Validating the Toronto Spatial Heat Vulnerability Assessment: Research Findings & Proposed Methods

Final Report December 2010

Prepared on behalf of and with the support of
Toronto Public Health

CONSULTANTS AND AUTHORS:
Kate Bassil
Claus Rinner
Dianne Patychuk

TORONTO PUBLIC HEALTH PROJECT TEAM:
Monica Campbell
Stephanie Gower

ACKNOWLEDGEMENTS:
Tanya Wolf, Colleen Reid, Margaret Loughnan, Olga Wilhelmi, Chona Sister, Glenn McGregor, Marie O'Neill, Daniel Johnson, Paul English, Gregoire Rey

With federal funding support through Natural Resources Canada's Regional Adaptation Collaboratives Program

Natural Resources Canada   Ressources naturelles Canada   Canada

For more information about Natural Resources Canada's Regional Adaptation Collaboratives Program, please visit http://adaptation.nrcan.gc.ca/collab/index_e.php

Background

The adverse effect of heat on health is an increasing concern across Canada. The presence of urban heat islands and a large susceptible population including the elderly, marginally-housed, and those with pre-existing illness make urban regions like Toronto particularly vulnerable. In an effort to predict and prepare for harmful hot weather, Toronto implemented a heat health alert system (HHAS) in 1999. This method uses a variety of meteorological variables including temperature, wind speed and direction, dew point, and cloud cover to identify conditions that are associated with excess mortality (Kalkstein, 1991; Sheridan and Kalkstein, 2004; Sheridan and Kalkstein, 1998). An essential component of the public health response to heat is having an effective response plan that is linked to the HHAS (Woodruff, 2005). The City of Toronto Hot Weather Response Plan includes interventions such as media announcements, opening of cooling centers, and outreach to vulnerable groups through community partners. However, these interventions are not currently linked to any spatial information regarding the geographical distribution of high-risk populations and areas. If the geospatial distribution of heat-related illness is known, then interventions can be specifically targeted to those areas to reduce morbidity and mortality. In response to this, a heat vulnerability assessment tool was recently developed for Toronto by Dr. Claus Rinner and colleagues, after evaluating methods and case examples from other jurisdictions (Rinner 2009). The focus of the current project is to develop methodological recommendations to validate this spatial heat vulnerability assessment tool using health data.

The following tasks were identified early in the current project and the findings are outlined in this report:

1. Colleagues and contacts identified in the spatial vulnerability assessment project with knowledge and experience in vulnerability assessments for heat were contacted. Information was sought regarding their approach to validation, lessons learnt, and any revisions to their approaches based on these experiences. This communication was facilitated through email, phone, and in-person at conferences and meetings.

2. A search of the peer-reviewed and grey literature (e.g. conference proceedings, technical reports, thesis manuscripts) was conducted to retrieve information about methods for the validation of vulnerability assessments for heat-related illness, as well as in the broader area of environmental health as applicable.

3. Methodological recommendations for validating the heat vulnerability index/indices have been developed based on the information collected from the sources noted above.

These activities started in September 2009, with interim reports submitted to Toronto Public Health in December 2009 and March 2010. The objective of this final report is to build upon the interim findings and outline all updates, concluding with recommendations for a validation approach that Toronto Public Health may use for the heat vulnerability assessment.

Introduction

Spatial vulnerability assessments aim to predict where hot spots of an impact will be located so that efforts to mitigate these effects can be planned and prepared in advance. Given concerns over increasing temperatures and the serious health effects that have already been demonstrated in recent heatwaves (i.e. Europe 2003, Chicago 1995), several jurisdictions have started to develop spatial vulnerability assessments for heat (Rinner 2009). However, the credibility of such a tool is dependent on its efficacy in terms of being able to differentiate between areas of actual low and high heat-related health outcomes (McGregor 2010). This can be a challenge particularly as there is no standard set of indices to measure vulnerability to heat stress. However, the literature points to several factors that influence the temperature/mortality-morbidity relationship and these are generally used to develop spatial assessment indices. While some factors show clear associations (i.e. older age), the role of other factors remains somewhat inconclusive and may vary depending on the geographic area. In light of this, recent focus has turned attention to developing methods to validate heat spatial assessment tools to determine if the combined factors selected accurately predict the health outcomes experienced by the population of interest.

Validation Case Examples

Having searched through the peer-reviewed and grey literature, and contacted researchers identified in the spatial vulnerability assessment project and others, it is clear that there is ongoing work in the development of validation methods for spatial vulnerability assessments, although somewhat limited at this time. However, there are three case examples that will be outlined below of jurisdictions that have validated their spatial assessment tool for heat (research in the United States, United Kingdom, and Australia). Although primarily academic research exercises at this stage, two of these examples are working closely with public health organizations so that these tools may ultimately be used in practice. Unless otherwise stated with a peer-reviewed reference, all of the findings have been generated through personal communication with the researchers noted.

1. <u>London, United Kingdom (Drs. Tanja Wolf, Glenn McGregor, King's College London)</u>

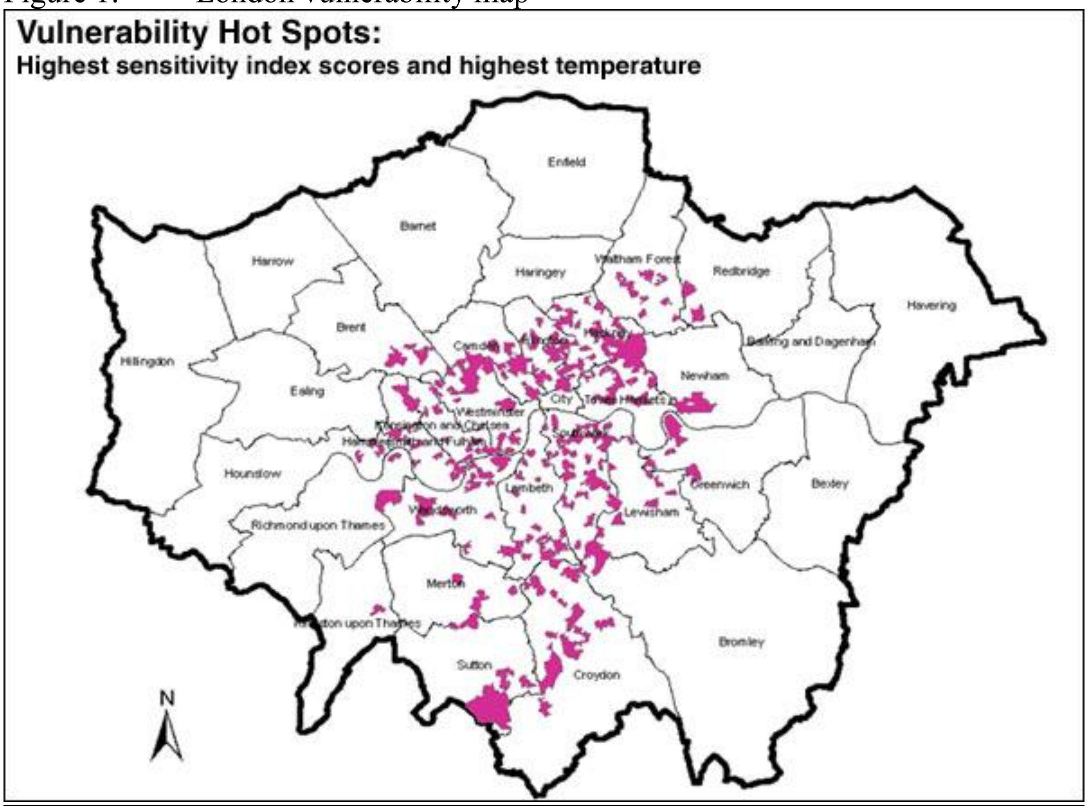
A heat vulnerability index was developed for the City of London, United Kingdom by Drs. Tanja Wolf and Glenn McGregor (Wolf 2009). This index was created using the following 11 indicators from census data:

