4.4 DETERMINING RISK ZONES FOR HUMAN HEALTH DURING HEATWAVES

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1. INTRODUCTION

Heatwaves are a common occurrence throughout the world and have substantial impacts on humans, including increased heat and pollution related illnesses during these events (Kilbourne 1997; Barnett et al. 2007; Lin et al. 2009). Several well-known heatwaves, resulting in numerous fatalities, include the Chicago Heatwave of 1995 (Krunkel et al. 1996), the European Heatwave of 2003 (Garcia-Herrera et al. 2010), and the Russian Heatwave of 2010 (Grumm 2011). These extreme heat events are especially dangerous within urban environments due to higher air pollutant concentrations and the Urban Heat Island (UHI) phenomenon. Temperatures within the more urbanized areas of cities tend to be warmer, especially during the nighttime hours, than their rural counterparts. At 2-meters, the nighttime temperature difference between these two environments can be as much as 2ºC (Basara et al. 2008). Previous research has even shown the UHI to enhance the effects felt from extreme heat events (Kunkel et al. 1996; Basara et al. 2010). Increasing urbanization also has the potential to increase the temperature differential felt from the UHI phenomenon (Hung et al. 2006).

Climate change is also expected to influence heatwaves. Current projections show an increase in the frequency, longevity, and intensity of such events (Luber and McGeehin 2008). As city populations continue to grow due to increased urbanization, more people will become engrained in these highly vulnerable urbanized areas. Thus, better mitigation and adaptation techniques are necessary. This study examined the 2008 summer heatwave that impacted Oklahoma City, Oklahoma from July 30 through August 6 in an attempt to explore the spatial variation of population vulnerability during extreme heat events. The ultimate purpose was to determine a potential methodology to display vulnerability at a community level scale by mapping atmospheric and demographic attributes using a geographic information system (GIS). Census tracts were assigned a vulnerability score according to four different variables, and the final analysis included combining these factors to determine a composite vulnerability level.

2. DATA AND METHODOLOGY

2.1 *Atmospheric Data*

Atmospheric data included maximum and minimum temperature from the Oklahoma Mesonet and Oklahoma City Micronet stations. The Oklahoma Mesonet consists of ~120 in situ stations scattered across rural areas of Oklahoma (McPherson et al. 2007). Each station measures a vast variety of data, including the 2-meter temperature data used in this project. Eleven stations were chosen for this project to help aid in interpolating temperatures since several of these reside on the exterior of the study area (black square in Figure 1). The Oklahoma City Micronet consists of ~36 stations mounted on traffic signals within the city itself (Basara et al. 2011). Again, each station measures a variety of data, including the 9-meter temperature data used in this project. All 36 stations were used and reside within the study area. Ozone concentration data was also explored but deemed insignificant since the values recorded for this event never reached significant health concern levels, according to the EPA Air Quality Index.

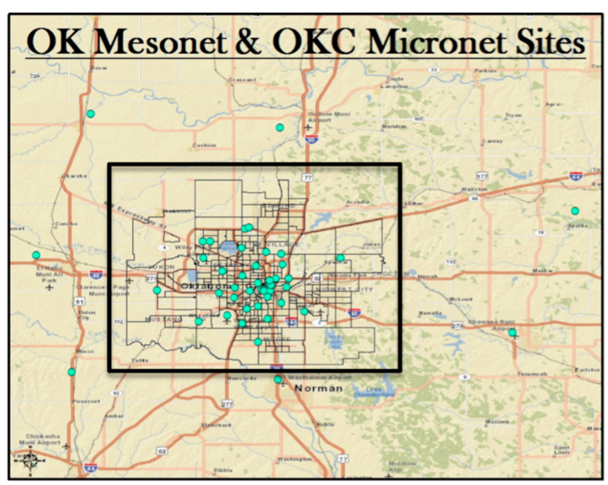

Fig 1: Mesonet and Micronet stations used in this study. Study area is outlined by the black square.

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2.2 *Demographic Data*

Demographic data included population density, education, income, and age from the 2000 Census. Population density was determined by dividing total population within each tract by the land area of that tract. The remaining demographic data was clustered together in a project done by Hall and Basara (2010) [poster]. They used a self-organizing algorithm to determine five different clusters within Oklahoma City. Within each cluster, tracts share similar demographic attributes. Using this dataset aided in simplifying data analysis.

