Atmospheric Environment 118 (2015) 7–18

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

Development of a national anthropogenic heating database with an extrapolation for international cities

David J. Sailor [a, b, *], Matei Georgescu [b], Jeffrey M. Milne [c], Melissa A. Hart [d]

[a] Department of Mechanical and Materials Engineering, Portland State University, Portland, OR 97207, USA[1]
[b] School of Geographical Sciences and Urban Planning, Global Institute of Sustainability, Arizona State University, Tempe, AZ 85287-5302, USA
[c] School of Meteorology, University of Oklahoma, USA
[d] ARC Centre of Excellence for Climate System Science and Climate Change Research Centre, University of New South Wales, Sydney, Australia

HIGHLIGHTS

- City-specific anthropogenic heating profiles are needed for urban climate modeling.
- Diurnal and seasonal profiles of anthropogenic heating are developed for 61 US cities.
- An extrapolation method for calculating international city profiles is introduced.

ARTICLE INFO

Article history:
Received 2 May 2015
Received in revised form
9 July 2015
Accepted 10 July 2015
Available online 17 July 2015

Keywords:
Anthropogenic heating
Urban climate
Atmospheric models
Waste heat

ABSTRACT

Given increasing utility of numerical models to examine urban impacts on meteorology and climate, there exists an urgent need for accurate representation of seasonally and diurnally varying anthropogenic heating data, an important component of the urban energy budget for cities across the world. Incorporation of anthropogenic heating data as inputs to existing climate modeling systems has direct societal implications ranging from improved prediction of energy demand to health assessment, but such data are lacking for most cities. To address this deficiency we have applied a standardized procedure to develop a national database of seasonally and diurnally varying anthropogenic heating profiles for 61 of the largest cities in the United Stated (U.S.). Recognizing the importance of spatial scale, the anthropogenic heating database developed includes the city scale and the accompanying greater metropolitan area. Our analysis reveals that a single profile function can adequately represent anthropogenic heating during summer but two profile functions are required in winter, one for warm climate cities and another for cold climate cities. On average, although anthropogenic heating is 40% larger in winter than summer, the electricity sector contribution peaks during summer and is smallest in winter. Because such data are similarly required for international cities where urban climate assessments are also ongoing, we have made a simple adjustment accounting for different international energy consumption rates relative to the U.S. to generate seasonally and diurnally varying anthropogenic heating profiles for a range of global cities. The methodological approach presented here is flexible and straightforwardly applicable to cities not modeled because of presently unavailable data. Because of the anticipated increase in global urban populations for many decades to come, characterizing this fundamental aspect of the urban environment – anthropogenic heating – is an essential element toward continued progress in urban climate assessment.

1. Background and motivation

Energy consumption in cities leads to emissions of waste heat into the urban air shed. These emissions arise from the functioning of cars, electricity use in buildings (e.g., from building heating, ventilation and air conditioning (HVAC) systems), industry, and individuals (referred to as human metabolism). The magnitude of this anthropogenic heat flux (Q_f) correlates well with population

* Corresponding author. Department of Mechanical and Materials Engineering, Portland State University, Portland, OR 97207, USA.
E-mail addresses: sailor@pdx.edu, David.Sailor@asu.edu (D.J. Sailor).
[1] through Dec. 2016.

http://dx.doi.org/10.1016/j.atmosenv.2015.07.016
1352-2310/

density. At the continental scale anthropogenic heat emissions are small, averaging less than 0.4 W/m^2 in the United States, less than 0.7 W/m^2 in western Europe, and 0.2 W/m^2 in China (Flanner, 2009). The greater population density at the metropolitan or city scales results in substantially larger magnitudes of Q_f. For example, using energy consumption inventories at the city scale researchers have estimated anthropogenic heat emissions on the order of 10–100 W/m^2 for cities as diverse as Lodz, Poland (Klysik, 1996) and Philadelphia PA, USA (Fan and Sailor, 2005). Sailor and Lu (2004) present detailed summer and winter profiles for 6 cities in the United States (Atlanta, Chicago, Los Angeles, Salt Lake City, San Francisco, and Philadelphia). Their results illustrate the important role of both local climate and population density in affecting the magnitude of Q_f. For example, while San Francisco has a population density of roughly 0.00599 persons/m^2, the winter magnitude of Q_f in Chicago (with a population density of 0.00492 persons/m^2) is roughly 7 W/m^2 greater than that of San Francisco. Conversely, despite the relatively harsh winter conditions in Salt Lake City, its low population density results in a much lower winter Q_f (~12 W/m^2) than that of Los Angeles (~30 W/m^2).

The notion of scale must be considered when estimating urban-induced Q_f and subsequent impacts on urban meteorology and climate. At the scale of a city block, the magnitude of anthropogenic heating from the building sector increases proportionally with the height (number of floors) of buildings. Thus, in central Tokyo, Ichinose et al. (1999) found that Q_f exceeded 400 W/m^2 during the daytime and reached values up to 1590 W/m^2 in winter. Therefore, the magnitude of anthropogenic heating varies substantially both as a function of underlying climate, but also in direct proportion to the population density of the region under study. Furthermore, within any single city, the magnitude of anthropogenic heating varies as a function of the spatial extent of the area of analysis, necessarily incorporating diverse types of urban form and function (Stewart and Oke, 2012) with contributions depending on localized energy consumption, traffic patterns, and microclimate. Hence, Q_f is typically largest at the neighborhood scale in downtown areas, is lower in magnitude when averaged over the city, and lower still when averaged over the greater metropolitan region.

Anthropogenic heating can be an important component of the urban energy budget. For example, Fan and Sailor (2005) found that inclusion of anthropogenic heating in mesoscale modeling of Philadelphia resulted in air temperature elevations as large as 2–3 °C in winter. Salamanca et al. (2014) have similarly shown, via utility of mesoscale modeling with the Weather Research and Forecasting (WRF) model dynamically coupled to a building energy parameterization, that usage of air conditioning (AC) systems increased summertime nighttime air temperatures by more than 1 °C for the Phoenix metropolitan area. Notably, in addition to highlighting this non-negligible warming effect, the authors demonstrate that explicit representation of waste heat from AC systems improved 2m-air temperature correspondence to observations, thereby confirming the critical role of this aspect of the urban energy balance for improved predictability.

Inclusion of Q_f clearly has significant implications for urban climate, air quality, and energy demand. Thus, modeling efforts aimed at investigating the urban environment must appropriately characterize this aspect of the urban energy balance. At the present time, users have two choices. First, usage of the WRF system (which is easily coupled to a single layer urban canopy parameterization by means of a namelist setting the user may turn on), or other similar modeling systems, provides a default anthropogenic heating profile scaled by a magnitude parameter (in WRF, these default values are 90, 50, and 20 W/m^2 respectively for commercial, high-density residential, and low-density residential urban land categories). While these profiles (Fig. 1) are user-editable, the lack of available

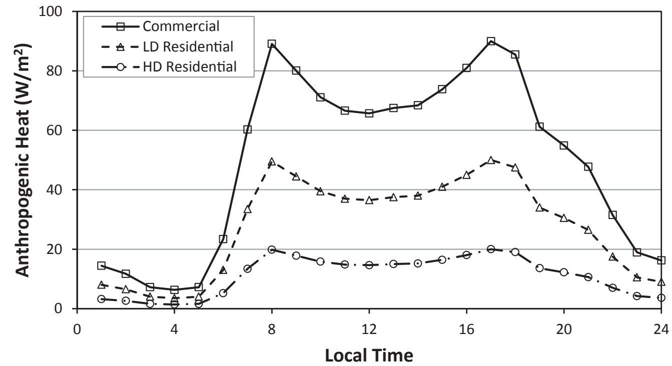

Fig. 1. Representative diurnal profiles of anthropogenic heating available in WRF.

