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# Building's Indoor Thermal Condition in Various Urban Neighbourhoods

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**Abstract**

*Heat waves are reported to be more frequent in recent years. The urban heat island (UHI) is severely exacerbated during the UHI, leading to an increase in mean/peak energy demand and an escalation in the heat-related mortality and disease. Beside the taken long-term actions by cities to mitigate UHI such as urban greening plans, the implementation of short-term mitigation strategies can reduce the immediate heat-related risks of the UHI. Predictive tools can help urban planners and decision makers in minimizing the mentioned risks. However, these tools are mainly developed based on stationary parameters of a city such as the average surface temperature, which cannot present the variation of land-use/land-cover (LULC) in various urban neighborhoods.*

*In this study, an artificial neural network (ANN) is developed to predict the indoor air temperature of buildings in different LULCs. A four-month measurement campaign of more than 50 buildings located on the island of Montreal was conducted to obtain indoor temperatures. The island of Montreal is then separated into 11 regions where the ANN model is trained to be sensitive to three types of neighborhoods, including high-rise, residential and industrial. Hence, the effective radius on buildings' indoor temperature 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. The effective radius was observed to lie within 320m to 380m.*

***Keywords: Urban heat island, Indoor environment, Artificial neural network, Health, Land-use/land-cover, Urban planning***

## 1. Introduction

Cities are significantly warmer than its surrounding rural area due to the urban heat island (UHI) effect. The blockage effect of constructed buildings and infrastructure, the generation of more anthropogenic heat, and the absorption of more solar irradiance are main reason of UHI formation. The UHI results in an increase in the mean/peak energy demand [1,2] and an increase in mortality and morbidity, especially during heat wave episodes [3,4]. Besides the log-term plans of cities against the UHI such as enhancing the urban ventilation with better design of future planned buildings, mid/long-term plans should be envisioned by cities to reinforce the vulnerable sectors of a city against the heat-related risks of the UHI. This can be accomplished with development of heat alert models to bring awareness to the local inhabitants and to encourage their assistance with anticipatory in the case of heat waves. These anticipatory models should help forecast the associated heat risk with high spatial resolution in the order of a few hundred meters [5]. The predictive models are mainly based on correlations, which are developed to show how the rate of mortality is dependent on the temperature increase [6,7].

In the mentioned studies, the correlations are mainly 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 [8,9,10]. 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.

In conclusion, the different types of LULCs throughout a city are the key elements in the alteration of UHI. This simply implies that, for example, tree planting can be less effective in a regions 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. The complexity of the contributing parameters in the formation of the UHI normally causes a considerable discrepancy in these models, so more advanced models such as artificial neural network (ANN) are proved to be more effective than the latter models [11,12].

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 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 with 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.

## 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 with 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 ANN divides the target data into three sets, 70% as the training set, 25% for the validation process, and 5% for evaluation of its final performance.

### 2.2. Radius of Influence

The heterogeneous surrounding environment factors impact on the UHI intensity and the resulting indoor conditions. Thus, it is necessary to investigate the influence of size of the surrounding environment that most significantly influences the indoor condition of a building; an area that is too small would result in an inaccurate and inconsistent correlation, as significant influential parameters may not be considered. On the other hand, investigating an area that is too large incorporates redundant information, and leads to an inaccurate representation of the surrounding influential environment. This radius will be defined as the effective radius, indicating that the environment beyond its limit has negligible influence on the indoor condition of the building. This study investigates the effective radius size for multiple buildings by analyzing the area around each building from 20m to 500m in increments of 20m. A separate ANN model is developed for each radius, allowing the model performance to be presented as a function of the radius of the surrounding influential environment.

## 3. Data Measurement Campaign

The data utilized for this study was acquired through a measurement campaign previously conducted in Montreal from May 1st to Sept. 8th, 2010 [11,12]. During which, the hourly indoor air temperature and relative humidity were recorded within 55 buildings throughout the Island of Montreal, each without mechanical ventilation systems. In addition, the physical characteristics of the buildings were recorded and used to evaluate additional input parameters that are defined below. The dwellings that were selected had no air conditioning equipment. The sensors were installed at a height of 1.5m from the finished floor and away from windows to prevent solar radiation from altering the temperature readings.

