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Spatial Modeling and Analysis of Heat-Related Morbidity in Maricopa County, Arizona

Chuyuan Wang · Patricia Solís · Lily Villa · Nayan Khare · Elizabeth A. Wentz · Aaron Gettel

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Abstract The objective of the present study was to examine the effects of a confluence of demographic, socioeconomic, housing, and environmental factors that systematically contribute to heat-related morbidity in Maricopa County, Arizona, from theoretical, empirical, and spatial perspectives. The present study utilized ordinary least squares (OLS) regression and multiscale geographically weighted regression (MGWR) to analyze health data, U.S. census data, and remotely sensed data. The results suggested that the MGWR model showed a significant improvement in goodness of fit over the OLS regression model, which implies that spatial heterogeneity is an essential factor that influences the relationship between these factors. Populations of people aged 65+, Hispanic people, disabled people, people who do not own vehicles, and housing occupancy rate have much stronger local effects than other variables. These findings can be used to inform and educate local residents, communities, stakeholders, city managers, and urban planners in their ongoing and extensive efforts to mitigate the negative impacts of extreme heat on human health in Maricopa County.

Keywords Heat-related morbidity · Census · Remote sensing · Multiscale geographically weighted regression · Spatial heterogeneity · Maricopa County

C. Wang (✉)
Department of Geography and Environmental Planning, Towson University, 8000 York Road, Towson, MD 21252, USA
e-mail: cwang@towson.edu

C. Wang · P. Solís · L. Villa · N. Khare · E. A. Wentz
Knowledge Exchange for Resilience, Arizona State University, Tempe, AZ 85287, USA

P. Solís · E. A. Wentz
School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ 85287, USA

L. Villa
School of Human Evolution and Social Change, Arizona State University, Tempe, AZ 85287, USA

A. Gettel
Office of Epidemiology, Maricopa County Department of Public Health, Phoenix, AZ 85012, USA

Introduction

Accelerated urbanization and urban expansion processes have taken place ubiquitously around the world to meet the ever-increasing demands related to population growth, resulting in extensive conversions from agricultural land and natural terrain to built-up areas and impervious surfaces [63]. These changes have had significant impacts on regional and global climate and exacerbated the urban heat island (UHI) effect [22, 42, 52, 64]. Climate change has increased regional and global temperatures and amplified the frequency and intensity of extreme heat events throughout the world [45, 46, 54, 56]. The combination of global temperature increases, frequent extreme heat events, and exacerbated UHI effects means that a growing percentage of the global

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population, especially urban residents, will face greater health risks due to excessive heat [53, 65, 72].

Intense and prolonged heat exposure can lead to a variety of heat-related illnesses such as short-term acute hyperthermia, heat exhaustion, and heat stroke as well as chronic problems that strain the immune system [40]. Acute symptoms of heat-related illnesses include muscle cramping, fatigue, headache, nausea or vomiting, and dizziness or fainting. These acute problems can develop into chronic or critical life-threatening symptoms because of the strains associated with body temperatures exceeding 103 °F (39.4 °C), and individuals may experience a rapid pulse, hot dry skin, confusion, and unconsciousness [11]. In extreme cases, belated or improper treatment may result in heat-related death [40].

Heat-related mortality issues have been studied from multiple perspectives in cities around the world. Frequent and intensive summer heat waves contribute to increased heat-related mortality, which has been well documented around the world (e.g., [16, 19, 25, 29, 31, 36, 61, 71]). The intensification of the UHI effect, especially during the summertime, has also exacerbated heat-related mortality in cities [15, 21, 30]. In addition to climatic and environmental factors, the magnitude of mortality increases can vary significantly by sociodemographic characteristics [23, 24, 57, 79, 84]. For example, research has reported that low-income populations of people of color and ethnic minorities are more vulnerable to heat than populations with other demographics [2, 3, 5, 12, 47, 51, 75]. Elderly people of all racial and ethnic groups have significantly higher heat-related morbidity and mortality than any other group of people due to high incidences of heart disease, isolation, loss of social networks, and poverty [1, 12, 41, 57, 59].

All the aforementioned factors that systematically contribute to increased heat-related mortality have also been extensively studied for Maricopa County, Arizona, which is one of the hottest regions in the USA. The literature has therefore paid specific attention to heat-related health issues, heat vulnerability, and heat resilience in Maricopa County (e.g., [12, 27, 28, 32, 55, 83]). Less attention, however, has been paid to the heat-related morbidity issue, which is an equally important threat to urban residents' health. In addition, these studies used all of Maricopa County based on the global distribution of observations and data, and neglected to consider spatial patterns and spatial heterogeneity. We believe that the spatial patterns of various contributing factors of heat vulnerability and the ability of local residents to withstand or respond to extreme heat events are unevenly distributed due to the diverse social and natural environments and the dynamic urban and rural landscape within Maricopa County. Therefore, the relative importance and actual local effects of a confluence of all the potential contributing factors may vary across regions.

Given the gaps in the literature, the overarching goal of the present paper is to analyze the spatial factors of an integrated socio-environmental system to characterize the complexity of a heat-driven public health issue. The objectives of this research are threefold. We first establish an empirical model using demographic, socioeconomic, housing, and environmental variables to predict heat-related morbidity in Maricopa County at the census tract level. The second objective is to analyze the spatial pattern and spatially varying relationships of the factors at local scales based on the empirical model. Finally, we aim to understand the people and locations that are among the most vulnerable to heat-related illness within the county.

Data and Methods

Study Area

Maricopa County, Arizona (Fig. 1), is part of the northeastern Sonoran Desert and features a subtropical semi-arid hot desert climate (Köppen climate classification—*BWh*). It is characterized by hot summers and mild winters [77]. June through August are the warmest months in a year with an average high of 105 °F (40.5 °C) and an average low of 81 °F (27.2 °C) ([74]). The daily maximum temperature can reach 120 °F (48.9 °C) with the all-time record highest temperature of 122 °F (50 °C), which occurred on June 26, 1990 [17]. The 30-year average annual precipitation between 1989 and 2018 is 8 in. (203 mm) with most of the rainfall taking place during the summer monsoon season [74].

Maricopa County is home to the cities of Phoenix, Scottsdale, Mesa, and 19 other mostly urban municipalities. It is Arizona's most populous county and the fastest growing county in the U.S. with an estimated 2019 population of nearly 4.5 million [73]. This has led to rapid urbanization and extensive land conversions from cooler agricultural land and natural terrain to built-up areas over the last several decades, which has

Fig. 1 Map of study area

exacerbated the UHI effect [8, 78]. The development environment largely consists of impervious surfaces for transportation infrastructure, residential neighborhoods (dominated by single family detached structures), commercial structures, and low-density vegetation.

Heat-Related Illness and Morbidity Data

The heat surveillance program of the Maricopa County Department of Public Health (MCDPH) collects and reports data including location, time, demographics, and circumstantial evidence for illnesses and deaths in which heat is the immediate cause or a contributing factor. MCDPH provided us with de-identified and aggregated data at the census tract level for heat-related illness cases that occurred between 2012 and 2016, for a total number of 10,741 cases. The number of heat-related illness incidents was then standardized by the population of each census tract to obtain morbidity values (Fig. 2). Heat-related morbidity was used as the dependent variable in the present study.

