ABSTRACT

Vegetation has been identified as an essential component of healthy urban environments, and the benefits of urban vegetation range widely from influences on the physical conditions of the city to the social well-being of the people who reside in these areas. As a result, ongoing research is important to understand the dynamic spatial components of urban vegetation to help urban planners and scholars manage this valuable resource.

Advanced remote sensing technologies, such as high spatial resolution sensors and laser scanning devices, are useful tools for examining urban environments since they can capture detailed information regarding the material and structural composition of the urban surface. By providing a complete coverage of urban environments remote sensing technologies enable new possibilities to quantify the contributions of urban vegetation for a wealth of active processes in urban areas. The studies in this thesis examine several remote sensing devices to demonstrate the influence of urban vegetation on both physical and social aspects of urban environments. Three studies comprise the body of this work. They present new geographic techniques using remote sensing for: 1) the detailed classification of urban vegetation conditions; 2) quantifying the contribution of trees to solar radiation available for building rooftops; and 3) examining socioeconomic disparities related to urban green-space.

In the first study Quickbird high spatial resolution satellite imagery is classified using spectral mixture analysis and decision tree classifications to extract detailed urban vegetation characteristics. Results indicate that this new methodology can accurately separate tree and
vegetated ground-cover classes (80% and 94% of variance explained respectively) in addition to higher order hierarchical vegetation categories such as manicured grasses, mixed grasses, deciduous trees and coniferous trees (with variance explained ranging from 67 to 100%). The second study uses LIDAR (light detection and ranging) data to quantify the diurnal and seasonal impact of trees on solar radiation available for urban residential dwellings. Results of this second study help to indicate the strength of the correlations between tree structure and rooftop received radiation, and suggests that these relationships are strongest around 10 a.m. and 3 p.m. Finally, the third study examines green-space-related environmental justice using Landsat imagery and national census data at both inter- and intra- city scales for three major Canadian cities. Here the results indicate that a strong global correlation between socioeconomic variables and vegetation cover exists while local regression analyses highlight the variability of environmental inequalities within individual cities.
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To my family of friends who add life to this wonderful city
CO-AUTHORSHIP STATEMENT

This thesis is the combination of three scientific manuscripts for which I am the lead author. The structure of the project was developed over time with the help of Dr. Nicholas Coops, Dr. James Voogt, Dr. Brian Klinkenberg, and Dr. Michael Meitner, with the purpose of examining remote sensing applications for urban analysis. For all three scientific journal articles, I performed all the research, data analysis, interpretation of the results, and prepared the final manuscripts. Dr. Nicholas Goodwin provided technical assistance with aspects of the LIDAR processing. Co-authors provided advice on methodology and made editorial comments and suggestions after the completion of the first draft of each manuscript.
1 INTRODUCTION

1.1 Urban environments

The Earth’s population is urbanizing at a rapid rate. In 1950, 30 percent of the world’s population lived in urban areas and over the following 50 years this grew to over 47 percent and is predicted to rise to 60 percent by the year 2030 (Kahn, 2006). As a result, urban environments are becoming the dominant landscape where people live their lives, requiring ongoing research to study dynamic processes that occur in these areas. Two recognized underlying features that distinguish cities from natural environments include the abruptness of surface change and the pervasive role of human activity (Oke, 1997). Together these features create spatial discontinuities at various scales that result in the extreme heterogeneic composition of urban environments.

The implications of urbanization on the environment are significant and include loss of vegetation and open spaces, declines in the extent and connectivity of wetlands and wildlife habitat, increased temperatures and greenhouse gas emissions, and reductions in soil and water quality (Grimmond and Souch, 1994; Booth and Jackson, 1997). As a result, a holistic understanding of urban environments requires that research integrates various human and ecological processes (Ellis & Ramankutty, 2008). The contemporary ecological paradigm recognizes that humans are components of ecosystems (McDonnell and Pickett, 1993). This paradigm is easily understood when observing urban areas where human interactions with the local environment produce dramatic spatial variations in physical and social processes. At the
same time, the fine-scale heterogeneous composition of these environments results in complex spatial processes that are becoming progressively better understood with the aid of advanced remote sensing technologies and geographic information systems (GIS).

In this research I investigate the spatial relationships between vegetation and both physical and social processes of urban environments using a range of remote sensing devices. Several satellite and aerially mounted sensors are used in conjunction with existing spatial statistics and metrics to quantify the interactions between urban vegetation cover, physical processes, and socioeconomic variables for the Metro Vancouver area in British Columbia, in addition to a broader analysis of Vancouver, Montreal and Toronto. Outcomes of this research can provide urban planners and scholars with techniques and methods for integrating spatial data technologies into urban planning practices.

1.2 The importance of urban vegetation

Vegetation has been identified as a vital component of healthy urban environments and the benefits of urban vegetation range widely, influencing both the physical conditions of the city as well as the social well-being of urban residents. These links form the foundation for studies examining social-ecological systems (SES), which suggest that many human and ecological systems are tightly and inextricably linked (Alessa et al., 2008). In a review of societal needs in urban areas, Matsuka and Kaplan (2008) suggest that human actions and attitudes are directly connected to the physical features of the environmental setting, of which trees are a major component.
Recent studies reveal that the surface composition of urban environments is correlated with important social processes such as crime (Kuo & Sullivan, 2001), health (Coen & Ross, 2006; Gidlof, 2007) and childhood development (Taylor et. al., 1998). Conversely, Grove et al. (2006) suggest that social components, such as people’s behavior, are an important predictor of vegetation cover on private land. Therefore, planners and decision makers must consider the social implications of vegetation management strategies in urban environments.

Physical and biophysical aspects of urban environments are also tightly linked to vegetation cover. Specifically, trees have been demonstrated to affect air and water quality, reduce air and surface temperatures, and control wind flow and rates of transpiration (Avissar, 1996; Grimmond et al., 1996; Nowak & Dryer, 2000). At a time of increasing climate variability, scientists are also examining the role that vegetation has on urban carbon budgets (Myeong et al., 2006; Christen et al., 2009). By examining vegetation on a finer scale, we can also begin to understand the direct influence that vegetation management strategies have on energy conservation (McPherson & Rowntree, 1993) and renewable energy production (Hofierka & Kanuk, 2009) in urban environments.

Conceptualizing urban landscapes in terms of their physical and social connections provides an opportunity to evaluate how urban systems emerge and evolve, and the reciprocal relationships between the natural and anthropogenic components of cities. The aforementioned studies add valuable information regarding the importance of vegetation in urban environments. Nonetheless, in the study of people-and-environment relationships, divisions are still apparent as
a result of the compartmentalized disciplinary focus of many scientists and professionals who adopt exclusive interpretations (Lawrence, 2003).

1.3 Humans as part of an ecosystem

Traditional ecology has depicted urban areas as alien phenomena that encroach upon biophysical systems. This logic has resulted in an extreme divergence between those people who study ecological processes and those people who engineer and plan our cities (Alberti et al., 2003). The discipline of urban ecology describes the multidimensional and highly variable spatial and temporal implications of sustained direct human interaction with their local environments (Alberti et al., 2003; Ellis and Ramankutty, 2008). Urban ecology is in an age where new spatial analysis technologies, including geographic information systems and remote sensing devices, can significant benefit the discipline. Additionally, this research can have a dramatic and immediate impact on the environments where the majority of the world’s human populations are destined to reside. As a result of these issues Alberti et al. (2003) have identified four fundamental questions that need to be addressed by urban ecology scholars:

- How do socioeconomic and biophysical variables influence the spatial and temporal distributions of human activities in human-dominated ecosystems?
- How do the spatial and temporal distributions of human activities redistribute energy and material fluxes and modify disturbance regimes?
• How do human populations and activities interact with processes at the levels of the population, the community and the individual to determine the resilience of human-dominated systems?
• How do humans respond to changes in ecological conditions, and how do these responses vary regionally and culturally?

At the foundation of these four questions is a need to fundamentally understand spatial patterns and the distribution of various urban features.

1.4 Remote sensing for urban analysis

Remote sensing technologies provide effective and efficient methods for monitoring the surface characteristics of urban environments. These technologies offer advantages over field-based surveys by enabling large spatial coverage and frequent data collection over many inaccessible areas at a relatively low cost. In recent decades remote sensing has been applied to various urban land cover analyses and these applications continue to evolve alongside technological advancements.

Traditionally, aerial photography has dominated urban remote sensing analysis because the heterogeneous composition of these landscapes which requires high spatial resolution imagery to capture the variability of surface cover types (Herold et al., 2003). However, high acquisition costs in addition to a narrow spectral resolution, has limited the application of aerial photographs for digitally investigating complex processes in urban environments. Vector-based land-use
maps have also been used in urban analyses, although often these simplistic representations do not properly represent the ecological heterogeneity of urban landscapes (Pickett et al., 2008).

Advances in sensors that are able to resolve small distances on the ground (<4m) enable sophisticated analysis of detailed urban processes by providing land cover information at a spatial resolution suitable for household-scale analysis (Grove et al. 2006). Earth observation satellites, such as IKONOS and Quickbird, provide multispectral data at resolutions up to 2.4m and panchromatic data up to 0.6m resolution. These technologies offer resolutions comparable to aerial photographs with the increased advantage of offering large areas of digital data encompassing wide spectral ranges and global coverages at regular intervals throughout the year. Rapid development of high resolution satellite sensors also promise an ongoing ability to examine incrementally more detailed processes of urban environments. These technologies are particularly pertinent to urban studies since the visible region of the electromagnetic spectrum provides the most prominent spectral information required for separating urban land cover materials (Herold et al., 2004).

Three dimensional aspects of city surfaces are also relevant for detailed urban analysis. Active remote sensing devices, such as LIDAR (light detection and ranging), can provide highly accurate estimates of surface heights that are crucial for understanding the structural composition of urban environments. LIDAR systems emit a laser pulse (most often in the near-infrared region of the spectrum) and then record the exact location of the sensor and time it takes each laser pulse to return, producing a detailed three dimensional dataset over a given area.
Although high spatial resolution and LIDAR imagery can provide a wealth of data for urban environments, the associated high costs and computational resources limit the applicability of these sensors for monitoring large areas of the Earth’s surface. Broad-scale remote sensing imagery is useful for urban analysis covering large areas and multiple cities. Specifically, by covering larger areas in a single image, broad-scale imagery complements finer scale datasets by focusing attention to areas requiring more detailed analysis. The Landsat group of sensors has been used extensively for Earth observation and as of January 1 2009 this archive of imagery has been released at no cost. Landsat data provides satellite imagery for medium-scale analysis over long periods of time. In addition, the spatial resolution of Landsat data is well matched to the geographical bounding areas of national census data.

1.5 Research objectives

This thesis is divided into three sections that focus on remote sensing applications for different aspects of urban vegetation management. As a whole, these chapters address the spatial variability of urban vegetation and seek to better understand the relation between vegetation and both physical and social characteristics of urban environments. The flow of this thesis begins at a very fine spatial scale analysis with the extraction of detailed information related to vegetation features then moves up in scale to an analysis of the relationships between individual objects and ends with a broad-scale examination of the interaction between groups of objects (Figure 1.1). The specific objectives for each chapter are discussed below.

My objective in chapter 2 was to utilize high spatial resolution imagery for sub-pixel urban vegetation extraction. This involved the use of spectral mixture analysis and statistically
developed decision trees to extract vegetation species and condition from Quickbird multispectral imagery. The results from this chapter provide the spatial extent of, and detailed information regarding, the composition of vegetation in Vancouver, British Columbia.

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Figure 1.1 Schematics representing the general theme of each chapter in addition to information about the scale and sensor used.

My objective in chapter 3 was to examine the influence that vegetation structure has on the solar radiation intercepted by urban residential building rooftops. For this chapter, LIDAR data is
used to provide the topographical information required to populate GIS-based radiation models, and to derive the form of individual features in the urban environment. Results provide an assessment of the seasonal and diurnal impacts that trees have on both direct and diffuse solar radiation for urban residential dwellings.

My objective in chapter 4 was to combine spatial data to quantify environmental justice issues related to urban green-space at inter- and intra-city scales. In this chapter, correlation and geographically weighted regression statistics are applied over three major Canadian cities to map areas in each city that demonstrate green-space-related environmental injustices.

Finally, in chapter 5, a discussion is provided regarding the significance and implications of this work, in addition to suggestions for future research.
1.6 References


Christen, A., Coops, N., Crawford, B., Liss, K., Oke, T., Tooke, R. 2009. The role of soils and lawns in urban-atmosphere exchange of carbon-dioxide. The 7th International Conference on Urban Climate (ICUC-7); Yokohama, Japan.


