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A Heat Vulnerability Index and Adaptation Solutions for Pittsburgh, Pennsylvania

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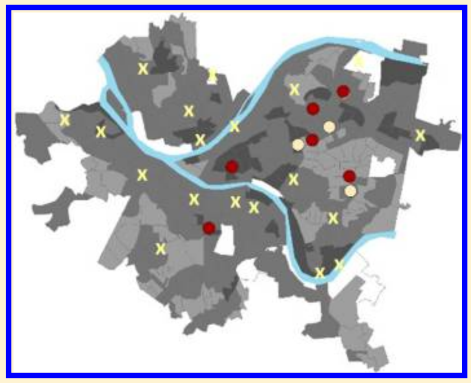
Supporting Information

ABSTRACT: With increasing evidence of global warming, many cities have focused attention on response plans to address their populations' vulnerabilities. Despite expected increased frequency and intensity of heat waves, the health impacts of such events in urban areas can be minimized with careful policy and economic investments. We focus on Pittsburgh, Pennsylvania and ask two questions. First, what are the top factors contributing to heat vulnerability and how do these characteristics manifest geospatially throughout Pittsburgh? Second, assuming the City wishes to deploy additional cooling centers, what placement will optimally address the vulnerability of the at risk populations? We use national census data, ArcGIS geospatial modeling, and statistical analysis to determine a range of heat vulnerability indices and optimal cooling center placement. We find that while different studies use different data and statistical calculations, all methods tested locate additional cooling centers at the confluence of the three rivers (Downtown), the northeast side of Pittsburgh (Shadyside/Highland Park), and the southeast side of Pittsburgh (Squirrel Hill). This suggests that for Pittsburgh, a researcher could apply the same factor analysis procedure to compare data sets for different locations and times; factor analyses for heat vulnerability are more robust than previously thought.



1. INTRODUCTION

Extreme heat events coupled with high humidity are the deadliest natural hazard in the United States.[1] These events are catastrophic both in terms of monetary damages and human mortality. Due to an increasingly aging population and a higher number of people projected to live in cities where heat is intensified by the urban infrastructure,[2,3] the impacts of extreme heat events are likely to be even more severe in the future. Currently 75% of extreme heat events can be linked to the 1−2 °C global climate change we have already experienced.[4] Therefore, if surface temperatures in the Northeast U.S. increase an additional 2−5 °C by 2100 as projected,[5] we may expect to experience even more frequent high intensity heat waves in the future.

Exposure to extreme heat can affect an individual's ability to regulate his body temperature, resulting in increased rates of heat stress, heat stroke, and premature death.[6−8] As extreme heat events are expected to increase in frequency and intensity, researchers as early as the 1990s began to investigate which regional characteristics (e.g., environmental and socio-economic factors) may increase an individual's susceptibility to heat-related illness.[9] Populations at risk from extreme heat may share several characteristics, called vulnerability factors, which can be unified into a vulnerability index through statistical methods.[10] A variety of literature has used factor analysis as a technique to identify which vulnerability factors contribute most to the variability of the set of all factors (e.g., Reid et al. (2009),[11,12] Aubrecht and Ozceylan (2013),[13] and Harlan et al. (2013)[14]). While robust heat vulnerability indices developed to date have primarily been region specific,[15] many vulnerability factors are consistent across studies, such as low educational attainment, high poverty levels, poor health, and lack of air conditioning.[16] In an attempt to characterize exposure levels, some of the vulnerability studies have used a land cover indicator or satellite data as a proxy for temperature, urban heat island effects,[17−21] or a series of hierarchical Bayesian models to examine associations between temperature and morbidity,[22] or exposure to climate change,[23] or other methods.[24] However, unlike other peer reviewed literature,[25−27] it has been difficult to validate our model due to lack of publicly available heat specific hospitalization data for Pittsburgh, PA.

