Sensitivity of building energy model predictions to spatial variations in climate under different levels of urbanization

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ABSTRACT

In the United States, approximately 40% of the primary energy use and 72% of the electricity use belong to the building sector. This shows the significance of studying the potential for reducing the building energy consumption and buildings' sustainability for ensuring a sustainable development. Therefore, many different efforts focus on reducing the energy consumption of residential buildings. Data-validated building energy modeling methods are among the studies for such an effort, particularly, by enabling the identification of the potential savings associated with different potential retrofit strategies. However, there are many uncertainties that can impact the accuracy of such energy model results, one of which is the weather input data. In this study, to investigate the impact of spatial temperature variation on building energy consumption, six weather stations in an urban area with various urban density were selected. A validated energy model was developed using energy audit data and high-frequency electricity consumption of a residential building in Austin, TX. The energy consumption of the modeled building was compared using the selected six weather datasets. The results show that energy use of a building in an urban area can be impacted by up to 12% due to differences in urban density. This indicates the importance of weather data in predicting energy consumption of the building. The methodology and results of this study can be used by planners and decision makers to reduce uncertainties in estimating the building energy use in urban scale.

INTRODUCTION

In the United States, buildings were responsible for 2.88E+10 MWh (9.82E+16 BTU) of energy consumption in 2017, or approximately 39% of the total primary energy consumption, 5.91E+9 MWh (2.01 E+16 BTU) (approximately 21%) of which originated from residential buildings [1]. The residential sector is also responsible for approximately 20% of U.S. carbon emissions, or about 4% of the world's total carbon emissions [2]. Therefore, designing buildings that use considerably less energy than existing buildings is an overarching goal for building designers and architects. Reduction in energy consumption in the residential sector will significantly reduce carbon emissions and work toward achieving climate change goals [3]. In some cases, aggressive energy saving goals work towards achieving 40% or better than code, to net zero-energy buildings designed to minimize the energy consumption and environmental impacts. In high performance buildings many possibilities exist to achieve these goals, such as modifications to building material selection, daylighting, natural ventilation, mixed mode ventilation, photovoltaic (PV), and passive solar strategies. These methods were developed with the goal of using less energy than comparable code-compliant buildings, and in most

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cases, their building envelope exceeds currently adopted ASHRAE 90.1 or 90.2 recommendations [4].

An important part of the implementation of energy savings measures is being able to accuracy model the predicted energy savings associated with various energy savings measures. This is often best accomplished through estimates produced from building energy simulation. Recent research efforts in the building energy simulation field recognize the significant uncertainties associated with estimating the energy performance of buildings using the results of energy simulation software and associated methods. For example, the results of recent work on high performance buildings indicate that better energy performance is achieved than standard practices, including net source energy savings among six buildings studied ranging from 22% to 77% and energy cost savings ranging from 12% to 67% [5]. However, it has also been noted that when compared to actual performance, most buildings do not perform exactly as predicted [5]. This can be due to variations in a wide range of input variables, including the weather conditions, building systems components, occupants loads and occupant behaviors among others [6]. These fundamental uncertainties involved in building energy modeling impact the gap often observed between the actual performance and designed models. To bridge this gap, these uncertainties must be better addressed. One of the important and impactful input parameters for energy models is the weather data input. Outdoor temperature in particular is a crucial parameter, and is widely recognized as such. For example, Yang et al. [7] identified different models that simulate the correlation between indoor and outdoor temperature, indicating that an increase in outdoor air temperature would increase indoor operative temperature which results in higher energy consumption.

For building energy model validation and verification, it is thus important to have accurate weather input to ultimately work towards bridging the energy performance gap between measured and predicted consumption. Currently weather data typically utilized for building energy performance efforts is mainly based on measured data from ground-based weather stations generally located at airports throughout the United States [8]. Most of the time these weather stations are outside of the city, thus the weather data collected does not see the impacts of anthropogenic activities in a city that the majority of the buildings in that city would experience. The main impact of such activities is typically defined as the increase in the ambient temperature of an urban area due to an increased level of impervious surfaces as compared to more rural areas. This impact is caused in part by the delayed release of heat by buildings and paved surfaces which absorb the heat during the day, combined with heat from vehicular traffic and from heating, venitilation and air condition (HVAC) system heat exhaust [9]. The extent of this effect, i.e. the change in temperature, depends on various urban parameters including the land use/land cover type(s), the amount of impervious surfaces, building sizes and heights and surface albedo, emissivity, and heat capacity of materials used in urban construction. These differences between the weather conditions experienced by buildings in an urban area and measured weather data, generally in a non-urban area, is a source of uncertainty between model prediction and actual energy consumption.

