# COMPARING THE COOLING ABILITY OF GREEN SPACES IN SUBURBAN AND URBAN AREAS USING LST AND NDVI

by

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**Abstract**

Urban green spaces have been found to effectively mitigate the effects of the Urban Heat Island through localized cooling. This study identifies how green spaces differ in their cooling characteristics in a suburban study area and an urban study area by focusing on the Surface Urban Heat Island effect. Remote sensing techniques are utilized to derive land surface temperature, the normalized difference vegetation index and urban cool islands. The patch features percentage of tree canopy cover, percentage of grass/shrub cover and patch size were also calculated. A forward multiple regression was used to determine which characteristics had more of an influence on surface temperature. Results showed that urban cool islands are formed in and around green spaces in their respective study areas. Patch characteristics played significant roles in dictating the temperature of suburban green spaces but not urban green spaces, which were more influenced by the surrounding land use.

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**List of Acronyms**

ATCOR – Atmospheric Correction

CMA – Census Metropolitan Area

DN – Digital Values

ETM+ – Enhanced Thematic Mapper plus

GTA – Greater Toronto Area

LST – Land Surface Temperature

NDVI – Normalized Difference Vegetation Index

NIR – Near Infrared

OLI – Operational Land Imager

PCI – Park Cool Island

SUHI – Surface Urban Heat Island

TIRS – Thermal Infrared Sensor

TM – Thematic Mapper

UCI – Urban Cool Island

UHI – Urban Heat Island

# CHAPTER 1: INTRODUCTION

## 1.1 Urban Heat Island

The Urban Heat Island (UHI) effect refers to elevated ambient air and land surface temperatures that are characteristic of urbanized areas when compared to adjacent rural regions (Voogt and Oke, 2003). This is due to many things, namely the high emissivity values of building materials, the increase in impervious surface area, reduced tree canopy cover, surface roughness and evapotranspiration. Additionally, the alteration of turbulent airflow from large buildings and anthropogenic influences (e.g. energy use) are known to influence the development of the UHI (Oke et al., 1989; Yuan and Bauer, 2007; Hamada and Ohta, 2010). This phenomenon was termed by Manley in 1958 but first documented in field research by Howard in 1818 (Hafner and Kidder, 1998). Health effects have been attributed to UHIs, specifically impacting the vulnerable population. This can include heat stress and asthma from poor air quality and extreme temperatures, sometimes resulting in mortality (Smoyer et al., 2000; Douglas et al., 2001; Zupancic et al., 2015).

Studies on the mitigation of the UHI often revolve around green spaces because they have been found to provide localized cooling and can counter UHI development. Areas of below average cooling have been termed Urban Cool Islands (UCIs) (Kong et al., 2015). A direct relationship between the UHI and green space characteristics has been established, which frequently includes vegetation cover type and the size of the green spaces (Tan and Li, 2013; Gioia et al., 2014; Ivanjnisc et al., 2014; Kong et al., 2014; Maimaitiyiming et al., 2014; Lin et al., 2015).

## 1.2 Study Objectives

The overall purpose of this study is to use remote sensing to evaluate the relationships between green spaces and land surface temperature (LST) in suburban and urban environments and determine whether they have an influence on the surrounding LST. The questions guiding this research include:

1) What characteristics of the green spaces have the greatest influence on their LST?
2) Do green spaces create UCIs in their respective study areas?
3) Do green space characteristics influence the LST surrounding it, and if so, how?

The ability for a green space to cool effectively is hypothesized to be different between the suburban and urban study areas because of differences in urban form and fabric, including land use and building and vegetation density distribution/type.

## 1.3 Study Area

A study performed by Natural Resources Canada found that the highest surface temperatures across the entire Greater Toronto Area (GTA) have been identified in the residential areas of Mississauga, Brampton and Vaughan (Maloley, 2009). Brampton was ranked second in 2014 for most residential development among all cities within the Toronto Census Metropolitan Area (CMA), and fifth in the entire nation (Bishun, 2014). Two study areas were chosen based on urban density to represent a suburban and urban area within the GTA (Figure 1.1). Suburban areas are commonly defined as small urban areas with a low population density, single-family homes, stores and services, and have more parks and green spaces than highly urbanized areas (National Geographic, 2015). The study areas used in this research are both classified under the Köppen classification system as a moist, mid-latitude climate with cold winters and year-round precipitation (Das, 2011). Vegetation classification falls into the mixed wood plains terrestrial ecozone (CanSIS, 1994).

The suburban study area is located in the City of Brampton. It was chosen because it is very homogenous in building structure, dominated by low-rise residential buildings (less than four storeys), and includes several neighbourhoods with small clusters of businesses and parks scattered throughout (Urban Forestry, 2009; Forsyth, 2012). Large commercial and industrial properties located close by were not included in the study area.

The urban study area chosen includes the downtown core of the City of Toronto and neighbourhoods north, east and west of it. It is considered the "heart" of the GTA (City of Toronto, 2014). This study area is much less homogenous in building type and is dominated by both mid-rise (four to eleven storeys) and high-rise buildings (twelve or more storeys), with some low-rise development throughout. It is representative of a combination of land use types including commercial, residential, industrial, and parkland distributed amongst small city blocks, which is very different to the design of the suburban study area (Urban Forestry, 2009; City of Toronto, 2014). Both study areas are based on a selection using a predefined neighbourhoods polygon (DMTI Spatial Inc., 2014). The area along the lake shore in the urban study area was removed to avoid including parts of Toronto Island.

The size and shape of the study areas are relatively similar and have a good representation of the type of urban fabric commonly associated with 'suburban' and 'urban' areas. The suburban study area is 30.43 $km^2$, and the urban study area is 29.93$km^2$. The design of residential housing in suburban neighbourhoods is very different from the type of residential development in and around downtown cores. New single detached home lot sizes are a minimum of 270 $m^2$ in the City of Brampton, which promote development of a large streetscape such as lawns, trees, and gardens (The City of Brampton, 2003). Houses are generally larger than downtown with dark shingled roofs that have a low reflectance and high absorption of thermal radiation, and front, back and side yards are generally larger relative to urban residential areas. The minimum setback of a house from the property line based on Brampton development design guidelines is 4.5 metres from front entrances and 6 metres from the garage (The City of Brampton, 2003). Conversely, new residential development in the City of Toronto is dominated by in-fill development, mainly encompassing new high-rise condo buildings and new townhouse builds. The new townhouse builds have many of the same characteristics as single detached homes, however the minimum setback of the house from the property line drops to 2-3 metres when private parking is not developed (Dill and Bedford, 2003). This reduces the space available for green infrastructure when compared to that available in suburban developments.

