Published in final edited form as:

Ann Am Assoc Geogr. 2019 ; 109(3): 875–886. doi:10.1080/24694452.2018.1511411.

Influence of the spatial resolution of the exposure estimate in determining the association between heat waves and adverse health outcomes

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Abstract

Background—Area-level estimates of temperature may 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 non-accidental death (NAD) using exposure metrics at varying levels of spatial resolution: ZIP codes, 12.5 km, and 1 km.

Method—Using geocoded residential addresses on birth (1990–2010) and death (1997–2010) records from Alabama, USA, 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 indices (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 (LST) from the Moderate Resolution Imaging Spectroradiometer (MODIS) product, to estimate fine spatial resolution HIs (1 km).

Results—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-

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Authors' Contributions

JMG, BFZ, and CYHW initially designed study. CYHW and BFZ prepared air temperature data. CYHW and SS downscaled air temperature data. CYHW and JMG conducted data analysis and prepared draft manuscript. All authors revised and contributed to the final manuscript.

Description of the process:

We downloaded NLDAS and MODIS LST data from NASA (<https://search.earthdata.nasa.gov/search>), then downscaled NLDAS air temperature data using methods described herein and following Crosson et al. (2014). We calculated heat wave indices using NLDAS air temperature data and downscaled air temperature data as described in methods. We obtained birth and death records from the Alabama Department of Public Health via submission of a data use proposal. We implemented a time-stratified case-crossover design to examine the association between heat waves and adverse health outcomes as described in methods.

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 associations in urban areas were more positive than in rural areas.

Conclusions—Comparing results of models with a varying spatial resolution of the exposure metric allows for examination of potential bias associated with exposure misclassification.

Keywords

Heat waves; Preterm birth; Non-accidental death; Temperature; Case-crossover design

1. Introduction

Climate change is resulting in an increased frequency, severity, and duration of heat waves (Meehl and Tebaldi 2004; Pachauri et al. 2014; Cowan et al. 2014; Jones et al. 2015; USGCRP 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 (Klinenberg 2015; Fouillet et al. 2006; Kent et al. 2014; Hajat, O'Connor, and Kosatsky 2010). According to the natural hazard statistics published by the National Oceanic and Atmospheric Administration (NOAA), the 10-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 (US) 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 of these heat-related effects (Basu 2009).

Preterm birth (PTB), defined as the birth of an infant before 37 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%), Louisiana (12.3%) and Alabama (11.7%) had the highest PTB rates in the US and the national PTB rate was 9.6% (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 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% (95% CI, 1.09% to 2.5%) in nine cities across the US during the warm months (May–September). Lee et al. (2016) further found a 2.05% (95% CI, 0.87% to 3.24%) 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% 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 (Knowlton et al. 2009; Ballester et al. 1997).

Previously, we used a time-stratified case-crossover design to estimate associations between adverse health outcomes [i.e., PTB and non-accidental 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 indices (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 $0.125^{\circ} \times 0.125^{\circ}$ (approximate 12.5 km) grid cells, derived from the National Centers for 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). Since ZIP code areas vary in geometric shape and size, cases may sometimes be inaccurately classified as controls (or vice versa) when using this methodology. In addition, previous research suggests exposure measurement error may 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 less known. 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 a) whether 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 b) whether rural-urban differences in the association between heat waves and PTB or NAD are more evident using a more spatially resolved exposure metric.

2. Materials and methods

2.1 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, while death records indicated the date of death, the deceased's street address, and the cause of death coded by the International Classification of Diseases 9th (ICD-9) or 10th (ICD-10) revision (World Health Organization 1992, 2009). PTB cases were defined as gestational age ≥ 24 and ≤ 36 weeks, and NAD were defined as deaths with ICD-9 codes < 800 , or ICD-10 codes with letters A–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 to 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). After geocoding and excluding records with missing information, 50,535 PTB records (82.69% of the original PTB records) and 199,021 NAD records (88.36% of the original NAD records) were available for subsequent analyses.

2.2 NLDAS data

We used air temperature in the meteorological data from Phase 2 of NLDAS. The NLDAS data have a spatial resolution of $1/8$ degree (approximate 12.5 km) and temporal resolution on an hourly basis. A 5 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 24 hourly data. We analyzed the NLDAS data over the warm season (May 1 to September 30) from 1990 to 2010.

2.3 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 of 2000 to 2010 from the NASA MODIS instrument on the Terra satellite, with a spatial resolution of 1 km. We used the 8-day composite dataset (MOD11A2), which is the average values of 8-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 (Crosson et al. 2014; Roth, Oke, and Emery 1989). 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 1990–2010. 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). After that, 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).