2 EXTRACTING URBAN VEGETATION CHARACTERISTICS USING SPECTRAL MIXTURE ANALYSIS AND DECISION TREE CLASSIFICATIONS

2.1 Introduction

As our understanding of urban systems has evolved, researchers have become increasingly aware of the importance of detailed land surface characteristics to many processes established in social and physical geographic sciences. These land cover features include both natural and anthropogenic attributes and are characterized as being in a state of constant change due to the pervasive influence of human activity (Ben Dor, 2006). Urban meteorology and hydrology provide examples of disciplines that apply spatial land cover information to explain biophysical processes. Specifically, the impervious surfaces of urban areas represent an essential component of macro-scale models representing established phenomena including urban heat island effects (Oke, 1982). Spatial variation in pervious and impervious surface composition have since been demonstrated to effect surface thermal and moisture conditions; attributes that are key determinants of urban climate (Grimmond et al., 1996; Voogt & Oke, 1997).

Understanding the more complex relationships among land surface characteristics and urban climates requires that meteorologists incorporate a wide range of features beyond the basic division between impervious and pervious surfaces. Detailed land cover characteristics including surface albedo, shade, and vegetation condition inform meteorological studies at local

---

Vegetation is of particular interest as it presents a versatile resource for effectively managing and moderating a variety of problems associated with urbanization. The spatial distribution and abundance of urban vegetation, for example, is recognized as a key factor influencing numerous biophysical processes of the urban environment, including air and water quality, temperature, moisture, and precipitation regimes (Avissar, 1996; Grimmond et al., 1996; Nowak et al., 2000). Detailed vegetation characteristics, such as the structure of plant canopies and their physiological condition, also exert a strong influence on more complex processes such as urban wind flow and rates of transpiration (Avissar, 1996; Wang et al., 2008). In addition, vegetated areas such as gardens, parks, and forests have been related to positive social outcomes including reductions in crime (Kuo & Sullivan, 2001), health benefits (Coen & Ross, 2006), and advanced childhood development (Taylor et al., 1998). Given the associations between vegetated land cover and the biophysical and social processes of urban systems there exists an ongoing demand for effective urban vegetation mapping and classification techniques.

Mapping detailed land cover attributes within urban environments has been primarily reliant on conventional cadastral information from municipal agencies. However, the high cost and time consuming nature of interpreting this data, as well as difficulties in accessing data, can restrict the capacity for quantitative studies of vegetation impacts on biophysical and social processes in urban areas. In addition, cadastral information is often limited to areas of public access, resulting in large gaps of detailed land cover information across cities. In contrast, remote sensing imagery can provide information that is well suited to extensive mapping of vegetated surfaces and recent developments in high spatial resolution sensors (e.g. < 5m) such as IKONOS and
Quickbird have further enabled detailed analysis of urban areas. Herold et al. (2004) suggest that the visible region of the electromagnetic spectrum provides the most prominent spectral information required for separating urban land cover materials. As a result, high resolution broadband sensors with multiple channels positioned in this region of the spectrum can begin to resolve some of the detailed land cover components necessary for informing current microclimate (Noilhan & Mahfouf, 1996; Voogt & Oke, 1997) and ecological models (Zipperer et al., 1997).

Critical for the interpretation of high spatial resolution remote sensing imagery in urban environments is the development of accurate remote sensing classification techniques. Traditional supervised or unsupervised classifications assign each pixel to a single class and, as a result, these classifications can significantly underestimate or overestimate land cover types in urban environments as pixels often contain a mixture of cover types. For example, research by Thomas et al. (2003) compared high resolution urban mapping methods and found that traditional supervised and unsupervised spectral classification methods resulted in map accuracies of around 50%. Urban environments also tend to contain fine scale heterogeneous land covers with narrow linear patterns (Zipperer et al., 1997; Collinge, 1998) that are not always captured within a single image pixel. Due to the inability of traditional classification algorithms to account for mixed pixels, techniques better suited to heterogeneous environments have been developed. Spectral mixture analysis (SMA), in particular, has been used to classify urban vegetation cover (Small, 2001; Small & Lu, 2006). This approach assign to a pixel the representative fractions of land covers that combine within the instantaneous field of view (IFOV) of the sensor.
In the past decade SMA has developed as the primary method for extracting multiple urban land covers from a single pixel value (Kressler & Steinnocher, 1996; Small, 2001; Rashed et al., 2001). Early urban land cover classification has been theorized according to Ridd’s (1995) V-I-S (vegetation-impervious surface-soil) classification scheme. This scheme provides a conceptual model that divides urban environments into three classes: vegetation, impervious surface, and soil. This approach remains problematic in a remote sensing context as it represents features that cannot necessarily be distinguished on the basis of reflectance values alone (Phinn et al., 2002, Powell et al., 2007). As a result, Small (2001) developed a more applicable model that establishes substrate, vegetation, and dark (SVD) features of the urban environment as components for SMA. These pure endmembers represent features at the apexes of the urban mixing space, yet it remains unclear whether more detailed vegetation characteristics including trees and vegetated ground cover can also be quantified in terms of their separability along the mixing line between the dark and vegetation endmembers (Small & Lu, 2006). Although higher order vegetation details including species and condition do not produce distinguishable pure pixels in three endmember mixture models, they represent physically and structurally distinct land cover features whose extraction at high spatial resolutions can inform micro- and local scale urban process models and consequently represents the central focus of the following research.

The objective of this study is to develop a technique to extract vegetation species and condition information using sub-pixel abundance values from high spatial resolution multispectral imagery. We produce fractions of vegetation, high albedo substrate (such as concrete, and metal
roofs), and dark features by applying spectral mixture analysis to a Quickbird image over the city of Vancouver, Canada. Shadow estimates from a LIDAR (light detection and ranging) hillshade model in addition to field based observations of vegetation condition and species were collected and provided training data for decision tree classifications. These parameters are used in conjunction with the SMA derived fractions of vegetation, high albedo and dark features to quantify the separability of various vegetation elements within the urban environment. Discussion of the results focuses on issues that may impede our procedure and considerations regarding the application of this technique for modeling various fine scale urban biophysical and social processes.

2.2 Methods

2.2.1 Study Area

The City of Vancouver (49° 15’N, 123° 6’W) on the mainland western coast of Canada is located within the larger urban region of metropolitan Vancouver and covers a 114 km² area. Vegetation including various evergreen needleleaf and deciduous broadleaf tree species, shrubs, and grasses comprise a large portion of the city’s surface area and, as a result of to the temperate climate of the region, much of the vegetation remains photosynthetically active for a majority of the year (Straley, 1992). Areas of manicured grass exist throughout the city on private lots and parks, while wild native grasses are less prevalent and tend to be found in designated protected areas. Trees are also abundant throughout Vancouver with native evergreen needleleaf species dominant in urban parks and deciduous broadleaf species dominant along streets and in residential areas.
2.2.2 Remotely Sensed Data

A Quickbird multispectral image was acquired on March 29\textsuperscript{th} 2007 over the study area, capturing a wide range of land cover types including residential, commercial, industrial, and forest (Figure 2.1). The image has a spatial resolution of 2.4m with four spectral bands (blue, 450-520 nm; green, 520-600nm; red, 630-690nm; and near-infrared, 760-900nm) and a 0.6m panchromatic band. The Quickbird multispectral image was initially calibrated to at-sensor radiance and atmospherically corrected to estimate surface reflectance using a dark-object subtraction technique (Chavez, 1988). Digital orthorectified aerial photographs acquired in 2004 with a spatial resolution of 0.2m were also available to provide additional land cover details.

Figure 2.1 Study area over Vancouver, British Columbia showing extent of Quickbird imagery and LIDAR dataset.
Airborne LIDAR data was acquired in March 2007 by Terra Remote Sensing (Sidney, British Columbia, Canada) using a TRSI Mark II discrete return sensor attached to a fixed wing platform. The sensor was configured to record first and last returns with a pulse repetition frequency of 50 kHz, platform altitude of 800 m, maximum off-nadir view angle of 15 degrees, wavelength of 1064 nm, and a fixed beam divergence angle of 0.5 mrad. The average pulse spacing equalled one laser pulse return per 0.7 m². Ground and non-ground returns were classified using TerraScan software (Terrasolid, Finland). The area surveyed includes a 1 km wide and 9 km long transect from Stanley Park, through downtown Vancouver which contains a large number of high rise buildings, to a research observation tower located in a residential area (Figure 2.1).

### 2.2.3 Field Data

In our analysis detailed vegetation characteristics including condition and species were recorded in early summer to provide the necessary training data for decision tree classifications of urban vegetation. Figure 2.2 displays a list of the vegetation characteristics recorded in the field to investigate the location of these features within the mixing space of high resolution satellite imagery, particular to the City of Vancouver. Vegetation is separated into tree and vegetated ground cover categories, and each category is further classified based on the species and condition of the vegetation. The vegetated ground cover class is separated into wild (unmanicured and long grasses), herbaceous plants, dry grasses (senesced and dead), and manicured grasses. The tree class is separated according to whether the vegetation is a deciduous broadleaf or evergreen needleleaf species.
2.2.4 Field Plots

Field locations were selected to capture a wide range of vegetation patterns, condition and species. Due to the significant areas of private land uses in the urban setting, sites were chosen in areas with minimal limitations to access and as a result most of the field plots were located in public spaces. Accessibility was evaluated using orthophotographs, street maps, and a priori knowledge of the region. Navigation to the field plots was done using a differential GPS unit applying wide area augmentation system (WAAS) technology and orthophotographs. The extreme heterogeneity of urban environments compared to natural landscapes provides new challenges when attempting to validate the results of high resolution imagery to field based observations. Because numerous contrasting surfaces are being analyzed according to their influence on the spectral response of a pixel or group of pixels, it is critical that the field plots representing those portions of the image align with sub-pixel accuracy. To address this issue imagery was referenced using spatial subsets from the orthophotographs and rectified to a pansharpened Quickbird image with RMS errors less than 1m.

![Field plot classification schematic](image)

Figure 2.2 Field plot classification schematic representing increasing levels of vegetation detail.

2.2.5 Shaded area estimation using LiDAR data
To identify image pixels representing shadow a hillshade model was developed using a LIDAR transect overlapping the center of the Quickbird scene. First return heights were gridded with 1 by 1 m pixels to represent the maximum height (urban vertical profile) across the study area. Using collection date specifications from the Quickbird imagery and a hillshade model, the incoming solar radiation was estimated. Input parameters tied to the acquisition date of the Quickbird imagery consisted of a sun zenith angle of 43.5 and azimuth orientation of 167.1 degrees. The resulting model and multispectral Quickbird image are shown in Figure 2.3.

2.2.6 Linear Spectral Mixture Analysis

SMA divides each pixel of an image into the representative fraction of selected endmember spectra. Each endmember consists of spectra that represent materials on the ground (Adams & Gillespie, 2006). Linear mixing assumes that the spectral reflectance profile of each pixel is a linear combination of the selected endmembers (Goodwin et al., 2005). To find the best combination of endmembers to explain the mixed reflectance signal of a pixel, linear spectral mixture analysis is performed by Eq. (1).

$$R_i = \sum_{j=1}^{n} f_j R_{E_j} + \epsilon_i \text{ and } 0 \leq \sum_{j=1}^{n} f_j \leq 1$$ (1)

where $R_i$ is the total pixel reflectance; $f_j$, the endmember image fraction; $R_{E_j}$, the reflectance of image endmember $j$ at band $i$; $n$, the number of endmembers; and $\epsilon_i$ is the residual error for band $i$. The number of possible endmembers equals the number of bands minus 1.
Figure 2.3 Comparison between Quickbird multispectral image and LIDAR (light detection and ranging) derived surface model depicting shadow for a,b) the central business district and c,d) a residential neighbourhood.

Our spectral mixture analysis procedure is performed following the methods presented by Small and Lu (2006). The first step involves a principal components (PC) analysis on the four bands of
the Quickbird image. Performing PC transformations on broadband imagery enables the topology of the mixing space to be constructed as a three dimensional model that encompasses all the combinations of theoretically pure physical elements within each pixel of the scene (Small & Lu, 2006). These pure features, referred to as endmembers, compose the apexes of the three dimensional mixing space (modeled as a convex hull) and must be carefully selected to ensure that accurate mixture models are produced. To maintain the integrity of the analysis, pixels are manually selected from the apexes of the mixing space and verified against georeferenced orthophotos. Similar to previous research (Rashed et al., 2001; Small, 2001; Small & Lu, 2006) the endmembers were defined as vegetation, high albedo substrate, and dark features. Dark endmember pixels include shadows typically cast by tall buildings in the central business district of the city, in addition to significant areas of shadowed forest canopies in evergreen needleleaf forests. Vegetation endmember pixels are characterized as highly manicured grasses typically located in golf courses and public parks. The final step in the analysis uses Eq. 1 to perform SMA and generate three abundance images representing each of the individual endmembers. To produce abundance images with meaningful values that can be coupled with field observations, sum to unity and positivity constraints are applied to the analysis and fractions represented as a percentage.

