Mapping the distributions of two invasive plant species in urban areas with advanced remote sensing data

by

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Abstract

Invasive plants are increasingly present in ecosystems, producing both positive and negative effects. Proactive management of plant invasions is critical to curbing their spreads, especially in urban areas which often act as centres of invasions. Therefore, municipalities require new tools to map invasions for both management and information. Remote sensing technologies provide opportunities to detect plant invasions over large areas at fine spatial resolutions. In Surrey, British Columbia, Canada, Himalayan blackberry (HB; Rubus armeniacus) and English ivy (EI; Hedera helix) are two understory invasive plants that can negatively influence native ecosystems and harm users of urban natural areas. Two remote sensing technologies, hyperspectral imagery and light detection and ranging (LiDAR) data, were utilized to map these two species across the entire area of Surrey.

Analysis of spectral characteristics of HB and EI were used with hyperspectral imagery to examine the feasibility of spectrally detecting these species. Spectra were obtained from a ground-based handheld spectrometer from the two species and other common species in Surrey and processed through a spectral channel selection algorithm to identify key wavelengths for distinguishing these species. Once identified, a spectral classification routine used these wavelengths and training plots to detect HB and EI across open areas in Surrey. Results showed accuracies of 76.4% for HB and 80.0% for EI.

Mapping HB and EI across all land covers of Surrey required detecting the two species in forested areas. Field plots, LiDAR-derived topographic and forest structure variables, hyperspectral data, a land cover classification, and a LiDAR-derived irradiance model were all used as inputs into random forest models to detect the species across the entire land base. Model
accuracies ranged from 77.8% to 87.8%. Open areas were classified better than forested areas. EI was found more across the city than HB.

The research in the thesis has advanced detection of invasive plants by demonstrating the feasibility of mapping understory invasions of EI and HB in urban areas at fine spatial resolutions and can form the basis for a future monitoring system using data acquired at regular intervals. Future work is recommended to enhance data collection and increase map specificity.
Preface

In this thesis, I was responsible for determining the research questions, methods, and writing manuscripts and this thesis. Dr. Nicholas Coops provided guidance throughout most of the project as well as editorial help. My research committee provided insights related to their various expertise. Dr. Andreas Christen helped me to understand urban climate modelling, specifically irradiance modelling. Ken Crosby provided me with ecological and operational information about the two species of interest in this study. Dr. Jeanine Rhemtulla assisted with relating the remote sensing products to ecologically-relevant results. Code for the irradiance modelling was provided by Dr. Rory Tooke. All co-authors on the following publications gave insight and editorial assistance.


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List of Abbreviations

AISA – Advanced Imaging Spectrometer for Applications
ASD – Analytical Spectral Devices
ATCOR – Atmospheric and Topographic Correction
AVIRIS – Airborne Visible / Infrared Imaging Spectrometer
CASI – Compact Airborne Spectrographic Imager
CHM – Canopy height model
DEM – Digital elevation model
DSM – Digital surface model
EI – English ivy
EO - Earth Observation
ETM – Enhanced Thematic Mapper
FR – Full range
GDD – Growing degree day
GPS – Global positioning system
HB – Himalayan blackberry
ISI – Instability index
LiDAR – Light Detection and Ranging
MMU – Minimum mapping unit
MODIS – Moderate Resolution Imaging Spectroradiometer
MSS – Multispectral scanner
NIR – Near infrared
P75 – 75th percentile height of LiDAR returns
P90 – 90th percentile height of LiDAR returns
P95 – 95th percentile height of LiDAR returns
RF – Random forest
SAM – Spectral angle mapper
SVF – Sky view factor
SZU – Stable zone unmixing
TM – Thematic Mapper
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First and foremost, I was extremely fortunate to be supervised and supported by Dr. Nicholas Coops. Nicholas gave the resources to succeed and achieve my goals during my time as his student. I would also like to thank all of my committee members. Dr. Christen provided insight into how urban climate modelling works, adding a novel dimension to my thesis. Dr. Rhemtulla provided valuable suggestions on how the results may fit within broader ecological and sociological frameworks. Finally, Ken Crosby helped me understand the operational considerations for invasive plant managers. Additional thanks to Neal Aven from the City of Surrey for providing numerous suggestions about the direction of the project, to Andrew Plowright, whose GIS knowledge and willingness to share data helped immensely throughout the project and to Rory Tooke, whose guidance on how to model solar irradiance was much appreciated. Thank you to Yuhao Lu, Ignacio San-Miguel, and Joanna Lee for help collecting data in Surrey.

