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Review

Perspectives on spatial representation of urban heat vulnerability

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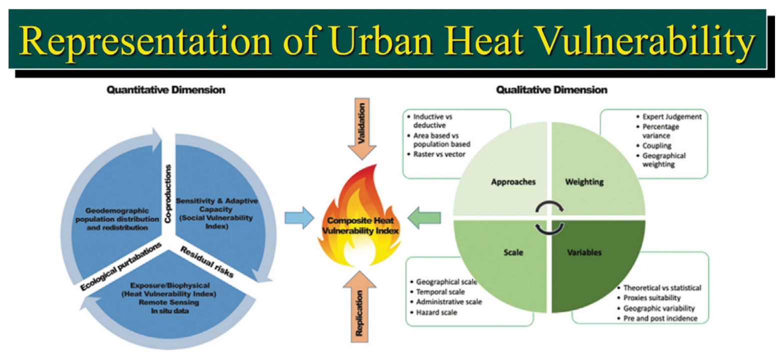
HIGHLIGHTS

- Disparate perspectives of urban heat vulnerability.
- Harmonizing theoretical and statistical relationships in spatial representation.
- Accurate detection of heat vulnerability in urban areas for targeted mitigation measures.
- The coupled heat vulnerability index with quantitative and qualitative dimensions.

GRAPHICAL ABSTRACT



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ABSTRACT

Extreme heat, the deadliest summer weather-related hazard in the USA, is projected to increase in intensity, duration, frequency, and magnitude, especially in urban areas that account for 80% of the population. Spatial visualization and representation are crucial in establishing the hotspots of vulnerability to the heat hazard. However, despite the progress in the science of vulnerability, there lacks a systematic and consistent conceptual framework. The quantification of variables is unchecked, resulting in subjective decisions regarding the weighting of variables, selection of indicators, and the suitability of the proxies. Moreover, contradicting approaches generate disparate outputs such as; inductive versus deductive, area-based versus population-based, and raster versus vector designs. The qualitative approach, meant to provide supplementary data, is often ignored. This review provides a perspective of the lacunae in the existing literature and builds on these gaps to derive a conceptual framework towards harmonizing theoretical and statistical relationships. The framework is anchored on the longitudinal study approach as the socioeconomic, biophysical, and geodemographic dimensions have an inherent temporal variance. The review calls for a precise and accurate depiction of heat vulnerability in urban areas to inform targeted adaptation and mitigation measures and the long term projection of coupled systems behavior.

Contents

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1. Introduction

The progressive detriment of the climate system is unprecedented over centuries to millennia, and the resulting deaths and economic losses continue to rise across the world (Formetta and Feyen, 2019; Intergovernmental Panel on Climate Change (IPCC), 2014). One of the most explicit evidence for the climate system's disruption is the ongoing global warming. The average temperature for 2019 was close to 1 degree Celsius above the 20th century average of 13.9 °C (National Oceanic and Atmospheric Association (NOAA), 2020). The period between 2015 and 2019 witnessed the deadliest heatwaves (World Meteorological Organization (WMO), 2019). The warming is projected to increase in intensity, magnitude, duration, and frequency, particularly in urbanized environments, which generally experience 6 °C to 8 °C higher than surrounding rural locations (Habeeb et al., 2015; Weber et al., 2015). Therefore, urbanization generates disproportionate geographies of thermal inequality, consistent with the Urban Heat Island (UHI) phenomenon (Depiettri et al., 2013; Krstic et al., 2017; Xu et al., 2019). The elevated temperatures in urban areas increase mortality by four times more than in surrounding rural areas (Maier et al., 2014). Despite the heat vulnerability in urban areas, there is minimal attention to heat hazard and its linkages to spatial policy planning in urbanscapes (Hersperger et al., 2018; Masuda et al., 2019).

Intelligent and proactive urban policy strategies are integral to limit the severity of hazards, including those accentuated by the UHI phenomena, hence the demand for spatially explicit information on hotspots (Atyia, 2015; Kashem et al., 2016; Preston et al., 2011). However, vulnerability studies represent a pool of conceptual clutter that lacks a systematic and consistent conceptualization to guide spatial representation (Eakin and Luers, 2006; Morabito et al., 2014). Precise and accurate mapping of susceptible groups is impaired, which undermines policy formulation. For instance, heat exposure is irregularly distributed in time and space, while community demographics shift continuously, posing a challenge to mapping and tracking of hotspots (Cutter, 2003; Eriksen and Kelly, 2007; Wilson and Chakraborty, 2019). The biophysical processes and population dynamics manifest on various geographic scales, temporal scales, and administrative levels, producing the Modifiable Area Unit Problem (MAUP) when mapping (Ho et al., 2015). Fine-scale mapping of coupled biophysical and socioeconomic indices (e.g., composite Heat Vulnerability Index) (HVI) is often disregarded, resulting in mixed pixel problems attributed to coarse-scale mapping (Aubrecht and Ozceylan, 2013; Mushore et al., 2018). Furthermore, there are no guidelines for selecting, weighing, and interpreting indicators (Jonsonn and Lundgren, 2015). The existing data aggregation techniques deplete the authenticity of the information from independent suites of variables (Abson et al., 2012; Kashem et al., 2016). Spatially explicit information challenges are non-trivial, whereas such visualization is highly on demand (Preston et al., 2011).

This review provides disparate perspectives on the existing conceptualizations of urban heat vulnerability. It develops a holistic iterative framework that integrates validation and replication to bolster accuracy and precision in spatial representations. The framework is anchored on the longitudinal study approach that effectively captures urban heat events' temporal dimension. The quantitative dimension acknowledges the ecological perturbations, the vulnerability co-productions, and residual risks emanating from the interactions of the biophysical exposure Index (HVI) and the Socioeconomic Vulnerability Index (SoVI). Since heat vulnerability is variable across multiple scale dimensions, and the approaches, weighting mechanics, and determination of variables are inconsistent, our conceptual model provides a novel overview towards a consistent, dynamic, and systematic spatial representation.

2. Vulnerability in perspective

2.1. Climate change and heat vulnerability

Each of the previous three decades has been consecutively warmer than any preceding decade since 1850 (IPCC, 2014). Surface temperatures are projected to rise in the 21st century across all emission scenarios, thereby amplifying risks and creating new threats that will be disproportionately distributed (Habeeb et al., 2015; IPCC, 2014; Weber et al., 2015; Xu et al., 2019). The current recorded temperatures are at least 1 degree Celsius above those of the pre-industrial period. The associated impacts will be intense and sooner, particularly in urban areas where 70% of the world population is projected to live by 2050 (Birkmann et al., 2017; Ho et al., 2015; World Meteorological Organization (WMO), 2019). Climatic changes are happening faster than the human capacity to respond, and aggressive mitigation and adaptation responses are indispensable; hence the compelling demand for spatial representation of vulnerability (Bera, 2019; IPCC, 2018). However, the applications of outputs of vulnerability studies remain limited as they are guided by users' interests instead of policy gaps and consistent scientific methodologies (Turner II et al., 2003).

Increased morbidity and mortality have been associated with extreme hot weather in urban environments (Krstic et al., 2017; Reid et al., 2009; Reid et al., 2012). The World Health Organization (WHO) reports that the number of people exposed to heat stress increased by 125 million between 2000 and 2016. Each 4.7 °C rise in apparent temperature corresponds to a 2.6% rise in cardiovascular mortality pegged on conservative estimates, while oppressive hot days increased mortality by 7.7% (Basu and Ostro, 2008; Maier et al., 2014). Extreme heat events are already the principal cause of summer weather-related fatalities in the USA, highlighting the imperative for research into heat risk assessment (Environmental Protection Agency (EPA), 2006; Morabito et al., 2014). In the USA, where 80% of the population is already urbanized, 620 residents die annually due to heat stress (Atyia, 2015; EPA, 2006). Data from the WHO indicates that heatwaves were responsible for more than 166,000 mortalities between 2000 and 2017. The 2003 heatwaves killed more than 15,000 people in France, 30,000 for the whole of Europe, while additional 70,000 deaths were recorded in the months following the summer, although the estimates were biased as health data was not specific (EPA, 2006; Laaidi et al., 2012; Robine et al., 2008). According to Sheridan and Dolney (2004), these impacts are understated yet underpin the necessity for heat vulnerability studies. It is unclear whether vulnerability is a constituent of the residual effects once adaptation and mitigation have set in or a pre-existing state or a cumulative hybrid of the two resulting in multiple definitions and conceptualizations that undermine its determination (Eriksen and Kelly, 2007).

