Sciences Department, 6631 SPH Tower, 1415 Washington Heights, Ann Arbor, MI 48109, USA

Abstract

Introduction—Climate change is increasing the frequency of heat waves and hot weather in many urban environments. Older people are more vulnerable to heat exposure but spend most of their time indoors. Few published studies have addressed indoor heat exposure in residences occupied by an elderly population. The purpose of this study is to explore the relationship between outdoor and indoor temperatures in homes occupied by the elderly and determine other predictors of indoor temperature.

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[*] Corresponding author. Present address: Union of Concerned Scientists, 1825 K St., N.W. Suite 800, Washington, DC 20006, USA. Fax: + 202 223 6162. jalonne@umich.edu (J.L. White-Newsome). [1] Fax: +734 763 2215. brisa@umich.edu (B.N. Sánchez). [2] Fax: +734 763 8095. ojolliet@umich.edu (O. Jolliet). [4] Fax: +734 936 7283. dvonch@umich.edu (J. Timothy Dvonch), marieo@umich.edu (M.S. O'Neill)..
zhzh@umich.edu (Z. Zhang)
[3]Present address: The University of Iowa, College of Public Health, E225A Iowa City, IA 52242, USA. Edith-Parker@uiowa.edu (E.A. Parker)

Appendix A. Supplementary material
Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envres.2011.10.008.

Materials and methods—We collected hourly indoor temperature measurements of 30 different homes; outdoor temperature, dewpoint temperature, and solar radiation data during summer 2009 in Detroit, MI. We used mixed linear regression to model indoor temperatures' responsiveness to weather, housing and environmental characteristics, and evaluated our ability to predict indoor heat exposures based on outdoor conditions.

Results—Average maximum indoor temperature for all locations was 34.85 °C, 13.8 °C higher than average maximum outdoor temperature. Indoor temperatures of single family homes constructed of vinyl paneling or wood siding were more sensitive than brick homes to outdoor temperature changes and internal heat gains. Outdoor temperature, solar radiation, and dewpoint temperature predicted 38% of the variability of indoor temperatures.

Conclusions—Indoor exposures to heat in Detroit exceed the comfort range among elderly occupants, and can be predicted using outdoor temperatures, characteristics of the housing stock and surroundings

Keywords

Indoor heat exposure; Building characteristics; Climate change; Elderly; Built environment

1. Introduction

Heat waves are "extended periods of unusually high-atmospheric related heat-stress, which causes temporary modification in lifestyle and which may have adverse health consequences for a population" (Robinson, 2001). Long-term climate change may result in more heat-related illness and death as the average temperature of the globe increases, along with increased frequency, intensity and duration of heat waves in some locations (Meehl and Tebaldi, 2004). Heat exposure caused more than eight thousand deaths in the United States from 1979 to 2003, more than the combined total from all other natural disasters (CDC, 2003, 2006).

Epidemiological studies of heat-related illness and death commonly use a time-series or case-crossover design to determine the association between ambient heat exposure and illness or deaths, recorded in vital statistics data and hospital records. Heat exposure is often estimated using an airport monitoring station and applied to residents of an entire community. Measuring ambient temperature exposure at this city/county scale likely misclassifies heat exposure that is more variable at the home or neighborhood scale (Basu, 2009). Additionally, elderly people spend approximately 90% of their time indoors (Environmental Protection Agency, 2009), especially older people who have been shown to be more vulnerable to heat (Kovats and Hajat, 2008). Thus, indoor temperatures are likely to better represent heat exposure of such vulnerable individuals (Smargiassi et al., 2008). However, few studies have addressed how indoor temperatures, housing, environmental characteristics, and ambient temperature measures are related in residences occupied by the elderly.

Filling gaps in knowledge regarding the role that ambient temperatures, housing, and other environmental characteristics may play in personal temperature exposure among the elderly is important for improving heat epidemiology and guiding prevention programs. Little information exists on (a) indoor temperature variance between homes and (b) differences in temperature exposure estimates between city/county level and more localized temperature monitors. The present study addressed some of these gaps by exploring the relationship between ambient and indoor temperatures in homes occupied by elderly individuals in metropolitan Detroit, Michigan, using data on indoor and outdoor temperatures, housing characteristics and environmental surroundings.

2. Materials and methods

The purpose of this analysis was (1) to document, during summer 2009, hourly indoor temperatures in thirty different residences in the city of Detroit and (2) to evaluate sensitivity (i.e. calculated effect estimates) of these indoor temperatures to changes in meteorological measurements, housing characteristics and environmental surroundings.

2.1. Study population

Out of 95 personal contacts at Detroit area senior service agencies, recreation centers, senior residences, and churches thirty volunteer participants over age 65 in Detroit were enrolled in our study based on written consent and their willingness to allow temperature monitoring in their homes. The target population for this study included senior citizens that reside in the city of Detroit, live in a home or apartment building in the city of Detroit, represent various neighborhoods and socio-economic status, and in general, possess characteristics that have been shown in the literature to increase vulnerability to heat related health issues, such as living on the top floors of apartment high rise buildings, physical mobility issues, social isolation and health concerns. Participants represented a wide range of neighborhoods and housing types. Individuals living in single family residences or high rise apartment buildings, with and without air conditioning, were sought to determine how access to air conditioning affected residential temperatures. Research staff entered their homes every two weeks to collect temperature data and compensated participants ten dollars per visit. The University of Michigan Institutional Review Board approved this study.

