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Area-level estimates of temperature might lead to exposure misclassification in studies examining associations between heat waves and health outcomes. Our study compared the association between heat waves and preterm birth (PTB) or nonaccidental death (NAD) using exposure metrics at varying levels of spatial resolution: ZIP codes, 12.5 km, and 1 km. Using geocoded residential addresses on birth (1990–2010) and death (1997–2010) records from Alabama, we implemented a time-stratified case–crossover design to examine the association between heat waves and PTB or NAD. ZIP code and 12.5-km heat wave indexes (HIs) were derived using air temperatures from Phase 2 of the North American Land Data Assimilation System (NLDAS–2). We downscaled NLDAS–2 data, using land surface temperatures from the Moderate Resolution Imaging Spectroradiometer product, to estimate fine spatial resolution HIs (1 km). The association between heat waves and PTB or NAD was significant and positive using ZIP code, 12.5-km, and 1-km exposure metrics. Moreover, results show that these three exposure metric analyses produced similar effect estimates. Urban heat islands were evident with the 1-km metric. When analyses were stratified by rurality, we found that associations in urban areas were more positive than those in rural areas. Comparing results of models with a varying spatial resolution of the exposure metric allows for examination of potential bias associated with exposure misclassification. *Key Words: case–crossover design, heat waves, nonaccidental death, preterm birth, temperature.*

地区层级的温度评估，可能导致检验热浪和健康后果的关联性研究产生暴露的错误分类。我们的研究运用在各空间分辨率层级的暴露指标，比较热浪与早产（PTB）或非意外死亡（NAD）之间的关联性：邮政区号、12.5公里，以及1公里。我们运用阿拉巴马州出生（1990至2010年）与死亡（1997至2010年）的地理编码之居住地址，执行时间分层的交叉研究设计，以检视热浪和PTB或NAD之间的关联性。本研究运用北美土地数据模拟系统（NLDAS-2）第二阶段的空气温度，推导邮政编码与12.5公里的热浪指标(HIs)。我们运用中分辨率成像光谱仪产出的地表温度，缩减NLDAS-2数据，以评估精细的空间分辨率His (1公里)。运用邮政编码、12.5公里以及1公里暴露指标时，热浪与PTB或NAD之间的关联性相当显着。此外，研究结果显示，这三大暴露指标分析生产了相似的效应评估。1公里指标中的城市热岛相当明显。我们发现，当分析以乡村性进行分层时，城市地区的关联性较乡村地区更为明显。比较不同空间分辨率的暴露指标之模型结果，得以考量检视与暴露的错误分类相关的潜在偏见。 *关键词: 交叉案例设计, 热浪, 非意外死亡, 早产, 温度。*

Los cálculos del nivel-área de la temperatura podrían conducir a una mala clasificación en estudios dedicados a examinar las asociaciones entre las olas de calor y las consecuencias para la salud. Nuestro estudio comparó la asociación entre olas de calor y alumbramientos prematuros (PTB) o muerte no accidental (NAD) usando métricas de exposición a varios niveles de resolución espacial: códigos ZIP, 12.5 km, y 1 km. Usando registros de direcciones residenciales geocodificadas al nacimiento (1990–2010) y muerte (1997–2010) de Alabama, implementamos un diseño de caso cruzado estratificado en el tiempo para examinar la asociación entre olas de calor y PTB o NAD. El código ZIP y los índices de olas de calor de 12.5 km (HIs) se derivaron usando las temperaturas del aire de la Fase 2 del Sistema de Asimilación Norteamericano de Datos de la Tierra (NLDAS–2). Bajamos la escala de los datos NLDAS–2 usando temperaturas de la superficie terrestre del producto de Imagen Espectro-radiométrica a Resolución Moderada, para calcular los HIs de resolución espacial fina (1 km). La asociación entre olas de calor y PTB o NAD fue significativa y positiva usando el

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código ZIP, 12.5 km y métricas de exposición de 1 km. Aún más, los resultados muestran que estos análisis métricos de tres exposiciones produjeron estimativos de efectos similares. Las islas de calor urbanas fueron evidentes con la métrica de 1 km. Cuando los análisis fuero estratificados por la ruralidad, hallamos que las asociaciones en áreas urbanas eran más positivas que en áreas rurales. La comparación de los resultados de los modelos con la métrica de la exposición a variable resolución espacial permite el análisis de sesgo potencial asociado con clasificación equivocada de la exposición. *Palabras clave: alumbramiento prematuro, diseño de caso cruzado, muerte no accidental, olas de calor, temperatura.*

Climate change is resulting in an increased frequency, severity, and duration of heat waves (Meehl and Tebaldi 2004; Cowan et al. 2014; Pachauri et al. 2014; Jones et al. 2015; U.S. Global Change Research Program 2017). Although there is no universally accepted definition of a heat wave, extremely hot weather events, such as the 1995 Chicago and 2003 Paris heat waves, have caused serious health consequences, including dehydration, respiratory conditions, and heat stroke (Fouillet et al. 2006; Hajat, O'Connor, and Kosatsky 2010; Kent et al. 2014; Klinenberg 2015). According to the natural hazard statistics published by the National Oceanic and Atmospheric Administration (NOAA), the ten-year average (2006–2015) for heat-related fatalities was higher than the numbers for other weather fatalities, and heat was the leading weather-related contributor to death in the United States in 2010, 2012, and 2013 (NOAA 2016). Subpopulations, such as infants, children, outdoor workers, pregnant women, and the elderly, are considered to be the most at risk for these heat-related effects (Basu 2009).

