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CITY-SCALE ENERGY MODELING TO ASSESS IMPACTS OF EXTREME HEAT ON ELECTRICITY CONSUMPTION AND PRODUCTION USING WRF-UCM MODELING WITH BIAS CORRECTION

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Abstract: The energy consumption of buildings at the city scale is highly influenced by the weather conditions where the buildings are located. Thus, having appropriate weather data is important for improving the accuracy of prediction of city-level energy consumption and demand. Typically, local weather station data from the nearest airport or military base is used as input into building energy models. However, the weather data at these locations often differs from the local weather conditions experienced by an urban building, particularly considering most ground-based weather stations are located far from many urban areas. The use of the Weather Research and Forecasting Model (WRF) coupled with an Urban Canopy Model (UCM) provides means to predict more localized variations in weather conditions. However, despite advances made in climate modeling, systematic differences in ground-based observations and model results are observed in these simulations. In this study, a comparison between WRF-UCM model results and data from 40 ground-based weather station in Austin, TX is conducted to assess existing systematic differences. Model validations was conducted through an iterative process in which input parameters were adjusted to obtain to best possible fit to the measured data. To account for the remaining systemic error, a statistical approach with spatial and temporal bias correction is implemented. This method improves the quality of the WRF-UCM model results by identifying the statistic properties of the systematic error and applying several bias correction techniques.

1 INTRODUCTION

Studies comparing actual, measured building energy consumption and model-predicted energy consumption indicate that there can be significant differences between these two sets of values (Torcellini et al. 2004; Coakley, Raftery, and Keane 2014; Karlsson, Rohdin, and Persson 2007). These differences can be due to variations in a wide range of input variables, such as weather conditions, building systems components, occupant and internal loads and energy-influencing occupant behaviors (De Wilde 2014). To improve the performance of building energy models, uncertainties within the input data must be better addressed. One of the most important and impactful input parameters utilized by building energy models is the weather data. U.S. weather data used for building simulations typically originates from measurements taken at ground-based weather stations located at airports (Stewart and Oke 2012). Given that airports are not typically directly adjacent to city centers where most commercial and residential buildings are located, the weather data collected at airports does not necessarily represent the actual weather conditions at the location of a studied building. Therefore, methods to enable a better understanding of local weather conditions for buildings can significantly improve the accuracy of the weather data input to energy models.

There are several studies (Bhandari, Shrestha, and New 2012; Salamanca et al. 2011; EPA 2017; Crawley 2008) that highlight the importance of utilizing local weather data for building energy modeling purposes. For example in a study done by Bhandari et al. (Bhandari, Shrestha, and New 2012), two different weather datasets were compared as the inputs for energy model: *i)* data available from public providers, and *ii)* data from service providers that provide historical weather data at a 15–40 km^2 grid across the globe. The comparison showed that depending on the provided weather data, annual modeled building energy consumption can vary by ±7% and monthly building loads can vary by ±40%. In another study (Gros, Bozonnet, and Inard 2014), the authors emphasis the importance of high resolution weather data and simulation of the different physical processes that exist in urban areas. A new numerical approach was developed to assess building energy demand, including microclimate interactions with buildings. Considering that the cost of installing a significant number of ground-based weather stations to capture variations in climate conditions in a small geographic region is quite high, it is beneficial to explore the use of lower cost methods to capture the spatial variations in weather parameters.

To capture localized climate characteristics in urban areas, the Weather Research and Forecasting (WRF) model (Skamarock et al. 2005) can be used. WRF is a physics-based atmospheric model that, given initial atmospheric conditions over a 3D domain (e.g., temperature, relative humidity, wind speed and direction, and precipitation), numerically solves for the future state of the atmosphere. In this study, the WRF solves for atmospheric variables at a grid resolution down to 1 km over a 24-hour forecast window. To account for urban effects on the local climate, a single-layer urban canopy model (UCM) (Bueno et al. 2014; Chen, Yang, and Zhu 2014) is coupled with WRF model. Some features of UCM include, shadowing from buildings, reflection of short and longwave radiation, and a wind profile in the canopy layer and multi-layer heat transfer equation for roof, wall and road surfaces (Kusaka and Kimura 2004).These features as facilitated by providing urban parameters such as the land use and land cover information, percentage impervious surface, building dimensions, the surface albedo, emissivity, and thermal properties of materials used in urban construction as inputs into the model. Thus, UCM coupled with WRF model can help to provide more accurate forecasts for urban regions.