Extreme heat events most often occur in cities. Due to the urban infrastructure and characteristic lack of green space, developed areas are on average 1−3 °C warmer than their rural surroundings during the daytime,[28−30] and potentially up to 12 °C warmer at night.[29] This is called the urban heat island (UHI) effect and is known to intensify synergistically with extreme heat events.[31] Despite expected increased frequency and intensity of heat waves, the health impacts of such events in urban areas can

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Table 1. Data Used in This Study

Data	Source	Pittsburgh	Reid	Harlan	Aubrecht and Ozcelyan
% by population					
Over 65 years of age	1	✓	✓	✓	✓
Living alone	1	✓	✓	✓	✓
Over 65 years of age + Living alone	1	✓	✓	✓	
Below poverty line	1	✓	✓	✓	✓
Poor English skills	1	✓			✓
Less than high school diploma	1	✓	✓	✓	✓
Ethnic minority	1	✓	✓	✓	
Latino immigrant	1	✓		✓	
Diabetes	1, 2	✓	✓		
Lack central air conditioning	3	✓	✓	✓	
Lack air conditioning of any kind	3	✓	✓		
% by area					
Lack of green space (mean)	4	✓	✓	✓	✓
Lack of nearby green space (std dev)	4	✓		✓	
Sources					
1: American Community Survey (2008-2012)					
2: Behavioral Risk Factor Surveillance System					
3: Allegheny County Tax Property Office (2014)					
4: United States Geological Survey (2013)					

be minimized with careful policy and economic investments,[1] and officials have already begun to focus efforts on emergency response plans, adaptation, and hazard mitigation.[32−37,41] Some mitigation options include **green roofs**,[38−40] **cool roofs**,[39] **urban forestry**,[41] **cool pavements**,[28] **water parks**, and **improved emergency response** such as providing bottled water. One possible adaptation solution to extreme heat events is to ensure proper access to cool spaces, especially in dense urban centers and neighborhoods with vulnerable populations. Several cities have begun using public buildings such as senior centers or libraries as **cooling centers** where residents can seek relief from extreme heat.[42] Cooling centers can help the public to escape the heat, obtain adequate drinking water, and avoid long-term outdoor exposure.[43] Cooling centers have proven an effective solution to mitigating the effects of extreme heat for vulnerable populations;[38] however, their strategic placement requires an understanding of the spatial variability of heat-related vulnerability in a given city. In this study, we develop a methodological approach for policy makers to use heat vulnerability indices to identify optimal cooling center locations.

Here we focus on Pittsburgh, Pennsylvania as a case study and ask two questions. First, what are the top factors contributing to heat vulnerability and how do these characteristics manifest geospatially throughout Pittsburgh? Second, assuming the City wishes to deploy additional cooling centers, what placement will optimally address the vulnerability of these at risk populations? We use national census data, ArcGIS geospatial modeling, and statistical analysis, to determine a range of heat vulnerability indices for the city of Pittsburgh and to identify optimal cooling center placement to address the highest proportion of vulnerability possible given limited resources.

2. MATERIALS AND METHODS

This adaptation study had two steps. First, we calculated a heat vulnerability index (HVI) for Pittsburgh and compared it to HVIs derived in previous studies for other regions. Then, using the results of the heat vulnerability index, we optimized the location of additional cooling centers under two Policies, in which the City takes a structural approach and builds new structures to meet the cooling demand for at risk populations (Policy 1), or in which the City takes a nonstructural approach and offers pre-existing public spaces as cooling centers during periods of high heat (Policy 2).

2.1. Heat Vulnerability Index. Although demographic variables may initially appear independent thereby eliminating the need for further statistical comparisons, the proper method to create a vulnerability index follows Cutter et al. (2003)[10] and involves a combination of testing for multicollinearity and subsequent factor analysis. This type of statistical analysis provides an ordinal measurement for each data set; since it does not create a cardinal measurement, it is statistically incorrect to compare a factor analysis from data set A for data set B. This implies HVIs are unique to a given region. However, off-the-record discussions suggest that due to a lack of researchers to guide them, decision-makers have begun to erroneously apply a factor analysis calculated for one data set to another data set. We wondered: How correct might it be to use the HVI calculated specifically for one geographic region in a different area? More specifically, (a) can areas be widely different in their climate and demographics, or must they be very similar in order to repurpose an HVI calculated in another region?, and (b) will a much simpler statistical method derived in a climatologically and demographically similar region yield a similar HVI? To answer this, we compared a Pittsburgh specific HVI using the commonly applied factor analysis method to the HVIs derived from inputting Pittsburgh specific data to (1) the commonly applied factor analysis method that averages over many climate zones,[12] (2) the commonly applied factor analysis method for a very different (much hotter and much dryer) climate, Maricopa County, Arizona,[14] and (3) the HVI using an entirely different procedure for a relatively similar climate, Washington DC.[13] All HVIs were calculated in IBM SPSS Statistics 22.

