5.6 AN ANTHROPOGENIC HEATING DATABASE FOR MAJOR US CITIES

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1. INTRODUCTION

Anthropogenic heating is an important but often ignored component of the urban energy budget, with potentially significant ramifications for modeling urban climate and air quality. Diurnal profiles of anthropogenic heating are not commonly available, however, making it difficult to account for anthropogenic heat release in analyses of the urban environment. To address the growing need for such profiles we have applied a published top-down methodology to develop representative month-specific anthropogenic heating profiles for 61 large US 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 (US Department of Transportation), the Energy Information Administration (US Department of Energy), the National Climatic Data Center (US Department of Commerce), and the Urban Transportation Planning Package (US Census). For each urban area we have calculated diurnal profiles for two spatial scales - city scale, and greater metropolitan area. Details of all profiles will be made available on our website (www.fuse.pdx.edu). For presentation purposes, however, we will summarize only the city-scale results here.

2. OVERVIEW OF METHODOLOGY

There are two fundamental approaches to estimating diurnal profiles of anthropogenic heating. Starting at the neighborhood scale one approach is to monitor energy consumption of individual buildings and to use roadway traffic count 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 an entire city. The other approach is to start with coarser resolution data – in time and space – and scale as needed to estimate anthropogenic heating profiles at finer scales. This latter approach is particularly useful for the present work where the goal is to produce detailed anthropogenic heating profiles for many cities using a standardized approach.

The actual method used in this study to create anthropogenic heating profiles 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 anthropogenic heating is divided into three components representing the major sources of waste heat in the urban environment:

$$Qf = Q_V + Q_B + Q_M \qquad (1)$$

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 population. Analyses of detailed population data from the US Census (BTS, 2003) suggest that the daytime urban population is typically 50 to 100% higher than the resident population. In the present study a simple 75% daytime increase factor was assumed for city-scale analyses and all population data were obtained directly from the resident population data available from the US census. At the larger metropolitan scale the daytime increase in population is much smaller and 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 paper (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 the fact that intra-state climate variability leads to differences in per capita

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energy consumption rates for different cities within any particular state. While city-scale energy data are not commonly available we have found 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, 2005). 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 as many US cities as possible. The availability of data ultimately limited the selection of available cities to 61 of the largest US cities. The selected cities, resident population density data (persons per square meter), and daily vehicle distance estimates are given in Table 1. This table also presents a summary of the maximum hourly winter and summer values of anthropogenic heating as described later in this paper.

3.1 Weather Data

The National Climatic Data Center 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 (NCDC, 2004a; NCDC, 2004b). For the city-level degree day data we accessed the station normals database (NCDC, 2001). These data were downloaded by year from www.cpc.ncep.noaa.gov in a *preliminary* form. This database allows evaluation of monthly deviations from the monthly normals of heating and cooling degree days. From these resources we extracted the year 2000 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 very small component (~ 2-3%) of the total anthropogenic heating profile. Nevertheless it is readily incorporated in our population density-based methodology. Specifically, the typical US diet consists of 2000 to 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 2-hour linear transition in morning and evening hours) we constructed metabolism profiles for each city.

Table 1. Cities used in the anthropogenic heating database project.