In spite of the presence of detailed data which can be utilized as input into the UCM and WRF models, model errors can arise from such sources as imperfect model representation of atmospheric physics, incorrect initialization of the model or errors in the parameterization chain (Ehret et al. 2012). In addition, in some locations of study, all required input data for the WRF and UCM models may not be available or are unknown, thus in this case initial assumptions must be made. As such, there is a need to investigate the presence of and correction for systematic biases in the WRF/UCM model results to improve the accuracy of the simulated local weather conditions resulting from the WRF/UCM model. In a study done by Christensen et al (Christensen et al. 2008), 13 regional climate models (RCM) were utilized with the European Centre for Medium Range Weather Forecasting Reanalysis (ERA40). The results were compared to a high resolution gridded observational dataset, to explore the systematic bias in simulated monthly mean temperature and precipitation. Although there are several studies done which utilize bias correction of high resolution of regional climate models, they are mainly focused on correcting the bias for hydrological aspects of the data (Berg, Feldmann, and Panitz 2012; Teutschbein and Seibert 2012; Bum, Kwon, and Han 2015; Piani, Haerter, and Coppola 2010). To the best of the authors' knowledge, no research has considered bias correction of the WRF/UCM results focusing on temperature.

In this study, a WRF/UCM model was developed for the city of Austin, TX. Given the significant extreme heat events in terms of high levels of building energy consumption and the impacts of these events on electric grid operations, this study focuses on three historical heatwave events that occurred in Austin, TX in 2011, 2013, and 2017. The simulation results of the WRF/UCM are compared to high-resolution ground-based measured weather data at 40 ground-based weather stations. Utilizing these comparisons, two bias correction methods are assessed in terms of their ability to reduce the error between measured data and model results.

2 METHODOLOGY

First, a dense network of measured data was obtained across the city of Austin, TX. Next the WRF/UCM model was developed and simulated over three historical heat wave events of which measured data also existed. Finally, the measured data and modeled data are compared, and two bias correction methods are tested to improve the overall fit of the modeled and measured data.

2.1 Observational weather data

Ground-based weather station data was collected from a dataset of 40 weather stations located in the Austin, TX area (Figure 1). Most weather stations are installed at schools, stadiums and businesses (Earth Networks 2014a). At each weather station, temperature (+/- 0.5 ˚C), humidity (+/- 3.5%), wind direction (+/- 3 degrees), wind speed (+/- 3 kph), pressure (+/- 1.7 hPa), and rainfall (+/- 1%) are measured (Earth Networks 2014b). All the data undergo data quality control procedures and are assigned a tag to represent the level of data verification (Earth Networks 2014a). Data was available from 2011 to 2018, however not all 40 weather stations were collecting data at any given time. For each heatwave event considered, the number of weather stations with hourly measured data are reported in Table 1.

Table 1. Number of available ground-based weather stations (GBWS) in Austin during the considered historical heatwave events

Heatwave event date	Number of available GBWS
8/28/2011	13
8/8/2013	14
7/24/2017	17

