Energy and Buildings 77 (2014) 171–179

Contents lists available at ScienceDirect

Energy and Buildings

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

Urban heat island effect on energy application studies of office buildings

Yuming Sun*, Godfried Augenbroe

College of Architecture, Georgia Institute of Technology, 245 4th St. NW, Atlanta, GA 30332, USA

ARTICLE INFO

Article history:
Received 16 April 2013
Received in revised form 20 March 2014
Accepted 24 March 2014
Available online 1 April 2014

Keywords:
Urban heat island
Building energy simulation
Energy savings analysis

ABSTRACT

Because of the urban heat island (UHI) effect a metropolitan area is typically warmer than its surrounding rural area. This has led to a growing concern that the use of standard (mostly rural) weather data leads to inadequate decision-making with regard to the energy efficiency of buildings in metropolitan areas. This paper conducts a series of computational studies that explore the UHI effect on two routine applications of building energy simulation: (1) predicting the magnitude of energy use and (2) predicting energy savings. We present the results based on case studies of office buildings in 15 representative cities across different climate zones in the U.S. The results show that the UHI considerably modifies the urban climate measured by cooling and heating degree days. As a consequence, ignorance of the UHI effect remarkably underestimates building total energy use in hot climate zones where cooling energy use is dominant, yet causes overestimation in cold climate zones where heating energy use is prevalent. In mild climate zones, the UHI effect only has a moderate effect because the effects on cooling and heating mostly average out. When building simulation is used to assess energy savings that is measured as the ratio to the corresponding baseline such as in a comparative analysis of retrofit measures, the UHI effect is less of a factor.

1. Introduction

By the year 2010, 50% of the population of the world and 79% of that of the United States were living in urban areas, and this percentage is projected to grow in the future [1]. Because built-up areas have distinctly different characteristics compared to natural surfaces, urban climates could be distinctly different from the original natural environment. One of the most well-studied urban climate modifications caused by anthropogenic activities is the urban heat island (UHI). Many literature sources have confirmed that the UHI is strongly correlated with urban land use [2] and that the magnitude of the UHI increases during the urbanization process [3,4]. Arnfield [5] provided a review on the studies of the UHI effect with a broad geographic scope.

Computer models have been advocated to understand and quantify the UHI in various weather and land-use conditions [6]. Among these models, the Town Energy Budget (TEB) model and the Interaction Soil–Biosphere–Atmosphere (ISBA) model are well-established and validated against measurements by many studies [6–11]. Hence the TEB and ISBA model (TEB–ISBA) are used as part of our computational study, with the objective to simulate the UHI under different combinations of built-up surfaces and vegetation covers. We describe the models in more detail in Section 2.

As a consequence of the UHI, many studies worldwide indicate that buildings in urban areas consume more energy for cooling but less energy for heating than the rural counterparts [12–15]. In London, one study [12] showed that buildings in rural environments demanded 16% less cooling energy than similar buildings in urban environments during a typical hot week. Another study [15] showed that compared with rural buildings urban ones consumed 25% more energy for cooling while they used 22% less energy for heating. In Tokyo, a study [14] indicated that mitigating the UHI magnitude by merely 0.2 to 1.2 °C in the summer would reduce cooling energy consumption by 4% to 40%. Thus, it has been noticed that using standardized (mostly rural) weather data for the design of a building and its building systems is not adequate if it is situated in a dense urban environment.

Building energy simulation is extensively used with two major purposes: (1) predicting the magnitude of operational energy use and corresponding greenhouse gas emissions, and (2) predicting the savings from novel architectural design or energy-efficiency technologies over a given baseline. In either case appropriate weather data is crucial to the accuracy of the computational outcomes. Typical meteorological years (TMY) are widely used, which

* Corresponding author. Tel.: +1 303 588 9246.
E-mail address: yumingsun@gatech.edu (Y. Sun).

http://dx.doi.org/10.1016/j.enbuild.2014.03.055
0378-7788/

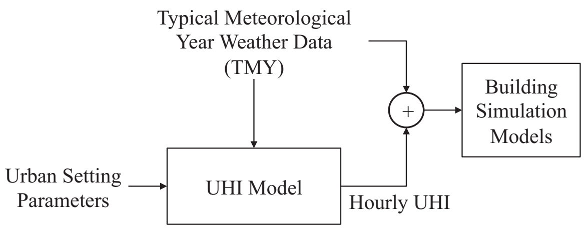

Fig. 1. Modification of TMY data by modeled hourly UHI magnitudes.

is derived from weather data collected in meteorological stations. Because the data collection station is usually located in rural environments, simulation results of urban buildings based on the TMYs can considerably deviate from the actual ones. There are many reasons why this performance gap occurs, but in this paper we aim to single out the cause of the UHI effect, all other things being equal. Building simulation studies [16] have revealed that energy predictions using TMY data without taking the UHI into account remarkably underestimate both energy consumption and peak power for cooling. To overcome this, one study [17] proposed to modify the TMY weather file to account for the UHI effect. They found that using the modified TMY weather increased overall energy consumption of air-conditioning by over 10% in both office buildings and residential apartments.

Previous studies worldwide indicated that the UHI was a significant factor to both building cooling and heating energy consumption and the magnitude of its impact depended on a variety of factors from both climate conditions and building characteristics. Most of the results were reported through cases at the individual building scale in a given climate location. Thus, there is limited work that explores the UHI effect across broader geographical areas that cover different climates such as the United States nationwide. Although it is well known that the UHI leads to an increase in cooling cost and a decrease in heating cost, it needs more work to understand when the effect is most significant if the total energy cost is of one's primary interest. Additionally, the magnitude of the UHI has a certain spatial variation in metropolitan areas so it is worthy to explore the UHI effect in locations of different urban densities. More importantly, we have seen few studies that scrutinized the impact of the UHI on the second use of building simulation, i.e., to predict energy savings as the result of an intervention, such as the planned deployment of energy efficiency technologies. For example, ASHRAE's new building energy code 90.1-2010 targets a decrease in energy consumption by 30% in comparison with the baseline as defined by ASHRAE, 90.1-2004. The question arises then whether proof of obtaining this saving percentage requires the inclusion of UHI in the simulation. Another instance is in comparing energy improvements from retrofit alternatives. This type of application may not need accurate predictions of the magnitudes of absolute energy consumption, but needs to accurately identify the relative change in energy use after improvements to the building.

The objective of this paper is to quantify the UHI effect on two types of energy application studies across 15 climate zones in the United States. The rest of this paper is organized as follows. Section 2 presents the methodology. Section 3 presents the results. Finally, we summarize and conclude in Section 4.