2.3 *Assigning Vulnerability*

Each census tract was assigned a vulnerability score for each of the four variables previously mentioned (clustered demographic data, population density, maximum temperature, and minimum temperature). In all assessments, a linear relationship between the variable and vulnerability was assumed (Reid et al. 2009). For the clustered demographic data, each attribute (age, income, and education) was assigned a vulnerability score and then those were averaged together to determine the clustered demographic data vulnerability. Elderly populations resulted in higher vulnerability scores (Hajat and Kosatky 2010). Low income and education levels also resulted in higher vulnerability scores (Reid et al. 2009). Population density vulnerability was determined by dividing the range of densities into five equal groupings and assigning higher vulnerability scores to higher population densities (Medina-Ramon and Schwartz 2007). Maximum temperature (minimum temperature) vulnerability was calculated where the highest vulnerability level corresponded to a 10ºC increase (decrease) above (below) the climatological maximum (minimum) for the city. The climatological maximum for Oklahoma City is 32.76ºC (90.97ºF), while the climatological minimum is 20.56ºC (69.0ºF). Each of the scores was normalized for comparison purposes and the total vulnerability assessment. For the total vulnerability assessment, all variables were assumed to hold equal weight (Reid et al. 2009). ArcGIS 10 was used to aid in layering and manipulating the data, in addition to interpolating the temperature data.

3. RESULTS AND DISCUSSION

From the clustered demographic vulnerability (Figure 2), we see the highest vulnerability scores of 0.833 and 0.750 coupled with census tracts associated with clusters 3 (south-central OKC) and 4 (eastern OKC), respectively. These two clusters have the lowest incomes and lowest education levels of the five clusters. Cluster 3 was determined by Hall and Basara (2010) [poster] to have greater than 40 percent of the residents having less than a high school diploma, while cluster 4 has ~25 percent of the residents having less than a high school diploma. The lowest vulnerability scores are associated with clusters 2 and 5, which reside more in the rural exterior of the city. These two clusters have some of the highest income and education levels of the five clusters.

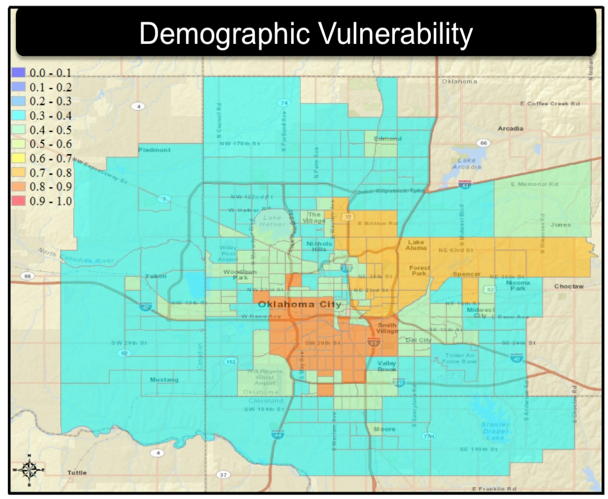

Fig 2: Demographic vulnerability. Highest levels are seen within tracts associated with clusters 3 (south-central OKC) and 4 (eastern OKC), both characterized by the lowest income and education levels. Lowest levels are seen in clusters 2 and 5 (rural exterior), characterized by the highest income and education levels.

Population density vulnerability displays that higher vulnerabilities, which are associated with higher population densities, reside within the more urbanized areas as compared to the areas characterized as rural (Figure 3). What is interesting to note here is how several tracts associated with cluster 3 reside within these densely populated, and subsequently, highly vulnerable areas. These census tracts no only experience a 0.833 vulnerability score from the clustered demographic variable but now also experience a 0.8 and greater vulnerability score from population density.

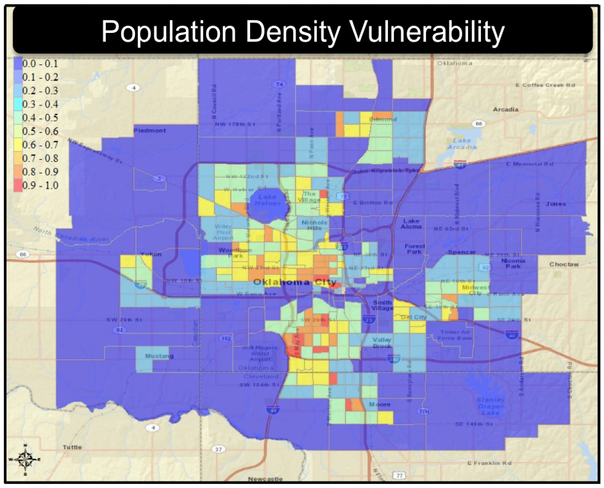

Fig 3. Population density vulnerability. Highest levels are seen in more the urbanized landscapes. Note how several tracts within cluster 3 (dark orange colored tracts in Fig. 2) also reside in these densely populated areas, enhancing their cumulative vulnerability.

Maximum temperature vulnerability, unlike the other variables, tends to be relatively constant across the entire study area (Figure 4). Most of the area experienced a vulnerability score between 0.3 and 0.4 for this specific event. When looking at the daily plots for maximum temperature vulnerability, days with higher maximum temperatures were shown to have higher vulnerability scores (not shown). However, vulnerability still tended to remain relatively constant across the area.