Coupled with the global temperature rise there is a rising trend in an urban population in the United States, with an estimated 18.8% increase in the percent of the population living in cities between 2000 and 2020 (Research Application Laboratory 2019). Salamanca et al. [11] investigated the impact of air conditioning systems on the air temperature with the most developed urban scheme for the two simulated days in August. It is reported that the waste heat increased the air temperature by 0.5°–2°C (2.7°F) depending on the location inside the city and the meteorological conditions. In addition, a study of major metropolitan areas in the U.S. concluded that the peak electricity load would increase by 1.5–2% for every 0.5°C (0.9 °F) increase in ambient temperature [12]. Thus, accounting for the local weather in energy modeling will help to reduce the uncertainties associated with predicting energy consumption trends. In order to investigate the impact of urbanization on different aspects of energy consumption, it is important to consider the urban fraction, and remaining green fraction. Urban fraction can be obtained from the land surface physical characteristics such as albedo, emissivity, vegetation fraction, and roughness, which control land-atmosphere interactions. This is obtained from land cover data from the National Land Cover Data (NLCD) datasets, and has three spatial resolutions (30m, 100m, 1km) (98ft, 328ft, 3280ft). NLCD includes three urban types, which correspond to the three aforementioned urban categories as low-intensity residential, high-intensity residential, and industrial/commercial

[13].

As such further study is needed to understand the potential impacts of correcting for spatial variations in weather conditions that differ from those predicted from the utilization of typical airport-based weather station data. This study works to investigate the impact of spatial variation of temperature on energy consumption of residential buildings by comparing the energy consumption predictions of a calibrated energy model using weather data stations in locations with a range of urban densities. The results of this work help to contribute to a better understanding of energy prediction impacts of spatial variations in weather conditions, and provides motivation for further study in this area.

METHODOLOGY

The methodology is divided into two sections. First is the development of an energy model for the studied residential building and validation of this model using actual, measured electricity consumption data. The outcome of this step is a validated model that can be used for investigating the impact of spatial temperature variation on annual building energy consumption, which is the second step of this study. To investigate the impact of the spatial temperature variation effect, the measured data from several weather stations located in areas with different levels of urbanization were used. These stations were chosen to represent the impact of urban characteristics on temperature and consequently on the electricity consumption of a representative residential building.

Observational data

Ground-based weather station data was collected from a dataset of 40 weather stations located in the Austin, TX area. Most weather stations are installed at schools, stadiums and businesses [14]. At each weather station, temperature (+/- 0.5 ^{o}C(0.9°F)), humidity (+/- 3.5%), wind direction (+/- 3 degrees), wind speed (+/- 3 kph (1.9 mph)), pressure (+/- 1.7 hPa), and rainfall (+/- 1%) are measured [15]. All data undergo data quality control procedures and are assigned a tag to represent the level of data verification [14]. Data was available from 2011 to 2018, however not all 40 weather stations were collecting data at any given time. The weather data time window utilized for evaluating the developed energy model is from August 19, 2011 to September 3, 2011. During this time period, one of the the most significant heatwave events since 2000 with respect to heatwave duration and absolut temperature that occured in Austin, TX [16].

For energy consumption data, the Pecan Street Research Institute's (PSRI) Dataport was utilized. This database includes 1-minute level electricity consumption data, including whole-home and disaggregated data for nearly many single family homes and apartments in the Austin, TX area [17]. It also includes information on the physical characteristic of a portion of the monitored buildings, as well as energy audit data for some homes.

Developing a Calibrated Energy Model for Residential Buildings

Several steps were followed to develop and validate a residential building energy model. For developing the model, energy audit data and high-frequency electricity consumption of a residential building in the Mueller neighborhood region of Austin, TX were used. A home with both detailed energy audit data, and 100% of one year of whole-home energy use data was chosen. A building energy model of the building was then developed using a rectangular building plan, the dimensions of which were 14 x 9 m (46 x 30 ft) on the first floor and 10 x 9 m (32 x 30 ft) on the second floor. Based on another recent study's findings [18], the use of this layout versus another will have approximately 2% impact on the accuracy of the predicted annual energy consumption.

