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Assessing climate change and health vulnerability at the local level: Travis County, Texas

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We created a measure to help comprehend population vulnerability to potential flooding and excessive heat events using health, built environment and social factors. Through principal component analysis (PCA), we created non-weighted sum index scores of literature-reviewed social and built environment characteristics. We created baseline poor health measures using 1999–2005 age-adjusted cardiovascular and combined diabetes and hypertension mortality rates to correspond with social–built environment indices. We mapped US Census block groups by linked age-adjusted mortality and a PCA-created social–built environment index. The goal was to measure flooding and excessive heat event vulnerability as proxies for population vulnerability to climate change for Travis County, Texas. This assessment identified communities where baseline poor health, social marginalisation and built environmental impediments intersected. Such assessments may assist targeted interventions and improve emergency preparedness in identified vulnerable communities, while fostering resilience through the focus of climate change adaptation policies at the local level.

Keywords: adaption, excessive heat, floods, health, mitigation, vulnerability mapping

Introduction

Climate change affects human health both directly and indirectly. Direct health effects caused by climate change include greater morbidity and mortality due to increases in severity and frequency of extreme weather events, decreases in air quality and increases in heavy rainfall events (Haines and Patz, 2004). Indirect health effects may be caused by altered disease ecologies and expansion of existing disease geography (Gage et al., 2008). Persons most affected directly by climate change are socioeconomically marginalised populations such as the elderly, children, minorities and persons with certain pre-existing medical conditions. Health vulnerability assessments focus on understanding population sensitivity to the effects of specific exposures, measuring the ability to respond to and recover from these effects. A greater understanding of how health might be affected by climate change will help identify populations facing disproportionately higher burdens. Additionally, public health entities may contribute to future policies where climate change and health issues intersect (Frumkin et al., 2008).

Assessments of health vulnerabilities, on varying spatial and temporal scales, are typically based on demographics and anthropogenic built environment measures that use multivariate regression and simulation models (Balica et al., 2009; Connor and Hiroki, 2005; Harlan et al., 2006; Johnson et al., 2009). We aimed to balance the computational complexity of the approach in identifying health, social and environmental vulnerabilities with the resources available to local public health departments through a downscaled vulnerability analysis. Using Travis County, Texas, we identify measures to help comprehend population vulnerability to climate change. We used social factors, built environment and age-adjusted mortality rates to create a social–built environment index and measures of baseline health at the community level. The simplicity of the method and the use of hazard-relevant health data at that scale increase the relevancy to local planning efforts, as compared to county or census tract levels where neighbourhood and community level variations are often masked.

Travis County has a humid, subtropical climate with hot summers and mild winters. According to the National Climatic Data Center, the county experienced seven excessive heat events during 1999–2005 (NCDC, 2011). In addition, the county is located in Central Texas's Flash Flood Alley and experienced 44 flood events during 1999–2005 (NCDC, 2011). Because climate change affects excessive heat and flooding events, we assess baseline population health, social marginalisation and the community's built environment impediments as they relate to these two natural hazards.

Principal component analysis is a practical data reduction method that adds components together to create measurable vulnerability indices. Here, population vulnerability to climate change is defined as the sensitivity of a community, location or place—through the intersection of social marginalisation, built environment impediments and poor population health—to respond to and recover from natural hazards likely to be exacerbated by climate change. This view of vulnerability, without implying causation, allows integration of disparate information already available at the local level. Access to information about social marginalisation and the built environment help local officials to better implement and monitor climate-change policies through the lens of health. Potentially, policy makers may reduce existing vulnerabilities through targeted outreach, education interventions and improved emergency response and preparedness activities.