Preterm birth (PTB), defined as the birth of an infant before thirty-seven completed weeks of gestation, is the leading cause of newborn deaths worldwide and the second largest direct cause of death, only after pneumonia, among children under five years old. In 2014, Mississippi (12.9 percent), Louisiana (12.3 percent), and Alabama (11.7 percent) had the highest PTB rates in the United States and the national PTB rate was 9.6 percent (Centers for Disease Control and Prevention 2016). Previous studies, including Keller and Nugent (1983), Basu, Malig, and Ostro (2010), and Kent et al. (2014), reported that PTB was significantly associated with high temperatures, but Porter, Thomas, and Whitman (1999) did not find a significant correlation between high temperatures and gestation length.

Previous studies have also demonstrated a significant association between mortality and high temperatures. For instance, Zanobetti and Schwartz (2008) found that a 5.5 °C increase in apparent temperature was associated with an increase in mortality of 1.8 percent (95 percent confidence interval [CI], 1.09 percent to 2.50 percent) in nine cities across the United States during the warm months (May–September). Lee et al. (2016) further found a 2.05 percent (95 percent CI, 0.87 percent to 3.24 percent) increase in mortality for each 1 °C increase in the temperature above 28 °C in Georgia, North Carolina, and South Carolina. Lippmann et al. (2013) focused on the association between apparent temperature and emergency department visits with heat-related illness in North Carolina and found that the estimated incidence rate ratio was 1.43 (95 percent CI, 1.41, 1.45) for each 1 °C increase in temperature above 15.6 °C. Other investigations reported that the elderly were at the highest risk of mortality following heat waves (Ballester et al. 1997; Knowlton et al. 2009).

Previously, we used a time-stratified case–crossover design to estimate associations between adverse health outcomes (i.e., PTB and nonaccidental death [NAD]) using different heat wave definitions (Kent et al. 2014). The results demonstrated that associations varied widely depending on the chosen heat wave definitions and showed significantly positive associations between heat wave days and PTB or NAD using relative heat wave indexes (HIs; Kent et al. 2014). This previous work was based on defining exposure to a heat wave by estimating HIs on a given day from the temperature data from Phase 2 of the North American Land Data Assimilation System (NLDAS; Kent et al. 2014). NLDAS provides estimated air temperature in $0.125° \times 0.125°$ (approximate 12.5 km) grid cells, derived from the National Centers from Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) data with 32-km spatial resolution. This and other previous studies examined the association between adverse health outcomes and high temperature based on a ZIP code–level exposure estimate (Basu, Malig, and Ostro 2010; Kent et al. 2014; Lee et al. 2016). Because ZIP code areas vary in geometric shape and size, cases might sometimes be inaccurately classified as controls (or vice versa) when using this methodology. In addition, previous research suggests that exposure measurement error could contribute to bias when using widely spaced monitoring stations and would underestimate the health effects of soot and NO_2 (Thomas, Stram, and Dwyer 1993; Spiegelman 2010). For example. Sarnat et al. (2013) found greater estimated effects of air pollutants (i.e., CO and NO_x) on respiratory outcomes when they used spatiotemporally refined ambient concentrations (compared with central site monitoring data). To bridge this research gap, this study uses the reported residential addresses and gridded NLDAS air temperature data to estimate the air temperature at the residence and whether it was in a heat wave on the days leading up to birth or death.

Many PTB or NAD cases are clustered in densely populated areas; however, both ZIP code–level and NLDAS grid-level data cannot reflect the urban heat island effects adequately. Therefore, whether finer spatial resolution data that can capture the urban heat island effects would result in more accurate associations between heat waves and adverse health outcomes is unknown. To address this issue, we downscaled NLDAS 12.5-km grid data to 1-km grid level by using Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) data. This more spatially resolved exposure metric was then used to evaluate the association between heat waves and PTB or NAD stratified by rurality and compared to the associations using lower resolution exposure metrics.

In summary, the objectives of this study are to determine whether (1) a more spatially resolved exposure metric results in a different association between heat waves and adverse health outcomes (i.e., PTB and NAD) when compared to lower resolution exposure metrics and (2) rural–urban differences in the association between heat waves and PTB or NAD are more evident using a more spatially resolved exposure metric.

