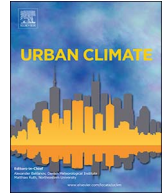




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Urban heat island intensity and spatial variability by synoptic weather type in the northeast U.S.

A.W. Hardin^a, Y. Liu^{b,c}, G. Cao^{b,c}, J.K. Vanos^{a,d,*}

^a Atmospheric Science Research Group, Department of Geosciences, Texas Tech University, Lubbock, Texas, USA

^b Department of Geosciences, Texas Tech University, USA

^c Center for Geospatial Technology, Texas Tech University, USA

^d Climate, Atmospheric Science, and Physical Oceanography, University of California San Diego, La Jolla, California, USA

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ABSTRACT

Understanding regional air temperature (T_a) variability and urban heat island (UHI) magnitude has posed challenges given the minimal observational stations in urban areas. This study uses a dense network to evaluate the degree to which synoptic weather influences the UHI intensity and fine scale T_a variability on days of extreme heat. We examine daytime and nighttime temperatures in four large northeastern cities (urban-suburban-rural) using a dataset with relatively high spatiotemporal resolutions (100–200 stations per area, 5 min or 60 min intervals) for May–Sept, 2006–2013. Results show stronger UHI intensity and enhanced T_a variability under hot, dry weather types, with the most intense UHIs overnight in dry conditions. Absolute T_a magnitudes within both urban and rural areas remain heightened under moist weather type conditions. New York City presents the highest average nighttime UHI intensity (3.51°C). Minimal, and at times negative, UHIs are often present in the daytime, appearing on 38% and 28% of days in New York City and Boston, respectively. An exploratory analysis demonstrates a significant ability to predict average T_a at each station using common environmental predictors. Findings emphasize the importance in distinguishing between absolute maximum T_a versus UHI intensity by weather type for communication and translation of heat mitigation practices and health protection by public health and urban planning agencies.

1. Introduction

Currently, 54% of the world's population lives in urban areas with an expected increase to 66% by 2050 (United Nations, 2014). This urbanization combined with large-scale climate warming presents important impacts on social, economic, and health systems in cities both now and in the future (Grimmond et al., 2010). The summertime urban heat island (UHI) effect exacerbates already strong heat waves (Habeeb et al., 2015; Li and Bou-Zeid, 2013; Tan et al., 2010) with many studies showing increasing long-term urban temperatures trends worldwide (Golden, 2004; O'Neill and Ebi, 2009), particularly overnight (Mishra et al., 2015).

Due to longwave emission at nighttime from daytime heat storage in the city fabric, the strongest UHI intensity often occurs overnight near dawn in calm conditions, followed by a weakening in the intensity throughout the day (Oke, 1987; Tan et al., 2010). This diurnal temperature difference between an urban and rural area is also altered by the amount of moisture in the air (Gedzelman et al., 2003; Oke, 1982; Theeuwes et al., 2015), which is largely controlled by synoptic-scale meteorology (Dixon and Mote, 2003) and land use (Henry et al., 1985). There is wide consensus that clear skies and low vapor pressure, especially at night, result in

* Corresponding author.

E-mail address: jkvanos@ucsd.edu (J.K. Vanos).

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stronger UHI intensities than cloudy skies and higher vapor pressure (Gedzelman et al., 2003; Oke, 1982; Park, 1986; Schatz and Kucharik, 2014), and thus the nighttime growth in UHI intensity is limited to the ability of the rural area to cool down (Oke et al., 1991). However, minimal meteorological observation stations in urban-to-rural networks have resulted in a lack of information addressing how synoptic weather types influence intra-urban and rural variations in T_a as compared to surface temperature.

Microclimate variations are present due to the changing design, densities, geometry, contiguity, and composition of urban areas, factors which also alter the shape and magnitude of the UHI profile (Debbage et al., 2016). Spatial differences in intra-urban/sub-urban temperature variability are therefore common (Gedzelman et al., 2003; Klysiak and Fortuniak, 1999; Oke and Cleugh, 1987; Oswald et al., 2012; Park, 1986; Unger et al., 2001), and also found to a lesser extent within rural areas (Hawkins et al., 2004). For this reason, the ‘classic’ UHI shape between the urban/rural boundary (‘cliff’, ‘plateau’, ‘peak’) does not always hold true. Many studies that have examined the UHI have used one urban and one rural station (Ackerman, 1985; Hawkins et al., 2004; Kim and Baik, 2002; Magee et al., 1999; Redway, 1919; Sakakibara and Owa, 2005; Schmidlin, 1989; Tan et al., 2010; Unger, 1996), completed automobile traverses (Acero et al., 2013; Deosthali, 2000; Moreno-Garcia, 1994; Park, 1986; Unger et al., 2001; Yamashita et al., 1986), applied remote sensing techniques that provide a surface UHI (SUHI) (Ben-Dor and Saaroni, 1997; Martin et al., 2014; Yuan and Bauer, 2007; Zhou et al., 2013), and/or averaged multiple urban and rural stations/small sensors (Basara et al., 2008, 2010; Gedzelman et al., 2003; Scott et al., 2016; Stone, 2007).