anthropogenic heating data for many cities increases the likelihood that users simply use the profiles unchanged. In some cases, lack of data leads urban modelers to either set anthropogenic heating magnitudes off (e.g., Holt and Pullen, 2007), or to use custom profiles that neglect some key emissions component such as the vehicle sector (e.g., Lin et al., 2008). Maximum values occur at 8am and 5pm local time, regardless of city or season. A second option within WRF is to use the BEP + BEM (building effect parameterization with integrated building energy model) option. However, as noted by Salamanca (Salamanca et al., 2012) this approach may lead to underestimation of the anthropogenic heat effect as it completely ignores emissions from transportation. Alternatively, researchers can develop their own city-specific diurnal profile of Q_f for their region of interest. Development of detailed representations for select regions (Chow et al., 2014) has begun, but coordinated local agency (e.g., for provision of readily accessible and appropriate data) and institutional efforts (e.g., for comprehensive multi-scale modeling of the urban air shed coupled to the overlying atmosphere) are required for the representation of spatially explicit, time-varying profiles of Q_f. Such coordination remains costly and therefore elusive for many cities, but the need for the creation of a national (and by extension international) anthropogenic heating database is as essential as ever given the current, and projected, hydroclimatic significance of urban areas (Georgescu et al., 2014), and is therefore in high demand for individual researchers, as well as local, state, and national planning agencies addressing urban sustainability concerns.

To address the growing need for a national database of anthropogenic heating profiles, we have applied a published top-down methodology (Sailor and Lu, 2004) to develop representative month-specific Q_f profiles for 61 of the largest U.S. cities. The method is "top-down" in that it uses suitably downscaled coarse spatial and temporal resolution data to estimate diurnal profiles for cities. These data have been obtained from the Bureau of Transportation Statistics (U.S. Department of Transportation), the Energy Information Administration (U.S. Department of Energy), the National Climatic Data Center (U.S. Department of Commerce), and the Urban Transportation Planning Package (U.S. Census). For each urban area we have calculated diurnal profiles for two spatial scales: city scale, and the accompanying greater metropolitan area. For presentation purposes, however, we will summarize only the city-scale (i.e., municipal definition of the spatial extent) results here, but have made these and metropolitan area results available online at geoplan.asu.edu/research-and-outreach/projects/AHdata.

2. Methodology

There are two basic approaches to estimating diurnal profiles of Q_f. Starting at the neighborhood scale, one approach is to monitor individual building energy consumption and to use roadway traffic count and fuel economy data to assess heat released from neighborhood traffic. Such a bottom-up approach is tedious, particularly if the goal is to develop detailed profiles for many cities. However, in a recent variation of this approach, Lee et al. (2014) applied regression modeling to the national emissions inventory database (NEI), to arrive at 4 km resolution hourly estimates of anthropogenic heat emissions across the U.S. While promising, the method's accuracy is limited by the underlying assumption that locations of pollutant emissions are coincident with locations of heat emissions—which is not true of the building sector. Further, the approach is limited to the spatial boundaries of the NEI dataset (U.S.). Alternatively, one can start with coarser resolution data, in time and space, and scale as needed to estimate Q_f profiles at finer scales. This latter approach is particularly useful for the present work, where the goal is to produce detailed profiles for many cities using a standardized technique.

Table 1
Cities used in the anthropogenic heating database project and their corresponding population densities, per capita daily vehicle distance traveled (DVD), and annual cooling and heating degree days (CDD and HDD).

City	State	Pop. Dens (pers/km^2)	DVD (km/day)	CDD (°C-day)	HDD (°C-day)
Albuquerque	NM	1123	46	909	4884
Anchorage	AK	66	29	2	10193
Atlanta	GA	1218	54	1883	2768
Austin	TX	1024	50	2751	1903
Bakersfield	CA	944	29	2258	2175
Baltimore	MD	2962	34	1164	4764
Birmingham	AL	561	56	2058	2677
Boston	MA	4939	33	747	5681
Buffalo	NY	2498	31	544	6617
Charlotte	NC	949	48	1518	3388
Chicago	IL	4572	33	843	6340
Cincinnati	OH	1471	45	824	5473
Cleveland	OH	1972	34	817	5762
Colorado Springs	CO	826	29	455	6292
Columbus	OH	1399	42	1035	5250
Corpus Christi	TX	734	40	3524	898
Dallas	TX	1358	50	2756	2284
Denver	CO	1515	36	769	6058
Detroit	MI	1986	39	803	6137
El Paso	TX	982	30	2331	2474
Fort Worth	TX	842	50	2756	2284
Fresno	CA	1706	34	2124	2346
Houston	TX	1352	59	3155	1367
Indianapolis	IN	876	52	1066	5378
Jacksonville	FL	425	46	2665	1349
Kansas city	MS	564	47	1360	5133
Las Vegas	NV	1660	31	3568	1951
Lexington-Fayette	KY	403	48	1190	4611
Los Angeles	CA	3124	37	551	1419
Louisville	KY	709	45	1614	4097
Memphis	TN	793	40	2258	2964
Miami	FL	4300	31	4575	128
Milwaukee	WI	2389	33	641	6894
Minneapolis	MN	2737	39	753	7580
Nashville-Davidson	TN	489	61	1646	3688
New Orleans	LA	784	23	3005	1280
New York	NY	10430	25	1105	4750
Oakland	CA	2704	36	138	2873
Oklahoma city	OK	369	39	1968	3634
Omaha	NE	1242	30	1113	6167
Philadelphia	PA	4394	30	1301	4613
Phoenix	AZ	1080	44	4607	935
Pittsburgh	PA	2132	37	736	5710
Portland	OR	1689	38	424	4278
Raleigh	NC	1091	49	1730	3247
Riverside	CA	1446	39	1756	1446
Sacramento	CA	1839	34	1178	2619
Salt Lake city	UT	648	40	1160	5607
San Antonio	TX	633	47	3131	1496
San Diego	CA	1552	38	720	1225
San Francisco	CA	6633	36	164	2653
San Jose	CA	2069	38	730	2001
Seattle	WA	2800	42	189	4697
St. Louis	MO	1991	46	1646	4535
Stockton	CA	1826	30	1320	2643
Tampa	FL	1143	37	3610	538
Toledo	OH	1374	38	793	6145
Tucson	AZ	886	35	3146	1511
Tulsa	OK	769	36	2036	3573
Washington	DC	3806	37	1549	4031
Wichita	KS	927	34	1686	4594

The actual method used in this study is based on the work published in Sailor and Lu (2004). A summary of this approach is presented here for reference. As a starting point, Q_f is divided into three components representing the major sources of waste heat in the urban environment:

$$Q_f = Q_V + Q_B + Q_M, \tag{1}$$

where the subscripts are for vehicles (V), building sector (B), and human metabolism (M). The building sector can be further divided into heat rejected directly from electricity consumption and heat released from point-of-use heating fuels such as natural gas and fuel oil.

Each component of the anthropogenic heating profile is based on a population density formulation. That is, we first calculate per capita energy intensity for the city and sector and then multiply this value by the population density. While urban populations generally swell during the day, most readily available population data are for the resident population, which represents the nocturnal populace. Analyses of detailed population data from the U.S. Census (Bureau of Transportation Statistics, 2003) suggest the daytime urban population is typically 50–100% higher than the resident (or nocturnal) population. In the present study a daytime increase factor was assumed for city-scale analyses. The scale factor took on a value of 1.0 from 7pm in the evening until 6am in the morning. It then transitioned linearly to a daytime value of 1.75 over the 2-h period from 7am to 9am, ramping back down to 1.0 from 5pm to 7pm. All nighttime population data were obtained directly from the resident population data available from the U.S. Census. At the larger metropolitan scale the daytime increase in population is much smaller and was assumed negligible in this work. The population data were then used with per capita data for electricity, heating fuels, and transportation fuel use.

