

A sensitivity analysis to investigate urban heat island impact on building energy consumption

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Abstract

The purpose of this study was to investigate urban heat island (UHI) effects on building energy consumption and energy costs for dwellings in a neighbourhood of Des Moines, Iowa, USA. The innovation we present is a sensitivity analysis rather than a traditional simulation. Parameters in this analysis included building materials, trees, and two sets of weather data, which we analysed using the Urban Modelling Interface. Including the UHI effect decreased annual heating loads by 7.5% for buildings with trees present, and increased annual cooling load by 21.2 %. In naturally-ventilated buildings, UHI effects reduced annual heating load by 8.5%.

Key Innovations

- Impact of UHI on building energy consumption was analysed.
- Remote sensing was used to provide weather data for urban heat island (UHI) effects on building energy consumption.
- A sensitivity analysis was conducted to determine which parameters are important in controlling model behaviour.

Practical Implications

This study can support designers and policymakers in understanding the effect of the urban heat island (UHI) on urban climate and building energy consumption. This study assesses the effect of the urban heat island (UHI) in a climate with cold winters and warm, humid summers. The results can be used by decision-makers and designers to prioritize mitigation strategies.

Introduction

Investigations of urban heat island (UHI) impact on building energy consumption are of central importance to sustainable development in a changing climate. Warmer urban areas lead to increases in cooling loads, and those loads in turn increase carbon dioxide emissions. Reviewing previous research, Li et al. (2019) reported that UHI could result in a median increase of 19.0% in cooling energy consumption and a median decrease of 18.7% in heating energy consumption based on multiple studies. Different approaches have been used to assess the UHI effect on building energy consumption predictions via modelling and simulation. Souza et al. (2009) used actual measurements taken at 40 urban reference points in a study area, a medium-sized city, and compared their

results to rural temperature data collected at an urban meteorological station. Doddaballapur and colleagues (2011) gathered and processed annual recorded weather data for the period 1950-2005 to study the impact of naturally increasing night-time minimum low temperatures in the severely hot summer months on typical buildings in the Phoenix metropolitan area. The study simulations were based on 56 years of weather data (actual measured data) and typical meteorological year data (TMY1, TMY2, and TMY3). They also used three additional climate change timeline scenarios (extending to 2020, 2050 and 2080) to understand the predicted effect of climate change in the study area. Streutker (2003) adopted a novel approach of using thermal satellite imagery (a remote sensing technique) to evaluate the level, expansion, spatial extent, seasonal and diurnal pattern of the UHI for Houston, TX, USA for the period 1985 to 2001. Li and co-workers (2009) used an integrated geographic information system and remote sensing (GIS-RS) approach, including spatial autocorrelation and semi-variance analyses to quantitatively characterize patterns of recent UHI effects in the Shanghai, China metropolitan area for the period 1997 to 2004.

Wang et al. (2019) used a Linear Spectral Mixture Model to extract land cover information. They used this model to study the effects of urban land cover types on land surface temperature (LST) and heat budget components based on Landsat 8 remote sensing images of Shenzhen, China. Litardo et al. (2020) quantified the UHI effect in Duran, Ecuador, an example of a tropical climate study area. They used the k-means clustering technique, a statistical method to classify 28 randomly-sampled urban areas. Based on this method, they classified the areas into four clusters. They then determined parameters for urban area characteristics (ratios for site cover, façade-to-site, weighted average building height, tree cover, and vegetation cover), thermal properties of building materials (mainly albedo), and non-building sensible anthropogenic heat (primarily from traffic). They also used the Urban Weather Generator (UWG) tool to estimate the UHI intensity of each cluster. Finally, the impact of UHI on energy consumption of buildings was presented using TRNSYS 17 software. In an additional study, Hashemi and colleagues (2020) used a novel method to investigate the effect of UHI on building energy consumption prediction. Their findings indicated UHI effects on building energy consumption in the early

stages of the design process. Their method coupled use of the Local Climate Zones (LCZs) classification scheme and the Urban Weather Generator (UWG) model to predict UHI effects on energy consumption for different building types in the local climate zone in Philadelphia, PA, USA.