2.2. The vulnerability imperative

Unprecedented demand for spatially explicit visualization of vulnerability hotspots has accelerated the discourse on adaptation and mitigation to the (UHI) (Preston et al., 2011; Rizvi et al., 2019; Zhou et al., 2014). However, a universal conceptualization of vulnerability remains elusive, raveling the conception of formal models (Cutter et al., 2003; Fussel, 2007; Turner II et al., 2003; Zhou et al., 2014). For instance, Lee (2014) defined it as the probability of risk exposure, while Atyia (2015) referred to it as the state of a community preceding a disaster. Other studies (e.g., (Carr et al., 2014; Turner II et al., 2003) define vulnerability as a composite of the biophysical and socioeconomic indices characterized by a temporal dimension. Even with the rare chance of convergence in definitions, disparate assumptions could still mask the accurate and precise representation of hotspots (Fussel, 2007). Despite the growing number of studies on vulnerability (e.g., Abson et al., 2012; Atyia, 2015; Borden et al., 2007; Kelly and Adger, 2000; Stennett et al., 2019), the concept remains overdetermined yet equivocal; hence its application in decision making is limited (Tran et al., 2010). For instance, Fussel (2007) argued that vulnerability encompasses four dimensions, i.e., a system, attributes of concern, the hazard, and its temporal reference, subject to perturbations. Conversely, Brenkert and Malone (2005) equate it to exposure, sensitivity, and adaptive capacity. Therefore, vulnerability is predominantly interdisciplinary, and its precepts evolve overtime (Cutter et al., 2003; Otto et al., 2017). Although methodological variations are necessary to expose its full complexity, novel comprehensive and comparative approaches are a pressing concern to mainstream vulnerability in policymaking.

3. Constructing heat vulnerability indices

3.1. Exposure/biophysical index

The characterization of biophysical vulnerability remains imprecise, and many studies attempt to justify the approach applied due to the absence of a formal methodology. For instance, Fussel (2007) argued that the exposure index must encompass topographical characteristics, land cover, and environmental parameters. Others (e.g., Maier et al., 2014; Morabito et al., 2014) have advocated for apparent temperature, a measure of the human thermal comfort, but differed on constitutive components. Morabito et al. (2014) incorporated the indoor and outdoor temperature differences, including the insulation provided by clothing. In contrast, Maier et al. (2014) only accounted for humidity and recorded temperatures above the 90th and 95th percentiles of local average conditions, whereas Weber et al. (2015) used the 85th percentile. Heatwave definition varies depending on the length of consecutive days, the temperature metric (maximum, minimum, average), thresholds defined, and accounting for humidity (Shepherd and Zhou, 2009). Despite the acceleration in the number of heat studies, the conceptualization of the exposure index, upon which potential impacts are projected, remains unsettled within the scientific community. The construction of different thermal indicators generates different results across space and time, whose correlations are unknown.

Various studies (e.g., Chen et al., 2006; Chen et al., 2019; Guha et al., 2018; He et al., 2010; Li et al., 2013; Sun et al., 2017; Wang et al., 2019) have derived Land Surface Temperatures (LST) and Spectral Indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Bareness Index (NDBaL), Normalized Difference Water Index (NDWI) and Enhanced Normalized Difference Impervious Surface Index (ENDISI), from satellite images. The spectral indices overcome the mixed pixel problem (Mushore et al., 2018). However, challenges persist even when using satellite images. LST is produced from different algorithms and using diverse satellite sensors. None has been validated to be optimal as getting sites for in situ measurements of LST representative of satellite pixel scale is difficult and limited to a few rare homogenous locations (Chen et al., 2019; Li et al., 2013). Inconsistencies are apparent when coupling LST and heat-related mortality Johnson et al. (2012), while the forcing of air pollutants (Depiettri et al., 2013; Heaton et al. (2014) is often ignored and the associated formation of ground ozone (Habeeb et al., 2015; Lo and Quattrochi, 2003). It is unclear whether the derived spectral indices and LST combine additively and whether they should be assigned equal weighting when coupled. It is underwhelming to validate an instantaneous index based on a snapshot of a scene taken with a satellite lag of 16 days that undermines the capturing of episodic heat waves (Wilson and Chakraborty, 2019). Also, cloudy conditions could impede the accurate capturing of heat events using remote sensing (Johnson et al., 2012).

3.2. Social Vulnerability Index (SoVI)

The SoVI measures the adaptive capacity and sensitivity, although methodological shortcomings persist. Limited access to quality data and conceptual limitations derail consistent development of the metric (Cutter and Finch, 2008). The SoVI should capture the social and economic well-being and political, property rights, institutional context, and cultural norms (Clifford and Travis, 2018; Kelly and Adger, 2000). However, processes that define the SoVI are not sufficient, and it may be unwise to conclude that a given prescribed framework should befit the dominant discourse. The rational prediction of the biophysical parameters has limitations; hence answers to how and to what extent social systems are geared to respond are inevitable (Burton et al., 2002; Lee, 2014). Unfortunately, studies on SoVI rarely have one specific hazard, yet it should be the primary yardstick for the potential to prepare, respond and recover (Frigerio and Amicis, 2016; Johnson et al., 2012). Statistical models that incorporate geodemographic dynamics are needed since population distribution and re-distribution have substantive ramifications on vulnerability whose extent is unknown (Ho et al., 2018; Krstic et al., 2017; Shepherd and Zhou, 2009). The parameterization of the SoVI is thus a fuzzy endeavor, and using different indicators generates different assessment outputs. Also, reliance on census datasets not ideally suited for vulnerability mapping raises queries on the relevance of the indices created (Preston et al., 2011).

Social vulnerability exists in many facets, but only certain specific factors or their proxies can substantially manifest or attenuate disasters' impacts. For instance, Lee (2014) illustrated that a scientist has to decide on particular and general factors, objective and subjective indicators that pose divergent challenges when constructing the SoVI. These factors compound to generate negative ramifications before, during, and after occurrences of disasters. Existing literature only provides fragmented insights on the relative importance of the factors and fails to capture the co-productions of vulnerability. Arising from these challenges, our current understanding of social vulnerability is in infancy, as Cutter et al. (2003) concluded since their generated SoVI had no correlations with Presidential declarations on disasters. However, the validity test could be inappropriate since Presidential proclamations could have political motives and not purely scientific guidance. Therefore, not only is the construction of SoVI hazy, but parameters for its validation need to be carefully determined. The SoVI lacks an independent variable upon which it can be calibrated (Zhou et al., 2014). The utility value of the SoVI cannot be understated; however, the scientific discourse should shift to how well-generated SoVI accurately portrays society's intrinsic characteristics.

The credibility of the SoVI is an emerging discourse given that social interactions are indeterminate and multivariate (e.g., Eriksen and Kelly, 2007; Heaton et al., 2014). The pursuit of credibility raises a number of questions. For instance, is it justifiable to correlate the SoVI with heat mortality data when its construction is not hazard specific? Although correlations may exist, how sure are we it is not a statistical chance occurrence attributed to weaknesses of cross-sectional studies? Additionally, data on morbidity and mortality are rarely available and geocoded (Heaton et al., 2014; Weber et al., 2015). While considering new and inclusive models, the pre-incident and post-incident variables differ (Atyia, 2015); therefore, the model must acknowledge these changes. Another perspective by Cutter et al. (2003) raises fundamental concerns on tests of validity. i.e., should validity tests be based on massive singular hazards or small chronic losses? The meanings of variables are consistently contested in respective research disciplines (Cutter and Finch, 2008). For instance, correlating the losses with SoVI presupposes that the most socially vulnerable have most to lose, which may not be the case. The credibility of the SoVI must be interrogated to investigate the relationship of actual damage to the statistically generated indices.

3.2.1. Variables for SoVI and their proxies

Vulnerability assessment is a multivariable problem that has to capture all dimensions of a society, either directly using variables or through their appropriate proxies (Maier et al., 2014) (Table 1). The indicators are both qualitative and quantitative and elicit different interpretations when observed across space and time, with most studies focusing only on the quantifiable indicators (Frigerio and Amicis, 2016). There is also a risk of filtering out variables that cannot be spatially represented, which could be crucial determinants of vulnerability (Eakin and Luers, 2006). Consequently, the variety of circumstances that impact vulnerability have not been explored consistently and systematically (Bera, 2019; Borden et al., 2007). There is no consensus on selecting and interpreting variables likely because SoVI is not hazard-specific, whereas hazard-specific studies tend to apply the broad and general conceptualizations (Reid et al., 2009; Zhou et al., 2014). For instance, is wealth an enabler of quickly absorbing disaster impacts, or does it enhance loss potential?