2. Methodology

Fig. 1 shows the procedure of this study. We use the TEB–ISBA model to generate hourly UHI magnitudes in various urban environments, which are characterized by urban setting parameters. The results lead to a modification of the rural TMY weather data used in the building simulation model, in our study EnergyPlus, to derive building cooling and heating energy consumption.

Table 1
Climate zones and representative cities in the U.S.

Climate zones	Representative cities
1A: very hot, humid	Miami, Florida
2A: hot, humid	Houston, Texas
2B: hot, dry	Phoenix, Arizona
3A: warm, humid	Memphis, Tennessee
3B: warm, dry	El Paso, Texas
3C: warm, marine	San Francisco, California
4A: mixed, humid	Baltimore, Maryland
4B: mixed, dry	Albuquerque, New Mexico
4C: mixed, marine	Salem, Oregon
5A: cool, humid	Chicago, Illinois
5B: cool, dry	Boise, Idaho
6A: cold, humid	Burlington, Vermont
6B: cold, dry	Helena, Montana
7: very cold	Duluth, Minnesota
8: subarctic	Fairbanks, Alaska

2.1. Modeled weather files

This study models the UHI in various urban settings, with the aim to generate modified TMY weather files that reflect the UHI effect in any urban setting.

2.1.1. Climate zones

The entire United States is divided into eight temperature-oriented climate zones based on heating degree days (HDDs) and cooling degree days (CDDs) used by the International Energy Conservation Code and ASHRAE. Each zone can also be further divided into three moisture-oriented regions. 15 specific cities in the U.S. listed in Table 1 are selected as representatives of different climate zones based on ASHRAE Standard 90.1.

2.1.2. Urban parameter settings

Another issue of UHI modeling pertains to a representation of urban density. To that end we use an urban parameterization by which complex three-dimensional urban surroundings are approximated by parameterized regular urban layouts. Fig. 2 shows the urban parameterization schema in which all buildings are identical and homogeneously distributed over a regular grid with varying urban density. This parameterization enables a three-dimensional urban layout to be characterized by a two-dimensional urban canyon with four geometric parameters: (1) canyon height H, (2) canyon aspect ratio H/W, (3) coverage of vegetation α_{veg}, and (4) coverage of buildings α_{bld}. Even though this urban parameterization largely decreases the complexity of urban form, it can still capture the three-dimensional characteristics necessary for the UHI effect [18]. In fact, the urban canyon is the mostly used representation for urban-scale climate modeling, which can yield a spatial resolution of a few hundred meters [7,19]. For the urban parameter settings, we utilize a dataset [20] that includes urban topologies and building physical characteristics across 33 regions in the world and subdivides urban areas into four categories according to urban density as follows: tall-building districts, and high-, medium-, and low-density cities. In total, this dataset consists of 125 instances.

In ASHRAE fundamentals [21], inland built environments are categorized into three terrain types (i.e., large city centers, urban and suburban areas, open country) to initially account for the variations of wind speed in different sites. Since the building simulation community is familiar with this categorization, this paper intends to analyze whether this categorization is significant to account for the UHI effect within metropolitan regions. Compared with the four categorizations in the dataset, we find that the tall building

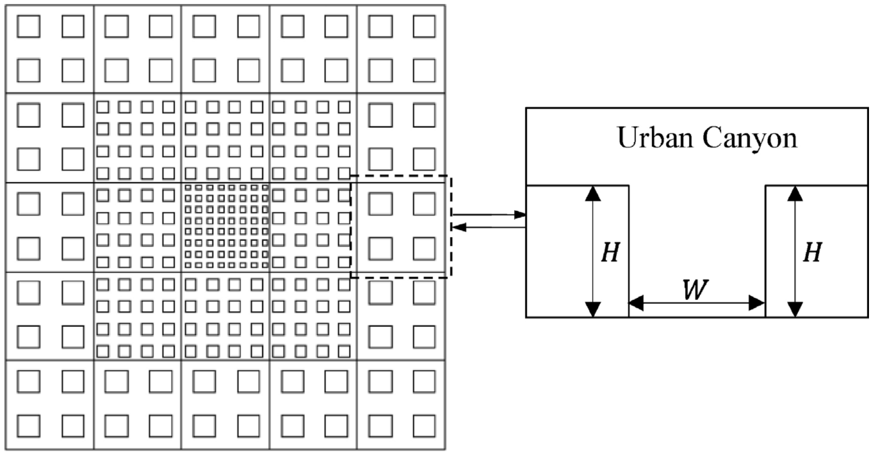

Fig. 2. Urban parameterization schema.

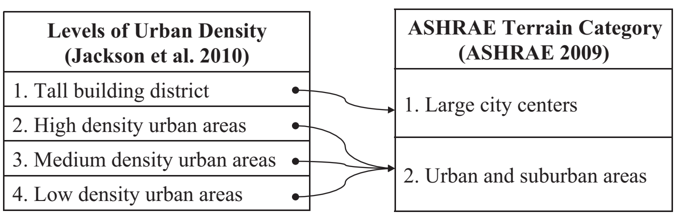

Fig. 3. Mapping from different levels of urban density to ASHRAE terrain category.

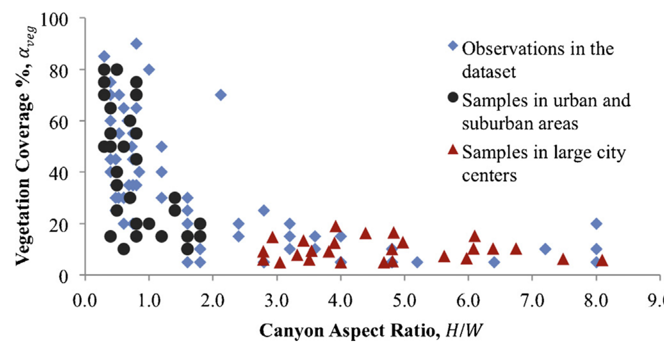

Fig. 4. Plots of observations in the dataset and generated samples within two terrain types.

districts are equivalent to large city centers, and the other three types (i.e., high, medium, and low urban densities) are equivalent to urban and suburban areas. Fig. 3 shows the mapping from the dataset to the ASHRAE terrain categorization. We obtain 26 and 99 instances in large city centers and urban and suburban areas, respectively. These instances are then used to explore the parameter spaces of the urban settings in two terrain types. We focus on urban geometric parameters consisting of H, H/W, α_{bld}, and α_{veg}, while leaving the other urban parameters constant (e.g., material thermal properties). The reasons are as follows: (1) urban geometry has the most significant impact on UHI [22,23]; (2) variations in the other parameters are relatively small. Therefore, the other parameters (other than the four mentioned urban setting parameters) are defined based on a typical city in the U.S. [23].