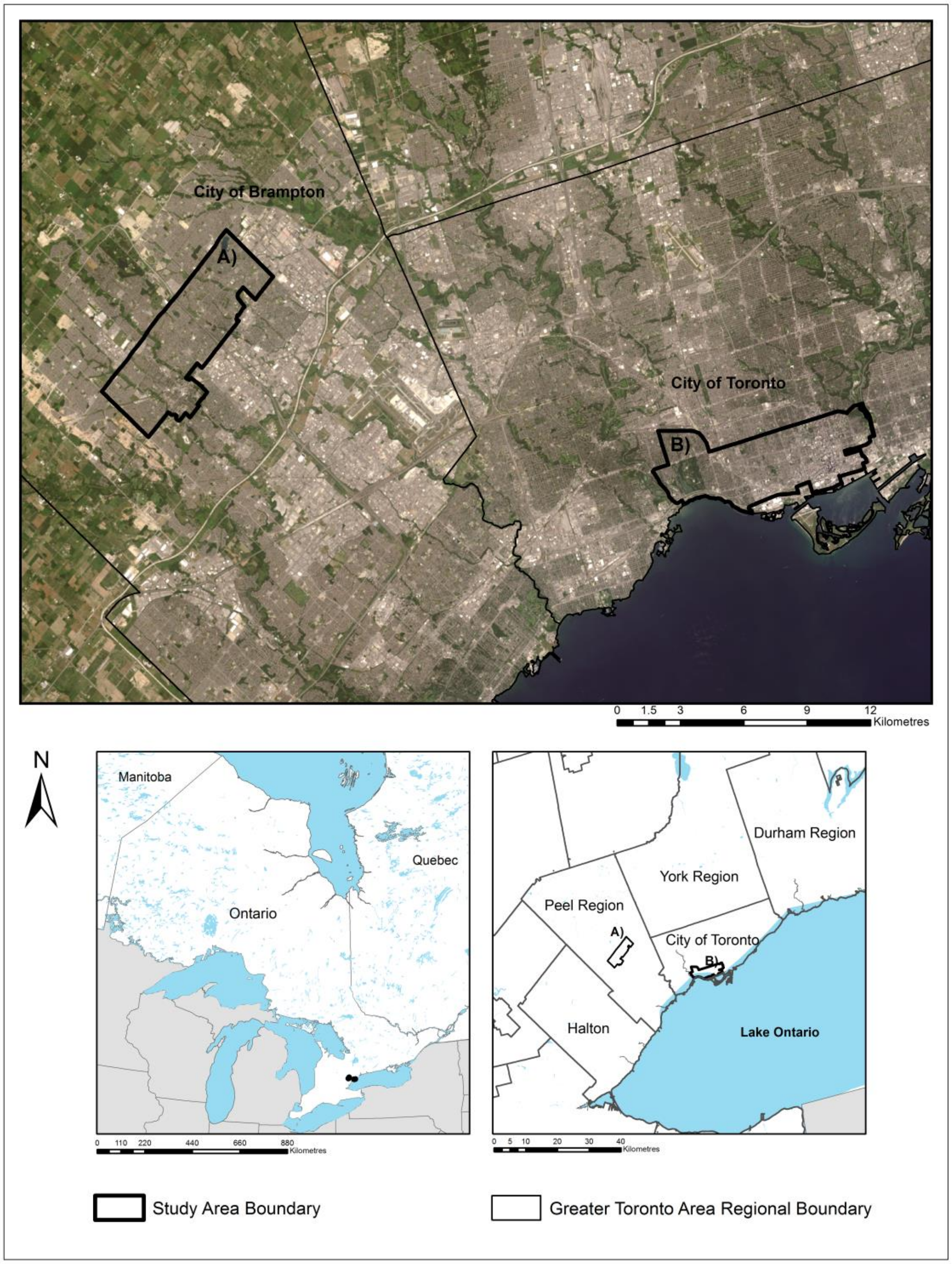


**Figure 1.1: A) The suburban study area, and B) the urban study area chosen for this analysis located within the Greater Toronto Area in Ontario, Canada.**

# CHAPTER 2:LITERATURE REVIEW

## 2.1 UHI Studies

The UHI effect can exist at different intensities based on time of day, year, and weather conditions (Schrijvers et al., 2015). The intensity of the UHI is most pronounced during the mid-summer months when incoming solar radiation is highest, in mid-winter, and at night when stored heat is released (Mirzaei and Haghighat 2010; SENES, 2011). Lee et al. (2014) provide an overview of fifteen UHI study findings in fourteen major cities around the world in different seasons (Table 1.1). The overall pattern shows that cities can be anywhere from one to seventeen degrees Celsius warmer than the surrounding rural areas when ideal conditions for UHI development exist. This includes very calm and clear anticyclonic weather conditions. This also shows that the UHI effect is very commonly studied in large, densely populated cities.

The UHI phenomenon is divided into three separate effects based on building height, including the canopy layer heat island, the boundary layer heat island, and surface layer heat island (Voogt and Oke, 2003). The canopy layer and boundary layer heat island effects refer to the increased ambient air temperature of a city influenced primarily by building height and density which dictates air flow through a city landscape. The surface layer heat island refers to the temperature of physical surfaces based on their spectral reflectance of incoming solar radiation. This is dictated by building materials such as pavement, asphalt, gravel, concrete, and roof shingles, but also by airborne particulate matter and water vapour. When studied independently of the canopy layer and boundary layer heat islands, this phenomenon has been termed the surface urban heat island effect (SUHI) (Voogt and Oke, 2003).

**Table 2.1: UHI findings in major cities worldwide (modified after Lee et al., 2014)**

| City | Heat Island Effect between urban-rural temperatures |
|---|---|
| Mexico | 5°C (dry season) |
| Seoul | 1-3°C (wet season) |
| Chongqing | 1.4°C (average) |
| New York | 4°C (summer) |
| Melbourne | 1.1°C (annual) |
| | 1.3°C (summer) |
| | 1.2°C (spring) |
| | 1.0°C (autumn) |
| | 1.0°C (winter) |
| Washington DC | 10.8°C (average) |
| Los Angeles | 12-17°C |
| Lisbon | 2.5°C (nocturnal) |
| Granada | 3.7°C (annual) |
| Hong Kong | 12°C (max) |
| Beijing | 2.3°C (max) |
| Wuhan | 8-10°C (spring/summer) |
| | 4°C (winter) |
| London | 6-8°C (nocturnal max) |
| Taiwan | 4-5°C (rainy season) |
| | 2°C (cloudless night) |

## 2.2 Methods for Studying the UHI

Remote sensing is commonly used to study the SUHI and UHI because it can provide empirical information about large areas to quantify land surface temperature (LST) (Voogt and Oke, 2003; Imhoff et al., 2010; Tan and Li, 2013; Gioa et al., 2014; Kong et al., 2014; Maimaitiyiming et al., 2014; Lin et al., 2015; Martin et al., 2015).

This technique can be more beneficial than using observational techniques (Hamada and Ohta, 2010) that can limit the analysis to a small sample size and produce highly variable results (Hamada and Ohta, 2010; Mirzaei and Haghighat, 2010), or computationally heavy and complex atmospheric modelling (Jiang et al., 2014). Other remote sensing data are often used in conjunction with LST such as the normalized difference vegetation index (NDVI) (Weng et al., 2004; Yuan and Bauer, 2007; Tan and Li, 2013; Gioia et al., 2014). This index is used as a proxy for the amount of vegetation within a pixel and is used to help explain the distribution of LST in a study area.

### 2.3 Green Spaces and the UHI

Urban green spaces have been found to successfully reduce the impacts of the UHI by creating local UCIs. The UCI refers to the cooling phenomena that urban green spaces can have to mitigate the UHI and can be studied using LST derived from remotely sensed images (Kong et al., 2014). Cooling from green spaces mainly occurs due to lower land surface temperatures that result from direct shading and increased evapotranspiration. This also reduces the ambient air temperature within and surrounding the green spaces (Kong et al., 2014). This has been determined by correlating green space characteristics such as shape, size, and land cover with LST (Tan and Li, 2013; Gioia et al., 2014; Ivanjnisc et al., 2014; Kong et al., 2014; Maimaitiyiming et al., 2014; Lin et al., 2015). Research results show that parks in Toronto can be up to 7$^{o}$C cooler than their surroundings, with a reach of 100 metres outside the park boundary (Slater, 2010). The cooling extent of a green spaces has also been studied by Lin et al. (2015) who found a cooling distance between 35 and 840 metres outside the boundary. This is largely influenced by green space size and shape, but is also due to the thermal influence from the surrounding land use (Kong et al., 2014; Lin et al., 2015). Thus, the best practices for urban development are based on strategic green space planting, and building design and layout to effectively mitigate the growth of the UHI by paying particular attention to development around the green spaces (Kleerekoper et al., 2012).

These examples show how green spaces have impacted LST and ambient air temperature, and what characteristics are the most influential at performing this task. In these UHI studies and most others, green spaces and UHI development in suburban areas are often not studied independently, with the exception of Eastwood (2012) and Ivanjnsic et al. (2014). Suburban neighbourhoods are either grouped with urban study areas (Das, 2011), used as a reference temperature point to compare with urban temperatures (Mohsin and Gough, 2012), or are omitted completely with the focus of the analysis on the urban core where building density is highest. This creates a gap in the literature and in the research surrounding SUHI development and the performance of green spaces in mitigating the UHI in suburban areas. This review also shows how UHI studies have deviated from explicitly considering the temperature of urban areas versus rural areas.

# CHAPTER 3:METHODS

## 3.1 Calculating LST

The remotely sensed image used for this analysis was acquired on July 18, 2014 by the Landsat 8 satellite. This satellite uses the operational land imager (OLI) and thermal infrared sensor (TIRS) for image acquisition. The OLI is an enhanced version of the Enhanced Thematic Mapper Plus (ETM+) on-board the Landsat 7 satellite. A new spectral band one (blue) and band nine (near-infrared) have been added. The TIRS sensor collects thermal information at a 100 metre spatial resolution in two bands (ten and eleven) and is resampled to 30 metres prior to release to match the resolution output of the other sensors (USGS, 2015).