Methodology

Social and built environment

We conducted a public health literature review of social and built environmental measures associated with excessive heat and flooding. The socio-environmental measures identified in the literature present a strong association with either heat or flood vulnerability, such as the presence of air conditioning as a protective factor in heat vulnerability (Reid et al., 2009). However, not all of the data for these strong measures were available at the needed spatial-temporal scale. Such indicators were identified

as potential measures but ultimately excluded from the vulnerability index if the data were not available (see Appendix, Tables 1 and 2). We selected pre-existing, freely available, geo-referenced national data sources primarily to assist in the simplicity and reproducibility of the methods at the local level (Appendix, Table 2). However, due to the location-specific nature of flash floods and heat vulnerability, local data also served to supplement nationally available data. For example, the City of Austin Watershed Protection Department provided additional information regarding the most dangerous low-water crossings in the study area. In addition, the Texas Natural Resources Information System (TNRIS) provided access to Landsat-5 and Landsat-7 data and developed the average surface temperature map used in the study (Houghton et al., 2012).¹

We used the 2000 US Census block groups to represent temporal and spatial scales of vulnerability. Based on data availability for Travis County at the block-group level, we selected a subset of social and environmental measures from the literature. Our approach was based on the following three focal points:

- 1) identification of location-relevant (Travis County) natural hazards affected by climate change (excessive heat and flood);
- 2) selection of previously identified health, social and built environment measures associated with the location-relevant natural hazard (Appendix, Table 1);
- 3) analysis based on data availability of previously identified measures with relevant spatial-temporal scale (that is, block groups from the 2000 US Census) (Appendix, Table 2).

We used principal component analysis to create indices that collapsed previously identified social and built environmental variables associated with vulnerability to excessive heat and flooding events (Appendix, Table 2). Table 3 (see Appendix) highlights the variable combinations that created components yielding the highest explained cumulative variance. We used varimax rotation to account for as much variation as possible through a linear combination. We selected components based on eigenvalues greater than one to account for at least 10 per cent of the total variances. We then normalised and summed selected components with the *a priori* assumption of equal weights to reduce subjective complexity (social indicators carried the same weight as environmental indicators in determining social–built environment index scores) (Balica et al., 2009; Connor and Hiroki, 2005; Reid et al., 2009).

Baseline poor health

The clinical manifestations of excessive heat exposure include heat cramps, heat syncope, heat exhaustion, heat stroke and mortality caused by hyperthermia (Luber and McGeehin, 2008). Persons with pre-existing medical conditions such as cardiovascular diseases are at greater risk for heat-related morbidity or mortality when exposed to excessive heat (Wainwright et al., 1999). This complex interaction that heat imposes on specific chronic conditions likely leads to underestimated reports of hyperthermia mortality.

The primary causes of mortality associated with flooding events are drowning, injury or trauma (CDC, 1993). Floods are extremely localised events, and more than half of flood-related drowning occurs when a vehicle is driven into hazardous flood waters (CDC, 2000). However, the long-term effects of flooding such as those seen during the recovery phase are often underestimated. During the disaster recovery phase, chronic healthcare needs for vulnerable populations may be exacerbated, with diabetes and hypertension identified as chronic diseases that present post-disaster management issues (Mokdad, 2005).

The Texas Department of State Health Services provided the cardiovascular, diabetes and hypertension mortality data used to estimate pre-existing baseline measures of health vulnerabilities for Travis County during 1999–2005. We geocoded the deceased's residence at time of death and by cause of death (ICD-10) to serve as a baseline measure of population health, and calculated age-adjusted mortality rates per block group. To reduce statistical variability by block groups ($n = 516$) with small populations, we removed the block groups with fewer than 30 residents ($n = 8$) and aggregated recorded deaths over the five-year period in which data were available (1999–2005). All rates were age adjusted using the year 2000 US population standard.

