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Approaches for identifying heat-vulnerable populations and locations: A systematic review

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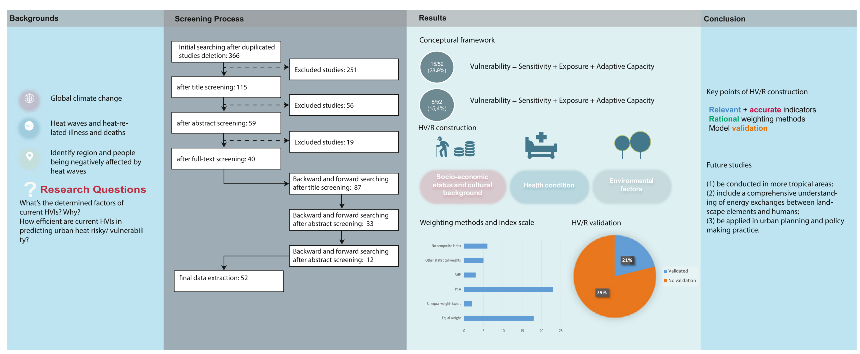
HIGHLIGHTS

- Review indicator selection, weighting method, and validation of heat vulnerability and risk models and indices (HV/R) using PRISMA framework.
- Lack of consistency in theory interpretation and indicator selections
- Both explicit and statistical weighting methods used in constructing HV/Rs have biases.
- No standard criteria to state the efficiency of assessing or predicting heat vulnerability.
- HV/R need to include relevant and accurately measured indicators, select rational weighting methods and conduct model validation.

GRAPHICAL ABSTRACT



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ABSTRACT

Heat related morbidity and mortality, especially during extreme heat events, are increasing due to climate change. More Americans die from heat than from all other natural disasters combined. Identifying the populations and locations that are under high risk of heat vulnerability is important for urban planning and design policy making as well as health interventions. An increasing number of heat vulnerability/risk models and indices (HV/R) have been developed based on indicators related to population heat susceptibility such as sociodemographic and environmental factors. The objectives of this study are to summarize and analyze current HV/R's construction, calculation, and validation, evaluate the limitation of these methods, and provide directions for future HV/R and related studies. This systematic review used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework and used 5 datasets for the literature search. Journal articles that developed indices or models to assess population level heat-related vulnerability or risks in the past 50 years were included. A total of 52 papers were included for analysis on model construction, data sources, weighting schemes and model validation. By synthesizing the findings, we suggested: (1) include relevant and accurately measured indicators; (2) select rational weighting methods and; (3) conduct model validation. We also concluded that it is important for future heat vulnerability models and indices studies to: (1) be conducted in more tropical areas; (2) include a comprehensive understanding of energy exchanges between landscape elements and humans; and (3) be applied in urban planning and policy making practice.

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Contents

1. Introduction

The combination of global climate change and urban heat island intensification is leading to more frequent and more intense heat events, increasing the heat-related risk for populations around the world. Heat waves can result in high numbers of heat-related illnesses and deaths. During 2016–2018, the average heat-related death in U.S. was more than 700 per year (Sheridan et al., 2021).

Exacerbating the impacts of heat are social and economic vulnerabilities experienced by certain populations. Previous epidemiologic studies have identified elevated rates of heat-related morbidity and mortality among the poor, elderly and minority populations in urban neighborhoods (e.g. Harlan et al., 2006; O'Neill, 2003). People with chronic respiratory and cardiovascular diseases are physically more susceptible than the healthy population (McGeehin and Mirabelli, 2001). Inner urban areas that experience higher temperatures because of urban heat islands also have high concentrations of economically disadvantaged and minority populations, leading to higher health risks (Harlan et al., 2006). Low socioeconomic status, high density residential zoning, and age were related with high heat mortality risk in fine-scale (Hondula et al., 2012).

Climate response plans, environmental designs to cool cities down, and behavioral adaptation programs are promising tools to mitigate the health risks of heat (Luber and McGeehin, 2008). In this regard, effective plans and actions by the local governments, agencies, and private sectors are critical in protecting residents from future heat events. However, before any action can be taken, identifying the locations and populations that are highly heat-vulnerable is important for targeted and effective interventions. An increasing number of studies have proposed multi-dimensional heat-related indicators contributing to public hazard vulnerability or risk, which typically refers to the capacity to withstand harm due to exposure to a hazard (Turner et al., 2003), to predict or assess the area and population with great most susceptible to adverse health outcomes. In heat vulnerability assessments, a set of indicators are used to calculated composite Heat Vulnerability/Risk indices and models (HV/R). These indicators use information from previous empirical studies, social theory, and/or local context, including both social economic status, physical environment, and climate related factors.

Before 2000, there were few specific assessments for heat hazard. Cutter et al. (1997) developed the handbook for assessing general hazard zones and social vulnerability using geographic information system (GIS) at the county level, and the method was used by later studies (e.g. Vescovi et al., 2005) to produce maps of estimated public health risk. Between 2000 and 2010, heat vulnerability mapping/modeling studies were still rare. Reid et al. (2009) mapped and analyzed heat vulnerability in 39,794 census tracts in U.S. using ten indicators, which provided a template for mapping regional heat vulnerability. Since 2010, there has been a significant increase in HV/R development around the world. For examples: Wolf and McGregor (2013) used nine indicators for heat exposure and sensitivity in 4765 census districts in Great London in U.K.; Azhar et al. (2017) developed heat wave vulnerability map using 17 indicators for 640 districts in India; Zhang et al. (2018) used 13 indicators to map urban vulnerability in Sydney, Australia; Zheng et al. (2020) used 8 indicators to map heat- related risk in Northern Jiangxi Province of China.

However, the major indicators and model construction methods used in the literature vary considerably, causing challenges in comparing results. Often the indicators used to develop the HV/Rs and the relative weights depended on local data availability and the researcher's subjective judgement. The geographical, demographic and cultural diversity also contributed to the complexity of HV/Rs' development. To discuss the universal versus locally-appropriate approaches and summarize the best practices, there is a need for a systematic review to identify the state of the art methods for construction, composition and validation of these HV/Rs, especially the methodological details such as indicator selection criteria, factor weights, calculation approaches and validation. The objective of this study was to conduct a systematic review of the literature on the methodology of heat vulnerability index development and application, and to evaluate the rigor, validity, and limitations of these methods. The results from this study provide a comprehensive picture of the construction and validation of HV/R, offer directions for future studies to improve the accuracy of heat-related at risk population identification, and facilitate heat-responsive plans and strategies, as well as public health interventions.

2. Method

2.1. Search strategy

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (PRISMA, 2015). The literature search for this systematic review was performed in August 2020. Five databases were queried: Web of Science, PubMed, Scopus, ProQuest and JSTOR, which provide a good coverage of articles in science, social science, and medicine (Singh et al., 2021; Frandsen et al., 2019; Web of Science Core Collection - Web of Science Group, 2019). To ensure that the search captured all relevant studies that involved a heat vulnerability or risk assessment, we included three categories of keywords: a). heat, b) vulnerability or risk, and c) index, approach, model, metric, or map. The search syntax mandated that studies needed to have at least one word from each of the three categories in the title, abstract, or keywords. Wildcards were used whenever possible to make sure alternative forms of the included keywords with truncation were also included. An example of the search syntax is included in Appendix A. In addition to the database search, we used citation chaining by Greenhalgh et al. (2020) and Boland et al., 2017 identifying high-impact articles that met inclusion criteria and identified the their reference lists (backward chaining) and who have cited these articles (forward chaining). Specifically, we selected the top 10 cited studies that met the eligibility criteria, and performed forward and backward searches, followed by screening of all yielded articles to ensure our review set show adequate coverage of relevant materials.