Previous studies varied in terms of investigators' consideration of the UHI effect and the need to use a secondary tool, such as an urban weather generator, to create/simulate weather data. The contribution of this paper is to use remote sensing-derived data to develop the Energy Plus Weather (EPW) input file to compute UHI effects on building energy consumption. The study presented here is based on integration of gridded daily datasets of maximum and minimum air temperature, which were created using geographically weighted regression models driven by gap-filled daily land surface temperature (LST) and elevation data. First, daily 1-km resolution seamless Moderate Resolution Imaging Spectroradiometer (MODIS) LSTs were built using a hybrid gap-filling method. Then, geographically weighted regression models, driven by measured air temperature at weather stations and gap-filled daily LSTs and elevations were used to estimate daily maximum and minimum air temperature for 1-km grids (Li et al., 2018a; Li et al., 2018b).

The goal of this study was to optimize an approach to accurately include UHI in weather data preparation for urban energy models. The current study is based on a sensitivity analysis approach. The primary goal for conducting a sensitivity analysis is to determine which of the parameters are important in controlling model behaviour (Reed et al., 1984). Sensitivity analysis is particularly useful to assess the effect of different variables influencing building energy consumption. To identify the source for the majority of variation in the simulation results, our study considered these variables: building materials, outdoor vegetation and weather data. In addition, buildings were divided into two groups: air-conditioned (AC) and naturally ventilated (NV) structures. Sensitivity analysis is used here to refer to the generic approach of using different techniques to quantify how variability in model output can be apportioned to changes in model input parameters (e.g., Kristensen et al., 2016).

Understanding how systems respond to input values can reveal the effect of UHI on building energy consumption, in essence serving as a quality assurance tool. Confidence in the model will increase if it responds as expected to changes in parameter values. Unexpected behaviour, on the other hand, could lead to re-evaluation and modification of the model and its parameters. Sensitivity analysis can reveal the relationships between input parameters and predictions, and provide an opportunity to examine model behaviour under a variety of conditions (e.g., Reid et al., 1993). In the present study, we introduce the use of satellite-based weather data for estimating the UHI effect. Two sets of simulations were performed using data for a residential neighbourhood in the US, Midwest

using the Urban Modelling Interface (*umi*) to investigate how UHI affects annual heating and cooling loads.

We sought to describe effects of the UHI on energy consumption and energy bills in a study area which is representative of regions characterized by cold winters and warm, humid summers. Future studies could also compare the effect of changes in climate conditions.

Methods

This project is a part of an interdisciplinary research effort to create a system-of-systems analytical framework to integrate social and biophysical models for urban Food-Energy-Water System (FEWS). We use an innovative co-simulation approach to describe current and predict future conditions, with an emphasis on local (urban and urban-adjacent) food production. In the research presented here, the effect of UHI on building energy consumption was investigated to complement previous research (Koupaei et al., 2020). In this case study, the impacts of UHI on buildings in the Capitol East neighbourhood (Des Moines, Iowa, USA) are investigated through a sensitivity analysis (Figure 1). This neighbourhood is bounded by an interstate highway (I-235) on the North, railroad tracks on the east and south, and E.14th Street on the west. There are 340 buildings in the portion of the neighbourhood we included in our study. Weather data collected in 2010 are used in this simulation. The annual weather summary for Iowa in 2010 shows that this was the 66th coolest and second wettest year among 138 years of state records (Iowa Department of Agriculture and Land Stewardship, 2021). As noted earlier, several scholars have evaluated the effect of UHI on building energy consumption. This study focuses on how UHI affects energy consumption and residential energy costs under this set of climate conditions. In general, the Köppen Climate Classification subtype for this region is "Dfa" (Hot Summer Continental Climate). The average temperature for the year in Des Moines is 50.9°F (10.5°C). The warmest month is July, with an average temperature of 76.3°F (24.6°C). The coolest month is January, with an average temperature of 22.6°F (-5.2°C). The highest recorded temperature in Des Moines was 108.0°F (42.2°C), recorded in August 2020. The lowest recorded temperature was -26.0°F (-32.2°C) in February 2020 (Des Moines, Iowa Köppen Climate Classification, 2021).

