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Urban neighborhood characteristics influence on a building indoor environment

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ABSTRACT

The urban heat island (UHI) is exacerbated during heat waves, which have been reported to be more frequent in recent years. Unwanted consequences of the UHI not only include an increase in mean/peak energy demand, but an escalation in the heat-related mortality and disease. Although UHI mitigation strategies are being implemented by cities, they serve as mid to long-term solutions. The implementation of short-term mitigation strategies is paramount for cities to reduce the immediate risks of the heat-related hazards. Various prognostic tools have been developed to empower urban planners and decision makers in minimizing the related risks. These tools are mainly based on stationary parameters, such as the average surface temperature of a city, and are independent of land-use/land-cover (LULC). Furthermore, the outdoor temperatures are utilized to develop such models. However, heat-related risks occur mostly in indoor spaces, and correlations between indoor and outdoor spaces are rarely considered.

In this study, a predictive model for the indoor air temperature of buildings is developed using the artificial neural network (ANN) concept. A four-month measurement campaign was conducted to obtain indoor temperatures of more than 50 buildings located on the island of Montreal. The area is then separated into 11 regions, each containing at least one of the measured buildings. The ANN model is then trained to be sensitive to the neighborhood's characteristics and LULC of each region. The surrounding radial area that influences the building's indoor temperature is first defined within an effective radius, by analyzing areas with radii ranging from 20 m to 500 m in 20 m increments. Hence, the effective radius is found for each region to be within a radial area, where the environment beyond its limit does not significantly impact the building indoor air temperature. This technique trains a single model for the city, encompassing the unique characteristics of the sub-regions that contain buildings under study. An effective radius was established to lie within 320–380 m. Analyzing surrounding radial areas within this range enabled the network to effectively forecast future indoor conditions resulting from UHI effects, producing hourly indoor temperature predictions with an MSE of 0.68. Furthermore, the ability of the developed tool in the city planning is investigated with an additional case study.

1. Introduction

Heat waves have become longer, more intense and more frequent (Meehl & Tebaldi, 2004). Such temperature increases are exacerbated by urban heat island (UHI) effect, where the metropolitan area is significantly warmer than its surrounding rural area. UHI effects occur within cities as the energy balance of the landscape becomes artificially unbalanced with the blockage effect of constructed buildings and infrastructure, the generation of more anthropogenic heat, and the absorption of more solar irradiance. The resulting consequence of such effects is an inhomogeneous tempo-spatial temperature elevation within urban environments. Furthermore, the UHI causes an increase in the mean/peak energy demand (Mirzaei & Haghighat, 2010; Santamouris, 2014). It is also well documented that there is an increase in mortality and morbidity associated with the UHI as the temperature in cities increases (Doyon, Bélanger, & Gosselin, 2008; Gabriel & Endlicher, 2011).

To mitigate the UHI, several mid/long-term diagnostic plans (e.g. vegetation and greenery) have been proposed and adapted by cities. From an urban-planner or a decision maker's point of view, however, providing a prognostic short-term plan (e.g. enhancing the urban ventilation with better design of future planned buildings) for the vulnerable sectors of a city and reinforcing the poorly designed areas against the heat-related risks of the UHI with

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mid/long-term plans is of paramount importance. Among many efforts, cities attempt to bring awareness to the local inhabitants and to encourage their assistance with anticipatory heat alert systems in the case of heat waves. The relation between the ambient temperature and heat-related morbidity/mortality rates is commonly utilized to develop predictive models, enabling the public to understand the level of the heat-related risk. Thus, the developed anticipatory models should help forecast the associated heat risk with high spatial resolution in the order of a few hundred meters. For example, Mirzaei et al. (2012) developed an alert system for the island of Montreal to recognize the vulnerable regions during UHI.

The predictive models are mainly based on correlations, which are developed to show how the rate of mortality is dependent on the temperature increase. This includes simple linear regressions and more advanced methods such as time-series analysis. In these models, the parameters such as the threshold temperature, the number of hot days, daily mean, maximum and minimum temperature, peak temperature, extremes/weekly/10-day average temperatures, and age of occupants are the key parameters in heat-related mortalities. More advanced correlations include the social and environmental aspects such as vegetation, age of occupants, genetics, socioeconomic status, health behaviors, and physiologic differences. The form of these correlations is mainly J and U-shaped, defining the mortality rate against the temperature extremes (Basu & Samet, 2002). For example, Chen et al. (2014) identified mortality rate to be a function of urban vegetation ratio, the mean daily indoor temperatures exceeding 28.5 °C and the building orientation. Moreover, Doyon et al. (2008) anticipated that the annual mortality rate increases from about 0.5% in 2020 and reaches 3% around the year 2080.