City	State	PopDens (per sq. m)	DVD (km/day)	Maximum Hourly Qf (W/m^2) Winter	Summer
Albuquerque	NM	9.6E-04	46	12.1	8.9
Anchorage	AK	5.9E-05	29	0.7	0.5
Atlanta	GA	1.2E-03	54	18.6	13.2
Austin	TX	1.0E-03	50	11.6	11.2
Bakersfield	CA	8.4E-04	29	6.2	6.0
Baltimore	MD	3.1E-03	34	36.6	24.7
Birmingham	AL	6.3E-04	56	8.3	7.4
Boston	MA	4.7E-03	33	47.5	31.7
Buffalo	NY	2.8E-03	31	30.4	20.9
Charlotte	NC	8.6E-04	48	10.2	8.6
Chicago	IL	4.9E-03	33	76.8	37.6
Cincinnati	OH	1.6E-03	45	26.0	15.8
Cleveland	OH	2.4E-03	34	36.7	20.6
Colorado Springs	CO	7.5E-04	29	8.1	5.3
Columbus	OH	1.3E-03	42	20.8	12.4
Corpus Christi	TX	6.9E-04	40	8.3	6.9
Dallas	TX	1.3E-03	50	16.2	14.8
Denver	CO	1.4E-03	36	15.8	10.9
Detroit	MI	2.6E-03	39	39.3	22.5
El Paso	TX	8.7E-04	30	8.7	7.5
Fort Worth	TX	7.1E-04	50	8.6	7.8
Fresno	CA	1.6E-03	34	13.0	11.7
Houston	TX	1.3E-03	59	16.1	15.4
Indianapolis	IN	8.4E-04	52	14.2	9.1
Jacksonville	FL	3.7E-04	46	3.2	3.3
Kansas City	MS	5.4E-04	47	8.7	5.5
Las Vegas	NV	1.6E-03	31	17.7	16.0
Lexington-Fayette	KY	3.5E-04	48	5.9	3.7
Los Angeles	CA	3.0E-03	37	22.6	21.5
Louisville	KY	1.6E-03	45	25.9	16.1
Memphis	TN	9.0E-04	40	10.8	8.8
Miami	FL	3.9E-03	31	25.5	28.5
Milwaukee	WI	2.4E-03	33	34.4	18.5
Minneapolis	MN	2.7E-03	39	41.6	23.8
Nashville-Davidson	TN	4.4E-04	61	6.7	5.2
New Orleans	LA	1.0E-03	23	9.1	8.6
New York	NY	1.0E-02	25	96.3	69.4
Oakland	CA	2.8E-03	36	21.6	19.4
Oklahoma City	OK	3.2E-04	39	4.0	3.0
Omaha	NE	1.3E-03	30	21.1	11.8
Philadelphia	PA	4.3E-03	30	50.4	30.4
Phoenix	AZ	1.1E-03	44	9.2	10.3
Pittsburgh	PA	2.3E-03	37	30.1	18.5
Portland	OR	1.5E-03	38	17.9	12.4
Raleigh	NC	9.3E-04	49	11.2	9.4
Riverside	CA	1.3E-03	39	9.8	10.0
Sacramento	CA	1.6E-03	34	13.5	11.4
Salt Lake City	UT	6.4E-04	40	8.8	5.3
San Antonio	TX	1.1E-03	47	12.1	11.7
San Diego	CA	1.5E-03	38	10.9	10.6
San Francisco	CA	6.4E-03	36	52.0	44.7
San Jose	CA	2.0E-03	38	16.2	14.2
Seattle	WA	2.6E-03	42	33.3	23.7
St. Louis	MO	2.2E-03	46	33.1	22.0
Stockton	CA	1.7E-03	30	13.7	11.7
Tampa	FL	1.0E-03	37	7.6	8.2
Toledo	OH	1.5E-03	38	24.4	13.7
Tucson	AZ	9.7E-04	35	7.5	7.8
Tulsa	OK	8.3E-04	36	10.1	7.7
Washington	DC	3.6E-03	37	57.6	42.2
Wichita	KS	9.8E-04	34	14.1	8.8

3.3 Electricity Data

Utilities within the United States are required to report monthly totals of consumption of electricity (and other fuels) aggregated at the state level. These sector-specific data are archived by the US Department of Energy's Energy Information Administration (EIA, 2003; EIA, 2003). For each state in our analysis these monthly consumption data were obtained, converted to daily per capita consumption, and then 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 that the hourly electricity consumption (E_{BE}) for any city can be written as $E_{BE} = E_{\mathrm{DPC}} \cdot f(hour)$, where

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

In prior work (Sailor and Lu, 2004) we obtained hourly load profile data from a number of independent service operators (ISO). 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, LPG, kerosene, fuel oil). While natural gas (NG) is the dominant heating fuel in the US the contribution 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 in the range of 0.50 to 0.90, depending upon the state and sector. The approach taken here was to scale the 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.

3.5 Transportation Data

Estimation of heat released from vehicles requires detailed hourly profiles of traffic on major and minor roadways throughout a metropolitan area. It is also desirable to have detailed fleet information, including an estimate of the fleet-averaged hourly speed and fuel economy. In past work we had simply estimated that fleet-averaged fuel economy was 20 miles per gallon (~ 8.5 km/liter). We have since updated this estimate to 24.4 mpg (10.4 km/liter) to reflect published estimates from the U.S. EPA (www.fueleconomy.gov).

The U.S. Department of Transportation publishes annual summaries of Daily Vehicle Miles Traveled (DVMT) for major urbanized areas (USDoT, 2003). These data are readily available for 69 US cities with populations greater than 500,000. We subsequently converted these data to per capita daily vehicle distance (DVD) in units of km/person. 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.