2.2.7 Decision Tree Classification

Decision trees (DTs) have emerged recently as an alternative land cover classification method and may provide improved accuracies over maximum likelihood and neural network classifications when applied to multispectral imagery (Mahesh & Mather, 2003). DTs offer advantages over these other types of classification methods in that they can process data measured at different scales and no assumptions are made concerning the frequency distributions
of the data. In addition DTs are relatively quick; requiring minimal computational time compared to neural networks (Mahesh & Mather, 2003). The basic process of DT construction involves the repeated division of a set of training data into increasingly distinct subsets based on tests to one or more of the feature values. Once a set of hierarchically structured rules, or branches, are produced based on the provided training data, these rules can be applied to an entire image in order to produce accurate land cover maps and inventories for further spatial analysis.

Figure 2.4 Location of the field plots and shadow plots within the spatial extent of the Quickbird imagery.
In our analysis, the training data are derived from the field observations of vegetation species and condition in addition to the LIDAR derived shadow plots (Figure 2.4). Single trees for each hierarchical level of vegetation class are developed with DTREG software using a 10 V-fold cross validation technique that has been demonstrated to produce highly accurate results without requiring an independent dataset for assessing the accuracy of the model (Sherrod, 2008). A more detailed explanation of decision tree validation and pruning techniques can be found in Sherrod (2008). The V-fold cross validation technique used in this paper involves first developing an initial large tree using all the available data, known as the reference tree. Secondly, the total dataset is partitioned into 10 groups (or folds) and 10 new subsets of the total are created using 9 out of 10 of the folds. Ten test trees are then built using the reduced datasets with the unused 10% in each case then run through each test tree and the classification error for that tree computed. Once the 10 test trees have been built, their classification error rate, as a function of tree size, is averaged and the reference tree is pruned to the number of nodes matching the size that produces the minimum cross validation cost (Breiman et al., 1984).

2.3 Results

The principal component analysis on the 4 band Quickbird image showed over 99% of the image variance contained within the first three primary principal components, which is in agreement with earlier research (Small, 2003; Small & Lu, 2006). The resulting distribution of pixel values within the mixing space produced distinctive linear dispersions between the vegetation-dark and dark-high albedo apexes, while a concave dispersion was observed between the vegetation-high albedo apexes indicating that few pure binary mixtures of these features exist within the city (Small & Lu, 2006).
The abundance images produced from the SMA for the vegetation, high albedo substrate and dark features of the imagery, in addition to the true colour multispectral Quickbird and orthophoto images, is shown in Figure 2.5. The dark abundance image shows the dominance of dark features throughout the scene resulting from significant shadowing which comprises this endmember. Comparing the areas of vegetation in the orthophotograph (Figure 2.5) with the corresponding dark and vegetation abundance images also indicates that certain forms of vegetation are underestimated in a three endmember mixing model; specifically trees that have moderate fractions of both dark and vegetation features. High fractions displayed in the vegetation abundance image are localized in grassy areas, while surfaces including roads and parking lots are highlighted in the representative high albedo substrate image.

To determine the location and separability of various vegetation features within the image mixing space, field observations were organized into classes representing hierarchical levels of vegetation detail. The first order represents vegetated ground cover and trees and the second order represents species and condition attributes related to the vegetation. Data collected for each hierarchical level were used as input into decision tree classification models and determined which categories or combination of categories could be separated and successfully classified within the decision tree models. A total of three decision trees were successfully produced, the first representing broad divisions of vegetation (vegetated ground cover and tree) and the second two representing more detailed vegetation classes as subsets of the broader categories (manicured, mixed, evergreen, and deciduous).
Figure 2.5 True colour a) multispectral Quickbird image and b) aerial photograph compared with image fractions for the three endmembers: c) vegetation, d) high albedo substrate, and e) dark.
The first model representing the first level of vegetation detail explained 94% of the variance within the vegetated ground cover class and 80% of the variance within the tree class. The primary factor for dividing these two classes is the dark abundance image (Figure 2.6). The first split involved separating the dark values at 52%. Pixels with less than 52% dark features were then classified into vegetated ground cover pixels with a further rule applying high albedo abundance values of greater than 2%. Dark values greater than 52% include both shadow and tree classes and these image features were separated using the vegetation abundance with a threshold of 41%, where pixels less than this value were classified as shadow and pixels greater than 41% were classified as tree. Results from this classification are mapped in Figure 2.7b.

Figure 2.6 Statistically developed decision tree classification for the extraction of broad level vegetation characteristics including trees and vegetated ground cover.

Successful extraction of the first order vegetation classes enabled the application of our decision tree technique for extracting the more detailed second order classes. Pixels classified as
Figure 2.7 Mapped decision tree results comparing a) the true colour multispectral Quickbird image with extracted b) grass and vegetated ground cover classes, c) manicured and mixed vegetated ground cover classes and d) deciduous and evergreen tree species classes.
vegetated ground cover from the previous step were input into a new DT to extract the classes of manicured, dry, herbaceous and wild. The best result involved combining dry, wild, and herbaceous categories into a new class labelled ‘mixed’, while the manicured class remained unchanged from the original data. This classification used the dark abundance values as the primary feature for classification (Figure 2.8). The first rule establishes a threshold of 40% dark and all pixels less than this value were classified as manicured grass. An additional rule was required to separate the remaining classes and used the high albedo abundance value of 2% to derive mixed grasses (less than 2%) and the remaining manicured grass class (greater than 2%). Variance explained for this DT classification was 100% for the manicured class and 73% for the mixed grass class (mapped in Figure 2.7c).

The final classification extracted evergreen and deciduous classes from the broader tree category. This classification used the dark abundance values as the first feature for classification (Figure 2.9). The only branch in this DT establishes a threshold of 57% dark with tree pixels less than this value classified as evergreen and pixels greater than 57% dark classified as deciduous. Variance explained for this DT classification was 80% for the evergreen class and 67% for the deciduous class (mapped in Figure 2.7d).

2.4 Discussion

2.4.1 Vegetation Separability

Mapping the location and spatial extent of trees, vegetated ground cover, and high level vegetation detail provides a valuable addition to urban land cover mapping using high spatial
resolution imagery. Image classification techniques developed to date extract a basic vegetation class which encompasses a broad range of features whose structural and spectral diversity have a

Figure 2.8 Statistically developed decision tree classification for the extraction of detailed second order vegetation characteristics related to vegetated ground cover condition including: manicured and mixed.

Figure 2.9 Statistically developed decision tree classification for the extraction of detailed second order vegetation characteristics related to tree species including: deciduous broadleaf and evergreen needleleaf.
variety of impacts on urban processes (Mueller et al, 2005; Voogt & Oke, 1997). Spectral mixture analysis provides a successful technique for extracting the fractional abundance of general land cover features well suited to the heterogeneic composition of urban environments. Small and Lu (2006) explain that high spatial resolution image vegetation fractions provide more informative vegetation estimates than moderate resolution imagery due to the reduction of possible distinct mixtures and add that Quickbird pixels can resolve many of the individual components representing urban vegetation. Nonetheless, the dimensionality of the imagery still produces a three endmember mixture model encompassing various vegetation conditions and species. Fractional abundance values (Figure 2.5) from our analysis show that vegetation is generally represented by manicured grasses and as a result underestimates the spatial extent of trees within the mixing space since trees are best represented as a combination of both the vegetation and dark endmember.

To improve the classification of vegetation features and explain the endmember variability within high spatial resolution mixing space, we applied a decision tree classification using field observations and the SMA derived abundance images. Of significance, this enabled accurate estimates of the separability and location of vegetation features including tree species and vegetated ground cover condition within the mixing space.

Several hierarchical orders of classes were established with increasing levels of detail regarding vegetation condition and species. The first order classification involved separating trees from vegetated ground cover. As the results indicate, this procedure explains 94% of the variance for
the vegetated ground cover class and 80% of the variance for the tree class. The spectral
distinction between these two vegetation categories is largely a result of structural differences.
Vegetated ground cover tends to be close to the ground with closely-spaced foliage resulting in
little shadowing, enabling a strong reflectance of photosynthetically active vegetation back to the
sensor. Alternatively, the horizontal variation in vertical structure of trees causes significant
shadowing interspersed throughout the foliage. These structural differences result in varying
amounts of shadow captured within a Quickbird pixel which are extracted in the ‘dark’ branch of
the DT model (Figure 2.6). As a result of greater shadowing, trees are separable from vegetated
ground cover in the mixing space and are localized closer towards the apex of the dark
endmember along the vegetation-dark mixing line.

After the successful extraction of the general vegetation classes of vegetated ground cover and
tree, the same technique was applied to provide estimates of more detailed characteristics
including species and condition. Several important discussion points are raised as a result of the
analysis. Separating evergreen needleleaf and deciduous broadleaf trees using our technique
explained 80% and 67% of the variance respectively. Deciduous trees have significant variations
in leaf characteristics in terms of shape, size, and pigment compared with many evergreen
species. In addition, the Quickbird image was captured in spring (March 2007) when the
spectral response of deciduous broadleaf trees is strongly affected by the seasonal variability
associated with tree phenology (many deciduous species are beginning to bud in Vancouver).
We suggest that the leaf-off condition of deciduous trees results in the counterintuitive decision
tree shown in Figure 2.8 where pixels with higher dark fractions are classified as ‘deciduous’
resulting from branches and soils dominating the reflectance values associated with deciduous tree species.

Figure 2.10 displays a model based on the DT classifications indicating how various levels of vegetation features localize within the mixing space. This model is image specific and, in this case, represents the location of vegetation features during the spring season. Future work may be undertaken to study the seasonal variation of feature location and separability within the mixing space, and might also benefit from quantifying the location of higher level mixing spaces within the original three endmember model. Seasonal selection of high resolution imagery is an important consideration which will vary the location and separability of vegetation features. Selecting a spring image for our analysis provided good separability of vegetated ground cover and trees and associated condition and species details.

2.4.2 Applications

Mapping and modelling tree and vegetated ground cover characteristics from high spatial resolution satellite imagery in urban areas enables significant advancements in our understanding of urban systems. Boundary-layer climates are significantly influenced by the distribution, abundance, condition and characteristics of urban vegetated surfaces at local and micro-scales (Voogt & Oke, 1997). Imagery representing vegetation dynamics across urban areas can provide urban planners with vital information required to mitigate heat island effects and reduce building energy requirements associated with heating and cooling (Grimmond, 2007). At the same time, vegetation characteristics across a city can inform epidemiologists of the spatial distribution of
health risks related to urban air quality (Corburn, 2007). Separating vegetation into more
detailed classes also has strong potential to inform urban ecologists of species occurrence and

Figure 2.10 Model depicting where shadow and vegetation characteristics including trees and vegetated
ground cover and associated condition and species locate within the three endmember mixing space of a high
spatial resolution image over Vancouver.
vulnerable plant, animal, and bird habitats associated with urban vegetation cover and its spatial pattern across the landscape (Zipperer et al., 1997).

2.5 Conclusion

Refining our understanding of urban systems through accurate vegetation mapping is critical to the wellbeing of urban residents and the sustainability of our cities. This paper examined the abundance of urban endmembers in a Quickbird image over the City of Vancouver and applied decision tree classifications to quantify and separate various orders of vegetation detail. Results demonstrate successful extraction of trees and vegetated ground cover using our technique. This technique also proved successful in extracting vegetation species and condition including evergreen needleleaf, deciduous broadleaf, manicured and mixed grass, and highlights the phenological impacts of more detailed vegetation features on the separability of species and condition classes within the mixing space. Our analysis provides an operational technique to enable vegetation extraction and related studies across a variety of urban areas and will help parameterize models related to urban biophysical processes. Further research will involve the collection of summer imagery and a comparison of the accuracy at which the vegetation classes can be extracted compared to this current analysis.
2.6 References


3 IMPACTS OF TREE STRUCTURE ON SOLAR RADIATION RECEIVED BY URBAN RESIDENTIAL DWELLINGS

3.1 Introduction

Increased global urbanization is motivating planners worldwide to examine how they capture and utilize the energy required to sustain growing demand. If current trends in urbanization and energy-use continue, the successful development of cities will depend on their ability to negotiate both reductions in energy consumption and the production of new energy from renewable sources. Trees provide a vital natural resource within cities and have a significant impact on both of these urban energy options. Specifically, the strategic placement of shade trees has been demonstrated to increase passive cooling in summer months, with consequent reductions in building energy consumption for cooling and indirect benefits in the form of urban heat-island mitigation and air pollution reduction (Akbari & Konopacki, 2004). Shade trees also impact the radiation available for solar energy technologies (Hofierka & Kanuk, 2009).

A growing body of literature exists examining the potential of using trees as a resource for passive cooling of buildings in urban environments. Much of this research arises from attempts to mitigate urban heat island effects (the increase in urban air temperatures relative to those of the rural periphery) (Oke, 1982). This increase in temperature has direct effects on energy consumption, specifically related to the energy required to cool buildings. In response to this phenomenon a number of heat-island reduction strategies have been introduced including solar-reflective roofs and the strategic placement of trees (Akbari et al., 2001), It is suggested that the

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residential sector could account for the majority (59%) of economic savings associated with such strategies (Akbari and Konopacki, 2004).