1. Percentage of population over 65 years old
2. Percentage of population of ethnic group other than "white British"
3. Percentage of population with long-term limiting illness
4. Percentage of population with self-reported health status "not good"
5. Percentage of population receiving any kind of social benefit, as indicator for low socioeconomic status
6. Percentage of single pensioner households
7. Percentage of households accommodated in a flat
8. Percentage of households with no central heating
9. Percentage of households in a rented tenure

10. Percentage of population living in any kind of communal establishment
11. Population density in person per hectare

The vulnerability index was then built using Principal Component Analysis (PCA). Essentially, PCA reduces the indicators to components, adds them together, and then weights them according to the variance they explain in order to build the index. Using the index, maps were created for London, indicating the areas with greatest vulnerability. The map in Figure 1 provides an example of this, where areas with high sensitivity scores have been joined with areas with high temperatures. This group has since validated the index using mortality and ambulance dispatch data using a contingency table approach.

Figure 1: London vulnerability map



Source: http://news.bbc.co.uk/2/hi/uk_news/5284126.stm

A contingency table, or cross-classification analysis is typically used to validate weather forecast predictions, but has applications to the method for validating heat vulnerability maps. A contingency table assesses dichotomous outcomes (i.e. “yes, an event will happen” or, “no, an event will not happen”). In the context of weather forecasts, rain/snow/fog predictions are examples of yes/no forecasts that may be predicted. The contingency table is then used to illustrate the frequency of “yes” and “no” occurrences. In the context of the heat vulnerability maps the dichotomous forecast is either, “yes, a vulnerability hotspot does have higher health impacts than its counterpart areas” or “no, the vulnerability hotspot is not a real hotspot as validated using health outcome data”.

To build the contingency table the vulnerability score for each neighbourhood would be compared with an aggregated health outcome measure for that neighbourhood, using one or a combination of health outcome data sources. An outline of possible data sources for the Toronto exercise is provided in the next section. A threshold value representing “above average impacts” would be decided a-priori (e.g. vulnerability index score > 5 on a 10 point scale, and mean number of ER visits/911 calls above a certain value). Using a 2 x 2 contingency table there would then be 4 possible outcomes (Table 1). A “hit” occurs when both the vulnerability score and health impact score are above average. If vulnerability is above average but the observed health impact is not it is a “false alarm”. A low vulnerability score with a high observed health impact is labelled a “miss”. The last combination, an estimated below average vulnerability confirmed by a low average health impact is labelled a “correct negative”. A vulnerability index that has a high performance in predicting hot spots of vulnerability will have a high number of “hits” and “correct negatives” and few “misses” and “false alarms”. Contingency tables can be created for each neighbourhood. The identification of appropriate threshold values for both the health outcome measure and the vulnerability index will be an important step in differentiating between “yes” and “no” binary scores.

Table 1: Example contingency table

Contingency table		Above average health impact observed? (class 6 to 10)		
		Yes	No	Total
Vulnerability estimated above average? (class 6 to 10)	Yes	Hits	False alarms	Above average vulnerability? Yes
	No	Misses	Correct negatives	Above average vulnerability? No
	Total	Above average health impact observed? Yes	Above average health impact observed? No	Total

From Tanya Wolf, personal communication, PhD unpublished

Once the contingency tables are created, a number of summary statistics can be calculated to describe the forecast performance quantitatively in greater detail. The contingency table serves as the basis for these statistics. A summary of these statistics and their method of calculation is provided in Table 2.

Table 2: Statistics to evaluate the findings of the contingency table

Accuracy (fraction correct) **Answers the question: Overall, what fraction of the forecasts were correct?** **Range: 0 to 1** **Perfect score: 1**	$Accuracy = \frac{hits + correct\ negatives}{total}$
Bias score (frequency bias) Answers the question: How did the forecast frequency of "yes" events compare to the observed frequency of "yes" events? Range: 0 to infinity Perfect score: 1	$BIAS = \frac{hits + false\ alarms}{hits + misses}$
Probability of detection (hit rate) Answers the question: What fraction of the observed "yes" events were correctly forecast? Range: 0 to 1 Perfect score: 1	$POD = \frac{hits}{hits + misses}$
False alarm ratio Answers the question: What fraction of the predicted "yes" events actually did not occur (i.e., were false alarms)? Range: 0 to 1 Perfect score: 0	$FAR = \frac{false\ alarms}{hits + false\ alarms}$
Threat score (critical success index) Answers the question: How well did the forecast "yes" events correspond to the observed "yes" events? Range: 0 to 1, 0 indicates no skill Perfect score: 1	$TS = CSI = \frac{hits}{hits + misses + false\ alarms}$
Hanssen and Kuipers discriminant (true skill statistic, Peirce's skill score) *Answers the question: How well did the forecast separate the "yes" events from the "no" events?* *Range: -1 to 1, 0 indicates no skill.* *Perfect score: 1*	$HK = \frac{hits}{hits + misses} - \frac{false\ alarms}{false\ alarms + correct\ negatives}$

Source: Joint Working Group in Forecast Verification Research, World Meteorological Organization (http://www.wmo.int/pages/prog/arep/wwrp/fvr.html)

For the UK research, ambulance dispatch and mortality data were used to validate the vulnerability index. For mortality, total daily number of deaths per geographical area was used, without any specification of cause of death. Similarly, ambulance dispatch for all calls was used rather than for a specific set of predefined codes. The contingency table results showed that the vulnerability score and health outcomes matched in approximately 65% of geographical areas (Wolf, PhD thesis, unpublished).

2. Melbourne, Australia (Dr. Margaret Loughnan, Monash University)

A vulnerability index has recently been created for use in Melbourne, Australia (Loughnan 2010). This index is based on 10 indicators of health, social, and environmental risk factors, identified from the heat-health literature. Many of the variables included in the index were selected from the Australian Bureau of Statistics (ABS) 2006 census. Table 3 provides further details of the indicators included in the Melbourne vulnerability index.

Table 3: Vulnerability index factors

Variable	**Risk factor**	**Data source**
1	Age (65+, 0-4)	ABS BCP census data
2	Burden of disease	DHS health intelligence unit
3	Aged care facilities	Dept Health and Ageing (DHS)
4	Socioeconomic status	ABS SEIFA
5	Urban design (non-separate dwellings)	ABS BCP census data
6	Single person households over 65 yrs	ABS BCP census data
7	Measure of disability	ABS BCP census data
8	Population density of vulnerable age groups	ABS BCP census data
9	Ethnicity ("language other than English")	ABS BCP census data
10	Urban heat island	Satellite-based measurements

Note: ABS – Australian Bureau of Statistics
BCP – Basic Community Profile (provides detailed census data for small areas)
DHS – Department of Human Services
SEIFA – Socioeconomic index for areas (comprised of several variables)
*Specific details about each of the vulnerability index factors can be found in the report at:
http://www.health.vic.gov.au/environment/downloads/heatwaves_hotspots_project.pdf

To create the vulnerability index, the relevant data were extracted at the Postal Area (POA) geographic scale. For each category, the number of people in the variable category was divided by the total number of people residing in the POA to calculate a proportion. The proportion of each variable in each POA was then assigned a decile rank with the lowest 10% as decile 1 and the highest 10% as decile 10. The decile ranks for each index category in each POA were then added to produce an index value for each POA. This was then mapped to create a spatial vulnerability map for Melbourne, which was considered a theoretical map of vulnerability pending further validation.