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:

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

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

$$EV = \frac{NHC \cdot \rho_{fuel}}{FE} \quad , \qquad (4)$$

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}). If one assumes a mean fuel economy of 10.4 km per liter (~24.4 miles per gallon), typical heat of combustion of 45×10^6 J kg^{-1} , and a nominal fuel density of 0.75 kg l^{-1} , EV takes on a value of 3258 J m^{-1} of vehicle travel. If detailed fleet fuel economy data are available for a particular application, that data could be substituted into the above equation to get a better estimate of EV.

4. RESULTS

The anthropogenic heating database project for US cities represents a compromise between detail and breadth of analysis. In order to facilitate the application of the methodology we implemented it using a spreadsheet approach that allowed for automation of the data input and manipulation processes. The result is a series of spreadsheets with city names in the first column, state names in the second column, and corresponding population, area, traffic, and energy consumption data in the remaining columns. 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. It was immediately recognized that this is far too much data to effectively communicate in a presentation or paper. So, for presentation purposes, we nominally divide the 61 cities into two climate types – cold climate and warm climate cities.

There are two additional modes of accessing the results of this research. Any investigator interested in detailed monthly profiles for one of the 61 cities in this study (listed in Table 1) can find these profiles at our website (www.fuse.pdx.edu). Investigators interested in estimating anthropogenic heating profiles for cities not represented in this list of cities can apply the regression formulae presented in section 4.1, but should carefully consider the caveats contained therein.

As illustrated in Table 1 the vast majority of the cities analyzed had anthropogenic heating profiles that peak in winter. In fact, only 6 cities in the states of Florida, California, and Arizona 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. Wintertime profiles, however, show more dependence on climate region. These effects are illustrated in Fig. 1 which presents a non-dimensional anthropogenic heating profile for 2 representative warm climate cities (Miami FL and Phoenix AZ) and 2 colder climate cities (Chicago IL and Milwaukee WI). This non-dimensionalization is accomplished by dividing the hourly profile values by the maximum value for that city. The individual magnitudes of these profiles vary substantially – Chicago has a peak of 37.6 W/m^2 while the peak in Phoenix is just about 10 W/m^2. The non-dimensional summer profiles, however, vary by less than 2% for the majority of the cities.

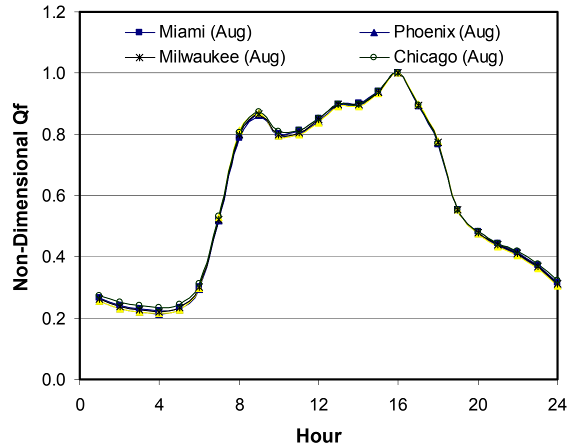

Figure 1. Non dimensional summer anthropogenic heating profiles for a representative sample of cold and warm climate cities.

Anthropogenic heating profiles in winter show more variability depending upon the local climate. As shown by the non-dimensional profiles in Fig. 2 cold climate cities have relatively higher nocturnal heating, a larger morning peak, and less variability during the day.

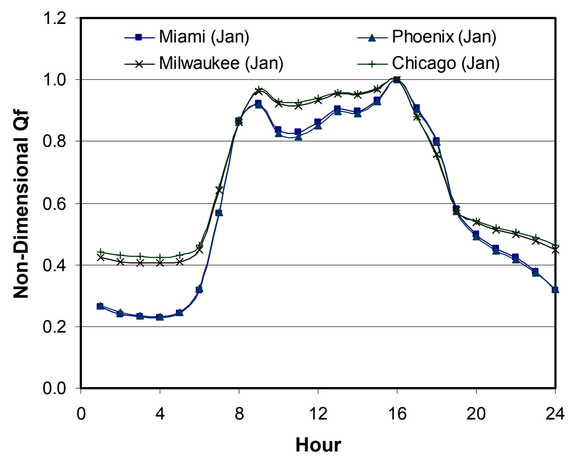

Figure 2. Non dimensional winter anthropogenic heating profiles for a representative sample of cold and warm climate cities.

Results for the 4 cities with the largest winter anthropogenic heating profiles are illustrated in Fig. 3. New York tops the list with a peak magnitude of about 94 W/m^2. It is important to note that these profiles are all at the city-scale. As one focuses in at finer resolutions, say the census tract within the central business district it is reasonable to expect that the local magnitude may increase by a factor of 10 to 20, but that at the same time the vertical height over which this heat is released increases according to building heights

(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 to 20 larger than those at the metropolitan scale (average factor for the 61 cities studied here was ~17). This is a direct consequence of the higher population densities at the city scale.