Analysis

We linked the social–built environment index score to baseline mortality measures by block group for excessive heat and separately for flood. We ranked index scores by percentile as lowest (lower than 50th percentile) to highest (99.1th percentile and higher) measure of social–built environment vulnerability. We classified mortality rates as low, medium or high, based on the same percentile ranking for the indices. We linked the mortality and index percentiles categorically by block groups. We then mapped the block groups containing the categorical index score and mortality rate to identify communities where poor health, social marginalisation and built environment impediments intersected. We checked the maps for spatial autocorrelation, describing cluster patterns using Global Moran's I test. We performed all statistical analyses using SAS 9.2 developed by SAS Institute, Inc[®] in Cary, North Carolina, United States. Geospatial mapping was performed using ArcMap 9.3 software developed by ESRI[®] in Redlands, California, United States.

Results

Excessive heat

We assessed excessive heat vulnerability through a linked social–built environment index score with baseline cardiovascular mortality rate (Figure 1). For the social–built environment index, final variables (Appendix, Table 2) included in the analysis for excessive heat yielded three factors (measuring social, physiological and environmental components) that explain 79.6 per cent of the cumulative variance (Appendix, Table 3).

Figure 1. Heat and health vulnerability map for Travis County, Texas, by US Census block group

Notes: Low overall vulnerability denotes block groups with the lowest percentiles in heat vulnerability AND baseline cardiovascular mortality rates (the scores or rates fall at or below the 50th percentile). High overall vulnerability denotes US Census block groups with the highest percentiles in socio-environmental vulnerability to heat AND baseline cardiovascular mortality rates (the scores or rates are at or above the 99th percentile).

Source: created by the authors using public domain data provided by the US Census Bureau.

Average age-adjusted cardiovascular mortality rate was 2.49 (95 per cent CI = 2.32, 2.67) per 10,000 population for all of Travis County, and increased from 1.84 (1.69, 1.99) to 7.69 (4.89, 10.49) per 10,000 population as the social-built environmental index for excessive heat increased from low to high, respectively. The geocoded parameters for cardiovascular mortality data included street-level coding for an overall 94.8 per cent of the records included in the analysis.

When we tested for spatial autocorrelation, the vulnerability map (Figure 1) exhibited more pronounced clustering than expected (Moran's I = 0.09), given the underlying clustering (Moran's I = 0.03) of the Travis County block groups with p-values less than 0.001. We identified block groups east of Interstate-35 within the city of Austin where poor health, social marginalisation and built environment impediments for excessive heat vulnerability intersect (Figure 1). These block groups contain large minority populations and are located within a 2000 US Census tract where 64 per cent of the population attained only a high school diploma or less education, and 22.6 per cent lived below the poverty level. One block group northeast of the city contained both high cardiovascular mortality and high socio-environmental index score for excessive heat vulnerability (Figure 1). This block group is situated within an industrial area that lacks green space, contains income-based senior living apartment homes,

and where 64 per cent of households have at least one person aged 65 years or older based on the 2000 US Census.

Flood

We assessed flood vulnerability through a linked social–built environment index score with a baseline mortality rate for combined diabetes and hypertension (Figure 2). For the social–built environment index, we included final variables (Appendix, Table 2) in the analysis for flooding that yielded three factors (measuring neighbourhood stability, biophysical and social components) that explained 80.7 per cent of the cumulative variance (Appendix, Table 3). The average age-adjusted mortality rate for combined diabetes and hypertension was 0.50 (95 per cent CI = 0.44, 0.56) per 10,000 population for all of Travis County, and increased slightly from 0.48 (0.39, 0.57) to 0.87 (0.07, 1.68) per 10,000 population as the socio–environmental index for flooding increased from low to high, respectively. The geocoded parameters for diabetes and hypertension included street-level coding for an overall 94.7 per cent of the records included in the analysis.

Figure 2. Flood and health vulnerability map for Travis County, Texas, by US Census block group

Notes: Low overall vulnerability denotes block groups with the lowest percentiles in flood vulnerability AND baseline combined diabetes and hypertension mortality rates as a proxy for medical displacement risk (the scores or rates fall at or below the 50th percentile). High overall vulnerability denotes block groups with the highest percentiles in socio–environmental vulnerability to flooding AND baseline combined diabetes and hypertension mortality rates as a proxy for medical displacement risk (the scores or rates are at or above the 99th percentile).