The climatic conditions on July 17 and 18 can be found in Table 3.1 (Government of Canada, 2015). Climatic conditions are important to consider because they dictate the ability for a UHI to develop and its severity (Smoyer et al., 2000). When studying the development of the SUHI phenomenon, the most important climatic condition to consider is cloud cover which blocks much of the incoming solar radiation that causes a SUHI. Other climatic conditions such as air temperature, precipitation, and wind speed indicate the type of conditions that the city was under during the time of image acquisition.

Using the image processing software PCI Geomatica (2014 version), LST was calculated. To determine LST, the ATCOR_T surface temperature tool was used. This tool converts the raw digital numbers (DN) received from the satellite to radiance values, then brightness values, and finally to surface temperature in degrees Celsius. Solar zenith, solar azimuth, and sensor calibrations were determined based on image metadata and used in the calculation process. Emissivity values were adopted based on literature where water, vegetation, and built-up areas were given the values of 0.995, 0.98, and 0.97 respectively (Sobrino et al, 2004; Lin et al, 2015). Additionally, the tool ATCOR_T offers an atmospheric transmittance parameter that stipulates what the conditions are above the study area to correct for in the calculation. This is a split-window algorithm that uses the atmospheric absorption difference between two adjacent long wave infrared bands in the calculation (Rosenstein et al., 2014). Since the Landsat 8 satellite has two thermal bands, both bands 10 and 11 were used. The LST results can be seen in Figure 3.1 for both study areas.

**Table 3.1: Study area (Toronto Pearson International Airport) climate conditions the day before and day of image acquisition**

| Date | Minimum Air Temperature (ºC) | Maximum Air Temperature (ºC) | Average Air Temperature (ºC) | Precipitation (mm) | Max Wind Speed (km/h) |
|---|---|---|---|---|---|
| July 17, 2014 | 10.9 | 24.4 | 17.7 | 0.0 | 43 |
| July 18, 2014* | 11.9 | 24.6 | 18.3 | 0.0 | 32 |

*Image acquisition day

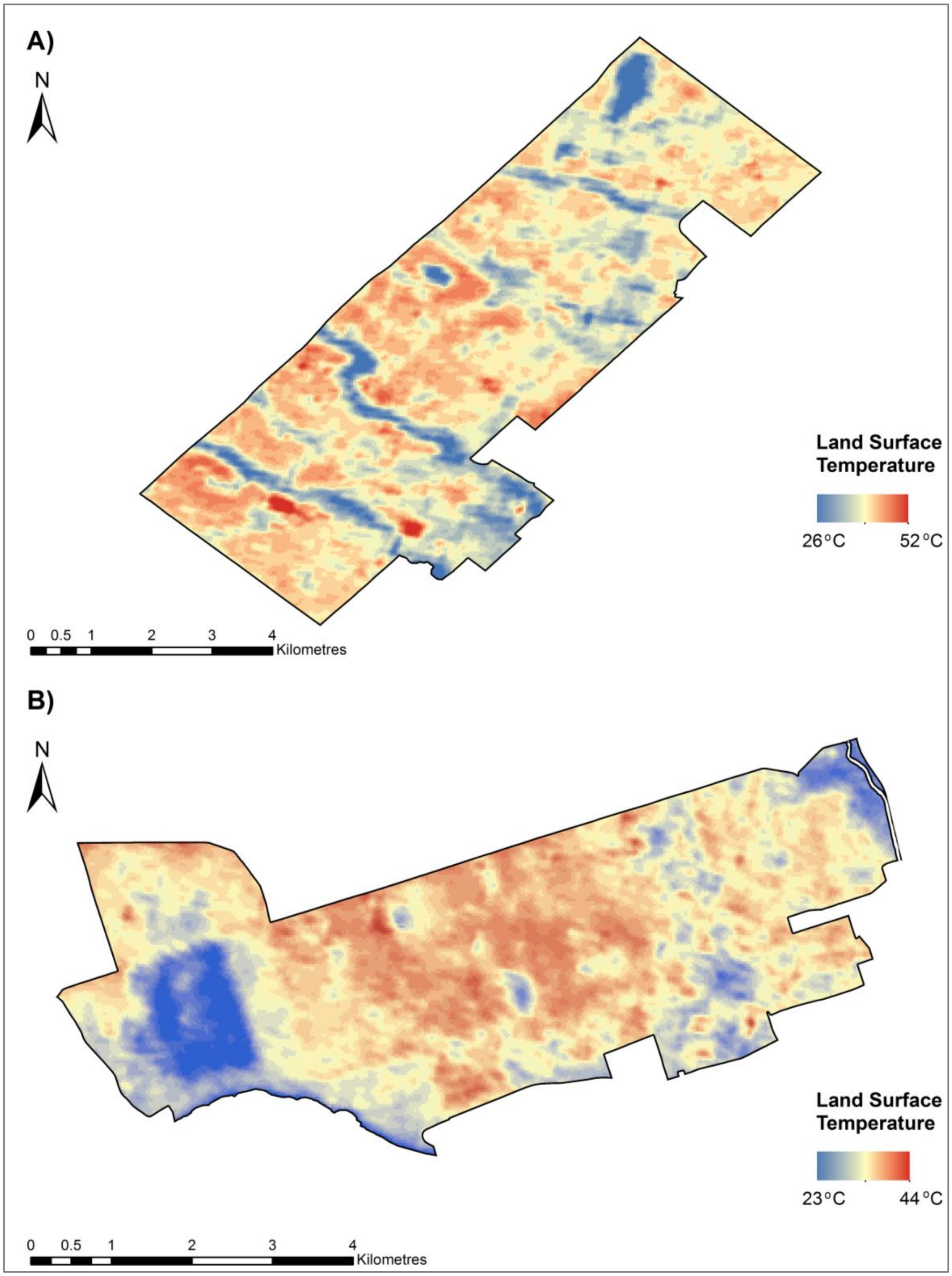


**Figure 3.1: LST temperature results for A) the suburban study area, and B) the urban study area.**

### 3.2 NDVI

The same Landsat 8 image was used to derive NDVI at a spatial resolution of 30 metres in the visible and near-infrared bands. PCI Geomatica was also used to calculate NDVI based on this equation:

$$\boldsymbol{NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}}} \quad \textbf{(1)}$$

where $R_{NIR}$ is reflectance in the near-infrared region (band 5) and $R_{RED}$ is reflectance in the visible red region (band 4). Results of this equation range from -1 to +1 and are representative of photosynthetically active vegetation, where healthy leaves will have high reflectance in the near infrared spectral region and high absorption in the visible spectral region (Figure 3.2). High positive values are associated with large amounts of healthy vegetation within the pixel area, low values suggest bare rock, asphalt and concrete, and negative numbers often represent water bodies (Ivajnsic et al., 2014). The NDVI was not assumed to be dramatically different between vegetation types at the resolution of the Landsat 8 image because of mixed vegetation within it. Tan and Li (2014) assume that edge effects and fragmentation of vegetation in urbanized areas will help reduce major differences between the NDVI of different types of vegetation. Regarding the UHI, Yuan and Bauer (2007) discuss the importance that high NDVI (i.e. high amounts of healthy vegetation) can have on influencing the latent heat flux from the surface to atmosphere in the hot season when the UHI is at its highest. This is achieved by increasing evapotranspiration and shading in a city, hence why NDVI was used as a parameter for green space in this study. Thus, NDVI is used as an overall indicator of land cover where low values are considered sparsely vegetated or built up areas, and moderate to high values are indicative of highly vegetated areas at the resolution of the Landsat 8 image.