2.2. Housing characteristics

Home-specific characteristics that can influence indoor temperature were obtained from the city of Detroit property tax assessment database. These included exterior construction (brick/asphalt, vinyl paneling or wood siding); date of construction (1912–1939, 1940–1970, or after 1970) and housing type (single family, high rise, two-family flat). Number of floors, air conditioning status, and prevailing surroundings were also obtained through participant interviews and principal investigator observation. Prevailing surroundings were defined as the dominant surroundings (i.e. concrete, urban, residential or yard/park) directly north, east, west, and south of the home.

2.3. Indoor temperatures

Each residence's indoor temperatures were monitored and recorded continuously at half hour intervals from June 1 to September 1, 2009 using a HOBO Temperature Logger H08-001-02 from the Onset Corporation: a one-channel temperature recorder, with selectable sampling intervals and temperature accuracy of ±0.71 at 21 °C (±1.27° at 70 °F).

All loggers were pre- and post-calibrated for 27 h using a National Institute of Standards and Technology probe, EXTECH Instruments 407445 Heavy Duty Hygro-Thermometer. The HOBO loggers were placed in an enclosed room with the probe among them to assess their accuracy and precision. Across all homes, approximately 56,000 hourly indoor temperatures were measured over the entire study period. The monitoring initiation dates ranged from June 1st to August 1st.

To minimize individual indoor factors that could influence temperature readings, all loggers were affixed to a wall or piece of furniture using double-sided tape and installed on walls without windows or vents, approximately 1.5 m from the floor, away from any heat sources (e.g., kitchen, floor heater/air conditioner) or a door in the inside of the home. Two loggers were installed in each residence, primarily in rooms frequently used by the resident. An average indoor temperature (i.e. referred to as a residence temperature) was calculated by taking the average temperature of both rooms being monitored.

2.4. Outdoor weather data

Hourly ambient temperature and dewpoint temperature were downloaded from Detroit metropolitan airport weather archives taken from http://gis.ncdc.noaa.gov/map/isd/ website.

2.5. Solar radiation data

Solar radiation can affect indoor temperatures through heat absorption. Daily estimates of average solar radiation measures in mega joules per square meter (MJ/m^2) were obtained from the Midwestern Regional Climate Center in Champaign, Illinois for Detroit Metropolitan Airport. The 24 h average was used to minimize the influence of measurement error and to account for possible lagged effects of solar radiation on home indoor temperatures. We used $Solar_{(avg)}$ in our model instead of hourly solar radiation data due to a large number of missing data points from the hourly data source.

2.6. Developing the mixed effects model

To develop a model evaluating indoor temperature sensitivity estimates to external stimuli across residences, we initially used methodologies from energy and building science to create a conceptual model for predicting the residence's thermal performance. Energy balances are a systematic way of accounting for energy flows in and outside of a controlled space. The flow of energy relates to our research goals because this flow can alter indoor temperature. Energy balances are typically used to calculate cooling and heating loads for buildings based on climate, design and building conditions. Therefore we reduced this conceptual equation to represent terms for which data was collected (indoor temperature, outdoor temperature, solar radiation, dewpoint temperature) that enabled us to derive a house specific regression model to fit the data. We then transformed the house specific regression model into a mixed model that allows an understanding of the average sensitivity (i.e. effect estimates β_0, β_1, ..., β_4) across locations, as well as the location specific sensitivities (i.e. β_{0i}, β_{1i}, β_{2i}, β_{3i}, and β_{4i}) that can be written as, for example, $\beta_{0i}=\beta_0+b_{0i}$, where β_0 is the average internal heat source contribution across all homes and b_{0i} is the difference between house *i*'s internal heat and the average internal heat sources contribution. For example, the sensitivity to outdoor temperature, $\beta_{3,}$ shows the magnitude of change of the indoor temperatures given a 1 °C increase in outdoor temperature, holding all other factors constant. This same interpretation can be used for the effect estimates calculated for each of the other predictors. A positive deviation, e.g. b_{1i}, from the average effect, β_1, means the location i will have a greater change in indoor temperature associated with the external stimuli, e.g. solar radiation, compared to the overall average response of the thirty homes. Supplementary material further defines the variables included in the autoregressive mixed model.

2.7. Implemented mixed model versions

The mixed model allows us to address how well indoor heat exposure can be estimated using outdoor environmental data by evaluating the predictability of indoor temperatures. The first step in this process was to create several versions of the base model, Model 1. Model 1 contained all four parameters (solar radiation, outdoor temperature, previous hourly indoor temperature and dewpoint temperature); Model 2 omitted solar radiation; Model 3 omitted previous hourly indoor temperature; Model 4 omitted solar radiation and previous hourly indoor temperature; and Model 5 omitted only dewpoint temperature. Models 3 and 4 are the models of most relevance for use by public health practitioners to estimate heat exposure for epidemiology studies, since direct indoor measurements are rarely available.

We calculated how well these models worked to predict actual indoor temperatures by fitting models 1–5 to the entire summer's data, and then used the intercepts and coefficients of these models to create a series of predicted hourly indoor temperatures based on the measured values of the predictors (solar radiation; outdoor temperature; previous hourly indoor temperature, dewpoint temperature). We calculated squared correlation coefficients, R^2, between the actual measured indoor temperatures and the predicted indoor temperatures for each of the models.