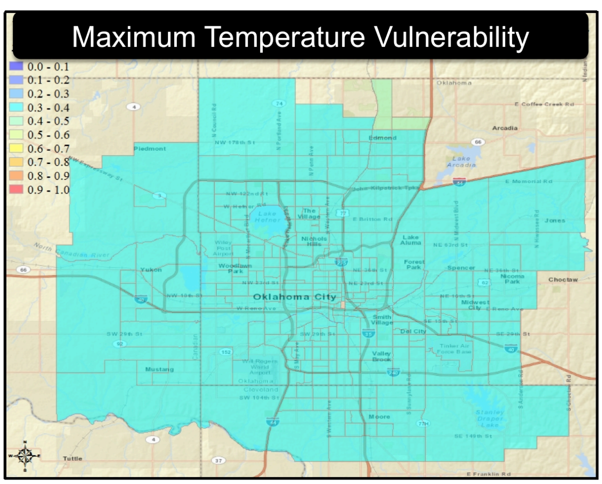

Fig 4: Maximum temperature vulnerability. Note the relatively constant nature of vulnerability levels across the study area. Therefore, averaged maximum daily temperature did not seem to strongly influence vulnerability spatially.

Minimum temperature vulnerability exhibits quite different results from the maximum temperature vulnerability (Figure 5). The UHI phenomenon and the UHI plume were more prominent in the nighttime temperatures. Overall, the highest vulnerability scores of 0.6 to 0.7 are seen within the more urbanized areas of the city. The elongated area of higher vulnerability in the central portion of OKC displayed in Figure 5 was hypothesized to result from the UHI plume. A UHI plume occurs when warmer temperatures associated with the UHI become advected to surrounding areas. Further analysis is needed to determine if indeed this is a feature from a UHI plume.

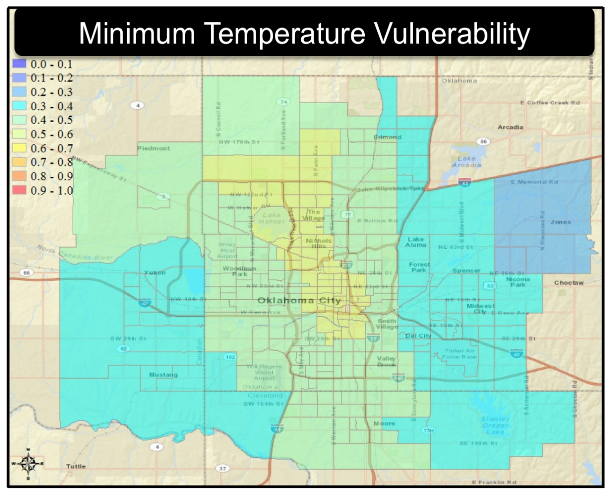

Fig 5: Minimum temperature vulnerability. Highest levels are seen within the more urbanized landscapes. Note the difference spatially as compared to the maximum temperature vulnerability.

The total vulnerability assessment shows that the highest levels of 0.6 to 07 correspond to several tracts associated with cluster 3 (Figure 6). Again, this cluster has the lowest income levels and lowest education levels, and several tracts reside in the most densely populated areas of OKC. Another interesting result is the general trend that higher vulnerability scores occur more often within the urbanized landscapes as compared to the rural landscapes. This is important to note with the trend of increasing urbanization that will result in more people residing in these vulnerable urbanized areas.

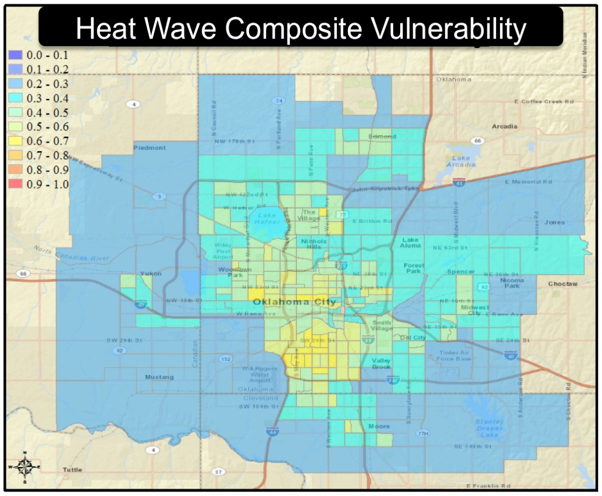

Fig 6: Composite vulnerability. Highest levels overall are seen in tracts that reside within the more urbanized landscapes.

4. CONCLUSIONS

From this project, the authors were able to develop a potential methodology to display vulnerability on a community level scale using a limited dataset. In some situations, data availability can be a problem and thus the authors wanted to show that even with a limited dataset, vulnerability mapping could be accomplished. Unfortunately, verification of these results was not within the scope of the project but could be accomplished via public surveys and interviews or medical data. The methodology presented here has the ability to allow users to visually see where the most vulnerable populations reside in a given city, and thus send immediate care and cooling resources to these populations first. One limiting factor of this method, however, is that data is only comparable within cities since the vulnerability scoring was relative to the dataset.

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