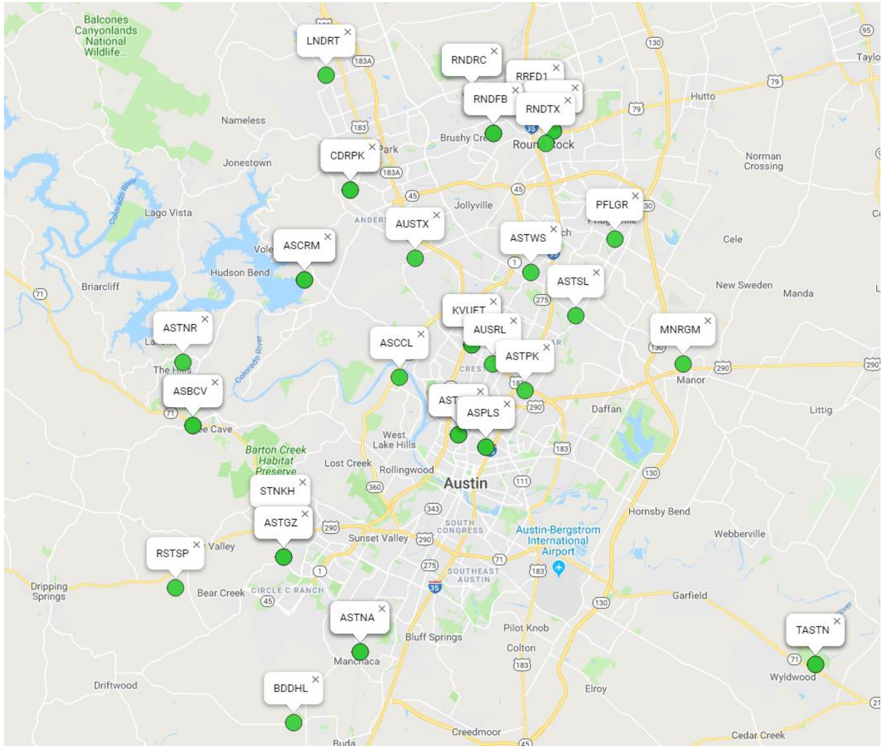

Figure 1. The location of all available ground base weather stations for the studied heatwave events

2.2 WRF and UCM model configuration

WRF forecasts are generated using 4 nested domains with a horizontal grid spacing of 36 km, 12 km, 4 km and 1 km. The outer domain comprises most of the U.S. and the inner domains consist of the central U.S., the state of Texas, and the city of Austin respectively. The boundary conditions of the outer domain and the initial conditions are provided by the archived data of the Global Forecast System of the NOAA's National Centers for Environmental Prediction (NOAA n.d.). The WRF model is initialized for each heatwave event starting at 12 UTC (7:00 a.m. CDT) and forecasts are generated hourly for a 24-hour forecast horizon.

The physical processes such as the exchange of heat, momentum, and water vapor in urban environment in mesoscale model can be better represented when the WRF model is coupled with an UCM model (Bueno et al. 2014; Chen, Yang, and Zhu 2014). The UCM model divides the urban area into three urban categories, namely (a) low-intensity residential (constructed materials account for 30 to 80 percent of the cover), (b) high-intensity residential (constructed materials account for 80 to 100 percent of the cover), and (c) commercial/industrial, which includes all other highly developed areas not included in the (b) high-intensity residential (Tewari et al. 2007). The UCM model has 51 urban parameters representing land use, anthropogenic heat, building dimensions, surface albedo, emissivity, and thermal properties of materials for each of the three urban categories. In this study, all UCM parameters are kept as default values (Skamarock et al. 2005), with the exception of the building height, roof surface albedo, wall surface albedo, and the Akanda parameter. Table 2 provides the values for these parameters utilized in the models. These values are modified for better model performance and according to the Austin, TX urban landscape. Together, the WRF model coupled with the UCM improves the depiction of the lowest levels of the atmosphere in consideration of urban heat effects associated with the city of Austin, and should result in improved model-based forecasts for urban regions.

Table 2. List of UCM parameter values that differ from WRFv3.9 (Skamarock et al. 2005) default values(Kusaka and Kimura 2004).

Parameter	Value	Unit
Roof level (building height)	5.0, 6.5, 6.5	[m]
Roof surface albedo	0.2	-
Wall surface albedo	0.2	-
Road surface albedo	0.2	-
Akanda parameter	0.3, 0,4, 0.5	-

Note: Multiple entries indicate values respectively for low-density residential, high-density residential, and commercial/industrial urban fraction

2.3 Bias Correction Methods

The hourly WRF/UCM results are first compared with the measured data for each of the three heatwave events individually. To improve the resulting WRF/UCM model prediction, two statistical techniques, including linear regression and an average delta correction method are investigated to improve the WRF/UCM results and reduce the bias of the modeled results as compared to the measured data. For each considered bias correction method, for each heatwave event, 70% of the stations' data are used as the training data to develop the model. The remaining 30% of the stations' data are kept as a control set for use in holdout cross validation, to determine the fit of the model to out-of-sample data. A combination of stations are considered for the control and training data from the set of available stations for each event. The WRF/UMC results are then updated using the resulting equation and compared with GBWS data which are held as a control dataset. The total root mean squared error (RMSE) values for the control stations are then compared to the original WRF/UCM results. This value indicates the impact of the bias correction method on the agreement of the WRF/UCM model results with the measured data. The results of the two methods are then compared to determine which of these techniques performs better for the heatwave events considered in this study.