Daily morbidity and mortality data were then used to validate the Melbourne heat vulnerability index. Morbidity data included emergency hospital admissions provided by the Victorian Admitted Episodes Database, and mortality data was all-cause mortality from the Department of Justice, Registry of Births, Deaths, and Marriages. Table 4 provides the ICD-10 codes selected for the hospital admission data. Daily data from these two datasets for the summer-time periods from 2001-2006 were combined to form one composite measure to describe the daily anomalous health outcomes (AHO).

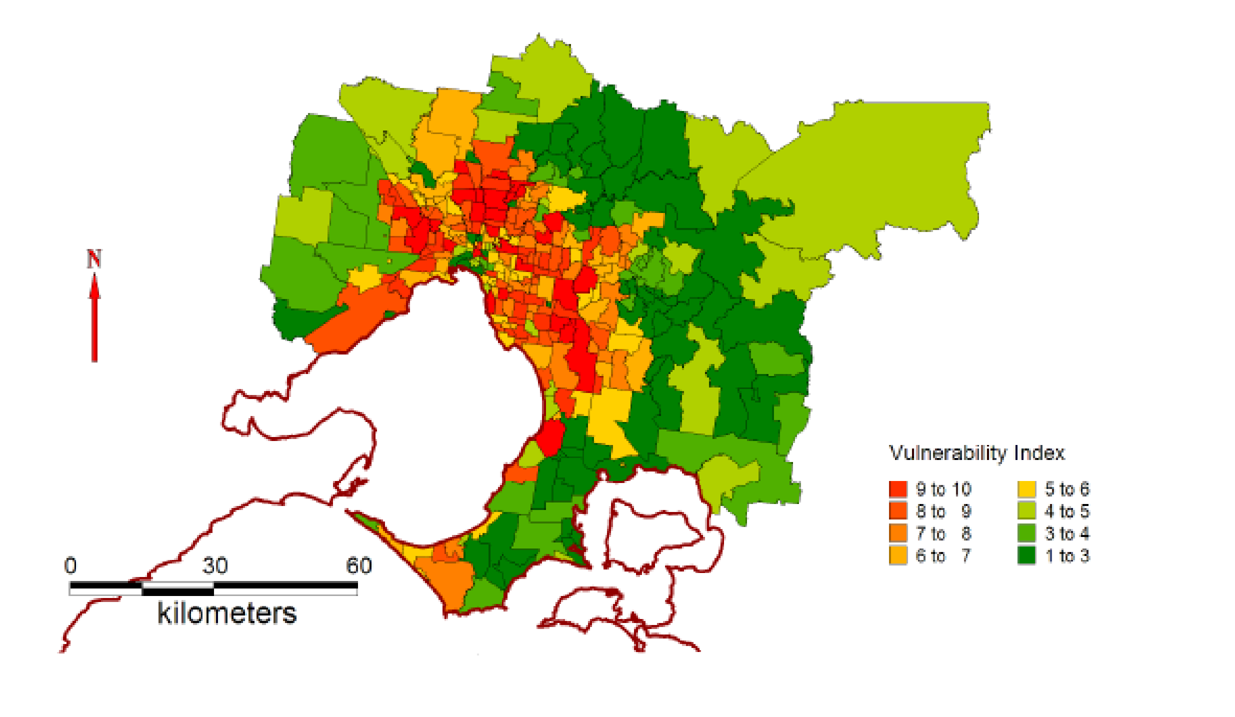
Table 4: ICD-10 codes used for the Melbourne validation exercise

Disease category	**ICD-10 codes**
Circulatory system	I00-I79, I95, I97, I99
Endocrine	E00-07, E09-14, E20-35, E66, E84, E86-87
Respiratory	J00-84, J96-98
Mental health/behaviour	F00-99
Chronic renal disease	N00-N39
Diseases of nervous system	G00-09, G10-13, G20-26, G30-32, G35-37, G40, G41, G43, G44, G45, G70-73, G80-83
Neoplasm	C00-96
Pregnancy	O00-16
Other disease	X30, X32, T67, L55-56, and R50.0

Source: "Hot Spots Project: A spatial vulnerability analysis of urban populations to extreme heat events" (Loughnan 2010). Accessed at: http://www.health.vic.gov.au/environment/downloads/heatwaves_hotspots_project.pdf

To validate the vulnerability assessment, a stepwise linear regression model was used to assess which of the variables in the index best predicted the distribution of the AHO on days exceeding a daily threshold, a mean temperature of 29°C as illustrated in earlier research by this group (Nicholls 2008). The incidence rate of AHO per POA was used as the dependent variable, and each of the 10 factors used to construct the index were entered as independent variables. The individual variables that best predicted vulnerability in each POA were: the proportion of aged care facilities (variable 3), ethnicity where a primary language spoken at home was not English (variable 9), high population density of elderly and very young (variable 8), households with single persons over the age of 65 (variable 6), and people living in single dwellings (variable 5). These variables were then weighted using coefficients from the regression analysis and used to recalculate the vulnerability index. A mapped version of this validated index can be found in Figure 2.

Figure 2: Melbourne heat vulnerability map after validation with health data



Source: "Hot Spots Project: A spatial vulnerability analysis of urban populations to extreme heat events" (Loughnan 2010). Accessed at: http://www.health.vic.gov.au/environment/downloads/heatwaves_hotspots_project.pdf

In this analysis, the factor that accounted for the greatest spatial variation in AHO was the proportion of aged care facilities (variable 3). The authors conclude that this finding highlights the vulnerability of elderly people, despite being cared for by health professionals. This corresponds with findings from the European heatwaves in 2003, particularly in France, where the elderly in aged care facilities suffered the greatest impact. In Melbourne, aged care facilities generally have air-conditioning in communal areas, but not in individual rooms. So while it does provide some relief this is only during the day, and does not include those residents who are bedridden.

Ethnicity was the second largest factor contributing to the spatial heterogeneity in vulnerability. However, these clusters corresponded to industrial areas of Melbourne which are more likely to be areas of low socioeconomic status. Although the Melbourne index did include a measure of socioeconomic status (variable 4) this was not found to be a strong predictor of increased vulnerability. The authors conclude that there are multidimensional aspects of ethnicity beyond socioeconomic status that determine vulnerability within the ethnicity index variable (i.e. level of education, which was not included in the Melbourne index).

Other factors were not major contributors to predicting vulnerability. For example, the distribution of households consisting of elderly people only explained approximately 2% of the spatial variability of AHO on hot days. While social isolation has been suggested in the literature as a predictor of vulnerability to heat stress it could also be true that elderly people who live alone have sufficient ability to protect themselves or can seek help when required, which partly explains why they are able to live independently in the first place.