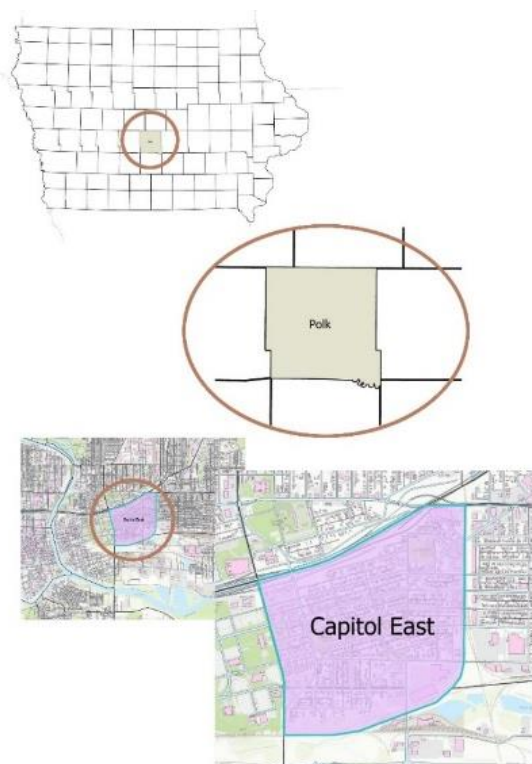


Figure 1: Capitol East Neighborhood, Des Moines, IA. Image created by S. Ghiasi based on City of Des Moines GIS data (City of Des Moines, GIS Data, 2021)

We used Grasshopper 3-D, a Meerkat plug-in, and Arc-GIS Pro to create a 3-D model of the neighbourhood (Figure 2).

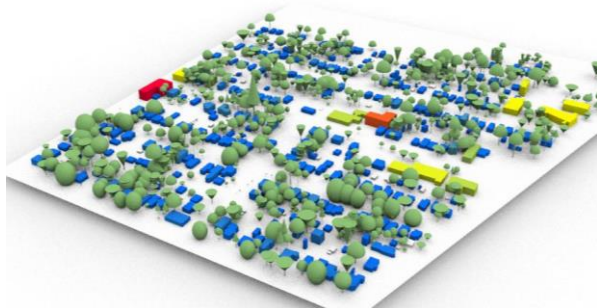


Figure 2: A 3-D model of the study portion of the neighborhood created in Rhino-Grasshopper

We used the urban modelling interface (umi) for simulation of energy consumption. This modeling program uses a Windows-based NURBS modeler (Rhinceros) and EnergyPlus for thermal calculations (Reinhart et al., 2013; DOE, 2021). The first step to develop the 3-D model of the neighbourhood was to obtain basic information for building properties based on GIS shapefiles acquired from the City of Des Moines Assessor's office. That included the building footprints, elevations, material characteristics, thermal conditioning systems (HVAC), and year of construction for the structure on each parcel. Trees were modelled based on the shape and size of their canopies, trunk height, species, and their exact position per a spatially explicit comprehensive inventory that was used to integrate tree inventory data into an urban energy model for the same

study area (Hashemi et al., 2018). In this study, trees were considered as a simple shading source. Simulations were initiated by assigning a template to the 340 buildings under consideration. Of these, 259 buildings were equipped with an active air-conditioning (AC) system, and 81 were naturally ventilated (NV). All buildings were heated with natural gas. In order to develop the templates for simulation, insulating material resistances (R-value) between 1 and 4 m² K/W were assigned to the templates, as were air infiltration rates, which varied between 0.34 and 0.75 ACH (also per Hashemi et al., 2018). Based on data obtained from City of Des Moines Assessor's office, we categorized buildings according to their construction material. We then defined 28 different building templates that included information on heating and cooling systems as well as shade from nearby trees (Figure 3).