Physical characteristics of urban form have been examined to help inform heat-island reduction strategies. For example, Shashua-Bar and Hoffman (2003) discuss the importance of the geometry and orientation of built features (streets and buildings) on air temperature and demonstrate that shade trees can reduce these impacts when utilized strategically. In a study of various heat-island reduction strategies for the City of Toronto, Akbari and Konopacki (2004) suggest that shade trees could account for 30% of the total possible energy savings. Recognizing the importance of shade trees has also led to a variety of studies investigating the location of trees relative to buildings (Simpson & McPherson, 1996) in addition to physical vegetation characteristics such as size, shape, species, crown density, and cluster geometry (Carver et al., 2004; Parker, 1993; Shashua-Bar & Hoffman, 2004). Trees can also provide added cooling effects on buildings by reducing ambient temperatures through the process of evapotranspiration (Heisler, 1986).

Energy savings provided by trees can vary greatly between cities and estimates require location specific parameters to provide relevant results (Arboit et al., 2008). Many of these inter-city differences relate directly to seasonal variations in temperature and sun angles. Parker (1983) suggests that in many North American cities less energy is expended for space cooling than space heating, and although shade trees reduce cooling-energy use in the summer, cities may notice an increase in winter heating-energy use resulting from the interception of available solar radiation by tree canopies (Akbari & Konopacki, 2004). Nevertheless, further studies in
mid-latitude cities suggest that the cooling potential and associated reductions in electricity costs and biogenic emissions provided by shade trees during the summer can outweigh any decreases in solar radiation observed in the winter (Arboit et al., 2008; Simpson & McPherson, 1998), confirming the utility of shade trees as an effective heat island reduction strategy. Many of the aforementioned studies have focused on reducing the energy requirements for building cooling and heating, deemed crucial to achieving more environmentally sustainable cities. However, focusing solely on the impact of trees on energy savings neglects the potential to offset traditional fossil fuel based energy sources with renewable technologies such as rooftop solar thermal and photovoltaic systems.

Concerns about large scale climate warming and a decrease in the supply of fossil fuels are causing cities to examine the adoption of alternative energy technologies to provide clean and renewable sources of energy. Solar energy technologies, including photovoltaics and solar thermal, have been recognized as viable energy alternatives for urban residential areas (Alsema & Nieuwlaar, 2000) due to the ability to retrofit existing buildings with the small scale roof-mounted equipment. While these technologies are already available, bridging the gaps between technological developments and urban planning and decision making policies are necessary to ensure effective incorporation of solar energy systems into current urban infrastructure.

At present a variety of tools are available to help inform decision makers of estimated urban energy consumption, in addition to the economic and environmental potential of incorporating various energy technologies. Some of the more commonly used North American tools include DOE-2(www.doe2.com) and RETScreen (www.retscreen.net). Additionally, geographic
information systems (GIS) provide a useful platform for conducting user specific analysis across space. While software has been developed to work within a GIS - e.g. BREDEM-8 (Gadsden et al., 2003a) and CITYgreen (www.americanforests.org/productsandpubs/citygreen) - current models require substantial user interaction and inputs regarding physical and biophysical features of the environment (Gadsden et al., 2003b). Developments in urban energy models will benefit from greater automation, and such changes will promote the accessibility and popularity of these tools.

Remote sensing data has the ability to provide accurate and objective measures of environmental features. One of the primary benefits of using remote sensing data for spatial analysis is its ability to provide complete coverage across a defined area. Previous urban shade tree studies such as Akbari & Knopopacki (2004); Carver et al. (2004); Compagnon (2004); Jo & McPherson (2001); Shashua-Bar & Hoffman (2003); Shashua-Bar & Hoffman (2004); and Simpson & McPherson (1996) provide vital information regarding the influence of specific biophysical and structural attributes of vegetation on building energy demands; however complicated experimental design, computational resources, and manual data collection make it difficult to examine more than a few small study areas within the city. At the same time, recent advances in remote sensing technologies, specifically LIDAR (light detection and ranging) data, enables highly accurate extraction of three dimensional urban structures including buildings, trees, and the underlying terrain, which have the potential to provide a wealth of parameters for urban energy modeling. Nonetheless, while LIDAR has been used extensively in the natural resource sector its application to urban energy planning remains relatively unexplored.
The objective of our research is to automate the extraction of structural characteristics of urban residential areas in a mid-latitude North American city and provide a set of methods that can be used to assess the diurnal and seasonal effects of trees on the solar radiation intercepted by building rooftops. LIDAR data is used to provide structural data related to the area, height, and volume of building and tree cover. Diurnal and seasonal GIS-based solar radiation models are produced to provide absolute values of direct and diffuse radiation intercepted by building rooftops. Results are discussed in terms of the influence of structural characteristics of buildings and trees on the available radiation for residential dwellings. Finally, applications of our techniques and results are discussed in terms of their utility for informing initiatives to manage energy demands in urban areas.

3.2 Study area and data

3.2.1 District of North Vancouver

This study is conducted for the District of North Vancouver (DNV) located within the Metro Vancouver Region in British Columbia, Canada. In 1990 the DNV adopted an official community plan to address the future of sustainable developments and council has set a vision to become one of the world’s most sustainable communities by the year 2030. To achieve this objective the DNV has established a number of initiatives for reducing greenhouse gas emissions and building energy use.

The DNV is a largely residential city, characterized by low-density single family buildings on medium sized lots (~5000m²). The DNV covers a large variability in elevation ranging from...
sea-level to mountainous areas; however the city has established a 320m elevation limit for housing developments. Due to the mountainous terrain, low-building density, and coastal climate many tall evergreen trees dominate the landscape. Coverages of residential private lots are available from zoning and lot cadastral vector layers provided by the DNV; these form the bounding geographic areas used to summarize the extent of tree and building cover in this analysis.

### 3.2.2 LIDAR data

Light detection and ranging (LIDAR) is an active remote sensing device that emits and receives laser pulses. Similar to orthophoto cameras, LIDAR sensors are typically mounted to an aerial platform. By recording the exact location of the sensor and the time it takes each laser pulse to return, a detailed three dimensional dataset is produced over a given area. Airborne LIDAR for this project was acquired by McElhanney Consulting Services (Vancouver, Canada) using a discrete return sensor attached to a fixed wing platform. The sensor was configured to record first, second, and last return laser hits; ground and non-ground hits were classified using in-house software. The average pulse spacing equaled one laser return per 0.5m\(^2\). The area surveyed includes the developed residential area of the DNV, covering approximately 20km\(^2\).

First return, second return, and ground return layers were interpolated and gridded to individual 1m spatial resolution raster images using a natural neighbor interpolation algorithm (Sambridge et al., 1995). To smooth holes and spikes in the raster images resulting from lack of data, edge effects, water absorption and birds, preprocessing techniques were applied as follows. First, extreme height values were removed by setting maximum and minimum thresholds at 699m and...
-1m respectively. Once height values were within a reasonable range, a 3 by 3 pixel median filter kernel was passed over the image and subtracted from the original gridded layers (Omasa et al., 2008). Pixels with a difference of ± 50m were selected as bad pixels and replaced using Delaunay triangulation.

### 3.2.3 Meteorological data

To provide estimates of atmospheric conditions over time we use data available from a meteorological tower located approximately 10km south of the study area in the City of Vancouver. The tower stands 28m above the ground and includes various instrumentation including a Kipp and Zonen CNR1 four component net radiometer used to provide incoming shortwave radiation measurements at 15 minute intervals between June 2008 and January 2009.

To present a general estimate of the atmospheric condition for different times of the year we calculate a clearness index at 12:00 over a 30 day period surrounding the solstices. The clearness index is calculated using measured insolation from the tower instrumentation and top of atmosphere radiation values provided by the University of Oregon Solar Radiation Monitoring Laboratory (http://solardat.uoregon.edu/SolarPositionCalculator.html) in equation 2:

\[
K_t = \frac{I_i}{I_o} \quad (2)
\]

where \( K_t \) is the clearness index, \( I_i \) is the observed incoming shortwave radiation from the tower instrumentation, and \( I_o \) is the calculated top-of-atmosphere radiation.
Once the clearness index has been calculated a number of algorithms exist to further derive diffuse fraction. Jacovides et al. (2006) reviewed a suite of developed equations and suggest a first-order model of the diffuse fraction $K_d$ proposed by Orgill & Hollands (1977) be used with the derived clearness index:

$$K_d = 1.557 - 1.84k_t \text{ for } 0.35 \leq k_t \leq 0.75, \quad (3)$$

$$K_d = 1.0 - 0.249k_t, \text{ for } k_t < 0.35, \text{ and } K_d = 0.177 \text{ for } k_t > 0.75.$$  This diffuse component is represented as a fraction of global radiation received at the Earth’s surface, with the remaining fraction providing the direct radiation component.

### 3.3 Methods

Direct and diffuse radiation are important physical components critical to the examination of energy demands in urban areas. While solar radiation indirectly drives almost all biophysical processes on the Earth, when discussing urban household energy, the predominant technologies of interest are passive cooling, photovoltaics, and solar thermal. Producing accurate estimates of the amount of solar radiation available for solar technologies requires knowledge of the solar radiation as it passes through the atmosphere and its interaction with features on the Earth’s surface. The interaction of shortwave radiation with surface features can be understood in terms of the shade cast, the multiple reflections, and the transmission through the texture of the surface. This is of particular interest in an urban environment since the structural heterogeneity of these landscapes is largely influenced by the architectural, engineering, and landscaping initiatives implemented by those people who manage and reside in the city. Due to the active involvement
humans have in developing the structure of urban areas, planning tools and techniques are essential to ensure that existing natural resources are managed effectively. The following section describes the methods used to 1) extract building and tree features from LIDAR data, 2) model direct and diffuse radiation for different atmospheric conditions, and 3) select structural attributes and samples for statistical analysis.

### 3.3.1 LIDAR feature extraction

The procedure used to extract building and tree features from the LIDAR data follows the techniques of Goodwin et al. (2009). Isolating the LIDAR returns that interact with vegetation is the first step required to quantify the structure of trees and buildings in urban environments. To do this, the LIDAR second return layer was examined. Since the solid form of building rooftops typically reflects the entire laser pulse, few building returns tend to be represented in the last return layer, while gaps in the three-dimensional structure of trees allows the laser pulse to produce a second signal return lower in the canopy. Nonetheless, some urban features, such as building edges and powerlines, also generate second pulse returns; therefore a spatial filtering step is applied. A 9 by 9 pixel moving kernel was used to iteratively assess the number of pixels containing second returns from a series of projected vectors between 1 and 180 degrees. When the number of cells intercepting a given vector is greater than 4 they are classified as linear features (generally representing building edges) and subsequently removed. Finally, a second filter is applied to indentify clusters of trees by establishing a threshold where 80% of the total pixels within the kernel are identified as tree pixels. These clusters are then grown by reassigning pixels with non-tree pixels in the moving window as tree. The resulting layer is a binary image of LIDAR pixels representing the planar extent of trees (Figure 3.1).
The extracted tree layer is then used to mask the original first return LIDAR grid producing a layer of the maximum height of non-tree features. Area and height thresholds of 40m² and 3m, respectively, are then applied to each remaining object to select buildings from the LIDAR dataset. The output result from this technique is a classification layer that describes the spatial extent and number of 1) tree crown or clusters of tree crowns and 2) buildings.

### 3.3.2 Solar radiation

The intensity of solar radiation received at the surface of the Earth (insolation) can vary significantly depending on the following three factors: the transparency of the atmosphere, the latitude of the place in question, and the seasonal and diurnal variations (Saha, 2008). As a result, it is critical to incorporate all of these factors when conducting solar radiation analysis.
Additionally, global solar radiation received at the Earth’s surface is comprised of direct and diffuse radiation that can be accurately modeled with various GIS software (Fu & Rich, 2002; Pierce et al., 2005).

In this work solar radiation is calculated based on methods from the hemispherical viewshed algorithm (Rich et al., 1994; Fu & Rich, 2002), which involves an algorithm that produces viewsheds directed upward based on digital surface models (DSMs) of the physical surface across an area of study, then uses each viewshed to calculate incoming direct and diffuse radiation from each sky direction (Rich et al., 1994). Direct radiation for a given location is a function of the extraterrestrial solar flux, atmospheric transmisivity, the relative optical path (determined by the solar zenith angle and elevation above sea level), the duration of a defined time interval, and the effect of the surface orientation (Garner & Ohmura, 1968). Diffuse radiation is calculated as a fraction of the global radiation (without correcting for the angle of incidence), the duration of the defined time interval, the proportion of visible sky, and the effect of the surface orientation.