U.S. Census Data

To characterize the demographics associated with the morbidity data from MCDPH, we used 2012–2016 American Community Survey (ACS) 5-year estimates from the U.S. Census Bureau to derive demographic, socioeconomic, and housing variables at the census tract level. The rationale for selecting the independent variables is based on the existing literature on heat vulnerability research in Maricopa County (e.g., [12, 13, 27, 34]). The demographic variables included age group, gender, race, and ethnicity. Socioeconomic variables include educational attainment, English proficiency level, annual income, poverty status (population under

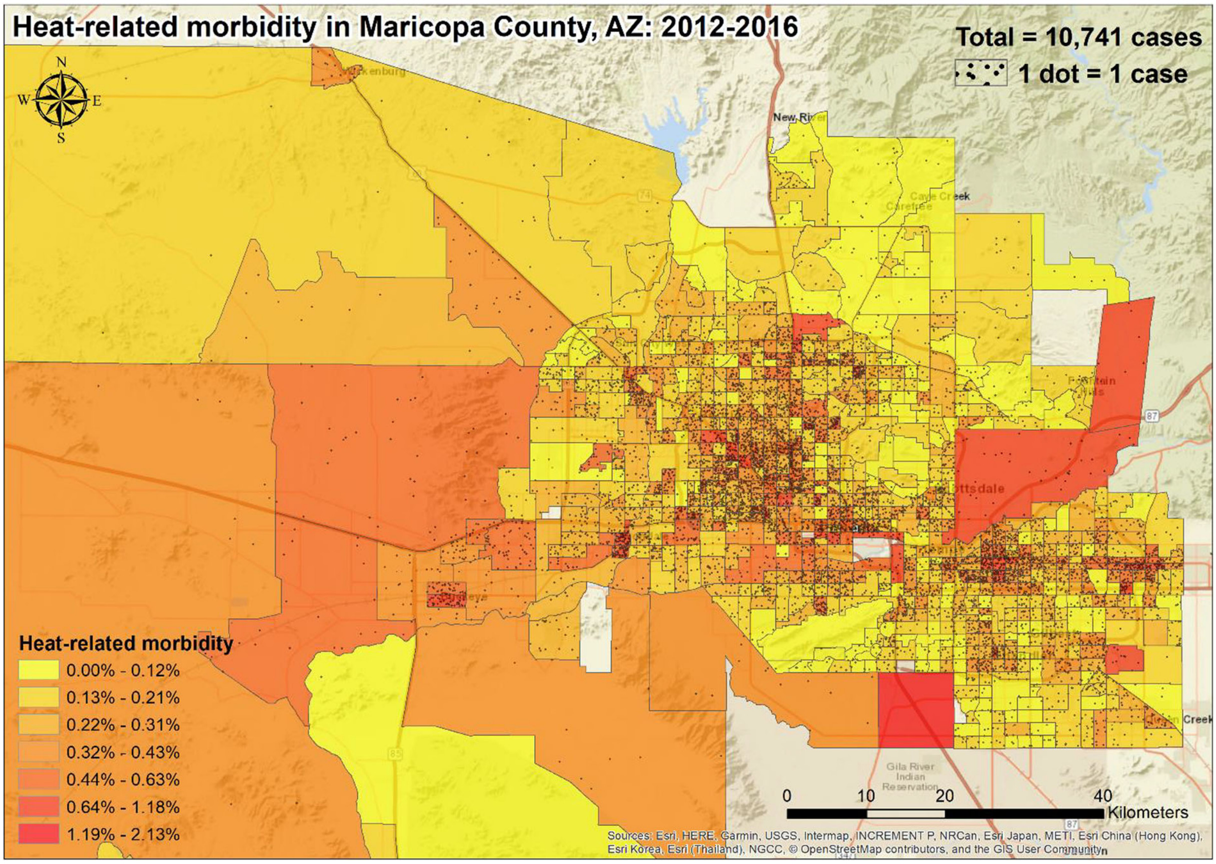

Fig. 2 A choropleth map showing the distribution of heat-related morbidity in Maricopa County, Arizona at census tract level between 2012 and 2016. Polygons are census tract boundaries. The black dots represent heat-related illness incidents, which are randomly generated in each census tract that do not necessary represent the exact physical location of each incident

150% of the federal poverty line (FPL)), disability status, and vehicle ownership. All the demographic and socioeconomic variables were standardized by the population of each census tract to obtain percentage values for subsequent analyses. The housing variables included number of housing units, median home value, housing occupancy rate, tenure in occupied units, and number of mobile homes.

Remotely Sensed Data

Remotely sensed data were used in the present study to derive environmental variables that included the land surface temperature (LST), surface reflectance, normalized difference vegetation index (NDVI), percent tree canopy, and percent developed imperviousness. The LST data were acquired from Landsat 8 level-2 provisional surface temperature products and ASTER surface kinetic temperature (AST-08) products from the U.S. Geological Survey (USGS). Landsat 8 and ASTER LST data have 100-m and 90-m spatial resolutions, respectively. Surface reflectance and NDVI images were acquired from Landsat 5 and Landsat 8 level-1 data products that have a 30-m resolution. All the cloud-free images in the summer months (June through September) between 2012 and 2016 were acquired from the USGS EarthExplorer website. Images of summer mean LST, mean surface reflectance, and mean NDVI were generated and resampled to 30-m resolution.

The National Land Cover Database (NLCD) provides land cover products for the entire USA using Landsat imagery with a 30-m spatial resolution and hybrid pixel-based and object-based digital image classification techniques [81]. We used percent developed imperviousness and tree canopy percentage products from the most recent 2016 NLCD to derive the land cover variables.

Statistical Analyses

We utilized ordinary least squares (OLS) regression and multiscale geographically weighted regression (MGWR) [18] to quantify the relationship between heat-related morbidity and all the contributing factors. OLS regression was used to examine the empirical relationship between heat-related morbidity (dependent variable) and all the predetermined demographic, socioeconomic, housing, and environmental variables (independent variables). A logistic regression using the stepwise selection method was first implemented in IBM SPSS Statistics software (version 26) for the initial screening of candidate predictors from the pool of preselected variables. Some candidate variables selected by stepwise regression were statistically insignificant or had multicollinearity issues with other variables. We therefore assessed and adjusted the candidate model slightly by adding or removing some variables based on their statistical relationships, model diagnostics, established theoretical framework from the existing literature, and expert knowledge to achieve the highest model predictive power and the most realistic result. This expert knowledge included a multidisciplinary team of academic researchers from geography, public health, sociology, and urban planning, as well as expertise from MCDPH, who participated as co-authors of this work.