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First we created a heat vulnerability index for Pittsburgh using factor analysis and the 13 vulnerability factors identified by Reid et al., (2009),[12] Harlan et al., (2013), and Aubrecht and Oscelyan (2013),[13] as listed in Table 1. Values were coded such that higher values meant greater vulnerability (e.g., we converted **amount of green space** to **lack of green space**). To determine whether multicollinearity existed, we performed a multiple regression rotating through each variable as the new dependent variable, with the remaining 12 variables as independent variables. This multiple regression tests for multicollinearity in groups of variables, which makes it more robust than a *t* test comparing only two variables at a time. After removing variables that failed the multicollinearity test, we performed a principal components analysis for the HVI variables using varimax rotation and standard statistical criteria (e.g., the fewest number of factors that explain 70% of the variance). Following Reid et al. (2009, 2012)[12,44] and Harlan et al. (2006, 2013),[14,21] for each factor, we calculated the value at each census block group, then divided the results into six equal increments of 1.0 standard deviation, and finally assigned each census block group an integer value ranging from 1 (more than two standard deviations below mean) to 6 (more than two standard deviations above mean). These principal factors were then averaged to achieve a final HVI ranging from 1 (least vulnerable) to 6 (most vulnerable).

Second, we calculated the vulnerability indices using Pittsburgh data with the factors from the factor analyses conducted in two of our comparative studies: Reid et al. (2009)[12] and Harlan et al. (2013).[14] Each of these two studies followed the methods outlined above, for example, identified relevant data as given in Table 1, coded such that higher values meant greater vulnerability, tested for multicollinearity, conducted a factor analysis using varimax rotation, and assigned each census block group an integer value ranging from 1 (more than two standard deviations below mean) to 6 (more than two standard deviations above mean). For many climate zones, Reid et al. (2009)[12] found 4 principal factors; for a much hotter climate, Harlan et al. (2013) found three principal factors. Finally for each study, the principal factors were averaged to achieve an HVI ranging from 1 to 6.

Finally, we applied the heat vulnerability index method as calculated in the entirely different method used in Aubrecht and Ozceylan (2013)[13] for a relatively similar climate, that of the Washington DC.Metropolitan area. In this method, we used six data sets as given in Table 1. Most data were given as fractions of the population (on a 0 to 1 scale); all other data were rescaled linearly to a 0 to 1 scale. We then averaged the data sets to obtain a final HVI score between 0 and 1, with 0 indicating low vulnerability and 1 indicating high vulnerability. While Aubrecht and Ozceylan end here, for the comparative analysis, we further rescaled the HVI scores at each census block group to an integer value ranging from 1 (more than two standard deviations below mean) to 6 (more than two standard deviations above mean).

2.2. Location of Cooling Centers. Pittsburgh currently has four Healthy Active Living Centers which serve as cooling centers.[45] Additionally, Pittsburgh's 15 senior centers are often used as cooling centers during heat waves.[46] Otherwise, Pittsburgh has 268 other public buildings, including existing schools, recreation centers, and libraries that could potentially be temporarily opened overnight or permanently converted into a cooling center. A map of these locations is in the Supporting Information.

We assumed all 19 cooling centers and senior centers open during a heat wave. We then used the GIS Network Analyst tool to optimize for additional locations based on the census block group heat vulnerability indices. Our "service area" around each cooling center was defined as approximately 15 min of walking (0.8 miles) along existing roads or sidewalks (see Supporting Information for more detail). While not studied here, this method also allows for investigating transit to a cooling center location by bicycle, car, or public transportation along any defined transit path.