The gridded 1m spatial resolution first return LIDAR image provided the DSM necessary for the radiation model. The model was run at hourly intervals for hours of illumination during the summer and winter solstices and equinox. These dates represent the full range of solar zenith angles for a year and provide maximum, minimum, and median clear sky insolation values. The models are first produced using clear atmospheric conditions; calculated using the maximum transmissivity values observed from the tower measurements for a 30 day window surrounding the selected dates. Diffuse fraction was 0.177 for each of the dates and clearness index values
were 0.88, 0.85, and 0.80 for the winter solstice, summer solstice and equinox, respectively. Modeling radiation for clear atmospheric conditions provides estimates of the maximum solar radiation received in various seasons, which is often used to discuss the energy generation potential of solar energy technologies. In addition to clear atmospheric conditions, more representative radiation estimates for each date are also computed. In this case, the average clearness index for 30 days surrounding the solstices is used instead of the maximum value, providing a clearness index of 0.34 (0.92 diffuse proportion) for the winter and 0.54 (0.56 diffuse proportion) for the summer.

Radiation maps are produced across the entire study area covered by the LIDAR data. Each map is then intersected with the LIDAR derived building footprints and both direct and diffuse radiation estimates are extracted for individual dwellings and summarized as an average value for each individual building rooftop. Figure 3.2 provides an example of a three dimensional subset depicting the average height of each building overlaid with the modeled global radiation estimates for each square meter of roof, in addition to a three dimensional representation of trees and the ground topography.

### 3.3.3 Sample stratification

To stratify the private lands within residential areas we first summarize the extent of trees on developed single-family residential lots in the DNV. This is performed by representing the extracted extent of trees from the LIDAR data as a fraction of the total area of each individual
lot. Each lot is then categorized into segments representing the amount of tree cover in 10% increments. A total of 10 lots are randomly selected from each segment to provide an equivalent number of samples for the broad range of potential tree cover. Since no lot displayed more than 90% tree cover the values range from 0 to 90% providing a total of 90 observations for the analysis.

3.3.4 Feature structural attributes

A number of structural attributes related to trees and buildings were examined to investigate their relationship to solar radiation received for building rooftops. Each attribute was calculated for individual lots and include: average tree height, maximum tree height, tree height variability, normalized tree volume, average building height, maximum building height, building height variability, building volume, primary building roof orientation, and various ratios between tree
and building attributes. Correlation matrices were then performed to select the strongest independent attributes for further analysis. Those results yield the following six variables (Figure 3.3):

- Average tree height: calculated as the mean value for all pixels classified as trees for each selected lot.
- Tree height variability: calculated as the standard deviation of all pixels classified as trees for each selected lot.
- Normalized tree volume: calculated as the sum of all pixel heights classified as tree and divided by the total area of each selected lot.
- Average building height: calculated as the mean value for all pixels classified as a building on each selected lot.
- Building height variability: calculated as the standard deviation of all pixels classified as building for each selected lot.
- Ratio building to tree height: calculated as a fraction of the average building height compared to the average tree height.

Each attribute was related to solar radiation estimates for the winter solstice, summer solstice, and equinox. Furthermore, to examine changes to the relationship between radiation and feature structural attributes, the set of calculated surface feature values was also correlated to the atmospherically adjusted radiation models.
3.4 Results

Estimating the global solar radiation received at the surface of the city under clear atmospheric conditions provides an indication of the maximum radiation available for passive heating, solar thermal production, and photovoltaic electricity generation. Modeled radiation estimates averaged for each selected residential dwelling in the District of North Vancouver demonstrates a maximum radiation flux of 7.2 MJ m$^{-2}$ day$^{-1}$ for the winter solstice, 34.5 MJ m$^{-2}$ day$^{-1}$ for the summer solstice and 18.3 MJ m$^{-2}$ day$^{-1}$ for the equinox, while the minimum radiation fluxes for individual buildings are 0.3 MJ m$^{-2}$ day$^{-1}$, 2.5 MJ m$^{-2}$ day$^{-1}$, and 0.5 MJ m$^{-2}$ day$^{-1}$ respectively. At the same time, when preparing location-specific energy simulations, it is important to understand the representative atmospheric conditions for different times during the year. Radiation flux estimates calculated using representative atmospheric conditions for the summer and winter solstices reveal noticeable differences in absolute values for both direct and diffuse radiation components (Figure 3.4). Clear condition winter solstice values demonstrate a broader range of direct radiation estimates over those values calculated for the representative atmospheric conditions (5.8 MJ m$^{-2}$ day$^{-1}$ versus 0.1 MJ m$^{-2}$ day$^{-1}$). On the other hand, the winter diffuse radiation values demonstrate the opposite trend with the clear condition radiation flux values.
reaching 1.8 MJ m⁻² day⁻¹ and the representative atmospheric condition estimates ranging up to 2.2 MJ m⁻² day⁻¹. Similar trends exist for the summer solstice with modeled clear and representational atmospheric condition radiation estimates of 30.0 MJ m⁻² day⁻¹ and 5.8 MJ m⁻² day⁻¹ respectively for the direct radiation component and 4.9 MJ m⁻² day⁻¹ and 1.8 MJ m⁻² day⁻¹ for the diffuse component.

![Histograms of radiation estimates](image)

**Figure 3.4** Histograms of the distribution of radiation estimates considering both clear and representative atmospheric conditions for diffuse and direct solar radiation components.

The range in solar radiation estimates (Figure 3.4) demonstrates the important role that the atmospheric condition has on absolute estimates of solar radiation, which needs to be considered
when planning and implementing various urban solar energy strategies. At the same time, it is also critical to understand the influence of the current urban form on available solar radiation. Although there are large variations in the range and distribution of radiation values depending on atmospheric conditions, these differences have a minimal impact on the statistically derived relationships with selected structural attributes of the urban surface. For each selected date, measures of tree structure had significantly stronger relationships to rooftop received radiation compared to measures of building structure (Table 3.1). Specifically, for all three dates examined diffuse radiation is most strongly correlated with average tree height and direct radiation is more strongly correlated with normalized tree volume. Additionally, the impact of tree structure on estimated direct radiation is more pronounced in the summer than the winter, while the influence of all structural variables remains unchanged when observing diffuse radiation throughout the year.

Tree structural attributes and radiation estimates demonstrate a negative relationship, indicating that less radiation is received by the dwelling on an individual lot when the three dimensional extent of trees increases. This trend is essential to understand when planning urban tree management strategies. To facilitate the interpretation of the results from this research, individual radiation values were converted into a percentage of the maximum values calculated for each diffuse and direct radiation estimate, to quantify rooftop radiation reduction. These values are then graphed against average tree height, tree height variability, normalized tree volume, and building height variability to explore the relationship each variable has on reducing the rooftop radiation of residential dwellings (Figure 3.5). For each of the tree structure
variables an increase in rooftop radiation reduction is observed, with less total change apparent in the winter than in the summer. Diffuse and direct summer radiation values and average tree

Table 3.1 Correlations ($R^2$) between modeled radiation estimates for building rooftops and LIDAR derived tree and building structural attributes.

<table>
<thead>
<tr>
<th></th>
<th>Average Tree Height</th>
<th>Tree Height Variability</th>
<th>Normalized Tree Volume</th>
<th>Average Building Height</th>
<th>Building Height Variability</th>
<th>Ratio Building to Tree Heights</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Winter Solstice</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Clear</td>
<td>0.15</td>
<td>0.15</td>
<td>0.21</td>
<td>0.00s</td>
<td>0.01s</td>
<td>0.01</td>
</tr>
<tr>
<td>Direct Adjusted</td>
<td>0.15</td>
<td>0.14</td>
<td>0.19</td>
<td>0.00s</td>
<td>0.01s</td>
<td>0.01</td>
</tr>
<tr>
<td>Diffuse Clear</td>
<td>0.64</td>
<td>0.52</td>
<td>0.59</td>
<td>0.05</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Diffuse Adjusted</td>
<td>0.65</td>
<td>0.53</td>
<td>0.60</td>
<td>0.04</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td><strong>Summer Solstice</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Clear</td>
<td>0.47</td>
<td>0.41</td>
<td>0.47</td>
<td>0.02s</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Direct Adjusted</td>
<td>0.47</td>
<td>0.41</td>
<td>0.48</td>
<td>0.02s</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>Diffuse Clear</td>
<td>0.64</td>
<td>0.51</td>
<td>0.58</td>
<td>0.05</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Diffuse Adjusted</td>
<td>0.64</td>
<td>0.52</td>
<td>0.59</td>
<td>0.05</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td><strong>Equinox</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Clear</td>
<td>0.41</td>
<td>0.36</td>
<td>0.48</td>
<td>0.00s</td>
<td>0.04s</td>
<td>0.06</td>
</tr>
<tr>
<td>Diffuse Default</td>
<td>0.64</td>
<td>0.52</td>
<td>0.59</td>
<td>0.05</td>
<td>0.10</td>
<td>0.10</td>
</tr>
</tbody>
</table>

n/s = not significant (p>0.05)
adjusted = representative atmospheric conditions
clear = clear atmospheric conditions

height display a plateau between 18 and 24m, where increases in height above this point have little effect on changes in rooftop radiation. In contrast to the tree structural attributes, building height variability has a lesser influence on rooftop radiation reduction, with no discernable trends. The observations discussed so far examine only daily radiation totals, and when considering changes in solar radiation with the movement of the sun across the sky, it becomes
important to also examine the diurnal influence of tree structure on radiation estimates for hours of illumination.

Figure 3.5 Graphic representations of the reduction of radiation received by building rooftops in relation to selected structural variables extracted from the LIDAR data: a) average tree height, b) tree height variability, c) normalized tree volume, and d) building height variability.

Direct radiation is calculated at hourly intervals and correlated with average tree height throughout each observed date to determine times of the day when trees have the most influence on radiation (Figure 3.6). For the winter solstice, average tree height has the greatest impact on
direct radiation around 12:00 with little influence in the morning and afternoon. For the summer solstice, two peaks are observed during the day around 9:00 and 15:00 where average tree height is more strongly correlated with direct radiation, while a much lower correlation is observed at 12:00. The trend during the equinox demonstrates a more constant correlation from 9:00 to 15:00.

3.5 Discussion

The results from this study suggest that trees play a vital role in determining the amount of radiation received by single-family dwellings in urban residential areas. In this study the average building height was approximately 5.9m with a standard deviation of 1.3m. With such minor variations in building height structure, we expect to see few differences on the radiation intercepted by building rooftops when related to aspects of the building form itself. The remainder of this section will discuss the results in terms of the biophysical considerations that should be taken into consideration with this type of analysis, the applications of using our approach for urban energy planning, and deliberations on further research.

3.5.1 Biophysical considerations

From a large set of structural attributes related to surface objects we observe that tree structural attributes are better determinants of rooftop received radiation than building form. However, it is important to consider the specific derivation of these metrics. Average tree height, for example, is calculated using the mean height of all pixels identified as tree; whether part of a stand or an individual tree. Forest research using LIDAR data suggests that at the stand level, average tree
height correlates strongly with tree canopy cover (Ferster et al., in press), therefore when observing the effects of average tree height on solar radiation, we may also be noticing more structural effects of the vegetation canopy. These effects vary significantly whether examining direct or diffuse radiation.

Figure 3.6 Correlations of direct radiation and average tree height for one hour intervals during hours of illumination for the summer solstice, winter solstice and equinox.

Calculating received solar radiation takes into consideration atmospheric conditions, variable solar positions, and the structure of the features on the surface of the Earth. These two physical contributions have specific effects on the radiation modeled for this study. First, direct radiation estimates are a function of the position of the sun in the sky throughout the day, which impacts both hourly and daily radiation depending on the time of year. The relationship between direct radiation and average tree height is greater in the summer, due to the increased solar angles. At
the same time, because the sun passes higher in the sky in the summer, the shadows cast by trees at solar noon are projected on the surface beneath, resulting in minimal shading effects on adjacent features (Figure 3.6). In contrast, diffuse radiation is a function of the vertical structure of peripheral objects and since we assume a static surface throughout the year, diffuse radiation estimates remain constant throughout the day (Table 3.1). Not considered in the applied radiation model is the transmissivity of tree crowns, which requires a wealth of knowledge about canopy density, tree species, and physiological conditions (Simpson, 2002).

Discussion of the cooling potential and the availability of solar radiation for energy production are considered in terms of the shade that trees produce. This shade determines whether adjacent features are illuminated or not, and how much radiation is available for a given time period. However, added cooling benefits are also available from the biophysical impacts trees have on micrometeorology in urban environments. Specifically, in addition to the intercepted direct radiation, trees influence ambient air temperatures through evapotranspiration, convective sensible heat exchange, and increasing the surface roughness (Oke, 1989). Understanding available direct and diffuse radiation is also important for determining photosynthesis and the growth regime of vegetation. Diffuse radiation is of particular interest since it has been demonstrated to increase the light use efficiency in plant canopies (Gu et al., 2002). While much value is gained by understanding the influence of trees on available building radiation, it is important not to omit the other benefits trees provide in an urban environment, such as ground shading, slowing the infiltration of precipitation, and filtering air pollutants.
3.5.2 Implications for energy planning

3.5.2.1 Tree shading for solar energy production

By choosing to summarize variables only within individual lots we highlight considerations for homeowners, architects, and developers who wish to influence the energy demand for personal dwellings. Specifically, to realize the economic benefits of implementing solar energy technologies, people need to be able to accurately predict the energy output of these technologies. Because the electrical output of a photovoltaic array is dependent on cell temperature and array irradiation (Evans, 1981), solar radiation models can provide the necessary information required to predict the potential energy output of various solar technologies. Moreover, this research suggests that reductions in available rooftop radiation increase with tree height (Figure 3.5); therefore we suggest that trees on the south side of residential buildings are best positioned to facilitate the production of energy if they do not extend significantly higher than the roof itself. Furthermore, consideration needs to be given to difference between deciduous trees and conifers. Deciduous trees have the benefit to open up the canopy in winter and allow large amounts of radiation to the roofs and walls of buildings, which enables greater energy generation when compared to the negative effect of shading by conifers.