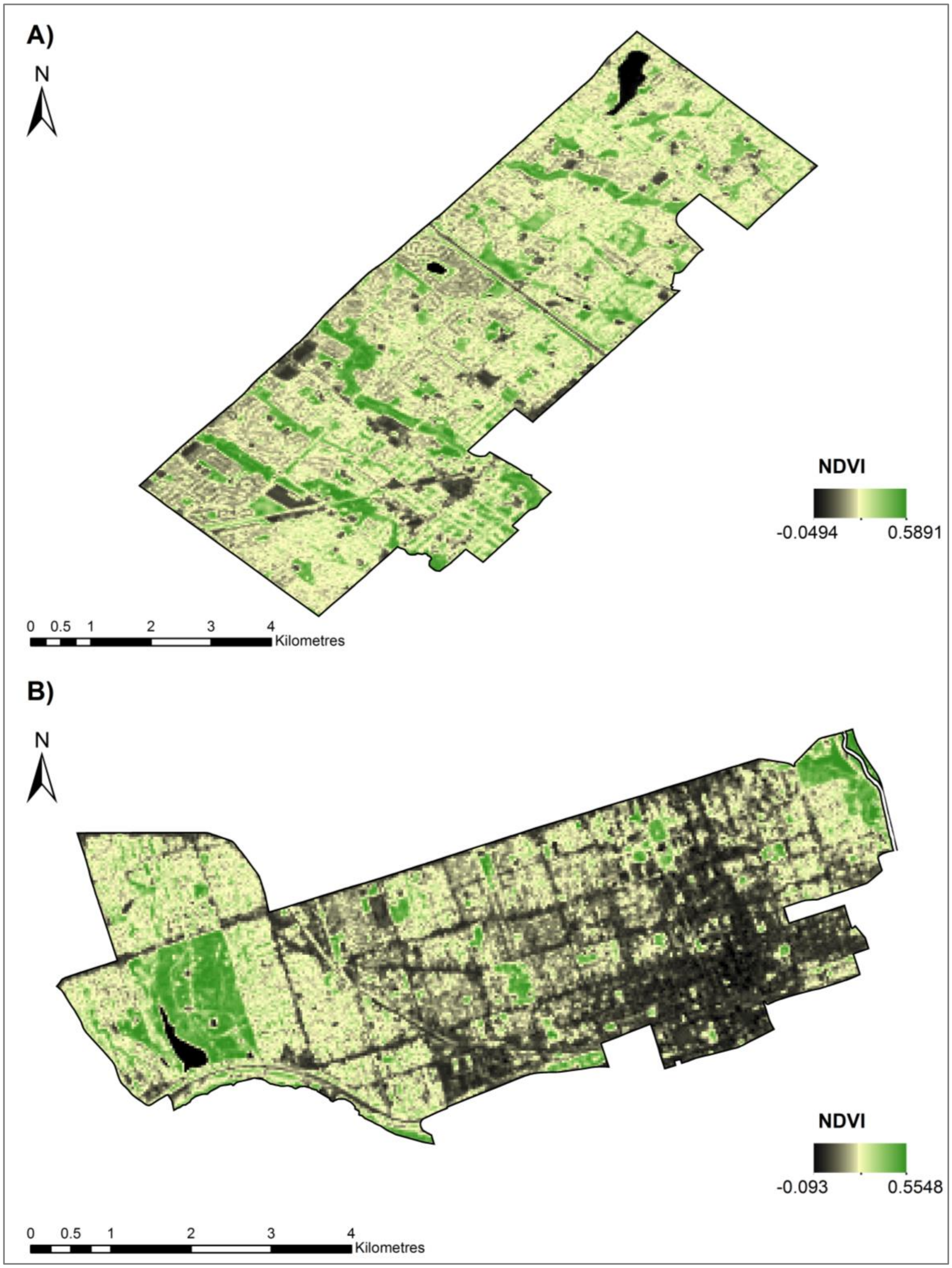


**Figure 3.2: NDVI calculated for A) the suburban study area, and B) the urban study area.**

### 3.3 Green Space Delineation

Green spaces were defined based on the NDVI results calculated above and can be considered an ecological perspective of delineation (Bilgili et al., 2013). Predefined park boundaries were not used to define green spaces in this study because they are highly dependent on land ownership and protection policies, and may not capture vegetation growing around the periphery of a park boundary. Studying the UHI and cooling extent only within the park boundary can bias the results considering that vegetation can grow around a park boundary and result in high cooling extents from the growth of vegetation within and surrounding the park. This can be seen from interpretation of previous study results and the recognition that the surrounding thermal characteristics highly influence park temperatures (Cao et al., 2010; Das, 2011; Rinner and Hussain, 2011; Weber et al, 2014). In this case, the cooling extent may in fact be related to the surrounding vegetation, and not simply from the characteristics of the park. When park boundaries are used, the term park cool island (PCI) has been used instead of UCI to acknowledge that predefined boundaries are being used (Cao et al., 2010). Using NDVI to define green spaces does not subject this analysis to the limits of defined park borders, but considers all large patches of vegetation.

Using a NDVI threshold cut-off of 0.2 to define green spaces as Bilgili et al. (2013) did proved problematic for this study area. The amount of photosynthetically active vegetation present in the suburban neighbourhood initially classified the majority of the suburban study area as green space. NDVI values between 0.2 and 0.3 are often representative of short vegetation such as shrubs and grasses, which are highly prominent on suburban properties (e.g. in back and front yards) (SimWright Inc., 2007; Bilgili et al., 2013). To account for this, a threshold NDVI value of 0.35 was used as the minimum to define green spaces and was determined based on the literature (SimWright Inc., 2007; Bilgili et al., 2013), experimentation, and ground truthing. Green spaces smaller than 3,600 $m^2$, a spatial resolution of four pixels, were removed. This was done to ensure that some amount of continuity is maintained between larger patches, and to help remove minor edge effects from reflectance of adjacent pixels (Figures 3.3 and 3.4).

An accuracy assessment was done to determine how representative the chosen NDVI classes were for green space delineation. There was an overall accuracy of 96.33% with a kappa statistic of 0.918. The confusion matrix and accuracy statistics generated by this assessment can be seen in Tables 3.2 and 3.3 (respectively) and show that NDVI at the 0.35 threshold level and larger than 3,600 $m^2$ accurately defined green spaces.

**Table 3.2: NDVI classification accuracy assessment – confusion matrix**

| | **Unvegetated** | **Vegetated** | **Total** |
|---|---|---|---|
| **Unvegetated** | 198 | 6 | 204 |
| **Vegetated** | 1 | 95 | 96 |
| **Total** | 199 | 101 | **300** |

**Table 3.3: NDVI classification accuracy assessment – statistics**

| Overall Accuracy | **95% Confidence Interval** | Kappa Statistic | Overall Kappa Variance |
|---|---|---|---|
| **96.33%** | (94.04% 98.63%) | **0.918** | **0.009** |
| Class Name | Producers Accuracy | User's Accuracy | Kappa Statistic |
| Unvegetated | **99.5%** | **97.1%** | **0.9126** |
| Vegetated | **91.73%** | **96.74%** | **0.9518** |