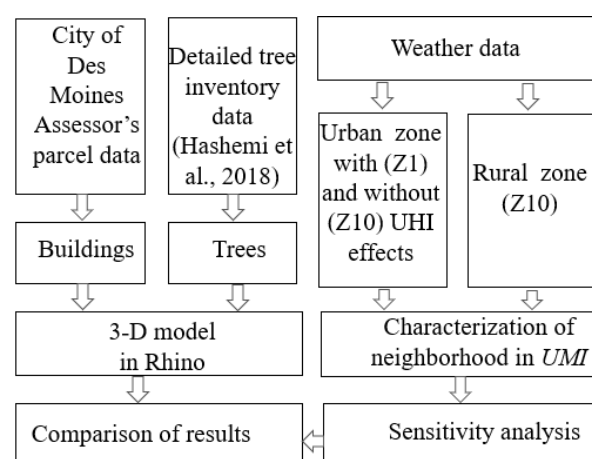


Figure 3: A workflow for our study process

To represent UHI effects, the City of Des Moines was divided into ten concentric thermal zones starting at the urban core and extending to nearby rural areas (Figure 4). The weather data sets for all zones were developed using satellite-based techniques previously described (Li et al., 2018a; Li et al., 2018b). One location was selected within each zone, with Z1 nearest to the study area, and Z10 nearer to a rural area. Two major scenarios were developed for estimating UHI effect on energy consumption for the area of study (Figure 5). Both scenarios were simulated with and without trees. All simulations were based on the ASHRAE 90.1 standard for building occupation schedules. Simulations were performed using two weather datasets: For the first simulation we used only weather data for the rural zone (Z10). For the second simulation we used weather data for the urban zone (Z1).

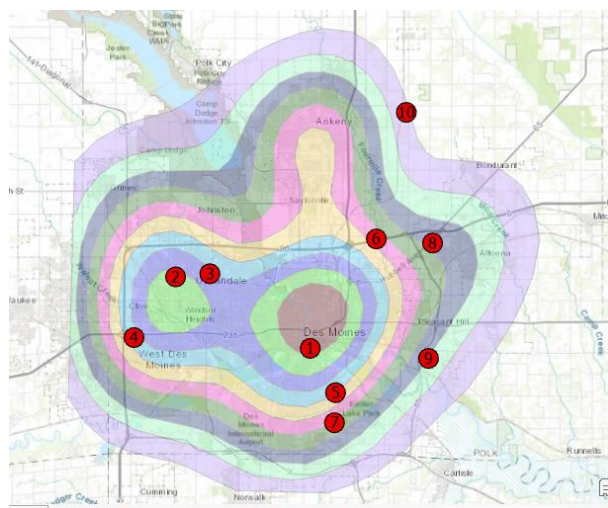


Figure 4: Des Moines, IA is divided into 10 zones from the urban core to rural areas. In each zone one representative location was selected. Image prepared by S. Ghiasi.

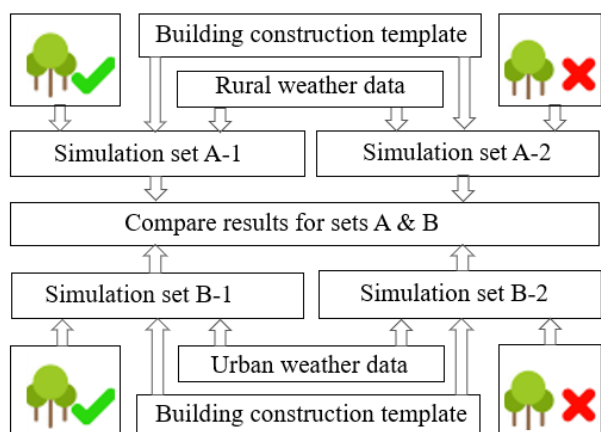


Figure 5: Scenarios used for simulations to estimate the effect of UHI on energy consumption for the study area.

Results

We conducted *umi* simulations for heating and cooling loads with and without the UHI effect for air-conditioned buildings (Figure 6). we used these results for estimating the rate of natural gas and electricity use in the neighbourhood. For the different building templates, heating loads were decreased and the cooling loads were increased in scenarios that included the UHI effect. Heating demand and cooling loads with and without UHI effects were also tabulated for our *umi*-generated models for both AC and NV buildings (Table 1).