Source: created by the authors using public domain data provided by the US Census Bureau.

When we tested for spatial autocorrelation, the vulnerability map (Figure 2) exhibited more pronounced clustering than expected (Moran's $I = 0.04$), given the underlying clustering (Moran's $I = 0.03$) of the Travis County block groups with p -values less than 0.001. We identified block groups further east within a historical minority community traversed by US Highway-183, where poor health, social marginalisation and built environment impediments for flooding vulnerability intersect. The area is within a 2000 US Census tract where 11.1 per cent of the population lives below the poverty line and 52 per cent of the population attained a high school diploma or less education. In addition, the area contains creeks that have historically exceeded their banks during past major flooding events (AWD, 1995).

Discussion and conclusions

Climate change directly and indirectly affects health. Public health tools must be enhanced to include not only human health but also socio-environmental factors that help identify vulnerability to climate-related hazards. Using principal component analysis, we created a measure for understanding population vulnerability to climate change using health, built environment and social measures at the community level. Through the intersection of social marginalisation, built environment impediments and poor population health, we defined climate change vulnerability as the sensitivity of a community, location or place to respond to and recover from natural hazards likely to be exacerbated by climate change.

Through the literature review we identified social and built environment variables associated with flooding and excessive heat events. We used principal component analysis to create separate non-weighted indices by block group. Separately, we identified mortality rates by block group for cardiovascular disease and combined diabetes and hypertension as measures of negative baseline health likely to be exacerbated during excessive heat and flooding events, respectively. We linked social-built environment index scores to baseline mortality measures by block group, then mapped the links to identify communities where poor health, social marginalisation and built environment impediments for excessive heat and flooding intersected as measures of population vulnerability to climate change. We found that poor health, social marginalisation and built environment impediments do intersect, and specific areas within Travis County exhibit higher vulnerability.

Several studies use principal component analysis despite inherent limitations, while more comprehensive studies look at weighted regression analysis that may or may not feed into artificial neural networks (Cutter, 2003; Cutter and Finch, 2008; Harlan et al., 2006; Johnson et al., 2009; Reid et al., 2009; Uejio et al., 2011). Such studies with weighted regression models and other predictive network models provide more precise forms of vulnerability measurements but are more data and labour intensive, producing narrowly applicable and complex models. These methodological models, despite their precision, are not easily transferable to other locations.

Although we chose not to apply weights outside of the mathematical component loading associated with principal component analysis, decision makers may apply weights of importance to variables. Use of such weighting necessitates a higher order of mathematical specification that, despite its precision, is not easily transferable to other locations. Non-weighted principal component analysis is more basic, providing a coarser form of vulnerability heavily dependent on variable quality. However, the added advantage is the flexibility for decision makers to streamline their approach towards assessing vulnerability as it relates to climate change. Principal component analysis is less data intensive yet provides the foundation to continue with more comprehensive predictive analysis through its data-reduction steps. We do not predict health outcome based on vulnerability. However, more robust predictive analyses will bring further understanding and higher specificity in understanding climate and intra-urban vulnerability. For the purposes of this article and replication at the local health department level, we chose more flexible methods to help understand population vulnerability to climate change.

Combined diabetes and hypertension mortality rates served as a proxy for potentially increased sensitivity to displacement with medical needs during floods. As the social-built environment index score increased with baseline mortality, more robust evidence supports the association between excessive heat and increasing cardiovascular mortality; flooding vulnerability and combined diabetes and hypertension mortality as a proxy for displacement with medical needs had weaker associations and require more research. Despite these limitations, the use of hazard-relevant health data provides more specificity in understanding vulnerability, which would otherwise be masked in total mortality data.