Next we used the GIS Network Analyst tool to determine the location of additional cooling centers optimized to meet the highest demand of at risk populations based on the heat vulnerability indices. Since the census block groups had very different populations, we developed a randomly distributed set of demand points in the census block group, with each demand point representing 100 people weighted by the HVI of their census block group (further discussion on this choice is in the Supporting Information). We tested two placement policies. For Policy 1, or **Structural**, we optimized assuming new cooling centers could be constructed anywhere except where there is a barrier (e.g., water, highway, or a nonaccessible location). Here we assumed the decision-maker would be economically resource constrained, which suggests a limited number of cooling centers could be constructed. Therefore, we examined optimizing up to a doubling in Healthy Active Living Centers, or up to four additional cooling centers. For Policy 2, or **Non-Structural**, we assumed that the City would convert existing schools, recreation centers, libraries, senior centers, or any other public building into a cooling center. Here we assumed the decision-maker would again be resource constrained such that not all public buildings could be opened simultaneously, but instead would like to optimize cost-effectiveness by meeting at least 50% of vulnerability weighted demand while opening the fewest number of buildings possible. We then compared each of the maps and recommend locations to expand the Pittsburgh cooling center network through both structural and nonstructural solutions. Finally, we conducted a sensitivity analysis to the percentage of demand met for both policy options. Additional details on the procedure are in the Supporting Information.

3. DATA

We collected Pittsburgh data for the variables used in Reid et al. (2009);[12] Aubrecht and Ozceylan (2013)[13] and Harlan et al. (2013)[14] as given in Table 1. These data include levels of green space, prevalence of air conditioning, and demographic parameters. All variables were coded so that higher scores denote higher vulnerability. The finest resolution available for all data sets was the census block group level; since there is no single agreed-upon definition of neighborhood, despite widespread interest in neighborhood effects[47] census block or census tract level could be equally viable subdivisions of interest.

Citizens **over 65 years of age** are believed to be vulnerable to intense heat because they often suffer from chronic issues that decrease ability to maintain homeostasis and recovering from physical activity in the heat.[48−50] A variety of studies have shown that the elderly have higher mortality rates during heat waves,[51−56] and higher hospital admission rates during heat waves.[57,58] We obtained these data came from the American Community Survey five-year 2008−2012 surveys.[59]

Increased vulnerability due to **living alone** can occur because socially isolated people may be less likely to notice physical symptoms that may be associated with a heat stroke, and/or may be unwilling to contact paramedics to receive medical care.[21] While some studies do not find conclusive evidence of a relation

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between living alone and heat-related death,[60,61] most studies find that people living alone are in fact more likely to have increased vulnerability during an extreme heat event.[54,62−64] Furthermore, studies that do not examine social isolation but instead examine a close proxy of marital status find increased vulnerability among those who are single, widowed, divorced, or never married as compared to those who are married.[52,55] We obtained census block group level data on "living alone" from the American Community Survey five-year 2008−2012 surveys.[59]

Vulnerability factors may work synergistically to make a person with several risk factors have an elevated vulnerability to heat-related events. Previous HVI studies have suggested a significant interaction, such that a person **over 65 years of age and living alone** has a higher chance of suffering from a heat related illness than a person with only one of these factors.[12,14] Unfortunately, the census values reported for these data were of poor quality; to obtain these data, we multiplied the fraction of residents **over 65 years of age** and the fraction of residents **living alone**.

Residents living **below poverty line** may be more vulnerable because they may not be able to afford air conditioning, hospital trips, information resources, or other preventative measures to forestall heat related deaths.[21,49,65−67] This relation has been demonstrated in a variety of studies.[54,68,69] We obtained "poverty status of individuals in the past 12 months" from the American Community Survey five-year 2008−2012 surveys.[59]

Poor English skills, or *linguistic isolation*, causes an individual to not have efficient access to distributed emergency information, which is important when the community is notified about extreme heat events.[15,49] We used aggregated records of speaking English "not well" and "not well at all" from the American Community Survey five-year 2008−2012 surveys.[59]

Having **less than a high school diploma** could increase vulnerability because the education learned by graduating high school helps in critical thinking and problem solving-both of which are important when identifying extreme heat circumstances. While area-level indicators are not predictive[70,71] at census tract and finer resolution, studies show a connection between vulnerability and lack of high school diploma.[68,72,73] We derived this data using the variable "less than high school" from the American Community Survey five-year 2008−2012 surveys.[59]

Ethnic minority populations, including **Latino immigrant** populations, have been shown to be more vulnerable to heat.[8,51,74−77] In our opinion, it is unclear whether these relations are mediated by characteristics suggested in other literature, such as environmental health problems due to local neighborhood conditions, tendency not to trust local officials, or residents with poor English skills. Indeed, some studies have not found a relationship between heat and mortality and race.[71] We chose to test for multicollinearity to determine whether to keep these variables or not. We used "nonwhite" populations and 'foreign-born Spanish-only speakers' from the American Community Survey five-year 2008−2012 surveys to represent **ethnic minority** and **Latino immigrant** populations, respectively.[59]

Individuals with pre-existing medical conditions such as **diabetes** are more vulnerable to heat induced illnesses and mortality.[58,74] We calculated diabetes prevalence from the 2015 Behavioral Risk Factor Surveillance System[1] state prevalence rates, which are reported by gender group. From the 2008−2012 American Community Survey,[59] we obtained population estimates for each gender group in each census block group and multiplied these by the BRFSS state diabetes rate for that gender group, obtaining an estimate of diabetes cases for that group in that census block group.