Mixed model 3 (which includes parameters outdoor temperature, solar radiation, and dewpoint temperature) was also used to generate heat sensitivity estimates, e.g., β_{0i}, β_{1i}, β_{2i}, β_{3i}, for each home in the following categories: exterior construction (brick, asphalt, vinyl paneling, wood siding); occupancy (high rise, non-high rise); date built (1912–1939, 1940–1970, after 1970); prevailing surroundings (concrete, These sensitivities can be interpreted as the change in indoor temperature per one unit increase in the external stimuli. For example, an estimate of β_{3i}=0.50 corresponding to T_{out}), can be interpreted as “in location *i* we expect to see an average 0.50° increase in indoor temperature as a result of 11 increase in outdoor temperature”. Because only one home was represented in each of the exterior construction categories “vinyl paneling” and “wood siding”, and only two in “asphalt”, linear regressions were fit for data from these four homes, rather than the mixed models, which were used for all the remaining stratified sensitivity analyses.

2.8. Statistical analyses and representation

The SAS procedure PROC MIXED was used to fit the models. From the mixed model results, we obtained the average and location specific sensitivities for each parameter. These sensitivities can be interpreted as the mean change in indoor temperature per increase in one of the parameters.

2.9. Checking model assumptions

Residual diagnostics revealed no violations of the normality, linearity or constant variance assumptions for the regression models. The Durbin–Watson d statistic revealed the presence of autocorrelation between the residuals of indoor temperature with the residuals at the previous hour for most locations. Such autocorrelation would typically lead to underestimation of standard errors of regression coefficients. However, we used robust standard errors, which protect from deviations from independence within locations.

3. Results

We explored the relationship between ambient and indoor temperatures in thirty homes occupied by elderly individuals in metropolitan Detroit, Michigan, using data on housing characteristics and environmental surroundings, during summer, 2009. The homes spanned an area totaling 72 square miles (Fig. 1). Over half of the homes had central air conditioning (53%), and 86% were constructed of brick (Tables 1 and 2). The prevailing surroundings of 40% of the homes were residential, while equal percentages of homes had prevailing surroundings defined as either “concrete” or “urban”.

The initial goal was to have all volunteers recruited before June 1st, in order to allow indoor temperature monitoring from June 1st to August 31st. 26 of the volunteers were recruited by June 30th; 29 by July 30th, and the last volunteer was recruited on August 1st. The average number of days measured for study across all the homes were 79 days. Our sample included seniors living in occupancies ranging from low-income housing to upper middle class homes; homes that spanned east, west, north and south sides of the city; residents living on the higher floors of the high rise buildings; three volunteers were physically handicapped and had to utilize a wheel chair or another walking device; and many of the volunteers had health challenges and concerns, which out of their own will they discussed with the principal investigator. Hence, sampling from our target population was achieved.

3.1. Outdoor temperature, solar radiation, and indoor temperatures

Average daily values of solar radiation ranged from 8.6 to 29.7 MJ/m^2, with a mean of 20.0 MJ/m^2. Outdoor temperatures at Detroit Metropolitan Airport ranged from 7.2 to 34.3 °C, with a mean temperature of 21.0 °C. The highest daily residence temperatures across all homes ranged from 16.7 to 34.8 °C. Specifically, the highest daily maximum residence temperatures were experienced by Locations 8 and 13, 34.8 °C and 34.4 °C, respectively. For homes with central air conditioning, the temperatures ranged from 19.2 to 34.8 °C; homes without central air conditioning ranged from 16.7 to 34.4 °C. The highest room temperature amongst all the study homes was 35.2 °C.

We examined the differences in residence temperatures across the study population by room type, occupancy type, prevailing surroundings, date built, and exterior construction. Dining rooms had the highest temperatures of all rooms, reaching a maximum of 35.2 °C in the dining room of location 8. For occupancy type, single family residences and locations with residential prevailing surroundings had absolute maximum daily residence temperatures reaching as high as 34.8 °C. The locations (n = 14) built between 1940 and 1969 experienced a range of absolute maximum daily indoor temperatures from 18.8 to 34.8 °C, approximately 2.81 (on average) higher than other homes. In terms of exterior construction, the two asphalt homes had the highest absolute maximum residence temperatures, reaching a maximum of 34.8 °C.

3.2. Mixed model results

The results in the next three subsections are intended to enhance the understanding in three areas: determining which parameter had the strongest influence on indoor temperature across all homes, homes with air conditioning and homes without air conditioning; learning how the characteristics of homes can influence indoor temperatures; and, selecting the best model for predicting indoor temperatures.

3.2.1. Distribution of heat sensitivity estimates—Fig. 2 displays the range of heat sensitivity estimates generated from performing a regression on Mixed Model #3, which includes the parameters outdoor temperature (NTairport), Dew-point temperature (Ndewp_C), and Solar radiation (NSolar). These estimates quantify the strength of the influence of a parameter on indoor temperature. Fig. 2A–C include vertical lines to display three sensitivity estimates. Across the stimuli, the sensitivity estimate was larger for homes without air conditioning, compared to homes with air conditioning.