Materials and Methods

Vital Records and Outcomes

A total of 797,302 Alabama vital records (i.e., 534,792 for live births in 1990–2010 and 262,510 for deaths in 1997–2010) for the warm months (May–September) were obtained from the Alabama Department of Public Health (ADPH; Montgomery, Alabama). The research protocol was reviewed and approved by the Institutional Review Board of Virginia Polytechnic Institute and State University (Protocol #15-1145). Birth records included the date of birth, gestational age, birth weight, and the maternal street address, and death records indicated the date of death, the deceased's street address, and the cause of death coded by the *International Classification of Diseases* ninth (ICD-9) or tenth (ICD-10) revision (World Health Organization 1992, 2009). PTB cases were defined as gestational age between twenty-four and thirty-six weeks, and NAD was defined as deaths with ICD-9 codes <800, ICD-10 codes with letters A through R, or heat illness–related codes (i.e., E900.0, E900.9, and 992.0–992.9 for ICD-9 and X30 and T67.0–T67.9 for ICD-10). Latitude and longitude coordinates of residences were determined through geocoding based on street address and city data using ArcGIS 10.3 (ESRI, 2014). After geocoding and excluding records with missing information, 50,535 PTB records (82.69 percent of the original PTB records) and 199,021 NAD records (88.36 percent of the original NAD records) were available for subsequent analyses.

NLDAS Data

We used air temperature in the meteorological data from Phase 2 of NLDAS. The NLDAS data have a spatial resolution of 1/8° (approximate 12.5 km) and temporal resolution on an hourly basis. A five-hour time offset from Universal Time Coordinated (UTC) in original NLDAS data to Central Daylight Time (CDT = UTC − 5) was applied. We calculated the daily minimum, mean, and maximum temperature using the twenty-four-hour data. We analyzed the NLDAS data over the warm season (1 May–30 September) from 1990 to 2010.

Downscaled NLDAS Data

Because the spatial resolution of NLDAS is around 12.5 km, it might not be able to capture small-scale features (e.g., the urban heat island effect and near-coastal temperature gradients). Therefore, we downscaled NLDAS 12.5-km air temperature data by using MODIS 1-km LST data in this study. We obtained LST data across Alabama between the years 2000 and 2010 from the NASA MODIS instrument on the Terra satellite, with a spatial resolution of 1 km. We used the eight-day composite data set (MOD11A2), which are the average values of eight-day daily LST data (MOD11A1) in clear-sky conditions. The MOD11A2 product contains daytime and nighttime LST data, and we used the average of those two sets of data as the daily data.

Theoretically, air temperature and LST have similar spatial patterns because the ground often affects air temperature by heat flux, particularly when there is no strong horizontal temperature advection (Roth, Oke, and Emery 1989; Crosson et al. 2014). Moreover, land use is a primary driver of spatial patterns of air temperature at sub-NLDAS spatial level and is constant from day to day within seasons (Crosson et al. 2014). Following the approach of Crosson et al. (2014), we use MODIS 1-km LST to downscale 12.5-km NLDAS air temperatures in Alabama between 1990 and 2010. We first created summer (May–September) composite (mean of all available observations) on MODIS MOD11A2 LST data from 2001 to 2010. Then, from the composite LST grid, we calculated normalized MODIS LST departures [$Z_{MOD} = (T_{MOD} - MEAN_{MOD})/\sigma_1$], in which MODIS LST data (T_{MOD}), the spatial means ($MEAN_{MOD}$), and standard deviation (σ_1) were calculated within a local neighborhood (local neighborhood = 5 × 5 NLDAS grid cells). Then, we calculated daily mean air temperature (T_{NLDAS}) from NLDAS hourly data and calculated the downscaled NLDAS daily mean temperature ($= T_{NLDAS} + Z_{MOD} \times \sigma_2$) by using the normalized MODIS LST departures (Z_{MOD}) and standard deviation of NLDAS daily mean air temperature over the same local neighborhood (σ_2).

Heat Wave Indexes

We selected two daily mean temperature-based HIs: (1) the daily mean temperature >95th percentile for two or more consecutive days (Mean95th) and (2) the daily mean temperature >99th percentile for two or more consecutive days (Mean99th) because they were previously shown to be most associated with NAD and PTB in Alabama (Kent et al. 2014). For comparison, we also examined absolute HIs – Mean31.75, which is the daily mean temperature >31.75 °C (89.15 °F) for two or more consecutive days, to compare with Mean99th for PTB-related results and Mean30.22, which is the daily mean temperature >30.22 °C (86.40 °F) for two or more consecutive days, to compare with Mean95th for NAD-related results. We chose these two absolute thresholds (i.e., 31.75 °C and 30.22 °C) to

Table 1. Summary data on four HIs on ZIP code, NLDAS grid, and downscaled grid level in Alabama during 1990 to 2010