2.2. Eligibility criteria and screening process

Peer-reviewed, English-language journal articles from January 1970 to August 2020 were included. Studies were included if they are:

1. Empirical and population level study;
2. Evaluate heat-related vulnerability or risks, rather than other types of environmental risks;
3. Construct a summary vulnerability index (or several sub-dimensional indices) using multiple indicators, rather than relying on an individual indicator alone;
4. Report data-based results that describe the vulnerability/risk levels across populations/geographies. Geographical scales can be from community to country, regional or continent level.

Studies were excluded if they:

1. Focus on analyzing the association between socioenvironmental factors and heat-related mortality rates without constructing any summary vulnerability/risk index;
2. Use indicators from a single dimension (e.g. social- demographic indicators only);
3. Focus on hazards other than heat.

Title screening, abstract screening, full-text screening and forward/backward searching were included in the process to yield the set of eligible studies. The initial database search yielded a total of 540 records. After removing the duplicates, 366 records remained. After title screening, 115 articles were entered into the next step. The abstract screening excluded 56 articles, and the full-text screening excluded 16 articles; 40 articles were considered eligible. Based on the citation chain search, an initial set of 87 articles were included in the title screening and 12 additional articles were identified as eligible studies. As such, a total of 52 articles were included in the final review set (Fig. 1). Two researchers independently conducted the all of the title screening, overlapped 34.7% (40 out of 115) of abstract screening, and 33.9% (20 out of 59) of full-text screening. The initial agreement rates between two researchers were 98.1% (359 out of 366) for title screening, 75.0% (30 out of 40) for abstract screening, and 80.0% (16 out of 20) for full-text screening. Any discrepancies were resolved by a third researcher. Fig. 1 shows the entire process of identification, screening, eligibility, and inclusion, as well as the number of articles included/excluded in each step.

2.3. Data extraction

We extracted information from each study regarding overall characteristics of the study (publication year, journal field, region/county of the study, climate region, area of study site, urbanicity, total population of study area); indicators used to develop HV/Rs (e.g., theory used for index construction, sub-dimensions, total number of indicators, list of indicators, indicator normalization, and data sources); model construction (e.g., calculation of composite score, metric of the final index); model validation related information (e.g., data used for validation, validation results). The included studies did not miss any information regarding the methodological details. Data compilation, query, summarization, and chart creation were performed using Microsoft Excel 2016.

2.4. Evaluation of bias

As this systematic review focuses on methodological approaches of the development and validation of HV/R, conventional quality assessment and bias evaluation metrics developed for observational and experimental studies may not serve purpose well. Therefore, we generated the metrics by adapting questions from the Office of Health Assessment and Translation (OHAT) Risk of Bias Rating Tool for Human and Animal Studies with customized questions. The OHAT is a tool for evaluating the risk of bias of whether the design and conduct of a study compromised the credibility of the link between exposure and outcome. 10 risk-of-bias questions used in this study are listed in Appendix B. Based on the criteria provided by OHAT, we rated the included articles based on four levels of potential risk of biases: definitely low (++), probably low (+), probably high (−NR), and definitely high (–) (National Toxicology Program, 2015). Upon assigning ratings to each article, the sum of items receiving plus sign was calculated, and the value was further classified as good, fair, or poor. It is worth noting that our evaluation only pertains to the vulnerability modeling methods and therefore may not account for the potential biases of the other aspects of the studies. Overall, 34 (65.4%) papers were in good quality, and 18 (34.6%) were in fair quality. Results of assessments were in Appendix C.

3. Results

3.1. Basic bibliometric profile

Publication year, region/county of the study, climate region, area of study site, urbanicity, total population of study area, as well as disciplines in the publication journals were summarized (Appendix D). Fig. 2 shows the number of published articles from 2005 to 2020, portraying a general steady and continued increase in articles published in this area. There were only two research articles conducted during the 2000s, while 2010s witnessed a considerable growth. Countries where the most number of studies were conducted included United States (19 papers, 36.5%), China (9 papers, 17.3%), and Canada (6 papers, 11.5%). Considering continents, North America (24 papers, 46.2%) had the highest share of study location, followed by Asia (14 papers, 26.9%), Europe (7 papers, 13.5%). Oceania (3 papers, 5.7%), Lating

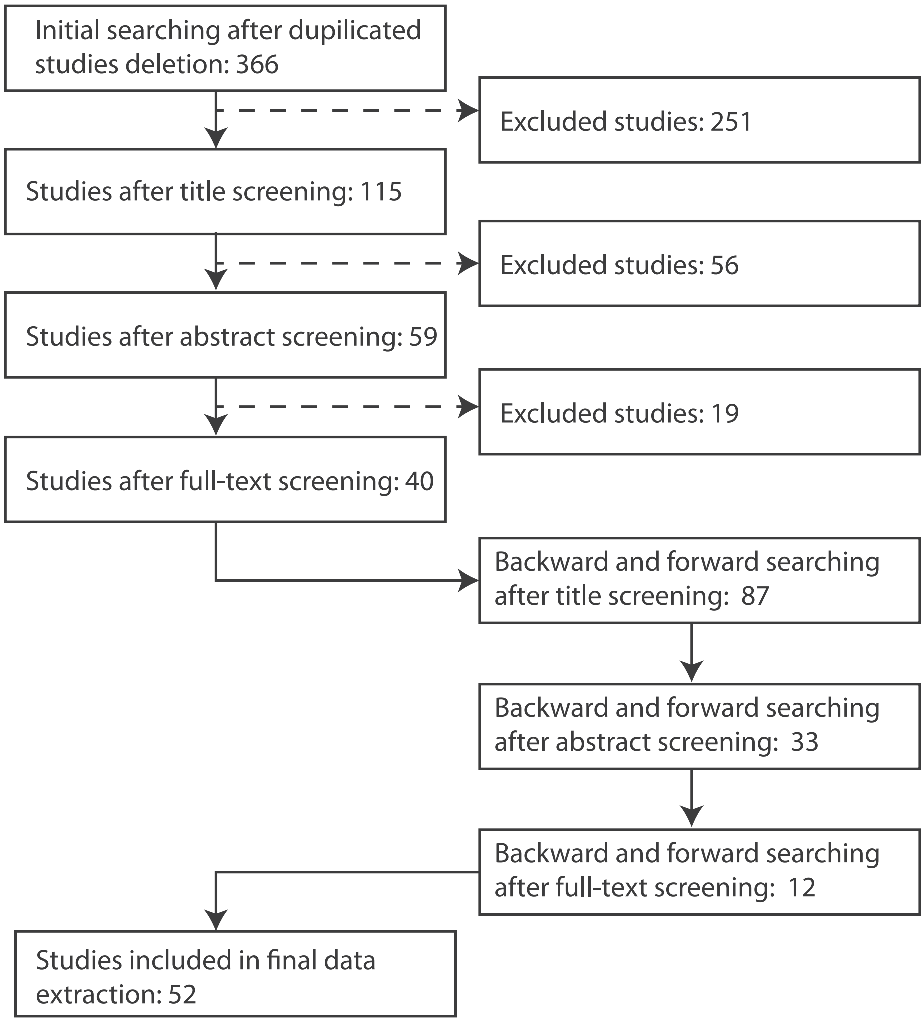

Figure 1. Numbers of studies included/excluded in each screening.