3.2.2. Heat sensitivity estimates by category—Table 2 shows results of Mixed Model #3 stratified by (1) exterior construction, (2) occupancy, (3) date built, (4) prevailing surroundings, and (5) air conditioning status. Locations with higher sensitivity estimates to outdoor temperature were made of asphalt and wood siding, non-high rise, built between 1912 and 1939, and had no central air conditioning. Solar radiation was a significant predictor of indoor temperature in all location categories. Locations that had the highest effect estimates to dew-point temperature were asphalt, non-high rise locations, homes built between 1940 and 1970 and those with prevailing urban surroundings and those with no central air conditioning. The estimate for solar radiation was especially high with prevailing concrete surrounding and for non-brick houses.

3.2.3. Prediction of indoor temperatures—The intercepts and coefficients of the five variations of the mixed model (fit to data for the entire summer) were used to generate the five versions of the mixed model to create the predicted series of indoor temperatures.

Table 3 gives squared correlation coefficients to describe the ability of various sets of predictors to predict indoor temperature for heat exposure studies. Models 1, 2, and 5 explained 98% of the variance in indoor temperatures. Models 3 and 4, reduced forms of the mixed model explained 38% and 34% of the variance in indoor temperature, respectively.

Graphs comparing predicted indoor temperatures using each of the modeling equations were generated for the following: specific home locations (location #26, location #13, location #8), and homes with air conditioning, made of brick and non-high rise homes (shown in Supplementary material).

4. Discussion

This analysis explored the relationship between ambient and indoor temperatures in homes occupied by elderly individuals in metropolitan Detroit, Michigan, using data on housing characteristics and environmental surroundings. A variety of dwellings were monitored—single family homes, high rise apartments and two family flats; and those with or without air conditioning. Outdoor temperature, solar radiation, dew point temperature and previous indoor temperatures were used to generate predictive models for indoor temperatures. The sensitivity of indoor temperature to outdoor temperature varied based on residence type, outdoor temperature, and city location.

Overall, the average monthly temperatures during summer of 2009 were cooler than mean temperatures measured during 30 past summers from 1971 to 2000 ("the 30 year normal"). Observed weather reports from the Detroit/Pontiac National Weather Service office archives (http://www.weather.gov/climate/index.php?wfo=dtx) show that the average monthly temperatures for June, July and August 2009 were 19.9 °C (1.2° less than the 30 year normal), 20.5 °C (4.6° less than the 30 year normal), and 21.7 °C (0.6° less than the 30 year normal), respectively.

Despite these below-average temperatures, surprising maximum temperatures over 29 °C were reached in 24 locations, and 5 locations (primarily asphalt construction or single family homes) had maximum temperatures above 32 °C. For sedentary activities, a typical comfort temperature with limited air movement has a maximum of no more than 28 °C (82.4 °F) (Evans, 2003). This suggests that the indoor temperatures we measured were likely to induce discomfort if not more serious effects in occupants. The locations with lowest average temperatures were located outside the downtown area of the city.

As the frequency and intensity of heat waves continue to increase, understanding the sensitivity of different home types to outdoor temperature, especially those homes occupied by the elderly, is important. In this study, individual room indoor temperatures for some of the locations reached maximums of almost 35 °C. Further, the high temperatures we observed inside homes were all the more notable given that our monitoring took place during a relatively cool summer in the Detroit area. If the number and intensity of heat waves indeed continue to increase, indoor heat exposures among the elderly such as those characterized by this study may also increase.

Based on models, which included all external stimuli (except previous indoor temperature), locations without central air conditioning had higher heat sensitivity to outdoor temperature, solar radiation and dewpoint temperature. Homes more sensitive to outdoor temperature and solar radiation were made of asphalt, non-high rise, built between 1912 and 1939. Our limited observations suggest that the higher heat capacity of the brick buildings contribute to keep the home protected from high ambient temperatures. The locations built during the earlier years could have less insulation or none at all, thus possibly explaining the higher outdoor heat sensitivity observed for older buildings. However, for the dewpoint temperature, the highest effect estimate was seen in homes built between 1912 and 1939, as well as homes in residential surroundings since dewpoint is a measure of humidity, it is possible that the homes built before 1940 could be more vulnerable to humidity due to aging, lack of sealing, insulation and other structural concerns.

For seniors who spend a lot of time indoors, indoor temperature is a more accurate measure of exposure than relying on outdoor temperature in epidemiological studies. Similar to Smargiassi et al. (2008), we compared the predictive capacity of several variations of our complete model. Models including previous hour's indoor temperature, rarely available in large-scale epidemiological studies, explained 98% of the variance in current hour indoor temperature. The predictive capacity of our models that did not include previous indoor temperature was weaker, as we expected. This points to a large degree of measurement error and thus possibly attenuated effect estimates in epidemiological studies assessing health effects of heat. We were able to reliably predict indoor temperatures based on our full model suggesting that future epidemiological studies could use models like the one we developed to improve exposure assessment accuracy. While the correlation coefficient in the model using only outdoor temperature was not large, the robustness of the model could be improved by adding more predictive parameters to the model.