HI abbreviation	Level	HI days/year/spatial unit[a]		PTB[b]		NAD	
		n	%	*n*	%	*n*	%
Mean95th	ZIP code	6.60	4.32	2,475	4.90	11,386	5.72
	NLDAS grid	6.59	4.31	2,462	4.87	11,363	5.71
	Downscaled grid	6.59	4.31	2,460	4.87	11,612	5.83
Mean99th	ZIP code	1.26	0.83	564	1.12	2,336	1.17
	NLDAS grid	1.27	0.83	563	1.11	2,337	1.17
	Downscaled grid	1.27	0.83	559	1.11	2,375	1.19
Mean30.22	ZIP code	3.78	2.47	1,460	2.89	6,490	3.26
	NLDAS grid	3.79	2.48	1,462	2.89	6,585	3.31
	Downscaled grid	3.99	2.61	2,744	5.43	11,621	5.84
Mean31.75	ZIP code	0.62	0.40	300	0.59	1,268	0.64
	NLDAS grid	0.59	0.39	299	0.59	1,282	0.64
	Downscaled grid	0.63	0.41	565	1.12	2,391	1.20

Note: HI = heat index; NLDAS = North American Land Data Assimilation System; PTB = preterm birth; NAD = nonaccidental death.
[a] *n* is the HI days per year per spatial unit (i.e., ZIP code, NLDAS grid, or downscaled grid) and % is the percentage of HI days/year/spatial unit among the days ($N = 153$) from 1 May to 30 September.
[b] *n* is the number of PTB cases on the heat wave days and % is its percentage among all PTB cases.

match sample size (have similar numbers of PTB and NAD cases) when using the Mean99th and Mean95th HIs at the downscaled level, respectively (Table 1). Percentile-based HIs (Mean95th and Mean99th) were determined by ranking all daily temperatures between 1990 and 2010 in the warm season (1 May–30 September).

To develop daily ZIP code–level HI estimates, this study determined a ZIP code to be in a heat wave if more than fifty percent of its land area was covered by the heat wave on a given day, as was done previously (Kent et al. 2014). We assigned HIs at the level of the ZIP code, NLDAS grid, and downscaled NLDAS grid to each PTB and NAD record based on residential address.

Rurality Measures

We examined associations between heat wave days and adverse health outcomes in urban and rural areas. There are different definitions and measures to classify rural and urban areas in the United States (Hall, Kaufman, and Ricketts 2006). Following Kent et al. (2013), we use two ZIP code–level measures of rurality to classify rural, suburban, and urban areas in Alabama (Figure 1). The first measure is the Rural–Urban Commuting Area Codes (RUCA) version 3.10, using the suggested "categorization B," which divides ZIP codes into "urban," "large rural city/town," and "small rural and isolated town" categories (U.S. Department of Agriculture 2014). The second measure is classifying Census 2010 population densities into tertiles (U.S. Census Bureau 2012).

Study Design and Statistical Analysis

We adopted a time-stratified case–crossover design (Basu, Dominici, and Samet 2005; Janes, Sheppard, and Lumley 2005a; Crouse et al. 2012), where each person serves as his or her own control; therefore, known and unknown time-invariant confounders, such as body mass index, seasonality, and overlap bias, are inherently adjusted by study design (Maclure 1991). This design is frequently used in environmental health studies examining short-term exposures and acute outcomes (Basu, Dominici, and Samet 2005; Janes, Sheppard, and Lumley 2005a, 2005b; Crouse et al. 2012; Tong, Wang, and Guo 2012). The control period includes the same days of the week within the same month as the case day. Analyses were run using IBM SPSS Statistics Version 20.0 (SPSS Inc., 2011) and conditional logistic regression models were implemented to estimate odds ratios (ORs) and 95 percent CIs for

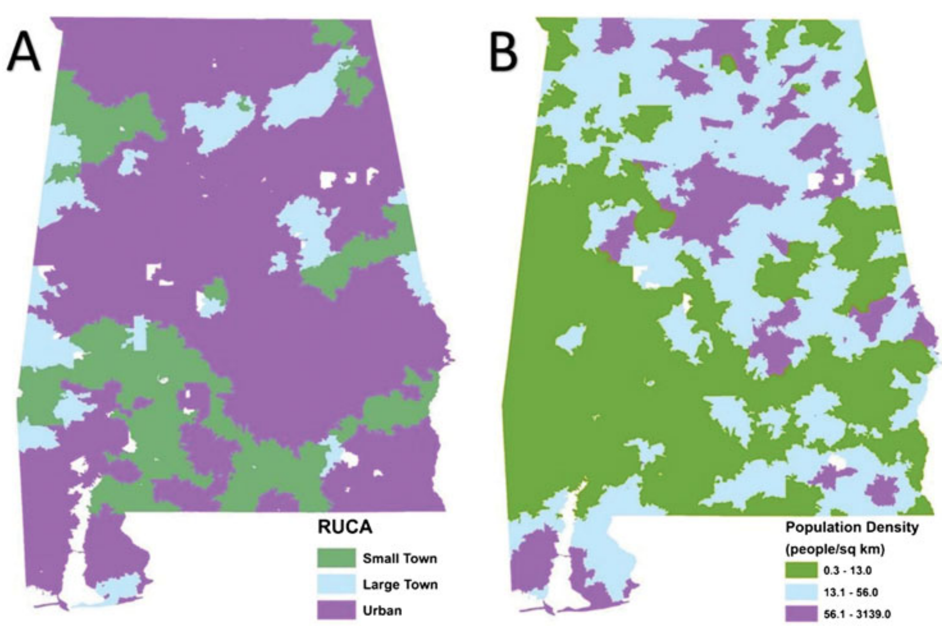

Figure 1. Spatial distributions of rural–urban commuting area code categories (A) using RUCA version 3.10 and "categorization B" and (B) population density tertiles, using Census 2010 population densities calculated from total populations and land surface areas on ZIP code level in Alabama. RUCA = Rural–Urban Commuting Area Codes. (Color figure available online.)