MGWR was then used to analyze the spatial pattern and spatial heterogeneity of the contributing factors of heat-related morbidity. We opted for MGWR over the classical GWR [9] because MGWR relaxes the assumption that all independent variables operate the model at the same spatial scale. MGWR provides a means to measure the geographic scale over which different processes operate and include those measures in the model. This is achieved by calculating an optimal bandwidth in which each element indicates the spatial scale at which a particular process takes place [18]. All the independent variables from the final global model derived from the OLS regression were used as inputs in the MGWR. The model was calculated using MGWR software (version 2.0) [18].

Results

OLS Regression Results

Among all the predetermined independent variables, we ultimately selected 11 variables using OLS regression to establish the empirical model. The model is formulated as

$$\begin{aligned} P_{morb} = {} & 0.372 \times P_{age65} + 0.147 \times P_{white} - 0.108 \\ & \times P_{Hisp} + 0.235 \times P_{disab} + 0.241 \times P_{b150FPL} \\ & + 0.149 \times P_{noveh} + 0.429 \times P_{LHS} - 0.058 \\ & \times P_{occup} + 0.105 \times ref - 0.069 \times NDVI \\ & + 0.06 \times LST + \varepsilon \end{aligned}$$

In this model, P_{morb}, P_{age65}, P_{white}, P_{Hisp}, P_{disab}, $P_{b150FPL}$, P_{noveh}, P_{LHS}, P_{occup}, ref, $NDVI$, and LST represent heat-related morbidity, percentage of the population aged 65 and older, percentage of the white population, percentage of the Hispanic population, percentage of the population with a disability, percentage of the population with an annual income below 150% of the FPL, percentage of the population that does not own a vehicle, percentage of the population with less than high school diploma, housing occupancy rate, surface reflectance, normalized difference vegetation index, and land surface temperature, respectively. Only the standardized estimated coefficients are reported so that coefficient values can be compared among the variables.

Table 1 shows the summary of the OLS regression results. The model used 904 observations (census tracts) in Maricopa County and yielded an R^2 of 0.594, which means that 59.4% of the total variance in heat-related morbidity can be explained by the selected independent variables. The p value of the F test of the model's overall significance is smaller than 0.01 ($p < 0.01$), suggesting that the model is statistically significant at the 0.01 level. The variance inflation factor (VIF) is less than 5 for most variables, which indicates that the probability of multicollinearity is low.

Based on this global model, four demographic variables were selected: percentage of the population aged 65 and older (P_{age65}), percentage of the white population (P_{white}), percentage of the Hispanic population (P_{Hisp}), and percentage of the population with a disability (P_{disab}). P_{Hisp} has a negative contribution to heat-

Table 1 Summary of the OLS regression results

Number of observations	R^2	Adjusted R^2	RMSE[a]	F statistic	p value
904	0.594	0.589	5.058	118.72	0.000

	Variables	Standardized coefficients	SE	t statistic	p value	VIF[b]
Demographic variables	Percent population ages 65 and older (P_{age65})	0.372	0.038	9.664	0.000	3.15
	Percent white population (P_{white})	0.147	0.030	4.859	0.000	1.85
	Percent Hispanic population (P_{Hisp})	− 0.108	0.062	− 1.740	0.082	5.50
	Percent population with a disability (P_{disab})	0.235	0.045	5.247	0.000	4.33
Socioeconomic variables	Percent population with income below 150% FPL ($P_{b150FPL}$)	0.241	0.058	4.173	0.000	5.31
	Percent population with no vehicle ownership ($P_{novehicle}$)	0.149	0.031	4.837	0.000	1.87
	Percent population with lower than high-school diploma ($P_{LHSGrad}$)	0.429	0.061	7.056	0.000	5.39
Housing variable	Housing occupancy rate (P_{occup})	− 0.058	0.027	− 2.145	0.032	1.57
Environmental variables	Surface reflectance (*ref*)	0.105	0.025	4.238	0.000	1.34
	Normalized Difference Vegetation Index (*NDVI*)	− 0.069	0.034	− 1.998	0.046	2.58
	Land surface temperature (*LST*)	0.060	0.037	1.655	0.098	2.91
	Intercept	0.000	0.021	− 1.827	0.068	–

[a] Root mean square error

[b] Variance inflation factor

related morbidity and is statistically significant at only the 0.1 level, while the other variables are positively correlated with morbidity and are statistically significant at the 0.01 level. In other words, higher heat-related morbidity is found in census tracts in which a higher percentage of the people in the population are aged 65 and older, a higher percentage are non-Hispanic white population, and a higher percentage are disabled, while lower heat-related morbidity is found in census tracts with a larger Hispanic population.

The statistically significant socioeconomic variables include the percentage of the population with an annual income below 150% of the FPL ($P_{b150FPL}$), percentage of the population without a vehicle (P_{noveh}), and percentage of the population with less than high school diploma (P_{LHS}). These three variables are all significant at the 0.01 level and have strong positive contributions to heat-related morbidity. This means that a higher heat-related morbidity is found in census tracts with a higher percentage of the people living in poverty, a higher percentage of people that do not own a vehicle, and a higher percentage of undereducated people.

Only one housing variable was statistically significant: housing occupancy rate (P_{occup}). It was significant at the 0.05 level and had a negative relationship with morbidity, which means that higher heat-related morbidity is found within census tracts with lower housing occupancy rates. This means that smaller household sizes—especially trending toward living alone—are more vulnerable than larger households where families can monitor each other's health.

The model selected three environmental variables: surface reflectance (*ref*), NDVI (*NDVI*), and LST (*LST*). None of the land cover variables (percentage imperviousness and percentage tree cover) was statistically significant. *NDVI* was significant at the 0.05 level and negatively correlated with heat-related morbidity, which means that greater coverage of green, healthy vegetation lowers heat-related morbidity. *LST* ($p < 0.1$) and *ref* ($p < 0.01$) have positive relationships with morbidity, which indicates that higher surface temperature and reflectance contribute to higher heat-related morbidity.

It is important to note that all the selected demographic and socioeconomic variables have larger standardized estimated coefficient values than the housing and environmental variables in the model (Table 1), which means that social vulnerability overall has a stronger contributing effect to heat-related morbidity than housing and environmental factors in Maricopa County.

MGWR Results

The results of the MGWR analysis are shown in Table 2. The MGWR model improves the goodness of fit ($R^2 = 0.691$) by 10% compared with that of the global regression model ($R^2 = 0.594$), which means that the spatially varying relationship between the dependent and independent variables is an essential factor that influences the model performance. The "Mean" column in Table 2 shows that the sign of the mean coefficient estimate of each variable from the MGWR analysis is generally consistent with that in the global model (Table 1), but the actual local effects of different contributing factors vary across regions. For example, some variables have local coefficient values ranging from negative to positive, such as P_{Hisp}, P_{disab}, P_{occup}, and *NDVI*, which means that these variables may have positive contributions to heat-related morbidity in some regions, but the effect may be opposite in other regions of the county.

The magnitude of the spatially varying relationship can be evaluated using the optimal bandwidth. If the optimal bandwidth of a variable (Table 2) is significantly smaller than the total number of observations, that particular process operates at different geographic scales. It also means that the variable has a stronger local effect rather than being a global variable that has even local influence on the entire study area. The "Bandwidth" column in Table 2 shows that the optimal bandwidths of P_{age65}, P_{Hisp}, P_{disab}, P_{noveh}, and P_{occup} are much smaller than the total number of observations ($n = 904$), indicating their spatially varying relationships and strong local effects on heat-related morbidity in Maricopa County.