2.3.1 Linear regression

In this bias correction method, a linear regression model is created using the training dataset, which includes a predictor variable as WRF/UCM model temperature results and a dependent variable as measured temperature at the GBWS. A linear regression line has an equation of the form $Y = a + bX$, where X is the WRF/UCM model temperature results and Y is the dependent variable considered as the measured temperature at GBWS. The slope of the line is b, and a is the intercept. To calculate a and b, the method of least squares is applied.

2.3.2 Average delta correction

In this bias correction method, the hourly temperature difference between the WRF/UCM results and measured data in the training dataset are calculated for all available stations for each event. Next, the average delta value is calculated for each time span considering all stations. The

WRF/UCM results for the control stations are then adjusted by adding the delta value for each time span to WRF/UCM results.

2.3.3 Methods comparison

As the RMSE values for the control stations were calculated for both linear regression and average delta correction methods, the applicability of these methods is compared considering the percentage of RMSE improvement for each method.

3 RESULTS AND DISCUSSION

3.1 Linear regression

For each of the three heat wave events, the hourly measured data at each ground-based weather stations are plotted versus the WRF/UCM results for the training dataset and three linear regression equations are fitted to the modeled data as shown in **Error! Reference source not found.**. An R-squared value of 0.87 to 0.9 is found, indicating a reasonably strong fit to the data. We also note that the regression lines are close to that of the 1:1 lines shown in **Error! Reference source not found.**. Using these equations for each event, the WRF/UCM results for the control stations were modified accordingly and are compared to the measured data (**Error! Reference source not found.**). The percentage of RMSE improvement due to the WRF/UCM bias correction (**Error! Reference source not found.**) ranges from 2% to 37%, indicating that in all cases the linear regression improved the resulting RMSE values. However, the percentage of improvement varies by heat wave event considered.

Table 3. Comparison of RMSE values (i) before and (ii) after applying linear regression on WRF/UCM results for three historical heatwave events

	RMSE		
Date	WRF/UCM	Adjusted WRF/UCM	% Improvement
8/28/2011	2.213	1.387	37%
8/8/2013	1.495	1.466	2%
7/25/2017	1.367	1.233	10%

As the ground-based weather stations are located in various locations spatially throughout the city of Austin and also have different urban characteristics, e.g. urban fraction, land use, etc., choosing a different set of control stations affects the final linear equation and results. To address this variability, all possible combinations of control stations from the available stations are thus investigated to determine the range of the possible RMSE improvements for each combination. Details of the results of this analysis for one heatwave event are included in this work for brevity. The total number of available stations on 8/28/2011 is 13 stations; all possible combinations for choosing four control stations from all available stations results in 715 cases. The same methodology is applied for all 715 cases. The resulting RMSE improvement for all the possible cases is shown in **Error! Reference source not found.**. The mean value of RMSE improvement for all the cases is 43% with a standard deviation of 10%. This is slighting higher than the 37% determined in Table 2.