The adequacy and representativeness of proxies have not been examined in vulnerability studies. Many of the proxies may not be representative and often overlap, failing the test of independence (Brenkert and Malone, 2005). If the actual variables fail the test of credibility, then the results based on proxies cannot be dependable. The lack of a sound methodology designates scientists to arbitrariness in determining proxies. For example, Basu and Ostro (2008) used educational attainment as a proxy for socioeconomic status. In contrast, Kashem et al. (2016) used the poverty rate, income, unemployment, and black race as surrogates for socioeconomic status. Evidently, proxies are at the researcher's discretion, which could undermine the constructed metrics' validity. Also, not all factors and proxies are amenable to policy measures; thus, studies differ significantly in the identification of

Table 1
Examples of variables that have been used in different studies to generate the Social Vulnerability Index.

Variables of vulnerability (Percentage or number of)	Examples of studies that have utilized the variable	Description of the variable
Population aged over 25 years without a high school diploma	(Wilson and Chakraborty, 2019; Macnee and Tokai, 2016; Ho et al., 2015; Reid et al., 2009; Zhou et al., 2014; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Borden et al., 2007; Atyia, 2015; Krstic et al., 2017; Ho et al., 2018; Johnson et al., 2012; Lee, 2014; Reid et al., 2012; Maier et al., 2014)	Education
Female-headed households with no spouse present	(Wilson and Chakraborty, 2019; Kashem et al., 2016; Borden et al., 2007; Johnson et al., 2012)	Gender
Female population	(Reckien, 2018; Kashem et al., 2016; Lee, 2014)	
Population aged under 18 years	(Wilson and Chakraborty, 2019; Cutter and Finch, 2008; Sunhui, 2017; Stennet et al., 2019; Zhou et al., 2014)	Age
Population aged over 65 years*	(Wilson and Chakraborty, 2019; Reckien, 2018; Macnee and Tokai, 2016; Mushore et al., 2018; Ho et al., 2015; Nayak et al., 2018; Reid et al., 2009; Cutter et al., 2003; Zhou et al., 2014; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Tran et al., 2010; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Stennett et al., 2019; Mitchell and Chakraborty, 2014; Krstic et al., 2017; Ho et al., 2018; Johnson et al., 2012; Lee, 2014; Reid et al., 2012; Zhou et al., 2014; Aubrecht and Ozceylan, 2013; Maier, et al., 2014)	
Population aged under 5 years*	(Mushore et al., 2018; Ho et al., 2015; Cutter et al., 2003; Kashem et al., 2016; Tran et al., 2010; Borden et al., 2007; Mitchell and Chakraborty, 2014; Krstic et al., 2017, Ho et al., 2018; Lee, 2014)	
Population of blacks/ African-American*	(Wilson and Chakraborty, 2019; Reckien, 2018; Nayak et al., 2018; Reid et al., 2009; Cutter et al.,	Race

Population change	(Zhou et al., 2014; Cutter and Finch, 2008; Tran et al., 2010; Borden et al., 2007)	Population
Urban population	(Zhou et al., 2014; Borden et al., 2007)	
Population using public transport	(Cutter et al., 2003; Kashem et al., 2016; Atyia, 2015)	Transportation
Mobile housing units	(Wilson and Chakraborty, 2019; Ho et al., 2015; Cutter et al., 2003; Kashem et al., 2016; Borden et al., 2007; Ho et al., 2018)	Housing
The average number of people per household	(Cutter et al., 2003; Kashem et al., 2016)	
Population that has disability 18-64 years	(Nayak et al., 2018; Sunhui, 2017; Atyia, 2015; Lee, 2014)	Disability

Population change	(Zhou et al., 2014; Cutter and Finch, 2008; Tran et al., 2010; Borden et al., 2007)	Population
Urban population	(Zhou et al., 2014; Borden et al., 2007)	
Population using public transport	(Cutter et al., 2003; Kashem et al., 2016; Atyia, 2015)	Transportation
Mobile housing units	(Wilson and Chakraborty, 2019; Ho et al., 2015; Cutter et al., 2003; Kashem et al., 2016; Borden et al., 2007; Ho et al., 2018)	Housing
The average number of people per household	(Cutter et al., 2003; Kashem et al., 2016)	
Population that has disability 18-64 years	(Nayak et al., 2018; Sunhui, 2017; Atyia, 2015; Lee, 2014)	Disability

[a]The most commonly used variable.

Wilson and Chakraborty, 2019; Macnee and Tokai, 2016; Ho et al., 2015; Reid et al., 2009; Zhou et al., 2014; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Borden et al., 2007; Atyia, 2015; Krstic et al., 2017; Ho et al., 2018; Johnson et al., 2012; Lee, 2014; Reid et al., 2012; Maier et al., 2014); (Wilson and Chakraborty, 2019; Kashem et al., 2016; Borden et al., 2007; Johnson et al., 2012); (Reckien, 2018; Kashem et al., 2016; Lee, 2014); (Wilson and Chakraborty, 2019; Cutter and Finch, 2008; Sunhui, 2017; Stennett et al., 2019; Zhou et al., 2014); (Wilson and Chakraborty, 2019; Reckien, 2018; Macnee and Tokai, 2016; Mushore et al., 2018; Ho et al., 2015; Nayak et al., 2018; Reid et al., 2009; Cutter et al., 2003; Zhou et al., 2014; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Tran et al., 2010; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Stennett et al., 2019; Mitchell and Chakraborty, 2014; Krstic et al., 2017; Ho et al., 2018; Johnson et al., 2012; Lee, 2014; Reid et al., 2012; Zhou et al., 2014; Aubrecht and Ozceylan, 2013; Maier et al., 2014); (Mushore et al., 2018; Ho et al., 2015; Cutter et al., 2003; Kashem et al., 2016; Tran et al., 2010; Borden et al., 2007; Mitchell and Chakraborty, 2014; Krstic et al., 2017, Ho et al., 2018; Lee, 2014); (Wilson and Chakraborty, 2019; Reckien, 2018; Nayak et al., 2018; Reid et al., 2009; Cutter et al., 2003; Kashem et al., 2016; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Mitchell and Chakraborty, 2014; Johnson et al., 2012; Reid et al., 2012; Maier et al., 2014); (Wilson and Chakraborty, 2019; Reid et al., 2009; Cutter et al., 2003; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Reid et al., 2012; Maier et al., 2014); (Wilson and Chakraborty, 2019; Reid et al., 2009; Cutter et al., 2003; Kashem et al., 2016; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Johnson et al., 2012; Reid et al., 2012; Maier et al., 2014); (Wilson and Chakraborty, 2019; Reckien, 2018; Nayak et al., 2018; Reid et al., 2009; Cutter et al., 2003; Kashem et al., 2016; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Mitchell and Chakraborty, 2014; Johnson et al., 2012; Reid et al., 2012; Maier et al., 2014); (Wilson and Chakraborty, 2019; Reckien, 2018; Reid et al., 2009; Cutter et al., 2003; Kashem et al., 2016; Maier et al., 2014; Borden et al., 2007; Atyia, 2015; Mitchell and Chakraborty, 2014; Johnson et al., 2012; Reid et al., 2012; Maier et al., 2014); (Macnee and Tokai, 2016, Mushore et al., 2018, Ho et al., 2015; Nayak et al., 2018; Zhou et al., 2014; Sunhui, 2017; Kashem et al., 2016; Bera, 2019; Borden et al., 2007; Krstic et al., 2017; Ho et al., 2018; Lee, 2014); (Cutter and Finch, 2008; Kashem et al., 2016; Borden et al., 2007); (Wilson and Chakraborty, 2019; Mushore et al., 2018; Ho et al., 2015; Cutter et al., 2003; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Krstic et al., 2017; Johnson et al., 2012); (Wilson and Chakraborty, 2019; Reckien, 2018; Nayak et al., 2018; Reid et al., 2009; Cutter and Finch, 2008; Sunhui, 2017; Kashem et al., 2016; Maier et al., 2014; Borden et al., 2007; Mitchell and Chakraborty, 2014; Ho et al., 2018; Lee, 2014; Reid et al., 2012; Aubrecht and Ozceylan, 2013; Abson et al., 2012; Maier et al., 2014); (Reckien, 2018: Macnee and Tokai, 2016; Ho et al., 2015; Nayak et al., 2018; Reid et al., 2009; Maier et al., 2014; Atyia, 2015; Ho et al., 2018; Johnson et al., 2012; Reid et al., 2012; Aubrecht and Ozceylan, 2013; Maier et al., 2014); (Zhou et al., 2014; Cutter and Finch, 2008; Tran et al., 2010; Borden et al., 2007); (Zhou et al., 2014; Borden et al., 2007); (Cutter et al., 2003; Kashem et al., 2016; Atyia, 2015); (Wilson and Chakraborty, 2019; Ho et al., 2015; Cutter et al., 2003; Kashem et al., 2016; Borden et al., 2007; Ho et al., 2018); (Cutter et al., 2003; Kashem et al., 2016); (Nayak et al., 2018; Sunhui, 2017; Atyia, 2015; Lee, 2014).