To model energy consumption for the building, the Energy Plus-based building energy modeling software BEopt (version 2.8.0.0) was used to build the initial model. BEopt is capable of evaluating residential building energy performance and cost analysis, and can be used to analyze both new construction and existing home retrofits, as well as both single-family detached and multi-family buildings [19]. In this study the energy model was created in BEopt, using the relevant inputs on building characteristics acquired from the PSRI data. Values that were not available in the database for the building, were based on assumptions in the Building America House Simulation Protocols [20].

Input real weather data for the home's location in the required ".epw" format is needed for validation. The weather data from the closest available location to the building that is associated with the time period of the utilized energy consumption data (1 year, in 2014) is used. This data originated from the NSRDB (The National Solar Radiation Database) [21]. The applicable weather data available included dry bulb temperature, dew point temperature, relative humidity, pressure, wind speed, wind direction, direct and diffuse solar radiation and cloud cover. These values were arranged in the appropriate file format to be used as an input for the energy model.

ASHRAE Guideline 14 [22], which focuses on the validation of building energy simulation models to measured data, suggests that the results of a model should fall below suggested thresholds for Coefficient of Variation of Root Mean Square Error (CV-RMSE) (%) and Mean Bias Error (MBE) (%), calculated based on Equations (1) and (2). For validating the model, the energy consumption from the simulation model was compared with the actual energy consumption for 2014 using MBE and CV-RMSE. Per ASHRAE Guideline 14 [22], the acceptable tolerances for these values are +/- 10 % for MBE and +/- 30 % for CV-RMSE for hourly data [23]. The model is thus considered to be validated if it is within this range for both values. Several trials were implemented to reduce the MBE and CV-RMSE of the original model.

$$MBE(\%) = \frac{\sum_{i=1}^{N_p}(m_i - s_i)}{\sum_{i=1}^{N_p}(m_i)} \tag{1}$$

$$CV\ RMSE(\%) = \frac{\sqrt{(\sum_{i=1}^{N_p}(m_i - s_i)^2/N_p)}}{\bar{m}} \tag{2}$$

Investigating Spatial Temperature Variation Impact on Residential Buildings

With a validated energy model, to predict the impact of spatial temperature variation on annual energy consumption of the studied building, eleven ground-based stations were used, where four stations have values for the 30m, five have values for the 100m, and nine stations have values for the 1km urban fraction. Using the stations in each urban fraction class (30m, 100m, 1km), all possible combinations of the two stations were developed and the differences between each pair of stations were calculated and compared with the average daily temperature difference between the pairs. Linear regression is applied to determine the relationship between the urban fraction difference and average daily temperature difference between each pair of stations. In this study, to indicate the maximum impact of temperature variation on annual building energy consumption, six stations which have the highest average daily temperature difference due to variation in urban fraction were chosen to estimate their impact on annual building energy consumption. All of the selected sites are located in an urban area but with different urban fractions. The calibrated energy model was then run using the weather data developed from each of these weather datasets.

RESULTS AND DISCUSSION

Energy Model Validation

For model validation, the results of the model were initially compared with the actual electricity consumption at the monthly level. In the initial stages of validation, the monthly electricity consumption in winter closely matched the results from the model, while in summer the actual electricity consumption was higher than the modeled electricity consumption. As shown in Figure 1, the peak values of actual electricity consumption are higher than the values for the model, which was found to originate from occasional charging of an electric car owned by the homeowners. Since charging electric cars does not impact the energy performance of a building and is not represented in a building energy model, the submetered data was used to determine the demand of the electric car, which was then eliminated from calculated values for actual energy consumption of the building. As shown in Figure 2 the elimination of electric car charging improved model results and decreased the differences between model prediction and actual values.