In order to explore the parameter space of urban settings we apply the techniques from the well-established field of design of computer experiments [24,25]. The first step is to construct discrete samples of urban settings, which are accomplished by using maximum Latin hypercube designs. The details of the design of computer experiments were presented in a previous paper [26]. Applying the sampling techniques not only alleviates computational cost, it also ensures the selected samples have a good space-filling property. Fig. 4 shows the observations in the dataset and shows how samples correspond to the two terrain types by plotting canyon aspect ratio, H/W, against vegetation coverage, α_{veg}. The figure shows high correlation between the two parameters. It indicates that all high-density urban areas have lower vegetation coverage. The vegetation coverage in lower-density areas has significant variations however. Nevertheless, the samples reflect this relationship and are evenly spread over the whole parameters space.

In total, 58 samples are drawn from the dataset with 26 and 32 samples in large city centers and urban and suburban areas, respectively. Hence, 58 weather files are generated for these sampled urban parameter settings in each representative city. Because this dataset contains samples from cities worldwide, the variation should be wide enough to cover most possible urban situations. This paper uses these samples to estimate a preliminary range of the UHI effect on building energy application studies. If desired, the range of the UHI effect in both terrain types can be further refined if the variations of urban setting in each city can be better estimated.

2.1.3. Computer models for the UHI effect

We simulate the UHI in TEB–ISBA model by the following three steps: (1) we apply the model to predict air temperatures in urban areas, T_{urban}, whose surfaces consist of built-up and vegetation covers; (2) we then apply the model to predict air temperatures in rural areas, T_{rural}, whose surfaces consist of only grassland; (3) we compute the differences between T_{urban} and T_{rural} to quantify the hourly magnitudes of temperature differences due to the UHI effect. The forcing weather data are derived from the TMY data using U.S. standard atmosphere [27].

2.1.4. Sample results of the UHI models

This section presents the UHI in Houston (i.e., city in the hot and humid climate zone) as an example of the computational results. Fig. 5 shows the box-and-whisker plots of the annual averaged UHI magnitude in two terrain types. Box-and-whisker plots are popular to summarize a few key statistics and visualize skewness of the data, highlighting the median with the central mark, 25th and 75th percentiles with box edges, and the most extreme data with the whiskers. In general, a metropolitan area is warmer than its surrounding rural areas by an annual average of $2 \pm 1\,^{\circ}$C. The median of the annual average UHI magnitude in the large city centers is slightly higher than that in the urban and suburban areas. The annual UHI variation comes from the variation of four urban setting parameters. The variation in the terrain of urban and suburban areas, which contains low-, medium-, and high-density urban areas

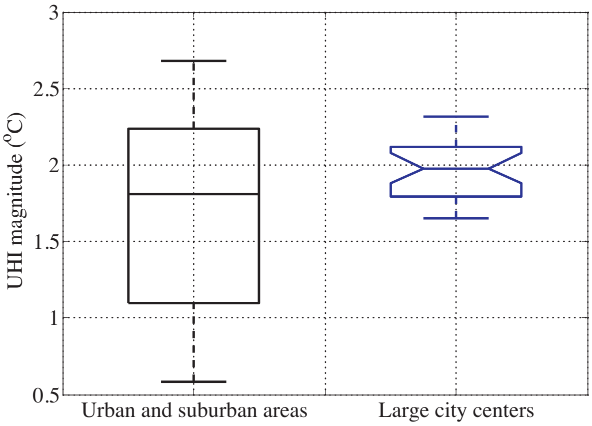

Fig. 5. Annual UHI magnitude in Houston.

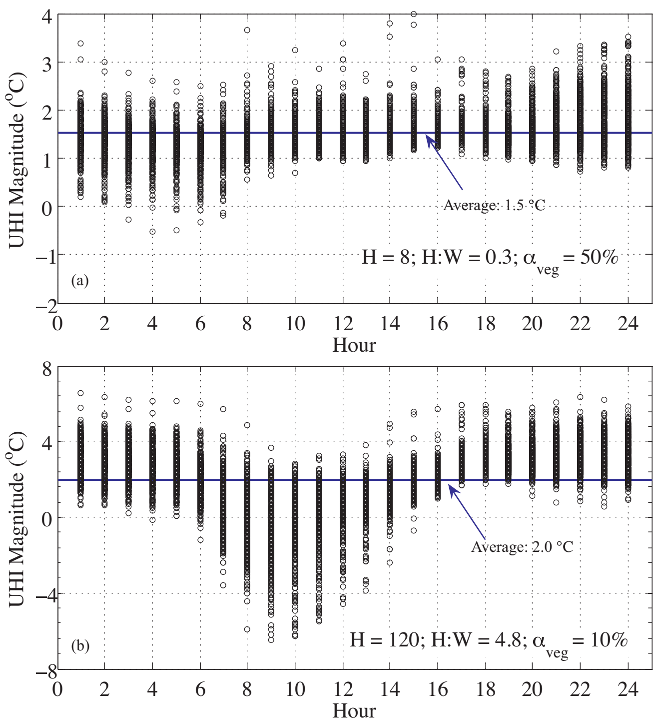

Fig. 6. Hourly UHI magnitudes in Houston (a): a scenario in urban and suburban areas; (b): a scenario in large city centers).

is measurable larger than that in the terrain of the large city centers. Further analysis reveals that variation of the vegetation coverage is a primary contributor. This also explains that the variation in urban and suburban areas is much larger than that in the large city centers, as is visible in Fig. 4. Since the ranges of two boxplots overlap, the UHI effects in the two terrain types are not significantly different.

As we are interested in the daily pattern, we take one sample from each group and show the hourly UHI magnitude over 365 days in Fig. 6. The hourly UHI magnitudes in the large city centers repeat a clearer diurnal pattern compared with those in the other group. The peak of the UHI magnitude usually appears during nighttime, and there are a considerable number of hours with negative UHI during daytime because of the shading effect within the urban canyon. On the other hand, the UHI magnitude shows a mild variation over time in the urban and suburban areas, and negative UHI rarely occurs in this case. Because of the differences in both magnitudes and diurnal patterns between these two situations, it is difficult to tell which one has a bigger impact on building energy application studies without detailed building simulations.

2.2. Building models

In this paper, we deploy reference building models developed by the department of energy in the United States [28]. These models are categorized into16 building types that intend to represent the majority of the commercial building stock. They are widely used for assessing the effects of energy efficiency technologies, new building energy codes and standards, and advanced operation and control strategies. These models are available in the form of EnergyPlus input files [28,29]. In addition, each building type has several versions of the building model. All versions have the same building geometry and operation schedules but differ in envelope insulation, lighting and HVAC system efficiencies. Our study focuses on two versions of three office building models, i.e., a small, medium, and large office complying with ASHRAE, 90.1-2004 and 90.1-2010, respectively. The EnergyPlus input files were developed by the Pacific Northwest National Laboratory (PNNL) to support the development of the ASHRAE, 90.1-2010 standard for achieving the 30% energy savings goal in comparison to 90.1-2004 [29]. For each case we run simulations in parallel with 58 generated UHI weather scenarios and with the original TMY weather as the baseline. The goal is to perform two types of building energy application studies (i.e., absolute energy consumption and comparative analysis of energy savings) while taking the UHI effect into account and inspect its impact. We do this for different size of office buildings in 15 representative cities to establish when the UHI effect is significant.

