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Short Communication

Urban heat and air pollution: A framework for integrating population vulnerability and indoor exposure in health risk analyses

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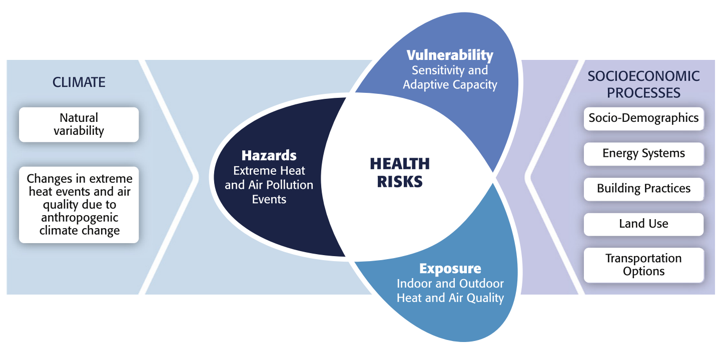
HIGHLIGHTS

- Indoor & outdoor exposure to extreme heat and air pollution affects human health.
- New framework integrates social & health sciences approaches to understanding risk.
- Household survey characterizes indoor and outdoor exposure and vulnerability.
- Novel application of building energy modeling quantifies indoor exposure.

GRAPHICAL ABSTRACT



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ABSTRACT

Urban growth and climate change will exacerbate extreme heat events and air pollution, posing considerable health challenges to urban populations. Although epidemiological studies have shown associations between health outcomes and exposures to ambient air pollution and extreme heat, the degree to which indoor exposures and social and behavioral factors may confound or modify these observed effects remains underexplored. To address this knowledge gap, we explore the linkages between vulnerability science and epidemiological conceptualizations of risk to propose a conceptual and analytical framework for characterizing current and future health risks to air pollution and extreme heat, indoors and outdoors. Our framework offers guidance for research on climatic variability, population vulnerability, the built environment, and health effects by illustrating how health data, spatially resolved ambient data, estimates of indoor conditions, and household-level vulnerability data can be integrated into an epidemiological model. We also describe an approach for characterizing population adaptive capacity and indoor exposure for use in population-based epidemiological models. Our framework and methods represent novel resources for the evaluation of health risks from extreme heat and air pollution, both indoors and outdoors.

Abbreviations: AC, air conditioning; HVAC, heating, ventilation, and air-conditioning systems; IES, Integrated Energy Systems; IPCC, Intergovernmental Panel on Climate Change; AR5, IPCC Fifth Assessment Report; TRNSYS, Transient System Simulations.

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1. Introduction

A broad literature base provides evidence of association between adverse health outcomes and ambient air pollutants including ozone, nitrogen oxides, and particulate matter (Dockery et al., 1993; Dockery and Pope, 1994; Dominici et al., 2006; Jerrett et al., 2013; Peel et al., 2005; Peel et al., 2007; Sarnat et al., 2015; Strickland et al., 2010; U.S. Environmental Protection Agency, 2009, 2013; Vinikoor-Imler et al., 2014). Extreme heat is also a well-documented cause of human mortality and morbidity (Anderson et al., 2013; Basu, 2002, 2009; Basu and Malig, 2011; Benmarhnia et al., 2015; Braga et al., 2002; Bunker et al., 2016; Carreras et al., 2015; Cheng et al., 2014; Gasparrini et al., 2015; Green et al., 2010; Kovats et al., 2004; Laaidi et al., 2012; Li et al., 2014; Lin et al., 2009; Michelozzi et al., 2009; Winquist et al., 2016; Xu et al., 2013; Ye et al., 2012). In large cities where air pollution sources are abundant and temperatures are amplified by the urban heat island effect (Conlon et al., 2016; Luber and McGeehin, 2008; Stone et al., 2010; Winquist et al., 2016; Zhou and Shepherd, 2009), these environmental hazards occur concurrently and pose considerable health challenges to urban populations. Increasing evidence suggests that indoor environments in metropolitan areas may represent a large proportion of overall exposure to unhealthy environmental conditions as people from more industrialized nations, especially the elderly, have reported spending approximately 80–90% of their time indoors (Klepeis et al., 2001; U.S. Environmental Protection Agency, 2013). To date, the vast majority of population-based epidemiological studies have not considered indoor exposures, particularly among the elderly. Rather, they have focused primarily on exposure to outdoor conditions, typically assessing health risks among the general urban population because of data availability. This disproportionate focus on outdoor exposure in health effects research results in a limited understanding of exposure-response relationships and the importance of the built environment in effecting population vulnerability.

Given that urbanization and climate change may negatively impact indoor air quality and thermal comfort by altering the frequency or severity of adverse outdoor conditions (Institute of Medicine (IOM), 2011; Oleson et al., 2015), it is imperative to examine the contribution of the indoor environment on air quality-health associations and to better characterize the impacts among sensitive populations. However, quantifying associations between indoor conditions and human health presents a considerable research challenge, as indoor conditions are related to outdoor conditions, and because the risk of heat and air pollution-related health outcomes is not borne equally by all members of society due to differential vulnerability (Kinney, 2018; Uejio et al., 2016; Wilhelmi and Hayden, 2010). Addressing such gaps in our understanding of current and future health risks from exposure to indoor heat and air pollution will require greater focus on the following areas of research: (1) new approaches to explicitly include indicators of population vulnerability within an epidemiological model; (2) new methods of estimating indoor air quality with high temporal and spatial resolution; (3) population-based epidemiological studies that include improved estimates of indoor air quality, along with highly resolved ambient estimates; and (4) studies that utilize high-resolution projections of future air quality and heat to estimate the health impacts of climate change.

In this Short Communication, we explore the linkages between vulnerability science frameworks and epidemiological conceptualizations of risk to propose a conceptual and analytical framework through which estimates of indoor conditions, household-level vulnerability data, and spatially resolved ambient air pollution and meteorological data can be leveraged to characterize current and future health risks to indoor and outdoor exposures. We briefly discuss opportunities with regard to evaluating indoor exposures in large epidemiological studies, and describe an approach for estimating population adaptive capacity and indoor exposure in U.S. cities.

2. The indoor environment

Although outdoor and indoor environments are closely connected, indoor air quality may be substantially different than outdoor air quality depending on the tightness of a building's envelope, the functioning of heating, ventilation, and air-conditioning systems (HVAC), characteristics of the proximal built environment, occupant behavior, and sources of indoor and outdoor pollutants (Institute of Medicine (IOM), 2011; Mitchell et al., 2007). Notably, occupant behavior with regard to smoking and the ability or willingness to use climate control are dominant influences on indoor air quality and thermal comfort (Frey et al., 2014; Klepeis et al., 2017; Kuras et al., 2017). While associations are well-described between indoor air pollutants (e.g. particulate matter, nitrogen dioxide, carbon monoxide, environmental tobacco smoke, mold) and cardiorespiratory disease (Jones, 1999; Mendell et al., 2011; Mitchell et al., 2007; Samet et al., 1987), few studies have examined the health effects of indoor heat exposure (Kuras et al., 2017; McCormack et al., 2016; Uejio et al., 2016; Van Loenhout et al., 2016; White-Newsome et al., 2012). The results from the indoor heat-health literature suggest that certain urban populations experience elevated indoor temperatures, even in cities with a high prevalence of air conditioning, and that increases in indoor temperatures are associated with increases in adverse health outcomes. Studies on heat-related deaths during the 2003 Paris and 1995 Chicago heat waves suggest that poor, socially isolated, and elderly populations are at the greatest risk of heat-related mortality (Fouillet et al., 2006; Kaiser et al., 2007; Semenza et al., 1996). In the Paris 2003 heat wave, decedents were more likely to succumb to heat in their own homes. Similarly, a 2008–2011 New York City medical examiner case study of 48 decedents reported that approximately 85% of heat-related deaths occurred inside the decedents' home (Centers for Disease Control and Prevention (CDC), 2013). Despite the substantial role indoor heat exposure has played in temperature-related mortality, knowledge gaps regarding indoor heat-health thresholds, vulnerability, and adaptive capacity persist. These findings and the scarcity of information on indoor-heat health relationships underscore the importance of characterizing harmful indoor conditions and including estimates of heat indoor exposure in population-based health studies.