hotspots even after applying similar data reduction techniques such as the Principal Component Analysis (PCA) (Morabito et al., 2014; Eriksen and Kelly, 2007). It is unclear whether theoretical or statistical relationships should determine vulnerability indicators as both approaches have limitations. Besides, the meaning of vulnerability indicators varies with geographical scale (Lee, 2014).

3.3. Composite Heat Vulnerability Indicator (HVI)

The composite HVI stems from the necessity for integrative approaches that expand on the computation of contingencies and probabilities associated with a hazard without leaving out its unintended consequences (Cutter, 2003). Areas with the highest exposure vulnerability would not always overlap with areas of most heightened socioeconomic vulnerability (Chow et al., 2012; Cutter and Finch, 2008). Several studies (e.g., Johnson et al., 2012; Zhou et al., 2014) have asserted that hazard is a component of risk and not risk itself given that socioeconomic indicators explained 70% of the variance while biophysical only accounted for 12% of the variance. On the other hand, Macnee and Tokai (2016) emphasized that biophysical exposure must be considered. Despite the progress on vulnerability studies, the relative weights of the biophysical and the socioeconomic paradigms have not been determined when coupling. Integrating the paradigms without a proper definition of relationships could generate arbitral conclusions related to their relative contribution to the combined HVI (Preston et al., 2011). Other studies (e.g., Bera, 2019; Chow et al., 2012; Kim et al., 2017; Wilson and Chakraborty, 2019) explain that a composite HVI should incorporate sensitivity, exposure, and adaptive capacity, although the adaptive capacity dimension is often ignored as it involves qualitative approaches.

4. The quantitative dimension

4.1. Variable selection and weighting

Studies on heat vulnerability have failed to construct a standard set of variables for uniformity and comparative analysis. Any consensus among studies is driven by the resemblance in chosen measures rather than convergence of insights (Eriksen and Kelly, 2007). The variables selected should encompass sensitivity, adaptive capacity, and exposure (Kim et al., 2017; Wilson and Chakraborty, 2019). Lee (2014) identifies the SoVI as representing a system's internal state, which is paramount compared to the threats' nature. Reckien (2018) observed that variables of social vulnerability might differ depending on the stressor, hence giving prominence to physical vulnerability risk. Variable selection could also be altered by the availability of data (Lee, 2014). Therefore, the determination of appropriate indicators is a subjective process that should strike a balance between statistical relationships of variables and the theoretical understanding of relationships (Eriksen and Kelly, 2007).

The general trend in scientific approaches has been to assign equal weights to all indicators for lack of a theoretical underpinning (Abson et al., 2012; Brenkert and Malone, 2005; Kashem et al., 2016). The debate is only limited to the relative influence of variables, yet several studies (e.g., Cutter et al., 2003; Nayak et al., 2018; Reid et al., 2009; Reid et al., 2009; Zhou et al., 2014) have shown that there exists distinct geographical variability in vulnerability that is augmented in downtown areas. Therefore, studies have to explore the weighting of indicators pegged on geographic scale variability and distance from downtown locations. Another dimension of weighting that is least explored occurs when coupling the biophysical and the socioeconomic indices. It is unknown which one should be given prominence. For instance, Mushore et al. (2018) assigned an equal weighting of 25% to four final components that encompassed the NDVI, NDBI, NDWI, and the SoVI. In this argument, the SoVI was essentially assigned 25%, while the biophysical accounted for 75% of the weighting. It is unknown whether the spectral indices have an additive effect or provide different dimensions of the same vulnerable group. An increase in the number of biophysical indices resulted in a decrease in the proportional weighting of the SoVI without any substantive argument presented. When coupling the spectral indices, it is further assumed that they have equal weighting, which is not supported by any theoretical construct.

Another mechanism fronted by Ho et al. (2015) assigns an equal weighting to the SoVI and the biophysical layers (50% to 50%) regardless of the number of components that define the biophysical. In this approach, the SoVI is a composite of 8 layers, while LST represents the biophysical. Also, there is no theoretical underpinning to assume equal weighting of the biophysical and the SoVI components of vulnerability. Another weighting controversy emanates from the PCA. Several studies (e.g., Borden et al., 2007; Johnson et al., 2012; Nayak et al., 2018: Zhou et al., 2014) have subjected the biophysical and the socioeconomic variables jointly into the PCA. In some instances, the PCA indicators are weighted based on the percentage variance they explain (Reckien, 2018). In common practice, equal weighting of final PCA components is favored. No study has evaluated the implications of these weighting mechanics on the final composite HVI developed.

4.2. Approaches in constructing the composite HVI

Challenges abound when constructing the coupled HVI, yet it is inadequately addressed in the literature (Macnee and Tokai, 2016). The socioeconomic and biophysical systems interact across administrative boundaries, while census data are based on administrative units creating a mismatch in spatial representations (Lee, 2014; Li et al., 2019). The use of census data weakens the correlation between population density and LST (Mushore et al., 2018). Census data are household-based, yet most adults spend most of their daytime elsewhere (Ho et al., 2015). Besides, ecological perturbations may impact the capacity to respond through co-production of vulnerability that creates a challenge on the best way to represent the overlapping stressors. Consequently, relationships between the SoVI and the biophysical hazard need to be explored as vulnerability is a complex multi-dimensionality of causes, outcomes, and pathways (Carr et al., 2014; Cutter et al., 2003). The generated composite index can only have meaning when it measures and represents what was initially intended. For instance, Johnson et al. (2012) used land use and land cover classes to map only residential spaces since the SoVI is a derivative of census data. This is a unique approach that raises weighty concerns as humans are not confined to residential zones. In a different representation, Mitchell and Chakraborty (2014) excluded pixels representing water features and conducted regression analysis with LST as a dependent variable and census data as an independent variable.

The approaches adopted are context-specific and dependent on questions of interest, the audience, and disciplinary composition of the research team; hence the challenge lies in uniting the disparate perspectives (Depiettri et al., 2013; Eakin and Luers, 2006). Although the diversity of approaches provide rich perspectives on the multi-dimensionality of vulnerability, the lack of a widely applicable theoretical framework could deter progress in the intellectual development of whole encompassing visual representations. For instance, Wilson and Chakraborty (2019) argue that planning interventions favor the built environment and not the socioeconomic conditions; therefore, they opt to solely incorporate sensitivity and adaptive capacity dimensions to align their recommendations with policy interventions. Excluding the exposure dimension could undermine the robustness of the conclusions and subjecting science to vulnerability as elucidated in (Cutter, 2003).

Visual representations are presented as area-based or population-based whose outputs are anchored on the construction methods and input data metrics (Abson et al., 2012; Reckien, 2018). For additive methods, area-based metrics generated minor deviations with a smoother spread than population-based, although vulnerability patterns were relatively the same. Conversely, using PCA in an inductive method, Reckien (2018) established that area based model explained 87% of the total variance while the population-based accounted for 64% of the total variance. The patterns of vulnerability were substantively different, even when utilizing similar variables. According to Abson et al. (2012), variable reduction assumes that highly correlating indicators are interchangeable, hence the idea of using proxies. However, additive approaches should suffice when the influence of individual indicators is known to be high (Reckien, 2018). Generally, Reckien (2018) noted that area-based methods explained more variance and produced lower differences in different models; hence, the technique's infrequent use is unwarranted. However, such an approach of comparing metrics, models, and methods has not been widely replicated in different locations to validate the observation made by Reckien (2018). The techniques adopted in vulnerability studies appear to be guided by convenience and familiarity rather than efficacy (Preston et al., 2011).