ASHRAE 90.1

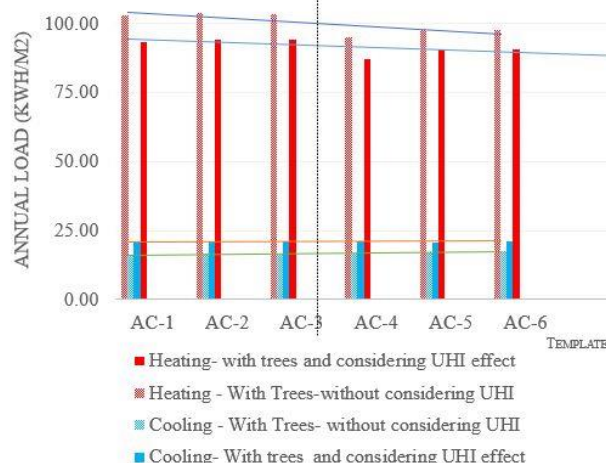


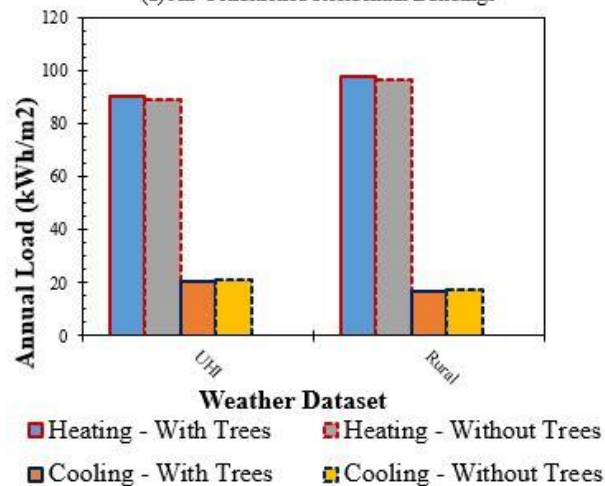
Figure 6: Results of *umi* simulation with trees and weather data for UHI (Z1), and without UHI (Z10)

Table 1: Heating and cooling with or without UHI.

Unit type	UHI vs. rural area	Annual load (kWh/m ²)		Annual load (kWh/m ²)	
		Heat - with trees	Cool - with trees	Heat - no trees	Cool no trees
AC	UHI	90.3	20.6	88.8	21.4
	Rural	97.6	17.0	96.1	17.6
NV	UHI	90.4	0.0	88.5	0.0
	Rural	98.8	0.0	96.4	0.0

The *umi* output for two scenarios, including annual heating and cooling load for rural and urban weather data for air-conditioned residential buildings and naturally ventilated residential buildings show large variations (Figure 7). The effect of UHI on annual energy costs was also visualized in *umi* simulations (Figure 8).

(a) Air-Conditioned Residential Buildings



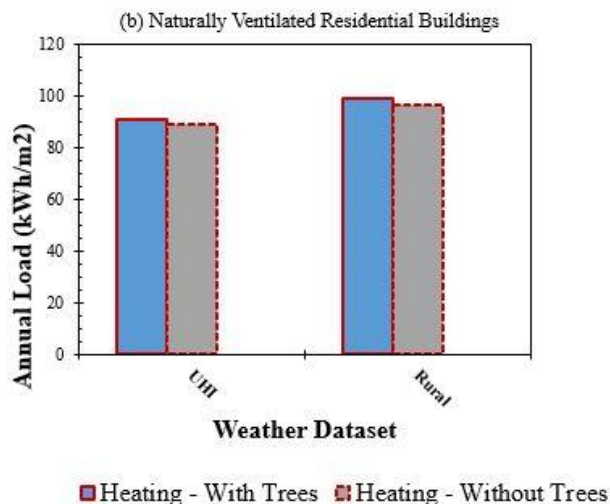


Figure 7: Results of umi simulations for two scenarios, including annual heating and cooling loads for rural and urban-influenced weather data for a) air-conditioned residential buildings, and b) naturally ventilated residential buildings.