One enhancement in the present work relative to the original manuscript (Sailor and Lu, 2004) is that we now correct for variations in weather from the state-level to the city-scale. Specifically, the original method mapped monthly state-level energy consumption data to the city scale simply by multiplying by the appropriate population ratio. This approach ignored intra-state climate variability, leading to similar per capita energy consumption rates for different cities within any particular state. While city-scale energy data are not commonly available, we have developed a simple method for scaling state-level consumption data that reflects the weather-dependency of utility loads. Specifically, we employed a method whereby regression models relating state-level degree-days to state-level published consumption data are applied using the corresponding city-level degree-day data (Sailor and Vasireddy, 2006). This approach has been shown to significantly reduce the error associated with the assumption that per capita energy consumption is constant within any state.

3. Data resources

The goal of this study was to apply a standardized modeling technique in an automated way to a wide range of U.S. cities with diverse climates, geographies, and populations. The availability of data ultimately limited the selection of available cities to 61 of the largest U.S. cities, but the approach presented here can easily be extended to other municipalities as data becomes available. The selected cities, resident population density data (i.e., persons per square kilometer), and daily vehicle distance estimates are provided in Table 1. This table also presents a summary of the annual heating and cooling degree-days for each city (Arguez et al., 2012) using the standard base temperature of 18.3 °C (65 °F).

3.1. Weather data

The National Climatic Data Center (NCDC) maintains climate normal and actual weather data needed for incorporating weather sensitivity into the mapping of state level energy data to the city scale. Specifically, we used population-weighted state values of monthly cooling and heating degree-days, courtesy of NCDC (series 5-1, 5-2, 2010). For the city-level degree-day data we accessed the station normals database (Arguez et al., 2012). These data were downloaded by year from ncdc.noaa.gov. This database allows evaluation of monthly deviations from the monthly normals of heating and cooling degree-days. From these resources we extracted the year 2010 specific monthly heating and cooling degree-days for all cities and states involved in our analysis.

3.2. Metabolism data

In prior work (Sailor et al., 2003), we found that metabolism is generally a small component (~2–3%) of the total anthropogenic heating profile. Nevertheless it is readily incorporated in our population density-based methodology. Specifically, the typical U.S. diet consists of 2000–2500 kCal daily. Using a representative diet of 2400 kCal and assumed nocturnal and daytime metabolic rates of 70 and 140 Watts, respectively (with a suitable 3-h linear transition in morning and evening hours), we constructed metabolism profiles for each city. Since this metabolism happens both inside and outside of buildings, it is important to make sure that the method for estimating waste heat from buildings does not result in double counting of human metabolism. As described below, the evaluation of waste heat from the building sector only accounts for direct energy use, and not for metabolic heat rejected by the HVAC systems from buildings. Thus, separate inclusion of the metabolism component is appropriate.

3.3. Electricity data

Utilities within the U.S. are required to report state level

Table 2
Numeric values of hourly non-dimensional profile function values for the universal summer (August) profile and the two winter (January) profiles, where Qf_{max} is daily maximum Qf. Cold winter cities have annual HDD >4000 °C -day (18.3 °C base).

Hour	Summer profile	Winter profile	
		Cold winter cities	Warm winter cities
1	0.25 Qf_{max}	0.37 Qf_{max}	0.28 Qf_{max}
2	0.23 Qf_{max}	0.35 Qf_{max}	0.26 Qf_{max}
3	0.25 Qf_{max}	0.35 Qf_{max}	0.25 Qf_{max}
4	0.21 Qf_{max}	0.34 Qf_{max}	0.25 Qf_{max}
5	0.22 Qf_{max}	0.35 Qf_{max}	0.26 Qf_{max}
6	0.29 Qf_{max}	0.40 Qf_{max}	0.34 Qf_{max}
7	0.53 Qf_{max}	0.62 Qf_{max}	0.58 Qf_{max}
8	0.82 Qf_{max}	0.86 Qf_{max}	0.87 Qf_{max}
9	0.87 Qf_{max}	0.95 Qf_{max}	0.92 Qf_{max}
10	0.80 Qf_{max}	0.89 Qf_{max}	0.84 Qf_{max}
11	0.80 Qf_{max}	0.88 Qf_{max}	0.83 Qf_{max}
12	0.84 Qf_{max}	0.91 Qf_{max}	0.86 Qf_{max}
13	0.89 Qf_{max}	0.93 Qf_{max}	0.90 Qf_{max}
14	0.89 Qf_{max}	0.93 Qf_{max}	0.90 Qf_{max}
15	0.93 Qf_{max}	0.96 Qf_{max}	0.93 Qf_{max}
16	1.00 Qf_{max}	1.00 Qf_{max}	1.00 Qf_{max}
17	0.90 Qf_{max}	0.89 Qf_{max}	0.90 Qf_{max}
18	0.78 Qf_{max}	0.77 Qf_{max}	0.79 Qf_{max}
19	0.56 Qf_{max}	0.58 Qf_{max}	0.57 Qf_{max}
20	0.48 Qf_{max}	0.52 Qf_{max}	0.50 Qf_{max}
21	0.44 Qf_{max}	0.49 Qf_{max}	0.45 Qf_{max}
22	0.41 Qf_{max}	0.47 Qf_{max}	0.43 Qf_{max}
23	0.36 Qf_{max}	0.44 Qf_{max}	0.39 Qf_{max}
24	0.30 Qf_{max}	0.40 Qf_{max}	0.33 Qf_{max}

aggregated monthly totals of electricity consumption (and other fuels). These sector-specific data are archived by the U.S. Department of Energy's Energy Information Administration (EIA 2010a, b). For each state in our analysis these monthly consumption data were obtained, converted to daily per capita consumption, and scaled to reflect weather-related differences at the city scale. These data provide a sense of the daily per capita magnitude of electricity consumption (E_{DPC}), but do not provide detail regarding the diurnal variability of this usage. In order to develop such a diurnal profile, we assumed the hourly electricity consumption (E_{HR}) for any city can be written as $E_{HR} = E_{DPC} \cdot f(\text{hour})$, where

$$\sum_{1}^{24} f(\text{hour}) = 1.0 \tag{2}$$

In prior work (Sailor and Lu, 2004), we obtained hourly load profile data from a number of independent service operators (ISOs). After suitable non-dimensionalization of the profiles we found that load profiles could be represented reasonably well with two "standard" profiles – one for summer, and one for winter.

3.4. Heating fuel data

The EIA also collects and archives state monthly usage totals for various heating fuels (e.g., natural gas (NG), liquid petroleum gas (LPG), kerosene, fuel oil). While NG is the dominant heating fuel in the US, the contributions by other heating fuels to the total anthropogenic heating profile cannot be neglected. The fraction of total heating fuel demand met by natural gas (F_{NG}) is generally in the range of 0.60–0.90, depending upon the state and sector. The approach taken here was to scale NG profiles by F_{NG} to estimate total heating fuel profiles.

While data for hourly electricity consumption rates are relatively easy to obtain (for ISO service areas) the required data to generate the corresponding diurnal profiles for heating fuels are not typically available. Due to this lack of data, we opted to neglect the diurnal variability of heating fuel consumption in the present analysis. It is believed that this causes relatively little error in the summertime profiles, but may have the unintended result of lowering the midmorning peak in anthropogenic heating for winter months, and can therefore be considered a conservative estimate for this time of year.

3.5. Transportation data

Estimation of heat released from vehicles requires detailed hourly profiles of traffic on major and minor roadways throughout a city's area. It is also desirable to have comprehensive fleet information, including an estimate of the fleet-averaged hourly speed and fuel economy. The U.S. Department of Transportation publishes annual summaries of Daily Vehicle Miles Traveled (DVMT) for major urbanized areas (USDoT, 2013). These data are readily available for U.S. cities with populations greater than 50,000 (see www.fhwa.dot.gov/policyinformation). We converted these data to per capita daily vehicle distance (DVD) in units of km/person and combined these DVD estimates with per capita state-level gasoline sales (USDoT, 2011) to arrive at estimates of fleet fuel economy within each city. For the case of Washington D.C., where the location of purchase may not correlate well with location of use, data from the surrounding states of Virginia and Maryland were averaged with those from Washington D.C. to arrive at an estimate of D.C. area fleet fuel economy. New Jersey and Alaska were the states with the lowest average fuel economies of 17.9 (7.6 km per liter) and 16.1 (6.8 km per liter) miles per gallon, respectively. Wyoming and Indiana were the states with the highest fuel economies, at 26.0 (11.1 km per liter) and 25.0 (10.6 km per liter) miles per gallon, respectively. The median fleet fuel economy across all states was 22.3 miles per gallon (9.5 km per liter).