**Figure 3.3: Green space delineation for A) the suburban study area, and B) the urban study area.**

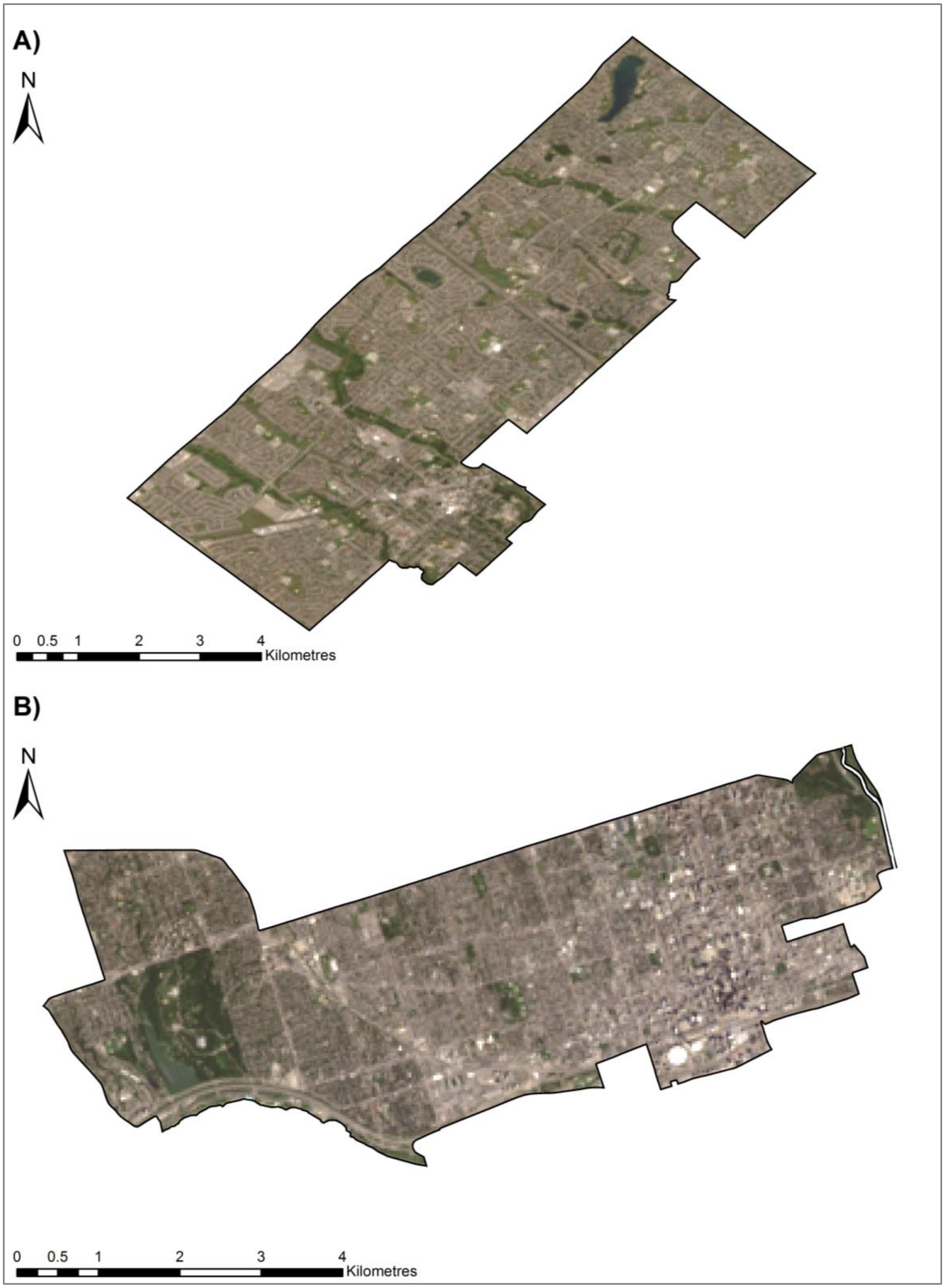


**Figure 3.4: Landsat 8 image viewed in natural colour for A) the suburban study area, and B) the urban study area.**

### 3.4 Urban Cool Island

An approach used to quantify the UCI by Tan and Li (2013) used the average LST of the area immediately surrounding each green space as the reference temperature on which to base the calculation. The difference, or intensity, is calculated by subtracting the reference LST (chosen from a land use type around the green space) from the green space LST to determine if the patch creates a cool island within that respective area, and is repeated for all parks. This method has a stronger focus on localized cooling of green spaces within their respective locations in the study area. Due to the resolution restriction of the Landsat 8 image used for this study, localized cooling is not as apparent as it would be at a higher resolution. In addition, this method only focuses on green spaces as being potential cool islands, therefore, the method proposed by Kong et al. (2014) was adopted to quantify the UCI. This method quantifies UCIs by subtracting the average LST for the study area and calculating the difference across the entire area based on this single reference value. It is a reflection of the thermal signature of the urban fabric that makes up the study areas. Anywhere that the change in LST is less than or equal to zero, a cool island exists. This method considers the characteristics of the entire suburban and urban study area, and can also identify cool islands that may exist outside of green spaces. The results of this UCI delineation can be seen in Figure 3.5.

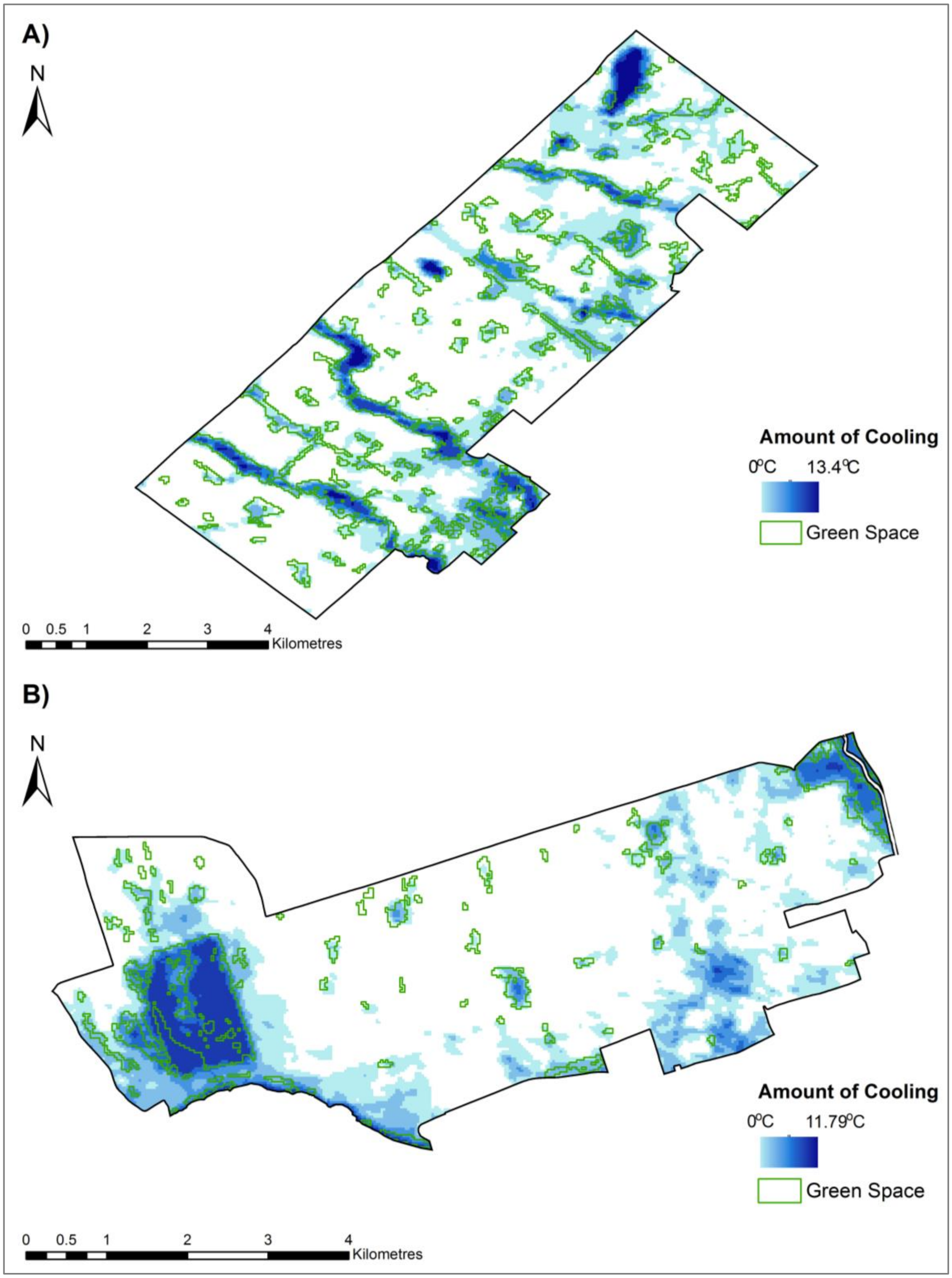


**Figure 3.5: Urban cool islands in A) the suburban study area, and B) in the urban study area with defined green spaces.**

### 3.5 Analysis

A forward multiple regression was done to determine the relationship between LST and green spaces. This regression type differs from a backward or stepwise regression in that the model begins with no independent variables. The first variable that is added is the one which has the highest $R^2$ of all candidate variables. Additional variables are added only if they are found to be significant influencers on the dependant variable and they increase model fit. (NCSS, 2015). This method was chosen to ensure that maximizing the $R^2$ value was not the sole purpose of the analysis, which backwards multiple regression is prone to do (NCSS, 2015). Additionally, a stepwise regression was not used to ensure that unnecessary variables are not included in the model by testing the significance of variables that the model has already selected and potentially removing them in favour of others (NCSS, 2015). The forward regression technique reveals which parameters are not significant influences on the dependent variable and keeps them out of the model, and does not remove variables that it has already deemed significant to the model.

The adjusted $R^2$ result was used as the final measure over the $R^2$ value. The adjusted $R^2$ accounts for the number of predictors that are in the model and changes when a new variable is added that improves the model more than chance would (Frost, 2013). Since the number of variables in the model can change in a forward multiple regression based on their significance to the dependent variable, the adjusted $R^2$ value was considered the most appropriate result for this study. All assumptions of multiple linear regression were tested for and met for this analysis.