The Hazard of Place Model (HPM) (Cutter et al., 2003) and the Vector and Raster Based Model (RVM) (Ho et al., 2015) are the fundamental conceptual models in vulnerability studies. The HPM holds that risk would always interact with mitigation measures resulting in a hazard potential, modulated by site, situation, proximity, and social fabric of a locality. The model assumes that the hazard is a social construct of demographic characteristics and residual impacts after adaptation and mitigation. However, the HPM fails to provide a weighting mechanism and means for overcoming the MAUP, zonal effects, and the mixed pixel problem. Furthermore, it is not hazard-specific and does not account for unmitigated risks. The decision criteria for spatial representation perspectives are not specified as the qualitative non-measurable components of vulnerability are not incorporated. On the other hand, the RVM relies on remote sensing datasets and harmonizes the spatial resolutions of the biophysical and socioeconomic through re-sampling to overcome the MAUP. The RVM allows outputs of raster and vector models enabling for comparative analysis where the selection of variables is expert-based (additive approach); hence PCA is disregarded. It is not clear whether expert judgment studies generate significantly different results compared to systematic studies under PCA. However, both models fail to incorporate the qualitative non-measurable components of vulnerability and do not provide consistent weighting guidelines.

In this review, we modify the HPM (Fig. 1) and narrow it to the heat hazard, which provides a focused approach to the definition of vulnerability. The model acknowledges that a hazard potential is not only defined by interactions between heat risk and mitigation measures, but there exist unexpected perturbations and co-productions of vulnerability which the HPM failed to capture. Therefore, a hazard potential constitutes the residual risks after mitigation, and the unmitigated risks comprising maladaptations and unexpected systemic shocks. The model also provides for broad spatial representation decision considerations, including; area or population-based visualization, theoretical and statistical considerations, inductive and deductive approaches, and weighting mechanics. The conceptualization recognizes the need for hazard specificity, the potential for risk co-productions and unintended perturbations, and enlarging the decision criteria alternatives to allow for comprehensive comparative spatial representations. The decision criteria visualize and define the hazard dimensionality, whereas the hazard potential could influence decision considerations.

4.3. Principal Component Analysis

Several studies (e.g., Abson et al., 2012: Tran and Formannn, 2009) have used the PCA as a data reduction technique that allows for a consistent set of indicators to be monitored over time. However, the use of PCA varies in the number of input indicators, variable rotation techniques, criteria for determination of final factor components, and correlational algorithms. Some studies (e.g., Johnson et al., 2012; Maier et al., 2014) have used the varimax rotation method, and the Kaiser criterion then normalized the components and classified them using standard deviations from the mean. Other studies (e.g., Tran and Formannn, 2009) use Parallel Analysis (PA) rather than the Kaiser criterion, which is influenced by sample size and the type of correlation coefficient used. The Kaiser eigenvalue rule has been criticized for not accounting for random fluctuations of correlations and only held true in large samples. Frigerio and Amicis (2016) combined three selection methods; the Kaiser Criterion, The Broken Stick Model, and the PA. The Kaiser criterion and the PA both retained four components explaining 76% of the total variance, while the broken stick model retained three components explaining 67% of the variance. Therefore, it is not clear which model is sufficient. Also, the criteria for evaluation of the best model is non-existent despite the significant differences. For instance, should a model be assessed as superior based on the number of retained components or percentage variance explained, or should the robustness of the statistical algorithm suffice? Frigerio and Amicis (2016) opted to use the Kaiser criterion, and the PA guided by equivalence in their outputs.

Some studies (e.g., Abson et al., 2012; Johnson et al., 2012) eliminated variables deemed to exhibit a complex structure, which meant their direction of influence could not be ascertained. The excluded variables were total population, males under 5, females under 5, the poor over 65, and populations below the poverty level. However, these factors are significant in other studies. Therefore, we have a justification for doubting the complexity assigned to variables after the PCA. For example, Zhou et al. (2014) had a screening procedure before PCA by using Bartlett's test of sphericity and the Kaiser-Meyer-Olkin test, which determined the suitability of the variables for factor analysis. The effectiveness of the prior screening should be explored to determine its efficacy in eliminating variables with complex structures. Instead of removing variables without a clear direction of influence, some studies (e.g., Cutter et al., 2003; Zhou et al., 2014) assigned them absolute values. Others (e.g., Reckien, 2018) opted to adjust for cardinality by multiplying all scores by −1 to transform all components to have unidirectional influence. Also, Nayak et al. (2018) had a series of criteria for determining final components, including; eigenvalue greater than 1, cross-checking elbows of scree plots, each component had to explain a minimum variance of 10%, and the total variance explained had to be a minimum of 70%. However, neither the relative advantage of the different subjective criteria used nor their utility functionality have been assessed.

The number of input variables differs across studies. For instance, Macnee and Tokai (2016) started with eight variables and ended with three variables that explained 77% of the variance. A study by Reid et al. (2009) began with ten variables and ended with four that explained 75% of the total variance. Cutter et al. (2003) began with 211 variables and ended with 11 variables that accounted for 76% of the total variance. The focus should be on identifying a few substantive variables that explain a significant variation instead of many insignificant indicators and creating clutter in the PCA. A few studies (e.g., Abson et al., 2012; Reckien, 2018) have opined that the PCA merges components based on statistical relationships and not rational content-driven reasoning.

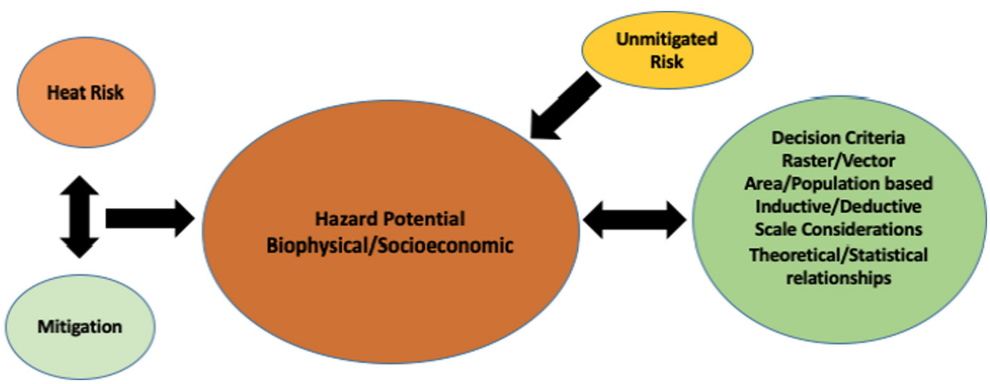

Fig. 1. The heat hazard potential representation model. Hazard constitutes the biophysical and socioeconomic perspectives, including residual and unmitigated risks. The broad decision criteria offer a range of perspectives that could help generate comparative outcomes. (c.f., Cutter et al., 2003).

The PCA approach seems useful when the relative strength of vulnerability indicators, correlations, contributions, and roles is unknown (Reckien, 2018). It is challenging to accurately dissolve complex socioeconomic and environmental interactions to a single number (Brenkert and Malone, 2005). The authenticity by suites of individual variables and drivers could be depleted through data aggregation, yet their quantification in isolation may not provide a rich understanding (Abson et al., 2012). The PCA trades off dimensionality and communicability but fails to provide absolute measures of vulnerability for lack of a distinct defensible guidance framework (Hung et al., 2018; Kachigan, 1986). The PCA cannot be performed in datasets with missing values. For instance, Cutter et al. (2003) substituted missing values with the value zero. The implications of such a decision have not been investigated on the eventual vulnerability index. For example, why shouldn't the tracts with missing values be dropped or assigned mean values? Also, what is the criteria for the scientific community to accept a subjective justifiable technique? Although the PCA has limitations, scientists find it useful since it is difficult for policymakers to strategize based on many discrete variables that could be overlapping and contradictory.