It is generally reasonable to assume that per capita vehicle distance traveled has little seasonal variation (Hallenbeck et al., 1997). The hourly profile for vehicle emissions can be estimated using hourly traffic data, where traffic counts are suitably converted to fractions of daily traffic occurring within each hour. Given the similarity among such profiles, we simply use the national profile created by Hallenbeck et al. (1997).

With the hourly fractional traffic profiles (F_t) defined above, and the values for per capita daily vehicle distance (DVD), one can calculate the total anthropogenic heat release in any hour from vehicles by:

$$Q_V(h) = DVD \cdot F_t(h) \cdot \rho_{pop}(h) \cdot EV, \tag{3}$$

where $\rho_{pop}(h)$ is the hourly population density and EV is the energy release per vehicle per kilometer of travel, given by:

$$EV = \frac{NHC \cdot \rho_{fuel}}{FE}, \tag{4}$$

where NHC is the net heat of combustion of gasoline (J kg^{-1}), ρ_{fuel} is the fuel density (kg l^{-1}), and FE is the mean fuel economy (km l^{-1}). The typical heat of combustion for automotive gasoline is

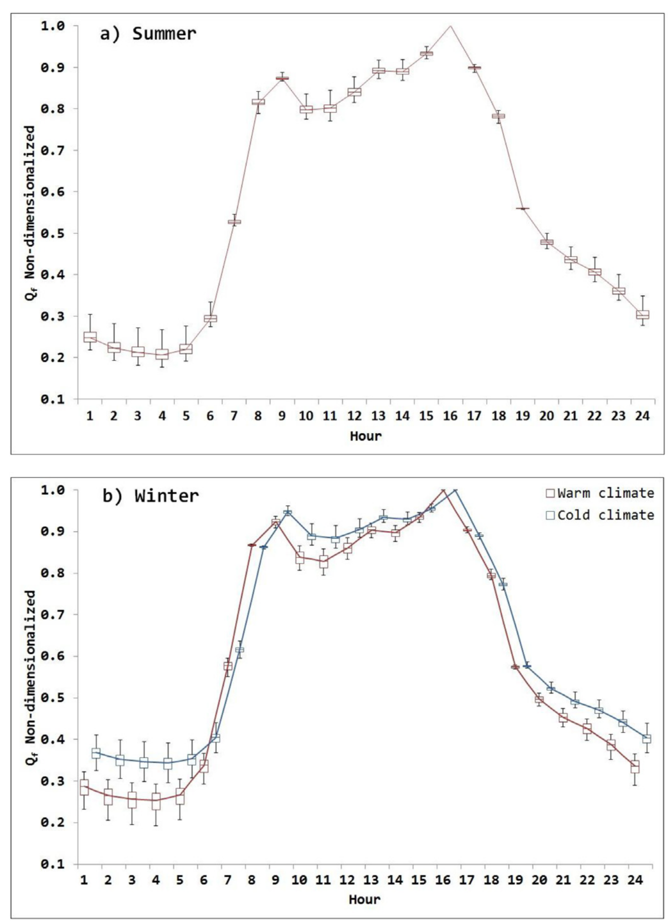

Fig. 2. (a) Box plot of non-dimensional summer (July) anthropogenic heating profiles for all cities. (b) Box plot of non-dimensional winter (January) anthropogenic heating profiles for cold and warm climate cities.

45×10^6 J kg^{-1}, and its nominal density is 0.75 kg l^{-1}. For a fleet fuel economy of 9.5 km per liter, EV takes on a value of 3605 J m^{-1} of vehicle travel.

4. Results

The anthropogenic heating database project for U.S. cities represents a compromise between detail and ease of analysis. In order to facilitate the application of the methodology, we implemented it using a spreadsheet approach allowing for automation of the data input and manipulation process. A final set of twelve monthly spreadsheets was compiled from these data. These spreadsheets provide hourly anthropogenic heating estimates for each of the 61 cities. Thus, a total of 732 distinct anthropogenic heating profiles have been developed. This is far too much data to effectively communicate in a single manuscript. For presentation purposes, we nominally divide the 61 cities into two climate types: cold climate and warm climate cities.

Table 3
Profile characteristics for city-scale anthropogenic heating in summer (August) and winter (January).

City	State	$Q_{f,max}$ summer (W/m^2)	$Q_{f,max}$ winter (W/m^2)	Winter profile
Albuquerque	NM	7.86	10.8	Cold
Anchorage	AK	0.47	0.8	Cold
Atlanta	GA	11.87	13.3	Warm
Austin	TX	9.65	9.8	Warm
Bakersfield	CA	5.88	6.1	Warm
Baltimore	MD	25.49	34.9	Cold
Birmingham	AL	6.45	6.7	Warm
Boston	MA	41.06	62.3	Cold
Buffalo	NY	17.44	28.5	Cold
Charlotte	NC	8.40	9.9	Warm
Chicago	IL	34.64	57.5	Cold
Cincinnati	OH	13.36	19.3	Cold
Cleveland	OH	16.23	24.3	Cold
Colorado Springs	CO	5.83	8.3	Cold
Columbus	OH	11.95	17.2	Cold
Corpus Christi	TX	7.53	7.1	Warm
Dallas	TX	13.99	14.3	Warm
Denver	CO	11.80	15.7	Cold
Detroit	MI	16.92	26.2	Cold
El Paso	TX	8.27	9.0	Warm
Fort Worth	TX	8.67	8.9	Warm
Fresno	CA	11.61	12.3	Warm
Houston	TX	13.00	12.6	Warm
Indianapolis	IN	8.79	12.0	Cold
Jacksonville	FL	3.82	3.7	Warm
Kansas city	MS	5.64	7.4	Cold
Las Vegas	NV	15.38	14.2	Warm
Lexington-Fayette	KY	3.67	4.8	Cold
Los Angeles	CA	21.54	22.6	Warm
Louisville	KY	7.61	9.3	Cold
Memphis	TN	7.81	8.4	Warm
Miami	FL	34.46	29.8	Warm
Milwaukee	WI	17.88	27.8	Cold
Minneapolis	MN	23.90	36.5	Cold
Nashville-Davidson	TN	5.68	6.4	Warm
New Orleans	LA	7.27	7.1	Cold
New York	NY	62.87	96.6	Cold
Oakland	CA	17.47	20.0	Warm
Oklahoma city	OK	4.25	5.0	Warm
Omaha	NE	10.64	15.7	Cold
Philadelphia	PA	34.22	49.0	Cold
Phoenix	AZ	9.22	7.7	Warm
Pittsburgh	PA	16.35	25.5	Cold
Portland	OR	11.74	14.4	Cold
Raleigh	NC	10.29	11.8	Warm
Riverside	CA	10.91	10.9	Warm
Sacramento	CA	12.43	13.9	Warm
Salt Lake city	UT	4.92	6.6	Cold
San Antonio	TX	6.11	5.9	Warm
San Diego	CA	10.84	11.2	Warm
San Francisco	CA	42.77	48.5	Warm
San Jose	CA	14.11	15.5	Warm
Seattle	WA	23.08	28.2	Warm
St. Louis	MO	20.84	26.0	Warm
Stockton	CA	12.18	13.6	Warm
Tampa	FL	9.48	8.4	Warm
Toledo	OH	11.76	17.9	Cold
Tucson	AZ	7.11	6.6	Warm
Tulsa	OK	8.17	9.8	Cold
Washington	DC	41.86	54.4	Cold
Wichita	KS	8.44	11.2	Cold

As illustrated in Table 2 the vast majority of the cities analyzed had anthropogenic heating profiles that peak in winter. In fact, only 10 cities in the states of Florida, California, Arizona, Nevada, Texas, and Louisiana had summer profiles that were larger than their corresponding winter profiles. In comparing anthropogenic heating profiles, however, it was generally found that summertime anthropogenic heating profiles have a common shape regardless of the underlying climate.