Figure 3 shows the MGWR local coefficient estimates for the population percentage aged 65 and older. All the census tracts have positive local coefficient values indicating that the senior population is highly vulnerable to heat-related morbidity. This map shows a distinct horizontal pattern, with larger local coefficient values found in the west and lower values in the east, which means that the senior population percentage variable shows strong local effects and the seniors are more vulnerable to heat-related illness in the western, northern, and central areas (in red) of Maricopa County, which host a large number of retirement communities, because these local coefficient values are relatively larger than other areas.

The local coefficient estimates of the Hispanic population percentage are shown in Fig. 4. Most census tracts have negative coefficient values, while some census tracts in the northwest have small positive coefficients. This map suggests that heat-related morbidity has a much weaker relationship with the Hispanic population distribution in the central region (in yellow), but shows a relatively stronger relationship in the western and northwestern areas of the county (in red).

Figure 5 shows the local coefficient estimates of the percentage of the people in the population with a disability. The coefficient values range from negative to positive. The map shows that the disability factor has a relatively weak contribution to heat-related morbidity in the central and northern areas of the county (in yellow and orange), but that the influence is much stronger in the western, southwestern, southern, and eastern parts of the county (in red), which indicates that populations with a disability are more vulnerable to heat-related illness in these areas.

The local coefficient estimate map for the percentage of the population that does not own a vehicle is shown in Fig. 6. All the census tracts have positive coefficient values, which indicate that people who do not own a vehicle are highly vulnerable to heat-related illness. The map reveals that the populations that are more vulnerable to heat-related illness due to a lack of vehicle ownership are in the western, southwestern, and eastern areas (in red), while this relationship is much weaker in the central and northeastern areas of the county (in yellow).

Figure 7 shows the MGWR local coefficient estimates of the housing occupancy rate. Generally, a lower housing occupancy rate has a stronger positive contribution to heat-related morbidity. The regions that are more vulnerable to heat-related illness are in the western, northwestern, and southwestern parts of the county

Table 2 Summary of the MGWR results

R^2	Adjusted R^2	RSS[a]	AICc[b]
0.691	0.662	279.185	1677.771

	Variables	Bandwidth	Adjusted t value (95%)	Adjusted significance (95%)	Mean	Minimum	Maximum	SD
Demographic variables	Percent of population aged 65 and older (P_{age65})	612	2.358	0.019	0.232	0.116	0.422	0.111
	Percent of white population (P_{white})	903	1.171	2.030	0.092	0.089	0.098	0.001
	Percent of Hispanic population (P_{Hisp})	157	11.598	2.862	− 0.292	− 0.526	0.072	0.151
	Percent of population with a disability (P_{disab})	90	27.483	3.128	0.072	− 0.228	0.707	0.148
Socioeconomic variables	Percent of population with income below 150% FPL ($P_{b150FPL}$)	902	1.038	1.979	0.382	0.377	0.396	0.004
	Percent of population with no vehicle ownership (P_{noveh})	290	5.006	2.582	0.165	0.016	0.437	0.071
	Percent of population with lower than high-school diploma (P_{LHS})	902	1.067	1.990	0.612	0.607	0.625	0.005
Housing variable	Housing occupancy rate (P_{occup})	641	3.004	2.399	− 0.049	− 0.089	0.088	0.021
Environmental variables	Surface reflectance (*ref*)	900	1.632	2.165	0.047	0.024	0.082	0.017
	Normalized Difference Vegetation Index (*NDVI*)	903	1.192	2.037	− 0.007	− 0.014	0.006	0.003
	Land surface temperature (*LST*)	903	1.227	2.049	0.014	0.007	0.024	0.004
	Intercept	106	21.372	3.052	0.088	− 0.205	0.739	0.182

[a] Residual sum of squares

[b] Corrected Akaike information criterion

(in red) due to lower housing occupancy rates. Even though a large area in Maricopa County has positive or small negative local coefficient estimates, the number of census tracts and the total population affected are relatively low.

Discussion

Identifying Heat-Vulnerable Populations and Regions

The OLS regression results confirm that the selected demographic, socioeconomic, housing, and environmental factors all have significant contributions to heat-related morbidity in Maricopa County to a certain degree. The MGWR results demonstrate that not all the factors contribute to heat-related morbidity evenly across different regions in Maricopa County. Some processes have geographically varying relationships and stronger local effects. In addition, the local effect of some processes is inconsistent with the overall effect discovered in the global model. This finding demonstrates that the actual effects of different heat vulnerability factors are unevenly distributed across the county.

The confirmed significant demographic variables in the global model (Table 1) suggest that, from a demographic perspective, the people who are most vulnerable