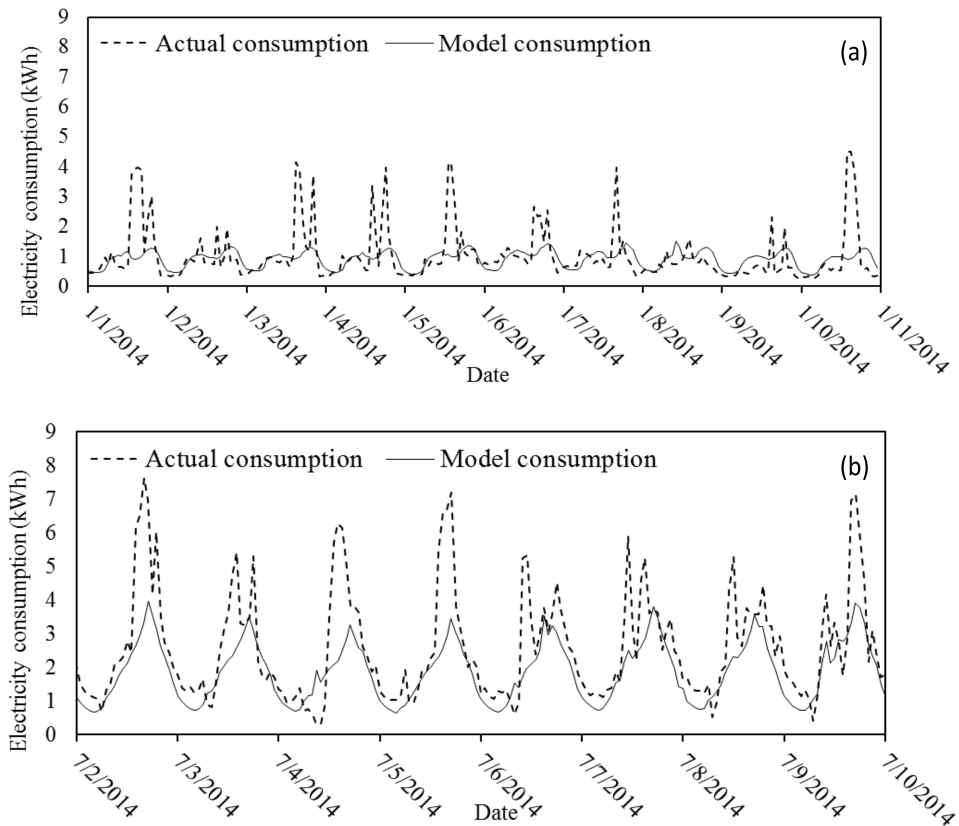

Figure 1. Comparison of hourly electricity consumption between actual electricity consumption and results of the original energy model from (a) Jan 1 to Jan 10, 2014 (10 days in winter), and (b) July 1 to July 10 (10 days in summer)

In the original model during summer, the actual energy consumption is higher than the modeled consumption. To reduce the difference between model prediction and actual demand during summer, the window area and shading conditions were modified slightly to increase sensible loads. To improve agreement with the data in the winter months, the size of heating system and the AFUE value were adjusted slightly. These changes resulted in an improvement in the model (Figure 3) MBE values from 4.2% to 1.1%, which is an acceptable range for model validation. The CV-RMSE values were also improved from 43.1% to 38.8% with these adjustments, which is closer to the ASHRAE Guideline 14 recommended values of +/- 30%. Other reasons for such variations include occupant behavior which is challenging to capture in such a model using current modeling methods and the available data.

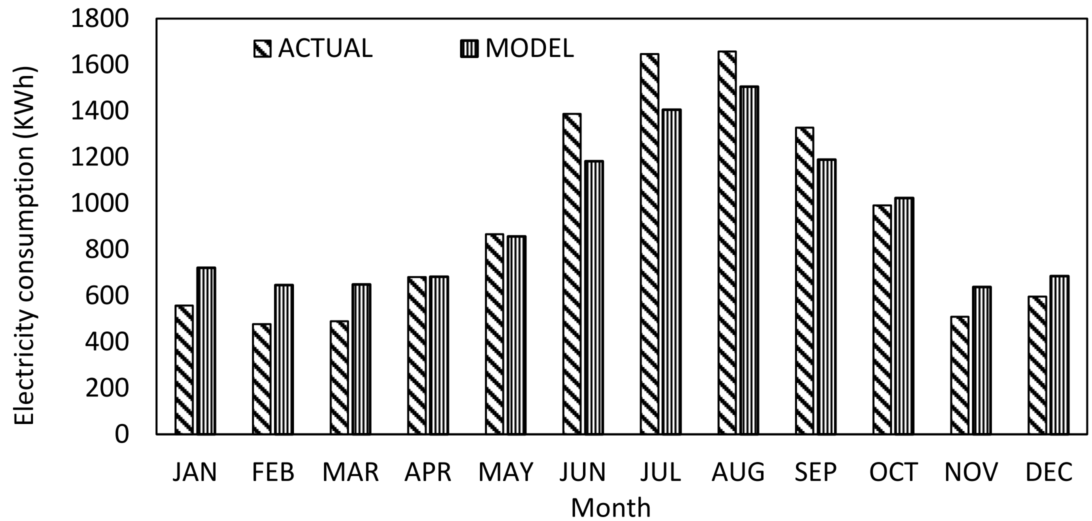

Figure 2. Monthly comparison of actual electricity consumption with results of the final calibrated energy model