To determine if representative profiles could be used to represent anthropogenic heating, we undertook a two-stage (hierarchical average-linkage, followed by non-hierarchical k-means) cluster analysis on non-dimensionalized profiles for the 61 U.S. cities. This non-dimensionalization is accomplished by setting the hourly maximum value of Q_f for each city as characterized in Eq. (1). Clustering of representative summer (July) profiles resulted in all profiles falling into one cluster. This suggests that, provided a city-scale multiplying factor can be determined, a single non-dimensional profile function can be used to represent summertime anthropogenic heating in U.S. cities. Fig. 2a presents a box plot of non-dimensional summer (July) profiles for all cities.

Wintertime profiles, however, show more dependence on climatic region. Fig. 2b presents the results of a cluster analysis of winter profiles. Two clusters of profiles resulted, one for cities with cold winter climates and one for cities with warm winter climates. This suggests that it is reasonable to define two non-dimensional profiles for anthropogenic heating in winter—one that applies to warmer cities, and one for colder cities. As shown by the non-dimensional profiles in Fig. 2b, cold climate cities have relatively higher nocturnal heating, a larger morning peak, and less variability during the day. Those cities that fell within a cold winter Q_f

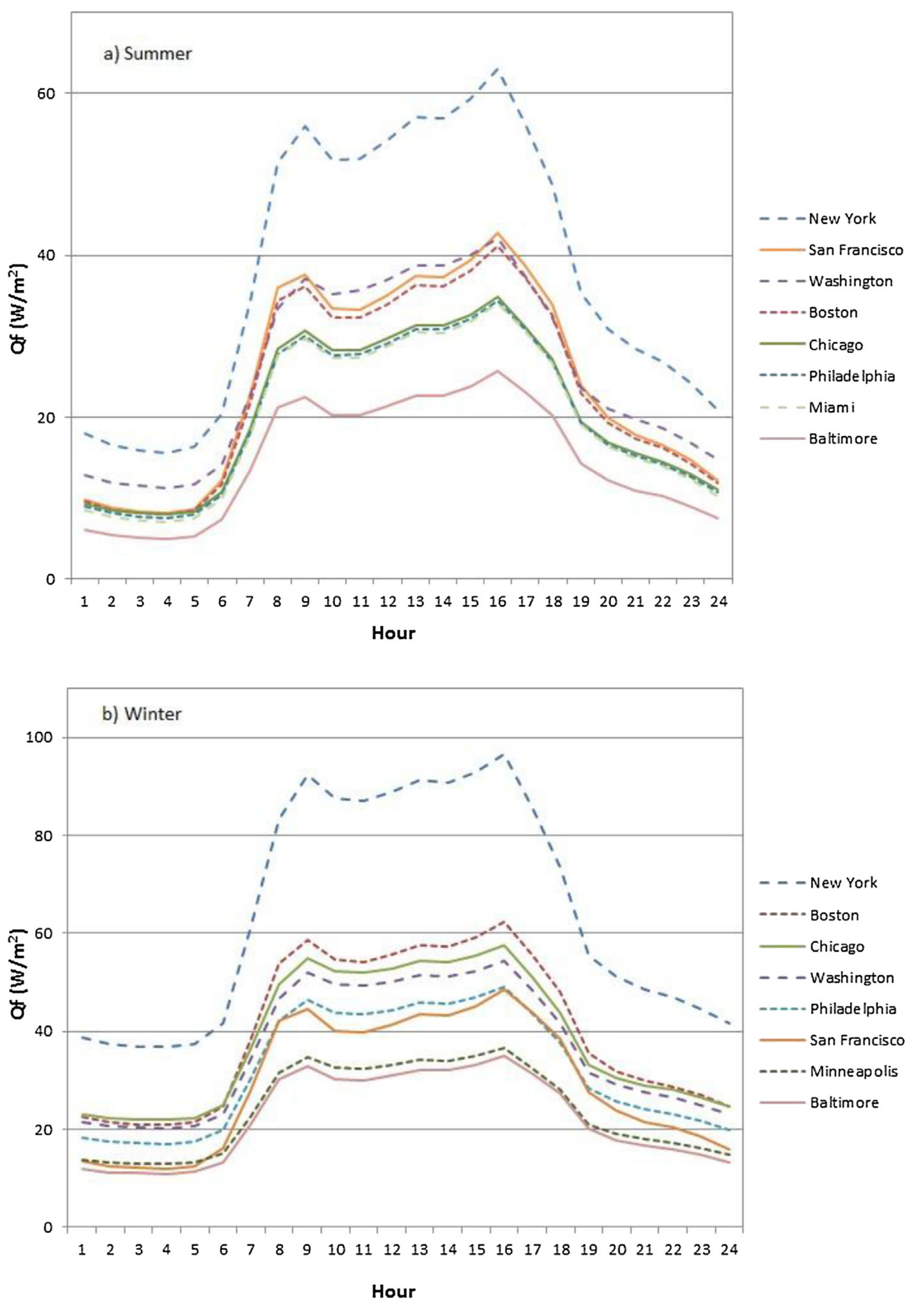

Fig. 3. January diurnal profiles for the 8 U.S. cities with the largest anthropogenic heating magnitude for (a) summer, and (b) winter.

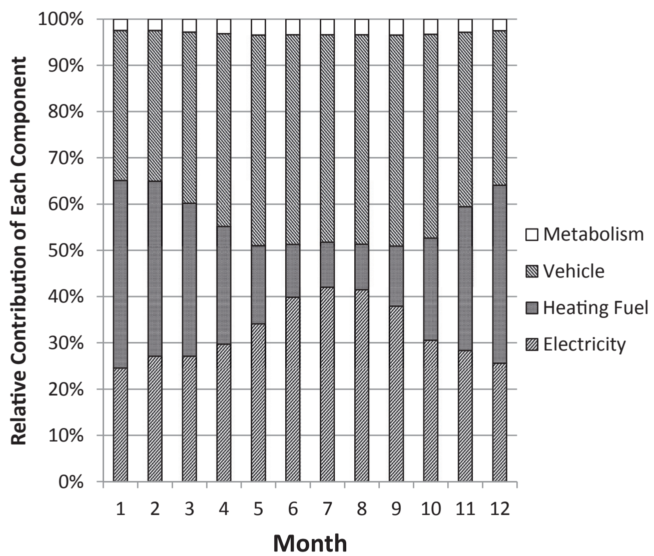

Fig. 4. Relative contribution of each component to anthropogenic heating, averaged over all cities for each month.

Table 4
Coefficients for regression models (Eqs. (5) and (6)) for seasonal maximum anthropogenic heating results for all 61 cities.

Month	β_0	β_1	β_2	RMSE (W/m^2)	R^2
Winter	−6.638	0.010	0.009	3.94	0.94
Spring	−0.160	0.007	0.007	2.84	0.95
Summer	2.554	0.000	0.007	2.89	0.94
Autumn	0.618	0.006	0.007	2.70	0.95

profile could be classified as cities with total annual HDD >4000 °C-days. Table 2 presents profile characteristics that can be used in conjunction with maximum Q_f values listed in Table 3, depending upon whether the city is classified as a warm or cold winter climate (e.g., HDD > 4000 °C-days). The summer and winter multipliers used in these tables are for July and January, respectively.