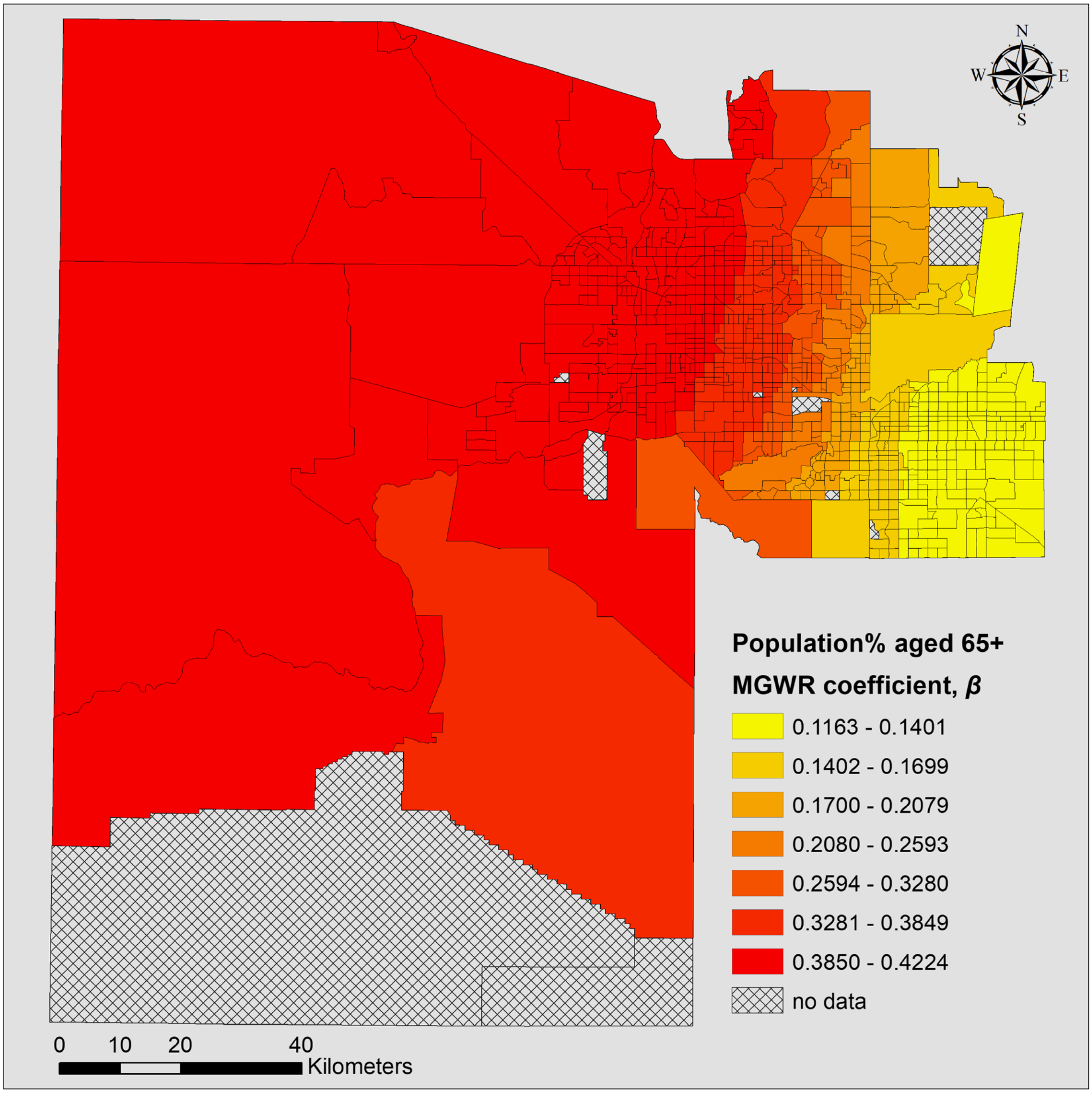

Fig. 3 The MGWR local coefficient estimates for the population percentage aged 65 and older. Some census tracts are not reported because of missing data

to heat-related illness are mainly white, non-Hispanic seniors with a disability. According to the ACS 2016 5-year estimates, a total of 149,542 individuals (3.66% of the total population) in Maricopa County fell into this category [73]. The statistically significant sociodemographic variables include poverty level, vehicle ownership, and educational attainment. Between 2012 and 2016, Maricopa County had 437,337 individuals (10.7% of the total population) who had an annual income below 150% of the FPL, did not own a vehicle, and had less than high school diploma [73]. To better understand who were suffering from heat vulnerability, due to the multiplicity of significant drivers, we took all the demographic and socioeconomic factors into consideration. From this convergent analysis, we identified a population of 4980 individuals (0.12% of the total population) [73] in Maricopa County who were among the most vulnerable to heat-related illness.

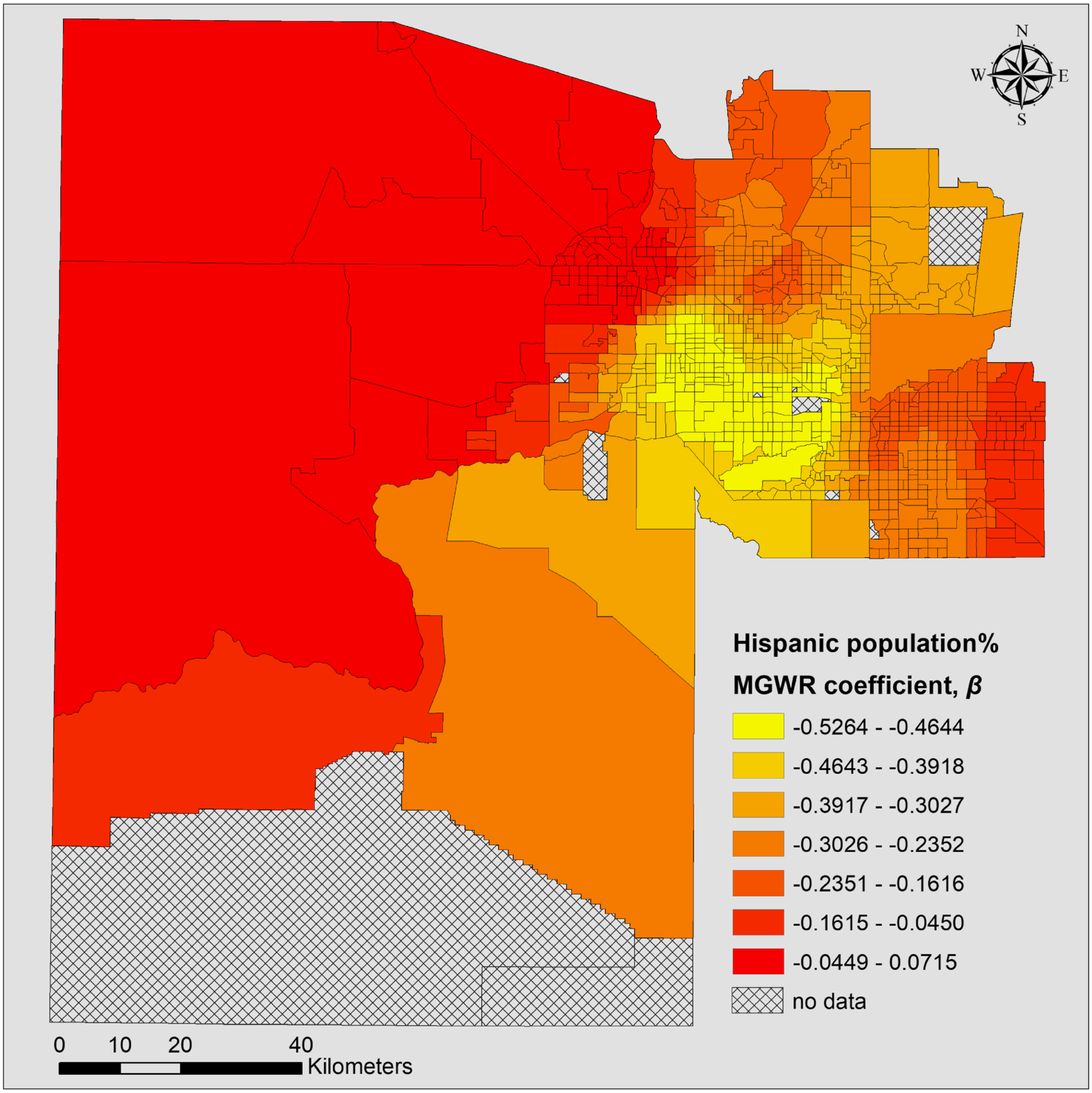

Fig. 4 The MGWR local coefficient estimates for the percentage of the Hispanic population. Some census tracts are not reported because of missing data

If we combine Figs. 3, 4, 5, 6, and 7 to examine the spatial patterns of the local coefficient values of all the independent variables, it is obvious that some regions in Maricopa County experienced greater effects across multiple dimensions of vulnerability to heat-related morbidity relative to others. The western, southwestern, and northwestern parts of the county around Buckeye city appeared more vulnerable due to larger populations of seniors, people with disabilities, and people who did not own vehicles, and low housing occupancy rates. The southeastern part of the county to the east of Gilbert City and Chandler City was more vulnerable to heat-related illness due to a higher percentage of the people in the population having a disability and not owning vehicles. These specific populations and