America (2 papers, 3.8%) and Africa (1 paper, 1.9%) were generally underrepresented (Fig. 3).

With respect to Köppen-Geiger climate zone distribution, most studies were conducted in humid subtropical climate zone (Cfa, 14 papers, 26.9%), followed by Oceanic climate (Cfb, 7 papers, 13.5%) and Hot summer continental climates (Dfa, 6 papers, 11.5%). Six papers' (11.5%) studied regions included multiple climate zones (Fig. 4).

Regarding the total population evaluated in the study area, studies conducted on populations between 1 and 10 million, rank first (28 papers, 53.8%), followed by more than 10 million (14 papers, 26.9%), and

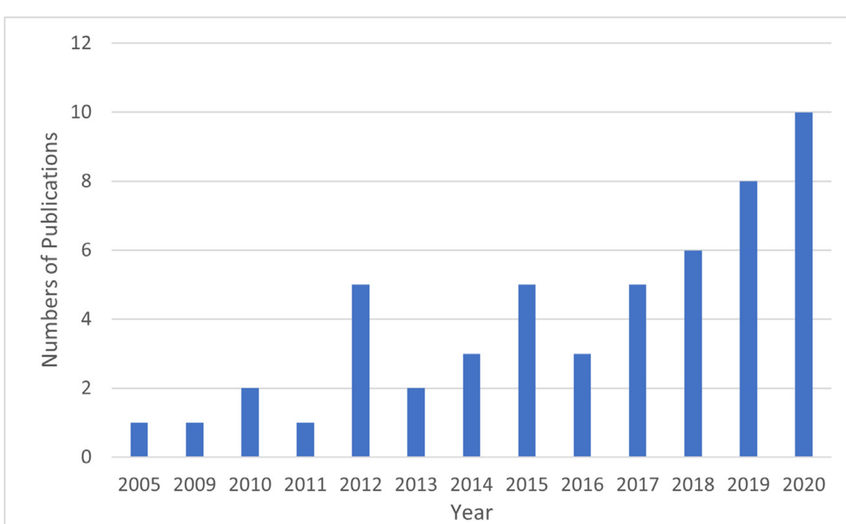

Fig. 2. Quantity of published HV/R articles from 2005 to 2020.

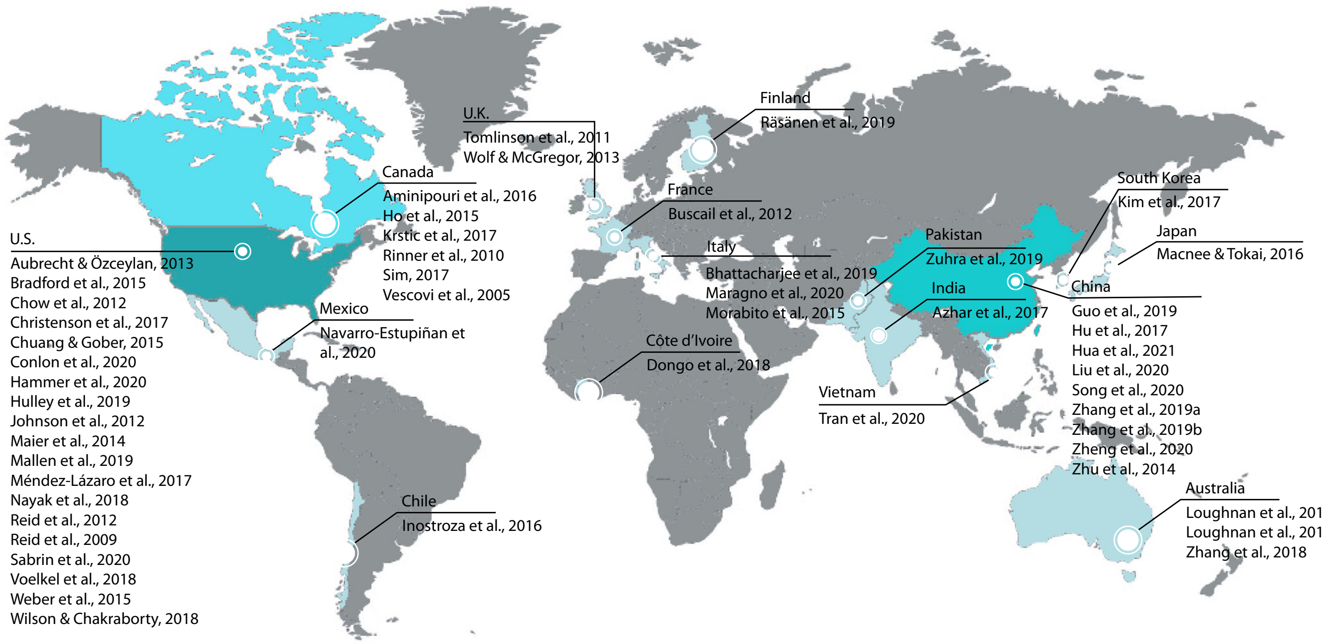

Fig. 3. Major continents and contries by reviewed studies.

less than 1 million but more than 100,000 people (9 papers, 17.3%). Studies with a population of less than 100,000 comprised the smallest group (1 paper, 1.9%).

Scale wise, reviewed papers were conducted mostly at the city scale (33 papers, 63.4%), including comparative studies examining multiple cities that do not belong to the same metropolitan area or region (4 papers, 7.7%). Another 7.7% of the studies (4 papers) were conducted at the national scale. The rest 28.8% (15 papers) of the studies examined conditions of a region with a scale in between a city and a nation.

When considering the discipline of the journals in which each article was published, 'environment' (17 papers, 32.7%), 'earth science' (15 papers, 28.8%), 'medicine' (4 papers, 7.7%), 'business' (4 papers, 7.7%), and 'agriculture' (4 papers, 7.7%) were among the top disciplines (Fig. 5).