the associations between adverse health outcomes (either PTB or NAD) and heat wave day indicator at ZIP code, NLDAS grid, and downscaled grid levels. To further examine the importance of location, downscaled grids matched to maternal street addresses (PTB) or deceased street addresses (NAD) were replaced with randomized downscaled grids to build 500 simulated data sets. Additional simulated data sets ($N = 10$) were generated by randomly selecting a day between 1 May and 30 September for each PTB or NAD case in the same year as the real case. Randomization was performed with replacement using the "randi" function in MATLAB R (Mathworks Inc. 2017). To summarize statistical results, associations are reported as the percent age difference in the odds of the health outcome (i.e., PTB and NAD) on heat wave days compared with non-heat-wave days [percent age difference = (OR–1) × 100].

Results

NLDAS Grid Data versus Downscaled Grid Data

Absolute, but not relative, HIs derived from finer spatial resolution data sets identify urban heat islands. As an example, Figure 2 shows heat wave grids in Alabama on 6 August 2000 at the NLDAS 12.5-km grid level and downscaled 1-km grid level using HIs defined as Mean95th (daily mean temperature >95th percentile for two or more consecutive days) and Mean30.22 [daily mean temperature >30.22 °C [86.40 °F] for two or more consecutive days). Mean30.22 at downscaled 1-km grids presents the urban heat island effect in Birmingham, Montgomery, and Mobile (Figure 2D), whereas Mean95th and NLDAS 12.5-km grids (Figure 2A–2C) cannot. The urban heat island effect is not visible for Mean95th even at downscaled 1-km grids (Figure 2B) because relative HIs tend to present synoptic conditions using the percentile threshold (Figure 2A, 2B), whereas the absolute HIs (e.g., Mean30.22; Figure 2D) pick out locations, like cities, that have absolute temperatures higher than the surrounding area.

Table 1 shows the number of HI days per year per spatial unit for the ZIP code, NLDAS grid, and downscaled grid analyses. For relative HIs, these three exposure metrics had close numbers on HI days per year per spatial unit, as well as close numbers of PTB and NAD cases on heat wave days. For instance, when defining heat waves as Mean99th (daily mean temperature >99th percentile for two or more consecutive days), the average number of heat wave days per year was 1.26, 1.27, and 1.27 for ZIP code, NLDAS grid, and downscaled grid, resulting in a total of 564, 563, and 559 PTB and 2,336, 2,337, and 2,375 NAD records on heat wave days, respectively. For absolute HIs, the downscaled grid level had a higher number of PTB and NAD cases on heat wave days, compared with the ZIP code and NLDAS grid levels because higher temperatures are found in densely populated urban areas. For instance, when defining heat waves using Mean 31.75 (daily mean temperature >31.75 °C [89.15 °F] for two or more consecutive days), the number of PTB cases on heat wave days was 300, 299, or 565 on the ZIP code, NLDAS grid, and downscaled grid levels, respectively.

PTB cases were positively associated with heat waves when heat wave days were defined by eight of the eleven HIs. Figure 3A presents the associations using Mean99th and Mean31.75 indexes and shows an increase of 18.8 percent (95 percent CI, 6.5 percent, 32.5 percent) using the ZIP code–level, 19.4 percent (95 percent CI, 7.0 percent, 33.2 percent) using the NLDAS grid-level, and 17.4 percent (95 percent CI, 5.2 percent, 31.0 percent) using the downscaled grid-level exposure metric for the relative Mean99th index. For the absolute (Mean31.75) index, a 25.9 percent (95 percent CI, 8.3 percent, 46.5 percent), 22.4 percent (95 percent CI, 5.2 percent, 42.3 percent), or 17.6 percent (95 percent CI, 5.3 percent, 31.2 percent) increase in the odds of PTB is predicted based on ZIP code–level, NLDAS grid level, and downscaled grid-level metrics, respectively. Similar associations are seen between PTB and heat wave days across ZIP code, NLDAS grid, and downscaled grid levels when defining heat waves using Mean99th and Mean31.75 HIs (Figure 3A), as well as an additional nine HIs with different definitions.