Residents who **lack air conditioning of any kind**, especially those who **lack central air conditioning**, are at an increased risk of heat related death.[78,79] Access to cool spaces allows for increased comfort and adequate restoration of body temperature after outdoor heat exposure.[43] However, due to a colder climate most of the year, only about 13% of homes in Pittsburgh currently have air conditioning installed (American Housing Survey, 2011). We used the Allegheny Tax Property Records (Quarter 4, 2014) to determine the percentage of single-family homes that **lack central air conditioning** and that **lack air conditioning of any kind** in each census block group.[80] These records were used to identify single family residential homes in each census block that feature any type of air conditioning system and central air conditioning systems. The homes were geo-spatially joined (ArcGIS 10.2) using home addresses to find the percentage of homes with AC and central AC in each block group.

Lack of green space and **lack of nearby green space** in a specific community have been associated with an increase in heat stress[21] and heat-related deaths.[18,81] This may be because more urban areas tend to have lower levels of vegetation and more impervious surfaces, which directly relates to the heat island effect.[12] Since this effect is nonlinear, both the lack of total green space and the lack of nearby green space matter. Furthermore, since a study at county level resolution was too coarse to properly capture dynamics,[82] we chose to use the fine resolution Natural Difference Vegetative Index (NDVI). The NDVI uses light reflectance properties of plants to measure of the density of green vegetation at a given moment in time[83] and can be used to measure the amount of green space in each census block group. We downloaded a Landsat 8 image of Pittsburgh from September 26th 2013 at 4 pm local time.[84] For improved accuracy, this day during the late summer was chosen because it had no cloud cover and high levels of green vegetation. Using geospatial analysis software (ERDAS 2015), the NDVI was calculated for each 30 × 30 m pixel. The zonal statistic tool (ArcMap 10.2) was used to aggregate pixels and determine the mean and standard deviation NDVI value for each block group. These values were rescaled across a range of 0 to 1, with 0 indicating high levels of vegetation and low vulnerability and 1 indicating low levels of vegetation and high vulnerability. The mean can be thought of as a **lack of green space**, and the standard deviation can be thought of as a **lack of nearby green space.**

Other. This list is of course not exhaustive. Some studies have used 20 or more data sets in their analysis.[85] For instance, it is well-known there are synergistic effects between heat stress and air pollution,[86] so one might want to include pollution indicators as a vulnerability factor. Similarly, while none of our three targeted HVIs included data on medication, cardiovascular, respiratory, and mental health data at the census tract level due to medical security restricting access to such data, much literature exists suggesting these are important.[52,54,58,60,63,87] Medications such as tricyclic antidepressants, antihistamines, and neuroleptic drugs "predispose patients to hyperpyrexia by interfering with the body's heat control mechanisms".[88] A combination of medication inhibiting the maintenance of an internal body temperature and pre-existing chronic illnesses have been shown to be associated with deaths/hospitalizations due to heat-related events. Furthermore, this analysis does not capture transient