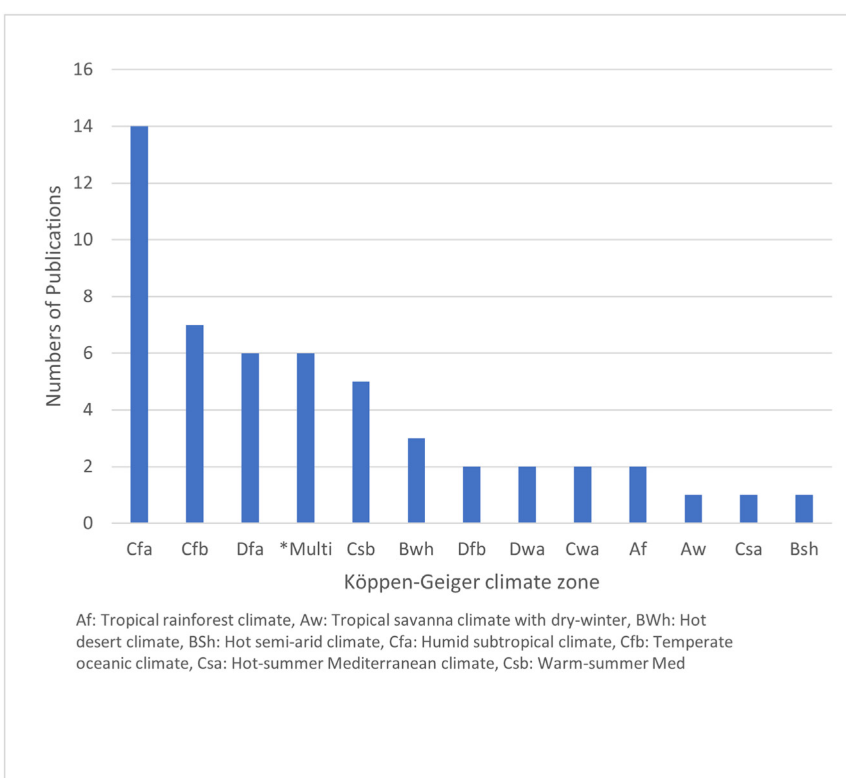

Fig. 4. Koppen-Geiger climate zone distribution of reviewed.

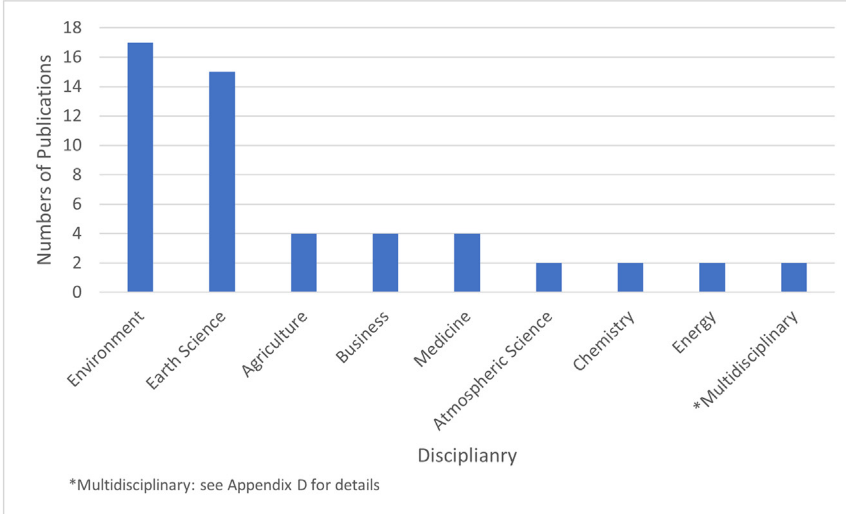

Fig. 5. Disciplines of reviewed studies.

3.2. Conceptual framework

The concept of risk or hazard plays the fundamental role in index construction and indicators selection. Two population vulnerability/risk conceptual frames, population vulnerability to environmental hazards (Cutter et al., 2003; Change, I. P. O. C, 2001) and risk triangle (Crichton, 1999; Field and Barros, 2014) were among the most utilized conceptual frameworks.

Fifteen papers (28.8%) constructed their heat vulnerability models based on the **population vulnerability equation**:

$$\text{Vulnerability} = \text{Sensitivity} + \text{Exposure} + \text{Adaptive Capacity}. \quad (1)$$

In this equation *sensitivity* refers to the internal characteristics of the population that cause them to be vulnerable or susceptible to increased heat exposure, such as socio-demographic factors and health related factors (e.g. elderly population and disabled population) (Inostroza et al., 2016; Kim et al., 2017; Wilson and Chakraborty, 2019). *Exposure* was considered as the external, environmental impacts on a population, which can be the intensity and spatial distribution of the environmental heat, such as climatic and environmental factors (e.g. land surface temperature and annual average temperature growth) (Kim et al., 2017; Zuhra et al., 2019). Some physical environmental factors that indicating potential heat exposure such as less green space coverage, living in high-density dwellings, living in inner city are also grouped into *exposure* in some studies (Mallen et al., 2019; Rinner et al., 2010; Wolf and McGregor, 2013). *Adaptive capacity* is the ability to actively adapt to increased heat exposure, usually refer to the accessibility of amenities/facilities that mitigate heat exposure, such as access to communication technologies/water supply/medical services/roads/cooling facilities (Mallen et al., 2019; Zuhra et al., 2019).

Eight studies (15.4%) developed HV/R based on the **risk triangle** (Crichton, 1999) and Intergovernmental Panel on Climate Change's (IPCC) conceptions (2014) that:

$$Risk = hazard + exposure + vulnerability. \quad (2)$$

In this model *hazard* refers to the spatial distribution of severe extreme hot events or climate phenomenon, such as the temperature during very hot days and nights, extremely high temperature days, LST (Buscail et al., 2012; Hu et al., 2017). *Exposure* refers to the elements at the risk of exposure. A typical indicator of exposure is population density (Buscail et al., 2012; Hua et al., 2021). *Vulnerability* refers to the lack of material to mitigate heat effects. Population socio-demographic characteristics, building characteristics such as built year, building without AC/water supply, built environment such as density of high ways, are indicators of vulnerability by many studies (Buscail et al., 2012; Ho et al., 2015).

3.3. HV/R construction

The indicators typically considered in HV/R studies involved both human and environmental characteristics. Details of each study's construction are included in Appendix D. To perform a direct comparison among all studies, we summarized all indicators used to construct HV/R from the 52 papers into three categories: *socio-economic status (SES) and cultural background*, *health condition*, and *environment*. Three sub-categories were identified under *environment*: *climate, urban morphology, and housing condition* (Table 1).

3.3.1. Socio-economic status and cultural background

Sociodemographic and cultural factors are important to heat vulnerability because of the physiological conditions that changes based on sex and age (Knowlton et al., 2009; Fouillet et al., 2006; Voelkel et al., 2018), financial and other deprivations limiting people's coping strategies (Harlan et al., 2006), and culturally appropriate heat adaptation behaviors (O'Neill et al., 2003). A total of 18 indicators have been used that are related to *socio-economic status (SES) and cultural background* of the population. Percentage of population at extreme old or young age (over 65 and under 5) is the most widely considered indicator (50 papers, 96.2%). Evidence has demonstrated that there are higher heat-related mortality risk and higher hospital admission rates for respiratory and other heat-related diseases during heat waves for population above the age of 65 (Knowlton et al., 2009; Kilbourne et al., 1982). This population is more vulnerable to heat due to its reduced ability to thermally regulate and limited ability to transport to caregivers (Luber and McGeehin, 2008; Cheng and Brown, 2020). The second mostly considered indicator is percentage of population living in poverty, which has been demonstrated to be associated with increased heat stress level (Harlan et al., 2006) and heat-related morbidity (Jones et al., 1982; Naughton et al., 2002), because of less affordability of air conditioning, unaffordable hospital expenses, and less accessibility to information resources (Naughton et al., 2002; Kim and Joh, 2006). Population with low levels of education have also been demonstrated to have higher heat-related death rates (O'Neill et al., 2003; Medina-Ramón et al., 2006). Percentage of people living alone, especially elderly women, is associated with higher vulnerability during extreme heat events (Stafoggia et al., 2008; Fouillet et al., 2006) as they have less support. Other less

Table 1
Indicators in constructing HV/Rs.