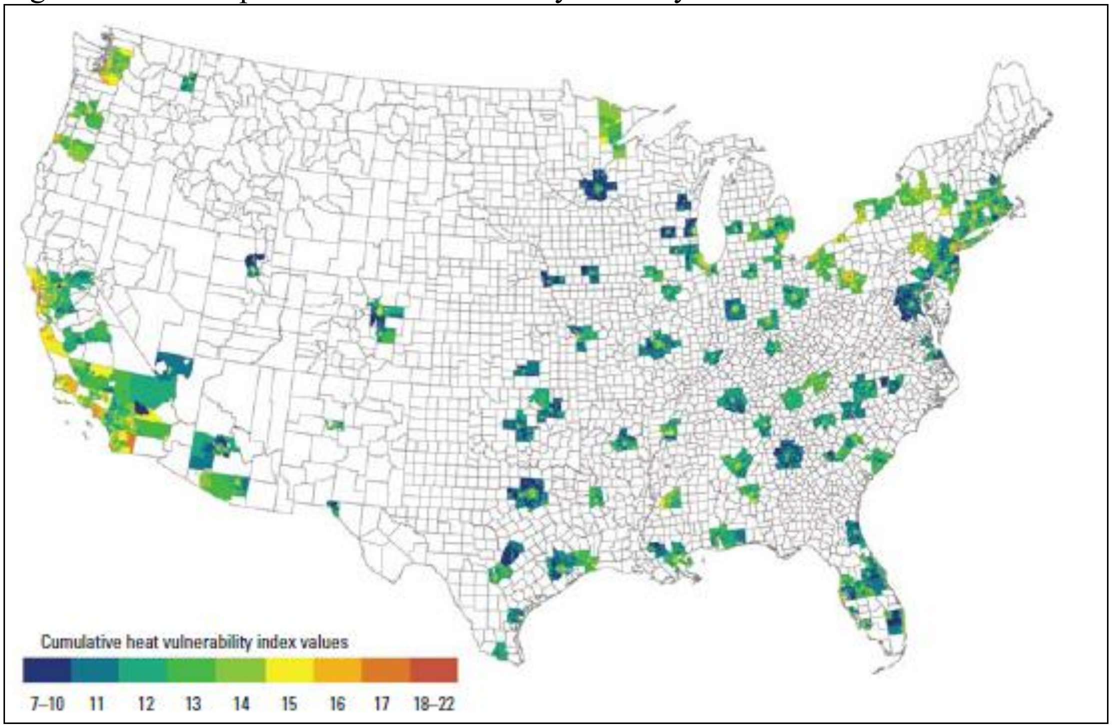
3. United States (Ms. Colleen Reid, University of California, Berkeley and Dr. Marie O'Neill, University of Michigan)

Ms. Colleen Reid, a PhD candidate at the University of California and Dr. Marie O'Neill, from the University of Michigan, recently published a spatial vulnerability approach for the United States (Reid 2009). In this research, the following ten vulnerability factors for heat were selected, based on evidence from the literature and availability of data at the national level:

1. Percent population living below the poverty line (US Census, 2000)
2. Percent population with less than a high-school diploma (US Census, 2000)
3. Percent population of a race other than white (US Census, 2000)
4. Percent census tract area not covered in vegetation (National Land Cover Database, 2001)
5. Percent population living alone (US Census, 2000)
6. Percent population over 65 and living alone (US Census, 2000)
7. Percent households without central air conditioning (American Housing Survey, 2002)
8. Percent households without air conditioning of any kind (American Housing Survey, 2002)
9. Diabetes prevalence (Behavioural Risk Factor Surveillance System, 2002)
10. Percent population over 65 years of age (US Census, 2002)

Census-tract level data was used for the analysis, which was restricted to areas with populations of at least 1000 people. As used in the London vulnerability assessment, Principal Component Analysis was used for these 10 variables, to reduce the number of variables and create factors to be included in the index. This resulted in four factors: 1. socio-economic and environmental (combined poverty/educational attainment/race/lack of green space), 2. social isolation (combined living alone/population over 65 living alone), 3. air conditioning prevalence (combined no central air conditioning/no air conditioning), 4. pre-existing health conditions (combined diabetes prevalence/population over 65 years of age). This index was then applied at the national scale to create risk maps for the United States, as illustrated in Figure 3.

Figure 3: US map of the heat vulnerability index by census tract



Source: Reid 2009

This group has now started to validate this vulnerability index using health data in collaboration with the National Environmental Public Health Tracking Program based out of the CDC (Colleen Reid, personal communication). This tracking system integrates data about environmental hazards and exposures so that state public health departments can use these data to distribute information to stakeholder and advance research. Four universities have been awarded grants to work with these state departments and enhance their capacity to do analysis with these data, including the University of California, where Reid is leading the validation research using the data provided to the Tracking Program (i.e. the health data described below).

Specifically, Reid and colleagues used hospitalization and mortality counts for each day and each ZIP code from May-Sept (i.e. the warm season) between 2000-2007 and applied this to a regression model to determine if there was a consistent relationship of increasing adverse health impacts due to heat with increasing heat vulnerability index score (Reid 2010). Hospitalization data included:

- Internal causes
- Diabetes
- Electrolyte imbalances
- Cardiovascular diseases
- Acute myocardial infarction
- Cerebrovascular disease
- Respiratory illness
- Nephritis and nephritic syndrome
- Acute renal failures
- Heat-related illness

- All hospitalizations
- Asthma

Mortality data included:

- All-cause mortality minus accidents and injuries
- Cardiovascular causes of death
- Respiratory causes of death

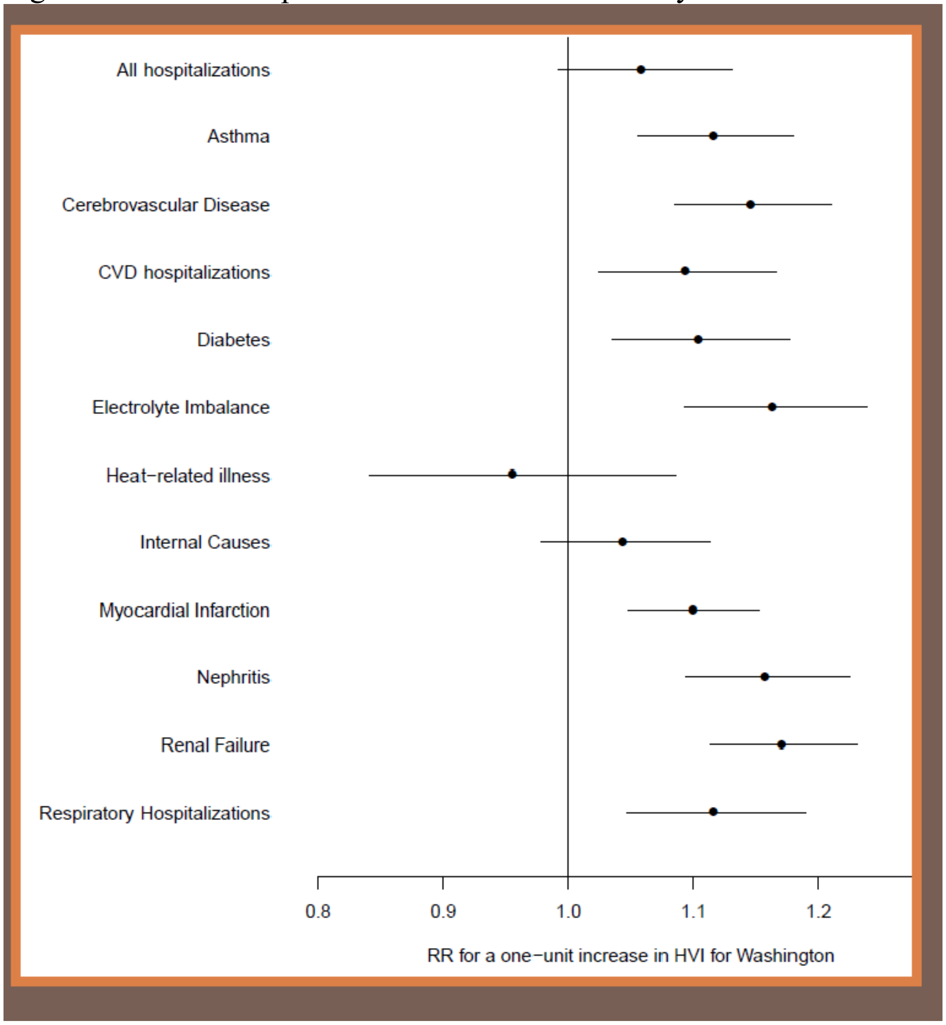
The regression model applied was:

$$\ln(\text{outcome}) = \beta_0 + \beta_1{*}\text{HVI} + \beta_2{*}\text{deviantday} + \beta_3{*}\text{HVI}{*}\text{deviantday} + \beta_4{*}\text{dayofweek} + \beta_5{*}\text{ozone}$$

where
outcome: hospitalization/mortality counts by zipcode-day
exposure: deviant day (i.e. days at or above the 95th percentile of temperature)
effect modifier: heat vulnerability index
confounders: day of week, ozone

The analysis suggests that the heat vulnerability index alone was associated with increased risk of morbidity and mortality, as illustrated in Figure 4. Interestingly, in this example there is not an increase in heat-related illness, while there is for the other outcome studied. Reid suggests that it varied from state to state (this figure is just one example from one state), and that it could partly be due to the very small numbers in the heat-related illness category. Deviant days had higher rates of morbidity and mortality. However, when the heat vulnerability index was added to the model with deviant days, the effect of the deviant day disappeared. The authors suggest that this may indicate that the vulnerability index created is detecting vulnerability in general, rather than only specifically related to heat.

Figure 4: Relationship between the heat vulnerability index and health outcomes



Source: Reid 2010

Other Relevant Validation Research

Although the three case examples presented provide the most detailed information available that is relevant for the Toronto context, there is ongoing research relevant to the heat vulnerability validation elsewhere, although at an earlier stage of development.

Dr. Daniel Johnson, at Indiana University, is currently leading two major heat projects:

1. Developing a heat health warning system (HHWS) for Indianapolis:
   This is a joint initiative between academic and municipal partners in Indianapolis to develop a HHWS, with a spatially-specific focus. While it will not adopt the synoptic methods developed by Kalkstein and colleagues, developers of the synoptic system are being consulted with in the development of this system. The key difference between the new Indianapolis HHWS and the synoptic method will be inclusion of a spatial element. This project is currently in the early stages of development. Emergency department visits and 911 calls are currently under consideration for validating this novel system.

(1) NASA ROSES Project: Using NASA data and models to improve HHWS's for decision support:
This project was funded by NASA and started in October 2009, and will continue over the next 3-4 years. The aim of this research is to model the thermal properties of 3 US cities (Philadelphia, Dayton, Phoenix), incorporating socioeconomic risk factors and heat-related mortality data. Thermal properties will be measured using a combination of the MODerate resolution Imaging Spectroradiometer (MODIS), Landsat Enhanced Thematic Mapper (ETM+), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and once available the Visible/Infrared Imager/Radiometer (VIIRS) system. Health outcome data will include all-cause mortality as well as mortality for heat-specific reasons, as identified by ICD-10 codes. Using logistic regression and Bayesian methods, a spatially-explicit risk model of vulnerability for heat will be created for each of the 3 cities. This builds on previous work that created a risk model for Philadelphia for the 1993 extreme heat event using satellite imagery, census variables, and mortality data to develop risk maps (Johnson 2009a). By creating a spatially-explicit risk model for each city, high-risk areas will be identified and public health interventions can be targeted to these areas. Although there are not yet detailed plans on the approach for validating these models, this group is discussing possibly using public perception telephone surveys, in addition to health data.

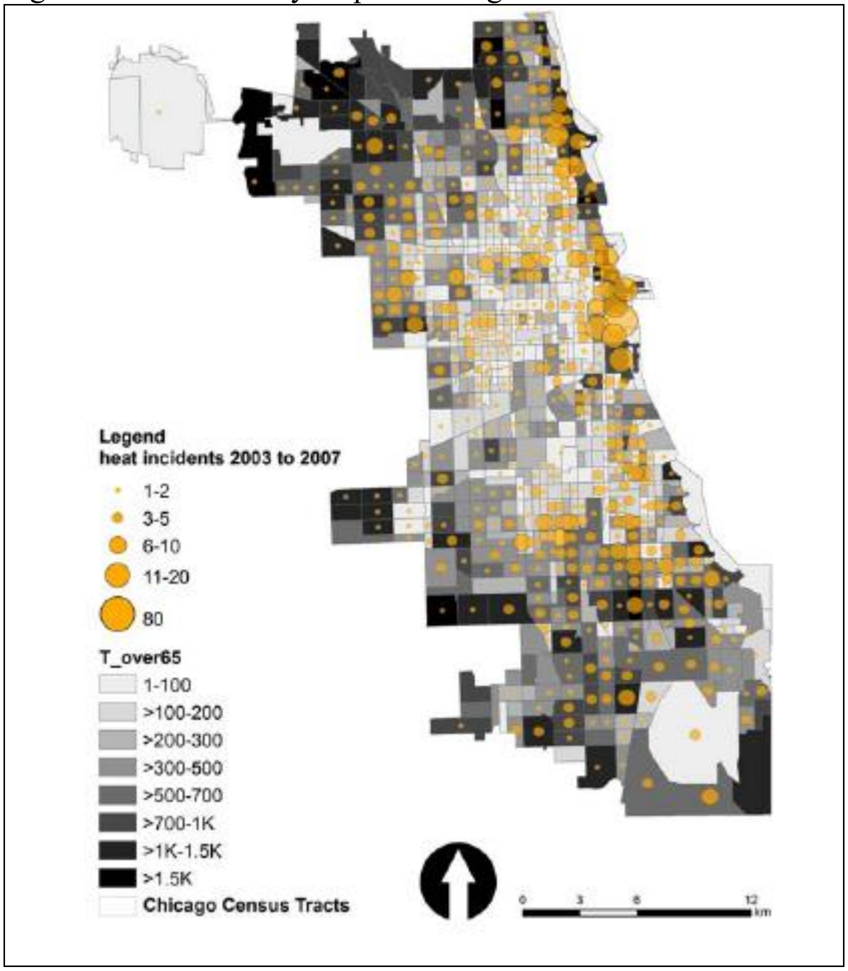
A recent paper by Johnson and colleagues (2009b) describes a unique approach to mapping heat vulnerability that incorporates both sociodemographic and physical factors. By developing a model that incorporates both surface temperature variations with socioeconomic indicators of heat-related vulnerability, the authors suggest that a more robust predictor of risk than one accounting for socioeconomic indicators alone is produced. Regression models showed that those with sociodemographic information (i.e. poverty and age 65 and over in poverty) combined with remote sensing data of mean temperature provided the best assessment of vulnerability, as compared with models of sociodemographic or remote sensing information alone.