2.4 Heat wave indices

We selected two daily mean temperature-based HIs: 1) the daily mean temperature >95th percentile for 2 consecutive days (Mean95th) and 2) the daily mean temperature >99th percentile for 2 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 2 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 2 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 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 1990–2010 in the warm season (May 1 to September 30).

To develop daily ZIP code-level HI estimates, this study determined a ZIP code to be in a heat wave if >50% 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.

2.5 Rurality measures

We examined associations between heat waves days and adverse health outcomes in urban and rural areas. There are different definitions and measures to classify rural and urban areas in the U.S. (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),

2.6 Study design and statistical analysis

We adopted a time-stratified case-crossover design (Basu, Dominici, and Samet 2005; Crouse et al. 2012; Janes, Sheppard, and Lumley 2005a), 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; Crouse et al. 2012; Janes, Sheppard, and Lumley 2005b, 2005a; 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 v20.0 (SPSS Inc., an IBM Company, Chicago, IL, USA) and conditional logistic regression models were implemented to estimate odds ratios (ORs) and 95% confidence intervals (CIs) for 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 datasets. Additional simulated datasets (N=10) were generated by randomly selecting a day between May 1 and September 30 for each PTB/NAD case in the same year as the real case. Randomization was performed with replacement using the randi function in MATLAB R2017b. To summarize statistical results, associations are reported as the percent difference in the odds of the health outcome (i.e., PTB and NAD) on heat wave days compared with non-heat wave days [percent difference = $(OR-1) \times 100$].

3. Results

3.1 NLDAS grid data versus downscaled grid data

Absolute, but not relative, heat wave indices (HIs) derived from finer spatial resolution datasets 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 2 consecutive days) and Mean30.22 [daily mean temperature >30.22°C (86.40°F) for 2 consecutive days]. Mean30.22 at downscaled 1 km grids presents the urban heat island effect in Birmingham, Montgomery and Mobile (Figure 2D) while Mean95th and NLDAS 12.5 km grids (Figure 2A–C) 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–B), 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 2 consecutive days), the average number of heat wave days/year was 1.26, 1.27, and 1.27 for ZIP code, NLDAS grid, and downscaled grid, resulting in a total of 564, 563, 559 PTB and 2336, 2337, 2375 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

since higher temperatures are found in densely populated urban areas. For instance, when defining heat waves using Mean31.75 [daily mean temperature $>31.75^{\circ}\text{C}$ (89.15°F) for 2 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 level.

PTB cases were positively associated with heat waves when heat wave days were defined by 8 of the 11 HIs. Figure 3A presents the associations using Mean99th and Mean31.75 indices and shows an increase of 18.8% (95% CI: 6.5, 32.5%) using the ZIP code-level, 19.4% (7.0, 33.2%) using the NLDAS grid level, and 17.4% (5.2, 31.0%) using the downscaled grid level exposure metric for the relative Mean99th index. For the absolute (Mean31.75) index, a 25.9% (95% CI: 8.3, 46.5%), 22.4% (95% CI: 5.2, 42.3%), or 17.6% (95% CI: 5.3, 31.2%) 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 additional 9 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 significant positive associations were found when heat waves were defined by Mean95th, with 3.7% (95% CI: 1.2, 6.3%) higher odds using ZIP code, 3.2% (95% CI: 0.7, 5.8%) using NLDAS grid, and 3.2% (95% CI: 0.7, 5.7%) using downscaled grid exposure metrics. For heat waves defined using a comparable absolute metric (Mean30.22), odds of NAD were 3.5% (95% CI: 0.2, 6.9%) higher using ZIP code, 3.7% (95% CI: 0.4, 7.1%) using NLDAS grid, and 1.3% (95% CI: -1.2, 3.9%) using downscaled grid exposure metrics.

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

Since 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 non-significant 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.

4. 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 3 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 a 18.8% (95% CI: 6.5, 32.5%), 19.4% (95% CI: 7.0, 33.2%), and 17.4% (95% CI: 5.2, 31.0%) 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 3 spatial resolutions [25.9% (95% CI: 8.3, 46.5%) for ZIP code-level, 22.4% (95% CI: 5.2, 42.3%) for NLDAS grid level, and 17.6% (95% CI: 5.3, 31.2%) for downscaled grid level for increased odds of PTB]. For NAD, associations were stable across the 3 spatial resolutions for the relative heat wave metric and moved slightly towards 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.