2.3. Model prediction accuracy

The prediction accuracy of the TEB model has been extensively evaluated in the domain of meteorology in many studies across different locations in the world over the last two decades [6–11]. Most of existing validation studies show very good agreement between the TEB model predictions and filed measurements. For example, Hamdi [9] showed that the TEB was able to predict the hourly temperature profile inside an urban canyon with errors less than 0.5 °C during the evaluation period. More recently, the TEB model has been implemented into the U.S. Weather Research Forecasting (WRF) system to enhance the weather prediction at refined spatial grids [30].

Different results in terms of model prediction accuracy exist. Specifically, it was reported that the urban climate model was adequate to predict the average magnitude of the UHI over a relatively long temporal scale (e.g., daily or monthly) but does not yield accurate hourly predictions. Accordingly, it was recommended to focus only on the monthly or annual results when it is used to quantify the UHI effect on building energy consumption for example [31]. Thus, the UHI model should be adequate in our study as we only evaluate the UHI effect on annual total building energy use, which is less sensitive to errors of hourly UHI predictions.

In spite of that, we conduct a sensitivity test to further evaluate the impact. In the test, the error of hourly UHI prediction is assumed to follow a normal distribution with zero mean and variance σ^2 ($\sigma = 2$ °C). We study the effect of this assumed error by randomly selecting one from the 58 weather files in Chicago climate zone, modifying the hourly predictions of the UHI magnitude by randomly sampling from the normal distribution, $N\left(0, 2^2\right)$. Therefore, the magnitude of UHI at each hour contains uncertainty that deviates from the modeled one by as much as ±4 °C at the 95% confidence interval.

We first explore the impact on the calculation of Cooling Degree Days (CDD) and Heating Degree Days (HDD). HDD and CDD are calculated based on the differences between daily averaged

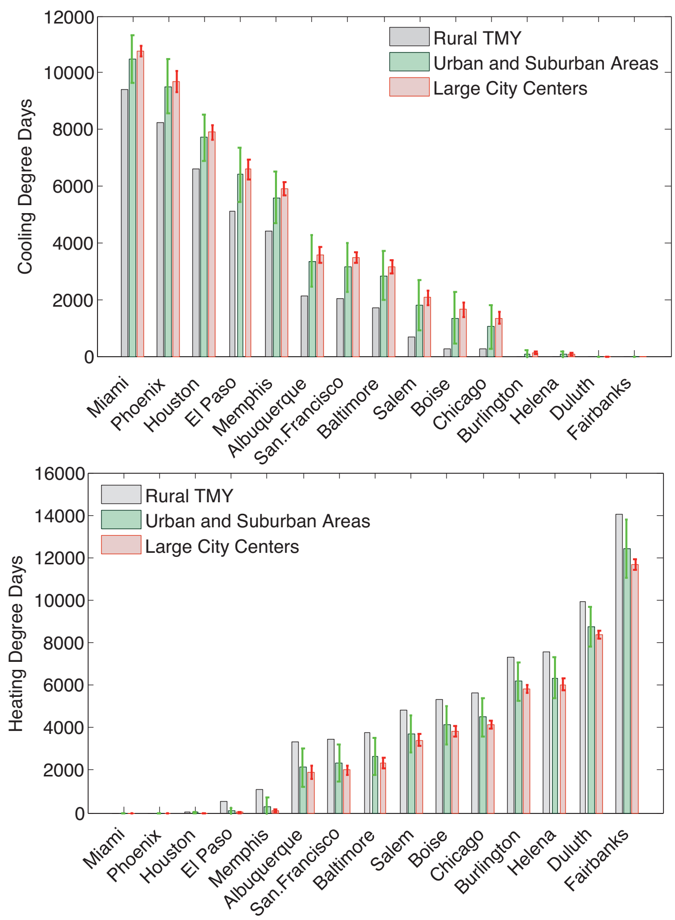

Fig. 7. Increases in CDD (base 10 °C) and reduction in HDD (base 18.3 °C) due to the UHI effect.

outdoor temperature and reference temperatures, indirectly reflecting building heating and cooling demand in a given climate. For commercial buildings, ASHRAE [28–32] suggests the base temperatures 10 °C (50 °F) and 18.3 °C (65 °F) for the calculation of CDD and HDD, respectively. The results show that prediction uncertainties in hourly temperatures have a negligible effect (<0.5%) on both CDD and HDD. The additional weather file generated in this fashion is then applied to a building model. The impact of the uncertainties on the simulated annual energy consumption is also negligible. Thus, we can assume with confidence that the urban climate model is adequate for studies that focus only on the annual aggregated energy use.

3. Results and discussion

This section presents a variety of results of the UHI effect on urban climates for two types of building energy analyses.

3.1. Cooling and heating degree days

In general, the UHI effect increases building cooling demand, yet decreases its heating demand. Depending on the prevailing climate conditions and building characteristics, the overall UHI effect on building energy use may be beneficial or detrimental. One may inspect the changes in HDD and CDD to indirectly estimate the UHI effect regardless of building details.

Fig. 7 shows the changes of annual CDD and HDD due to the UHI effect in 15 climate locations. It depicts the CDD and HDD calculated from rural TMY and modified TMYs due to the UHI in two terrain types, i.e., urban and suburban areas and large city centers. As explained in Section 2.1.3, 26 and 32 different urban settings are chosen from two groups so that we can compute both the means and standard deviations of the CDD and HDD. Fig. 8 shows the means as the bars and two standard deviations around the means. In general, the UHI measurably increases CDD and decreases HDD of the rural TMYs. The simple average of the 15 locations indicates that the UHI increases the CDD by 25.3% and decreases the HDD by 31.7%, respectively. Among different locations, the relative changes measured by percentage are sensitive to the base values, i.e., the corresponding rural TMYs. For example, the CDD in Miami (i.e., a hot climate location) increases by about 1000 degree days that is equivalent to about 10%, yet in Chicago the 800 degree days increase is equivalent to about 300%. Thus, if one intends to compare the UHI effect between different climate locations, the relative metric by itself may not be enough when the base value from which it is computed is not specified.