Results for the 8 cities with the largest summer and winter anthropogenic heating profiles are illustrated in Fig. 3. New York tops the list in both seasons with a peak magnitude of 93.0 W/m^2 in winter and 63 W/m^2 in summer. As mentioned earlier, the illustrated profiles are presented at city-scale. Focusing in at finer resolution, for example the census tract within the central business district, it is reasonable to expect the local magnitude to increase by a factor of 10–20, but that at the same time the vertical height over which this heat is released increases according to building height (Sailor and Lu, 2004). Likewise, as the scale of analysis becomes coarser, the magnitude of the anthropogenic heating diminishes. We found that magnitudes at the city scale are typically a factor of 10–20 larger than those at the metropolitan scale (average factor for the 61 cities examined here was ~17). This is a direct consequence of the higher population densities at the city scale.

It is also instructive to consider the relative contribution that each component makes to the total anthropogenic heating profile, and to do so, we have calculated the relative contribution of vehicles, electricity, heating fuels, and metabolism to the monthly anthropogenic heat emissions for each city. Fig. 4 presents this comparison summed across all cities. As would be expected, the heating fuel contribution is largest in winter (months 1, 2, and 12) and smallest in summer (months 6–8). The electricity sector anthropogenic heating contribution is largest in summer and smallest in winter. However, since electricity is also used for heating (electric resistance heaters and fan power for air distribution), the variation between summer and winter electricity use is less than it is for heating fuels. Monthly magnitudes for waste heat emissions from vehicles and metabolism (averaged for all cities) are constant throughout the year in our analysis at 3.85 and 0.29 W/m^2, respectively. Nevertheless, the relative contributions from the vehicle sector and metabolism increase in summer since the total anthropogenic heating is largest in winter. Specifically, averaged across all cities, the daily average values of total anthropogenic heating peak at 11.87 W/m^2 in January and are at a minimum value of 8.44 W/m^2 in September.

4.1. Estimation process for other U.S. cities

In order to automate the profile generation process we restricted ourselves to analysis of cities for which necessary data were readily available. Because the underlying method relies heavily on a population density formulation and is climate-dependent, it is reasonable to consider the prospect of developing a multiple parameter regression model to estimate the profiles. Once such a model is developed it can then be applied to any city not previously modeled. Before proceeding, however, it is important to note that this process is inherently tied to the underlying

Table 5
Per capita annual energy consumption ratios (f_{ec}) of various countries relative to that of the U.S. 2010 values have been used (source: IEA, 2010a, 2010b). Data are separated by country membership in the Organisation for Economic Co-operation and Development (OECD).

	Country	Relative energy consumption rates f_{ec} (see Eq. (7))
Selected OECD countries	Australia	0.69
	Canada	1.19
	Denmark	0.55
	France	0.51
	Germany	0.57
	Italy	0.44
	Japan	0.51
	Sweden	0.77
	United Kingdom	0.45
	United States	1.00
	Total all OECD	0.61
Selected non-OECD countries	Brazil	0.22
	Indonesia	0.13
	India	0.08
	China	0.23
	Nigeria	0.14
	Total all non-OECD	**0.17**

energy intensity of the U.S. economy.

The results from the 732 individual anthropogenic heating profiles (12 monthly profiles for 61 cities) were analyzed using a stepwise multiple regression analysis to quantify the relative importance of the factors that influence anthropogenic heat, in order to develop a predictive model of maximum Q_f for each season that can be applied to other cities. From the independent variables included in our analyses (HDD, CDD, DVD, population density), a final set of models was determined for each season. The models for winter, spring, and autumn comprised total monthly HDD and population density, whereas the model for summer is reliant on population density alone. The final predictive models are:

$$Q_{fmax}(winter, spring, autumn) = \beta 0 + PopDens^{*}\beta 1 + HDD^{*}\beta 2, \quad (5)$$

$$Q_{fmax}(summer) = \beta 0 + PopDens^{*}\beta 1, \quad (6)$$

where degree day variables are monthly totals in °C-days, based on a threshold temperature of 18.3 °C and PopDens depicts the population density in persons per square kilometer. The seasonal values for the regression coefficients are given in Table 4 along with Root Mean Square Error (RMSE) and R^2 values. The predicted value of maximum Q_f can be applied to the appropriate universal profile to estimate diurnal profiles for each season of the year.

4.2. Non-U.S. city extrapolation

It should be noted that the value of Q_{fmax} arrived at through application of Eqs. (5) and (6), and Table 2, may significantly overestimate anthropogenic heating in cities within other countries where differences in infrastructure, end-use efficiency, and demographics result in lower per capita consumption rates. Therefore a correction factor applied to the results provided by usage of Eqs. (5) and (6) is necessary, to account for the fact that individuals in a non-U.S. city would consume energy at a different rate than their counterparts in similar U.S. climates.

As a first order correction we can compare the ratio of per capita energy consumption in the target country to that in the U.S. The most readily available data for this purpose are raw energy consumption totals that can be converted to equivalent barrels of oil use per person and then non-dimensionalized by dividing by the U.S. consumption rate. Such sample energy consumption values (f_{ec}) are provided in Table 5 for a range of countries. If this ratio represents a suitable correction factor it could be applied as a straightforward multiplier to the value of Q_{fmax} obtained from Eqs. (5) and (6):

$$Q_{fmax}(non - U.S.) = f_{ec}^{*}Q_{fmax}, \quad (7)$$

Table 6 presents Q_{fmax} estimates for a number of countries using this approach and data for the corresponding ratio of energy consumption relative to U.S. consumption rates. The corresponding summer and winter hourly anthropogenic heating profiles for these 13 international cities are plotted in Fig. 5. Absolute differences among the summertime profiles are considerably less relative to the wintertime profiles. For example, the summertime daytime absolute magnitude for Toronto, which displays the greatest absolute values for this season, is about 3–4 times greater than anthropogenic heating for Copenhagen, which displays the least values. During winter, the daytime absolute magnitude for the city displaying the greatest anthropogenic heating (Toronto) is about an order of magnitude greater than the city displaying the least (Jakarta). The daytime wintertime values for Toronto exceed 100 W/m^2, and therefore exceed the values obtained for New York City. This higher value is a product of Canada's per capita energy consumption which in 2010 was 1.19 times greater than the U.S.

The values for Q_{fmax} estimated through this extrapolation process can be compared to similar studies investigating anthropogenic heat emissions for cities across the world. One such study employed the local scale urban consumption of energy (LUCY) model to compare Q_f in cities across a range of latitudes (Allen et al., 2011). Maximum values of heat emission calculated using the LUCY model were overall higher than our extrapolation method (e.g. 577 W/m^2 compared to 93 W/m^2 for New York; 178 W/m^2 compared to 41 W/m^2 for Tokyo). These differences, once again highlight the importance of scale when estimating urban anthropogenic heat emissions. The profiles presented in the current study were produced using city-scale data (with an added correction for energy consumption for non-U.S. cities), whereas the Q_{fmax} values estimated in Allen et al. (2011) come from the highest individual 2.5' × 2.5′ grid cell within a city and therefore highlights regions of the city with a higher magnitude of heat emissions. The issue of spatial resolution is also highlighted in Lindberg et al. (2013) where annual average Q_f across London is calculated using the LUCY model for spatial resolutions ranging from 30″ to 10′. Results from those simulations show a clear relationship between spatial averaging and maximum values of Q_f. There are also differences in methodology that preclude a direct comparison, for example: Q_f was calculated for the months of February and August in the LUCY study, compared to January and July for the current study, and the current study includes a daytime population increase factor, whereas population densities used in LUCY are purely residential.

Table 6
Estimated winter and summertime Q_{fmax} for a selection of cities calculated from Eqs. (5)–(7) and f_{ec}. Degree data are from 2010. Total monthly HDD data are for January or July, depending on hemisphere.