NAD cases were positively associated with heat waves when the heat wave days were defined by ten HIs. Similar to PTB-related associations, no differences in associations are seen across the three levels of spatial resolution (Figure 3B). For example, Figure 3B shows that significant positive associations were found when heat waves were defined by Mean95th, with 3.7 percent (95 percent CI, 1.2 percent, 6.3 percent) higher odds using ZIP code, 3.2 percent (95 percent CI, 0.7

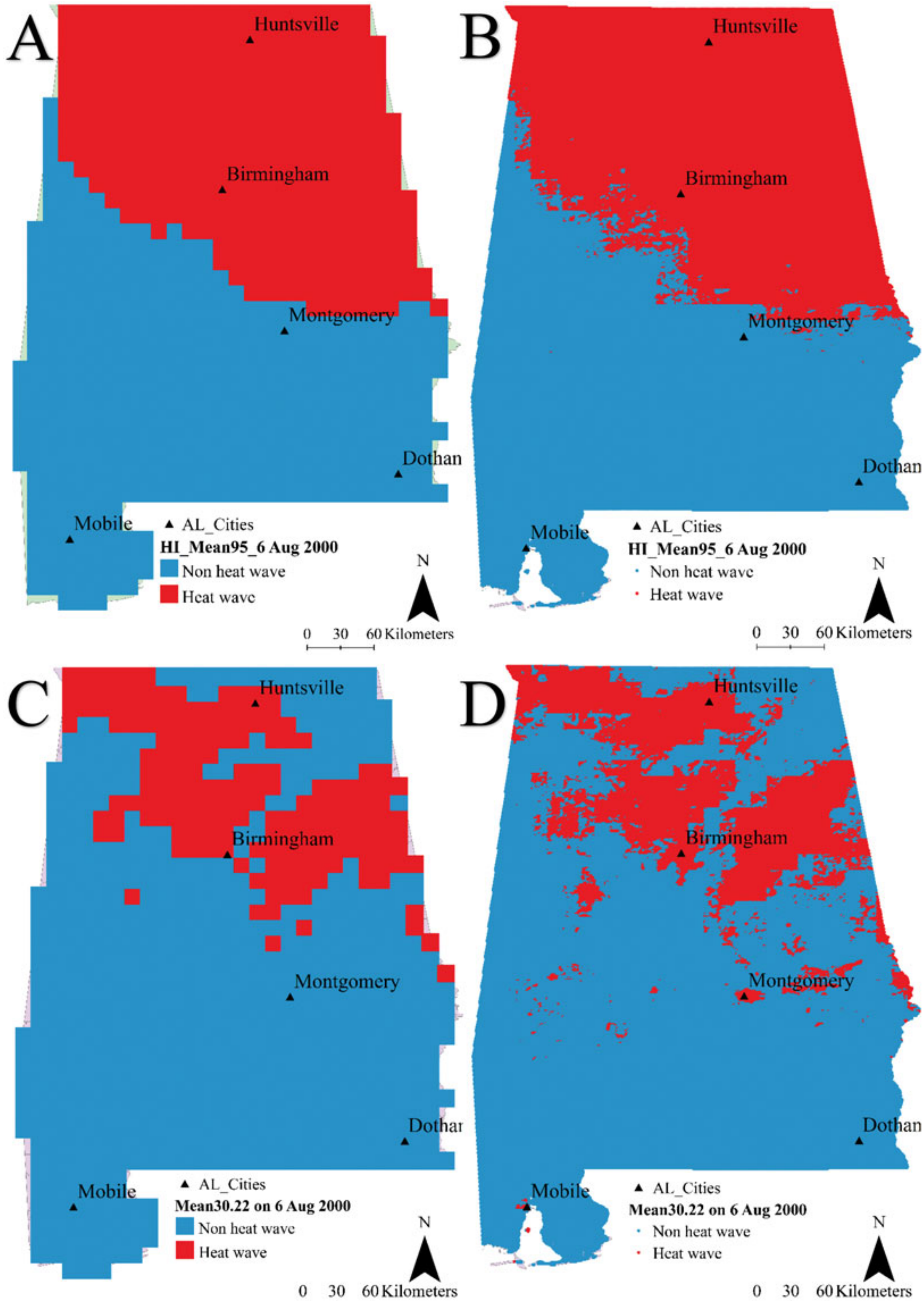

Figure 2. Heat wave grids in Alabama on 6 August 2000 at the North American Land Data Assimilation System 12.5-km grid level (A and C) and downscaled 1-km grid level (B and D) in heat indexess defined as Mean95th (A and B) and Mean30.22 (C and D). HI = heat index. (Color figure available online.)

percent, 5.8 percent) using NLDAS grid, and 3.2 percent (95 percent CI, 0.7 percent, 5.7 percent) using downscaled grid exposure metrics. For heat waves defined using a comparable absolute metric (Mean30.22), odds of NAD were 3.5 percent (95 percent CI, 0.2 percent, 6.9 percent) higher using ZIP code, 3.7 percent (95 percent CI, 0.4 percent, 7.1 percent) using NLDAS grid, and 1.3 percent (95 percent