Category			Amount of studies	Explanation
Socio-economic status and cultural background				
Age			50	% of elderly and young population
Poverty, income			37	% of population below poverty line
Education			32	% of population without high school diploma/never attended schools/only attended pre-elementary
Living alone/in group			31	% of people (or elderly) live alone, elderly live alone;
Ethnic minority			19	% of non-white/Hispanic/black/Asian
Population density			18	Density of inhabitant per living block/per square mile
Employment			15	% of unemployment
Language barrier			14	% of illiterate population/speaking a non-official language
Born in foreign/immigration			8	% of population born in foreign country/immigrated
Home ownership			7	% of rented household
Gender			6	Female ratio
Family structure			6	% of population of: single, widowed, divorced, separated, or single parent with children under 18
Job specification			5	% of: labor workers, agricultural workers, craft and related trade workers, plant and machine operators and assemblers
Vehicle ownership			4	% of household without any vehicle
Settlement/homeless			2	% of population with different residences from 5 years/homeless people
Urban population			1	% of urban population
Social class			1	% of population of scheduled castes and tribes
Health condition				Explanation
Morbidity		Health care/care giving service	12	% of population admitted for health services/receiving home care; % of children (12–23 months) fully immunized;% of population don't have health insurance
		Disability	9	% of population (or elderly) with disability
		General health condition	8	% of population with health issue/illness
		Specific physical illness	8	% of population with diabetes, asthma, hypertension, obesity, COPD (chronic obstructive pulmonary disease), CHD (congenital heart disease)
		Mental illness	2	% of population receive mental health services
Mortality			1	Infant mortality rate
Environment				Explanation
Climate	Land surface temperature		26	Satellite image of Landsat TM/ETM+/MODIS
	Air temperature (Ta)	Daily Ta	14	Daily maximum/minimum Ta
		Night Ta	2	Night maximum/minimum Ta
		Heat wave days	4	Number of days that daily maximum Ta exceeds a certain degree
	WBGT		1	Measure heat stress by considering temperature, humidity, wind and solar radiation
	Humidex		3	Describe how hot the weather perceived by person by considering heat and humidity
	Air quality		4	Average of PM2.5 concentration; maximum recorded ozone level
Urban environment	Street incoming solar radiation		1	Potential solar radiation incoming for street surface
	Roofs incoming solar radiation		1	Potential solar radiation incoming for roof surface
	Land use/land cover	Vegetation cover	26	NDVI; % of green space/water body area; Enhanced Vegetation Index (EVI)
		developed land cover	15	% of impervious land cover; normalized difference built-up index (NDBI)
	Accessibility/proximity	Proximity to parks/green space	3	% of population with limited park accessibility; number of woody pixels around each pixel
		Proximity to water bodies	4	Distance to major water bodies; Number of water body pixel around each pixel
		Proximity to cool shelters (community centers, homeless shelters, libraries)	5	Number of cooling facilities; distance to cooling facilities
		Proximity to public transportation/major road	3	% of population that does not live near transit station/major roads
		Proximity to hospitals	6	Distance to the nearest health care center; number of hospitals; % of area within a certain buffer to a public hospital to the total area
		Proximity to city center	1	Distance to city center
	Urban density	Building density	5	% land with high building intensity areas
		Paved road density	6	Paved road density
	Landform/elevation		4	Digital Elevation Model (DEM) data
	Sky view factor		2	% of the amount of sky hemisphere visible from ground level
	Urbanization rate		1	Urbanization rate
Housing condition	AC	Central AC	7	% of houses lack central air conditioning
		Air conditioning of any kind	10	% of houses lack air conditioning of any kind
	Water supply/electricity supply	Drinking water	4	% of households without running water/hygienic water
		Bathing water	2	% of households without water provision within the house
		Electricity supply	2	% of houses without electricity connections
	Housing type		9	% of multi-story apartment buildings, mobiles homes; % of high rise building
	Building age		6	% of households living in houses built prior to 1960, 1970, 1975, 1980, 1986
	Communication technologies		5	% of households without Internet, mobile phone, telephone and computer access, TV
	Surface material		3	% of households use wood lined septum, cement with fibrous materials, waste (tin, cardboard, plastic, etc.) and soil
	General condition		2	% of house needs maintenance/repairs;
	Overcrowd living		2	% of households with more than one person per room; % of households with per capita living area less than a certain area
	Appliances		1	% of houses without fridge or washing machine

used indicators included ethnicity, language proficiency, unemployment, occupation, home ownership, car ownership, and population density. In societies with explicit social classes like India, the percentage of people belonging to the scheduled castes and scheduled tribes were also used (Azhar et al., 2017).

3.3.2. Health condition

People with disabilities and chronic diseases especially diabetes, respiratory and cardiovascular related diseases are related to heat induced illnesses and mortality due to the physical and physiological vulnerability and limitation (Hammer et al., 2020; Ho et al., 2015). The indicators related to health and health-care condition can be summarized into three subcategories: *health care or care giving services*, *morbidity and mortality*. *Health care or care giving services* are often captured by the percentage of population that was admitted for both mental and physical care services in local department or at home (e.g. Christenson et al., 2017; Macnee and Tokai, 2016), percentage of children not fully immunized (Azhar et al., 2017) and percentage of population without health insurance (e.g. Christenson et al., 2017; Méndez-Lázaro et al., 2018). *Morbidity* includes percentage of population with disability (Inostroza et al., 2016; Liu et al., 2020), burden of diseases or with general health issues (e.g. Loughnan et al., 2012; Räsänen et al., 2019), specific physical illness (e.g. Reid et al., 2009; Zuhra et al., 2019) and mental illness (Christenson et al., 2017; Wolf and McGregor, 2013). People who have disabilities and people with a chronic disease often have a limited ability to respond to their surrounding conditions, and therefore are more vulnerable than the other population (Vandentorren et al., 2006). Diabetes is one of the most widely considered pre-existing medical conditions in heat related health risks (e.g. Hammer et al., 2020; Ho et al., 2015). Heat events can also exacerbate respiratory conditions such as asthma (Lin et al., 2009). Cardiovascular disease (Naughton et al., 2002; Henschel et al., 1969) and obesity (Mirchandani et al., 1996) are also known as risk factors for heat-related mortality. In addition to physical illnesses, studies have shown that some mental health conditions and medications (Batscha, 1997) and substance abuse (Page et al., 2012) can increase the risk of heat-related illness and mortality. Only one study considered mortality, specifically, infant mortality rate, as an indicator related to *sensitivity* to heat event (Zhu et al., 2014).