In the mentioned studies, however, the correlations are extracted between the mortality rate and an overall characteristic of the city such as the ambient air, meaning that the spatial distribution and intensity variation of the UHI throughout a city is mostly neglected and assumed to be constant. On the other hand, the impacts of the heterogeneity of land use/land cover (LULC) in the formation of UHI is well investigated, meaning that the heterogeneous nature of urban morphology and population density causes a different UHI intensity throughout a city. As a result, UHI analysis needs to be fractioned to a smaller scale, facilitating a more in-depth investigation of the parameters that influence the exacerbation of the UHI. For example, Ivajnsic, Kaligaric, & Ziberna (2014) developed a regression based on five parameters; distance to an urban area, topographic position index, land-cover diversity, building volume per area, and northern orientation. The regressive model was developed for Ljutomer city (Slovenia) to explain spatial variation in the mean air temperature. Another study of UHI within Chicago by Coseo and Larsen (2014) explains that during extreme heat events, 91% of air temperature variation is related to the urban block's percentages of impervious surface and tree canopy. Su et al. (2012) utilized geographically weighted regression to find the relationships between LULC (i.e. built-up, water, paddy field, and other vegetation) and the surface temperature of TaoYuan city-Taiwan. In another investigation, Zheng, Myint, & Fan, (2014) examined the effect of the composition and the spatial pattern of anthropogenic LULC temperature of Phoenix-Arizona. Furthermore, Chun and Guldmann (2014) reported the impacts of solar radiation, open spaces, vegetation, building rooftop areas, and water on the Columbus city's surface temperatures.

Thus, as these studies demonstrate, the heterogeneous relationships between the LULC and urban temperatures should be included in the development of alert systems as the intensity of UHI varies according to the geographical and climatic characteristics of a city. For example, in a neighborhood with high albedo surface materials, the solar radiation is more likely to be absorbed and stored. In highly populated areas, mainly with narrow street canyons and high-rise buildings, the released anthropogenic heat is less ventilated by wind. The socioeconomic level is also known to be an influential factor in the release of heat within buildings, mainly as a result of air conditioning systems being frequently installed when the standard of living is above a certain threshold. In conclusion, the different types of LULCs throughout a city are the key elements in the alteration of UHI as the portion of each above-mentioned parameter varies with them. The local nature of LULC therefore renders the UHI in a city heterogeneous in its temperature distribution. This evidently requires related countermeasures to be uniquely implemented within a city neighborhood. This simply implies that, for example, tree planting can be less effective in a region where the main source of UHI is low-albedo materials, while refurbishing the surface coating with high-albedo materials can be more effective in reducing the UHI in that particular region.

As discussed earlier, regression models are a common approach to understanding the relationship between the LULC and the temperature. The complexity of the contributing parameters in the formation of the UHI normally causes a considerable discrepancy in these models, so more advanced models seem to be more effective than the latter models. In a comparative study, Ashtiani, Mirzaei, & Haghighat (2014) proved that the artificial neural network (ANN) is a more accurate approach for the prediction of indoor air temperature.

The objective of this study is to understand the impact that neighborhood characteristics and surrounding LULC have on the indoor temperature of a building. For this purpose, the building's surrounding environment is analyzed as a radial area, with LULC categorized into five different types, including vegetation (grass and trees), buildings, water, and pavements (asphalt and cement). An ANN model is developed to investigate the correlation between indoor building temperature and the surrounding environment by analyzing areas with radii ranging from 20m to 500m in increments of 20m. Hence, the effective radius is found for each region to be within a radial area, where the environment beyond its limit does not significantly impact the building indoor air temperature. Parameters defining the influence of the surrounding environment include solar heat gain, local wind velocity, building orientation, outdoor conditions, vegetation, and thermal mass. The utilized data is obtained from a four-month measurement campaign in which indoor air temperature and relative humidity (RH) of more than 50 buildings located on the island of Montreal were measured for the summertime period of 2010.

2. Methodology

2.1. ANN technique

The artificial neural network package in MATLAB was used to develop a neural network model. The purpose of the model is to establish a correlation between the hourly-recorded building indoor air temperatures and the input parameters previously described. The Time Series Neural Network (TSNN) was utilized in this study to better encompass the dynamic nature of hourly temperature fluctuations within urban dwellings subjected to the UHI effects. The TSNN achieves such by incorporating past target data as additional input parameters while predicting the future target data. Therefore, when predicting the future hourly temperature within a dwelling, the TSNN incorporates past hourly temperatures in addition to the input parameters.

In order to establish a correlation between a set of input parameters and target data, the ANN divides the target data into three sets. The first set, designated as the training set, represents 70% of the target data that is chosen randomly by the network. The training set is used to establish the initial correlation between the input