Fig. 8 also shows the comparison between the two terrains, the UHI effect in the large city centers is slightly larger than that in the other terrain based on the mean differences of the former with the rural TMY. The two-sample *t*-test is also used to determine whether the means from two terrain types are equal. The *t*-test result implies terrain categorization is not significant to explain the variation of the UHI effect over metropolitan areas as the results in two terrains overlap.

3.2. Building energy cost for cooling and heating

The previous section shows how the UHI modifies the CDD and HDD. Next we want to evaluate how the changes affect building energy cost for cooling and heating in each climate location. Energy cost is calculated based on U.S. national average prices that are \$1.22/therm for natural gas and \$0.0939/kW h for electricity. The same prices were also used by the PNNL for building energy analysis of the ASHRAE 90.1 standard [20].

Two versions (i.e., ASHRAE 90.1-2004 and 2010) of three office buildings are simulated in each climate location with one rural TMY weather file and many modified ones in a variety of urban environments. Because we use the prototype buildings that are regarded to be representative of a building category, our results have broader significance as they reflect the average effect on buildings in the given category. We compare the annual energy cost obtained from the modified weather files with that obtained from the rural TMY. The three office buildings of ASHARE 90.1-2010 in Miami, i.e., the hottest location, are selected to illustrate the UHI effect on cooling energy cost in Fig. 8, and those in Fairbanks, i.e., the coldest location, are selected to illustrate the UHI effect on heating energy cost in Fig. 9. The left part of Fig. 8 shows cooling energy cost obtained from the rural TMY, and the means and two standard deviations calculated from the selected urban scenarios in two terrains. The simple average of energy cost over the three selected building sizes are also shown, which can be interpreted as the average UHI effect on the office building category across different sizes.

We also calculate the relative changes of each building in percentage with respect to the rural TMY condition. The UHI effect is presented in comparison with the rural values as a percentage:

$$\Delta = \frac{y|w_{urban} - y|w_{rural}}{y|w_{rural}} \times 100\% \quad (1)$$

where $y|w_{\mathrm{rural}}$ refers to a certain result y conditional on using the rural TMY weather data, $y|w_{\mathrm{urban}}$ is obtained in the UHI, and Δ measures the discrepancy between two values. The results in Fig. 8 show that the UHI leads to an average of 17.5% increase in annual energy cost for cooling the office buildings in Miami. Among the three offices, the large one receives the most influence due to the UHI effect of more than 20%. As for the buildings in a heating

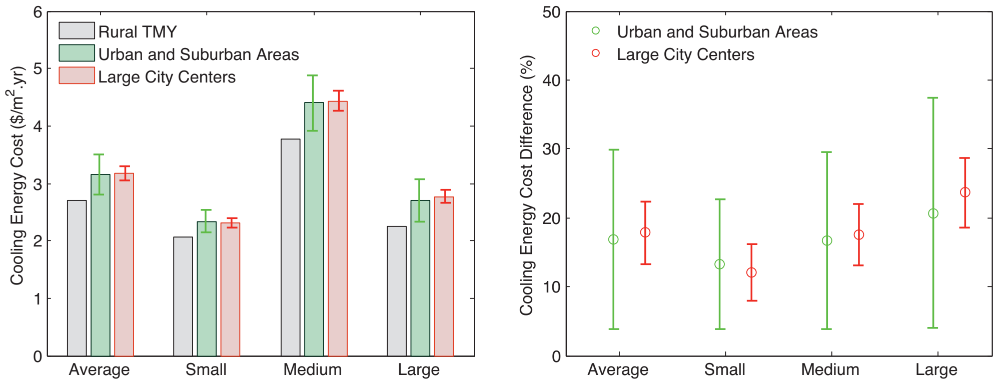

Fig. 8. Increase in building energy cost for cooling due to the UHI effect in Miami.

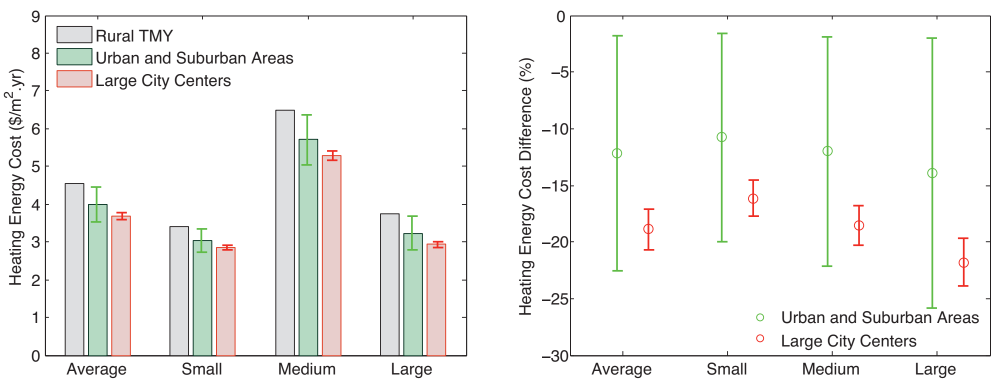

Fig. 9. Reduction in building energy cost for heating due to the UHI effect in Fairbanks.

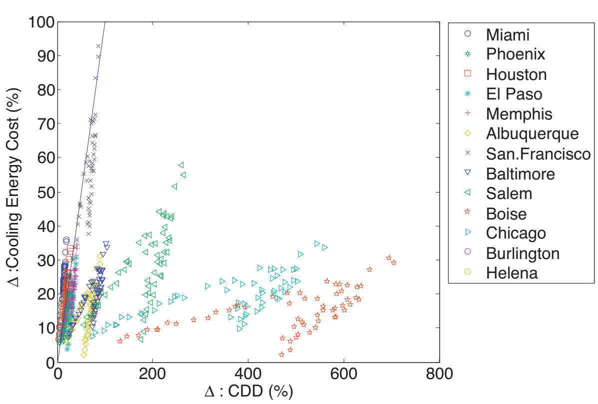

Fig. 10. The changes in CDD (°C) versus the changes in cooling energy cost.

dominant location, Fig. 9 shows that the UHI leads to an average of 12.5% reduction in heating for those in urban and suburban areas, and an average of 18.9% reduction for those in large city centers.

Among three buildings in the two selected locations, the variances in the urban and suburban areas are much larger than those in the large city centers. The variation of the UHI effect comes from the aforementioned variations of four urban parameters, i.e, H, H/W, α_{veg}, and α_{bld}. Sensitivity analysis shows that vegetation coverage α_{veg} is the top contributor, explaining more than 50% of the overall variations in any case. Figs. 8 and 9 also show the comparisons between the two terrains on the average and on each individual building. The results of two-sample t-tests suggest non-significant difference between the means of the two terrains in terms of cooling or heating energy cost.