3.3.3. Environments

Environmental indicators can directly reflect heat exposure level (e.g. land surface temperature) and the ability to mitigate heat effects (e.g. accessibility to cooling facilities). Environmental indicators can be classified into three sub-categories: *climatic related factors, urban environment*, and *housing conditions*. *Climate* refers to all climatic parameters (e.g., air temperature), climatic indices (e.g. Wet Bulb Globe Temperature, WBGT), and outcomes directly caused by climatic parameters (e.g. land surface temperature, LST). *Urban environment* includes all urban morphology (e.g. accessibility to green spaces), physical environments (e.g. sky view factor) and characteristics (e.g. urbanization rate). *Housing condition* refers specifically to the living construction (e.g. building age and appliances), and living conditions (e.g. overcrowded living).

3.3.4. Climatic related factors

Land surface temperature (LST) is the indicator most widely used in 26 reviewed papers (50.0%). Daytime and nighttime LST during heat waves can be obtained from satellite image such as Landsat ETM+ with a resolution of 60 m, or MODIS with 1 km resolution (Buscail et al., 2012; Zheng et al., 2020). Daily and nighttime maximum and minimum air temperature (Ta) were collected from weather stations (Hu et al., 2017; Kim et al., 2017). Also, heat wave days, or the annual growth in the number of hot days (daily or nighttime maximum Ta exceeds a specific temperature based on local definition) were calculated (Hu et al., 2017; Kim et al., 2017). Air quality data was also considered (Christenson et al., 2017; Chuang and Gober, 2015) for average PM2.5 concentration or maximum recorded ozone level, as the increases in air pollutants can be an indicator for rising temperatures (Kalisa et al., 2018). In addition, during prolonged heatwaves, high concentration of pollutants may exacerbate adverse effects on human health (Yang et al., 2019). Heat stress indices such as WBGT (Zheng et al., 2020) and Humidex (e.g. Aminipouri et al., 2016; Krstic et al., 2017) were calculated by using daily maximum Ta and relative humidity obtained from Landsat or weather station as previous studies indicating the association between humidex or WBGT with heat related mortality and hospital admissions (Isaksen, 2014; Heo et al., 2019).

3.3.5. Urban environment

Land use and land cover is one of the most important indicator of urban heat island (UHI) in most of the studies (41 papers, 78.8%) as built-up area is usually considered to intensify UHI, while vegetated areas can provide relief from urban heat by reducing the temperature (Hess et al., 2012; Gascon et al., 2016). The normalized difference vegetation index (NDVI) (e.g. Bhattacharjee et al., 2019; Guo et al., 2019; Weber et al., 2015), percentage of tree canopy/vegetate area (e.g. Bradford et al., 2015; Macnee and Tokai, 2016), the enhanced vegetation index (EVI) (Zhang et al., 2019b) were used to demonstrate vegetation coverage and healthy conditions, the normalized difference built-up index (NDBI), built area fraction, percentage of impervious area/no tree cover/non-vegetated area/paved road were used for presenting developed land cover (Aubrecht and Özceylan, 2013; Chow et al., 2012; Sim, 2017; Maier et al., 2014). Other studies considered accessibility to cooling facilities, parks, public transportation, hospital; building density; road density; land form and elevation; and sky view factor.

3.3.6. Housing condition

Housing conditions such as housing type, age, surface material, housing appliances, and water and electricity supplies are associate with heat-related health outcomes (Salamanca et al., 2013; Kilbourne, 2002; Navarro-Estupiñan et al., 2020). Housing types and characteristics were indicators considered in many studies (Hulley et al., 2019; Tomlinson et al., 2011). Large building footprints as well as tall and wide buildings can affect both LST and ambient air temperature (Rinner et al., 2010). Old buildings lacking of thermal insulation or AC system have been recognized as a main risk factor during past extreme heat because natural and lighter external wall material can reflect more light and absorb less heat.

Water and electricity availabilities were considered in studies conducted in the Global South as an important factor, as they can mitigate thermal stress and influence adaptive ability of the public. Low access to safe or drinkable water is specially considered in studies in India, Pakistan, Central Chile and Vietnam as relate to sensitivity or adaptive capacity. Availability of communication technologies such as internet, mobile phone, telephone or TV, was also considered as a determination for adaptive capability in some studies conducted in India, Chile, Mexico, and Australia. People with better access to heat-related information or guides released to the public have higher adaptive capacity to heat. Overcrowd living were also studied for the potential high heat risks.

3.4. Data source and resolution

Environmental factors such as LST and NDVI can be readily generated from multispectral remote sensing images such as Landsat TM/TEM+ and MODIS. Land use/land cover data can be obtained from the same satellite datasets, or local or national land cover database. Air temperature, humidity and air quality data or indices can be obtained from weather station (Vescovi et al., 2005) or national monitoring system such as the US EPA (Christenson et al., 2017; Sabrin et al., 2020) and China National Environmental Monitoring Centre (Zhang et al., 2019b; Zheng et al., 2020). Some recent studies started to discover technologies for finer resolution spatial data using orthophotos or LiDAR data. In several studies, vegetation height was obtained using point clouds from LiDAR data (Maragno et al., 2020). Housing condition such as communication technologies, and access to water and electricity, can be achieved from national datasets. Parcel-level residential AC data can be obtained from local tax appraisal's office or official statistics releases.

In most cases, socio-economic data were obtained from national census statistics or official household surveys. Health care or health condition data can also be obtained from household/community survey data, or open data from national disease control bureaus or state wide surveys. For example, Christenson et al. (2017) obtained a variety of county level health condition data from Behavioral Risk Factor Surveillance System (BRFSS) and Wisconsin Hospital Patient Data System.

3.5. Weighting methods and index scale

Due to the varieties of indicators typically used in heat vulnerability research, assessment of the composite vulnerability/risk depends on assigning weights that correctly capture the relative influences of each indicator. Studies have generally used either explicit weighting (20 papers, 38.5%) or statistical weighting (31 papers, 59.6%) schemes to create the composite vulnerability index (Fig. 6). A few studies (6 papers, 11.5%) created composites for subdimensions but not a single overall vulnerability/heat index. Explicit weighting, such as equal weights (18 papers, 34.6%) and expert weights (2 papers, 3.8%) were usually developed based on literature, judgement of the researchers, or decision made by an external panel of experts. In case of equal weighting, which is the most frequently used method for heat vulnerability, authors either used equal weights across all indicators, or a hierarchical scheme where equal weights were assigned to subcategories, and then evenly allocated to indicators under each subcategory. One study partially adopted the Delphi method to generate expert weights and compared the results based on each expert's weights (Räsänen et al., 2019). Some of these studies also performed correlational analysis against the validation dataset and only the significantly related indicators were entered to produce the weighted index.

Statistical methods included the principal component analysis (PCA) (23 papers, 44.2%), analytical hierarchal process (AHP) (3 papers, 5.8%), and other methods (5 papers, 9.6%). The PCA method selects components that form a few dimensions that explain the largest variance. Some studies used a combination of PCA and equal weights: lower-level indicators were summarized into subcategory scores using equal weights first, and then PCA was applied to subcategories (Song et al., 2020). The AHP method, on the other hand, utilizes judgement scales for alternative criteria and then calculates the eigenvector to determine the composite. A few studies used other statistic-based weighting schemes such as slope-based or indicator variance-based weighting (Dongo et al., 2018; Krstic et al., 2017). Although sometimes these statistically calculated weights were referred to as unequal weights in the articles, it is worth noting that these were statistically generated and therefore differ from expert created unequal weights.