4.1. Limitations

Without direct measures of solar radiation reaching each room, and data on home orientation, we might not have captured the entire influence of solar radiation on indoor temperatures for our volunteer homes. A complete data set of hourly solar radiation data for the Detroit area was difficult to acquire. Consequently, we used daily average solar radiation data generated by the Midwestern Regional Climate Center's solar radiation prediction model, which uses meteorological characteristics from Detroit Metropolitan Airport – surface pressure, dew point temperature, cloud height, fractional sky cover, and other factors – to predict a value of solar radiation. While it is clear that each home, based on its unique characteristics, will absorb solar radiation differently, we were unable to provide specific evaluation of solar radiation absorbed by each home. Further evaluation of homes with no shading, as well as measurements of solar radiation at each side of the home would be necessary for an improved evaluation of how much solar radiation contributes to indoor temperature”.

Other limitations are inherent in the diversity of the sample of homes types. A large sample of non-brick residences would have allowed a better model comparison to brick homes. While data on window size and house position were recorded, these were not included in the model due to the complications with adjusting for window treatment type for all 30 homes. Additional house-specific construction information related to insulation type and method of construction was unavailable. In future studies, it would be of interest to get an even wider representation of homes throughout Detroit, which could allow generalization to other homes in the area. A clustered sample of 2–3 homes per area would also be informative in comparing not only house-specific categories, but other environmental factors.

4.2. Future directions

The data collected in this study could be merged with other data sources to better examine intervention and prevention strategies to address heat vulnerability to heat for different populations. Geographic data resources like land cover/land use, surface imperviousness and satellite images could be useful additions to the prediction equation. Finding specific values for some of the equation parameters that are unique to different residences could be useful for urban planning and design for urban areas. For example, if this model is able to support that asphalt homes, built in the 1940s, with prevailing surroundings of concrete are more sensitive to temperature changes, then heat-vulnerable people could be advised to choose another home type or be made eligible for monies to weatherize the home (i.e. insulation, upgrades) before occupation.

This is the first study of its kind to be conducted in Detroit, Michigan, a location where heat and cold both have significant health effects in the population (O'Neill et al., 2003). Our modeling approach could be extended to study exposure to cold temperatures as well. While this particular study did not address human behavior, we recognize that methods of heat adaptation used by participants would impact the indoor temperatures achieved by different households.

5. Conclusions

The average home in Detroit experiences varying levels of indoor heat exposure, depending on weather conditions and the home's physical characteristics. People living in single family homes, made of asphalt, in a residential surrounding, built between 1912 and 1939, could be at higher risk during hot weather, as they may experience higher indoor temperatures. Education and outreach efforts could be focused on the elderly in these types of homes. This study provides valuable information on how different housing stock within the city of Detroit and similar cities respond to heat. These observations can be used to substantiate the need for policies and practices around home weatherization or greening activities for the elderly and other vulnerable populations.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations

C	equivalent thermal heat capacity, i.e. the capacity of a building to store heat that depends on the type of construction (units: Mega Joule/degrees Celsius, MJ/°C)
Dewpoint temperature	the temperature at which air becomes saturated and produces dew, another way of specifying humidity
High rise buildings	buildings with more than 5 floors
$\boldsymbol{h_0 + f_{open} \times hv}$	overall heat loss coefficient from window closing and opening, and heat loss to ventilation (unit: Watt/degrees Celsius, W/1°)
NIST	National Institute of Standards and Technology
Prevailing surroundings	the dominant type of surroundings in the four cardinal directions of the home
$\mathbf{R_{oin}}$	energy due to internal heat sources like cooking, lighting, etc. (unit: Watt, W)
RMSE	root mean squared error
$\boldsymbol{S_{absorption(t)}}$	apparent surface area of the house collecting solar energy (unit: square meters, m^2)
Sensitivity estimate	the magnitude of change of the home's hourly indoor temperature, given changes in the predictor variables
$\mathbf{Solar_{(t)}}$	amount of global horizontal solar radiation reaching the earth's surface (unit: Mega Joule/meter^2, MJ/m^2)
$\mathbf{Solar_{(avg)}}$	daily average amount of global horizontal solar radiation reaching the earth's surface (unit: Mega Joule/meter^2, MJ/m^2)
$\boldsymbol{T_{in(t)}}$	observed value of indoor temperature at current time *t* (unit: degrees Celsius, °C)
$\boldsymbol{T_{in(t-\Delta t)}}$	observed hourly value for indoor temperature at lagged interval to current temperature at time *t* (unit: degrees Celsius, °C)
$\boldsymbol{T_{in(t)} T_{in(t-\Delta t)}}$	the change in indoor temperature, i.e., previous hour minus the current hour's indoor temperature over a time interval of one hour (units: degrees Celsius, °C)
$\boldsymbol{\Delta t}$	time interval of one hour (hours, h)
$\boldsymbol{T_{out}}$	observed hourly outdoor temperature at current time *t* (unit: degrees Celsius, °C)
$\boldsymbol{T_{out(t)} T_{in(t)}}$	difference between current outdoor temperature and current inside temperature (units: degrees Celsius, °C)