Another important point to note is that the chronic diseases selected here are traditionally highest among populations that are socially and environmentally vulnerable (for example, the elderly, the poor and minorities), whether a climate-driven hazard event does or does not occur. To adjust accordingly, we presented mortality rates through percentile ranking, with the most extreme rates indicating measures of the poorest health (above the 99.1th percentile). Without implying a cause and effect, we sought to provide in this study snapshots of communities with historically elevated poor health measures where social and built environmental characteristics have the greatest potential to exacerbate the impacts of climate-related natural hazards.

This method of identifying neighbourhoods potentially can translate into product development for climate change adaptation, specifically enhanced communication tools and targeted local policies. For instance, heat-related illness is preventable, yet annually excessive heat exposure causes many hospitalisations and deaths. Identifying communities where disproportionate health, built environment and social vulnerabilities intersect and exacerbate heat exposure, such as the East Austin neighbourhoods, allows public health agencies to craft and rapidly disseminate key messages specific to those communities before excessive heat events occur. Conversely, policy makers

implementing long-term flood control projects may benefit from a more comprehensive view of vulnerable communities as neighbourhoods shift and redevelop. This approach potentially can assist decision makers outside the public health sector in allocating resources and implementing initiatives that promote emergency preparedness in the short term, while fostering resiliency through the focus of climate change adaptation policies in the long term.

Appendix

Table 1. Identified list of *potential* climate change and health measures

Social measures	
Demographics	
Race/ethnicity	Household income
Sex	Primary language spoken at home
Age	Population density
Gender affiliation	Social isolation (living alone)
Highest education level	
Coping mechanisms	
Emergency communication plans	Housing/shelters
Medical care/treatment access	Air conditioning
Mental health services	Home ownership
Pharmaceutical access	Security
Nutritional services	Legal services
Transportation	Crime prevention
Sidewalks	Education services
Public transit routes	Employment
Vehicle miles travelled	
Alternative fuel use	
Environmental measures	
Drought	
US drought monitor	Global vegetation index—vegetation health
Daily gridded standard precipitation index	Vegetation condition index (VCI)
Standardised precipitation index	Temperature condition index (TCI)
Vegetation drought response index	Normalised difference vegetation index (NDVI)
Palmer drought indices	Smoothed normalised difference vegetation index (SMN)
Soil moisture	Smoothed brightness temperature (SMT)
Runoff	Vegetation health index (VHI)
Evaporation	US rain days and dry days
Drought monitoring	FEWS—rainfall in inches
Flood/heavy rainfall events	
Evaporation	Stream flow index

Social measures	
Flood/heavy rainfall events (continued)	
Humidity index	Low-water crossings
Flood zone	Vegetative cover
FEWS—rainfall in inches	Impervious surface
Interactive basin-wide map	
Air quality	
Nitrogen dioxide (NO ₂)	Pollen
Sulfur dioxide (SO ₂)	Air mass stagnation events
Ozone (O ₃)	Humidity index
Particulate matter (PM10 and PM2.5)	
Excessive heat	
Humidity index	Air mass stagnation events
Apparent temperature	Surface temperature
Maximum temperature	Vegetative cover
Minimum temperature	Impervious surface
Baseline mortality measures (ICD-10 codes)	
Extreme weather	
X37 Cataclysmic storms	T68 Excessive cold
X38 Floods	T67 Excessive heat
Respiratory diseases	
J20–J21 Acute bronchitis and bronchiolitis	J40–J42 Bronchitis, chronic and unspecified
J22 Unspecified acute lower respiratory infection	J45–J46 Asthma
J40–J47 Chronic lower respiratory diseases	
Waterborne diseases	
A00–A08 Gastrointestinal diseases	A48.1 Legionnaire's disease
Vector-borne diseases	
A69.2 Lyme disease	B55 Leishmaniasis
A92 Chikungunya virus disease	A77 Rocky mountain spotted fever
A90–A91 Dengue fever	A92.3 West Nile virus
A78 Q fever	A95 Yellow fever
Chronic diseases associated with excess deaths	
E10–E14 Diabetes	I00–I78 Major cardiovascular diseases
I10, I12 Hypertension	I21–I22 Acute myocardial infarction
J45–J46 Asthma	E66 Obesity
I60–I69 Stroke	

Source: authors.