It is interesting to further analyze the correlation of degree days with energy cost. Fig. 10 plots the changes in CDD against the changes in cooling energy cost. The results show that the relative changes in CDD do not lead to a similar change in cooling energy use. The results show the necessity of running dynamic building energy simulations to evaluate the effect of weather on cooling energy use.

We then extend the analysis to the other locations with a focus on comparisons between climate zones so we only show the average effect. We calculate the simple average of energy use intensity (EUI) of three office buildings over 58 scenarios in the urban environments (i.e., 32 scenarios come from urban and suburban areas and 26 scenarios come from large city centers). Table 2 shows that with respect to rural buildings the urban counterparts require more energy for cooling, yet less energy for heating to maintain the same indoor temperature conditions. The UHI effect averages 17.25% and −17.04% over the 15 climate locations on cooling and heating, respectively. This provides references for the evaluation at a national scale. For individual climate location, the results suggest that ignoring the UHI effect when estimating the building energy use in urban areas will underestimate cooling energy cost, yet overestimate heat energy cost by an average of more than 15% in most locations. In case the energy use for either heating or cooling alone affects a decision, e.g., in deciding about installing an energy saving cooling technology, one may need to take the UHI effect into account to reduce the error in the prediction. There are also some situations that total energy use is more relevant. Fig. 11 shows the mean and two standard deviations of the UHI effect in 15 cities from hot to cold locations. The variation in each location comes from the aforementioned urban setting scenarios. For example, buildings located in urban areas of Miami consume more on air conditioning by 16 ± 10% than the rural counterpart. The means from each city show a linear decrease of the Δ (%) from hot to cold climate locations. In the U.S., the UHI results in considerable increase of energy use for air conditioning in climate zone 1, 2, and 3 where cooling

Table 2
The UHI effect on building energy cost for heating and cooling.

Location	Cooling energy cost ($\$/m^2$ yr)			Heating energy cost ($\$/m^2$ yr)		
	Rural	Urban	Δ (%)	Rural	Urban	Δ (%)
Miami	3.15	3.71	17.80	0.04	0.02	−44.62
Houston	2.40	2.80	16.59	0.53	0.40	−23.99
Phoenix	2.56	2.89	13.00	0.32	0.23	−28.49
El Paso	1.56	1.78	14.07	0.37	0.28	−24.46
Memphis	1.76	2.07	17.51	0.73	0.55	−24.30
San Francisco	0.60	0.81	35.44	0.47	0.32	−33.30
Albuquerque	1.18	1.34	14.16	0.72	0.57	−20.80
Baltimore	1.26	1.46	15.56	1.26	1.02	−19.24
Salem	0.65	0.80	22.46	1.08	0.83	−23.44
Chicago	1.00	1.17	17.28	1.91	1.59	−16.70
Boise	0.80	0.92	15.00	1.34	1.09	−18.69
Burlington	0.75	0.90	20.40	2.43	2.08	−14.50
Helena	0.61	0.72	17.23	2.02	1.71	−15.00
Duluth	0.50	0.61	22.02	3.35	2.90	−13.28
Fairbanks	0.31	0.40	29.30	5.38	4.62	−14.24
Average	1.27	1.49	17.25	1.46	1.21	−17.04

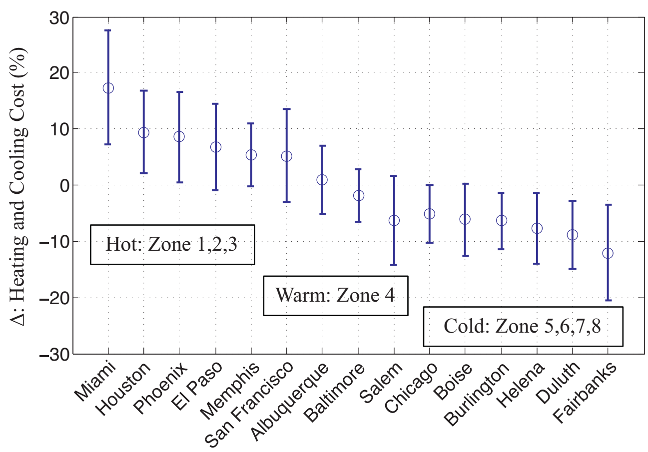

Fig. 11. The mean and two standard deviations of the UHI effect on total energy use for heating and cooling in 15 locations.

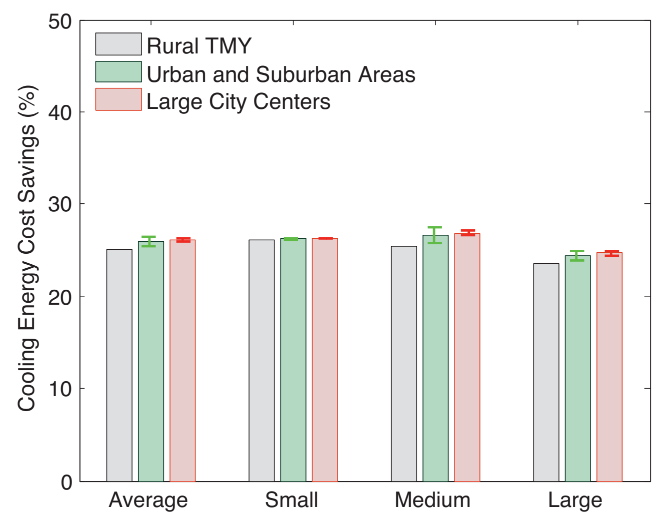

Fig. 12. The UHI effect on cooling energy savings: prototype office buildings in Miami.

energy use are dominant; while it may also be beneficial for building energy users in climate zone 5, 6,7, and 8 where heating energy use are prevalent. In climate zone 4 the UHI only has a moderate modification on air conditioning cost because the effects on cooling and heating mostly average out.

3.3. Energy savings analysis

Predicting energy savings is the second major application of building simulation studies. Intuitively one expects this type of comparative analysis to be much less affected by the UHI effect. Our analysis is meant to provide confirmation of this intuition. We use an example that is regularly conducted, i.e., energy savings of ASHRAE 90.1-2010 in comparison with 90.1-2004. ASHRAE 90.1-2010 updates the requirements of building envelopes, HVAC systems, ventilation, and lighting to improve building energy performance. Our analysis is based on calculation of energy savings of three office buildings in comparison to the corresponding baselines, i.e., the ASHRAE 90.1-2004 version. The following equation is used to calculate the energy savings:

$$E_{\text{Savings}}|w = \frac{\text{EUI}_{2004}|w - \text{EUI}_{2010}|w}{\text{EUI}_{2004}|w} \times 100\% \quad (2)$$

where $\text{EUI}_{2004}|w$ is the energy cost intensity of the ASHRAE 90.1-2004 buildings conditional on a given weather data, w, $\text{EUI}_{2010}|w$ the energy cost intensity of the ASHRAE 90.1-2010 buildings using the same weather data, $E_{\text{Savings}}|w$ the relative energy savings given w. The energy savings are simultaneously evaluated with the rural TMY data (i.e., w: rural TMY) and with the modified TMY data representing the weather condition in urban areas. The difference between them is thus ascribed to the UHI effect.