To further assess the viability of renewable energy sources researchers have detailed the energy inputs required to fabricate various technologies. For example, by calculating the energy requirements for the production of a typical photovoltaic (PV) module and assuming three irradiance levels (2200 kWh m\(^{-2}\)yr\(^{-1}\), 1700 kWh m\(^{-2}\)yr\(^{-1}\), 1100 kWh m\(^{-2}\)yr\(^{-1}\)) Alsema & Nieuwlaar (2000) suggest that the energy produced from the PV technology would take about 2-6 years to
offset the energy used to fabricate the technology. While this provides critical information for understanding the efficiency of a technology, it neglects the spatial variability of environmental variables that are critical to determining the location and placement of photovoltaics. By modeling and mapping the available solar radiation across a city, including the influence of trees on this radiation, we provide a replicable technique that can be used to help evaluate the feasibility of solar energy technology for individual buildings in urban areas.

3.5.2.2 Tree shading related to passive cooling

Determining diurnal and seasonal effects of trees on solar radiation is a useful step in offsetting grid-connected electricity during peak energy demand times (Parker, 1983). Electrical utility companies supply increases in power during winter months for space heating and during summer months for space cooling, which during both seasons peak at specific times of the day. Understanding the influence of tree on solar radiation needs to be considered to both maximize photovoltaic electricity production and offset cooling and heating energy demands during these peak periods. In the DNV, residential dwellings are expected to notice the greatest reductions in direct solar radiation around 9:00 and 15:00. For the study area in question we suggest that most urban tree management strategies be implemented with summer conditions in mind, since trees were demonstrated to have a greater impact on solar radiation at this time of year.

3.5.3 Further research

Developing a better understanding of vegetation effects on urban energy potential is an important component of sustainable urban management. Nonetheless, more complicated models are
necessary to incorporate the transmission of radiation through the trees and the seasonal effects of leaf-on and leaf-off conditions of deciduous vegetation. In addition, future models could incorporate solar loading on building facades including walls and windows, especially for considering more advanced passive cooling initiatives.

Continued exploration of the effects of trees on insolation can provide decision-makers with the necessary information for the implementation of passive cooling strategies and the adoption of photovoltaic and solar thermal technologies. This study highlights seasonal and diurnal effects of trees on solar radiation in residential areas, and although we expect residential areas to notice the greatest benefits from this type of study, there exist opportunities to research urban trees in other contexts. Furthermore, expanding techniques presented here to other cities at different latitudes will help to refine the implications and applications of urban tree management strategies.

3.6 Conclusion

Developing a good understanding of the influence trees have on building radiation can be used to help inform vegetation management strategies to minimize the energy consumed from fossil-fuel sources. The structural characteristics of urban trees across an entire city have traditionally been difficult to measure because of the time required to collect such data. New remote sensing technologies enable spatially rich information with complete coverage, providing a number of opportunities for detailed urban analysis. In this study, LIDAR data provides structural
information related to trees and buildings, and provides the input parameters necessary to populate spatial radiation models.

Our results suggest that various tree structural attributes are critical determinants of solar radiation intercepted by building rooftops. Additionally, we model radiation at hourly intervals and determine that this correlation is best observed with direct radiation around 9:00 and 15:00 for the summer solstice. Furthermore, atmospheric considerations are necessary to produce accurate radiation estimates, but have a minimal impact on the correlations observed with urban structural information.

Successful planning of energy in urban areas requires that renewable energy sources are investigated and that attempts are made to reduce energy consumption. We discuss the biophysical considerations and implications for energy planning related to the structural attributes of trees. Further research is needed to develop more complex radiation models that take into consideration the canopy transmissivity and vegetation phenology. Replications of this technique for other cities will also help develop a better understanding of the impacts and importance of trees as a sustainable resource for urban energy management.
3.7 References


4 A GEOGRAPHIC APPROACH TO IDENTIFYING GREEN-SPACE-RELATED ENVIRONMENTAL JUSTICE IN CANADIAN CITIES

4.1 Introduction

The basic tenet of environmental justice is that environmental impacts and amenities should be equitably distributed within society regardless of class, income, race, or education (Harner et al., 2002). Several key indicators have been applied to quantify inequalities in the relationship between groups of people and their local environment, including: proximity to emissions sources (Brulle and Pellow, 2006; Jerrett et al., 1997; Jerrett et al., 2001), exposure to toxic substances (Mennis and Jordan, 2005), and the distribution of environmental resources (Li and Weng, 2007). These relationships are inherently geographic, recognizing the varying spatial distribution of social and environmental features. In light of these spatial patterns, relationships can be analyzed and quantified using remote sensing technologies, geographic information systems (GIS) and spatial statistics.

Urban areas provide an optimal forum for analyzing environmental equity due to the heterogeneous social and physical composition of these landscapes. In addition, rapid urbanization is predicted to result in over 60 percent of the Earth’s population residing in urban areas by the year 2030 (Kahn, 2006), with the health and well-being of these urban residents depending significantly on their local environments (Brulle and Pellow, 2006). A critical indicator of the health of cities is the abundance and distribution of green space. Vegetated areas

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3 A version of this chapter has been submitted for publication. Tooke, T.R., Klinkenberg, B., Coops, N.C. A geographic approach to identifying green-space-related environmental justice in Canadian cities. Environment and Planning B.
such as parks, street trees, and lawns all produce spaces with positive social outcomes that can help to reduce crime (Kuo and Sullivan, 2001), increase health benefits (Coen and Ross, 2006), and advance childhood development (Taylor et. al, 1998). Understanding the geographical characteristics of these spaces provides an indication of the spatial dispersion of environmental inequalities.

Remote sensing technologies provide effective and efficient methods for monitoring the surface features of urban environments. These technologies offer advantages over field-based surveys as they enable spatial coverage and frequent data collection over many inaccessible areas at a relatively low cost. In recent decades remote sensing has been applied to various urban land cover analyses and applications continue to evolve alongside technological advancements. Vegetation, which can be accurately estimated from moderate spatial resolution (~30m) satellite imagery due to its unique spectral signature, has been recognized as an essential component of urban landscapes (Ridd, 1995; Small and Lu, 2006). Detecting vegetation from satellite sensors provides an accurate estimate of urban green space that can be coupled with other geographic data to help characterize urban environmental equity.

Recent studies relating land cover characteristics to socioeconomic data have extended the application of remote sensing products, GIS, and spatial statistics to urban planning and policy related research. A number of motivating factors have driven these types of analysis, including global increases in urbanization, as well as an increased recognition that urban vegetated areas have significant associated social benefits (Grove et al., 2006). One common approach for
assessing the relationships between socioeconomic variables and vegetation has been to combine national census data with vegetation estimates derived from multispectral satellite imagery. Using the Pearson correlation coefficient as a measure of the strength of association between census data and vegetation intensity estimates for Denver, Colorado, Mennis (2006a) found significant correlations for median family income ($r=0.27$, $p<0.05$), percent minority ($r=-0.32$, $p<0.05$), and educational attainment ($r=0.30$, $p<0.05$). Using similar methods in Indianapolis, Indiana, Li and Weng (2007) found comparable relationships between green vegetation and mean household income ($r=0.467$, $p<0.01$), and percentage of college graduates ($r=0.301$, $p<0.01$). In these studies multivariate methods were also used to explore nonlinear relationships between ecological and socioeconomic variables. These previous studies focused on a single city, and used global statistics to quantify the relationships. It is recognised, however, that urban areas are heterogeneous environments, and therefore it is anticipated that exploring the local relationships may provide insightful explanations of urban processes related to environmental justice (Mennis and Jordon, 2005; Mennis, 2006b). As discussed by Openshaw (1991) and Brunsdon et al (2002), spatial analysis using a global statistic can result in an over-reduction of the data across geographic space, which may hide some of the internal variability between ecological and socioeconomic variables when examining environmental equity within a city.

The objective of our research is to develop inter- and intra- city assessments of environmental equity for three major urban centers in Canada. To accomplish this objective vegetation fraction estimates are extracted from moderate spatial resolution satellite imagery and compared to socioeconomic indicators. In order to quantify these relationships, global correlation and local geographically weighted regression (GWR) models are applied to the study areas of Montréal,
Toronto, and Vancouver. It is anticipated that results will emphasize key socioeconomic variables and their relation to urban vegetation, which could then provide planners and community organizations with specific geographic locations where initiatives should be taken to mitigate environmental inequalities. In addition, the results could be of relevance to help guide the development of public policies that aim to establish environmental justice by highlighting those factors that appear to support environmental inequality.

4.2 Study Area

The cities of Montréal, Toronto, and Vancouver were selected as study areas for this analysis (Figure 4.1) as they represent the largest urban populations in Canada, and contain a variety of vegetated areas. Major urban parks are present in all three cities as well as a wide range of land cover types and building densities. Significant international migration to Canada in the last fifty years has resulted in these three cities representing important examples of multicultural urban centers with social, cultural, and economic diversity. In addition, all three cities have been recognized as world cities by the Globalization and World Cities Study Group and Network (GaWC) as a result of their direct cultural, political or economic influence on global affairs (www.lboro.ac.uk/gawc).

The city of Montréal is the second largest city in Canada and the most eastern city in this study. Located in the province of Québec and situated on the Island of Montréal at the confluence of the Saint Lawrence and Ottawa Rivers, Montréal has a variable climate with abundant precipitation. The urbanized core of Montréal is concentrated in the center and eastern portions of the island,
Figure 4.1 Location of study areas within Canada in addition to census tract boundaries. Black census tracts represent areas where data has been withheld for privacy purposes.

while the western portion of the island is characterized by lower population densities and more vegetated areas. The general spatial socioeconomic trend in Montréal involves a concentric pattern with wealthier residents located in the central parts of the city. This study includes the entire island in the analysis as it forms an easily recognizable and cohesive geographic boundary.
The city of Toronto is Canada’s largest urban area and represents the dominant economic center in Canada. Toronto, situated around the north shore of Lake Ontario, is located in the highly urbanized region of Southern Ontario and experiences a slightly milder climate than that of Montréal. Toronto has been recognized as one of the world’s most diverse cities and is an important destination for immigrants to Canada. The general socioeconomic trend is characterized as an east-west divide with more affluent residents residing in the western regions of the city. The bounding area for this study represents the census metropolitan area (CMA) and includes the districts of East York, Etobicoke, North York, Old Toronto, Scarborough, and York.

Vancouver is the third largest city in Canada and is located on the western coast of mainland British Columbia. Vancouver’s climate is significantly milder than those of Montréal and Toronto, which results in vegetated areas remaining photosynthetically active for a majority of the year. The city is ethnically diverse and continues to receive global attention as a result of its urban planning initiatives and the 2010 Winter Olympics. Similar to Toronto, Vancouver is characterized as having a pronounced east-west divide with affluent residents located in the west. Given data limitations only a portion of the Vancouver CMA was analysed, although the area considered represents the significant urban core including the cities of Vancouver, Burnaby, and New Westminster.
4.3 Data

4.3.1 Satellite Imagery

Landsat 7 Enhanced Thematic Mapper (ETM+) summer images were obtained for each of the
three cities between 1999 and 2001 (Table 4.1). These images represent times in the year when
the vegetation exhibits full leaf-on conditions and as a result captures the maximum cover of
vegetation in each city. The spatial resolution of the multispectral channels, ranging from the
visible to shortwave infrared region of the spectrum, is 30m. A top-of-atmosphere calibration
correction was applied to each satellite image to remove the effects of solar elevation and to
standardise the reflectance between the scenes (Ouaidrari and Vermote, 1999).

Table 4.1 Acquisition information for Landsat 7 ETM+ images

<table>
<thead>
<tr>
<th>City</th>
<th>Date</th>
<th>Raw Image Number</th>
<th>UL Latitude</th>
<th>UL Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montréal</td>
<td>Aug-04-2001</td>
<td>LE7013027000121650</td>
<td>48.403</td>
<td>-71.824</td>
</tr>
<tr>
<td>Toronto</td>
<td>Sep-02-1999</td>
<td>LE7018030009924650</td>
<td>44.121</td>
<td>-81.012</td>
</tr>
<tr>
<td>Vancouver</td>
<td>Jul-30-2000</td>
<td>LE7047026000021250</td>
<td>49.824</td>
<td>-123.783</td>
</tr>
</tbody>
</table>

4.3.2 Census Data

Socioeconomic data closely matching the collection date of the satellite images are available
from 2001 Statistics Canada census data. Census tracts (CTs) provide the geographical
boundaries for observation and are recognized as relatively stable geographic areas that contain
between 2500 and 8000 people (StatsCan, 2001: www.statcan.ca). CTs are the second smallest
units for which data is disseminated in Canada and are located within larger census metropolitan
areas and census agglomerations. For privacy purposes some CTs are subjected to area
suppression, which removes all characteristic data for geographic areas with populations below a
specified size. CTs that were included in the analysis for all three cities, and those CTs whose data have been suppressed, are displayed in Figure 4.1.