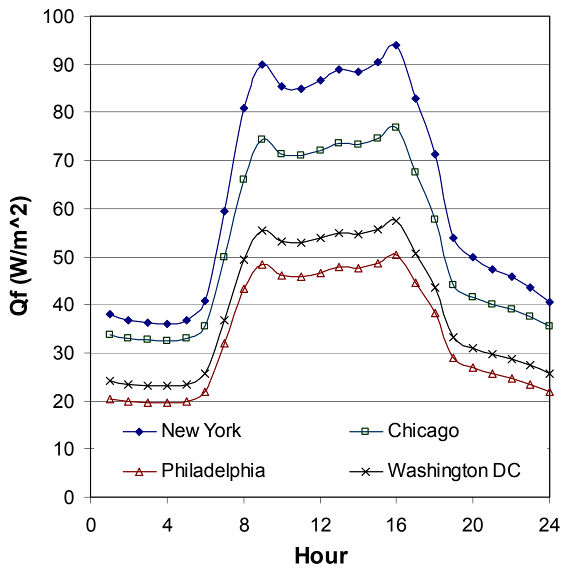

Figure 3. January profiles for the US cities with the largest anthropogenic heating magnitudes.

It is also instructive to consider the relative contribution that each component makes to the total anthropogenic heating profile. To address this point within a limited space we have calculated the relative contribution of vehicles, electricity, heating fuels, and metabolism to the monthly profile for each city. Fig. 4 presents a summary histogram of the average contributions over all 61 cities in the study. As one might expect the contribution from metabolism is small and relatively steady ranging from about 3% in months with little space conditioning demand down to about 2% for months where space conditioning loads are significant. Vehicles represent the dominant component of the heating profile regardless of month ranging from about 38% of the total in winter to about 50% of the total profile in summer. Overall, electricity plays a slightly more important role than heating fuels with heating fuels being more important in winter (November-March) and electricity being more important in the remaining months.

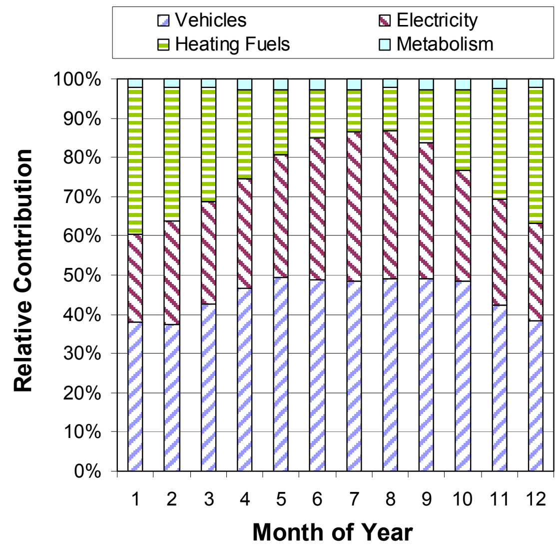

Figure 4. Relative contribution of each component to anthropogenic heating – averaged over all cities.

4.1 Estimation Process for Other Cities

In order to automate the profile generation process we restricted ourselves to analysis of cities for which the necessary data were readily available. Given that the method relies heavily on a population density formulation and is clearly 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 energy intensity of the US economy.

The results from the 732 individual anthropogenic heating profiles were analyzed to develop a regression model that relies on monthly values of heating and cooling degree days and representative values of population density and mean daily vehicle distance traveled per capita. Due to the complexity of the profiles it was decided that each hourly value for a month specific profile would be determined from an independent regression relationship. Hence, the model takes the form:

$$Qf_{hr} = \beta 0 + HDD*\beta 1 + CDD*\beta 2 + PopDens*\beta 3 + DVD*\beta 4 \qquad (5)$$

where the subscript hr refers to the hour of the day, both degree day variables are monthly totals in °C-days, based on a threshold temperature of

18.3 °C, PopDens is persons per square meter and DVD is daily vehicle distance traveled per person in units of km/day. The values for the regression coefficients are given in Table 2 along with Root Mean Square Error (RMSE) and R^2 values.

Table 2. Coefficients for regressions (eqn. 5) through hourly anthropogenic heating results for all 61 cities over 12 months.