As a consequence of existing limitations, this review modifies the Ho et al. (2015) RVM (Fig. 2), accounting for both low spatial resolution of in situ data and coarse temporal resolution for remotely acquired datasets. A weighting mechanics of spectral indices and LST is considered as it is currently unknown whether they act additively while the indicators' independence has not been explored. Furthermore, the PCA is not only a preserve of the socioeconomic dimension but accommodates arguments about subjecting the biophysical metrics alongside the socioeconomic to data aggregation. The modified model also provides for additive and reductive approaches while incorporating non-quantifiable variables and those incapable of being spatially visualized through the representation considerations. Pre-PCA screening ensures that input variables are suited for the PCA. The retained PCA components are subjected to different comparative statistical procedures, including the Kaiser criterion, the broken stick criteria, scree plot tests, and PA to bolster the robustness of the PCA. The model also acknowledges the existence of multiple representation approaches such as raster verse vector, area-based verse population-based, additive and reductive approaches. The mixed pixel problem and the MAUP are diminished through resampling and the use of spectral indices. The SoVI is validated through both singular significant hazards and small chronic risks while aligning it with policy formulation and implementation. Ultimately, several composite HVI would be produced and compared for consistency.

5. The missing links

5.1. The case for qualitative approach

Vulnerability studies are ostensibly conducted to help decision-making among stakeholders, yet many fail to incorporate direct engagement (Preston et al., 2011). The robustness of spatial representations is evaluated in their capacity to disclose sociopolitical barriers in the decision-making discourse and understanding multiple facets of vulnerability. The SoVI is not exogenous to policy and planning implications; hence the primary causes of the shifts can best be captured by qualitative data (Kashem et al., 2016; Wilson and Chakraborty, 2019). Consequently, the impacts of the various thermal indicators are best illustrated through qualitative and quantitative approaches (Turner II et al., 2003). For instance, Jonsonn and Lundgren (2015) identified that local contextualized knowledge that elucidated vulnerability drivers and their inter-relations is abundant within communities. However, this knowledge that could complement quantitative studies remains largely untapped by the research community, although it could have a significant influence on the policymaking agenda. Cultural impediments create maladaptations. The stakeholders must be involved in designing methodologies, determining visualization options, aggregation techniques, and mechanisms to communicate the results to align local needs, expectations, and perceptions with the research outcomes (Weber et al., 2015). Although the calls for qualitative data in vulnerability studies are valid, they are fraught with challenges. It is not clear about the best strategy to capture the data and integrate them into quantitative vulnerability studies (Depiettri et al., 2013; Eakin and Luers, 2006). For example, our mental representations are limited as time passes, and the scientist has to determine appropriate points in time when recalling of events is optimum (Wang et al., 2017).

5.2. Embracing the longitudinal approach

Vulnerability studies ache for broader, universally acceptable, and comprehensive theoretical and conceptual understanding, yet few

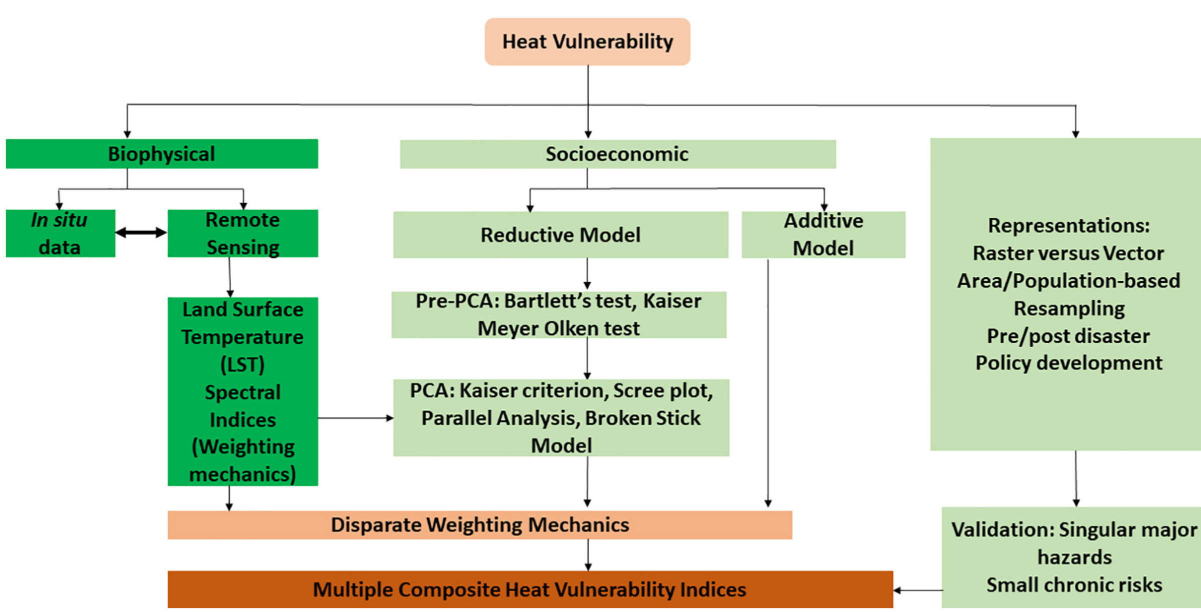

Fig. 2. The primary components of the multi-dimensional model. In situ data complements remotely acquired datasets, and the PCA process is enhanced by incorporating pre-PCA tests and broadening the criteria for determining final components. Spatial representation considerations are provided for efficacy in outputs (c.f., Ho et al., 2015).

attempts have been made to fill the lacunae (Caruana et al., 2015). Majority of the frameworks available have failed to harmonize the divergent scientific perspectives and are anchored on static cross-sectional study designs. Ideally, theories are explicitly and implicitly longitudinal (Ployhart and Vandenberg, 2010). Uncertainty on how to proceed with longitudinal studies could impede stable theoretical and conceptual underpinnings of vulnerability. Scientists shy away with the mindset that there is no guarantee that dynamics in focal variables are inherent when the time dimension is incorporated. Consequently, Ployhart and Vandenberg (2010) opine that differences between individuals at a given time do not constitute a change. Instead, the focus should be guided by substantive dynamic constructs. The existing theories may not be thoroughly tested unless having been an output of the longitudinal approach. Identifying processes that shape social susceptibility rather than merely aggregating the state of the social system is pertinent in determining representative indicators (Eriksen and Kelly, 2007).

Most vulnerability studies rely on census data, which are subject to consolidation, revisions, and splits. Boundary shifts present a likelihood of drawing invalid conclusions since interpolations are conducted on population and area weighting, which could have significant variations (Logan et al., 2014). Adopting the longitudinal approach further presents new challenges, as explained by Wang et al. (2017); for instance, should time be a substantive variable or a notion of temporal dynamics? Also, the is no clarity on how optimal time interval is determined, and the number of repeated measures to improve the validity of the inferences that cross-sectional studies fail to achieve. The chosen time interval must sufficiently allow the effect to register and be congruent with the system's inherent change process. The variables in use may not match overtime, and their definitions may change when using census data (Cutter and Finch, 2008), hence pushing scientists to opt for closely related variables rather than truly definitive variables. Although shortcomings persist, longitudinal studies provide details on the magnitude and direction of change and ostracize recall bias where data collection is prospective without prior knowledge of successive eventualities (Caruana et al., 2015).

5.3. Determination of scale

The associated effects of heat hazards are not spatially uniform, yet it is central in ascertaining the application and production of scientific knowledge integral for crucial decision making (Lee, 2014; Krstic et al., 2017). Urban heatwaves occur across large functional spatial and temporal extents, complicating response strategies (Kim et al., 2017; Preston et al., 2011). It is challenging to select geographic scales congruent with system dynamics and matching the biophysical and socioeconomic scales to avoid the MAUP (Ho et al., 2015). Therefore, Johnson et al. (2012) propose the development of models targeting specific locations that account for local variations. The appropriate scales must capture optimal points where socioeconomic and environmental interactions are most intense while ensuring compatibility with decision-making units (Borden et al., 2007; Eakin and Luers, 2006). It is imperative to doubt the utility of assessing vulnerability dictated by bound economic, population, and regional units to avoid the zoning effect in spatial visualization of hotspots. For instance, Ho et al. (2015) found that a spatial resolution of 500 m or coarser fails to capture temperature differences between neighborhoods, yet census data are mostly over 1 km.