Because strong and complex relationships exist among climate, local meteorology, and urban air quality (Fiore et al., 2015; Jacob and Winner, 2009), climate change related shifts in the relative magnitude of corresponding variables may impact the indoor environment through outdoor-to-indoor transport. Furthermore, more extreme conditions ushered in by climate change may cause increased failure of critical infrastructures (e.g. power grids) and disruption to residential HVAC systems (Institute of Medicine (IOM), 2011), resulting in prolonged exposure to indoor temperature extremes. Although the impacts of climate change have serious consequences for urban populations, the body of research at the intersection of climate change, indoor and outdoor air pollution and temperature, and population health is very small, and the data necessary to answer research questions at this nexus are limited. Generally speaking, estimates of future ambient air quality and temperature are numerous, robust, and publicly available for use in analyses. Various studies have used these datasets to perform climate risk assessments (Abatzoglou and Williams, 2016; Campbell-Lendrum and Woodruff, 2006; Chang et al., 2014; Hodges et al., 2014; Spracklen et al., 2009), evaluate the benefits of mitigation and quantify avoided impacts on physical, managed, and societal systems (Harlan and Ruddell, 2011; O'Neill et al., 2018), and estimate future impacts of ambient exposure on human health (Chang et al., 2010; Huang et al., 2011; Peng et al., 2011; Sujaritpong et al., 2014). Conversely, future estimates of indoor air pollution and indoor heat exposure are not yet established, and future scenarios of socio-economic or infrastructure influences on indoor air [e.g. building practices, changes in energy systems, and alternative transportation systems (electric cars)] are very limited or data are not available at scales relevant for indoor air-health modeling (Marsha et al., 2018). Thus, this is an area of research with considerable potential for growth, and the cities where these data already exist can be studied to advance the modeling of future health risks.

3. Connecting vulnerability science and epidemiology

In risk and vulnerability studies across disciplines, societal, individual, and geographic characteristics have been considered, with varying degrees of significance. While the notions of population risk and vulnerability are present in both health and social sciences, their framing, the characterization of indicators, and the analytical approaches vary, and are largely dependent upon the underlying school of thought as well as the key research questions.

Through a socio-ecological lens, vulnerability determines the extent to which a socio-ecological system or a group of people is susceptible to environmental hazards, and is often defined as a function of exposure, sensitivity, and adaptive capacity (Adger, 2006; Field et al., 2014). Socio-ecological frameworks and approaches to risk and vulnerability assessments (e.g. place-based vulnerability, assets-based, and sustainable livelihood approaches) typically evaluate the impacts of environmental hazards through the lens of social inequities, damages to assets, loss of livelihoods, and/or disparate experiences with external stressors (Cutter et al., 2010; Department for International Development (DFID), 1999; Polsky et al., 2007; Smit and Wandel, 2006; Turner et al., 2003), but rarely through health outcomes. The sustainable livelihood framework, for example, focuses on the relationships between environmental hazards and the assets that the households have access to in order to mitigate negative impacts of shocks and stressors. Here, the main focus is on the impact of loss of livelihood with indicators of vulnerability representing risk due to differential access to financial, human, natural, physical and social capitals (74). This and other vulnerability science frameworks [for reviews, see (Eakin and Luers, 2006), (Adger, 2006), (Preston et al., 2011), (Birkmann et al., 2013)] emphasize the *social construction of risk*. Vulnerability research, rooted in geography, human security, natural hazards, and human ecology, shows that risk and vulnerability are disproportionately distributed among certain socio-demographic groups and geographic locations (Burton, 1993; Hewitt, 1983; Wisner et al., 2004). With regard to the impacts of extreme heat and air pollution on human health, neighborhood and household characteristics as well as human behavior have been shown to influence risk (Hayden et al., 2011; Hayden et al., 2017). For example, in assessing population vulnerability to heat, (Uejio et al., 2011), (Harlan et al., 2013), (Eisenman et al., 2016) demonstrated that neighborhood-level socio-economic characteristics as well as features of the built environment contributed to the risk of heat-related mortality and morbidity. In a recent study, (Hayden et al., 2017) showed that household-level social and behavioral factors, such as access to social networks and use of protective measures, are important considerations in understanding heat-health risks.

The epidemiological approach, commonly used in health sciences, has traditionally evaluated the health impacts of environmental exposures on "vulnerable" populations (Benmarhnia et al., 2015; Gronlund et al., 2015; O'Lenick et al., 2017; O'Neill, 2003; Rappold et al., 2012; Reid et al., 2016; Schwartz, 2005; Stafoggia et al., 2006), but has not fully integrated vulnerability concepts and influences from a socio-ecological perspective. In population-based epidemiological analyses, associations between exposure characteristics (i.e., geographic, environmental, climatic, air quality characteristics) and health outcomes (morbidity and mortality) are explicitly quantified, while vulnerability is considered through effect measure modification by individual or neighborhood characteristics such as age, income, race/ethnicity or percentage of households living below the Federal poverty line. While population-based epidemiological studies can help identify vulnerable populations, and are statistically rigorous, such studies are observational in nature and not designed to uncover the root causes of vulnerability nor discern nuances within a population that engender risk.

Despite seemingly common goals (e.g., identifying thresholds of harm, explaining attributes of vulnerable systems and linking attributes to outcomes (Eakin and Luers, 2006)), the differences between epidemiological and social-ecological approaches stem from the focus question, the conceptual framing of the problem and the resulting analytical approaches. Traditionally, vulnerability science aimed to better understand the social constructs of risk to livelihoods within the context of environmental exposures, while epidemiological sciences focused on the environmental causes of health risks within the context of socio-demographic influences. Here we argue that an integrative approach that leverages the most robust methods from vulnerability science and epidemiology has the potential to tease apart social-ecological relationships and resolve complex interactions at the climate-health nexus. Recognizing the need for an interdisciplinary approach to better characterize population health risks to extreme heat and air pollution, in Section 4, we propose a conceptual and analytical framework that unites social-ecological science and epidemiology. In doing so, our framework illustrates how diverse data sources can be integrated to explicitly include traditional social-ecological indicators of population vulnerability within a health model.

4. Framing vulnerability in health risk analyses

In 2012, a Special Report on Extremes by the Intergovernmental Panel on Climate Change (IPCC) proposed a risk framework, which was adopted by the IPCC Fifth Assessment Report (AR5) and published in 2014 (Oppenheimer et al., 2014). The updated IPCC risk framework in AR5 characterizes risk as a function of hazard, exposure and vulnerability, with vulnerability consisting of the sensitivity and adaptive capacity components of the earlier IPCC frameworks. This new framing of risk more closely aligns with the epidemiological approach while incorporating elements of the socio-ecological characterization of vulnerability. In Fig. 1, we adapt the AR5 conceptualization of risks, hazards and vulnerability as well as the external climatic drivers and socioeconomic processes, to propose a conceptual and analytical framework for assessing population health risks from indoor and outdoor exposures to extreme heat and air pollution. In Fig. 1, we define health risk as a function of extreme heat and air pollution events (hazards), population sensitivity and adaptive capacity (vulnerability) and indoor and outdoor exposure to heat and air quality (exposure). These interrelated components of health risk are influenced by climate variability and change as well as current and future socioeconomic processes that may determine the extent to which communities and infrastructure are exposed and vulnerable. For example, socioeconomic processes at the national, regional, or local level could determine the use of clean energy technology for power generation, the reinforcement of existing infrastructure, and/or the availability and affordability of transportation options that are less polluting (e.g. electric cars, public transportation), as well as future land use and building design policies that may impact indoor and outdoor air. Similarly, socioeconomic processes could lead to socio-demographic shifts (e.g. urbanization, a growing elderly population) that influence exposure-response relationships and health risk. The Shared Socioeconomic Pathways introduced by O'Neill et al. (2014) are useful for understanding how socio-demographics may change (or not) in the future and how shifts in population dynamics may affect health risk related to extreme heat and air pollution (O'Neill et al., 2014).