Country	City	Total annual HDD	Total monthly winter HDD	Population density (pers/km^2)	Maximum Q_f summer (W/m^2)	Maximum Q_f winter (W/m^2)
Australia	Sydney	656	185	2100	24.48	21.81
Canada	Toronto	3428	685	2650	53.27	103.26
Denmark	Copenhagen	4305	639	1850	17.19	41.06
France	Paris	2586	516	3550	30.58	39.95
Italy	Rome	1123	314	2950	21.93	23.10
Japan	Tokyo	1633	348	4750	40.92	37.14
Sweden	Stockholm	4627	780	2700	35.12	74.50
UK	London	2681	457	5100	38.77	39.16
Brazil	Sao Paulo	330	29	9000	33.45	17.79
Indonesia	Jakarta	0	0	10500	23.06	11.97
India	Mumbai	0	0	29650	40.07	21.77
China	Shanghai	1633	398	13400	52.06	36.60
Nigeria	Lagos	0	0	18150	42.92	22.96

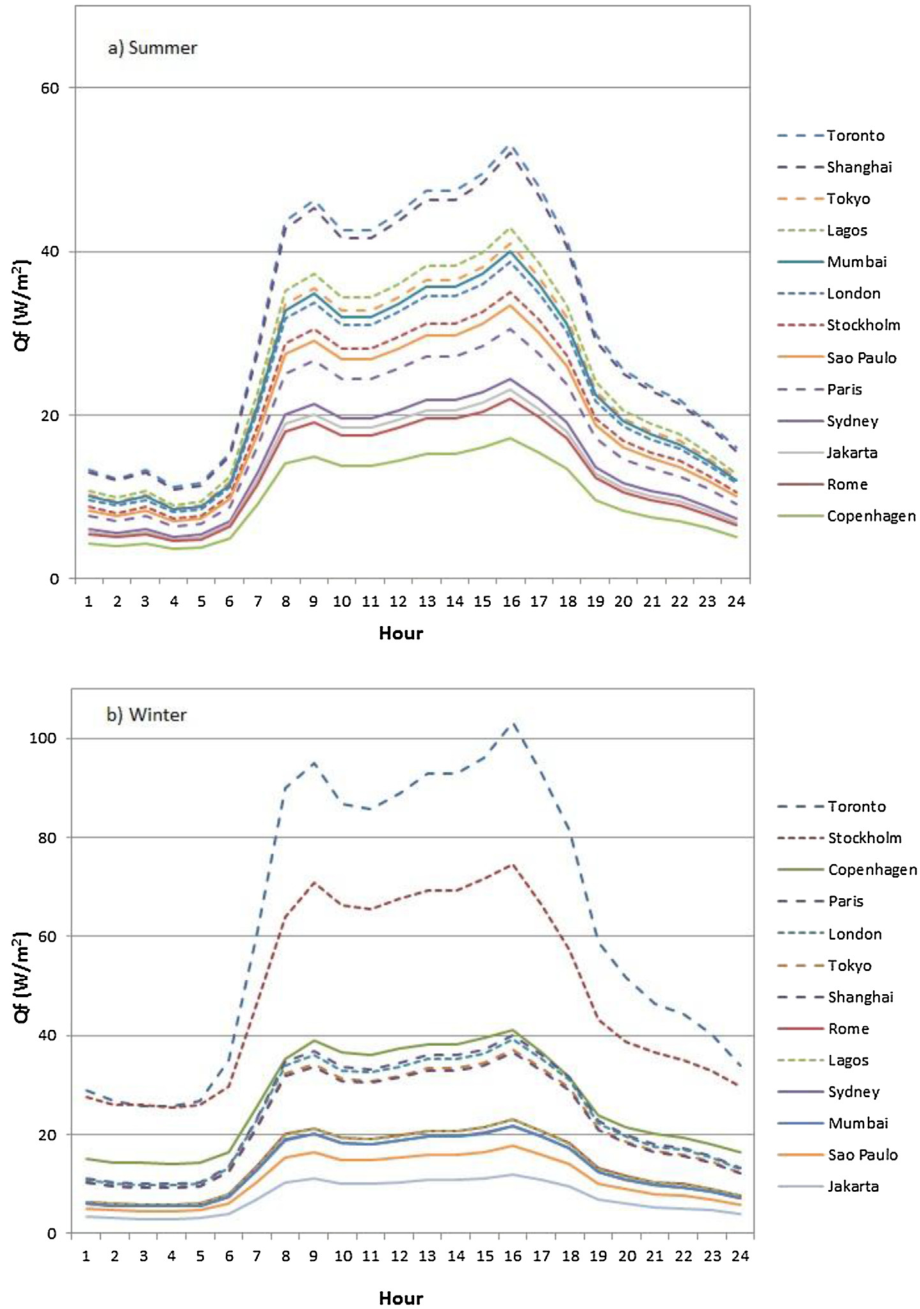

Fig. 5. (a) Summertime diurnal Q_f profiles for selected non-U.S. cities. (b) Wintertime diurnal Q_f profiles for selected non-U.S. cities. Note different axes scales for summer and winter.

5. Conclusions

The anthropogenic heating database developed here (available at geoplan.asu.edu/research-and-outreach/projects/AHdata) represents a valuable tool for urban climate modelers. With the growing use of anthropogenic heating as a source term in the energy budget of urban climate models (Khan and Simpson, 2001; Sailor and Fan, 2004; Feng et al., 2012; Georgescu et al., 2014), there exists an urgent need for easily accessible estimates of anthropogenic heating for large cities around the world. Such a database is especially relevant for large-scale modeling applications where diverse cities, both in terms of local geography and magnitude of anthropogenic heating, are simulated (e.g., Georgescu et al., 2014), and several distinct place-based profiles are necessary throughout the period of model integration.

At the same time it must be cautioned that the profiles developed here rely on a number of assumptions that limit their accuracy and general applicability. Chief among these limitations are (1) the lack of differentiation between workdays and non-workdays; (2) lack of spatial differentiation of the profiles; and (3) potential inaccuracies in the diurnal profile specifications for electricity and heating fuel consumption. The first limitation is relatively easily addressed through detailed analysis of traffic and energy consumption data. The second limitation — that of spatial differentiation can be addressed with readily available census data (as was done by Sailor and Fan (2004) and more recently by Chow et al.

(2014)). Of course, this requires significantly more effort and city-specific analysis. The lack of city-specific detailed energy profiles is believed to introduce relatively little error in the summer. This is based in part on transportation profiles appearing to be relatively similar across the country (Hallenbeck et al., 1997), and the fact that heating fuel consumption is lower in the summer and relatively less sensitive to temperature variability. In the winter, however, heating fuel consumption is highly dependent upon temperatures and may be expected to exhibit larger diurnal variation. Sailor and Lu (2004) have estimated the diurnal variability in winter using logarithmic models relating heating fuel consumption to temperature. The models were developed using monthly data, but applied to diurnal variations in temperature. While this approach has its place, it introduces uncertainty that is not easily estimated due to the lack of detailed data. We are currently addressing this issue through a bottom-up analysis approach in which we model hourly energy consumption of a representative suite of prototypical commercial and residential buildings. This analysis may lead to more realistic diurnal profiles of heating fuel consumption that can be applied in the automated approach used for the anthropogenic heating database project. It is also important to note that at the present time the correction algorithm suggested by Eq. (7) for cities outside the U.S. is preliminary and has yet to be validated. Nevertheless, it represents a reasonable method for scaling initial estimates of anthropogenic heating and hence makes the results of the anthropogenic heating database project widely applicable to cities around the world. At the present time a simplified software tool is being developed to allow researchers to implement the results of this study for any city of interest. Finally, although the data presented here has more immediate applicability for those in the modeling community whose urban representation consists of a single class (e.g., as available from the Moderate Resolution Imaging Spectroradiometer) we caution against the direct inclusion of the Q_f profiles developed in this manuscript into urban canopy models utilizing a multi-class urban representation (e.g., see Fig. 1). Therefore, users are urged to scale the city-specific data provided here appropriately, accounting for each urban land use class (e.g., Grossman-Clarke et al., 2005) utilizing readily available classification data (in the U.S. such detailed classifications are available from the National Land Cover Database; Fry et al., 2011) as well as class-dependent parameters from the equations presented earlier.