In addition to synoptic and built environment impacts on UHI magnitude and T_a variability, the estimation of T_a using available environmental information is also important. To understand the land surface influences, such as impermeable versus permeable land cover, studies commonly make use of land classification systems and remote sensing to quantify impervious surface cover and normalized vegetation index (NDVI) (Zhou et al., 2013; Coseo and Larsen, 2014). Such studies are valuable in demonstrating that impervious surfaces can also account for intra-urban variation in the SUHI (Ben-Dor and Saaroni, 1997; Coseo and Larsen, 2014; Yuan and Bauer, 2007), rather than near-surface air temperatures, yet are often coarsely scaled. Hence, we may miss critical microclimate variations that affect fine-scale heating or cooling in complex urban areas (Vanos et al., 2016; Middel et al., 2014; Solis et al., 2016) or affect the prediction of human health outcomes (morbidity, mortality) due to variable heat exposure (Hajat et al., 2010; Hondula et al., 2015).

Heightened urban temperatures also enhance anthropogenic energy consumption (Rosenfeld et al., 1998) and increase heat-related mortality by magnifying the severity of heat waves (Basara et al., 2010; Zhou and Shepherd, 2010; Stone et al., 2012; Li and Bou-Zeid, 2013; Tan et al., 2010). The effect of synoptic weather types on human health has been well-documented (e.g., Vanos et al., 2014; Sheridan and Kalkstein, 2010; Sheridan and Dolney, 2003), yet the strength of the UHI formation under different weather types is not as well-studied. Sheridan et al. (2000) found that the weather types already associated with elevated mortality (dry and moist tropical) also have some of the most intense UHIs, with minimal variation between weather types during the day as compared to day versus night differences.

By examining the spatial and temporal dynamics of T_a in four northeastern cities (New York, NY; Philadelphia, PA; Baltimore, MD; Boston, MA), this study aims to evaluate the degree to which synoptic weather types influence UHI intensities during day and nighttime conditions, with a focus on the hot and oppressive weather types. We make use of a novel dataset collected by Earth Networks, Inc. in combination with the spatial synoptic classification (SSC) system over an eight year period. We secondarily explore the performance of three environmental covariates – brightness of nighttime lights (NTL), NDVI, and distance to water – to predict the average T_a at each station.

2. Materials and methods

2.1. Meteorological data

Data consists of hourly (Boston) and five-minute (Baltimore, Philadelphia, New York City) averaged meteorological data from an observational surface research network run by the National Oceanic and Atmospheric Administration (NOAA) and Earth Networks, Inc. entitled ‘UrbaNet’, which currently operates in 17 U.S. cities. We focus data analysis on the months of May through September for the years 2006–2013. The cities of Boston, Baltimore, Philadelphia, and New York City were chosen as they are large cities located within the same climate zone (humid continental) in the northeast U.S. Further information on each city can be found in Table 1. The monitored meteorological data include T_a (°C), relative humidity (%), pressure (mb), wind speed (ms^{-1}) and wind direction (degrees), and rainfall (in.). The instruments used at each station include an R.M. Young Model 04101 Wind Monitor Junior, 6-in. diameter Texas Weather Instruments tipping bucket rain gauge, Motorola MPXA4115A integrated silicon pressure sensor, and a Dallas Semiconductor DS1624 silicon chip that consists of a digital thermometer and Honeywell HIH-4602-C Monolithic IC humidity

Table 1
Population, population density (people km^{-2}), city area (km^2), and study area (km^2) for each city (U.S. Census 2010).

City	Population	Pop. density	City area	Study area
Boston	617,594	33,136	125.0	3570
Baltimore	620,961	19,869	209.6	2970
Philadelphia	1,526,006	29,473	347.3	3382
New York City	8,175,183	69,963	783.8	3396

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