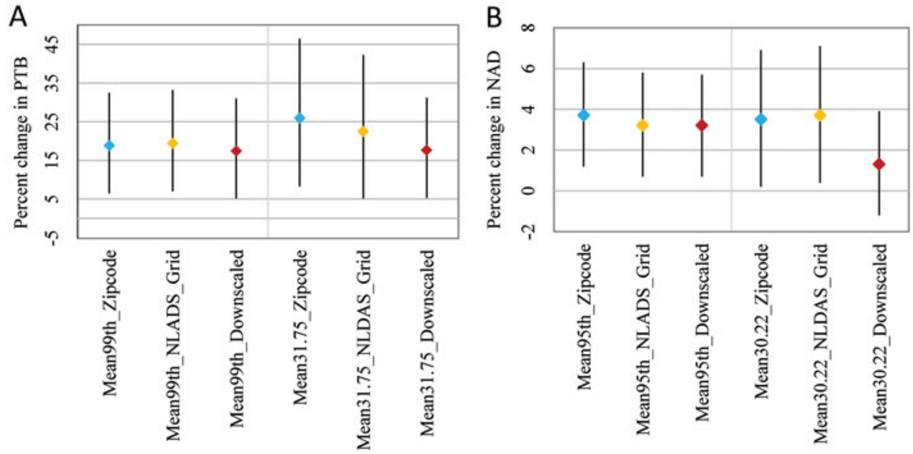

Figure 3. Percentage difference [= (OR – 1)*100], 95% confidence interval, in (A) PTB or (B) NAD on a heat wave day, compared with corresponding non-heat-wave days at ZIP code level (blue), North American Land Data Assimilation System grid level (yellow), and downscaled level (red), defined in selected heat indexes. PTB = preterm birth; NAD = nonaccidental death. (Color figure available online.)

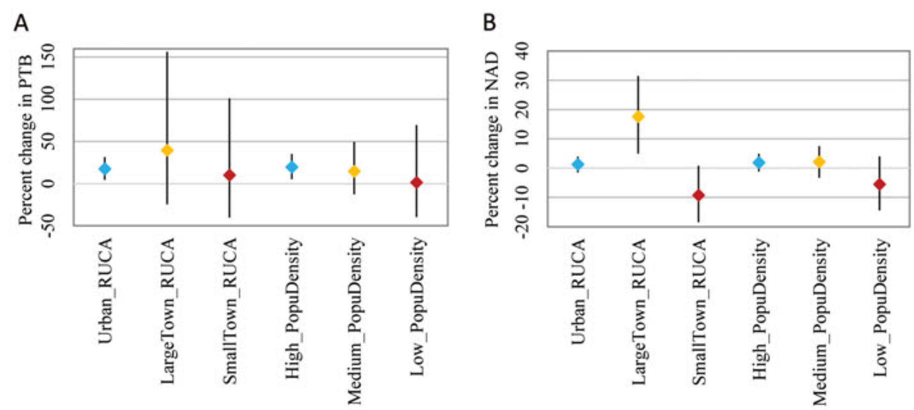

Figure 4. Percentage difference [= (OR – 1)*100], 95% confidence interval in (A) PTB or (B) NAD on a heat wave day stratified by Rural–Urban Commuting Area Codes and population density and using (A) Mean31.75 for PTB and (B) Mean30.22 for NAD. PTB = preterm birth; NAD = nonaccidental death. (Color figure available online.)

CI, –1.2 percent, 3.9 percent) using downscaled grid exposure metrics.

Additionally, we generated 500 simulated PTB and NAD data sets by randomly assigning downscaled grids to PTB and NAD cases on the same day. Additional examination of the associations between PTB or NAD and heat waves using the randomized location data sets show that the NLDAS- and downscaled-level analyses produced similar effect estimates, which is consistent with our results using real location data described earlier. Moreover, when randomizing the date of PTB and NAD, there is no association between heat waves and PTB or NAD. These results further suggest that temporal variability is more important than spatial variability in estimating the association between heat waves and PTB or NAD at the spatial scale of Alabama.

Because absolute HIs (Mean31.75 for PTB and Mean30.22 for NAD), but not relative HIs, capture the urban heat island using the downscaled metrics (Figure 2), we stratified the absolute metric analyses by rurality, using both RUCA and population density measures. Significant positive effect estimates were determined for urban strata but not rural areas for PTB, and nonsignificant negative associations are seen for NAD in the most rural categories (Figure 4). Across other HIs, similar increased positive associations in urban strata compared to rural strata are seen in additional analysis results.