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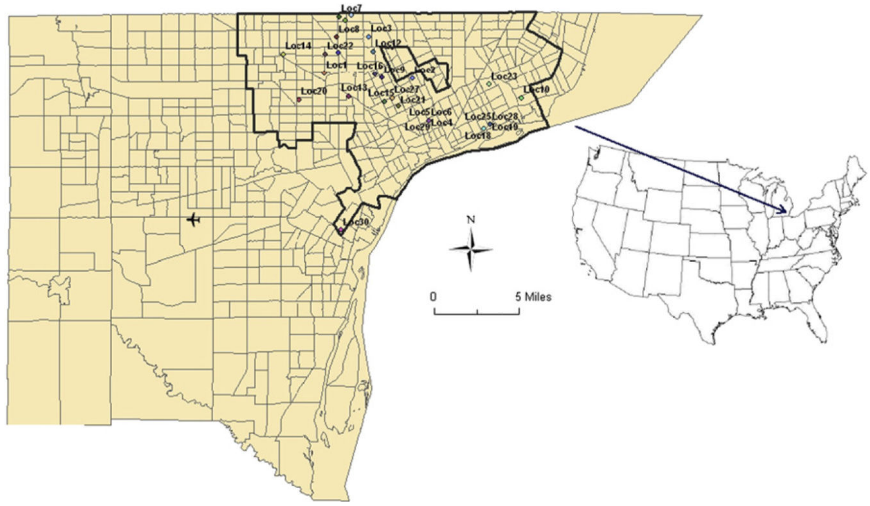

Fig. 1.

Map showing Wayne County, Michigan. City of Detroit boundary outlined with dark line. Map of study locations in Detroit, Michigan by location number. Detroit Metropolitan Airport displayed. Location of Detroit Metropolitan Airport indicated by airplane symbol.

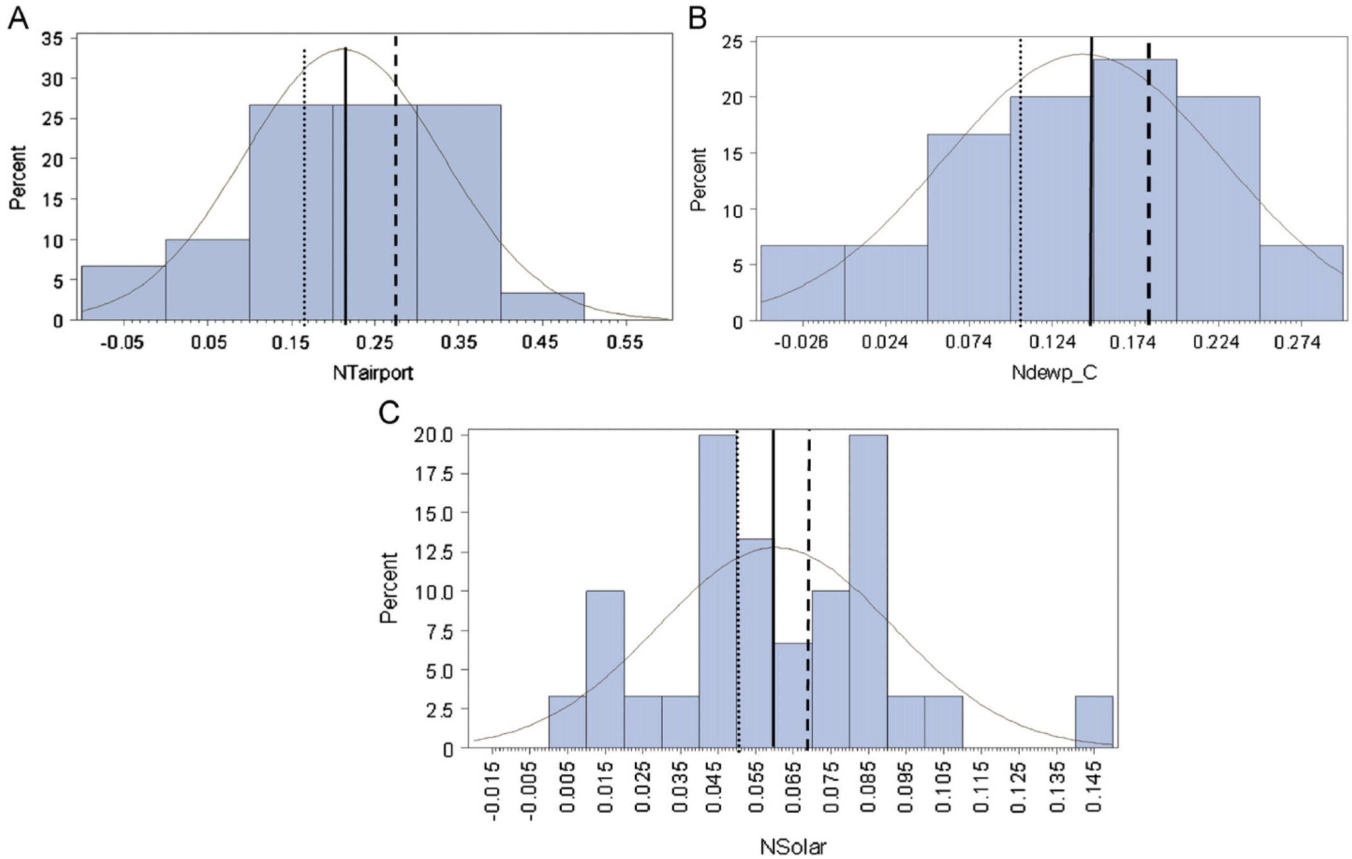

Fig. 2.