The interactions between indicators, structures, and stresses of vulnerability manifest on different spatial scales that translate to several dominant vulnerability factors at different geographic levels (Cutter and Finch, 2008; Eriksen and Kelly, 2007). Although this weakness exists, there lacks a formal and consistent methodology for the discernment of ideal spatial units (Bera, 2019). The theoretical conceptualization of processes that ultimately shape vulnerability is not deftly developed as it materializes intermittently (Eriksen and Kelly, 2007). The hazards act within and beyond the unit of analysis, yet the differences are only partially understood (Aubrecht and Ozceylan, 2013; Turner II et al., 2003). Most research work is confined to urban administrative units. Maier et al. (2014) determined that half of the vulnerable counties in Georgia were in rural areas, while some studies even fail to differentiate whether they are urban or rural-focused (Lee, 2014). Although the calls for specific local spatial scales are justified, it is at the national level where adaptation policies and international dialogues occur, hence an emerging debate on whether a top-down or bottom-up scale approaches for vulnerability studies (Preston et al., 2011). To date, debates persist whether vulnerability studies should correspond to the scale of governance and administration, or correspond to operating processes of the biophysical hazard, or optimal points where socioeconomic and environmental interactions are intense.

5.4. The space-time dimension

Heat vulnerability has an exceptionally high degree of spatial and temporal heterogeneity (Abson et al., 2012; Arnds et al., 2017). The dynamism could generate new unintended hazards; hence time should be considered as a substantive variable in longitudinal studies. To unravel the complexity and multi-dimensionality of vulnerability, the spatio-temporal patterns are essential, especially in the coupled HVI (Aubrecht and Ozceylan, 2013; Carr et al., 2014). The space-time analysis helps project future trends, understand shifts in population and their drivers, and how human and environmental conditions attenuate or amplify the changes (Turner II et al., 2003; Wilson and Chakraborty, 2019). However, the use of remote sensing could be limited since it is difficult to select images having similar atmospheric conditions for enhanced comparative analysis over a time lag. A snapshot analysis at a particular instance fails to accommodate the richness of the shifts. Besides, revealing how levels of vulnerability occur over time has more utility functionality than simply illustrating why a particular pattern exists (Eriksen and Kelly, 2007). Therefore, vulnerability assessment needs to be a continuous event that is dynamic and adaptive (Jonsonn and Lundgren, 2015). The population distribution and re-distributions could create new vulnerabilities hence the need to develop standardized datasets that harmonize consolidated or adjusted census tracts across time (Logan et al., 2014: Wilson and Chakraborty, 2019).

5.5. Shortcomings of the existing framework

The existing framework for characterizing sensitivity, exposure, and adaptive capacity has numerous weaknesses and is highly fragmented. The approaches adopted are not systematic and consistent, primarily guided by convenience and familiarity rather than efficacy. The framework fails to accommodate qualitative aspects that ensure linkages to policy formulation and incorporation of crucial aspatial variables to minimize overreliance on census datasets. Guidelines for selection and weighting of indicators are absent. The geodemographic dynamics are often ignored, while the theoretical and statistical relationships are not harmonized. Most studies fail to utilize the longitudinal approach, yet the theories are explicitly and implicitly longitudinal, thus failing to explain processes driving vulnerability. The frameworks are not hazard-specific, and correlations of the different metrics are unknown. The validity tests are often not incorporated in the methodology. When validity tests are conducted, they do not distinguish the small chronic events and large singular hazards.

Additionally, shifts in census boundaries remains a challenge when representing vulnerability and tracking its evolution over time. Geographic Information Science challenges related to MAUP, zonal adjustments, and mixed pixel problems are thus inevitable. Scales mismatches at geographic scales, temporal resolution, and administrative levels compromise integration of the biophysical exposure and SoVI metrics. Biophysical characterization is imprecise when applying different metrics ranging from apparent temperature, surface, and nearsurface metrics, accounting for humidity, Land Surface temperatures, and spectral indices. The existing models also fail to account for pre and post-incident variables. The meanings of indicators vary geographically and across time, and the over-reliance on census datasets, which are not explicitly meant for vulnerability studies, raises doubts about generated indices. More so, no study has evaluated the implications of weighting mechanics on the final derived indices. There is also over-reliance on the PCA as a data reduction technique, which has limitations in determining final components, variable rotational methods, pre-PCA screening, and fails to establish theoretical relationships within variables. The current focus seems to be on aggregating summative indices instead of identifying processes that shape vulnerability. It is vital to reveal how vulnerability levels occur over time than merely illustrating how a particular pattern exists. The assortment of weaknesses is non-trivial and calls for new conceptual frameworks to remedy the existing challenges in spatial representation, allowing for comparative analysis of multiple composite indices towards a consistent and systematic spatial model of heat vulnerability. The inclusive framework is thus proposed.

6. Synthesis: the inclusive framework

We are proposing a framework (Fig. 3) that is anchored on the longitudinal approach, which embraces the dynamism inherent in the systems, cognizant that theoretical and statistical relationships are comprehensively captured using an iterative framework. The quantitative dimension comprises of three components; the biophysical, the SoVI, and geodemographic dynamics, all interacting continuously as a system. The interactions generate unintended and random second-order risks in the form of co-productions, residual risks that occur after adaptation and mitigation have taken effect, and stochastic ecological perturbations. The biophysical index is an output of both in situ data and remote sensing techniques, providing a self-validation system on the accuracy of derived metrics.

The geodemographic dynamics represent population distribution and re-distribution, revealing inherent population change patterns, regardless of the populace's socioeconomic characteristics. The geodemographic dynamics in isolation could result in shifts in vulnerability, thus constituting a substantive suite of variables. Several studies (e.g., Ho et al., 2018; Krstic et al., 2017; Shepherd and Zhou, 2009) acknowledged that the effects of geodemographic dynamics are unknown, yet could have a significant influence on the vulnerability index, thus the necessity for inclusive conceptualizations. The consolidation, revisions, and splits of tracts have a bearing on the geodemographic dynamics (Wilson and Chakraborty, 2019). Cognizant of the geodemographics, Johnson et al. (2012) used dasymetric mapping only to visualize residential spaces. Therefore, geodemographic factors explain population changes, migration patterns, and census tract changes, occurring continuously, that supplement information derived from socioeconomic variables describing sensitivity and adaptive capacity. However, not all variables can be spatially represented and quantified, thus the imperative for the qualitative approach.

The qualitative dimension comprises four essential components; different approaches, weighting mechanics, scale considerations, selection of variables, and their proxies pre-incident and post-incident. The qualitative dimension mainstreams aggregated indices to policymaking and ensures that the theoretical and statistical perspectives are harmonized. The non-quantifiable attributes such as social capital, political economy, behavioral responses, perceptions of risk, and meaning of indicators are all considered. Qualitative variables bridge the gap between heat hazard and spatial policy planning, pinpointing processes that shape vulnerability, instead of merely aggregating the state of a complex system of interactions (Eriksen and Kelly, 2007). Derived quantitative metrics may not capture institutional context, cultural norms, and property rights, factors that impact communities' vulnerability (Clifford and Travis, 2018; Kelly and Adger, 2000). Integrating the quantitative paradigms of the biophysical and socioeconomic without a comprehensive definition of relationships may lead to arbitral conclusions. For instance, correlating the losses of the SoVI assumes that the most socially vulnerable have most to lose, which may not be the case (Cutter and Finch, 2008).

Communities' susceptibility is an intricate multi-dimensionality of causes, outcomes, and pathways which may not be effectively captured by a single quantitative index. The use of census datasets also limits quantitative studies to the data collected during the census process, which may not be exhaustive in explaining vulnerability. High biophysical vulnerability locations may not always overlap with areas of high socioeconomic vulnerability; hence, caution is needed when taking the coupled systems approach. Therefore, the qualitative dimension provides context, qualifies the quantitative metrics, ensures stakeholder engagement, enables targeted mitigation measures, clarifies assumptions, and provides supplementary data not captured in census datasets, bridging the gap between statistical and theoretical interpretations. The