A research group at Arizona State University has developed a social vulnerability index for heat for Chicago (Sister 2009). The following data were used for this analysis:

- 2003-2007 heat-related dispatch data from the Chicago fire department
- 2000 Census tract data
    - Neigbourhood stability (e.g. vacancy rates, renter vs. owner-occupied, crime)
    - Economic vitality (e.g. poverty levels, income, reliance on public assistance)
    - Quality of dwelling units (e.g. presence of plumbing units, median room number, proportion of housing units with only one room)
    - Proportion of highly vulnerable or marginalized individuals (e.g. relative to ethnicity, age, sex, and isolation).
- 2003 to 2007 crime incident data

Using census tract as the unit of analysis, a series of vulnerability maps were created (i.e. each census variable overlaid with heat incidents). Figure 5 provides an example of one of these maps using the population over the age of 65 years.

Figure 5: Vulnerability map of Chicago



Source: Sister 2009

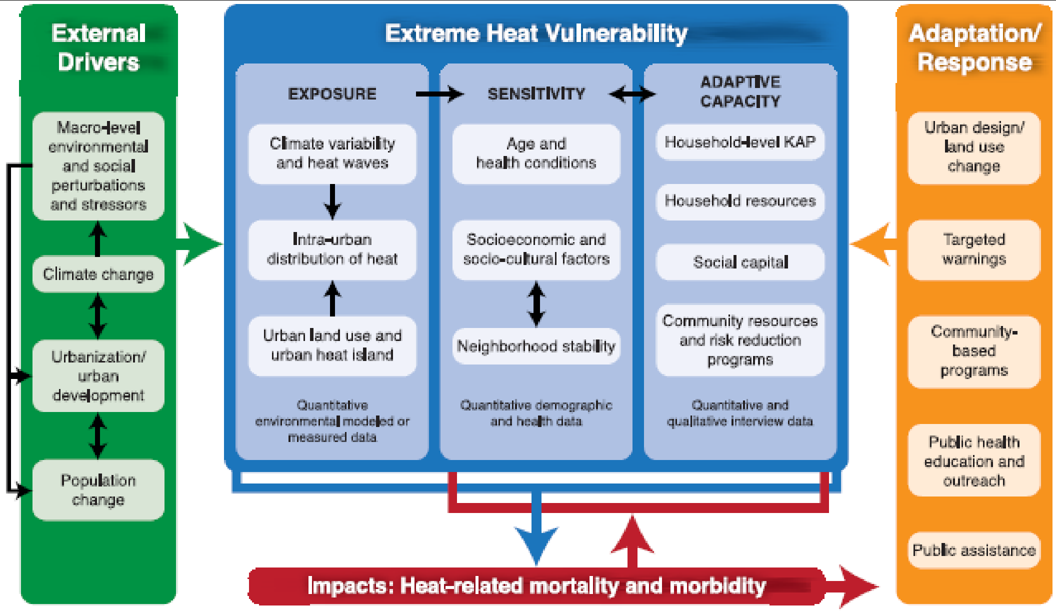
Regression analysis was used to quantify how well each of the variables predicted the heat-related emergency dispatches. They found that heat incidents were correlated with crime incidents, and only to a lesser degree with the other variables collected (in other words, the variables were not good predictors of heat morbidity across Chicago). However, this improved when they looked at smaller sub-sections of the city and used different variable combinations for these subsections, suggesting that there is not one set of variables that can predict heat-related morbidity and perhaps different indices are suited to different neighbourhoods. Interestingly, the highest number of heat incidents occurred in areas characterized as recreational, commercial and tourist destinations (an area that also has a higher number of homeless populations).

Dr. Paul English, Branch Science Advisor at the California Department of Public Health, created a heat vulnerability index for Alameda County, CA using two census variables: (1) percentage of the population living in poverty, and (2) percentage of households with elderly living alone (Paul English, personal communication). The values were centered to the mean (i.e. subtracted each value from its mean) and then summed to form a vulnerability index by census track. This group did attempt to validate the index created using emergency ambulance calls for heat-related illness. They conclude that the index did not validate very well and felt this was due to several factors: lack of thermal exposure surface measurements, and a high index around the Berkeley campus where students are classified in poverty by the census, but clearly wasn't the population of interest (Paul English, personal communication).

Compared to the US, there has been more limited spatial vulnerability assessment work in Europe, which is surprising given the heat waves in 2003. Dr. Gregoire Rey, a statistician-epidemiologist at the Centre d'epidemiologie sur les causes medicales de deces, recently published a study about the relationship between heat exposure and socio-economic vulnerability in the 2003 heat wave in France, and created maps to determine whether more deprived populations were more vulnerable to heat waves (Rey 2009). A heat exposure index was created using meteorological data and a deprivation index (using income and education information) were developed and compared with mortality data, so essentially a form of validation with health outcome data. Higher index levels were both associated with increased mortality (marked increase in mortality associated with heat wave exposure for all degrees of deprivation, but particularly for deprivation). However, at the current time there are no plans to further validate these indices or explore their use for practice; this was essentially an academic research study (Gregoire Rey, personal communication).

Novel research being led by Dr. Olga Wilhelmi and colleagues in Boulder, Colorado is putting a new spin on how vulnerability to heat should be considered. This group is developing a methodology to integrate quantitative and qualitative information spatially to create maps of heat social vulnerability in Phoenix, Arizona (Wilhelmi 2010). This project will incorporate qualitative interview data (surveys to assess knowledge of heat stress, barrier, resources) to develop a GIS-based map of social vulnerability. The rationale behind this work is that vulnerability to heat cannot be captured by census data only, but rather that the populations' coping ability, perceptions, and people-/place/based community resources must also be incorporated to provide a more complete picture. The research group has developed and recently published the research framework that will guide this work, as illustrated in Figure 6. Dr. Wilhelmi is currently leading the SIMMER project (System for Integrated Modeling of Metropolitan Extreme Heat Risk) which will apply this theoretical framework to Toronto and Houston.

Figure 6: Extreme heat vulnerability framework proposed by Wilhelmi et al (2010).



Source: Wilhelmi 2010

Potential Data Sources for Validating the Toronto Heat Vulnerability Maps

The aim of the validation will be to test whether the patterns of vulnerability identified in the heat vulnerability maps correspond to greater observed health impacts during periods of hot weather. Essentially, the validation will provide information as to whether there is a match between spatial units with high concentrations of populations with high heat risk factors and an observed increase in adverse health outcomes during hot weather. An important step in developing the method for validation is to determine appropriate sources of health outcome data. The following section outlines these data sources, highlighting issues to be considered in their use for this validation.

Mortality

Two outcome variables that are typically used in research exploring the relationship between mortality and hot weather and are possibilities for the validation methodology: (1) measuring mortality specific to heat-related causes, and (2) measuring "excess mortality", with the latter being the most common.

The primary challenge with measuring death due to heat-related causes is that this measure is subject to misclassification. Several studies have shown that deaths due to heat-related causes are underreported in mortality statistics. In general, although heat may contribute to death it is often not listed on the death certificate unless it is considered the underlying cause of death (see later discussion on the death certification process in Canada). For example, a study that counted deaths in which hyperthermia was listed as a contributing factor or other significant factor on the death certificate, but not the underlying cause, revealed that these deaths increased the number of heat-related deaths by 54% (Luber 2006). Furthermore, in the cases of isolated elderly who are found days after they have died, it is difficult to attribute death to heat as it must be assigned at the point of death. The lack of widely accepted systematic criteria for determining a heat-related death also creates outcome definition challenges (Basu & Samet 2002). Consequently, death certificate data is thought to underreport mortality due specifically to heat-related causes.