### 3.6 Defining Regression Variables

The dependent variable was LST and five metrics were used as independent variables from both study areas. These include: green space size, average NDVI, average NDVI around the green space, and the percent coverage of tree canopy and grass/shrub cover. Size was calculated by multiplying the number of raster cells in each green space by the spatial resolution. The average NDVI for each green space was determined using the zonal statistics tool, and the buffer NDVI was determined by creating a 30 metre buffer around each green space and averaging the NDVI in it. The extent of the buffer creation was set to match the resolution of the Landsat 8 image to ensure it aligned with the boundary of the raster cells. Any significant green space areas would have been captured in the green space delineation process, therefore everything in the buffer is considered sparsely vegetated or developed. Tree canopy cover and grass/shrub cover for both study areas is part of a freely available land cover open dataset published by each region in the GTA, which can be seen in Figure 3.6. This image was digitized based on a "top down" mapping perspective to capture what is being covered by tree canopy. This is beneficial to this study since it is the same as the satellite perspective that dictates the LST and NDVI derived for this analysis. This dataset was released at a very detailed resolution of 0.6 metres for the year 2007. Percent coverage of tree canopy and grass/shrub within each green space was derived using the zonal statistics tool. All regression variables where derived for both study areas and the results of the analyses were compared to address the research questions presented in this study.


**Figure 3.6: Land cover for 2007 based on "top down" mapping perspective in A) the suburban study area, and B) the urban study area (Urban Forestry. 2009).**

# CHAPTER 4: RESULTS

## 4.1 Characteristics of the Study Area

The percent of each land cover type in both study areas can be seen in Table 4.1 (see Figure 3.6). The residential structure common of suburban neighbourhoods can be seen by the patterns in housing and street layout that encompass patches of buildings, with 13.8% tree canopy cover and 41.38% grass/shrub cover. These neighbourhoods are generally surrounded by larger patches of vegetation. Some water bodies can be seen scattered throughout the study area of varying sizes. Land cover in the urban study area has a much different design layout. Blocks are much smaller with a high density of buildings and paved surfaces. Cumulatively, buildings, transportation networks, and paved surfaces make up 62% of urban study area coverage. The downtown core of Toronto is mainly comprised of buildings and paved surfaces, whereas the surrounding blocks display somewhat more variety in land cover. Despite this, tree canopy cover is the dominating vegetation type at 22% coverage with smaller amounts of grass/shrub throughout at 14% coverage. When comparing both images, it is clear that the urban study area is very high density in comparison to the suburban study area with variation in vegetation cover.

In total, 143 green spaces were defined in the suburban study area, and 83 green spaces were defined in the urban study area (see Figure 3.3). Table 4.2 shows some information about the characteristics of the study areas and the green spaces. The average LST was found to be lower in the urban neighbourhood compared to the suburban neighbourhood, and the same pattern is seen within the green spaces. More specifically, the suburban LST is 39.48$^{o}$C and 36.46$^{o}$C in the green spaces. The urban LST is 5.48$^{o}$C cooler at 34$^{o}$C, and

7.59$^{o}$C cooler in the green spaces at 28.87$^{o}$C. Maloley (2009) also found that higher LST values can be found outside of the high-density urban core of Toronto and instead in the commercial and industrial sectors of suburban areas of the GTA.

The average NDVI in the suburban study area was found to be higher than the urban, however the green spaces in the urban neighbourhood exhibit a slightly higher NDVI. Results show that the suburban study area has an overall average NDVI at 0.2701, and the urban study area has an overall average of 0.201. Regarding the green spaces, average NDVI results of the suburban green spaces were 0.4263, which is slightly lower than the NDVI of the urban green spaces at 0.4362. The higher green space NDVI in the urban area exists in spite of a reduced total number of green spaces and reduced total green space area coverage in the urban area compared to the suburban area.

**Table 4.1: Percentage of each land cover type in each study area**

| Landcover | Suburban | Urban |
|---|---|---|
| **Tree Cover** | 13.8% | 22.61% |
| **Grass/Shrub** | 41.38% | 14.29% |
| **Bare Earth** | 0.09% | 0.31% |
| **Water** | 1.27% | 0.8% |
| **Buildings** | 16.45% | 26.99% |
| **Roads/Railroads** | 12.82% | 18.3% |
| **Other Paved** | 14.19% | 16.88% |

**Table 4.2: Study area characteristics and basic LST and NDVI statistics**

| **Entire Study Area** | **Suburban** | **Urban** |
|---|---|---|
| Study Area Size | 30,424,580 m$^2$ | 29,930,106 m$^2$ |
| Average LST | 39.48 °C | 34 °C |
| Min. LST (Max. LST) | 26 °C (52 °C) | 23 °C (44 °C) |
| Average NDVI | 0.2701 | 0.201 |
| Min. NDVI (Max. NDVI) | -0.0494 (0.5891) | -0.093 (0.5548) |
| **Within Green Spaces** | **Suburban** | **Urban** |
| Total Area of Green Space | 7,314,300 m$^2$ | 3,262,500 m$^2$ |
| Number of Green Spaces | 148 | 83 |
| Average LST | 36.46 °C | 28.87 °C |
| Min. LST (Max. LST) | 29 °C (44 °C) | 24 °C (40 °C) |
| Average NDVI | 0.4263 | 0.4362 |
| Min. NDVI (Max. NDVI) | 0.3501 (0.5518) | 0.35 (0.5548) |

### 4.2 Urban Cool Island

The results of the UCI delineation process revealed that cool islands exist in each study area relative to their average LST, which is dictated by the urban fabric. In the suburban area (average temperature 39.48°C), the maximum cooling difference was 13.4°C, a few degrees warmer than the maximum cooling in the urban study area at 11.79°C (average temperature 34°C). The areas of highest cooling can be seen in the green spaces, particularly following highly vegetated ravines in the suburban study area, and in large parks such as High Park in the urban study area, and where there are large open water bodies with low thermal signatures. Water bodies have been found to contribute to cooling because of their high evaporation potential causing low surface temperatures (Cao et al., 2010; Rinner and Hussain, 2011; Tan and Li, 2013; Martin et al., 2015). The Lake Effect from Lake Ontario may also be the cause of the large cool island found along the lakeshore since water vapour is a known factor that influences reflectance (Weng, 2004). Although the method used to derive LST performs atmospheric correction, there is a chance that elevated water vapour is still an influencing factor.

Cooling extends beyond the boundary of most of the larger UCIs and seems to have a strong directionality associated with it. For example, in the suburban study area, the direction of cooling tends to move toward other green spaces or follows areas of high NDVI that were just below the threshold cutoff of green space delineation of 0.35, or along highway corridors where there are high amounts of vegetation. Conversely, there are large UCIs that are far removed from the green spaces in the urban study area where NDVI is very low, namely in the downtown core of Toronto and north of the largest urban green space on the west side of the study area. This same green space was explored by Rinner et al. (2011) where this cool patch exists in the same area.

### 4.3 Regression Analysis: Green Space and LST

Results of the forward multiple regression for the suburban study area selected buffer NDVI, percent grass/shrub cover and patch size respectively as the most significant variables influencing green space LST. The adjusted $R^2$ was 0.536 and was statistically significant ($p < 0.01$).

Regression results of the urban study area chose buffer NDVI as the only significant variable affecting LST of the green space. The adjusted $R^2$ was 0.248 and was found to be statistically significant ($p < 0.01$). These results suggest that the LST in the green spaces of both study areas can be explained in part by the NDVI surrounding them. This variable was the first chosen in the suburban model and the only variable chosen in the urban model. These are similar to the results found by Tan and Li (2013) who used the difference in NDVI across the green spaces to explain LST with an adjusted $R^2$ result of 0.3785.

Figure 4.1 and 4.2 show the correlation between the suburban and urban LST and the corresponding significant model variables. A negative correlation exists between the LST and buffer NDVI and patch size. LST within the green space is likely to decrease as the buffer NDVI increases and when size of the green space increases. Tan and Li (2013) found that patch size under ten hectares revealed uncertainty in the relationship between green space size and LST, which can be seen in the strong vertically oriented cloud of small patch size with variability in LST. Alternatively, there is a positive relationship between the amount of grass/shrub cover in the suburban study area and LST where increased coverage corresponds with an increase in LST.