We take Miami as an example to show the UHI effect on cooling energy savings. Fig. 12 shows negligible differences in the assessment of cooling energy savings because of the UHI effect. No significant difference is observed between the two terrain types because their means are almost identical. This result holds for all three building types and the other locations as well. Fairbanks is used to illustrate the effect on heating energy savings for each individual building. Compared with Fig. 9, the UHI effect is less evident in the assessment of heating energy savings (Fig. 13).

We extend the analysis to other climate locations and present the average savings of three offices over two terrain types in Table 3. It shows cooling, heating and total energy savings that are evaluated under rural and urban weather conditions, respectively. The different shown in a separate column is calculated by subtracting the rural from the urban values. The last row of the table shows the averaged energy savings over 15 locations, which may be relevant to energy analyses at the national scale. It shows consistently across the climate zones the UHI effect is significantly reduced when simulation is used to estimate energy savings measured as the ratio of

Table 3
The UHI effect on building energy savings of ASHRAE 90.1-2010 in comparison with 90.1-2004.

Location	Cooling energy saving (%)			Heating energy saving (%)			Total energy saving (%)		
	Rural	Urban	Diff.	Rural	Urban	Diff.	Rural	Urban	Diff.
Miami	25.13	25.98	0.85	53.39	57.5	4.11	25.52	26.18	0.66
Houston	28.09	29.06	0.97	47.23	47.81	0.58	31.89	31.65	−0.24
Phoenix	25.17	24.53	−0.64	58.14	61.85	3.71	29.56	27.91	−1.65
El Paso	24.06	23.76	−0.3	41.52	43.31	1.79	27.68	26.66	−1.01
Memphis	28.95	29.4	0.45	41.82	42.49	0.67	32.92	32.32	−0.61
San Francisco	46.69	43.47	−3.22	66.42	72.87	6.45	56.07	52.88	−3.19
Albuquerque	24.77	25.05	0.28	46.26	47.6	1.34	33.60	32.41	−1.19
Baltimore	31.8	30.86	−0.94	46.28	47.68	1.4	39.36	38.18	−1.18
Salem	28.69	27.98	−0.71	48.58	51.5	2.92	41.65	40.74	−0.91
Chicago	24.76	25.18	0.42	42.04	43.12	1.08	36.51	35.95	−0.55
Boise	26.91	27.46	0.55	43.78	45.08	1.3	37.86	37.44	−0.42
Burlington	26.61	25.69	−0.92	40.47	41.36	0.89	37.41	36.90	−0.51
Helena	30.21	29.24	−0.97	39.51	40.45	0.94	37.43	37.28	−0.15
Duluth	35.07	33.76	−1.31	38.92	39.87	0.95	38.43	38.83	0.40
Fairbanks	41.98	39.37	−2.61	27.05	28.09	1.04	27.93	29.07	1.14
Average	27.94	27.96	0.02	39.63	40.57	0.94	34.39	33.83	−0.56

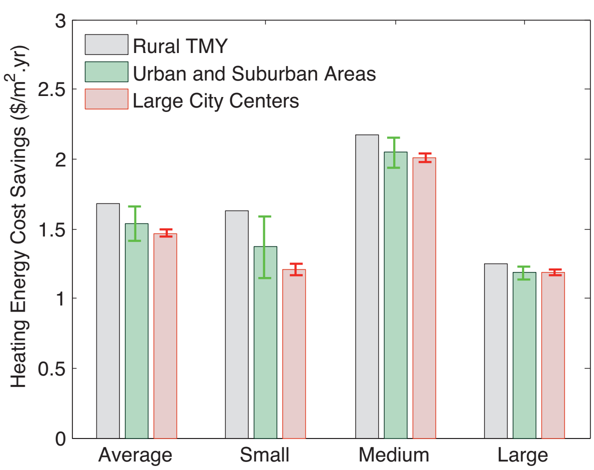

Fig. 13. The UHI effect on heating energy savings: prototype office buildings in Fairbanks.

relative energy use reduction with respect to the baseline. Therefore, compared with the UHI effect on the magnitude of energy use, it may be less crucial to include the UHI effect when the relative savings percentage is the only metric of the analysis, such as the 30% savings goal of ASHRAE Standard 90.1-2010. However, it is also interesting to note that the UHI effect on this total energy savings (i.e., the last column) is negative for most cities for this particular example. In other words, the total energy savings for heating and cooling is slightly underestimated if the rural TMY data are applied to buildings in metropolitan areas.

4. Conclusions and remarks

This study explores the urban heat island (UHI) effect on two routine applications of building energy simulation: (1) predicting the magnitude of energy use and (2) predicting the energy savings from energy-efficiency technologies through comparative analysis. The results from a series of computational studies on prototype office buildings in 15 climate zones in the U.S. lead to the following conclusions and remarks:

(1) Because of the UHI effect a metropolitan area is typically warmer than its surrounding rural area by an approximate annual average of 2 °C. This increase in air temperature leads to an average of 17.25% increase in building cooling energy use and an average of 17.04% decrease in building heating energy use over the 15 U.S. climate locations. This might provide a reference for the evaluation of the UHI effect on energy analysis on a national scale, but the weights assigned to each climate location need extra work. With respect to the total energy use in each individual climate location, our results suggest that the UHI causes considerable increase in climate zones 1, 2, and 3 where cooling energy use is dominant, yet it has a beneficial effect on building energy users in climate zones 5, 6,7, and 8 where heating energy use is prevalent. In climate zone 4 the UHI has a moderate change on the total energy use because the effects on cooling and heating mostly average out.

(2) When building simulation is used to assess energy savings that is measured as the ratio to the corresponding baseline, the UHI has a much smaller effect on the outcomes. Therefore, it may be less crucial to consider the UHI effect when the relative savings in percentage is the only metric of the analysis, such as the 30% savings goal of the ASHRAE Standard 90.1-2010 in comparison with 90.1-2004.

Acknowledgments

This research was funded through NSF-EFRI-SEED Award 1038248, “Risk Conscious Design and Retrofit of Buildings for Low Energy”, 2010–2014, (PI: Godfried Augenbroe, Georgia Institute of Technology).