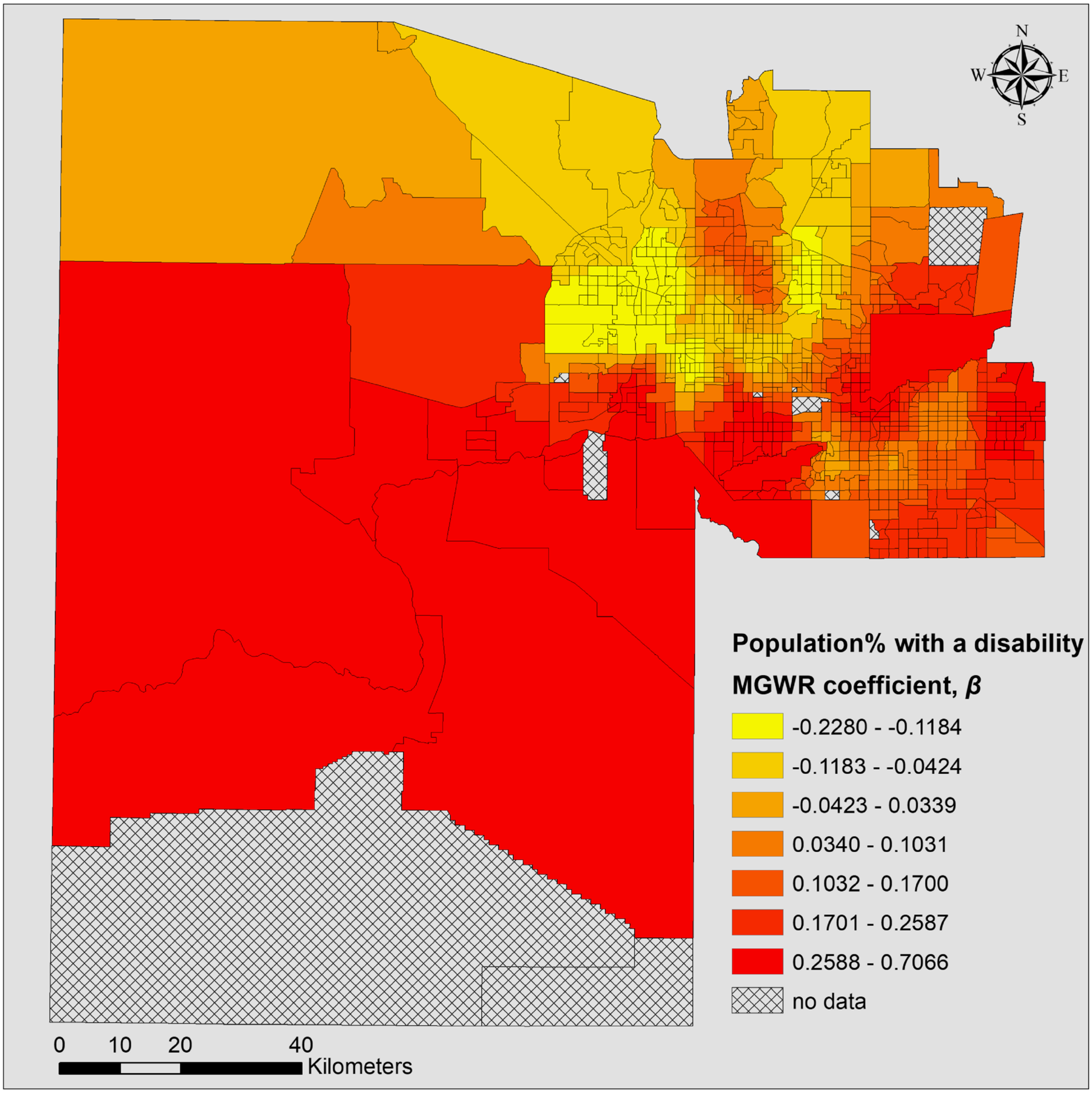

Fig. 5 The MGWR local coefficient estimates for the percentage of the people in the population with a disability. Some census tracts are not reported because of missing data

regions in Maricopa County require immediate attention and actions to prevent heat-related illness.

Demographic, Socioeconomic, and Housing Factors Contributing to Heat Vulnerability

Elderly people of all racial and ethnic groups are 75–100% more likely to suffer from heat morbidity than any other group of people [12, 41, 57, 59]. This fact is likely due to high risks from pre-existing health conditions, such as cardiovascular and cerebrovascular diseases, reduced thermoregulatory efficiency, social isolation, and poverty [1, 6, 26]. Furthermore, this demographic group is more likely to live alone, increasing their vulnerability. A survey from four North American cities of people who are 65 years and older found that even though people's