Discussion and Conclusions

Influence of Spatial Resolution of Exposure Metrics

This study examined the associations between adverse health outcomes (i.e., PTB and NAD) and heat waves by using estimated air temperature at three spatial resolutions: ZIP codes, NLDAS 12.5-km grids, and downscaled 1-km grids. Results produce similar effect estimates across the three spatial resolutions for the associations between PTB or NAD and heat waves. For instance, compared with non-heat-wave days, heat wave days were associated with an 18.8 percent (95 percent CI, 6.5 percent, 32.5 percent), 19.4 percent (95 percent CI, 7.0 percent, 33.2 percent), and 17.4 percent (95 percent CI, 5.2 percent, 31.0 percent) increased odds of PTB, using ZIP code–, NLDAS grid–, and downscaled grid–level exposure metrics, respectively. For absolute HIs, our analyses had higher sample sizes (PTB and NAD cases) using the downscaled exposure metrics (Table 1) because of the concentration of heat wave days in densely populated urban areas (Figure 2). The associations for absolute heat wave metrics become slightly less positive across the three spatial resolutions (25.9 percent [95 percent CI, 8.3 percent, 46.5 percent] for ZIP code level, 22.4 percent [95 percent CI, 5.2 percent, 42.3 percent] for NLDAS grid level, and 17.6 percent [95 percent CI, 5.3 percent, 31.2 percent] for downscaled grid level for increased odds of PTB). For NAD, associations were stable across the three spatial resolutions for the relative heat wave metric and moved slightly toward a null association for the finest spatial resolution (downscaled grid level) when an absolute HI was used (Figure 3). Based on these results, we conclude that increasing spatial resolution of exposure metrics did not substantially change estimated associations between heat waves and adverse health outcomes in Alabama, suggesting that exposure misclassification had minimal or no contribution to bias in previous studies using exposure metrics at lower spatial resolution.

Although we did not find a significant change in the association between heat waves and PTB or NAD in Alabama when comparing the associations using NLDAS grid and downscaled grid data, previous studies have suggested that stronger associations are seen between high temperature and PTB or NAD when more spatially resolved exposure metrics are employed (Kloog et al. 2015; Lee et al. 2016). For instance, Kloog et al. (2015) found that gestational age was negatively associated with predicted air temperature when using a 1-km spatially resolved metric based on remotely sensed data versus a positive association when using temperature from the nearest weather station. Alternatively, logistic regression model results reported in Kloog et al. (2015) for PTB are consistent with this study, showing minimal influence of a more resolved metric (OR for PTB with a 2.7 °C increase at the 1-km^2 resolution level reported as 1.02 [95 percent CI, 1.00, 1.05] compared with 1.07 [95 percent CI, 0.87, 1.27] using nearest weather station data). Lee et al. (2016) found that the percentage increase for mortality per 1 °C increase was 2.05 percent (95 percent CI, 0.52 percent, 2.91 percent) at the 1-km^2 resolution level compared with 1.14% (95 percent CI, 0.08 percent, 1.57 percent) using nearest weather station data. The current analysis suggests a slight decrease in the point estimate in the association between PTB and heat waves (22.4 percent vs. 17.6 percent increase) and NAD (3.7 percent vs. 1.3 percent increase) when comparing the lower spatial resolution model to the finer resolved model. Several differences between this study and the earlier studies might explain the differences in results. For example, the earlier studies examine relationships using temperature and gestational age as continuous variables. In addition, those studies incorporate numerous additional remotely sensed variables beyond temperature, including Normalized Difference Vegetation Index (NDVI), percentage urban area, elevation, distance to water bodies, and traffic density.

Differences in Associations According to Rurality Categories

Finer spatial resolution data capture the urban heat island (Figure 2), and results suggest stronger associations in urban and suburban areas using the downscaled exposure metric. This finding is consistent with previous findings that found stronger positive associations between NAD and heat waves in urban versus rural ZIP codes in Alabama (Kent et al. 2014) and adverse birth outcomes in Massachusetts (Kloog et al. 2015). Recent literature shows that rural–urban differences in heat–health associations depend on the health outcome data and also likely depend on study population and study location. For instance, some studies found that rural counties had higher emergency department visit rates for heat stress than urban counties did across the United States (Hess, Saha, and Luber 2014; Fechter-Leggett, Vaidyanathan, and Choudhary 2016) and in North Carolina (Lippmann et al. 2013; Sugg, Konrad, and Fuhrmann 2016). Basu (2009), however, suggested that mortality risk associated with heat waves was higher in urban areas.

Limitations

This study has its limitations. First, our downscaled method assumes that the ground affects air temperature by heat flux when there is no strong horizontal temperature advection. Thus, air temperature and LST exhibit a mimicking spatial pattern. This situation only often occurs within the warm season (Mann and Schmidt 2003; Crosson et al. 2014). Second, this study only examines associations in Alabama between 1990 and 2010; therefore, results cannot be generalized to different climates, demographics, housing characteristics, or time periods.

Conclusions

Our findings suggest that ZIP code– NLDAS grid– and downscaled grid–level analyses produce similar estimates for the associations between heat waves and adverse health outcomes (i.e., PTB and NAD) in Alabama. Our results suggest more consistent positive associations between heat waves and PTB or NAD in urban versus rural areas. If future studies further corroborate these findings, important implications of this work are (1) for studies designed to quantify the effect of ambient air temperature on health outcomes, fine spatial resolution for the exposure metric might not be required, and (2) heightened temperatures, or other urban specific parameters, might increase risk of adverse health outcomes in urban environments.

Supplemental Materials

Supplemental materials for this article can be accessed on the publisher's Web site.

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