4.1. Integrating indoor exposure and vulnerability in health models

While the conceptual framework (Fig. 1) demonstrates the broad relationships among climate-sensitive exposures, vulnerability, and health outcomes as they relate to indoor and outdoor air pollution and extreme heat, our analytical framework, illustrated in Fig. 2,

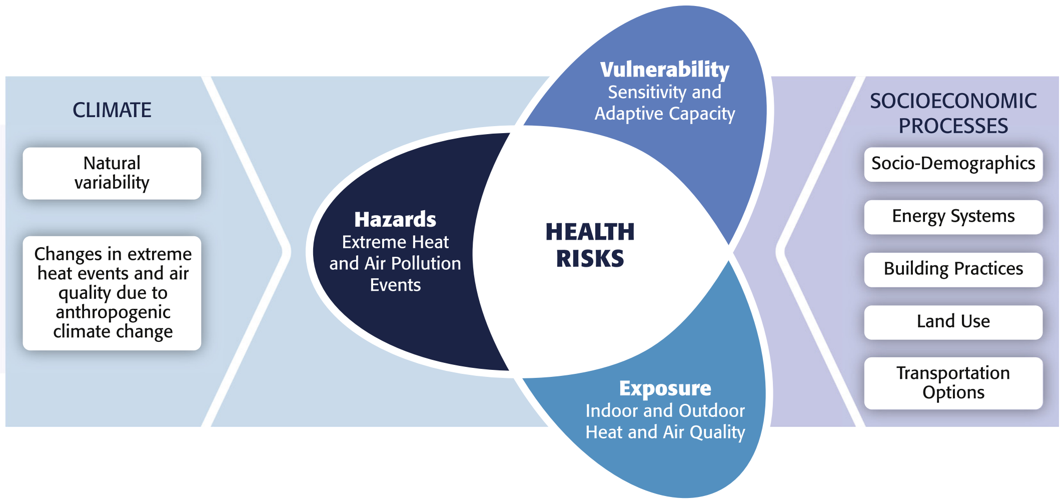

Fig. 1. Conceptual framework for assessing population health risks to extreme heat and air pollution. Based on Figure SPM.1 from Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

demonstrates how these concepts can be integrated into an epidemiological study. Fig. 2 presents indicators of vulnerability at the individual level; however, vulnerability can operate at the community level or higher (e.g. census tract or county percentage of the households below the Federal poverty line). Based on the relationships demonstrated in Fig. 2, indicators of *exposure* to outdoor and indoor environments lie along the causal pathway and are associated with adverse health outcomes (e.g. mortality and morbidity). Indicators of *sensitivity* and *adaptive capacity* (i.e. indicators of vulnerability) may act as effect measure modifiers on exposure-health associations. Although this conceptualization is well aligned with traditional air pollution-epidemiology, unlike the vast majority of air pollution-health studies, our framework distills vulnerability into its component parts. In doing so, it provides a mechanism to reduce vulnerability and adverse impacts within a socio-ecological system, since it is through responding to the root causes of vulnerability that health impacts can effectively be addressed (Hayes, 1991; Ribot et al., 1996; Wilhelmi and Hayden, 2010). Although, the intended use of our framework is to guide epidemiological studies with the objective of estimating associations between indoor and outdoor air quality and health, the framework is appropriate as a reference for any environmental health study that seeks to better elucidate the influence of population vulnerability on exposure-health relationships.

4.2. Indicators and data sources

Within Fig. 2, the exposure and vulnerability domains consist of a set of dynamic, spatially variable indicators that can be measured and included in causal analyses. Boxes with dashed borders represent parameters or concepts for which knowledge and data are lacking or uncertainty is high. In the *exposure* domain, outdoor air pollution and meteorological parameters are well estimated compared to indoor conditions. In air pollution-health studies, ambient air pollution metrics are almost always derived from quantitative modeled or measured data, and numerous methods are employed to estimate exposure to ambient conditions including measurements from fixed-site ambient monitors,

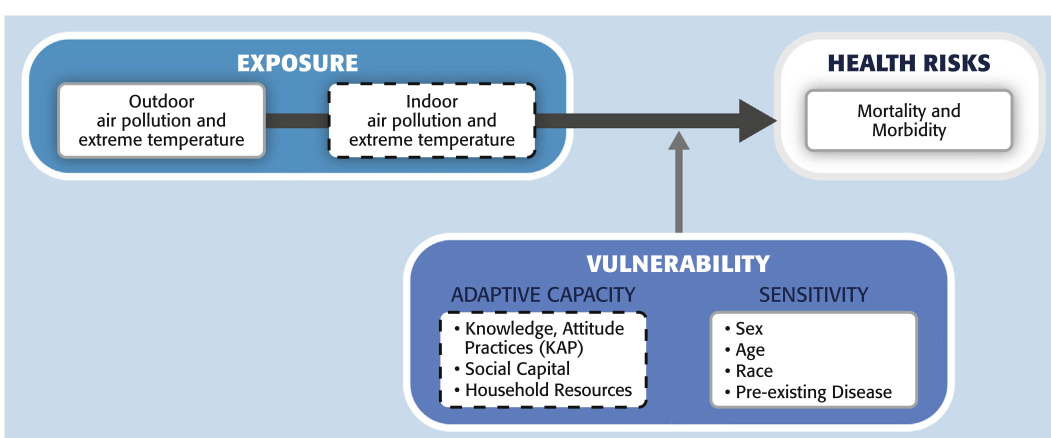

Fig. 2. Analytical framework for assessing population health risks from indoor and outdoor exposures to extreme heat and air pollution. This framework defines exposure as the physical characteristics of the ambient and indoor environment that directly that affect the severity of harm (i.e. mortality and morbidity); sensitivity as the physiological, health, and social factors that influence a population's likelihood of harm; and adaptive capacity as the potential to modify features and behaviors to better cope with or adapt to existing and anticipated hazards or stressors. Similar conceptualizations are commonly used in assessments of population vulnerability to climate and weather hazards (Morss et al., 2011; Polsky et al., 2007; Turner et al., 2003; Wilhelmi and Hayden, 2010). Indicators of sensitivity and adaptive capacity may act as effect measure modifiers of exposure-health relationships and may operate at multiple scales (e.g. individual-level, neighborhood level). Boxes with dashed borders represent parameters or concepts for which knowledge and data are lacking or uncertainty is high.

spatial interpolation, population-weighted exposure metrics (Ivy et al., 2008), chemical transport model simulations (e.g. Community Multiscale Air Quality Model), population exposure models (e.g. Stochastic Human Exposure and Dose Simulation), statistical downscaling (Berrocal et al., 2010; Crooks and Özkaynak, 2014), and data fusion models in which data from monitoring networks are combined with model output (Choi et al., 2009; Friberg et al., 2016; Fuentes and Raftery, 2005; Lindström et al., 2014; McMillan et al., 2010; Wilton et al., 2010). Similar methods are used to estimate meteorological parameters and exposure to extreme temperature (Guo et al., 2013; Habeeb et al., 2015; Hu et al., 2014; Kloog et al., 2014; Lee et al., 2016; Li and Bou-Zeid, 2013; Monaghan et al., 2014; Shi et al., 2016). Although high-resolution spatial and temporal estimates of indoor air quality can be measured at individual buildings, this is costly and time-consuming. Therefore, in place of modeled or measured indoor air quality data, proxy data such as building age and air exchange rates have been used in epidemiological studies (Chen et al., 2012; Sarnat et al., 2013). However, such indicators are typically averaged over long temporal scales (months or years) and do not attempt to characterize indoor air pollution and thermal comfort within buildings. In Section 5, we introduce a methodology that uses building energy models to simulate daily estimates of indoor air quality and indoor heat exposure for use in time-series epidemiological models.

The *vulnerability* domain encompasses two interconnected components: sensitivity and adaptive capacity. Conceptually, vulnerability can operate at multiple scales and potentially modify health associations. In our framework, the *sensitivity* construct suggests that vulnerability is not solely dependent on physical proximity to the source of the exposure (Wilhelmi and Hayden, 2010), but rather the intersection of exposure and socio-demographic factors that can influence inequalities and differential ability to respond to hazardous conditions. Indicators of sensitivity are typically fixed individual characteristics (e.g. age, sex, race, socioeconomic status, pre-existing disease) or immutable area-level features and are often considered as modifiers in epidemiological studies to identify vulnerable groups or risk factors. For example, pre-existing health conditions, lack of mobility, lower socio-economic status, and social isolation all contributed to increased vulnerability and adverse health outcomes among the elderly during recent extreme heat events in the U.S. and Europe (Fouillet et al., 2006; Naughton et al., 2002; Semenza et al., 1996; Wilhelmi et al., 2012). Indicators of sensitivity can be derived from aggregate census data (e.g. neighborhood-level poverty), from individual health records (age, sex, race), and from household-level survey data (Hayden et al., 2017).