While 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 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 the present study, showing minimal influence of a more resolved metric [OR for PTB with a 2.7°C increase at the 1 km² resolution level reported as 1.02 (95% CI: 1.00, 1.05) compared with 1.07 (95% CI: 0.87, 1.27) using nearest weather station data]. Lee et al. (2016) found that the percent increase for mortality per 1°C increase was 2.05% (95% CI: 0.52, 2.91) at the 1 km² resolution level compared with 1.14% (95% CI: 0.08, 1.57) 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% versus 17.6% increase) and NAD (3.7% versus 1.3% increase) when comparing the lower spatial resolution model to the finer resolved model. Several differences between the present study and above studies may explain the differences in results. For example, the above studies examine relationships using temperature and gestational age as continuous variables. In addition, the above studies incorporate numerous additional remotely sensed variables beyond temperature, including Normalized Difference

Vegetation Index (NDVI), percent urban area, elevation, distance to water bodies, and traffic density.

Differences in associations according to rurality categories

Finer spatial resolution data captures 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 rural counties had higher emergency department visit rates for heat stress than urban counties did across the US (Fechter-Leggett, Vaidyanathan, and Choudhary 2016; Hess, Saha, and Luber 2014) and in North Carolina (Lippmann et al. 2013; Sugg, Konrad, and Fuhrmann 2016). However, Basu (2009) suggested 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 (Crosson et al. 2014; Mann and Schmidt 2003). Second, this study only examines associations in Alabama between 1990–2010; 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 the present 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 may not be required; and 2) heightened temperatures, or other urban specific parameters, may increase risk of adverse health outcomes in urban environments.

Supplemental Material

We examined an additional eight relative and absolute HIs in the supplemental figures and tables (See their definitions in eTable S1). eTable S2 summarizes the numbers of HI days per year per spatial unit when using other HIs. eTable S3 shows the associations between heat waves and PTB or NAD when heat waves were defined by 11 different HIs. eTables 4 and 5 show the associations in urban strata compared to rural strata. We mapped daily mean temperature using NLDAS 12.5km grids and downscaled 1km grids to show their differing spatial patterns (in eFigure S1). An examination of the associations between PTB or NAD

and heat waves using the randomized location datasets show that the NLDAS and downscaled level analyses produced similar effect estimates (in eFigures S2–3). When randomizing the date of PTB/NAD, there is no association between heatwaves and PTB/NAD (in eFigures S4–5).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors are very grateful to Mr. Sung Ho Kim from the Department of Computer Science at Virginia Tech for helping us to develop the code for downscaling temperature data.

Source of funding:

The results reported herein correspond to specific aims of grant R01 ES023029 to investigator Gohlke from National Institute of Environmental Health Sciences. This work was also supported in part by CNIMS contract HDTRA1-17-0118 from Defense Threat Reduction Agency (DTRA) and grant 1R01GM109718 from National Institutes of Health (NIH).

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Figure 1. Spatial distributions of rural-urban commuting area code categories, using RUCA version 3.10 and “categorization B” (A), and population density tertiles, using Census 2010 population densities calculated from total populations and land surface areas on ZIP code-level (B), in Alabama.

Figure 2. Heat wave grids in Alabama on 6 August 2000 at the NLDAS 12.5 km grid level (A and C) and downscaled 1 km grid level (B and D) in HIs defined as Mean95th (A and B) and Mean30.22 (C and D)

Figure 3. Percent difference $[(OR-1)*100]$, 95% CI, in PTB (A) or NAD (B) on a heat wave day, compared with corresponding non-heat wave days at ZIP code-level (blue), NLDAS grid level (yellow), and downscaled-level (red), defined in selected HIs.

Figure 4. Percent difference $[(OR-1)*100]$, 95% CI, in PTB (A) or NAD (B) on a heat wave day stratified by RUCAs and population density and using Mean31.75 for PTB (A) and Mean30.22 for NAD (B).

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 [n (%)] ^a	PTB [n (%)] ^b	NAD [n (%)]
Mean95th	ZIP code	6.60 (4.32)	2475 (4.90)	11386 (5.72)
	NLDAS grid	6.59 (4.31)	2462 (4.87)	11363 (5.71)
	Downscaled grid	6.59 (4.31)	2460 (4.87)	11612 (5.83)
Mean99th	ZIP code	1.26 (0.83)	564 (1.12)	2336 (1.17)
	NLDAS grid	1.27 (0.83)	563 (1.11)	2337 (1.17)
	Downscaled grid	1.27 (0.83)	559 (1.11)	2375 (1.19)
Mean30.22	ZIP code	3.78 (2.47)	1460 (2.89)	6490 (3.26)
	NLDAS grid	3.79 (2.48)	1462 (2.89)	6585 (3.31)
	Downscaled grid	3.99 (2.61)	2744 (5.43)	11621 (5.84)
Mean31.75	ZIP code	0.62 (0.40)	300 (0.59)	1268 (0.64)
	NLDAS grid	0.59 (0.39)	299 (0.59)	1282 (0.64)
	Downscaled grid	0.63 (0.41)	565 (1.12)	2391 (1.20)

Note:

^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.