Comparison of spatial temperature variation due to urban fraction

Considering missing weather data for all ground-based weather stations, and also availability of urban fractions for the studied stations, five stations with their associated 30m and 100m urban fraction and nine stations with their associated 1km urban fraction were studied. All possible combinations of the two stations were developed for each of the urban fraction classes. Linear regression was applied to determine the relationship between the urban fraction difference (x axis) and average daily temperature difference (y axis) for each pair of the stations. As shown in Figure 3, the results indicate that in each class of urban fraction, with an increase in urban fraction, the average daily temperature difference between stations also increases. In other words, higher urban fraction differences between stations results in larger temperature differences.

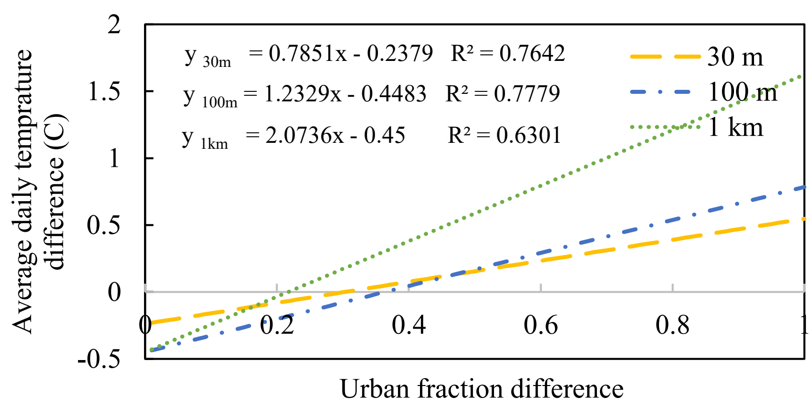

Figure 3. The linear relationship between urban fraction difference and average daily temperature difference in 30m, 100m, 1km urban fractions classes

Comparison of energy use of selected locations with different urban fractions

In each class of urban fraction (30m, 100m, 1km) a pair of stations which have the highest urban fraction difference and highest temperature difference were chosen. The urban fraction differences for these pairs of stations in the 30m, 100m and 1km urban fraction datasets are 0.94, 0.61, and 0.66 respectively. The validated energy model was used to generate hourly energy use of the representative residential building for the six selected stations during the studied period. The hourly energy difference for each pair of stations in each urban fraction class were compared and the percentage of hourly energy use difference is reported in a histogram as shown in Figure 4.

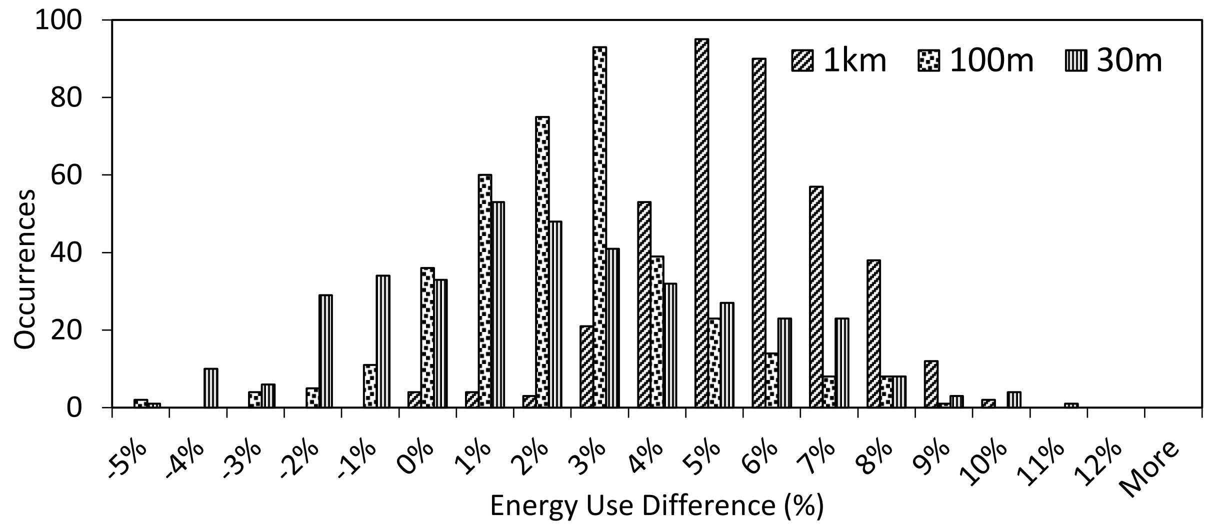

Figure 4. The hourly energy use difference between each pair of weather stations in 30m, 100m, and 1km urban fraction classes