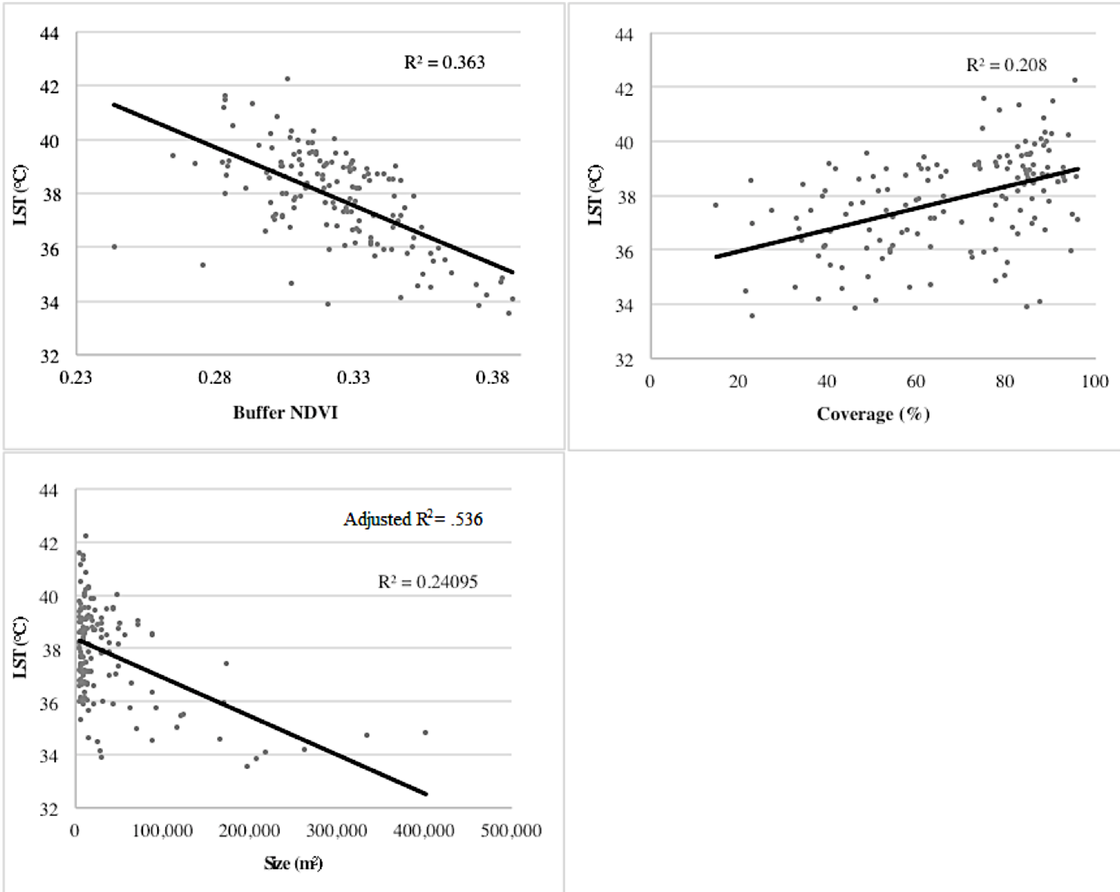


**Figure 4.1: Suburban green space LST versus independent model parameters displayed in order of addition to regression model with the final adjusted model $R^2$ value.**

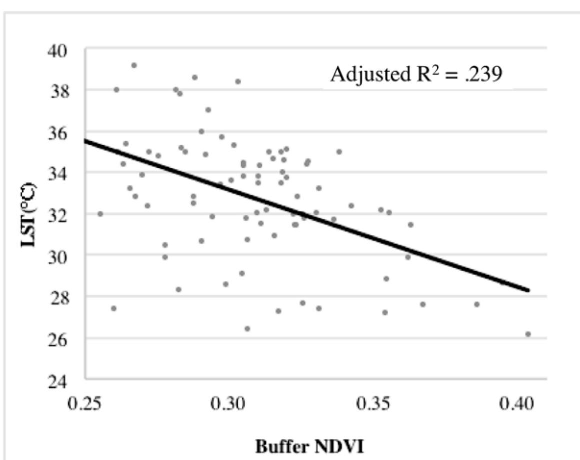


**Figure 4.2: Urban green space LST versus independent model parameter selected for the model with final adjusted $R^2$ value.**

### 4.4 Regression Analysis: Green Space and Surrounding LST

To determine if there is a relationship between LST surrounding a green space and green space characteristics, another set of forward multiple regression models were run using the buffer LST as the dependent variable. Results of this model selected percentage of tree canopy cover, buffer NDVI, percentage of grass/shrub coverage and patch size respectively as the most significant variables influencing LST around the green space in the suburban study area. The adjusted $R^2$ was 0.487 and was statistically significant ($p < 0.01$).

Regression results of the urban study area again chose buffer NDVI as the only significant variable effecting LST around the green space. The adjusted $R^2$ was 0.220 and was found to be statistically significant ($p < 0.01$).

Figures 4.3 and 4.4 show that there is a negative relationship between the LST and tree canopy cover, buffer NDVI, and green space size, where LST decreases significantly as these variables increase. Similar to the first model, there is a positive relationship between LST and percentage of grass/shrub coverage where higher LST values can be seen in areas with more grass/shrubs. A summary of all the multiple regression model results can be seen in Table 4.3.

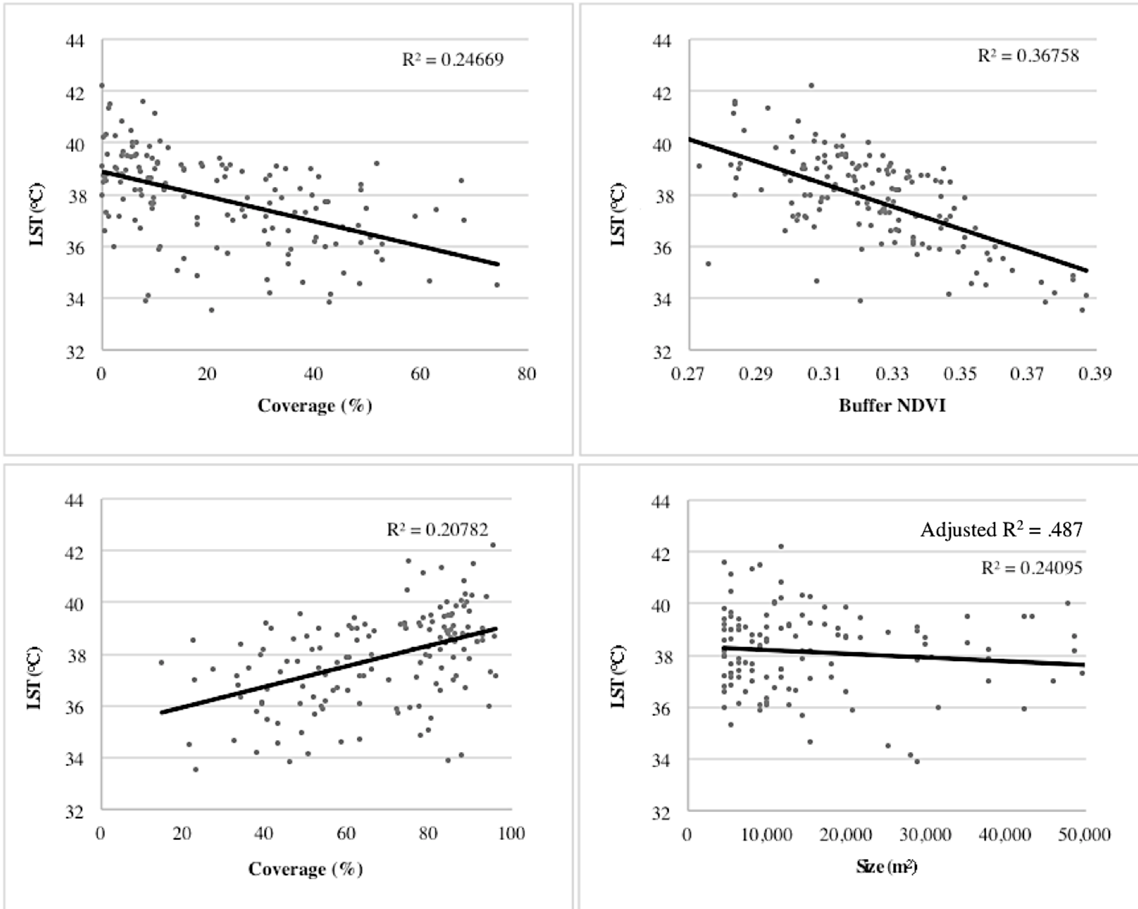


**Figure 4.3: Suburban area LST versus independent model parameters displayed in order of addition to regression model with the final adjusted model $R^2$ value.**