Upon creating the composite index, the indicator was usually normalized into a numeric scale (e.g., 0–1, 0–10). Some studies retained the continuous metric of the indicator (Reid et al., 2012); or used equal interval or percentile based classification methods to generate maps that use color gradient to visualize the comparative vulnerabilities/risks (Wolf and McGregor, 2013). Other studies rescaled the indices into categorical indicators with five to seven vulnerability/risk levels (e.g., low, medium-low, medium, medium-high, high) (Johnson et al., 2012; Rinner et al., 2010).

3.6. HV/R validation

It is essential for the developed indices or models to be validated in order to demonstrate the accuracy in predicting or estimating heat vulnerability or risk during extreme heat events. However, only a small portion of the studies (14 papers, 26.9%) that developed HV/R have involved validation. Datasets used for validation included heat-related morbidity (5 papers, e.g. Chuang and Gober, 2015; Loughnan et al., 2014), heat related mortality (4 papers, e.g. Hu et al., 2017; Johnson et al., 2012) or all-cause mortality data during heat (6 papers, e.g. Conlon et al., 2020; Krstic et al., 2017). Hospital admissions for heat stress (Chuang and Gober, 2015; Nayak et al., 2018), hospitalization due to cardiovascular diseases, cerebrovascular disease, respiratory illness, respiratory illness, acute renal failure and internal imbalance (Reid et al., 2012), total hospital visit in summer (Zhang et al., 2019b) or daily emergency service demand (Loughnan et al., 2014) were used to represent heat-related morbidity. Bivariate correlation (5 papers), linear or multivariable regression (7 papers) were commonly used as validation approaches. Bivariate correlation can be used to simply reflect the relationships between mortality/morbidity with HV/R scores, linear or multivariate regression can be used to further determine spatial distribution of vulnerability scores with mortality/morbidity in hot or normal days, which indicator contribute significantly to the morbidity/mortality, and how much HV/R model can explain the outcomes. Other studies classified the geographies into various levels of vulnerability, and compared the morbidity and mortality outcomes based on these levels.

The validation results varied greatly across studies and many showed low agreement between vulnerability assessments and heat-

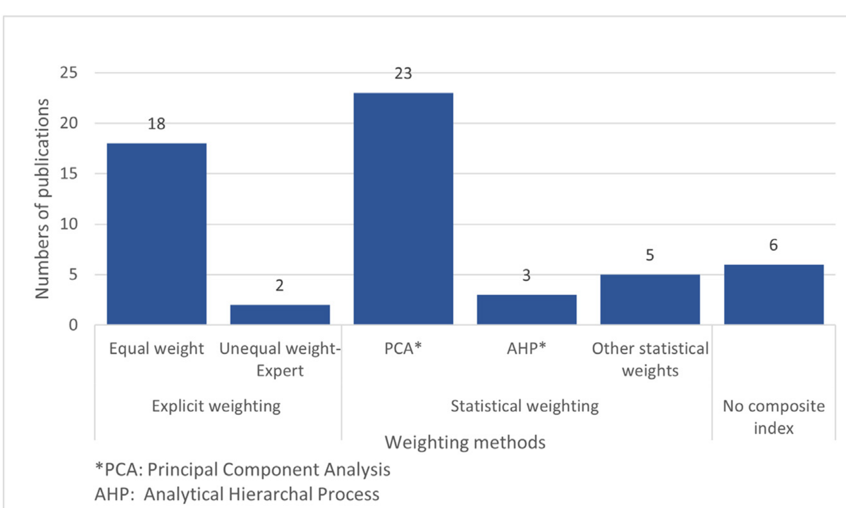

Fig. 6. Weighting methods for composite index creation.

related morbidity and mortality. For example, using bivariate correlation, the r square of Loughnan et al. (2012)'s study is only 0.03, Kim et al. (2017) is 0.32, Hu et al. (2017) is 0.608, and Zhang et al. (2019b) is almost 0.9; using linear regression, Liu et al. (2020)'s r square is 0.58 and 0.32 for equal weighted and PCA composition respectively, Song et al. (2020) is 0.60; Loughnan et al. (2014) used stepwise regression to decide the best indicators for vulnerability in capital cities in Australia, and the r square ranged from 0.04 to 0.62 with various selection of indicators. Specifically, Chuang and Gober (2015) evaluated the accuracy of the generic index developed by Reid et al. (2009) for the country level in a city context by comparing the geographical differences between the vulnerability map and the heat-related hospitalization map at the census-tract scale. The overall accuracy rate in classifying census tracts vulnerable level was only 54%. Hu et al. (2017) used heat-related deaths in Zhejiang, China and demonstrated that their estimates were significantly correlated in county level. The results showed that the accumulated heat risk estimates and the heat-related deaths were significantly correlated at the county level (Spearman's correlation coefficient = 0.76, $P \le 0.01$). Loughnan et al. (2014) used stepwise linear regression to select the indicators that made a significant contribution to morbidity during hot days. However, locally, some areas predicted as high vulnerability showed low demand of emergency services on hot days. Under the circumstance of applying different statistic methods and using different defined health outcome data, it is hard to compare the validation effectiveness of using morbidity or mortality data.

4. Discussion

4.1. Indicator selection

Studies that were grounded in different theoretical frameworks and considered various local conditions focused on different components of the conceptualization of the index. Many studies used population vulnerability to environmental hazards equation, or the risk triangle, while the interpretation and understanding of each element in the two conceptual frames which reflecting the indicator/factor selection or classification can be varied. For example, when using *population vulnerability*, LST was considered as an *exposure* factor by Inostroza et al. (2016), but as an *adaptive capacity* factor by Zhang et al. (2018). Educational and income level that indirectly help to avoid harm from heat were classified as a*daptability* in population vulnerability by Hulley et al. (2019), while were taken as *sensitivity* by Inostroza et al. (2016), Kim et al. (2017) and Mallen et al. (2019). Building conditions were interpreted as either a sensitivity indicator (e.g. building height by Hulley et al. (2019) and Zhang et al. (2019a) and *no access to water* by Tran et al. (2020)) or exposure indicators (old dwellings without AC by Rinner et al. (2010), high or multi story buildings by Wolf and McGregor (2013). Same for using *risk triangle* frame: total elderly population and elderly with low income and disability were considered as *exposure* indicators by Zhang et al. (2019b), while Morabito et al. (2015), Ho et al. (2015) and Hu et al. (2017) interpreted them as *vulnerability* indicators.

When selecting indicators for heat related vulnerability or risks, researchers need to ensure that as many relevant indicators are included as possible, and that selected indicators can be accurately acquired or measured. Some critical issues related to measurement accuracy, especially the climate factors, need to be developed further. For example, LST is the most widely considered indicator used in heat vulnerability indices to reflect urban heat island phenomena. However, previous studies indicated the inadequacy of LST for obtaining reliable UHI trends especially when using the maximum and minimum temperatures (Sun et al., 2020). A combination of satellite data for surface temperatures and data from monitoring stations for near surface air temperatures was recommended by EPA to offer the most complete picture of UHI (US EPA, O, 2014). Moreover, when considering the energy budget exchange between a human and the environment, although LST can partially determine terrestrial radiation from the ground, incident solar radiation is the most critical element influencing human thermal comfort (Brown and Gillespie, 1995). It is essential to include a more comprehensive analysis of the energy exchange and flow between human body and landscape in order to select the most relevant environmental indicators of heat vulnerability.