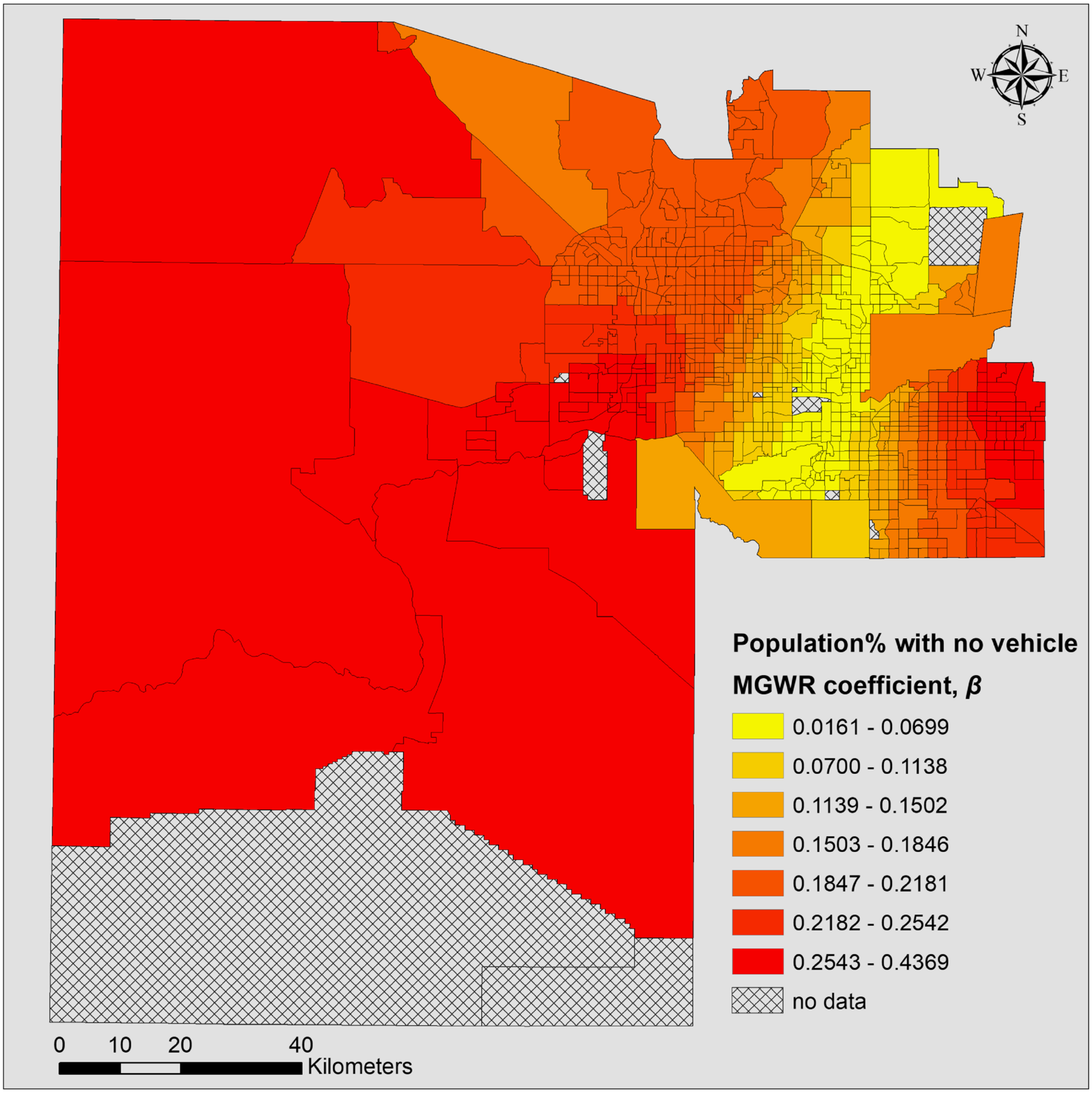

Fig. 6 The MGWR local coefficient estimates for the percentage of the population that does not own a vehicle. Some census tracts are not reported because of missing data

knowledge of extreme heat events was high, knowledge of preventive measures was low, and many at-risk individuals were unaware or unwilling to take appropriate preventive measures [67]. In addition, the media should be encouraged to detail more means of avoiding extreme heat than just avoiding outdoor activities, and the public, especially the elderly population, should be made aware that heat warnings are based on a general deterioration in human health [67].

Socioeconomic status affects individuals' ability to communicate and to protect themselves against extreme heat events. Increased temperatures in urban neighborhoods put the urban poor at a much higher risk than residents in suburban areas. Harlan et al. [28] found that urban neighborhoods in the Phoenix metropolitan area experience more deaths during heat-related events than higher income neighborhoods with cooler microclimates. The lack of higher education also contributes to

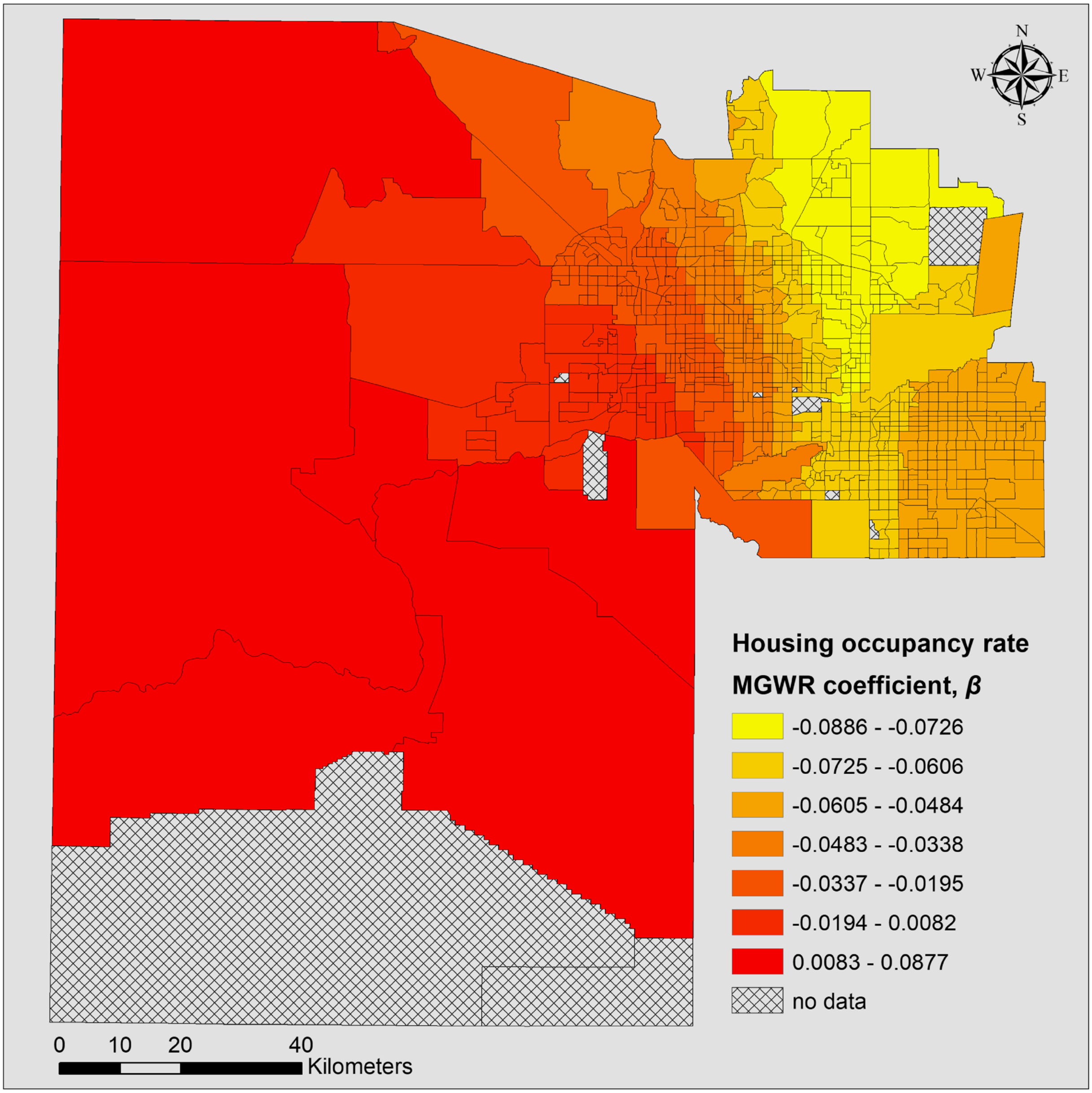

Fig. 7 The MGWR local coefficient estimates for the housing occupancy rate. Some census tracts are not reported because of missing data

heat vulnerability. A study of several US cities found that those with at most a high school education had higher heat-related death rates than individuals with higher levels of education [50]. Our findings correspond well to these studies. In addition, the present study showed that lack of vehicle ownership was another important contributing factor to heat-related morbidity because it hinders people's mobility and ability to access cooler places to protect themselves from heat. This finding corresponds to that of Karner et al. [37], who examined spatial and social disparities in heat exposure for San Francisco and found that zero-vehicle households are disproportionately exposed to transport-related heat.