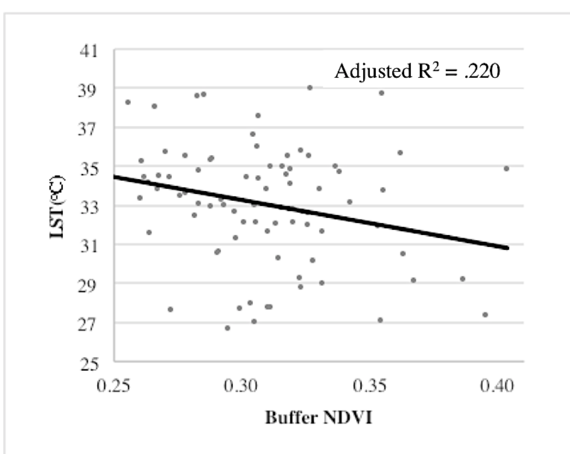


**Figure 4.4: Urban area LST versus independent model parameter selected for the model with final adjusted $R^2$ value.**

**Table 4.3: Summary of significant multiple regression variables and results for the green space LST and the surrounding LST models listed in order of variable selection.**

| | **Green Space LST** | | **Surrounding LST** | |
|---|---|---|---|---|
| | Variables Entered | Adjusted $R^2$ | Variables Entered | Adjusted $R^2$ |
| **Suburban** | Buffer NDVI; percent grass/shrub; size | 0.536 | Percent tree canopy; buffer NDVI; percent grass/shrub; size | 0.487 |
| **Urban** | Buffer NDVI | 0.239 | Buffer NDVI | 0.220 |

# CHAPTER 5: DISCUSSION AND CONCLUSIONS

## 5.1 Discussion

Based on the results of this analysis, a statistically significant relationship has been established between LST, NDVI and green space characteristics. Additionally, cool islands have been identified in both study areas, the majority of, and most intense of which are located in large green spaces, with some minor cooling beyond them. The lower average LST of the urban area compared to the suburban area, and the UCIs in the urban study area that are removed from the green spaces are interesting findings that may be related to the different surface cover characteristics. For example, a higher number of green spaces were found in the suburban study area, but the higher average LST compared to the urban area may be caused by the combination of surface properties with high thermal characteristics. This includes concrete and asphalt driveways, sidewalks, roads and dark shingled roofs. Additionally, the higher vertical extent of the buildings in the urban area may play a role in explaining the lower average LST results. In particular, shading from mid-rise and high-rise buildings in the downtown core of Toronto and north of the large green space can decrease the amount of solar radiation reaching the surface, and influence the thermal signature of this area and the area directly around it. Considering the image acquisition time of approximately ten o'clock in the morning, shadows would be very pronounced at this time. Shading effects are a factor that Ruffieaux et al. (1990) and Lin et al. (2015) state can be significant coolers in urban environments and should be considered when studying the SUHI and UHI effect in large cities using remote sensing techniques. Despite this, as mentioned previously, these findings are similar to those produced by Maloley (2009).

The results of the forward multiple regression for the urban study area show that green space LST is negatively influenced by the NDVI surrounding these urban green spaces. This suggests that the land cover and land use types in the urban area can be more imposing on the cooling ability of green spaces when compared to suburban neighbourhoods, where green space characteristics were also found to be influential for LST. In particular, some small urban green spaces do not produce any UCIs, and those that do have very little, if any, cooling extent beyond the green space. These patches correspond to areas of very high urban development and can help explain why green space characteristics do not play a significant role in their cooling ability. The suburban fabric is much more homogenous and less imposing on green spaces, and can help explain the greater extent of cooling seen beyond the boundary of those green patches, and the significance that their characteristics play in cooling. This finding is similar to that of Kong et al. (2015) and Lin et al. (2015) who state that the thermal properties surrounding a green space were influential on the ability of it to cool effectively.

The higher average NDVI values found in the urban green spaces may be explained by the more mature and denser patches of vegetation compared to the younger, less dense vegetation patches commonly found in subdivisions that are planted after construction. It has been suggested that the LST of different types of vegetation within a green space such as trees, shrubs and lawns do not differ from one another (Zhang et al., 2009; Tan and Li, 2013). However, the inclusion of two of these vegetation types in this study found that there were significantly different relationships between them and LST. This is similar to the conclusions reviewed by Kong et al. (2014) where trees are the most effective at cooling, followed by shrubs and grasses respectively. The green spaces in the suburban study area are dominated by grass/shrub cover which have a positive relationship with LST, whereas the urban green spaces are dominated by tree canopy cover which have a negative relationship with LST. The selection of both these variables in the suburban models show that they significantly influence LST in and around the green spaces, both positively and negatively. Particularly, tree canopy coverage was found to be the most significant variable positively influencing the LST surrounding suburban green spaces, likely due to the low amount of coverage across the study area.

This relationship can also speak to the 7.59°C difference in average LST found in the urban green spaces compared to the suburban green spaces, and the large cooling extent around the green spaces. The higher amounts of tree canopy cover in comparison grass/shrub coverage follow areas of highest cooling intensity, although this relationship was not tested statistically it can be seen by visual comparison of land cover and UCIs (Figures 3.5 and 3.6).

Although they are not exactly the same, Weber at al. (2014) state that LST and air temperature are highly correlated. A specific finding by Martin et al. (2015) resulted in an $R^2$ of 0.52 when LST and air temperature were compared at the satellite overpass time. Lin et al. (2015) cross referenced their LST results with ambient air temperature measurements taken 17 minutes after image acquisition and found them highly correlated with a coefficient of 0.81. These findings show how LST can influence ambient air temperature in the development of an UHI. Based on the results of this analysis, the elevated suburban LST at the time of image acquisition compared to the urban neighbourhood can cause a delay in the development of the SUHI and UHI in a large city because of shadow effects. Prolonged exposure to incoming solar radiation in the suburban neighbourhood because of low building height and density promotes accumulation of heat in the urban fabric, whereas the significant shading effect found in vertically developed areas produced UCIs. The accumulation of heat on the suburban fabric can provide more fuel for UHI development prior to the time of day when ideal conditions exist for development (i.e. maximum incoming solar radiation) because of the higher SUHI found here.

## 5.2 Conclusions

The main findings of this research show that the urban fabric of a city can highly influence the development of a SUHI. This suggest that suburban areas have the ability to develop UHIs that are strongly related to their SUHI development, but the cooling ability from green spaces was found to be more influential in suburban neighbourhoods where there is more homogeneity in surface characteristics. Green space cooling in urban neighbourhoods was strongly dictated by the urban fabric surrounding it, which limited their cooling ability.

The method of analysis followed in this study design was to quantify the relationship between the spatial distribution of LST and surface characteristics. To date, the extent of cooling beyond a green space has mainly been studied using observational measurement techniques with highly variable results (Hamada and Ohta, 2010; Slater, 2010). Lin et al. (2015) used remotely sensed images through the application of a watershed delineation tool to assess cooling. Although extent was not empirically quantified in this study, it was implied by using remote sensing and land surface characteristics in combination with regression analysis to determine if any relationships between the green space and the surrounding LST exist.

This research offers a new perspective on SUHI and UHI development and green space cooling ability through the comparison of two study areas comprised of completely different urban fabrics. It also opens the avenue for further analysis on suburban UHI development where a large portion of our population resides (Gioia et al., 2014). There are also possible implications for urban design/development and global climate change by identifying urban characteristics that highly contribute to atmospheric warming.

### 5.3 Limitations

This study does not consider anthropogenic influences on the development of the UHI, which may have a larger role on influencing ambient air temperature in the downtown study area than in the suburban neighbourhood. Factors that can increase the UHI include a higher population density and anthropogenic activity, and a difference in air circulation patterns from tall buildings (Voogt and Oke, 2003). Additionally, the Landsat 8 imagery (from 2014) used to derive LST, NDVI, and green spaces is seven years more recent than the land cover image derived from a 2007 image. This limitation requires the assumption that no change in vegetation cover has occurred between these years. Results of the LST calculation are likely over estimated based on the notice released from the USGS in 2014 stating that stray light is entering band 11 and it should not be used for LST retrieval (USGS, 2015). Despite these limitations, the relationship between LST and green space characteristics that has been established is not highly dependent on the accuracy of the values, but rather on the patterns of temperature associated with each land cover type.

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