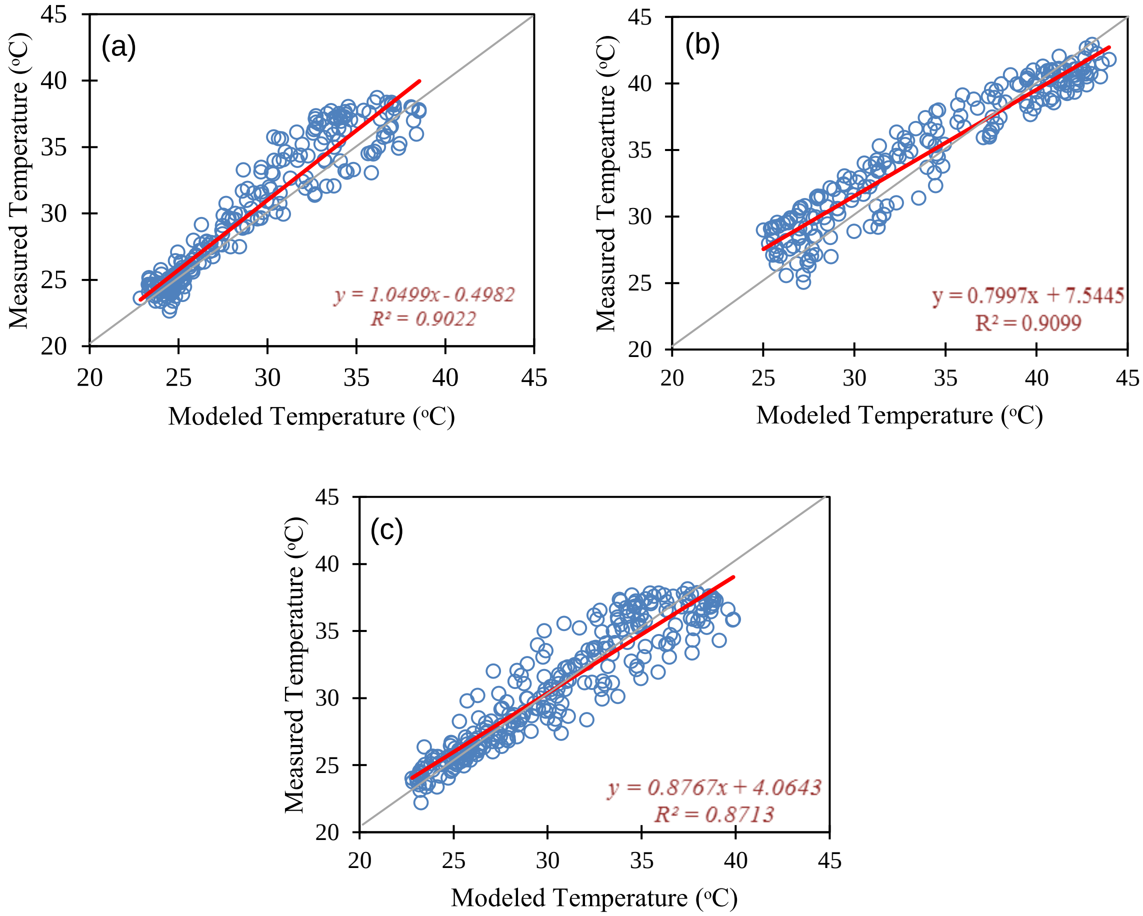

Figure 2. WRF/UCM hourly temperature results versus measured data during three heatwave events in Austin. TX, including (a) 8/82013, (b) 8/28/2011, and (c) 7/252017. (Note: grey line = 1:1; red line = bias correction linear regression line)

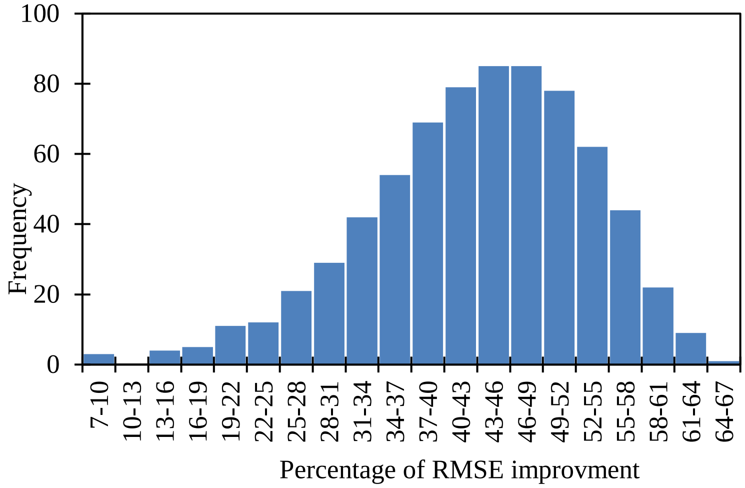

Figure 3. Percentage of RMSE improvement by applying linear regression for 715 possible cases during the 8/28/2011 heatwave event

3.2 Average delta correction

The average delta correction technique was applied for the three heatwave events. The RMSE values before and after applying this method are compared in **Error! Reference source not found.**. The percentage of RMSE improvement due to the WRF/UCM bias correction ranges from 31% to 54%, indicating that in all cases the average delta correction improved the resulting RMSE values. In all three heatwave events, the average delta correction results in a larger improvement in RMSE.