Adaptive capacity refers to individual or community-based coping and adapting mechanisms that are modifiable behaviors or circumstances. With regard to indoor air quality and thermal comfort, coping mechanisms include spending less time outdoors when the air quality is poor, well-functioning HVAC systems, and access to air-conditioned shelters (e.g., cooling centers). Barriers (e.g. economic constraints, perceptions of risk) to the use of existing coping mechanisms are also important indicators of adaptive capacity. Certain adaptive capacity data, such as the prevalence of air conditioning (AC), can be obtained from publically available datasets like the US Census American Housing Survey (Bell et al., 2009) or local tax assessor's databases (Harlan et al., 2013; Heaton et al., 2014). Adaptive capacity data can also be modeled using existing data sources. For example, Fraser et al. (2017) modeled access to publicly cooled spaces at the household level for Maricopa County, AZ and Los Angeles County, CA using tax assessor data, publicly available addresses of official cooling centers, and property assessment records. Based on their methodology, indicators of adaptive capacity (e.g. access to a cooling center) can be modeled at the household level and aggregated to other spatial scales (Fraser et al., 2017). Measuring behavioral factors of adaptive capacity, such as knowledge, attitude, and practices or AC use often requires using both quantitative (e.g., survey) and qualitative (e.g., open-ended survey questions; interviews) methods (Wilhelmi and Hayden, 2010). Prior research has utilized household-level survey data to characterize sensitivity and adaptive capacity among a study population (Hayden et al., 2011; Hayden et al., 2017), and to develop/validate composite indices of vulnerability or socioeconomic status (Fekete, 2009). Owing to the difficulty of measuring and obtaining data on adaptive capacity, this aspect of population vulnerability is not often included in epidemiological studies, and household-level adaptive capacity is not well-characterized among urban populations.

4.3. Operationalizing the framework for health studies

Our framework for assessing population health risks from indoor and outdoor exposures to extreme heat and air pollution endorses the use of diverse data types to address gaps in our understanding of current and future health risks from exposure to heat and air pollution. However, combining environmental, demographic, health, household survey, climate change, and building characteristic data into a generalizable and interpretable model requires careful consideration of the relevant temporal and spatial scales of analysis as well as appropriate statistical approaches for integrating spatio-temporal data. Typically, the temporal and spatial scale of analysis will be determined by the health data (e.g. daily mortality counts aggregated to census tract level). *Exposure* (outdoor and indoor conditions) and covariate data (e.g. meteorology) are then estimated at the relevant scales and linked to the health data. Individual and area-level data within the *vulnerability* domain can be evaluated for significant influences on health in several ways: (1) as interaction terms; (2) by comparing health models that are stratified on certain characteristics (e.g. male verses female); or (3) vulnerability data can be included as spatially varying covariates within a hierarchical model and tested for statistical interaction. Common statistical approaches that integrate data with complex spatio-temporal dependencies include Poisson regression, conditional logistic regression [case-crossover, e.g. (Carracedo-Martinez et al., 2010)], Bayesian hierarchical models, and latent Gaussian models with integrated nested Laplase Approximations.

5. Indicators of indoor exposure and adaptive capacity as model inputs

With regard to health studies estimating the effects of indoor and outdoor air pollution and heat on health, our framework suggests that knowledge gaps and uncertainty tend to be greater for indicators of indoor exposure and adaptive capacity compared to indicators of outdoor exposure and sensitivity (Fig. 2). This is a common limitation in this field, and numerous researchers have discussed how these knowledge gaps may result in under-informed risk assessments and policies, particularly relating to heat exposure (Harlan and Ruddell, 2011; Kuras et al., 2017; Morss et al., 2011; Wilhelmi and Hayden, 2010). More generally, to advance vulnerability and health research on climate sensitive exposures, innovative methods to better quantify personal exposure and adaptive capacity are necessary to advance our understanding of population risk. However, to improve estimation of indoor conditions and adaptive capacity, we argue that it is critical to integrate household survey data into these efforts. In this section, we briefly describe how household-level survey data can be utilized to develop indicators of vulnerability and inform indoor exposure estimation for the population under observation. We also introduce a novel approach for simulating daily estimates of indoor exposure for use in epidemiological models.

5.1. Adaptive capacity

Although household-level surveys provide robust and nuanced data for understanding population vulnerability, very few studies have used survey data as *inputs* into spatio-temporal health models (Acosta-Michlik and Rounsevell, 2008). However, household-level survey data that is representative of the study population can be a useful tool to develop indicators of population adaptive capacity with high internal validity, validate vulnerability assessments based on socio-demographic data obtained from public databases (e.g. American Community Survey), and contextualize results from epidemiological models. At the top of Fig. 3, we illustrate how the peer-reviewed literature and our framework can be used to design household-level surveys for informing indoor air models and characterizing population vulnerability to air pollution and heat, indoors and outdoors. We envision household-level survey development to be an iterative process that is informed initially by the overarching research design, the peer-reviewed literature, and which aspects of vulnerability investigators must define in order to address research objectives. In the context of characterizing a population's adaptive capacity to heat and air pollution, household-level survey data can be used to define indicators of adaptive capacity that are relevant for a given population (e.g. perceptions of risk, access to cooling centers, sources of information). As shown in Fig. 2, such indicators can be directly inputed into a health model as effect measure modifiers or covariates. We also argue that household-level survey data can be an extremely rich source of data for researchers who wish to model indoor conditions over a given period of time and study population or use simulations of indoor exposure in a health study. In Section 5.2, we discuss this novel application of household survey data in greater detail.

5.2. Indoor exposure

Physics-based whole-building energy models, originally developed to assess the energy performance of buildings, can estimate thermal conditions as well as air quality inside buildings. Existing simulation tools such as EnergyPlus, IES (Integrated Energy Systems), and TRNSYS (Transient System Simulations) dynamically solve mass and energy balance equations of a building in response to an outdoor signal under a certain operation scheme (Crawley et al., 2001). Outputs from these models are highly accurate in estimating different indoor exposure parameters inside buildings when all relevant building characteristics (e.g., envelope thermal properties, geometry, glazing properties), hourly outdoor weather and air quality data, and occupant behavior are properly inputted into the model (Witte et al., 2001). Household-level survey data can be used to inform operation schemes of building energy models by providing relevant inputs for indoor air simulations