Consistent with other studies [39, 75], the housing occupancy rate was negatively related to heat-related morbidity, which means that a higher proportion of vacant housing units increases heat-related morbidity. Although it is difficult to directly link housing occupancy to heat vulnerability, a higher unit vacancy rate has been associated with a greater occurrence of homelessness [49]. Yip et al. [83] found that two thirds of heat-related mortality incidents occurred among homeless people during the 2005 extreme heat event in the Phoenix metropolitan area. Extreme heat is therefore an important cause of mortality among homeless people, who account for 10–20% of the total mortality in Maricopa County [10]. Homeless people experience more intense and prolonged heat exposure, which may explain the higher heat mortality observed among the homeless population [7, 57, 58].

Environmental Factors Contributing to Heat Vulnerability

Many studies have suggested that using cool roofs with white paint or more reflective materials is an effective mitigation strategy for the UHI effect (e.g., [14, 434460, 62, 66, 70]). However, some studies have also claimed that even though these practices have made urban surfaces cooler, the heat reflecting off the surfaces would place a heat burden on the human body and increase the heat load, making people nearby feel even hotter [80, 82]. Our study found that higher surface reflectance contributed to higher heat-related morbidity, which indicated that using cool pavements would reduce human thermal comfort and increase heat vulnerability, especially in hot desert cities.

Urban vegetation and green infrastructure can lower heat risks and reduce heat-related health impacts [34, 38, 69]. Our study echoes this theory and suggests that NDVI had a strong negative relationship with heat-related morbidity. Urban vegetation provides evaporative cooling, which lowers ambient temperatures [4, 20, 48]. Vegetation is more efficient than other materials at cooling hotter neighborhoods [34, 48]. Trees can also provide shade, creating greater thermal comfort. However, no significant relationship was found between the tree canopy percentage and heat-related morbidity in the present study. This is because tree coverage in Maricopa County is significantly lower than that in other populated regions in the USA. Trees are naturally scarce in desert cities, and in Maricopa County, most are tall palm trees that do not cast much shadow on the ground. The highest tree cover percentage pixel value for Maricopa County was less than 60%, and the mean coverage was only 6.8% at the census tract level.

LST is directly associated with longwave radiation emitted from surfaces. It is therefore not surprising to find a strong positive effect of LST on heat-related morbidity in the present study. Higher surface temperatures are normally found in areas with a higher coverage of impervious surfaces and anthropogenic materials [48, 76, 78, 85]. People who have prolonged exposure to high surface temperatures absorb the thermal radiation from those surfaces; this increases the heat load on the human body, further increasing heat vulnerability and risks [33–35].

Recommendations

Actions should be taken with the special intention of protecting people and regions that are more heat vulnerable in Maricopa County in ways that align with the spatial pattern of heat vulnerability across the diverse regional landscape [68]. Having a clear understanding of the heat-vulnerable population and local effects of vulnerability factors can help inform more specific outreach and interventions that target the drivers in particular regions that may have the greatest impact.

In the present study, it was discovered that the population most vulnerable to heat-related illness is white non-Hispanic elderly individuals with disabilities. The greater Phoenix metro area hosts a large number of retirement communities. Other vulnerable groups include undereducated, low-income individuals, and people who do not own vehicles and have restricted mobility. These vulnerable groups need immediate public attention and protection from heat threats through the help of local communities and agencies. Using census data and mapping tools, one can easily identify regions that have high concentrations of the various vulnerable populations and devise interventions, actions, or policies tailored to the specific needs of the groups in question in the spaces they inhabit.

Special attention also needs to be paid to homelessness because homeless people experience extensive and prolonged exposure to heat that makes them more vulnerable than other people. In addition, homeless people often have pre-existing health conditions and experience other health threats that make them more likely to suffer from extreme heat [75]. Government agencies, nonprofit organizations, private companies, local communities, and universities should work together to provide better living conditions and cooling facilities to help homeless people overcome the physical difficulties of the summer. More hydration stations and cooling centers should be established in local communities and public places so that homeless people have easier access to cooled places. According to the preliminary results from our ongoing survey, most residents were not aware of nearby hydration stations or cooling centers. Most of these places are closed long before sunset, but the temperature in Maricopa County can exceed 100 °F throughout the night in the summer. Moreover, more publicity, outreach, and educational programs need to be organized to increase social awareness of heat prevention among vulnerable groups. These messages should be focused on the vulnerabilities of the groups in the ways that directly address their lived realities and the spaces they inhabit.

Urban planners and managers are encouraged to adopt heat mitigation strategies to create cooler urban environments. Such practices include increasing the areas of urban green spaces, water bodies, green roofs, and urban agriculture and planting trees with larger canopies. The use of cool pavements made from highly reflective materials should be limited in hot desert cities according to our results because surface reflectivity contributes to a higher morbidity rate. These implementations may be difficult in existing, well-established urban areas, but can be more effectively adopted in newly developed areas. By implementing these strategies as planned in the right locations for the right residents, the city will give heat-vulnerable populations more and better resources to combat extreme summer heat in the ways that it affects them most.

Limitations

There are three types of limitations in the present study. First, the census data and remotely sensed data used in the present study were aggregated at the census tract level, neglecting variations within the census tract. Therefore, our results may not reflect the real situations of individuals who are especially vulnerable to heat-related illnesses. Second, there is likely an underreporting in the dependent variable because there were people who suffered from heat-related illnesses but did not seek medical attention. The incident was therefore not reported, and we only had a sampling of the more severe cases of heat-related illnesses. Third, the present study was based on empirical modeling theory, which assumes that all the contributing factors have a potential influence on heat-related morbidity across all the census tracts. Although an MGWR technique was used to examine the spatially varying relationships between the dependent and independent variables in the different census tracts, some census tracts may be more strongly influenced by other variables rather than those included in the model. Moreover, interactions between variables were not considered in the present study. Future studies can use more detailed data collected from individuals to examine how these factors influence individuals specifically.

Conclusions

The present study has made a significant contribution to the body of knowledge by identifying demographic, socioeconomic, housing, and environmental factors that contribute to heat-related morbidity and analyzing their spatially varying relationships across the diverse urban–rural landscape in Maricopa County. In previous studies, it was assumed that the contributing factors of heat vulnerability were global variables that were equally important at a given spatial scale. With the help of local regression analysis using MGWR, we found spatially varying relationships among the contributing factors. Spatial heterogeneity is therefore another important factor that influences heat vulnerability at the local scale. We further discovered the most heat-vulnerable population groups and hot spots that experience multiple dimensions of vulnerability to heat-related illness, which mainly include the western, southwestern, and southeastern parts of Maricopa County.

These results and findings can be used to inform and educate local residents, communities, stakeholders, city managers, and urban planners in their ongoing and extensive efforts to mitigate the negative impacts of extreme heat on human health in Maricopa County. We suggest that decision-makers develop new spatially targeted strategies and public policies to improve heat resilience and the quality of life of heat-vulnerable residents. These strategies and policies should be focused on spatially varying drivers of heat vulnerability and the regions where they have the greatest effect.

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