Table 2. Selected list of identified climate change and health vulnerability measures for flooding (F) and excessive heat events (EHE)

Variables	Event	Source
Social measures		
Age (0–5 years; 65+ years)	F; EHE	US Census Bureau (2000) http://factfinder.census.gov
Ethnicity (black, non-Hispanic white, Hispanic, other)	F; EHE	US Census Bureau (2000) http://factfinder.census.gov
Population density	F; EHE	US Census Bureau (2000) http://factfinder.census.gov
Socially isolated (i.e. living alone)	F; EHE	US Census Bureau (2000) http://factfinder.census.gov
Renters status	F; EHE	US Census Bureau (2000) http://factfinder.census.gov
Environmental measures		
Impervious surface; lack of vegetative cover	EHE	US Geological Survey (2001) http://www.mrlc.gov/multizone_download.php?zone=10
Surface temperature	EHE	Landsat-7 and Landsat-5 satellite*
100-year flood plain	F	Federal Emergency Management Agency (2008) http://msc.fema.gov
Low-water crossing	F	Austin Watershed Department

Notes: A total of 12 variables were placed in the analysis for heat, and 13 variables were placed in the analysis for flood. The list met all three criteria: 1) location-relevant natural hazards affected by climate change (flood and heat); 2) data availability based on relevant spatial-temporal scale (US Census block group); and 3) quantifiable risks previously identified in public health literature.

* See endnote 1.

Source: compiled by authors using unpublished data from the Austin Watershed Department, Federal Emergency Management Agency (2008), US Census Bureau (2000) and USGS (2001).

Table 3. Standardised scoring coefficients for heat (cumulative variance explained: 79.6 per cent) and flood (cumulative variance explained: 80.7 per cent)*

Climate hazard	Components		
Heat variables	Biophysical	Physiological	Social
Lack of green space	0.50839*	0.22951	−0.07449
Average ambient surface temperature	0.34345*	0.01402	0.25316
Population density	0.41169*	−0.23077	−0.18421
Age 65+	0.06061	0.90887*	−0.02169
Non-Hispanic African Americans	−0.04967	−0.00998	0.93190*
Flood variables	Neighbourhood stability	Biophysical	Social
Floodplain ratio	−0.05824	0.62892*	0.05911
Low-water crossing density	0.10050	0.69437*	−0.05315
Socially isolated (i.e. living alone)	0.52972*	0.02433	−0.22150
Renters status	0.52117*	0.00685	0.22567
Hispanic population	−0.00622	0.00594	0.88968*

Notes: Table explains which variables are included in the components based on the principal component analysis. The variables seen under climate hazard come from Table 2.

Source: authors.

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Endnotes

¹ TNRIS provided a surface temperature average for the summers during 1999–2005. (Paraphrased from the map metadata available through the GEMSS GIS viewer [Geospatial Emergency Management Support System, <https://gemss.tnris.org/>]: Landsat-7 and Landsat-5 satellite thermal band data were used to develop temperature values in Fahrenheit degrees using a calibration equation for converting Kelvin degrees to Fahrenheit). Temperature maps for selected dates (24/7/99, 03/08/00, 21/07/01, 25/08/02 and 26/09/05) were created to estimate the cooling effect of lakes and heat islands in the city and barren lands during the summer. The images were greatly smoothed with a 99×99 array filter to create temperature averages to show a general pattern for the cooler and warmer spots in the region. Contours were then created at one degree Fahrenheit intervals. The spatial resolution for the contour map is one square foot.

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