The socioeconomic variables used in this analysis were selected according to their representation of critical indicators of environmental equity including income, education, family status, and immigrant status. Income from Canadian census data is represented as average and median values and for individuals and families. As a result, four combinations of income representations are available, each requiring a unique interpretation. Average income provides an appropriate representation of the total income within the geographically bounded area, while median income values are a closer representation of the actual received income for the majority of the population. In addition, summarizing income data for the individual provides an indication of the income distribution throughout the entire population, while summarizing income data for families provides an indication of the economic wellbeing of households. Income variables initially selected for analysis include average individual income (AVG INC), median individual income (MED INC), average family income (AVG FAM INC), median family income (MED FAMINC), and the percentage of low income individuals (LOW INC) defined as those respondents who spend 20% or more than average of their income of food, shelter and clothing. Education variables report the highest level of attained education and include no high school (NO HS), high school (HS), college certificate (CLG CERT), and bachelor degree (BAC). Family status relates to children and includes families and individuals with no children (NO CHILD) and the average number of children per household (CHILD P FAM). Finally, immigrant status is analysed according to whether respondents recognized themselves as a non-immigrant (NON IMG) or Canadian (CDN).
4.4 Methods

4.4.1 Linear Spectral Mixture Analysis

In the past decade spectral mixture analysis (SMA) has become the primary method for
extracting multiple land covers from a single pixel value over urban areas (Rashed et al, 2001;
Ridd, 1995; Small, 2001; Tooke et al., 2009). The approach allocates a representative fraction of
selected endmember spectra to each pixel of an image. Each endmember represents a land cover
with uniform spectral properties, and linear mixing assumes that the spectral reflectance profile
of each pixel can be described as a linear combination of the selected endmembers (Goodwin et
al., 2005).

Early urban land cover classifications using SMA were originally proposed according to Ridd’s
(1995) Vegetation-Impervious Surface-Soil (VIS) classification scheme. This scheme provides a
conceptual model that divides urban environments into the three classes; however, the approach
is problematic in a remote sensing context as it represents features that cannot necessarily be
distinguished on the basis of reflectance values alone (Phinn et al, 2002; Powell et al, 2007). As
a result, Small (2001) developed a more applicable model that establishes substrate, vegetation,
and dark (SVD) features of the urban environment as components for SMA. Using the SMA
process, accurate SVD fractions have been derived from Landsat 7 ETM+ imagery (Small and
Lu, 2006) and to a number of major cities across the globe (Small, 2001). The SMA process
involves several steps including transformations to remove noise correlations between bands and
a projected 6 dimensional scatter plot of the extreme image reflectance values used to establish
endmembers. When selecting image endmembers across several urban landscapes it is important
that the spectral signatures of the selected endmembers resemble actual SVD features. The
selected endmember spectra for Montréal, Toronto, and Vancouver are plotted in Figure 4.2 to
help demonstrate the coherence between images and SVD features.

The final step in the SMA procedure is to produce fractional images of SVD features that can be
used for further analysis. To generate fractional images with meaningful values sum-to-unity
and sum-to-positivity constraints were applied to the analysis, and fractional images were
produced for each of the SVD features. As the dark fractional images contain shadow (Small,
2001; Tooke et al., 2009), further analyses using this feature are limited; however, substrate and
vegetation fractions can be correlated with other geographic data in order to explore a variety of
relationships in urban areas (Li and Weng, 2007; Mennis, 2006a). The vegetation fractional
images for Montréal, Toronto, and Vancouver are depicted in Figure 4.3.

4.4.2 Geographically Weighted Regression

To quantify relationships between land cover and socioeconomic data, spatial statistics are often
applied in order to enable meaningful comparisons across space. Geographically weighted
regression (GWR) is an emerging statistical method for analyzing spatially-dependent
relationships between variables. Traditional global regression models summarize statistics
across an entire area, which may ignore any underlying spatial variability. In reality, many
processes are spatially non-stationary, resulting in the same independent variable potentially
producing different responses across an area of study (Fotheringham et al., 2002). GWR
Figure 4.2 Endmember spectra derived from spectral mixture analysis for a) Montréal, b) Toronto, and c) Vancouver.
Figure 4.3 Spectral mixture analysis derived vegetation fractional images for a) Montréal, b) Toronto, and c) Vancouver.
accounts for this spatial variability by extending regular regression, calculating local parameter estimates for every observation using a distance weighting function. Aspatial regression is expressed as

\[ \hat{y}_i = \beta_0 + \sum_k \beta_k x_{ik} + \epsilon_i \] (4)

where \( \hat{y}_i \) is the estimated value of the dependent variable for observation \( i \), \( \beta_0 \) is the intercept, \( \beta_k \) is the parameter estimate for variable \( k \), \( x_{ik} \) is the value of the \( k^{th} \) variable for \( i \), and \( \epsilon_i \) is the error term. To calculate local parameter estimates GWR generates a separate regression equation for each observation using a distance-dependent weighting of the observations contained in the data set. Each GWR equation can be expressed as

\[ \hat{y}_i = \beta_0(u,v_i) + \sum_k \beta_k(u,v_i)x_{ik} + \epsilon_i \] (5)

where \((u_i,v_i)\) captures the geographical coordinate location of \( i \) (Fotheringham et al., 2002).

The weight assigned to each observation is based on an inverse distance weighting function centered on observation \( i \) (Mennis, 2006b).

GWR is particularly useful for studying spatial relationships in urban areas due to the heterogeneous composition of these environments (Mennis and Jordon, 2005). Many of the processes in urban areas are present at a household, block, or neighbourhood scale, and using global regression models with spatially rich urban data neglects the potential significance of the underlying spatial variability.
An adaptive kernel (which sets a variable bandwidth based on a constant number of neighbouring observation data) was applied to analyse the local relationships. The number of adjacent census tracts was manually set to 10, supported by the assumption that people receive the greatest benefits from green spaces in close proximity to their homes. Multivariate statistics are used with the initial set of socioeconomic variables to help isolate single variables which best represent socioeconomic factors. In addition, multivariate statistics help in determining which variables exhibit multicollinearity; a necessary process to ensure that the GWR is properly specified. The final step in performing the GWR is to test the results of the model to ensure that the GWR is correctly specified. Several methods can be used to test the validity of the GWR model; Monte Carlo simulations and testing for spatial autocorrelation being two common techniques (Getis, 2007). In this paper, Moran’s I test of spatial autocorrelation is used with the standard residuals of the local modelled relationships to identify any spatial stationarity. A well-specified model should have randomly distributed residuals, while a clustering of the residuals indicates that the model may be missing one or more key explanatory variables.

4.3.3 Data integration

The socioeconomic variables used for the analysis were joined with the relevant geographic boundaries and non-percentage based variables were standardized using the total population, total households, or total families for each census tract depending on the selected variable. Vegetation and substrate fractions were then summarized for each census tract polygon and the mean values were calculated to provide an indication of vegetated and impervious land surface
cover. These values were added as an attribute along with the selected census variables in order to facilitate global and local regression calculations for individual census tracts.

4.3.4 GWR mapping technique

A variety of choices exist for mapping the results of a GWR analysis, and it is important that the technique adopted clearly represents the objectives of the research. In this paper we are concerned with areas in the city that demonstrate environmental injustices in relation to green space. For illustrative purposes, four distinct classes based on a mean / standard deviation classification will be considered (Figure 4.4). Selected areas exhibiting positive relationships between income and vegetation identify those census tracts that best exemplify green-space-related inequalities in each city, while the set of classes demonstrating negative relationships between income and vegetation represent more complicated scenarios where income and vegetation are inversely related.

4.4 Results

4.4.1 Global Correlations

The results of the Pearson correlation analyses between land surface cover and the socioeconomic variables for Montréal, Toronto, and Vancouver indicate that the highest correlations for all three cities exist between vegetation fractions and income variables (Table 4.2). All the variables that represent income demonstrate significant positive relationships; the highest correlations for all cities belonging to median family income. As mentioned earlier, median family income generally better reflects the lived condition for the majority of the people in the census tract; therefore, a higher median income would typically suggest that the census
tract is overall wealthier than one with a lower median income, while average values may be skewed higher or lower based on extreme values within the population data. Variables representing education also demonstrate significant relationships with vegetation, however more variability can be observed between cities. The strongest relation with education comes from the variable representing no high school degree, and is negatively correlated with vegetation for each city. Vancouver exhibits a stronger relationship \((r=-0.387, p<0.05)\) than Montréal \((r=-0.287, p<0.05)\) and Toronto \((r=-0.218, p<0.05)\). Family status indicators, specifically those families with no children, resulted in a higher positive correlation with vegetation for Montréal \((r=0.388, p<0.05)\) than Toronto \((r=0.138, p<0.05)\) and Vancouver \((r=0.127, p<0.05)\). Finally, immigrant status indicators were highest in Toronto with those people recognizing themselves as Canadian demonstrating a much higher correlation to vegetation \((r=0.316, p<0.05)\) than either Montréal \((r=0.088, p<0.05)\) or Vancouver \((r=0.120, p<0.05)\). These results clearly indicate the unique socio-economic circumstances in each city.

Table 4.2 Correlation results between the average vegetation fraction per census tract and socioeconomic variables for Montréal, Toronto and Vancouver

<table>
<thead>
<tr>
<th>Census variables</th>
<th>Montréal</th>
<th></th>
<th></th>
<th>Toronto</th>
<th></th>
<th></th>
<th>Vancouver</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>p</td>
<td>R</td>
<td>p</td>
<td>R</td>
<td>p</td>
<td>R</td>
<td>p</td>
<td></td>
</tr>
<tr>
<td>AVG INC</td>
<td>0.400</td>
<td>*</td>
<td>0.363</td>
<td>*</td>
<td>0.371</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MED INC</td>
<td>0.401</td>
<td>*</td>
<td>0.331</td>
<td>*</td>
<td>0.187</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AVG FAM INC</td>
<td>0.450</td>
<td>*</td>
<td>0.395</td>
<td>*</td>
<td>0.446</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MED FAM INC</td>
<td>0.473</td>
<td>*</td>
<td>0.467</td>
<td>*</td>
<td>0.456</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOW INC</td>
<td>-0.378</td>
<td>*</td>
<td>-0.278</td>
<td>*</td>
<td>-0.392</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO HS</td>
<td>-0.287</td>
<td>*</td>
<td>-0.218</td>
<td>*</td>
<td>-0.387</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HS</td>
<td>-0.035</td>
<td>n/s</td>
<td>-0.148</td>
<td>*</td>
<td>-0.020</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLG CERT</td>
<td>-0.108</td>
<td>n/s</td>
<td>0.048</td>
<td>n/s</td>
<td>-0.160</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAC</td>
<td>0.152</td>
<td>*</td>
<td>0.158</td>
<td>*</td>
<td>0.141</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NO CHILD</td>
<td>0.388</td>
<td>*</td>
<td>0.138</td>
<td>*</td>
<td>0.127</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHILD P FAM</td>
<td>0.210</td>
<td>*</td>
<td>0.105</td>
<td>n/s</td>
<td>0.234</td>
<td>*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NON IMG</td>
<td>0.125</td>
<td>n/s</td>
<td>0.305</td>
<td>*</td>
<td>0.004</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDN</td>
<td>0.088</td>
<td>n/s</td>
<td>0.316</td>
<td>*</td>
<td>0.120</td>
<td>n/s</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* = significant at \(\alpha < 0.05\) (Bonferonni adjusted \([\alpha / n]\))

n/s = not significant
4.4.2 Local Geographically Weighted Regression

The global correlation results above provide a measure of intercity environmental equity variability. However, trends exist at the neighbourhood scales that are ignored in any global statistic. The socioeconomic variability in cities results in certain pockets displaying more environmental (in)equity than others, and although a cross city comparison has beneficial application for urban planning, as discussed in the proceeding section, an analysis of local relationships is more insightful, with respect to the mitigation of inequalities, resulting from the ability to help geographically focus resources within individual cities.

In order to select an appropriate dependent variable for GWR a factor analysis was performed on the initial list of socioeconomic variables. Results from the factor analysis support the selection of median family income as the best representation of income. Additionally, factors 2 and 3 identify ancillary variables related to education and immigrant status that could be used in subsequent GWR analyses. Secondly, the Moran’s I measure of spatial autocorrelation using the residuals from the income-vegetation model are 0.01 for Montréal, 0.06 for Toronto and 0.11 for Vancouver. Values close to 0 indicate a random spatial distribution of the residuals, suggesting that this GWR model using income as the dependent variable is properly specified.