The City of Surrey and the Natural Sciences and Engineering Research Council of Canada (NSERC), through Engage, Engage +, and Master’s grants supported the research.

I would also like to thank all the fellow lab members at the Integrated Remote Sensing Studio (IRSS) for making the lab a great place to work.
Dedication

To my family.
Chapter 1

Introduction

1.1 Invasive species

Non-native species are present in most human-dominated landscapes (Ricciardi 2007). Many of these species are transported to foreign locations for use as agricultural crops, livestock, or plants in gardens (Boersma et al. 2006). However, some of these species spread beyond their intended use and colonize new areas to the detriment of native species. Such species are often termed invasive species.

Invasive species are often characterized as species foreign to an ecosystem that alter its traditional functioning and composition by propagating throughout it (Zavaleta et al. 2001). While not all invasive species are foreign, those associated with the largest changes in ecosystems usually are (Ricciardi 2007). The spread of these species is considered to be one of the greatest causes of ecological change, specifically causing changes in ecosystem functioning and biodiversity change, gain or loss, at various scales (Hooper et al. 2005, MacDougall and Turkington 2005).

Biodiversity has many different definitions, yet most emphasize its relationship to the overall diversity of biological material at the genetic to species to landscape scales (Gaston 1998). Thus loss of biodiversity could be loss of genes in a population, loss of species in an ecosystem, or loss of communities on a landscape. Consequences of these losses can include changes in ecosystem functioning (Loreau et al. 2001, Hooper et al. 2012). Ecosystem functioning can be viewed from both a biogeochemical perspective and an anthropogenic perspective (Schulze and Mooney 1994). Anthropogenically, ecosystem functioning is generally concerned with yield (i.e. harvest) that an ecosystem produces (Schulze and Mooney 1994). From a biogeochemical
perspective, ecosystem functioning describes processes that an ecosystem performs, such as nutrient cycling, water filtration, or forest succession (Schulze and Mooney 1994).

Specific examples of biodiversity loss and changes in ecosystem functioning caused by invasive species are numerous. Invasive plants in particular are problematic as they have been shown to change successional patterns, composition, and structure in forests (see Hartman and Mccarthy 2008), decrease wildlife habitat (see Lampert et al. 2014), and alter nutrient dynamics in their favour (see Chau et al. 2013). This list is not exhaustive, yet it provides insight into some of the effects that invasive plant species have within their resident ecosystems. Furthermore, plant invasions are associated with decreases in ecosystem services that cost more than $34 billion annually in the United States alone (Pimentel et al. 2005, Pejchar and Mooney 2009).

Halting the spread of plant invasions and reducing their negative effects is a difficult task as many invasive plant species have mechanisms that afford them advantages compared to native species. Examples of some of these mechanisms include greater dispersal abilities (Kowarik 1995, Pysek and Hulme 2005), capacity to hybridize resulting in increased fitness (Ellstrand and Schierenbeck 2000), and quick germination (Gundale et al. 2008). Additionally, individual species have different ways of spreading. For example, some plants are dispersed via relationships with animals, and others through almost entirely anthropogenic means (see Gosper et al. 2005, Von der Lippe and Kowarik 2007).

1.2 Invasive plants in urban ecosystems

Studies of urban ecosystems are relatively new in ecology, yet are increasing substantially over the last 15 years (Stearns 1970, Grimm et al. 2008, Pickett and Grove 2009). Despite the naissance of this field, relationships between urbanization, global homogenization of flora, and plant
invasions have been observed (Pimentel et al. 2000, Pysek and Hulme 2005, Grimm et al. 2008). Various mechanisms are responsible for these plant invasions in urban areas. First, because these areas are often novel ecosystems – those with human-built or modified niches (Hobbs et al. 2006) - many native species are not well adapted to them, and thus they are prime locations for plant invasions to spread (Shea and Chesson 2002, MacDougall and Turkington 2005, Gundale et al. 2008, Lampinen et al. 2015, Hawthorne et al. 2015). Specific examples of novel niches in urban areas include power line corridors, road sides, and housing developments (Von der Lippe and Kowarik 2007, Gavier-pizarro et al. 2010, Lampinen et al. 2015). Second, as most plant invasions spread anthropgoenically, urban areas are often their centre (Groves and Di Castri 1996, Pimentel et al. 2000, Pysek and Hulme 2005).