The development of the rich set of seasonally and diurnally varying anthropogenic heating profiles presented here serve as a fundamental step forward in the continued investigation of urban impacts on meteorology and climate, on air quality and energy demand, and on the livelihoods of the many millions of inhabitants moving into urban areas within the U.S. and globally. Accurate representation of physical urban-atmosphere processes, within state-of-the-art modeling systems, under contemporary climate is necessary given projected changes of the urban landscape and continued emissions of long-lived greenhouse gases. Therefore, strategic consideration of land-based adaptation and/or mitigation approaches fundamentally relies on the utility of applicable and reliant tools incorporating accurate and timely data.

Acknowledgments

The authors wish to acknowledge Barrett, The Honors College at Arizona State University for their support of JM Milne through his senior thesis project. MG was supported by National Science Foundation Grants EAR-1204774 and DMS-1419593, and U.S. Department of Agriculture NIFA grant 2015-67003-23508. The original methodological development (DJS and MAH) was supported by National Science Foundation Grant BCS-0410103.

References

Allen, L., Lingberg, F., Grimmond, C.S.B., 2011. Global to city scale urban anthropogenic heat flux: model and variability. Int. J. Climatol. 31, 1990–2005.

Arguez, A., Durre, I., Applequist, S., Vose, R.S., Squires, M.F., Yin, X., Heim, R.R.J., Owen, T.W., 2012. NOAA's 1981-2010 U.S. climate normals. Bull. Am. Meteorol. Soc. 92 (11), 1687–1697.

Bureau of Transportation Statistics, 2003. Census Transportation Planning Package. U.S. Department of Transporation, Bureau of Transportation Statistics.

Chow, W.T., Salamanca, F., Georgescu, M., Mahalov, A., Milne, J.M., Ruddell, B.L., 2014. A multi-method and multi-scale approach for estimating city-wide anthropogenic heat fluxes. Atmos. Environ. 99, 64–76. http://dx.doi.org/10.1016/j.atmosenv.2014.09.053.

Energy Information Administration, 2010a. Electric power monthly. In: Energy Information Administration. U.S. Department of Energy, Washington DC.

Energy Information Administration, 2010b. Natural Gas monthly. In: Energy Information Administration. U.S. Department of Energy, Washington DC.

Fan, H., Sailor, D.J., 2005. Modeling the impacts of anthropogenic heating on the urban climate of philadelphia: a comparison of implementations in two PBL schemes. Atmos. Environ. 39 (1), 73–84.

Feng, J.M., Wang, Y.L., Ma, Z.G., Liu, Y.H., 2012. Simulating the regional impacts of urbanization and anthropogenic heat release on climate across China. J. Clim. 25 (20), 7187–7203.

Flanner, M.G., 2009. Integrating anthropogenic heat flux with global climate models. Geophys. Res. Lett. 36 (2), L02801.

Fry, J., et al., 2011. Completion of the 2006 national land cover database for the conterminous United States. Photogramm. Eng. Remote Sens. 77 (9), 858–864.

Georgescu, M., Morefield, P.E., Bierwagen, B.G., Weaver, C.P., 2014. Urban adaptation can roll back warming of emerging megapolitan regions. Proc. Natl. Acad. Sci. 111 (8), 2909–2914. http://dx.doi.org/10.1073/pnas.1322280111.

Grossman-Clarke, S., Zehnder, J.A., Stefanov, W.L., Liu, Y., Zoldak, M.A., 2005. Urban modifications in a mesoscale meteorological model and the effects on near-surface variables in an arid metropolitan region. J. Appl. Meteorol. 44, 1281–1297. http://dx.doi.org/10.1175/JAM2286.1.

Hallenbeck, M., Rice, M., Smith, B., Cornell-Martinez, C., Wilkinson, J., 1997. Vehicle Volume Distribution by Classification. Washington State Transportation Center. University of Washington, Seattle WA 98105, Seattle, p. 54, 1107 NE 45th St. Suite 535. http://depts.washington.edu/trac.

Holt, T., Pullen, J., 2007. Urban canopy modeling of the New York City metropolitan area: a comparison and validation of single- and multilayer parameterizations. Mon. Weather Rev. 135, 1906–1930.

Ichinose, T., Shimodozono, K., Hanaki, K., 1999. Impact of anthropogenic heat on urban climate in Tokyo. Atmos. Environ. 33, 3897–3909.

IEA, 2010a. Energy Balances of Non-OECD Countries 2010. International Energy Agency. OECD Publishing, Paris, p. 554. http://dx.doi.org/10.1787/energy_bal_non-oecd-2010-en-fr.

IEA, 2010b. Energy Balances of Non-OECD Countries 2010. International Energy Agency. OECD Publishing, Paris, p. 350. http://dx.doi.org/10.1787/energy_bal_oecd-2010-en-fr.

Khan, S.M., Simpson, R.W., 2001. Effect of heat island on the meteorology of a complex urban airshed. Bound. Layer Meteorol. 100 (3), 487–506.

Klysik, K., 1996. Spatial and seasonal distribution of anthropogenic heat emissions in Lodz, Poland. Atmos. Environ. 30 (20), 3397–3404.

Lee, S.-H., McKeen, S.A., Sailor, D.J., 2014. A regression approach for estimation of anthropogenic heat flux based on a bottom-up air pollutant emission database. Atmos. Environ. 95, 629–633.

Lin, C.-Y., Chen, F., Huang, J.C., Chen, W.-C., Liou, Y.-A., Chen, W.-N., Liu, S.-C., 2008. Urban heat island effect and its impact on boundary layer development and land-sea circulation over northern Taiwan. Atmos. Environ. 42, 5635–5649.

Lindberg, F., Grimmond, C.S.B., Yogeswaran, N., Kotthaus, S., Allen, L., 2013. Impacts of city changes and weather on anthropogenic heat flux in Europe 1995–2015. Urban Clim. 4, 1–15.

NCDC, 2010a. Historical Climatology Series 5-1: Monthly State, Regional, and National Heating Degree Days Weighted by Population. National Climatic Data Center, Asheville, NC.

NCDC, 2010b. Historical Climatology Series 5-2: Monthly State, Regional, and National Cooling Degree Days Weighted by Population. National Climatic Data Center, Asheville, NC.

Sailor, D.J., Lu, L., Fan, H., 2003. Estimating urban anthropogenic heating profiles and their implications for heat island development. In: Fifth International Conference on Urban Climate, Lodz, Poland.

Sailor, D.J., Lu, L., 2004. A top-down methodology for developing diurnal and seasonal anthropogenic heating profiles for urban areas. Atmos. Environ. 38 (17), 2737–2748.

Sailor, D.J., Fan, H., 2004. The importance of including anthropogenic heating in mesoscale modeling of the urban heat island. In: AMS (Ed.), 84th Annual Meeting of the AMS, Symposium on Planning, Nowcasting, and Forecasting in the Urban Zone, Seattle.

Sailor, D.J., Vasireddy, C., 2006. Correcting aggregate energy consumption data to account for variability in local weather. Environ. Model. Softw. 21 (5), 733–738.

Salamanca, F., Georgescu, M., Mahalov, A., Moustaoui, M., Wang, M., 2014. Anthropogenic heating of the urban environment due to air conditioning. J. Geophys. Res. Atmos. 119, 5949–5965. http://dx.doi.org/10.1002/2013JD021225.

Salamanca, F., Martilli, A., Yague, C., 2012. A numerical study of the urban heat island over Madrid during the DESIREX (2008) campaign with WRF and an evaluation of simple mitigation strategies. Int. J. Climatol. 32, 2372–2386.

Stewart, I.D., Oke, T.R., 2012. Local climate zones for urban temperature studies. Bull. Am. Meteorol. Soc. 93, 1879–1900. http://dx.doi.org/10.1175/BAMS-D-11-00019.1.

United States Department of Transportation (USDoT), 2011. Monthly Motor Fuel Reported by States. U.S. Department of Transportation, Federal Highway Administration.

United States Department of Transportation (USDoT), 2013. Urbanized Areas – 2010: Miles and Daily Vehicle-Miles of Travel. Federal Highway Administration, U.S. Department of Transportation.