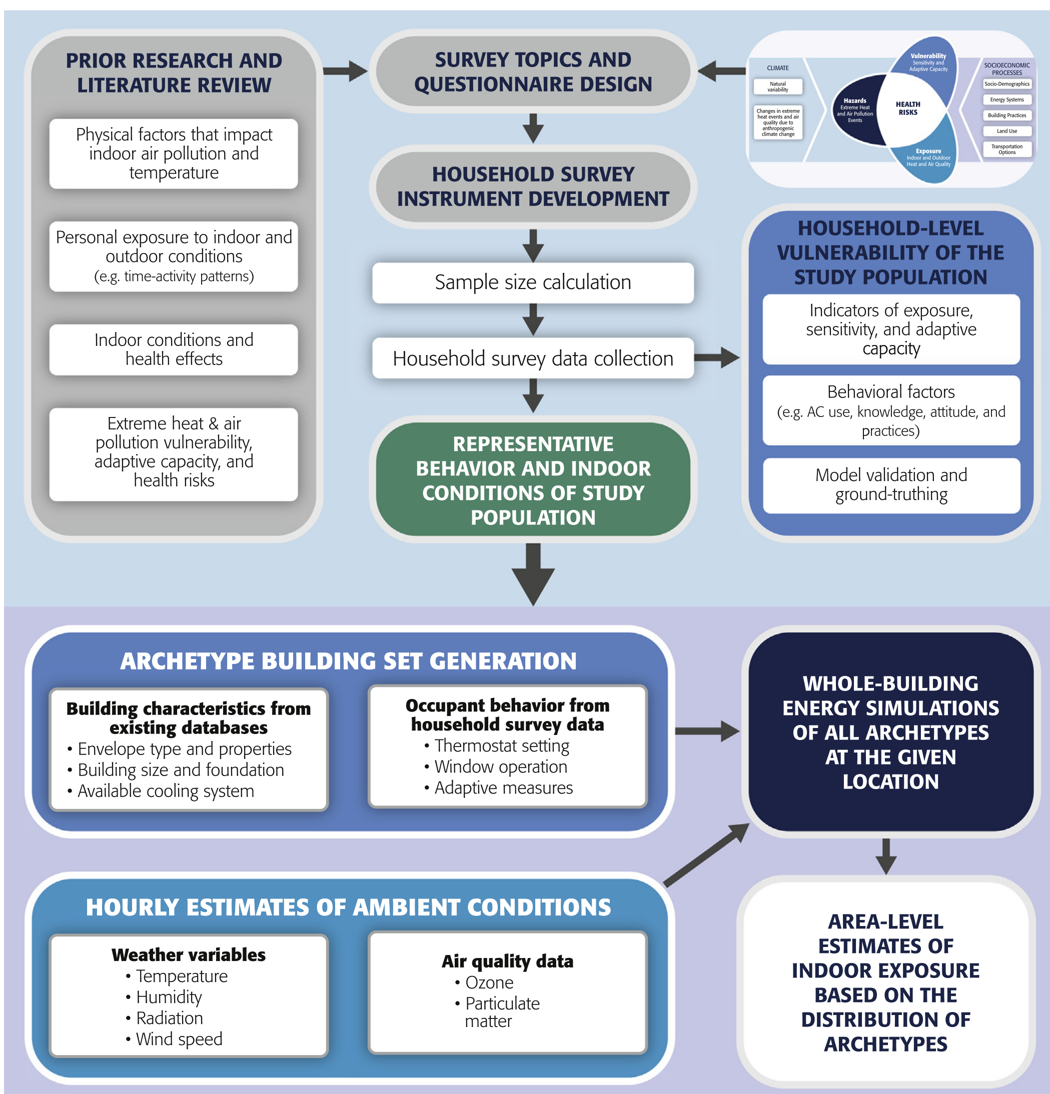

Fig. 3. Utilizing household-level survey data to better understand population health risks from indoor and outdoor exposures to extreme heat and air pollution. The top of this figure illustrates how household-level surveys can characterize population vulnerability and identify factors and behaviors that influence exposure to air pollution and extreme heat, indoors and outdoors. The bottom of this figure demonstrates how various inputs from diverse datasets, including household-level surveys, can be integrated to inform building energy models and support estimation of indoor air quality and thermal comfort.

(e.g. window operation strategy) or by helping to define a distribution of human behaviors and indoor conditions across the target population (e.g. temperature settings, presence of mold, experience with power outages, and presence and functioning of HVAC systems) (Fig. 3). By characterizing the spatial and/or socio-economic distribution of factors that influence exposure to indoor heat and air pollution, a variety of experiences can be simulated with building energy models (under available weather and building data) and uncertainty in indoor exposure estimation can be explored in a variety of contexts, including health studies and risk assessments.

When individual building characteristics are not available, researchers often use archetype buildings that provide reliable estimates of the average performance of the building stock in a specified area. The bottom of Fig. 3 illustrates the process of using archetype building simulations to estimate indoor air quality/thermal comfort over a large sample of buildings within a specified area using ambient monitor data, household-level survey data, and multiple, publicly available data sources (e.g., Residential Energy Consumption survey data or local tax assessor's data). Depending on the type of data available, more than one archetype could be developed for each spatial boundary. In such cases, indoor air quality or thermal comfort metrics would be weighed based on their prevalence in the sample and would be representative of indoor exposure for a specified area over a specified period of time. The result would be a time-series of desired indoor exposure parameters at any spatial and temporal resolution requested, over a simulated period. Building energy models combined with diverse datasets can predict almost all variables pertinent to indoor air quality and thermal comfort, and can be employed as an innovative tool for improving estimates of indoor exposure at the household or neighborhood level (Baniassadi and Sailor, 2018).

6. Conclusion

Coupled global and regional model simulations suggest that climate change will disproportionately impact urban populations through the projected worsening of air quality and more frequent and severe episodes of extreme heat, which in turn could affect the quality of indoor environments. Concomitantly, population growth and urbanization are projected to add another 2.5 billion people to the world's urban population by 2050 (United Nations, 2015). Given these projected changes, a better understanding of the interactions between indoor and outdoor air pollution and temperature, population vulnerability, disease etiology, and climate change is necessary to protect human health now and in the future. In addition, including estimates of indoor exposures in population-based studies may result in more accurate risk assessments and better-targeted policies that protect human health. Our framework aims to better characterize health risk from indoor and outdoor air pollution and extreme heat and illustrates how social-ecological indicators of population vulnerability can be fully integrated within a health model. Our framework and methods are broadly applicable across U.S. cities, and represent novel resources for the evaluation of health risks from extreme heat and air pollution.

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References

Abatzoglou, J.T., Williams, A.P., 2016. Impact of anthropogenic climate change on wildfire across western US forests. Proc. Natl. Acad. Sci. U. S. A. 113, 11770–11775.

Acosta-Michlik, L., Rounsevell, M., 2008. An agent-based framework for assessing vulnerability futures assessing. In: Patt, A.G., Schroter, D., RJT, Klein, Vega-Leinert, A.C. (Eds.), Assessing Vulnerability to Global Environmental Change. Earthscan, Sterling, VA, pp. 147–171.

Adger, W.N., 2006. Vulnerability. Glob. Environ. Chang. 16, 268–281.

Anderson, G.B., Dominici, F., Wang, Y., McCormack, M.C., Bell, M.L., Peng, R.D., 2013. Heat-related emergency hospitalizations for respiratory diseases in the medicare population. Am. J. Respir. Crit. Care Med. 187, 1098–1103.

Baniassadi, A., Sailor, D.J., 2018. Synergies and trade-offs between energy efficiency and resiliency to extreme heat – a case study. Build. Environ. 132, 263–272.

Basu, R., 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol. Rev. 24, 190–202.

Basu, R., 2009. High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ. Health 8, 40.

Basu, R., Malig, B., 2011. High ambient temperature and mortality in California: exploring the roles of age, disease, and mortality displacement. Environ. Res. 111, 1286–1292.

Bell, M.L., Ebisu, K., Peng, R.D., Dominici, F., 2009. Adverse health effects of particulate air pollution: modification by air conditioning. Epidemiology 20, 682–686.

Benmarhnia, T., Deguen, Sv, Kaufman, J.S., Smargiassi, A., 2015. Vulnerability to heat-related mortality: a systematic review, meta-analysis, and meta-regression analysis. Epidemiology 26, 781–793.

Berrocal, V.J., Gelfand, A.E., Holland, D.M., 2010. A spatio-temporal downscaler for output from numerical models. J. Agric. Biol. Environ. Stat. 15, 176–197.

Birkmann, J., Cardona, O.D., Carreño, M.L., Barbat, A.H., Pelling, M., Schneiderbauer, S., et al., 2013. Framing vulnerability, risk and societal responses: the move framework. Nat. Hazards 67, 193–211.

Braga, A.L.F., Zanobetti, A., Schwartz, J., 2002. The effect of weather on respiratory and cardiovascular deaths in 12 U.S. cities. Environ. Health Perspect. 110, 859–863.

Bunker, A., Wildenhain, J., Vandenbergh, A., Henschke, N., Rocklöv, J., Hajat, S., et al., 2016. Effects of air temperature on climate-sensitive mortality and morbidity outcomes in the elderly; a systematic review and meta-analysis of epidemiological evidence. EBioMedicine 6, 258–268.

Burton, I., 1993. The Environment as Hazard. 2nd ed. The Guildford Press, New York, NY.

Campbell-Lendrum, D., Woodruff, R., 2006. Comparative risk assessment of the burden of disease from climate change. Environ. Health Perspect. 114, 1935–1941.