Histograms showing the distribution of the range of effect estimates generated from the regression of Mixed Model #3, which includes the parameters for outdoor temperature (NTairport), Dewpoint temperature (Ndewp_C), and Solar radiation (NSolar). (A)–(C) use different vertical lines styles to display three effect estimates: the mean effect estimate of that parameter on indoor temperature calculated across all locations (——); the mean effect estimate of that parameter on indoor temperature calculated across homes with air conditioning (....); and the mean effect estimate of that parameter on indoor temperature across homes without air conditioning (——).

Table 1

Housing characteristics and average and maximum indoor temperatures (°C) for locations monitored during the indoor heat study in Detroit, Michigan in Summer 2009. June 25,2009 and August 8,2009 were two of the hottest days during the summer.

Home	Start date[a]	Type[b]	Floor area sq. ft.[c]	Date built	# of floors	Exterior construction	Central AC	Room 1[d]	Room 2[d]	Prevailing surroundings[e]	6/25/2009 (max, mean)	8/9/2009 (max, mean)
1	1-Jun	Single family	950	1951	2	Brick	Yes	lr[f]	br	Residential	27.5, 26.2	25.5, 24.6
2	1-Jun	Single family	1488	1914	2	Brick	No	dr	br	Residential	31.3, 30.5	25.5, 24.6
3	1-Jun	Single family	2600	1929	3	Brick	Yes	dn	br	Residential	28.3, 27.6	24.7, 23.9
4	1-Jun	High rise	800	1987	14	Brick	Yes	br	lr[f]	Urban	30.3, 29.5	27.7, 26.9
5	1-Jun	High rise	800	1987	14	Brick	Yes	lr[f]	br	Urban	28.7, 28.0	27.9, 26.8
6	1-Jun	High rise	800	1987	14	Brick	Yes	lr[f]	br[f]	Urban	26.9, 24.8	26.1, 24.4
7	1-Jun	Single family	1348	1940	1	Brick	No	br	lr	Residential	31.5, 30.3	26.5, 25.7
8	1-Jun	Single family	692	1944	2	Asphalt	Yes	dn	dr	Residential	34.8, 33.2	29.9, 29.1
9	2-Jun	Two family flat	2400	1925	2	Brick	No	dr	br	Residential	28.9, 28.5	26.1, 25.3
10	2-Jun	Single family	798	1913	2	Asphalt	No	lr	br	Residential	30.5, 29.1	24.7, 23.8
11	4-Jun	Single family	1255	1931	2	Brick	No	dr	lr	Yard/Park	32.7, 30.7	27.1, 25.8
12	4-Jun	Single family	1819	1927	3	Brick	Yes	dn	br	Residential	31.1, 29.9	24.5, 23.7
13	4-Jun	Single family	1457	1923	3	Brick	No	dn		Residential	33.5, 32.3	29.1, 26.7
14	5-Jun	Single family	2692	1931	3	Brick	Yes	dn[f]	br	Residential	30.7, 29.8	24.9, 24.2
15	5-Jun	Two family flat	2226	1922	2	Brick	No	dr	br	Concrete	30.7, 30.0	25.7, 25.2
16	8-Jun	Two family flat	2650	1925	2	Brick	No	dr	lr	Concrete	29.1, 28.3	24.5, 23.3
17	11-Jun	High rise	800	1982	13	Brick	Yes	lr[f]	br[f]	Concrete	27.9, 25.5	25.5, 23.6
18	11-Jun	High rise	800	1980	13	Brick	Yes	lr[f]	br[f]	Concrete	31.5, 29.1	29.1, 28.5
19	11-Jun	High rise	737	1980	18	Brick	Yes	br	lr[f]	Yard/Park	29.7, 27.1	27.3, 27.13
20	16-Jun	Single family	829	1949	2	Brick	No	br	dn	Yard/Park	29.3, 28.7	25.3, 24.4
21	16-Jun	Single family	2371	1919	2	Brick	No	lr	br	Residential	30.9, 29.1	27.3, 26.1
22	16-Jun	Single family	1267	1938	2	Brick	No	br	dn	Yard/Park	30.1, 28.5	25.3, 24.4
23	22-Jun	Single family	535	1919	2	Wood siding	No	lr	dn	Yard/Park	30.7, 29.5	25.1, 24.3
24	24-Jun	Single family	1046	1980	1	Brick	Yes	dn	br	Yard/Park	32.7, 31.1	27.9, 26.0
25	24-Jun	High rise	737	1980	18	Brick	No	lr	br	Concrete	30.7, 29.4	25.7, 25.1

Home	Start date[a]	Type[b]	Floor area sq. ft.[c]	Date built	# of floors	Exterior construction	Central AC	Room 1[d]	Room 2[d]	Prevailing surroundings[e]	6/25/2009 (max, mean)	8/9/2009 (max, mean)
26	24-Jun	Single family	970	1962	1	Brick	Yes	den	br[f]	Residential	28.9, 26.1	27.5, 26.2
27	10-Jul	Single family	6746	1912	2	Brick	Yes	dr[f]	dn[f]	Yard/Park	-	26.7, 26.6
28	14-Jul	High rise	737	1980	18	Brick	Yes	lr[f]	br	Urban	-	27.1, 26.4
29	14-Jul	High rise	800	1987	13	Brick	Yes	lr[f]	br	Urban	-	27.1, 26.4
30	1-Aug	Single family	908	1953	1	Vinyl paneling	No	lr	br	Yard/Park	-	24.9, 23.7

All locations were sampled until the end date of August 31, 2009.