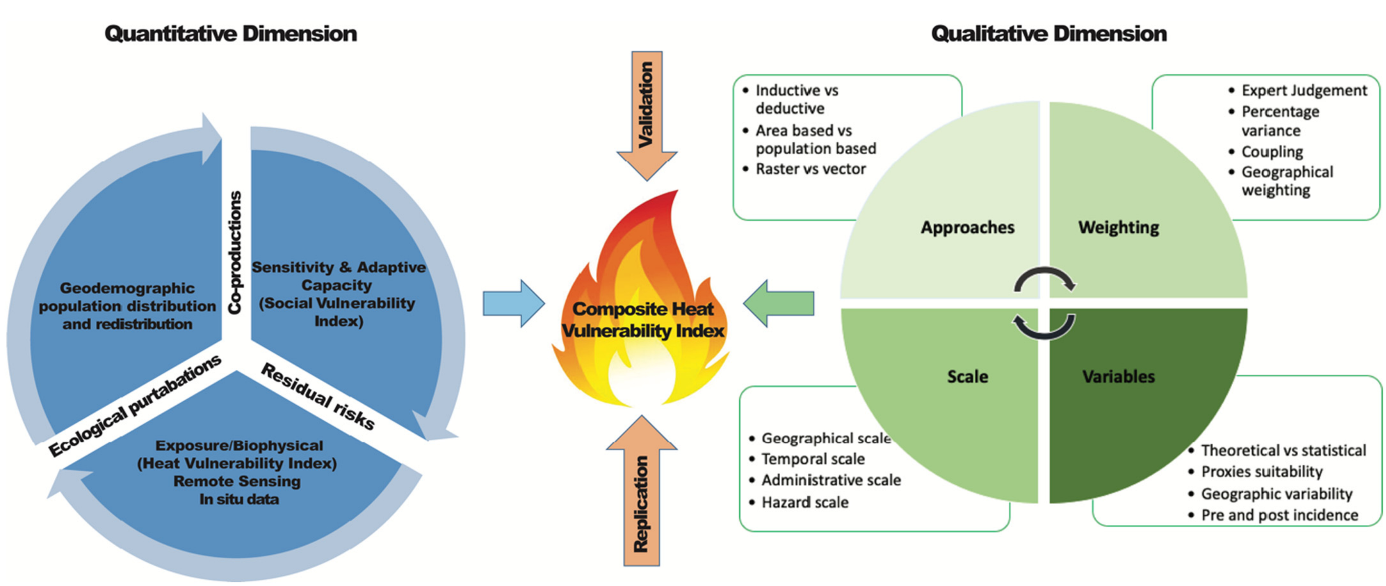

Fig. 3. The composite HVI represents an integration of quantitative and qualitative perspectives providing a guide for truly definitive variables that accurately and precisely allow spatial representation, subject to validation and replication.

qualitative dimension is a substantive methodological framework broadly characterizing the adaptative capacity often not deftly captured in socioeconomic variables, thus providing a crucial data collection tool. The selection of ideal indicators should be guided by specific criteria including; hazard specificity, pre-PCA screening; eigenvalue should be more than the value1, amenable to policy measures, validated by scientific precedence, encompassing sensitivity, adaptive capacity, and exposure. The selection process must go beyond census datasets incorporating spatial and aspatial variables emanating from the qualitative approach.

The conceptual model proposes the use of expert judgment; percentage variance explained, equal weighting when coupling, and geographical weighting with distance from downtown areas as probable weighting mechanics. Several studies (e.g., Brenkert and Malone, 2005; Eriksen and Kelly, 2007; Johnson et al., 2012; Zhou et al., 2014) used different weighting mechanics that significantly affect the derived coupled indices. All the proposed weighting mechanics have logical theoretical justifications, although they vary in spatial characterization. Transitioning to effective, consistent, and accurate spatial representation will require deriving multiple composite indices using different mechanics and subjecting to correlational analysis using geocoded heat mortality statistics. Continuous comparative analysis of the derived indices will provide the best variable weighting mechanics, accurately capturing spatial vulnerability patterns when validated by heat-health outcomes. The validation approach will provide an empirical and objective conceptualization that should inform subsequent heat vulnerability studies.

The various approaches could be pursued, and outcomes compared and validated towards establishing reliable methodologies. The appropriate geographical scale must capture geographic variability in the dominant variables with changing distance, allowing weighting to be pegged on distance. The temporal study scale has to accommodate scales of optimum interactions within coupled systems. The administrative units, reflecting decision-making levels, have to be streamlined with hazard occurrence levels, enabling the selection of indicators amenable to policy strategies.

The ultimate output, a composite HVI, represents a dynamic relative metric that may provide insights into transitioning to absolute measures when subjected to continuous objective validation and replication procedures. Therefore, replications that return similar output over time may form substantive discourse in providing a consistent, holistic, comprehensive, accurate, and precise conceptual framework. The model enriches spatial representations encompassing stochastic incidences and non-linear components, acknowledging that theories are explicitly and implicitly longitudinal, ensuring the use of truly definitive variables to quantify indices. Validation of the derived metrics should be subjected to small chronic hazards and singular significant hazards to guard against weak validation criteria. The composite indices would be the predictor variables in the validation, while geocoded mortality data would be the response variable. Multiple linear regression analysis between composite indices and heat-related mortality could be conducted to test the derived composite indices' effectiveness in predicting heat-health outcomes associated with small chronic hazards. For large singular events, the composite indices could be correlated with the frequency of county or state heat disaster declarations.

Replication is meant to check consistency in the approaches proposed. For instance, proposed techniques include inductive and deductive methods, vector and raster-based, area-based, and population-based, while applying equivalent weighting mechanics. It is expected that replicating similar approaches should generate similar distributions and classifications of vulnerability. Deriving multiple composite indices, and subjecting each to validity tests using heat mortality data, should provide comparative hints on the best approach that best fits with heat mortality outcomes. Therefore, a set of given visualization choices should have similarities in the determination of spatial patterns of vulnerability regardless of locality, providing a robust and consistent pathway for subsequent heat studies. When replicated and subjected to validation tests, comparative spatial visualization choices should determine the optimum methodological framework, identifying the optimum representation of heat vulnerability.

Climatic changes are happening faster than our capacity to respond hence the urgency to harmonize divergent scientific perspectives on heat vulnerability. The policy response strategies are not exogenous to derived composite indices; thus, local needs, perceptions, and cultural attributes have to be integrated into statistically derived indices. The model acknowledges the necessity for accuracy and precision in representing society's intrinsic characteristics and environmental systems for a robust scientific reference point. The scale mismatches often generate the MAUP and zonal effects in spatial representation; the model provides for raster representation that allows for resampling of datasets to standard spatial scales. The mixed pixel problem is overcome by the generation of spectral indices that quantify each pixel providing a reliable numeric output. The different weighting mechanics guided by expert judgment, percentage variance explained by a variable, and geographical variability of influencing indicators have to be explored while reflecting community stakeholders' input. Therefore, the model summarizes disparate spatial representation perspectives and applies a systematic synthesis to visualize optimum points of convergence, and enriches aspects of divergence in ideas, creating a harmonious blueprint for comparative scientific outcomes for heat specific hazard.

The conceptual framework provides a significant shift in vulnerability assessment. Although it proposes novel perspectives on heat vulnerability representation, the framework has not been subjected to actual tests using datasets. Our subsequent work would explore the various approaches suggested. Also, satellite and weather station datasets have temporal and spatial scale challenges, respectively, meaning biophysical vulnerability is impaired. The conceptual framework has not explored the possibility of data fusion techniques that could provide multi-temporal, spectral, and spatial resolution sources. More so, the conceptual framework relies on the census data temporal scale, which may not be ideal for detecting registration of vulnerability changes.

7. Conclusion

Urban heat stress will increase in magnitude, frequency, intensity, and duration hence the need to accurately and precisely visualize the most susceptible for a targeted policy response. We have provided an iterative holistic conceptual framework that integrates quantitative and qualitative approaches. The UHI phenomenon being multi-dimensional should not be a deterrent to effective spatial representation. Our model acknowledges that the interactions between the biophysical, geodemographics and socioeconomic dimensions generate stochastic ecological perturbations, residual risks, and hazard co-productions, often not accounted for in the existing frameworks. These interactions are iterative and need a longitudinal approach that recognizes that scientific theories are explicitly and implicitly longitudinal.

Targeted policy responses are enhanced when specific, accurate, and precise spatial representations are availed. The imperfections observed in the available frameworks are multiple. There is a need to harmonize the different approaches, scale choices, weighting mechanics, and manipulation of variables through longitudinal methods that acknowledge spatiotemporal reference. Alternatives pursued by scientists must meet certain thresholds and be subjected to replication and validation while incorporating the qualitative dimension. This review has provided a starting point for scientific discourse towards a consistent iterative spatial representation framework. The theoretical and statistical relationships are enhanced, and the definition of vulnerability is made hazard-specific. We have provided flexible decision criteria that transition from simple data aggregation to understanding processes that shape vulnerability. The model allows for pre and post hazard variables determination and avails rational content-driven reasoning in developing the composite HVI. It accommodates closely related variables, identifies definitive indicators for vulnerability, and provides a platform for replicating and validating robust, consistent, and systematic conceptualization for spatial representations.

Declaration of competing interest

Each of the authors (Joseph Karanja and Lawrence Kiage) declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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