Given these challenges in attributing deaths to heat-related causes and wanting to more broadly capture aggravation of pre-existing conditions, researchers have often used measures of “excess mortality”. Excess mortality is calculated by subtracting the expected mortality from what is observed, using a variety of methods including moving averages and averages from similar time periods in previous years. One of the advantages of this indicator is that it captures a broader set of deaths that may be caused by heat, such as those due to exacerbations of cardiovascular and respiratory conditions. Furthermore, researchers can use total numbers of daily deaths, rather than extract for specific causes, which in terms of feasibility, is typically data that can be accessed more easily and quickly. For the purpose of the validation, considering all excess deaths will increase the number of data points and therefore power in statistical analysis, as compared to those due to heat-specific causes only.

In Canada, the Vital Statistics-Death Database, housed at Statistics Canada, captures demographic and medical (cause of death) information annually for all deaths in Canada. The medical certificate of cause of death is completed by the medical doctor in attendance, or the coroner in the case of sudden and/or unexplained deaths. The certificate elicits the direct antecedent and underlying causes of death, other significant conditions, manner of death (for example, natural, accidental, suicide, homicide), and further information on injuries. Part I of the death certificate has 3 lines—labelled (a), (b) and (c)—and is used to record the underlying cause of death as well as any “immediate” and “antecedent” causes of death (Figure 7, Myers 1998). Part II of the certificate is used to record other significant conditions contributing to death. The underlying cause of death is the disease that triggered the chain of events leading to the person’s death and without which death would not have occurred. An immediate or antecedent cause of death may not be identifiable in all cases; thus, an underlying cause of death can stand alone as the only completed line in part I.

Figure 7: Cause of death section of a death certificate, Office of the Registrar General, Ontario

MEDICAL CERTIFICATE OF DEATH			
	Part I	**I**	Approx. interval between onset & death
	Immediate cause of death	(a) *due to, or as a consequence of*	
CAUSE OF DEATH	Antecedent causes, if any, giving rise to the immediate cause (a) above, stating the *underlying cause last*	(b) *due to, or as a consequence of*	
		(c)	
	Part II	**II**	
	Other significant conditions contributing to the death but not causally related to the immediate cause (a) above		

Myers and Farquhar, 1998

The clinical information from the death certificate is then coded according to the World Health Organization "International Statistical Classification of Diseases and Related Health Problems" (ICD-10). Reporting is virtually complete given that death registration is a legal requirement in Canada (with the exception of unidentified bodies and deaths of Canadians who die outside of Canada).

Morbidity

Morbidity is a less commonly studied outcome in heat health research, likely because it is a more challenging source of data to analyze as compared with mortality. Of the available data sources, the most frequently used are hospital admissions. Similar methodological challenges apply to morbidity studies as seen in mortality studies, particularly the lack of a universal case definition of heat-related illness (HRI). As a result, morbidity research typically includes measurements of all hospital admissions, rather than specific diagnoses. Aside from hospital admissions, other sources of morbidity data include calls from provincial nurse-led helplines, and ambulance dispatch data. Each of these may be considered for the validation work, particularly hospital admissions and ambulance dispatch data, as accessing Telehealth data will be a challenge for this work.

a. Toronto Emergency Medical Services (TEMS) – Ambulance Dispatch Data

All emergency medical services in Toronto are provided by a single municipal government agency, Toronto EMS. The Toronto EMS Communications Centre is responsible for coordinating and dispatching medical emergency calls and processes approximately 425,700 calls each year; approximately half of these are for emergencies and the other half for scheduled inter-facility patient transfer. EMS call receivers classify and prioritize calls for service with the Medical Priority Dispatch System (MPDS, Priority Dispatch Corporation, Version 1.1, Salt Lake City, Utah). This widely used computerized triage algorithm scripts the dispatcher's interview with the 911 caller to identify the nature of the incident and the probable acuity of the patient to determine the appropriate level of EMS response in the pre-hospital setting. Based on the caller's answers, MPDS's software assigns the call to one of more than 500 "determinants" and recommends a dispatch priority. Each call has its own individual record, which includes all data from the MPDS interview, and this information is stored in a database housed at TEMS. Case-definitions can be created using the MPDS codes; one approach for this for heat, using the Toronto MPDS system is outlined by Bassil et al (2008). Given the relative ease of accessibility, and previous relationships between TPH and TEMS, these data are likely a good source for consideration for the validation work.

b. Emergency department data

Toronto emergency departments (EDs) submit data on ED visits to the National Ambulatory Care Reporting System (NACRS), developed by the Canadian Institute of Health Information (CIHI). Demographic information, reason for visit (coded according to the Canadian Enhancement to the *International Statistical Classification of Diseases and Related Health Problems, Tenth Revision [ICD-10-CA]* introduced in 2001), and other diagnostic information is collected. Regular data quality reviews are performed on the NACRS data by CIHI. It is deemed to be thoroughly comprehensive as Ontario EDs are mandated to report.

The NACRS dataset collects emergency room visits (i.e. not hospitalized patients). Visits specifically related to heat can be selected based on the "reason for visit" field in the NACRS dataset, which are coded by ICD-10 codes. Having conducted a literature review to assess appropriate ICD-10 codes for heat-related illness, the codes in Table 5 seem the most relevant. These codes are noted to be identical to ones selected in another Canadian study using these data (Koutsavlis & Kosatsky 2003) and a study of ED visits for heat during the 1995 Chicago heat wave (Rydman et al. 1999). Clearly, codes for other health problems of interest could also be selected (e.g. cardiovascular, respiratory), in addition to examining numbers of all daily visits (for all causes).

Table 5: ICD-10 Codes for Heat-Related Illness

T67	Effects of heat and light
T67.0	Heatstroke and sunstroke
T67.1	Heat syncope
T67.2	Heat cramp
T67.3	Heat exhaustion, anhydrotic
T67.4	Heat exhaustion, due to salt depletion
T67.5	Heat exhaustion, unspecified
T67.6	Heat fatigue, transient
T67.7	Heat oedema
T67.8	Other effects of heat and light
T67.9	Effect of heat and light, unspecified

(International Statistical Classification of Disease and Related Health Problems, Tenth Revision [ICD-10-CA])

c. Hospital data - In-patient database

Patients who visit the emergency department, and are then admitted to hospital (rather than those who are released) are captured in the in-patient database. If both the NACRS dataset and in-patient database are used, admitted patients should be excluded from the NACRS data query to avoid duplication. The in-patient database also uses ICD-10 codes. Clearly, those patients captured in this dataset likely represent those with more severe illness as they end up being admitted to the hospital, but by combining it with the NACRS dataset both groups are captured.

Suggestions for the Toronto Validation

From the previous discussion of potential data sources there are three that seem most suitable for the Toronto validation: 1. Toronto EMS data, 2. all-cause mortality, and 3. emergency department data using the NACRS dataset. The rationale for choosing EMS and hospitalization data is that they are more likely to capture the health effects of heat, which act more immediately than other environmental exposures, such as cold exposure (which has the greatest impact over several days or weeks). All-cause mortality will be important to first consider given that the number of cases of mortality specifically due to heat-related illness will be too small to sufficiently analyze. That being said, a sub-set of mortality causes such as cardiovascular and respiratory could be examined in addition, depending on the extent of analysis desired. Retrospective daily data for several years, for the summer-time period, would be suitable for this analysis.