The results of the GWR analysis are displayed for the local relationships between vegetation and income in Figure 4.5. Situations A (low vegetation and low income), B (high vegetation and high income), and D (high vegetation and low income) are mapped for each city where
applicable, while situation C (low vegetation and high income) did not locate any relevant census tracts for any of the cities.

Figure 4.4 Flow chart displaying technique for mapping census tracts that demonstrate green-space-related environmental injustices. Census tracts with a $R^2$ of greater than 0.60 are selected from the data then classified according to whether the observed relationship is positive or negative. These polygons are then divided into different scenarios based on the deviation of the values from the regression trend line.

Examining the results of the mapped GWR for each city (Figure 4.5) provides some noticeable trends and differences between the cities. Looking first at the variance explained for the relationship between income and vegetation, several pockets of high values begin to emerge within each city. Investigating the location of these pockets provides a more informed interpretation of the results. Each city exhibits a variety of green-space-related environmental equity situations. All three cities demonstrate areas with high vegetation and high income (situation B). Toronto and Vancouver also exhibit the opposite situation (A) for a number of census tracts; highlighting areas with low vegetation and low income. Finally, one census tract in Toronto was extracted for the situation exhibiting high vegetation and low income (D).
4.5 Discussion

Performing both global and local assessments of environmental equity provides a suite of statistics that can be used to analyse various geographic trends in the distribution and abundance of inequalities between socioeconomic variables and vegetation fractions. The global method applied in this study uses the Pearson correlation coefficient; a standard but powerful statistic that enables the quantification of relationships between vegetation fraction and socioeconomic variables for selected cities. The results of this study validate long-standing beliefs that have described class-based environmental inequities and the pronounced existence of these situations in North American cities (Faber, 1998).

In this study the strongest relationships with vegetation fraction were observed with those variables related to economic status, in particular various representations of income from national census data. In all three study areas income variables were positively correlated with vegetation fraction, suggesting that the higher an individual’s income the greater chance they live in an area with increased amounts of vegetation. This correlation is consistent across Montréal, Toronto, and Vancouver, and is similar to that found in other American cities (Li and Weng, 2007; Mennis, 2006a). Although the consistent high correlation with income supports the general existence of environmental inequalities across urban areas, the variability in the correlations of the other socioeconomic variables highlight intercity differences with respect to equity and green space (and the unique socioeconomic characteristics of each city).
The global correlations illustrate the difference in socioeconomic and vegetation relationships across major Canadian cities (Table 4.2). It is important to note that this analysis cannot reveal the process of causation through which these relationships emerge. However, planners and community organizations can use the relationships to help guide policies and initiatives to help mitigate recognized inequalities. In addition, cross-city comparisons can help policy analysts examine the successes and failures of urban development processes in these major cities. At the same time, policy differences do not necessarily explain all the facets of urban development. The relationships derived from this analysis are partly a result of cultural and historical influences on urban development patterns that remain important to the diversity, originality, and differentiating characteristics of urban centers. As a result, the methods presented in this study should be viewed as a tool that could be applied by various individuals or organizations interested in the geographic relationships between people and the environment.

Global assessments of environmental equity can have valuable applications for inter-city comparisons and act as a general tool for recognizing the existence of inequitable relationships between urban environments and socioeconomic status. However, cities are inherently diverse landscapes composed of blocks, neighbourhoods and districts whose internal variability is masked by a simple global statistic. Geographically weighted regression can highlight relationships at various scales and allows planners and community organizations to quantify the geographic variability across a city. In practice, a local regression analysis enables the determination of location-specific allocation of environmental services and resources to efficiently reduce environmental inequalities.
Maps summarizing the geographically weighted regression results between income and green space highlight those areas where injustices exist within each city (Figure 4.5). Of interest are those census tracts which exhibit an over- and under- availability of green-space related to income. By targeting these areas urban planners and community organizations can allocate and manage resources towards alleviating inequalities in the most affected neighbourhoods. Specifically, those mapped areas where income and vegetation are both low are of immediate interest as residents in these locations face a disadvantage with regards to accessibility and availability of local green-space.

Local regression parameters from this study exhibited stronger relationships with vegetation than did the global correlation, which exemplifies the power and utility of GWR for analysing the relationships between socioeconomic status and environmental factors including vegetation. Reviewing the maps produced for each city reveals geographic trends that can act as a powerful tool for motivating initiatives to help manage and mitigate environmental inequalities. Mapping inequalities has been recognized as a valuable means of stimulating community members to become actively involved in the laws and policies which govern the distribution of local resources (Hutchinson and Toledano, 1993). In addition, epidemiologists have recently recognized the importance of neighbourhood-level social and environmental factors on the health and well-being of urban residents (Brulle and Pellow, 2006; Maantay, 2002; Ostfeld et al, 2005). By effectively mapping the inequalities between vegetation and socioeconomic status public health officials can target vulnerable populations in an attempt to reduce the risk of various diseases.
Figure 4.5 Maps displaying results of the GWR procedure to highlight green-space-related environmental injustice. Maps on the left highlight relationships from the GWR, while maps on the right depict census tracts of particular interest in relation environmental injustices.
In the past decade advances in high spatial resolution (< 5m) sensors have allowed for more sophisticated analysis of detailed urban processes. These technologies offer resolutions comparable to aerial photographs and hold great promise for allowing more detailed processes of urban environments to be observed. Integrating these technologies with equivalent scale socioeconomic data would allow for highly detailed analyses of the relationship between people and their local environments, which could inform planning policies and initiatives at a city block or individual lot scale.

4.6 Conclusion

In this study we demonstrate the application of global and local assessments of the spatial variability of environmental equity in urban areas. Our results indicate that income provides the strongest correlation with vegetation fractions, although other socioeconomic variables such as education, family status, and immigrant status also demonstrate significant relationships with green-space. Applying geographically weighted regression as a local regression model for analysing environmental equity has been demonstrated as a valuable method for quantifying internal varying relationships between vegetation fractions and socioeconomic status. The cities of Montréal, Toronto, and Vancouver provide prime study areas as they represent the largest urban centers in Canada and display significant variations in the distribution and abundance of vegetation fractions.

Integrating spatial data technologies and techniques including remote sensing, geographic information systems, and spatial statistics provides urban planners and community development organizations with a powerful suite of tools that can be used to quantify associations between
people and their local environments. With rapid global urbanization, addressing issues between people and place will have a direct impact on the well-being of the majority of the world’s population, and can help ensure that equal opportunities will be available for vulnerable populations.
4.7 References


5 CONCLUSION

As urban environments continue to grow and evolve, planners and scholars are becoming more aware of the importance and effectiveness of vegetation as a resource for moderating many of the problematic issues that accompany urbanization. At the core of urban vegetation management strategies is a fundamental understanding that humans and the environment are inextricably linked (Alessa et al., 2008). As a result, efficient planning requires an analysis of both physical and social aspects of urban areas at a wide range of scales.

The structural and social composition of urban areas are characterized by their extreme heterogeneity (Oke, 1987), which has traditionally hindered empirical analysis of detailed processes in cities (Camagni et al., 2002). However, the increased application of remote sensing technology is enabling city-wide studies to examine the spatial composition of these areas. In this thesis, studies were conducted using a range of remote sensing datasets to examine three critical areas of urban vegetation management:

1. Urban vegetation extraction techniques to provide new methods for gathering detailed information related to vegetation species and composition.
2. Analysis of the impact urban trees have on the radiation received by residential dwellings to inform future renewable energy initiatives.
3. Examination of the distribution of urban vegetation in relation to the socioeconomic status of urban residents to map green-space-related environmental injustice.
To demonstrate the applicability of remote sensing for urban vegetation management, this thesis has provided a pragmatic framework for integrating biogenic and anthropogenic spatial components of urban environments.

In the introduction of this thesis four fundamental questions for urban ecological scholars were identified (Alberti et al., 2003) including:

- How do socioeconomic and biophysical variables influence the spatial and temporal distributions of human activities in human-dominated ecosystems?
- How do the spatial and temporal distributions of human activities redistribute energy and material fluxes and modify disturbance regimes?
- How do human populations and activities interact with processes at the levels of the population, the community and the individual to determine the resilience of human-dominated systems?
- How do humans respond to changes in ecological conditions, and how do these responses vary regionally and culturally?

Although the specific focus of this thesis has been on using remote sensing for urban vegetation management, many of the questions above have been indirectly addressed in the presented studies.

In chapter 2 I developed a new vegetation extraction technique to classify the condition and species of both grasses and trees in urban areas using Quickbird imagery. This study indicated that classes including mixed and manicured grasses and deciduous and evergreen trees can be accurately extracted from high spatial resolution broadband satellite imagery, and provided a
useful technique for representing the spatial coverage of vegetation in urban areas. This research has the potential to address many of the questions presented above when combined with data related to anthropogenic patterns and structures.

In chapter 3 LIDAR data was used to quantify the three dimensional form of urban trees and buildings. Additionally, digital surface models produced from the LIDAR data provided input for solar radiation models. The structural information was then compared to modeled radiation estimates for different atmospheric conditions, and provided diurnal and seasonal assessments of the impact urban trees have on solar radiation available for building rooftops. This study can help explain the influence of built structures and vegetation management strategies on specific energy fluxes in urban environments.

Chapter 4 combined some of the vegetation extraction techniques from chapter 2 with census data related to socioeconomic attributes of urban residents. Landsat data was used to extract vegetation estimates for three major Canadian cities and then related them to census data using correlation and geographically weighted regression statistical methods. Results helped to explain and map inter- and intra- city differences related to green-space-related environmental justice. More generally, this chapter examined how socioeconomic and biophysical variables influence the spatial distributions of human activities in human-dominated ecosystems.

The principle benefit of remotely sensed imagery is its ability to provide complete spatial coverage of various areas on the Earth’s surface. Once this information is available, it requires integration and specific knowledge of various disciplines to promote its application within a
broad range of natural and social sciences. At the same time, analysis of urban environments can never be complete, as these areas are characterized by the dynamism that accompanies human populations.

5.1 Future Research

This research has highlighted the important role remote sensing can have for the monitoring of vegetation within urban environments at a range of scales. There are a number of additional areas where future research could be focused. First, while many of the spatial aspects of urban ecology are examined in this thesis, little mention is given to the temporal components of urban vegetation management. Remote sensing is particularly useful for temporal analysis of urban surface composition since vegetation is an exceptionally dynamic component of cities. Landsat imagery provides an optimal dataset for examining temporal patterns of surface composition, but has a limited application for urban analysis, resulting from an inability to resolve many of the detailed components of cities. At the same time, high spatial resolution imagery is expensive and relatively new, limiting its application for temporal analysis of urban areas. As archives of high spatial resolution imagery develop, a greater ability to perform sophisticated temporal analysis of urban environments will emerge.

A second area of potential research that is gaining attention in the natural sciences, is the development of detailed models to better explain carbon and water balances for different biomes. Cities present challenging landscapes to study, due to the variety of components that contribute to the natural fluxes in these areas, including anthropogenic activities and biogenic processes
Understanding the role of vegetation on the urban carbon and water balance is necessary for developing effective mitigation strategies. Remote sensing has the capacity to examine the spatial distribution and structure of urban vegetation, and can play an important role in the future of local-scale urban energy balance research.

Lastly, discussion is provided on Canada’s role in urban vegetation research. While international perceptions of Canada tend to be of vast forested landscapes and pristine natural environments, over 80% of Canada’s population resides in urban areas. For most Canadians, the natural areas that they most closely associate with are the parks, street trees, and woodlot remains in urban areas (Tree Canada, 2009). Although urban forests and green-spaces are making their way into municipal and provincial legislation and national strategic documents, relatively little empirical academic literature exists examining management strategies for urban vegetation. The urban nature of Canada’s population, diversity of cultures, range of climates and current expertise in natural resources research, positions Canada as an optimal country to undertake urban vegetation research.

Understanding the ways in which humans interact with vegetation in their local communities has been important to societies for centuries, however developing this knowledge for urban environments remains relatively unexplored. In this thesis, I have examined three areas of study related to urban vegetation for the Metro Vancouver region in British Columbia, Canada. Technological developments in remote sensing, such as high spatial resolution and active sensors, facilitate spatial analysis of both physical and social processes in the city. Results from these studies provide new techniques that decision-makers and scholars can adopt in future urban
vegetation management strategies. Finally, this thesis adds to a growing body of knowledge examining the important role vegetation has in urban environments.
5.2 References


Christen, A., Coops, N., Crawford, B., Liss, K., Oke, T., Tooke, R. 2009. The role of soils and lawns in urban-atmosphere exchange of carbon-dioxide. The 7th International Conference on Urban Climate (ICUC-7); Yokohama, Japan


**APPENDIX A**

**A1 Field Plots**

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