## 4. Influential Parameters on Indoor Temperature

In order to integrate the influence of the surrounding environment into the ANN, parameters that define the environment's influence are used as inputs to train the model. These parameters can be categorized into two major groups. First, land modification related parameters, which in fact represent the heat gained from sun and heat transferred by wind, including solar heat gain, wind speed, street canyon aspect ratio, elevation of the measured temperature and E-ratio. These parameters are comprehensively discussed in [11,12]. The only new parameters are revised solar heat gain using the land use ratios and E-ratio. Second, the thermal mass associated with pavement and the inhabitants who are living in the modified land.

### 4.1. Land Use Ratio

Alteration of the natural land with the artificial materials increases the total solar heat gain, which is calculated for each building as a function of time of the day and land-use ratio of the surrounding neighborhood. The method chosen to study the land use ratios of the neighborhoods of the selected buildings is to use satellite imagery. Fig. 1 shows the satellite image of the neighborhood around Chartrand Street in Northern Montreal. The land use ratios were thus entered in the ANN in the form of a percentage of the total area being analyzed.

### 4.1. E-ratio

E-ratio is defined to present the convective impact of the building's surfaces as the fraction of dwelling envelope that is exposed to the exterior environment. The dwelling envelope is defined as the walls and the ceiling while excluding the floor. Thus, E-ratio is the ratio of the exposed envelope area over the whole envelope area. E-ratio of 0 means that the entire envelope is adjacent to other rooms in a building and E-ratio of 1 indicates that all of the walls are exposed to the outdoors.

### 4.1. Pavement Thermal Mass

The thermal mass of pavement and asphalt was determined as the product of the average paving thickness and the land cover percentage obtained through the processing of satellite images. An average thickness of 0.3m was assumed for both asphalt and pavement.

### 4.1. Neighborhood Building Thermal Mass

The thermal mass of a neighborhood has also been shown to have an effect on the magnitude of the urban heat island [13]. The building thermal mass was determined as the product of the average neighborhood building height and the building land cover percentage obtained through the processing of satellite images.

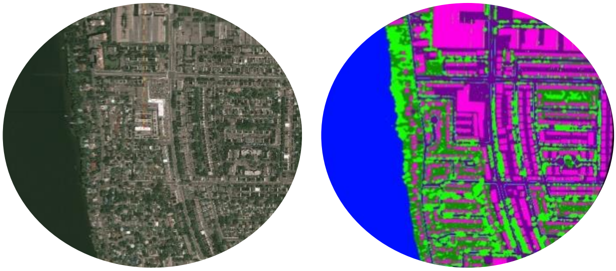

Fig.1. (Left) Satellite image of Chartrand street Montreal using Google Earth – (Right) processed satellite image of Chartrand street Montreal

## 5. ANN Model Performance

A parametric sensitivity study was conducted in which various sets of input parameters were used to develop multiple ANNs, each defined as a simulation package. This was to determine the influence of urban structural elements on air temperatures in the vicinity of the buildings and thereafter on the indoor air temperature of the buildings. Table 1 demonstrates simulation packages 1 through 3. Package 1 simulation represents the core parameters that have already been evaluated as critical in developing an accurate predictive ANN model [12]. Each subsequent package of simulation incorporates additional input parameters. Simulation packages 2 and 3 include the surrounding environment, and were therefore each simulated on 25 independent occasions, each with a unique prescribed radius, ranging from 20m to 500m in increments of 20m.