The results indicate that hourly energy use difference in each class of urban fraction varies from -5% to +12%, where negative values indicate a higher hourly energy use where there is a smaller urban fraction, and positive values indicate an increase in urban fraction increases the energy use. The average differences in energy use for 30m, 100m and 1km are 0.49, 0.62 and, 1.66 kWh, respectively. As shown in Figure 5, in the 1km urban fraction class, only 1% of the values are negative. Moreover, the negative values for the 100m and 30m urban fractions form 15% and 30% of the data, respectively. It should be noted that for the 1km data, for 78% of the cases the energy difference is in the range of 3% to 7%. Further detailed information is provided in Figure 5.

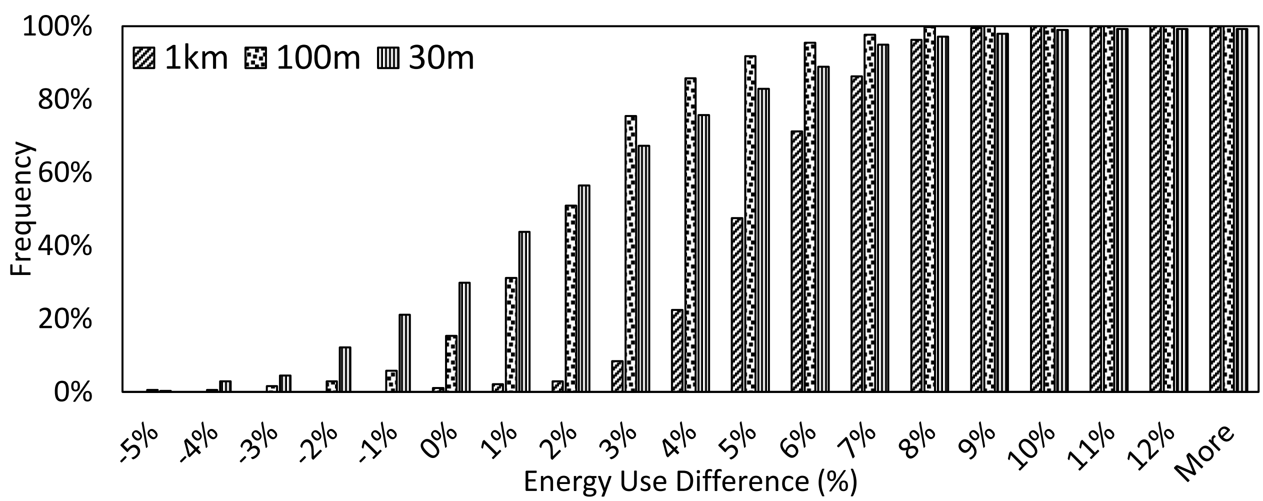

Figure 5. The cumulative percentage difference in energy use in three different urban classes, including 30m, 100m, and 1km

CONCLUSIONS

In this study an energy model was developed for a residential building in the Mueller neighborhood in Austin, TX. The model is validated with an annual hourly MBE of 1.14 % and an annual hourly CV-RMSE of 38.8 %. To investigate the impact of spatial temperature difference on building energy consumption, six weather stations in an urban area were selected to investigate the impact of temperature variation due to various urban densities on energy consumption. Using the validated model, the energy consumption of the modeled building was compared using six weather datasets. All the chosen weather datasets were located in an urban area but with different urban densities. The results show that the weather-related energy use of a building in an urban area with different urban fraction can vary to up to 12%, i.e. there can be up to a 12% increase in annual energy consumption from being located in a high density urban area versus low density urban area, due to differences in weather conditions. This indicates the importance of weather data in predicting energy consumption of the building. This also points to a need to further study the impacts of spatial variations in weather in cities in particular on the predictability of energy consumption, as well as the need to better develop methods for more appropriate site-specific weather data beyond that taken from airport weather stations.

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