Table 4. Comparison of RMSE values (i) before and (ii) after applying the average delta correction on WRF/UCM results for three historical heatwave events

Average delta correction			
	RMSE		
Date	WRF/UCM	Adjusted WRF/UCM	% Improve-ment
8/28/2011	2.180	1.010	54%
8/8/2013	1.495	0.860	42%
7/25/2017	1.367	0.948	31%

Similar to the linear regression model results, all possible combinations of control stations from the available stations are then used to determine the range of the possible RMSE improvements for each combination for the heatwave event on 8/28/2011. 715 combinations of control stations are investigated; the average delta correction method is applied for each case (**Error! Reference source not found.**). These results indicate that majority of the cases have 45% to 55% improvement in RMSE. The mean value of RMSE improvement for all the cases is 51% with a standard deviation of 7%.

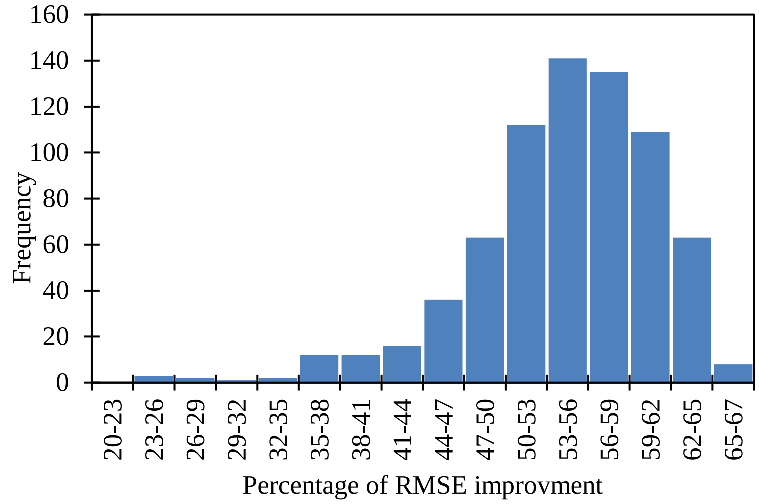

Figure 4. Percentage of RMSE improvement using the average delta correction method for 715 possible cases during the 8/28/2011 heatwave event

3.3 Comparison of two techniques

Both techniques are then applied for all heatwave events. The ability of each method to improve the RMSE values is reported in **Error! Reference source not found.**. Results indicate that overall the average delta correction method performs better with a higher percent RMSE improvement as compared to the regression method.

Table 5. Comparison of percentage improvement for average delta correction and linear regression bias correction methods

	Average Delta Correction			Linear Regression		
	RMSE			RMSE		
Date	WRF/UCM	Adjusted WRF/UCM	% Improv-ement	WRF/UCM	Adjusted WRF/UCM	% Improv-ement
8/28/2011	2.180	1.010	54%	2.213	1.387	37%
8/8/2013	1.495	0.860	42%	1.495	1.466	2%
7/25/2017	1.367	0.948	31%	1.367	1.233	10%

4 Conclusions

A WRF model coupled with a UCM was used to simulate the local weather conditions in the city of Austin, TX for three historical heatwave events which occurred in 2011, 2013, and 2017. These results were compared to data collected from a dense ground-based weather stations network located within the city. The resultant difference between the model and the measured data, represented using RMSE, found that there are systemic errors between the simulated temperature and the measured temperature data. This study aimed to reduce this error using two bias correction methods. These include the average delta correction and linear regression methods. For both methods, stations available for each heatwave event were divided into training and testing sets. The outcomes for the both methods indicated that bias correction is capable of improving model result agreement with measured data.

To assess spatial variation, all combinations of training and testing datasets were investigated for the heatwave events occurred in 2011. Considering all combinations, it is concluded that average delta correction performs better. This suggests that biases in the UCM/WRF results can be improved using these methods. To further improve these results, additional measured data and additional simulation results across additional years of data could be used to further assess the validity of the above-mentioned bias correction methods.

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