Carracedo-Martinez, E., Taracido, M., Tobias, A., Saez, M., Figueiras, A., 2010. Case-crossover analysis of air pollution health effects: a systematic review of methodology and application. Environ. Health Perspect. 118, 1173–1182.

Carreras, H., Zanobetti, A., Koutrakis, P., 2015. Effect of daily temperature range on respiratory health in Argentina and its modification by impaired socio-economic conditions and pm10 exposures. Environ. Pollut. 206, 175–182.

Centers for Disease Control and Prevention (CDC), 2013. Heat illness and deaths–New York City, 2000–2011. MMWR Morb. Mortal. Wkly Rep. 62, 617–621.

Chang, H.H., Zhou, J., Fuentes, M., 2010. Impact of climate change on ambient ozone level and mortality in southeastern United States. Int. J. Environ. Res. Public Health 7, 2866–2880.

Chang, H.H., Hao, H., Sarnat, S.E., 2014. A statistical modeling framework for projecting future ambient ozone and its health impact due to climate change. Atmos. Environ. 89, 290–297.

Chen, C., Zhao, B., Weschler, C.J., 2012. Assessing the influence of indoor exposure to "outdoor ozone" on the relationship between ozone and short-term mortality in U.S. communities. Environ. Health Perspect. 120, 235–240.

Cheng, J., Xu, Z., Zhu, R., Wang, X., Jin, L., Song, J., et al., 2014. Impact of diurnal temperature range on human health: a systematic review. Int. J. Biometeorol. 58, 2011–2024.

Choi, J., Fuentes, M., Reich, B.J., 2009. Spatial–temporal association between fine particulate matter and daily mortality. Comput. Stat. Data Anal. 53, 2989–3000.

Conlon, K., Monaghan, A., Hayden, M., Wilhelmi, O., 2016. Potential impacts of future warming and land use changes on intra-urban heat exposure in Houston, Texas. PLoS One 11, e0148890.

Crawley, D.B., Lawrie, L.K., Winkelmann, F.C., Buhl, W.F., Huang, Y.J., Pedersen, C.O., et al., 2001. Energyplus: creating a new-generation building energy simulation program. Energ. Buildings 33, 319–331.

Crooks, J.L., Özkaynak, H., 2014. Simultaneous statistical bias correction of multiple pm2.5 species from a regional photochemical grid model. Atmos. Environ. 95, 126–141.

Cutter, S.L., Burton, C.G., Emrich, C.T., 2010. Disaster resilience indicators for benchmarking baseline conditions. J. Homel. Secur. Emerg. Manag. 7.

Department for International Development (DFID), 1999. Sustainable Livelihoods Guidance Sheets (London).

Dockery, D.W., Pope 3rd, C.A., 1994. Acute respiratory effects of particulate air pollution. Annu. Rev. Public Health 15, 107–132.

Dockery, D.W., Pope, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., et al., 1993. An association between air pollution and mortality in six U.S. cities. N. Engl. J. Med. 329, 1753–1759.

Dominici, F., Peng, R.D., Bell, M.L., Pham, L., McDermott, A., Zeger, S.L., et al., 2006. Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA 295 (popost1127-1134).

Eakin, H., Luers, A.L., 2006. Assessing the vulnerability of social-environmental systems. Annu. Rev. Environ. Resour. 31, 365–394.

Eisenman, D.P., Wilhalme, H., Tseng, C.H., Chester, M., English, P., Pincetl, S., et al., 2016. Heat death associations with the built environment, social vulnerability and their interactions with rising temperature. Health Place 41, 89–99.

Fekete, A., 2009. Validation of a social vulnerability index in context to river-floods in Germany. Nat. Hazards Earth Syst. Sci. 9, 393–403.

Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., et al. (Eds.), 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge Unite Kingdome and New York, NY, USA).

Fiore, A.M., Naik, V., Leibensperger, E.M., 2015. Air quality and climate connections. J. Air Waste Manage. Assoc. 65, 645–685.

Fouillet, A., Rey, G., Laurent, F., Pavillon, G., Bellec, S., Ghihenneuc-Jouyaux, C., et al., 2006. Excess mortality related to the August 2003 heat wave in France. Int. J. Occup. Environ. Health 80, 16–24.

Fraser, A.M., Chester, M.V., Eisenman, D., Hondula, D.M., Pincetl, S.S., English, P., et al., 2017. Household accessibility to heat refuges: residential air conditioning, public cooled space, and walkability. Environ. Plan. B Urban Anal. City Sci. 44, 1036–1055.

Frey, S.E., Destaillats, H., Cohn, S., Ahrentzen, S., Fraser, M.P., 2014. Characterization of indoor air quality and resident health in an Arizona senior housing apartment building. J. Air Waste Manage. Assoc. 64, 1251–1259.

Friberg, M.D., Zhai, X., Holmes, H.A., Chang, H.H., Strickland, M.J., Sarnat, S.E., et al., 2016. Method for fusing observational data and chemical transport model simulations to estimate spatiotemporally resolved ambient air pollution. Environ. Sci. Technol. 50, 3695–3705.

Fuentes, M., Raftery, A.E., 2005. Model evaluation and spatial interpolation by Bayesian combination of observations with outputs from numerical models. Biometrics 61, 36–45.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., et al., 2015. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375.

Green, R.S., Basu, R., Malig, B., Broadwin, R., Kim, J.J., Ostro, B., 2010. The effect of temperature on hospital admissions in nine California counties. Int. J. Public Health 55, 113–121.

Gronlund, C.J., Berrocal, V.J., White-Newsome, J.L., Conlon, K.C., O'Neill, M.S., 2015. Vulnerability to extreme heat by socio-demographic characteristics and area green space among the elderly in Michigan, 1990–2007. Environ. Res. 136, 449–461.

Guo, Y., Barnett, A.G., Tong, S., 2013. Spatiotemporal model or time series model for assessing city-wide temperature effects on mortality? Environ. Res. 120, 55–62.

Habeeb, D., Vargo, J., Stone, B., 2015. Rising heat wave trends in large us cities. Nat. Hazards 76, 1651–1665.

Harlan, S.L., Ruddell, D.M., 2011. Climate change and health in cities: impacts of heat and air pollution and potential co-benefits from mitigation and adaptation. Curr. Opin. Environ. Sustain. 3, 126–134.

Harlan, S.L., Declet-Barreto, J.H., Stefanov, W.L., Petitti, D.B., 2013. Neighborhood effects on heat deaths: social and environmental predictors of vulnerability in Maricopa County, Arizona. Environ. Health Perspect. 121, 197–204.

Hayden, M.H., Brenkert-Smith, H., Wilhelmi, O.V., 2011. Differential adaptive capacity to extreme heat: a phoenix, Arizona, case study. Weather Clim. Soc. 3, 269–280.

Hayden, M.H., Wilhelmi, O.V., Banerjee, D., Greasby, T., Cavanaugh, J.L., Nepal, V., et al., 2017. Adaptive capacity to extreme heat: results from a household survey in Houston, Texas. Weather Clim. Soc. 9, 787–799.

Hayes, S.R., 1991. Use of an indoor air quality model (IAQM) to estimate indoor ozone levels. J. Air Waste Manage. Assoc. 41, 161–170.

Heaton, M.J., Sain, S.R., Greasby, T.A., Uejio, C.K., Hayden, M.H., Monaghan, A.J., et al., 2014. Characterizing urban vulnerability to heat stress using a spatially varying coefficient model. Spat. Spatio-Temporal Epidemiol. 8, 23–33.

The idea of calamity in a technocratic age. In: Hewitt, K. (Ed.), Interpretation of Calamities. Allen & Unwin Inc., Boston.

Hodges, M., Belle, J.H., Carlton, E.J., Liang, S., Li, H., Luo, W., et al., 2014. Delays in reducing waterborne and water-related infectious diseases in China under climate change. Nat. Clim. Chang. 4, 1109.

Hu, L., Brunsell, N.A., Monaghan, A.J., Barlage, M., Wilhelmi, O.V., 2014. How can we use Modis land surface temperature to validate long-term urban model simulations? J. Geophys. Res. Atmos. 119, 3185–3201.