Using these data, a simple approach to start would be to generate initial descriptive statistics (e.g. comparison of means of select health outcomes by vulnerability class). Specifically, does the mean number of ambulance calls and/or mortality counts, for example, increase as the vulnerability score increases, as would be expected on hot days? To do this, it would be useful to set a threshold temperature, or use some other benchmark such as heat alert days to define 'hot days'. The descriptive statistics could be done separately for each source of health data, to get a sense of how each one changes with increasing vulnerability score on hot days. This simple analysis will give one indication of how the vulnerability index score corresponds with health outcomes and if health outcomes increase with increasing vulnerability score, as would be expected.

The next level of analysis would be to apply a contingency table approach, as was conducted in the UK research. A contingency table could be created for each geographic area as well as overall, with summary statistics calculated (as outlined previously) to give a more quantitative estimate of the performance of the vulnerability index. The details of this procedure have already been described earlier in this document.

Although it is difficult to predict the next steps without first knowing the findings of the contingency table analysis, it is anticipated that the third step of analysis would be to develop stepwise regression models using each of the variables included in the index. This would provide a better sense of which variables in the index are the best predictors of vulnerability, and which ones are not good predictors. This will be important to consider particularly if it is determined that some factors should be revisited. This analysis should be conducted separately for each health outcome (i.e. mortality, TEMS, and hospitalization) to assess whether there are differences between these.

If there is interest to do some further exploratory analysis it may also be interesting to make comparisons between the index and a scale based only on age, for example, to assess performance with another scale. This type of exploratory analysis was conducted in the UK to make comparisons with their heat vulnerability index. Interestingly, while they found that the heat vulnerability index was better for predicting mortality on hot days, an age-based score could also be used to predict increases in mortality. However, this pattern was not seen for ambulance dispatch data where the vulnerability index was a better predictor of calls than the age-based score (Tanja Wolf, personal communication). It would be an interesting type of exploratory analysis to do, but may be more of an academic exercise suitable for a student research project.

One challenge in validating the index will be using similar health data that has been included in the original index. If the health data used is the same, it will obviously match well in the validation. However, the emergency room visits for respiratory and circulatory diseases that are used in the index only comprise a very small amount of the total index. One approach would be to validate the index with and without this emergency room data included in the original index to see if it makes any difference. Also, if the validation is conducted also using TEMS and mortality data it will help with this issue as will incorporate a broader range of health data.

Conclusions

To conclude, the limited validation work completed to-date suggests that it is likely that there is not one heat vulnerability index best for all areas. Variability of the characteristics of vulnerable populations in neighbourhoods precludes a single model to explain heat mortality and morbidity. Accordingly, conducting a local validation is a key step to assess these indices. There are several possible methods to validate the heat vulnerability maps as have been outlined above. One, or a combination of these methods could be used, depending on the needs and resources available, however, an analysis that includes simple descriptive statistics, a contingency table, and stepwise regression would likely provide significant insight into the validity of the heat vulnerability index.

Contributors:

Name	Organization
Tanya Wolf, Technical Officer, Climate Change & Health	World Health Organization
Paul English, Branch Science Advisor	California Department of Public Health
Colleen Reid, PhD candidate	University of California, Berkeley
Marie O'Neill, Associate Professor	University of Michigan
Daniel Johnson, Assistant Professor	University of Indiana
Margaret Loughnan, Researcher	Monash University, Australia
Olga Wilhelmi, Project Scientist	National Center for Atmospheric Research
Gregoire Rey, Statistician epidemiologist	Centre d'epidemiologie sur les causes medicales de deces, France
Chona Sister, Post-doctoral fellow	Arizona State University

References

Bassil KL, Cole DC, Moineddin R, Gournis E, Schwartz B, Craig A, Lou W, Rea E. Development of a surveillance case definition for heat-related illness using 911 medical dispatch data. *Can J Public Health* 2008;99(4):339-343.

Basu R, Samet JM. Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. *Epidemiol Rev* 2002;24(2):190-202.

Johnson DP, Wilson JS. The socio-spatial dynamics of extreme urban heat events: The case of heat-related deaths in Philadelphia. *Appl Geogr* 2009;29:419-434.

Johnson DP, Wilson JS, Luber GC. Socioeconomic indicators of heat-related health risk supplemented with remotely sensed data. *Int J Health Geogr* 2009;8:57.

Kalkstein, L.S. A new approach to evaluate the impact of climate on human mortality. *Environ Health Perspect* 1991;96:145-150.

Koutsavlis AT, Kosatsky T. Environmental-temperature injury in a Canadian metropolis. *J Environ Health* 2003;66(5):40-5.

Loughnan, M. , Nicholls, N., Tapper, N. Hot Spots Project - A spatial vulnerability analysis of urban populations to extreme heat events. 2010. Report submitted to the Department of Health, State Government of Victoria, Australia. Available at http://www.health.vic.gov.au/environment/downloads/heatwaves_hotspots_project.pdf

Luber GE. Heat-related deaths - United States, 1999-2003. *MMWR* 2006;55(29):796-8.

McGregor GR. The development of a vulnerability index for communicating risk information. 2010. To be presented at the American Meteorological Society meeting in January 2011.

Myers KA, Farquhar DRE. Improving the accuracy of death certification. *CMAJ* 1998; 158:1317-1323.

Nicholls N, Skinner C, Loughnan ME, Tapper N: A simple heat alert for Melbourne, Australia. *Int J Biometeorol* 2008;52(5):375-384.

Reid CE, Mann J, Flowers MH, et al. Climate change, heat waves, and population vulnerability: Using the environmental public health tracking network for validity texting of the heat vulnerability index. Presented at the 138th American Public Health Association conference. November 2010.

Reid CE, O'Neill MS, Gronlund C, et al. Mapping community determinants of heat vulnerability. *Environ Health Perspect* 2009;117:1730-1736.

Rey G, Fouillet A, Bessemoulin P, et al. Heat exposure and socio-economic vulnerability as synergistic factors in heat-wave-related-mortality. *Eur J Epidemiol* 2009;24:495-502.

Rinner C, Patychuk D, Jakubek D, et al. Development of a Toronto-specific, spatially explicit heat vulnerability assessment. 2009. Report prepared for the City of Toronto. Available at: http://www.toronto.ca/health/hphe/air_quality/pdf/finalreport.pdf

Rydman RJ, Rumoro DP, Silva JC, Hogan TM, Kampe LM. The rate and risk of heat-related illness in hospital emergency departments during the 1995 Chicago heat disaster. *J Med Syst* 1999;23(1):41-56.

Sheridan, S.C., Kalkstein, L.S. Progress in heat watch-warning system technology. *Am Meteo Soc* 2004;1931-1941.

Sheridan, S.C., Kalkstein, L.S. Health watch/warning systems in urban areas. *World Resource Review* 1998;10, 375-383.

Sister C, Boone C, Golden J, et al. Mapping social vulnerability to heat wave in Chicago. Presented at the American Meteorological Society 2009 Meeting.

Wilhelmi OV, Hayden MH. Connecting people and place: a new framework for reducing urban vulnerability to extreme heat. *Environ Res Lett* 2010;5:1-8.

Wolf, T., G. McGregor, and A. Analitis. Assessing Vulnerability to Heat Stress in Urban Areas. The Example of Greater London. 2009. Epidemiology 20(6): S24 (Abstracts: ISEE 21st Annual Conference, Dublin, Ireland, August 25-29, 2009)

Woodruff, R., 2005. Epidemic early warning systems. In: Ebi, K.L., Smith, J.B., Burton, I. (Eds.), Integration of Public Health with Adaptation to Climate Change: Lessons Learned and new Directions. Taylor & Francis, Leiden, The Netherlands, pp. 91-113.