Hour	β0	β1	β2	β3	β4	RMSE	R2
1	-3.515	0.013	0.008	2751	0.028	1.93	0.87
2	-3.366	0.013	0.008	2598	0.024	1.92	0.87
3	-3.347	0.013	0.008	2542	0.022	1.91	0.86
4	-3.341	0.013	0.008	2518	0.022	1.92	0.86
5	-3.378	0.013	0.007	2591	0.024	1.92	0.86
6	-3.771	0.013	0.007	3053	0.038	1.95	0.89
7	-5.461	0.016	0.009	4795	0.076	2.55	0.92
8	-7.391	0.020	0.011	6867	0.124	3.20	0.94
9	-8.124	0.023	0.013	7500	0.126	3.69	0.95
10	-7.662	0.023	0.014	6997	0.108	3.64	0.92
11	-7.598	0.023	0.014	6973	0.107	3.63	0.92
12	-7.751	0.022	0.014	7194	0.113	3.65	0.92
13	-7.968	0.022	0.014	7486	0.122	3.67	0.93
14	-7.927	0.022	0.015	7458	0.121	3.66	0.93
15	-8.125	0.022	0.014	7711	0.129	3.67	0.93
16	-8.453	0.022	0.014	8120	0.142	3.72	0.93
17	-7.474	0.019	0.012	7232	0.130	3.24	0.93
18	-6.432	0.016	0.010	6259	0.116	2.76	0.93
19	-4.840	0.013	0.008	4612	0.080	2.17	0.93
20	-4.448	0.013	0.008	4119	0.065	2.11	0.92
21	-4.231	0.013	0.008	3852	0.056	2.08	0.92
22	-4.121	0.013	0.008	3674	0.052	2.04	0.91
23	-3.961	0.013	0.008	3413	0.046	2.00	0.90
24	-3.737	0.013	0.008	3068	0.037	1.96	0.90

4.2 Non-US City Extrapolation

It should be noted that the value of Qf_{hr} arrived at through application of eqn. (5) 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.

What is needed is a correction factor that modifies results of eqn. (5) to account for the fact that individuals in a non US city would consume energy at a different rate than their US counterparts if exposed to identical weather conditions.

As a first order correction we can compare the ratio of per capita energy consumption in the target country to that in the US. 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 US consumption rate. Sample values for f_{ec} are given in Table 3. If this ratio represents a suitable correction factor it could be applied as a straightforward multiplier to the value of Qf obtained from eqn. 5:

$$Qf_{hr}\ (\text{non-US}) = f_{ec} * Qf_{hr} \qquad (6)$$

Table 3. Per capita annual energy consumption ratios of various countries relative to that of the US (source: IEA, 2001).

Country	Relative Energy Consumption Rates f_{ec} (see eqn. 6)
Australia	0.68
Canada	0.98
Denmark	0.44
France	0.51
Germany	0.49
Italy	0.36
Japan	0.49
Sweden	0.68
United Kingdom	0.47
United States	1.00

Unfortunately this approach is only accurate if the underlying climates are similar. As an example, consider the relative energy consumption rate for Canada. According to Table 3 Canadians use 98% as much energy per capita as their US counterparts. While this is true, it must be noted that this similarity in consumption rates is *despite* the fact that Canada as a whole experiences much colder winters than does the US. If the US infrastructure and people were suddenly transplanted into the Canadian climate it is likely that they would consume much more energy than their Canadian counterparts. Thus, a better correction scheme would also employ a weather standardization. In other words the correction factor in eqn. (6) should really represent the energy per capita that would be consumed in the target country if that country were exposed to US weather conditions. So, in cases of countries in mild climates the use of Table 3 is likely to overcorrect – and underestimate Qf. In cases of countries in harsher climates – either subject to intense summer heat, or extreme cold in winter Table 3 will likely undercorrect – and overestimate Qf.

5. CONCLUSIONS

The anthropogenic heating database developed here 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), there is an urgent need for easily accessible estimates of anthropogenic heating for large cities around the world. 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) 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 in Sailor and Fan, (2004)). 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 due in part to the fact that the electricity consumption profiles have been shown 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 variations. In the winter, however, heating fuel consumption is highly dependent upon temperatures and may be expected to exhibit larger diurnal variation. In Sailor and Lu, (2004) we estimated this 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 significant 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 eqn. (6) for cities outside the US is preliminary and has not been 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. This tool will be made available along with the detailed anthropogenic heating database spreadsheet results at the authors' web site (www.fuse.pdx.edu).

Acknowledgements

The authors wish to acknowledge partial support of this effort from the National Science Foundation under Grant No. (0410103) and NASA under Grant No. NNG05GH96G. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation or NASA. Funding from these agencies assisted in the development of the underlying methods and data resources that facilitated the development of the database.

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