Huang, C., Barnett, A.G., Wang, X., Vaneckova, P., FitzGerald, G., Tong, S., 2011. Projecting future heat-related mortality under climate change scenarios: a systematic review. Environ. Health Perspect. 119, 1681–1690.

Institute of Medicine (IOM), 2011. Climate Change, the Indoor Environment, and Health. The National Academies Press, Washington, DC.

Ivy, D., Mulholland, J.A., Russell, A.G., 2008. Development of ambient air quality population-weighted metrics for use in time-series health studies. J. Air Waste Manage. Assoc. 58, 711–720.

Jacob, D.J., Winner, D.A., 2009. Effect of climate change on air quality. Atmos. Environ. 43, 51–63.

Jerrett, M., Burnett, R.T., Beckerman, B.S., Turner, M.C., Krewski, D., Thurston, G., et al., 2013. Spatial analysis of air pollution and mortality in California. Am. J. Respir. Crit. Care Med. 188, 593–599.

Jones, A.P., 1999. Indoor air quality and health. Atmos. Environ. 33, 4535–4564.

Kaiser, R., Le Tertre, A., Schwartz, J., Gotway, C.A., Daley, W.R., Rubin, C.H., 2007. The effect of the 1995 heat wave in Chicago on all-cause and cause-specific mortality. Am. J. Public Health 97 (Suppl. 1), S158–S162.

Kinney, P.L., 2018. Interactions of climate change, air pollution, and human health. Curr. Environ. Health Rep. 5 (1), 179–186. https://doi.org/10.1007/s40572-018-0188-x.

Klepeis, N.E., Nelson, W.C., Ott, W.R., Robinson, J.P., Tsang, A.M., Switzer, P., et al., 2001. The national human activity pattern survey (NHAPS): a resource for assessing exposure to environmental pollutants. J. Expo. Anal. Environ. Epidemiol. 11, 231–252.

Klepeis, N.E., Bellettiere, J., Hughes, S.C., Nguyen, B., Berardi, V., Liles, S., et al., 2017. Fine particles in homes of predominantly low-income families with children and smokers: key physical and behavioral determinants to inform indoor-air-quality interventions. PLoS One 12, e0177718.

Kloog, I., Nordio, F., Coull, B.A., Schwartz, J., 2014. Predicting spatiotemporal mean air temperature using modis satellite surface temperature measurements across the northeastern USA. Remote Sens. Environ. 150, 132–139.

Kovats, R.S., Hajat, S., Wilkinson, P., 2004. Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in greater London, UK. Occup. Environ. Med. 61, 893–898.

Kuras, E.R., Richardson, M.B., Calkins, M.M., Ebi, K.L., Hess, J.J., Kintziger, K.W., et al., 2017. Opportunities and challenges for personal heat exposure research. Environ. Health Perspect. 125, 085001.

Laaidi, K., Zeghnoun, A., Dousset, B., Bretin, P., Vandentorren, S., Giraudet, E., et al., 2012. The impact of heat islands on mortality in Paris during the August 2003 heat wave. Environ. Health Perspect. 120, 254–259.

Lee, M., Shi, L., Zanobetti, A., Schwartz, J.D., 2016. Study on the association between ambient temperature and mortality using spatially resolved exposure data. Environ. Res. 151, 610–617.

Li, D., Bou-Zeid, E., 2013. Synergistic interactions between urban heat islands and heat waves: the impact in cities is larger than the sum of its parts. J. Appl. Meteorol. Climatol. 52, 2051–2064.

Li, S., Baker, P.J., Jalaludin, B.B., Marks, G.B., Denison, L.S., Williams, G.M., 2014. Ambient temperature and lung function in children with asthma in Australia. Eur. Respir. J. 43, 1059–1066.

Lin, S., Luo, M., Walker, R.J., Liu, X., Hwang, S.A., Chinery, R., 2009. Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. Epidemiology 20, 738–746.

Lindström, J., Szpiro, A.A., Sampson, P.D., Oron, A.P., Richards, M., Larson, T.V., et al., 2014. A flexible spatio-temporal model for air pollution with spatial and spatio-temporal covariates. Environ. Ecol. Stat. 21, 411–433.

Luber, G., McGeehin, M., 2008. Climate change and extreme heat events. Am. J. Prev. Med. 35, 429–435.

Marsha, A., Sain, S.R., Heaton, M.J., Monaghan, A.J., Wilhelmi, O.V., 2018. Influences of climatic and population changes on heat-related mortality in Houston, Texas, USA. Clim. Chang. 146, 471–485.

McCormack, M.C., Belli, A.J., Waugh, D., Matsui, E.C., Peng, R.D., Williams, D.A.L., et al., 2016. Respiratory effects of indoor heat and the interaction with air pollution in chronic obstructive pulmonary disease. Ann. Am. Thorac. Soc. 13, 2125–2131.

McMillan, N.J., Holland, D.M., Morara, M., Feng, J., 2010. Combining numerical model output and particulate data using Bayesian space–time modeling. Environmetrics 21, 48–65.

Mendell, M.J., Mirer, A.G., Cheung, K., Tong, M., Douwes, J., 2011. Respiratory and allergic health effects of dampness, mold, and dampness-related agents: a review of the epidemiologic evidence. Environ. Health Perspect. 119, 748–756.

Michelozzi, P., Accetta, G., De Sario, M., D'Ippoliti, D., Marino, C., Baccini, M., et al., 2009. High temperature and hospitalizations for cardiovascular and respiratory causes in 12 European cities. Am. J. Respir. Crit. Care Med. 179, 383–389.

Mitchell, C.S., Zhang, J.J., Sigsgaard, T., Jantunen, M., Lioy, P.J., Samson, R., et al., 2007. Current state of the science: health effects and indoor environmental quality. Environ. Health Perspect. 115, 958–964.

Monaghan, A.J., Hu, L., Brunsell, N.A., Barlage, M., Wilhelmi, O.V., 2014. Evaluating the impact of urban morphology configurations on the accuracy of urban canopy model temperature simulations with Modis. J. Geophys. Res. Atmos. 119, 6376–6392.

Morss, R.E., Wilhelmi, O.V., Meehl, G.A., Dilling, L., 2011. Improving societal outcomes of extreme weather in a changing climate: an integrated perspective. Annu. Rev. Environ. Resour. 36, 1–25.

Naughton, M.P., Henderson, A., Mirabelli, M.C., Kaiser, R., Wilhelm, J.L., Kieszak, S.M., et al., 2002. Heat-related mortality during a 1999 heat wave in Chicago. Am. J. Prev. Med. 22, 221–227.

O'Lenick, C.R., Winquist, A., Chang, H.H., Kramer, M.R., Mulholland, J.A., Grundstein, A., et al., 2017. Evaluation of individual and area-level factors as modifiers of the association between warm-season temperature and pediatric asthma morbidity in Atlanta, GA. Environ. Res. 156, 132–144.

Oleson, K.W., Monaghan, A., Wilhelmi, O., Barlage, M., Brunsell, N., Feddema, J., et al., 2015. Interactions between urbanization, heat stress, and climate change. Clim. Chang. 129, 525–541.

O'Neill, M.S., 2003. Modifiers of the temperature and mortality association in seven us cities. Am. J. Epidemiol. 157, 1074–1082.

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., et al., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim. Chang. 122, 387–400.

O'Neill, B.C., Done, J.M., Gettelman, A., Lawrence, P., Lehner, F., Lamarque, J.-F., et al., 2018. The benefits of reduced anthropogenic climate change (brace): a synthesis. Clim. Chang. 146, 287–301.

Oppenheimer, M., Campos, M., Warren, R., Birkmann, J., Luber, G., O'Neill, B., et al., 2014. Emergent risks and key vulnerabilities. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge, United Kingdom and New York, NY, USA. Cambridge University Press.

Peel, J.L., Tolbert, P.E., Klein, M., Metzger, K.B., Flanders, W.D., Todd, K., et al., 2005. Ambient air pollution and respiratory emergency department visits. Epidemiology 16, 164–174.

Peel, J.L., Metzger, K.B., Klein, M., Flanders, W.D., Mulholland, J.A., Tolbert, P.E., 2007. Ambient air pollution and cardiovascular emergency department visits in potentially sensitive groups. Am. J. Epidemiol. 165, 625–633.