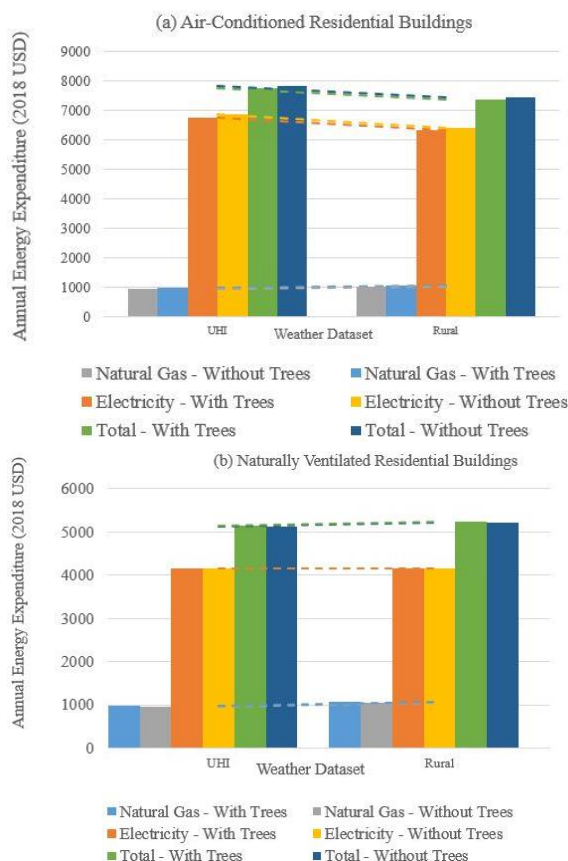


Figure 8: Simulations with umi indicate UHI can affect energy expenditures for annual heating and cooling for a) air-conditioned residential buildings, b) naturally ventilated residential buildings.

We measured important changes in percent of annual heating and cooling load due to the UHI effect (Table 2).

Table 2: Change in annual cooling load and heating load due to the UHI effect- output from the UMI model.

Unit type	Annual load (kWh/m ²)		Annual load (kWh/m ²)	
	Heating with trees	Heating without trees	Cooling with trees	Cooling without trees
AC	-7.47%	-7.59 %	21.17 %	21.59 %
NV	-8.50%	-8.19 %	NA	NA

Discussion

We considered 28 templates with different construction materials to integrate tree shade and UHI effects in estimation of building energy consumption. For this group of simulations, annual heating load (kWh/m²) with shading from trees ranges from 86.80 to 94.11 kWh/m², and without trees it ranges between 88.45 and 93.88 kWh/m². Annual cooling load with tree shade ranges from 20.45 to 21.28 kWh/m². The annual cooling load without tree shade effect is between 21.44 and 22.42 kWh/m². For NV residential buildings, annual heating load with trees was from 86.61 kWh/m² to 95.04 kWh/m², and without was between 84.86 and 93.01 kWh/m².

The UHI effect decreases annual heating load by about 7.6% and increases annual cooling load by 21.6%. Considering effects of both trees and UHI, annual cooling load can be increased by 21.2% and annual heating load can be decreased by 7.5%. For buildings with AC, annual expenditures for natural gas with tree shade will be decreased by 7.5% and for electricity expenditures will be increased by 7.1%. Without trees, annual cost for natural gas will decrease by 7.5% and for electricity will increase by 7.6%. In naturally-ventilated buildings, annual cost for natural gas will decrease by 8.5% with trees and will decrease by 8.2% without trees. For naturally-ventilated buildings annual cost for electricity would not change.

Conclusion

We conducted a sensitivity analysis to investigate the effect of trees and UHI on energy building consumption. The interdisciplinary nature of this research included consideration of trees and the UHI phenomenon. The UHI effect indicates the potential for significant increases in the annual cooling load by and decreases in the annual heating load. If trees are present these effects are slightly mitigated. Annual costs for electricity will also increase for buildings with AC. Without trees the UHI effect notably increases the annual cost for electricity, adding to costs for residents and the necessity for demand management by the energy provider. Preventive mitigation programs, such as tree plantings, could help residents reduce the impact of UHI on their energy use.

In this study we considered trees as simply providing shade. Future studies will include consideration of evapotranspirational cooling by trees to refine estimates for building energy consumption, and to further increase accuracy of modelling results.

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