[a]Start date: date temperature monitoring began at residence.

[b]Type of residence monitored: single family, high rise apartment building, two family flat (1 family living on 1st floor, 2nd family living on second floor).

[c]Floor are a square footage: floor area taken from the Detroit City Tax Assessor Office.

[d]Rooms monitored: lr (livingroom), dr (diningroom), br (bedroom), dn (den).

[e]Prevailing surroundings: 50% or more of the immediate surroundings on the North, East, South, and West side of the home are either residential, urban, concrete, or Yard/Park.

[f]These room shave airconditioning (i.e. a unit installed in the room or a portable unit).

Table 2

Effect estimates (95% confidence intervals) by home category, using a reduced mixed regression model for June 1-August 31,2009. Effect estimates can be explained as the change in indoor temperature associated with a one unit change in the specified parameter: outdoor temperature (degrees Celsius), solar radiation (Mega Joules/meter^2), and dewpoint temperature (degrees Celsius). The Intercept effect estimate represents the change as a result of internal heat gains (i.e. heat sources within the home). n represents the number of homes in that category.

Category	**Parameter effect estimates**				
	Intercept	**Outdoor temp**	**Solar radiation**	**Dewpoint temperature**	**n**
Average effect on all homes	17.8 (16.4, 19.2)	0.21 (0.16, 19.27)	0.06 (0.04, 0.07)	0.14 (0.11, 0.17)	30
Exterior construction					
Brick	17.90 (17.81, 17.99)	0.20 (0.20, 0.21)	0.05 (0.05, 0.06)	0.14 (0.14, 0.15)	26
Asphalt	15.79 (15.32, 16.25)	0.21 (0.19, 0.23)	0.11 (0.09,0.12)	0.25 (0.23, 0.27)	2
Vinyl paneling[a]	13.58 (13.08, 14.07)	0.45 (0.43, 0.48)	0.04 (0.03, 0.06)	0.01 (–0.01, 0.04)[b]	1
Wood siding[a]	12.95 (12.57, 13.33)	0.35 (0.33, 0.36)	0.06 (0.05, 0.07)	0.22 (0.20, 0.23)	1
Occupancy					
High rise	21.6 (19.34, 23.98)	0.09 (0.03, 0.16)	0.03 (0.01, 0.06)	0.10 (0.05, 0.15)	9
Non-high rise	16.21 (14.91, 17.50)	0.26 (0.21, 0.30)	0.06 (0.05, 0.08)	0.15 (0.12, 0.19)	21
Date built					
1912-1939	15.59 (13.97, 17.22)	0.26 (0.22, 0.30)	0.06 (0.05, 0.07)	0.18 (0.14, 0.22)	14
1940-1970	18.58 (16.16, 21.01)	0.19 (0.07, 0.30)	0.068 (0.009, 0.12)	0.13 (0.01, 0.25)	6
After 1970	21.05 (18.62, 23.48)	0.12 (0.04, 0.20)	0.04 (0.02, 0.06)	0.10 (0.05, 0.15)	10
Prevailing surroundings					
Concrete	18.18 (11.91, 24.45)	0.17 (0.02, 0.32)	0.05 (0.01, 0.10)	0.15 (0.01, 0.28)	5
Residential	16.88 (14.91, 18.85)	0.23 (0.17, 0.29)	0.06 (0.04, 0.08)	0.16 (0.10, 0.21)	12
Yard or park	16.52 (14.04, 19.00)	0.27 (0.17, 0.37)	0.07 (0.05, 0.08)	0.12 (0.06, 0.18)	8
Urban	21.93 (19.59, 24.27)	0.09 (0.02, 0.16)	0.02 (0.007, 0.05)	0.10 (0.06, 0.15)	5
Air conditioning status					
Central air	19.82 (17.86, 21.77)	0.15 (0.09, 0.22)	0.05 (0.03, 0.07)	0.11 (0.06, 0.15)	16
No central air	15.59 (14.11, 17.07)	0.27 (0.22, 0.32)	0.06 (0.05, 0.07)	0.17 (0.13, 0.21)	14

[a] Where only one home contributed data, a linear regression was performed to obtain the estimated parameters, as a mixed model was not necessary.

[b] Effect estimates that were not statistically significant.

Table 3

Ability of five different models to predict actual indoor temperatures (represented by squared Pearson correlations (R^2) between observed and predicted temperatures). Additionally, beta coefficients and their standard errors for each independent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5
R^{2a}(p-value)	0.98[b]	0.98[b]	0.38[b]	0.36[b]	0.98[b]
Intercept	1.08	1.07	17.85	18.82	0.995
Outdoor temperature (°C)	0.019 (0.0042)	0.021 (0.0042)	0.21 (0.021)	0.23 (0.022)	0.02 (0.00407)
Previous indoor temperature (°C)	0.93 (0.0061)	0.93 (0.0061)	-	-	0.94 (0.0062)
Solar radiation (MJ/m^2)	0.005 (0.00052)	-	0.06 (0.0058)	-	0.003 (0.00041)
Dewpoint temperature (°C)	0.01 (0.0010)	0.007 (0.00092)	0.14 (0.015)	0.12 (0.014)	-

[a]Squared correlation between measurements and predictions.

[b]*p* value < 0.0001.