4.2. Index composition

Explicit and statistical weighting methods have been used in constructing HV/Rs. Explicit weighting uses equal weights or expert-determined unequal weights and are therefore subject to biases. As there are no empirical grounds for such an assumption, the results can reflect inadequate knowledge of the causal relationships. As the subcategories and indicators, as well as the weights across studies varied greatly, critical inconsistencies exist in the actual influence of each individual indicator in the final index. Statistical method such as PCA can better capture the variances of the actual data, but the relative weights generated may not accurately reflect the importance of each individual indicator. Studies that utilize a consistent set of weighting schemes and compare the results may yield useful information regarding the appropriate index creation methods. The different methods used to construct the models and the biases involved in this process may also contribute to the inconsistencies and weak validation results. More studies that conduct sensitivity analysis and compare across different weighting schemes would help clarify the relative strengths and directions of biases of each method.

4.3. Index validation

Only 26.9% (14 papers) of current reviewed indices were validated by comparing with the heat related mortality, morbidity or all-cause mortality rates during heat. However, there is no consistent or standard criteria to state the efficiency of assessing or predicting heat vulnerability when comparing with actual adverse heat-related health consequences. Generally, validation results showed significant correlations between heat vulnerability indices and morbidity/mortality rates but the effect sizes are between low and medium. When regressed with mortality on extreme heat days, or heat stress hospitalizations, four studies showed r square values higher than 0.5, while the rest of the indices had r square values ranged from as low as 0.01 (Conlon et al., 2020) to 0.32 (Kim et al., 2017). Explanations for the low to moderate levels of agreement may be: 1) structural problems in HV/R conceptualization, indicator selection, or index construction, 2) spatial/temporal mismatches between the data used for vulnerability assessments and validation datasets, or 3) coverage issues or representativeness related to the validation dataset itself. Inaccuracy in HV/R indices may be due to reasons stated above, such as ill-conceived model framework, including irrelevant indicators, leaving out relevant indicators, invalid measurements, or biased weighting schemes. As established frameworks may not capture the actual risk factors experienced in local social and environmental contexts, we recommend researchers to critically examine the applicability of existing frameworks on the study geographies and populations, and focus on local knowledge and conditions instead of adopting a generic model. Often the time frame of the validation dataset did not match the time frame of the datasets used for developing the vulnerability index. Sometimes the indices were constructed at a finer or coarser scale than the validation dataset, leading to a loss of information in the validation process. The validation dataset itself may also be causing the low agreement. For example, all-cause morbidity and mortality may be influenced by a myriad of factors and would not serve as a strong validation dataset for heat vulnerability. In addition to these three reasons, as mortality during heat waves are often attributable to not only climatic and social environmental factors that are easier to obtain/measure, but also individual behaviors and hard-to-measure social interactions and institutional support. Given the complex reasons and scenarios, more studies that test diverse sets of indicators, involve previously hard to measure indicators, and compare across regions and populations would help elucidate these issues. For validation analyses that are more accurate and not subject to scaling errors, future studies can consider leveraging diverse data sources. For example, pooling together multiple datasets, such as hospital and emergency department inpatient and outpatient records, mortality, health survey records, and social media posts on heat-related emergencies may allow the capture of the full spectrum of heat-related health conditions. As electronic health record (HER) data becomes more important in health outcome assessment, these individual data can provide better scalability for validation and index construction.

4.4. Summary of future directions

Studies that assess heat vulnerability or risk are mainly conducted in North America, Asia and Europe. More studies that compare across countries and regions, especially in tropical climate zones would advance knowledge in this area. For indicator selection, we suggest to use a combination of common indicators already proven by previous empirical studies such as age, air temperature, elderly, together with locally appropriate social, economic and environmental indicators.

A comprehensive understanding of energy exchanges in the landscape, and between humans and their environment is essential for the base of environmental indicator selection and analysis. For example, LST is can provide an estimate of the level of terrestrial radiation, but incident solar radiation, air temperature, wind and humidity should also be taken into consideration for energy budget exchange calculations.

Application of developed HV/Rs is also needed. Current HV/Rs gave little guidance to local planners and designers of where actions are more urgently needed within the city or neighborhoods, and what kind of interventions are required under heat event. When assessing local vulnerability, cities should carefully consider which indicators should be included, and whether to emphasis on specific ones. Sensitivity test or stepwise regression can help planners to ensure which specific indicators are most important, and differential planning or design interventions can be applied based on local vulnerabilities and needs. For instance, if socio-economic indicator(s) was the determinant of the vulnerability, then policies targeting on vulnerable population's risk/hazard reaction should be enacted; if environmental factor(s) was the determinant indicator, climate-responsive urban design should be conducted.

4.5. Limitation

We selected studies developing or evaluating HV/R from January 1970–August 2020. Studies published after August 2020 were not included. Also, we only conducted forward and backward searches for the top 10 cited articles from our full text review results. There may be additional studies that conducted similar kinds of index development, but did not include the keywords such as “vulnerability” or “risk”. Besides, we didn't conduct a meta-analysis, because of the heterogeneities of model construction and indicators used in creating the HR/Vs.

5. Conclusion

HV/Rs are developed to identify the populations or geographies that are at high risk of heat hazard by using spatial socio-economic and environmental data that are associated with heat related adverse health outcomes, and provide knowledge to assist heat emergency planning and policy implementation. The objective of the study was to conduct a systematic review of the literatures on the methodology of heat vulnerability index/model development and validation, and to evaluate the rigor, validity and limitation of these methods. Indicator selections were based on theory, experiment studies, or local conditions. *Population vulnerability* and *risk triangle* were the conceptual frames commonly used in reviewed studies. However, there were inconsistencies in indicator selection and frameworks interpretation throughout different studies. We suggest that future studies should evaluate the applicability of recognized theoretical frameworks and construct models based on previously established methods as well as local contexts. Explicit weighting or statistical weighting schemes were generally used to create the composite vulnerability index. However, both explicit and statistical weighting methods have limitations. In terms of model validation, less than 1/3 of reviewed studies conducted validation to assess HV/R's efficiency in predicting heat vulnerability or risk. They compared the predicted results with actual adverse heat related health consequences. However, there was no consistent criteria or statistical measures in assessing the efficiency. Other than model construction and validation, we suggest HV/Rs should be conducted in more hot and less developed countries and regions. A comprehensive understanding of energy exchanges between landscape elements and humans can assist indicator selection and model construction. Also, we would like to see more practice of HV/R being applied in urban planning and policy making.

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Declaration of competing interest

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

Appendix A–D. Supplementary data

The following are available online. Appendix A: Search syntax for HV/Rs. Appendix B: Risk-of-bias questions. Appendix C: Risk-of-bias assessment results. Appendix D: Characteristics of included studies. Supplementary data to this article can be found online at doi: https://doi.org/10.1016/j.scitotenv.2021.149417.

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