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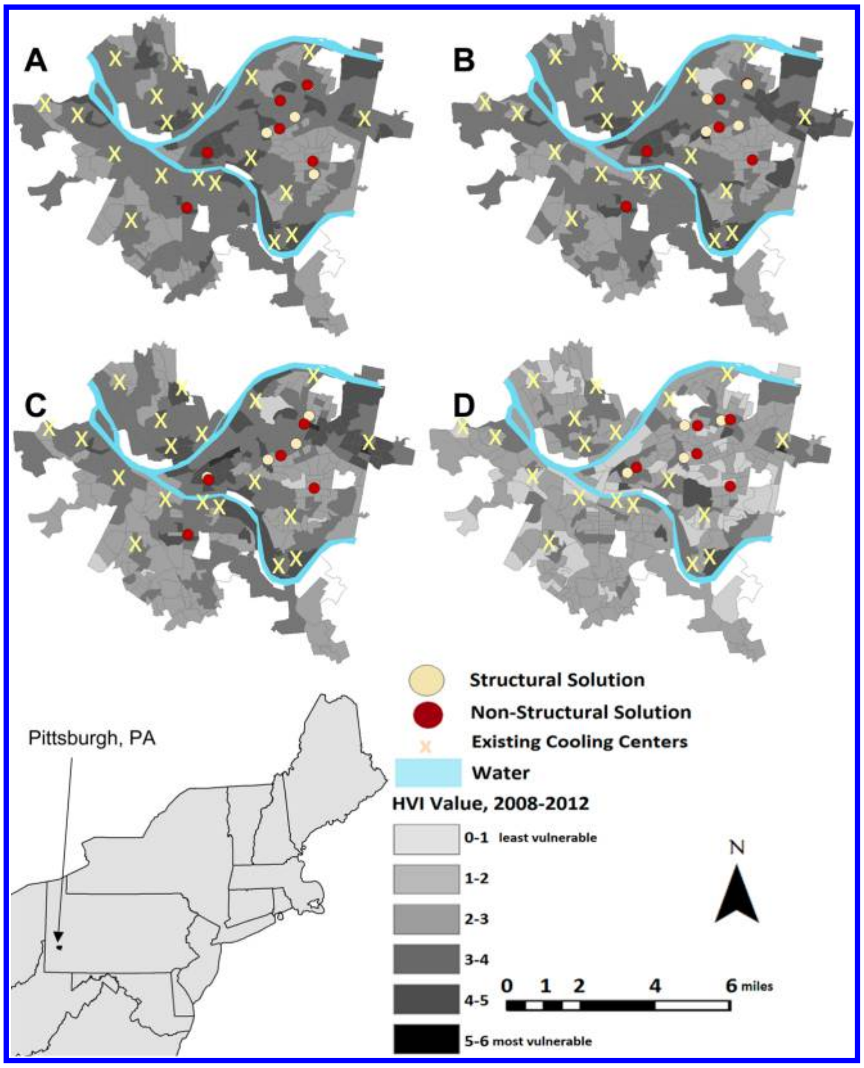

Figure 1. HVI images and cooling center locations for Pittsburgh, PA 2008−2012 on a 1 to 6 value, where 1 is less vulnerable and 6 is more vulnerable. White spaces have no single family residents, and hence no HVI. (A) Pittsburgh, (B) Reid, (C) Harlan, (D) Aubrecht and Ozcelyan.

populations such as students or homeless individuals; it can be difficult to obtain data on these residents' locations.

4. RESULTS

4.1. Pittsburgh Factor Analysis. For Pittsburgh, we found the two data sets of "No AC" and "No Central AC" to be collinear, likely because evaporative chillers are rare in Allegheny county and other types of ACs besides central AC and evaporative coolers do not need to be reported. We therefore removed the "No Central AC" data set from our analysis. Otherwise, all Vulnerability Index Factors (VIF) values were below 5, the typical tolerance level for testing for multi-collinearity.

Our consequent factor analysis yielded six principal factors (eigenvalues >1.0; total explained common variance >75%; slight break in the scree plot). The six identified factors can be loosely described as **Age and isolation** (explaining 18.1% of the variance), **Lack of economic resources** (16.5%), **Lack of cool spaces** (12.0%), **Lack of education** (10.3%), **Inability to speak English** (9.9%), and **Lack of nearby green space** (8.5%). The full tables and scree plot for the Pittsburgh HVI factor analysis can be found in the Supporting Information. We attempted to validate these results against actual hospitalization data as described in the Supporting Information, but the data were too sparse to test our hypothesis. Future work focused on regions with fewer privacy restrictions than Pittsburgh should obtain hospitalization data to further validate HVI results, as in Reid et al. (2012)[44] and Loughnan et al. (2009).[89]