Many novel habitats may occur in urban greenspaces, which are defined as parks, street trees, urban agriculture, lawns, and rooftop gardens (Breuste et al. 2013). These urban greenspaces are often created to conserve biodiversity (Kong et al. 2010). As invasive species can colonize in many novel habitats, the biodiversity values of these urban greenspaces are often threatened (Snep and Opdam 2010). As well, many people value the existence of native species and ecosystems (Pejchar and Mooney 2009), and for many residents of urban areas, the only interactions they have with natural or near-natural areas is within their communities (Dunn et al. 2006). Consequently, as more people move into urban areas, maintaining biodiversity of these ecosystems will become increasingly important (Corvalan et al. 2005, Hough 2014). Accordingly, authorities should be and have been dedicating resources to remove and slow the spread of harmful plant invasions (Hulme et al. 2009, Ishii et al. 2016).
1.3 Finding invasive plants

As plant invasions can occur through multiple pathways, they are difficult to prevent, and thus land managers are often forced to remove invasions after they have occurred (Mehta et al. 2007). In these cases, the first step to removing them and stopping future invasions is finding their current locations. Methods to locate the species generally fall under one of two categories: species habitat suitability modelling, or species detection (Bradley et al. 2012).

Species habitat suitability modelling, sometimes termed species distribution modelling, describes potential rather than actual habitat (Guisan and Zimmermann 2000). While this approach may be useful for predicting future invasions, it does not provide an accurate indication of the current locations of species in most cases (Hirzel et al. 2006). However, these models can be used to guide where to search for species when detecting them by highlighting relationships with important predictor variables (Hirzel et al. 2006, Andrew and Ustin 2009).

Species detection, for the purpose of this thesis, is defined as locating individual plants or clusters of plants. Because species detection can provide detailed information about the current coverage as opposed to the potential coverage of invasive plants, it is often preferred for management applications (Hauser and McCarthy 2009). Systematic methods of species detection range from field crews recording species presence or absence at random locations to collecting citizen science data to using remotely sensed data to detect individual plants (Hauser and McCarthy 2009, He et al. 2011, Hawthorne et al. 2015). As field crews often cannot census an entire area, this method may be inferior to using remotely sensed data which can record data for an entire area. Additionally, field crews and citizens may provide data derived from many different methods, decreasing its reliability. However, using field crews does not come with the uncertainty found in some remote sensing products. Yet, remote sensing has shown potential and success
detecting plant invasions. Additionally, as remote sensing gains popularity, its methods for detecting invasive plants may be increasingly effective.

1.4 Mapping invasive plant species with remote sensing

Remote sensing has many advantages for detecting invasive plants such as providing fast wall-to-wall coverage that is often cost-effective (Müllerová et al. 2013). The history of using remote sensing data to detect plant invasions spans over a decade and includes various sensors and numerous detection algorithms (Huang and Asner 2009).