Peng, R.D., Bobb, J.F., Tebaldi, C., McDaniel, L., Bell, M.L., Dominici, F., 2011. Toward a quantitative estimate of future heat wave mortality under global climate change. Environ. Health Perspect. 119, 701–706.
Polsky, C., Neff, R., Yarnal, B., 2007. Building comparable global change vulnerability assessments: the vulnerability scoping diagram. Glob. Environ. Chang. 17, 472–485.
Preston, B.L., Yuen, E.J., Westaway, R.M., 2011. Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. Sustain. Sci. 6, 177–202.
Rappold, A.G., Cascio, W.E., Kilaru, V.J., Stone, S.L., Neas, L.M., Devlin, R.B., et al., 2012. Cardio-respiratory outcomes associated with exposure to wildfire smoke are modified by measures of community health. Environ. Health 11, 71.
Reid, C.E., Jerrett, M., Tager, I.B., Petersen, M.L., Mann, J.K., Balmes, J.R., 2016. Differential respiratory health effects from the 2008 northern California wildfires: a spatiotemporal approach. Environ. Res. 150, 227–235.
Ribot, J.C., Magalhaes, A.R., Panagides, S.S. (Eds.), 1996. Climate Variability, Climate Change, and Vulnerability: Moving Forward by Looking Back. Cambridge University Press, Cambridge, UK.
Samet, J.M., Marbuery, M.C., Spengler, J.D., 1987. Respiratory effects of indoor air pollution. J. Allergy Clin. Immunol. 79, 685–700.
Sarnat, J.A., Sarnat, S.E., Flanders, W.D., Chang, H.H., Mulholland, J., Baxter, L., et al., 2013. Spatiotemporally resolved air exchange rate as a modifier of acute air pollution-related morbidity in Atlanta. J. Expo. Sci. Environ. Epidemiol. 23, 606.
Sarnat, S.E., Winquist, A., Schauer, J.J., Turner, J.R., Sarnat, J.A., 2015. Fine particulate matter components and emergency department visits for cardiovascular and respiratory diseases in the St. Louis, Missouri-Illinois, Metropolitan Area. Environ. Health Perspect. 123, 437–444.
Schwartz, J., 2005. Who is sensitive to extremes of temperature?: a case-only analysis. Epidemiology 16, 67–72.
Semenza, J.C., Rubin, C.H., Falter, K.H., Selanikio, J.D., Flanders, W.D., Howe, H.L., et al., 1996. Heat-related deaths during the July 1995 heat wave in Chicago. N. Engl. J. Med. 335, 84–90.
Shi, L., Liu, P., Kloog, I., Lee, M., Kosheleva, A., Schwartz, J., 2016. Estimating daily air temperature across the southeastern United States using high-resolution satellite data: a statistical modeling study. Environ. Res. 146, 51–58.
Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. Glob. Environ. Chang. 16, 282–292.
Spracklen, D.V., Mickley, L.J., Logan, J.A., Hudman, R.C., Yevich, R., Flannigan, M.D., et al., 2009. Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. J. Geophys. Res. Atmos. 114.
Stafoggia, M., Forastiere, F., Agostini, D., Biggeri, A., Bisanti, L., Cadum, E., et al., 2006. Vulnerability to heat-related mortality: a multicity, population-based, case-crossover analysis. Epidemiology 17, 315–323.
Stone, B., Hess, J.J., Frumkin, H., 2010. Urban form and extreme heat events: are sprawling cities more vulnerable to climate change than compact cities? Environ. Health Perspect. 118, 1425–1428.
Strickland, M.J., Darrow, L.A., Klein, M., Flanders, W.D., Sarnat, J.A., Waller, L.A., et al., 2010. Short-term associations between ambient air pollutants and pediatric asthma emergency department visits. Am. J. Respir. Crit. Care Med. 182, 307–316.
Sujaritpong, S., Dear, K., Cope, M., Walsh, S., Kjellstrom, T., 2014. Quantifying the health impacts of air pollution under a changing climate—a review of approaches and methodology. Int. J. Biometeorol. 58, 149–160.
Turner 2nd, B.L., Kasperson, R.E., Matson, P.A., McCarthy, J.J., Corell, R.W., Christensen, L., et al., 2003. A framework for vulnerability analysis in sustainability science. Proc. Natl. Acad. Sci. U. S. A. 100, 8074–8079.
U.S. Environmental Protection Agency, 2009. Integrated Science Assessment (ISA) for Particulate Matter (Final Report, Dec 2009). EPA/600/R-08/139F (Washington, DC).
U.S. Environmental Protection Agency, 2013. Final Report: Integrated Science Assessment of Ozone and Related Photochemical Oxidants. EPA/600/R-10/076F. U.S. Environmental Protection Agency, Washington, DC.
Uejio, C.K., Wilhelmi, O.V., Golden, J.S., Mills, D.M., Gulino, S.P., Samenow, J.P., 2011. Intra-urban societal vulnerability to extreme heat: the role of heat exposure and the built environment, socioeconomics, and neighborhood stability. Health Place 17, 498–507.
Uejio, C.K., Tamerius, J.D., Vredenburg, J., Asaeda, G., Isaacs, D.A., Braun, J., et al., 2016. Summer indoor heat exposure and respiratory and cardiovascular distress calls in New York City, NY, U.S. Indoor Air 26, 594–604.
United Nations, 2015. World Urbanization Prospects: The 2014 Revision. ST/ESA/SER.A/366.
Van Loenhout, J.A., le Grand, A., Duijm, F., Greven, F., Vink, N.M., Hoek, G., et al., 2016. The effect of high indoor temperatures on self-perceived health of elderly persons. Environ. Res. 146, 27–34.
Vinikoor-Imler, L.C., Owens, E.O., Nichols, J.L., Ross, M., Brown, J.S., Sacks, J.D., 2014. Evaluating potential response-modifying factors for associations between ozone and health outcomes: a weight-of-evidence approach. Environ. Health Perspect. 122, 1166–1176.
White-Newsome, J.L., Sanchez, B.N., Jolliet, O., Zhang, Z., Parker, E.A., Dvonch, J.T., et al., 2012. Climate change and health: indoor heat exposure in vulnerable populations. Environ. Res. 112, 20–27.
Wilhelmi, O.V., Hayden, M.H., 2010. Connecting people and place: a new framework for reducing urban vulnerability to extreme heat. Environ. Res. Lett. 5, 014021.
Wilhelmi, O.V., Sherbinin, Ad, Hayden, M.H., 2012. Exposure to heat stress in urban environments: current status and future prospects in a changing climate. In: King, B., Crews, K. (Eds.), Ecologies and Politics of Health. Routledge Press.
Wilton, D., Szpiro, A., Gould, T., Larson, T., 2010. Improving spatial concentration estimates for nitrogen oxides using a hybrid meteorological dispersion/land use regression model in Los Angeles, CA and Seattle, WA. Sci. Total Environ. 408, 1120–1130.
Winquist, A., Grundstein, A., Chang, H.H., Hess, J., Sarnat, S.E., 2016. Warm season temperatures and emergency department visits in Atlanta, Georgia. Environ. Res. 147, 314–323.
Wisner, B., Blaikie, P., Cannon, T., Davis, I., 2004. At risk. Natural Hazards, People's Vulnerability and Disasters, 2 ed..
Witte, M.J., Henninger, R.H., Glazer, J., Crawley, D.B., 2001. Testing and validation of a new building energy simulation program. Proceedings of Building Simulation, pp. 353–360.
Xu, Z., Huang, C., Su, H., Turner, L.R., Qiao, Z., Tong, S., 2013. Diurnal temperature range and childhood asthma: a time-series study. Environ. Health 12, 2–5.
Ye, X., Wolff, R., Yu, W., Vaneckova, P., Pan, X., Tong, S., 2012. Ambient temperature and morbidity: a review of epidemiological evidence. Environ. Health Perspect. 120, 19–28.
Zhou, Y., Shepherd, J.M., 2009. Atlanta's urban heat island under extreme heat conditions and potential mitigation strategies. Nat. Hazards 52, 639–668.