References

[1] Population Reference Bureau, World Population Data Sheet, 2010 (viewed Aug 2012) http://www.prb.org
[2] M. Kolokotroni, Y. Zhang, R. Giridharan, Heating and cooling degree day prediction within the London urban heat island area, Building Services Engineering Research and Technology 30 (3) (2009) 183–202.
[3] J.F. He, J.Y. Liu, D.F. Zhuang, W. Zhang, M.L. Liu, Assessing the effect of land use/land cover change on the change of urban heat island intensity, Theoretical and Applied Climatology 90 (3) (2007) 217–226.
[4] L.J. Hua, Z.G. Ma, W.D. Guo, The impact of urbanization on air temperature across China, Theoretical and Applied Climatology 93 (3) (2008) 179–194.
[5] A.J. Arnfield, Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island, International Journal of Climatology 23 (1) (2003) 1–26.
[6] P.A. Mirzaei, F. Haghighat, Approaches to study Urban Heat Island—abilities and limitations, Building and Environment 45 (10) (2010) 2192–2201.
[7] V. Masson, A physically-based scheme for the urban energy budget in atmospheric models, Boundary-Layer Meteorology 94 (3) (2000) 357–397.
[8] V. Masson, C.S.B. Grimmond, T.R. Oke, Evaluation of the Town Energy Balance (TEB) scheme with direct measurements from dry districts in two cities, Journal of Applied Meteorology 41 (10) (2002) 1011–1026.

[9] R. Hamdi, V. Masson, Inclusion of a drag approach in the Town Energy Balance (TEB) scheme: offline 1D evaluation in a street canyon, Journal of Applied Meteorology and Climatology 47 (10) (2008) 2627–2644.
[10] A. Lemonsu, S. Belair, J. Mailhot, S. Leroyer, Evaluation of the Town Energy Balance model in cold and snowy conditions during the Montreal urban snow experiment 2005, Journal of Applied Meteorology and Climatology 49 (3) (2010) 346–362.
[11] A. Lemonsu, C.S.B. Grimmond, V. Masson, Modeling the surface energy balance of the core of an old Mediterranean city: Marseille, Journal of Applied Meteorology 43 (2) (2004) 312–327.
[12] M. Kolokotroni, I. Giannitsaris, R. Watkins, The effect of the London urban heat island on building summer cooling demand and night ventilation strategies, Solar Energy 80 (4) (2006) 383–392.
[13] S. Oxizidis, A.V. Dudek, A.M. Papadopoulos, A computational method to assess the impact of urban climate on buildings using modeled climatic data, Energy and Buildings 40 (3) (2008) 215–223.
[14] Y. Kikegawa, Y. Genchi, H. Kondo, K. Hanaki, Impacts of city-block-scale countermeasures against urban heat-island phenomena upon a building's energy-consumption for air-conditioning, Applied Energy 83 (6) (2006) 649–668.
[15] M. Kolokotroni, Y. Zhang, R. Watkins, The London Heat Island and building cooling design, Solar Energy 81 (1) (2007) 102–110.
[16] S. Hassid, M. Santamouris, N. Papanikolaou, A. Linardi, N. Klitsikas, C. Georgakis, D.N. Assimakopoulos, The effect of the Athens heat island on air conditioning load, Energy and Buildings 32 (2) (2000) 131–141.
[17] A.L.S. Chan, Developing a modified typical meteorological year weather file for Hong Kong taking into account the urban heat island effect, Building and Environment 46 (12) (2011) 2434–2441.
[18] M. Nunez, T.R. Oke, The energy balance of an urban canyon, Journal of Applied Meteorology 16 (1977) 11–19.
[19] K.W. Oleson, G.B. Bonan, J. Feddema, M. Vertenstein, C.S.B. Grimmond, An urban parameterization for a global climate model. Part I: Formulation and evaluation for two cities, Journal of Applied Meteorology and Climatology 47 (2008) 1038–1060.
[20] T.L. Jackson, J.J. Feddema, K.W. Oleson, G.B. Bonan, J.T. Bauer, Parameterization of urban characteristics for global climate modeling, Annals of the Association of American Geographers (2010), Special Issue on Climate Change 2010.
[21] ASHRAE, ASHRAE Handbook Fundamentals, SI ed., American Society of Heating, Refrigeration and Air-Conditioning Engineers, Atlanta, GA, 2009.
[22] T.R. Oke, Canyon geometry and the nocturnal urban heat island: comparison of scale model and field observations, International Journal of Climatology 1 (3) (1981) 237–254.
[23] K.W. Oleson, G.B. Bonan, J. Feddema, M. Vertenstein, An urban parameterization for a global climate model. Part II: Sensitivity to input parameters and the simulated urban heat island in offline simulations, Journal of Applied Meteorology and Climatology 47 (4) (2008) 1061–1076.
[24] T.J. Santner, B.J. Williams, W. Notz, The Design and Analysis of Computer Experiments, Springer, New York, NY, 2003.
[25] C.F.J. Wu, M.S. Hamada, Experiments: Planning, Analysis, and Optimization, second ed., Wiley, New Jersey, 2009.
[26] Y. Sun, Y. Heo, M.H.Y. Tan, H. Xie, C.F.J. Wu, G. Augenbroe, Uncertainty quantification of microclimate variables in building energy models, Journal of Building Performance Simulation 7 (1) (2014) 17–32.
[27] U.S. Government, U.S. Standard Atmosphere, U.S. Government Printing Office, Washington, DC, 1976.
[28] M. Deru, K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, B. Liu, M. Halverson, D. Winiarski, M. Rosenberg, M. Yazdanian, J. Huang, J. Huang, U.S. Department of Energy Commercial Reference Building Models of the National Building Stock—Technical Report, TP-5500-46861, National Renewable Energy Laboratory, Golden, CO, 2011.
[29] B. Thornton, M. Rosenberg, E. Richman, W. Wang, Y. Xie, J. Zhang, H. Cho, V. Mendon, R. Athalye, B. Liu, Achieving the 30% Goal: Energy and Cost Savings Analysis of ASHRAE Standard 90.1-2010, PNNL-20405, Pacific Northwest National Laboratory, Richland, WA, 2011.
[30] F. Chen, H. Kusaka, R. Bornstein, J. Ching, C.S.B. Grimmond, S. Grossman-Clarke, et al., The integrated WRF/urban modelling system: development, evaluation, and applications to urban environmental problems, International Journal of Climatology 31 (2011) 273–288.
[31] M. Kolokotroni, M. Davies, B. Croxford, S. Bhuiyan, A. Mavrogianni, A validated methodology for the prediction of heating and cooling energy demand for buildings within the Urban Heat Island: case-study of London, Solar Energy 84 (12) (2010) 2246–2255.
[32] ANSI/ASHRAE/IESNA Standard 90.1-2004, Energy Standard for Buildings Except Low-Rise Residential Buildings, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA, 2004.