4.2. Heat Vulnerability Index. Figure 1 shows the HVI for all four methods (Figure SI4 shows the HVIs without the cooling center locations). A visual inspection suggests the most vulnerable areas differ only slightly for each study. These areas are the confluence of the three rivers (Downtown), the northeast side of Pittsburgh (Shadyside/Highland Park), and the southeast side of Pittsburgh (Squirrel Hill). This high degree of clustering is reflected in the Moran's I test results for each HVI (given in the Supporting Information). Using geospatial comparison techniques as described in Levine et al. (2009),[90] we compared the HVIs by conducting a t test of difference in the means, a histogram of the spread of the data, and a Cronbach's alpha reliability test.[91] We found that despite having been derived for different regions, the means and standard deviations of the HVIs developed via factor analysis (Harlan, Reid, and Pittsburgh) are statistically similar. While the Aubrecht and Ozceylan based HVI has a statistically different mean from the other calculations, the standard deviations (and thus the spread) are similar, and there is

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internal consistency across models. Full results are given in the Supporting Information.

Studies have examined uncertainty in social vulnerability indices, finding that while hierarchical design are the most accurate and inductive models are the most precise,[92] uncertainty analysis provides useful insights highlighting places where the model is most robust.[93] Therefore, we conducted sensitivity analysis on our results by varying both the methods and the input data. The first sensitivity analysis we did was to use the factor weightings to develop a weighted sum HVI, rather than simply weighting all factors equally. For each of the three factor analyses (Pittsburgh, via Reid, and via Harlan), we found that there is no statistical difference at 99% confidence between the means of the weighted and nonweighted HVIs.

A second sensitivity analysis we conducted was to investigate the impact of the census data's margin of error on the HVI. The purpose of this portion of the analysis is to understand if the city used their best available data (i.e., census data) to determine their factor weights, what happens given the uncertainty in the underlying data (how wrong does the census have to be before it might impact their decisions/investments in reducing heat vulnerability). We found that the Pittsburgh heat vulnerability index was most sensitive to the margin of error (uncertainty) reported for ethnicity (nonwhite; Latino immigrant) then secondly to the uncertainty in the diabetes rate.

4.3. Location of Cooling Centers. Figure 1 shows the location of Policy 1 (Structural, place 4 new cooling centers) and Policy 2 (Non-Structural, use existing buildings to serve 50% of HVI weighted demand) solutions for Pittsburgh, PA for all four HVI methods. Locations chosen are remarkably similar despite HVI used. In Policy 1 (Structural), all HVIs result in the four additional cooling centers located at the confluence of three rivers (Downtown), the northeast side of Pittsburgh (Shadyside/Highland Park), and the southeast side of Pittsburgh (Squirrel Hill), resulting in a demand served of approximately 43%. In Policy 2 (Nonstructural), again all HVIs result in the four buildings utilized as cooling centers located in same three areas. In addition, three of the HVIs also locate a cooling center on the southwest side of town (Southside); this is clearly the next spot that would be served after Downtown, Shadyside/Highland Park, and Squirrel Hill.

To understand the sensitivity of our results to of the number of cooling centers chosen, we examined changes in the demand served. The existing 19 cooling centers and senior centers currently serve 28% of Pittsburgh's population. If Pittsburgh were able to open all public buildings as cooling centers, 88% of the population would be served. Thus, we examined non-structural solutions using the Pittsburgh HVI. The Supporting Information shows the number of sites chosen for 30% 40%, 50%, 60%, and 70% of market demand to be, respectively, 1, 3, 6, 10, and 18 locations. This shows diminishing marginal returns for achieving higher market demand; depending on the cost to open additional cooling centers, there is likely a "sweet spot" for the additional number of cooling centers in order to most effectively use constrained adaptation financial resources.

5. DISCUSSION

In this article, we used national census data, GIS modeling, and statistical analysis to calculate a heat vulnerability index for Pittsburgh and determine the associated optimal cooling center placement for cost-effective investment by the City. This research will help inform policy makers' decisions on adaptation strategies if they decide to proactively reduce temperature related public health risks. We find that while different methods use different data and statistical calculations, in Pittsburgh all four HVIs locate additional cooling centers at the confluence of the three rivers (Downtown), the northeast side of Pittsburgh (Shadyside/Highland Park/), and the southeast side of Pittsburgh (Squirrel Hill). This is a highly robust finding for a Pittsburgh decision maker. Additionally, this suggests that for Pittsburgh, a researcher could apply the same factor analysis procedure to compare data sets for different locations and times; factor analyses for heat vulnerability are more robust than previously thought. We suggest that one reason for this finding is that there is a given set of characteristics that are believed to make populations vulnerable, and these factors exist in every city; furthermore even though certain characteristics are not statistically collinear, they do tend to be correlated (ex; low educational attainment and poverty). Therefore, although strictly statistically speaking HVIs should be region specific, the consistency across vulnerability factors may dominate over regional differences.