In order to maintain consistent and adequate evaluation of the ANN performance, specific segments of the data were not included in process of developing the ANN as they were reserved for the final evaluation of the network. These excluded data sets contain the measured data for the time period of Sept. 1st to 8th, 2010 and the entire data set for Building #37, located in Verdun (Fig. 2). The time period of Sept. 1st to 8th, 2010 was excluded from the network development process so that the network could be made to predict the hourly indoor temperature during that time period never yet seen by the network. Similarly, excluding the data set for Building #37 tests the network's ability to make predictions for buildings was not utilized in the development process. Building #37 was selected as it exists in a highly populated residential neighborhood with a high risk of mortality and morbidity related to the UHI. As illustrated in Fig. 2, building #26 (Downtown Building) was chosen, as it is located in downtown Montreal, where the majority of the surrounding environment is high-rise built up, with very little vegetation. In addition, building #37 (Residential Neighborhood Building) was chosen due to its relatively consistent LULC, encompassing significant amounts of both vegetation and low-rise built-up environment. Finally, building #11 (Industrial Neighborhood Building) was chosen due to the significant variations in the LULC of the surrounding environment resulting from the building's close proximity to industrial areas. Radii of 100m, 300m, and 500m can be seen in Fig. 2.

Table 1. Parameters within each simulation package

| **Package 3** | | |
|---|---|---|
| **Package 2** | | |
| **Package 1** | | |
| 1-Winds 2-Occupancy 3-Solar Radiation 4-Dry-bulb temperature at airport 5-Relative humidity at airport 6-Street aspect ratio 7-Floor location 8-Hour of the day 9-E-ratio | 10-Land-use ratios (Grass, Trees, Water, Rooftops, Asphalt, Pavement) | 11-Thermal mass (Building volume, Pavement/asphalt volume) |

## 6. Results and Discussion

### 6.1. Indoor Temperature Prediction for Different Neighborhoods

For the Downtown Neighborhood Building (Fig. 2b), influential parameters resulting from surrounding LULC have considerable impact on the indoor temperature of the building. Furthermore, the most predominant aspect of the LULC that influences the indoor temperature is thermal mass, as indicated by the performance of Package 3. This observation can be explained by the fact that, in downtown Montreal, the majority of the environment surrounding the building is mainly composed of other buildings, asphalt and pavement, each with substantial mass. Therefore, for the Downtown Neighborhood Building, the influence of LULC, relating to the amount of surrounding vegetation, water, and variance in diffuse solar radiation due to ground reflectance, has substantially less significance than the mass of the surrounding environment. The average MSE is consistently low for radii between 340 and 420m. The highest level of accuracy is achieved at 340m with a minimal MSE of 0.65. Fig. 3 shows the hourly temperature predictions of the Downtown Neighborhood Building from Sept. 1$^{st}$ to Sept. 8$^{th}$. In the event of a heat wave, surface materials surrounding buildings store a considerable amount of heat, releasing it gradually thereafter. In that sense, it follows that Package 3 achieved a high level of performance because it incorporates the presence of the considerable thermal mass within the surrounding environment.

The influential parameters resulting from the LULC of the surrounding environment have considerable influence over the indoor temperature for the Residential Neighborhood Building (Fig. 2c). Note that the addition of thermal mass has less influence in improving the accuracy and precision of the network than in the case of the Downtown Building. This observation can be explained by the fact that the environment surrounding the Residential Neighborhood Building has less mass (light weight low-rise residential) compared to those heavy concrete high-rise buildings located in downtown area. The network achieves highest performance levels within the range of 320 and 360m, reaching a minimal MSE of 0.681 at 340m. Fig. 3 shows the temperature predictions from a network utilizing Package 3. The close proximity of the time lag between the airport temperature and the building's internal temperature indicates that the network effectively incorporates the effects of the thermal storage capacity of the surrounding neighborhood. It can once again be noted that Package 3 demonstrates a moderate trend with increasing radius such that the greatest accuracy and precision occurs within a range of 340 and 380m for the Industrial Neighborhood Building, reaching a minimal MSE of 2.03 at 360m (Fig. 3).

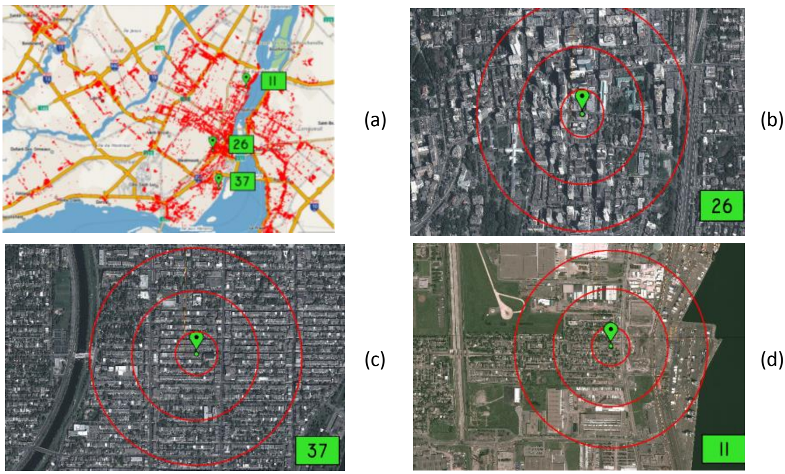


Fig. 2. (a) Montreal's significant UHI areas as well as the target buildings' locations (b) Downtown Neighborhood Building (#26) (c) Residential Neighborhood Building (#37) (d) Industrial Neighborhood Building (#11)

### 6.2. Mitigating Strategies of UHI Effect

The developed tool is capable of both forecasting future hazards, as well as evaluating the effectiveness of potential neighborhood mitigation strategies. Potential mitigation strategies relating to an increase in neighborhood vegetation and a subsequent decrease in solar absorbing surfaces are evaluated on the Residential Neighborhood Building (#37). In order to facilitate a feasible increase in neighborhood vegetation, it is assumed that the alleys would be completely replaced with green space and that some buildings would become equipped with green roofs.

The characteristics of the 360m radial area surrounding the Residential Neighborhood Building are adjusted to model the implementation of the proposed increase in neighborhood vegetation. The LULC ratio of vegetation is increased by 1.0% by increasing the ratios of grass and trees by 0.3% and 0.7%, respectively. Subsequently, surfaces with high solar absorption are decreased by 1.0% by decreasing the ratios of asphalt pavement and building rooftops by 0.8% and 0.2%, respectively.

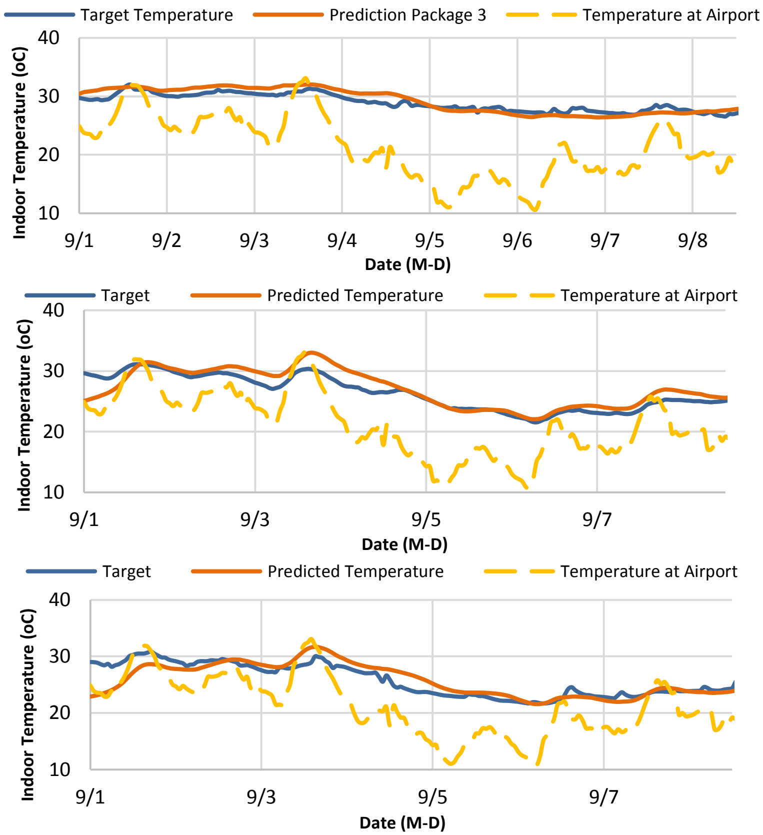


Fig. 3. Indoor temperature predictions for (top) Downtown (middle) Residential (bottom) Industrial Neighborhood Building from Sept. 1st-8th