Slight differences in cooling center placement occur whether the policy maker optimizes by repurposing existing public spaces or building new buildings. This suggests that the City can address the vulnerability by implementing nonstructural solutions without sacrificing effectiveness. This is desirable for two reasons. First, repurposing buildings requires comparatively less capital investment than building new infrastructure. Second, there is a potential that a cooling center will be unattractive for residents who do not wish to be labeled as vulnerable, but they might be quite happy to stop by the school to volunteer time for local students, or play Bingo at the local library. Thus, repurposing schools, hospitals, libraries, and other public buildings could simultaneously prevent stigmatization of cooling center attendance.

While the robustness across the sensitivity analysis demonstrates sound methodology, validating these vulnerability measures beyond a hypothetical risk index is challenging. First, as previously discussed, heat related hospitalization data for Pittsburgh is sparse and incomplete. Cities should consider collecting more of these hospitalization data that would better help characterize the impacts of intense heat events. Second, people move throughout the day. For example, while the downtown resident population is not as high as some surrounding areas, the daytime population swells due to the high density of jobs and social events. This suggests that a temporally dynamic HVI might be more relevant in capturing the true vulnerable areas at peak heat intensity (noon-afternoon hours), rather than relying solely on household demographic data. Existing research methods have used spatial proxies such as emergency dispatch data[26] in an effort to address this question of short-term dynamic population movement within a given day. However, these methods have not been applied to project long-term spatial-temporal shifts in vulnerability indices, which would be important for decision makers to understand when develop effective adaptation policies. More research could be conducted to understand if finer resolution data can be used as proxies (e.g., use crime events as a proxy for lack of economic resources), or whether a more complete vulnerability analysis would require an agent based modeling vulnerability scheme.

We also suggest that this type of analysis might not be equitable. Setting aside possible inherent biases in previous studies that could be missing certain types of vulnerability, this method optimizes by assuming the decision maker wants to cite cooling centers where a large number of vulnerable people live. However, is this equitable? Let us briefly consider a more obvious

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scenario. Which group is more vulnerable to a very heat wave: one person with a high vulnerability, or 100 people with the same high vulnerability? Assuming all else equal (building codes, survival strategy education, etc.) we would argue the higher population is significantly more vulnerable since more people are at this high risk. However, which group is more vulnerable to a very large earthquake: one person with a high vulnerability, or 100 people with moderately high vulnerable? Now the trade-off is less clear, and we need to have a good understanding of what the decision-makers care about. This description, or the utility function, can sometimes be described in a closed form solution. Indeed, we have presented just one of these closed form solutions in our paper. This methodology offers decision makers insight into how quantitative analysis can inform their decisions; decision makers must then identify their own value judgments. Once they do so, our work can help them understand the implications of those assumptions and regulatory choices on addressing heat vulnerability. Furthermore, the utility function becomes even more complicated when multiattribute utility function are considered; what if a decision-maker feels elderly are more vulnerable than those without air conditioning, and makes decisions accordingly? To help address this, future research could focus on eliciting the utility function more clearly. We suggest that future analyses consider equity issues and decision-makers' utility functions so the analyses specifically reflect the needs and priorities of a given region.

Finally, although the vulnerability indices discussed in this study include land use data as a proxy for exposure levels, we suggest that much more work could be done to map the urban heat island and provide a full risk profile. Aubrecht and Ozceylan (2013)[13] begin work in this area by using information on the number of heat wave days to create a risk profile. Finer resolution data might be obtained using satellite, LIDAR, or modeling efforts, for example, via Li and Bou-Zeid (2014).[94] Using satellite data, we have created a preliminary heat map for Pittsburgh (see Supporting Information), but this is map is limited to a single snapshot of the city. Much more data are needed in the Pittsburgh area to information a full risk assessment.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.5b03127.

> Optimization methods, the Pittsburgh factor analysis results, the validation of Pittsburgh HVI with hospitalization data, additional figures comparing HVIs, additional optimization figures, and the heat map of Pittsburgh, PA (PDF)

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Notes

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