Based on the adjusted LULC ratios, the network is then used to predict the hourly indoor temperature. The process of increasing the vegetation ratio by 1%, decreasing solar absorbing surfaces by 1%, and then predicting the hourly indoor temperatures of the building is repeated until the vegetation ratio is increased by 19%. Fig. 4 demonstrates the average hourly temperature change as a function of the percentage of increase in neighborhood vegetation ratio for the time periods of June 6th to Sept. 8th. As it is demonstrated in Fig. 4, the average hourly temperature continually decreases with increasing neighborhood vegetation. The rate of temperature reduction is moderate for the first 5% increase in vegetation, and then becomes more significant with further increase in vegetation. This indicates that for the case of the Residential Neighborhood, considerable increases in vegetation are required to produce significant improvements in the indoor environment of buildings within it. As it is shown in Fig. 5, increasing the vegetation ratio of the Residential Neighborhood by 15% would significantly reduce the resulting hourly indoor temperatures. The average difference between the original LULC prediction and the mitigated LULC prediction suggests that a 2.8 °C average reduction in building temperature can be achieved. Moreover, a maximum temperature reduction of 3.5 °C was predicted between Sept. 1st and Sept. 4th.

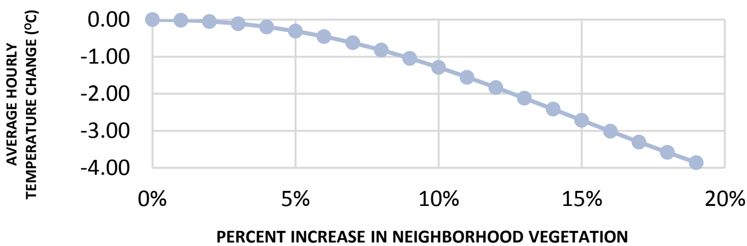


Fig. 4. Average temperature changes resulting from mitigation strategies for Residential Neighborhood Building for a 360m radius

## Conclusion

In this study, an ANN was developed in order to predict a building's interior temperature as a function of the surrounding environment for various buildings throughout Montreal. Thermal mass and LULC ratios were assessed as a function of radial distance from the buildings in order to establish the effective radius of influence. Moreover, the performance of the network for forecasting future indoor temperatures was evaluated. For example, it was shown that, with an increase in vegetation of 15% in terms of total LULC, the interior temperature of the Residential Neighborhood Building can decrease by as much as 3.5°C in a heat wave and 2.8°C on average over a summer season.

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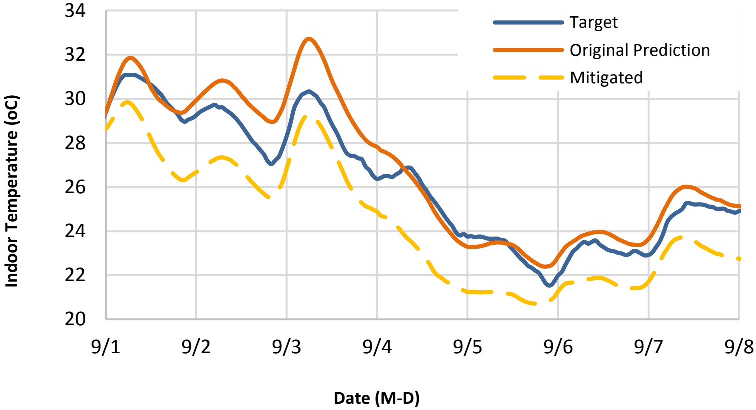


Fig. 5. Comparison between original indoor and mitigated indoor temperature prediction

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