Remote sensing technologies offer the ability to analyze vegetation at various scales. Most remote sensing technologies use the electromagnetic spectrum to record measurements. For analyzing vegetation, the part of the spectrum most often used ranges from the visible to near- and mid-infrared (400 nm to 2500 nm; Thenkabail et al. 2011). For optical sensors, this spectral range is divided into various spectral channels. The number of spectral channels and the exact range that they encompass varies by sensor. Spatially, pixel sizes differ according to the sensor. Multispectral imagery consists of between two and 20 to 30 discrete spectral channels from across the electromagnetic spectrum, generally from visible to near-infrared wavelengths (Schowengerdt 2007). The pixel sizes of multispectral sensors ranges from less than 1 m (i.e. QuickBird) to over 250 m (i.e. Moderate Resolution Imaging Spectroradiometer [MODIS]). Hyperspectral imagery consists of 20 or more continuous spectral channels, also commonly encompassing the visible and near-infrared wavelengths, and has varying pixels sizes depending on the sensor (Schowengerdt 2007). Unique spectral properties of invasive plants may allow them to be detected by at least one these of these sensors (Table 1.1; Huang and Asner 2009).
To date the most common multispectral sensors for detecting plant invasions have been from the Landsat series of satellites. Bradley and Mustard (2006) used various Landsat Thematic Mapper (TM) images and spectral indices - ratios between spectral bands - to detect grass invasions in open grasslands. While this study demonstrated the capacity of multispectral sensors to detect plant invasions, the accuracy was low (35%). Wilfong et al. (2009) mapped the coverage of an invasive shrub species in 30 m Landsat TM pixels in deciduous forests using various spectral indices and regression equations. The largest $R^2$ values were just above 0.6. Lastly, Shouse et al. (2013) compared hyperspectral imagery and multispectral imagery to detect understory invasive plant species and found that hyperspectral classification outperformed multispectral ones. Although important, multispectral sensors lack the ability to discriminate individual species from each other (Adam et al. 2010). Additionally, the spatial resolution of some of the sensors may be too coarse to detect some species or have meaningful management applications. Many hyperspectral sensors are able to discriminate between species and have finer spatial resolutions, and thus are more often used for mapping plant invasions.

Many preliminary studies using hyperspectral imagery to detect plant invasions used imagery from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) in a delta ecosystem in California (Hestir et al. 2008). This instrument provided imagery with 128 spectral channels from 450 nm to 2500 nm at a pixel resolution of 3 m (Hestir et al. 2008). To begin, Underwood et al. (2003) mapped invasive communities in this area with a 76% accuracy. Other studies in this area mapped invasive aquatic plants (Underwood et al. 2006), and invasive shrubs in open areas (Andrew and Ustin 2008), all with high accuracies. Many other studies have mapped invasive herbs with hyperspectral imagery, all in open areas, and with a variety of sensors (Parker Williams and Hunt 2002, Glenn et al. 2005, Lawrence et al. 2006, Miao et al. 2006). Recent studies have
mapped grasses, herbs, and single trees with hyperspectral imagery with accuracies ranging between 81% and 96% (Ishii and Washitani 2013, Calviño-Cancela et al. 2014).

Three dimensional aspects of ecosystems are also related to invasive plant distribution (Asner et al. 2008a). In vegetation studies, the most common form of remote sensing that provides three-dimensional data is light detection and ranging (LiDAR) data. LiDAR systems, usually flown on an airplane, emit a laser pulse (usually in the near-infrared part of the electromagnetic spectrum) that reflects from an object back to the sensor. Processing the exact location and the return time of the laser pulse creates a three-dimensional dataset.

Due to its relatively recent application, LiDAR data has been less widely used to detect plant invasions. Asner et al. (2008a) demonstrated that hyperspectral imagery and LiDAR data can be combined to detect invasive tree species, however only used the LiDAR data to create a shade mask. Andrew and Ustin (2009) used LiDAR to create some environmental predictor variables, however applied it in a relatively simple way. Additionally, this study mapped habitat suitability rather than species presence and absence. Only recently has LiDAR data been used to produce environmental predictor variables to be used in a detection model. Singh et al. (2015) used LiDAR data to detect understory plant invasions in deciduous urban forests. The method produced an invasive species map with an accuracy of 89%.

Invasive plant species have been mapped well in open areas and deciduous forests with remote sensing. For species under closed coniferous canopies, more research is needed. Furthermore, remote sensing in urban forests has only recently been studied. These research gaps lend an opportunity explore mapping the distribution of understory invasive plants in urban areas, whether open or densely forested.
Table 1.1. Studies mapping invasive plant species using remote sensing data. AISA = Advanced Imaging Spectrometer for Applications, AVIRIS = Airborne Visible / Infrared Imaging Spectrometer, CASI = Compact Airborne Spectrographic Imager, EO = Earth Observation, ETM = Enhanced Thematic Mapper, LiDAR = Light detection and ranging, MSS = Multispectral scanner, TM = thematic Mapper.

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<td>Leucaena leucocephala</td>
<td>Taiwan</td>
<td>Tree</td>
<td>Forest (national park)</td>
<td>EO-1 Hyperion (hyperspectral)</td>
<td>30m</td>
<td>220 channels, 355nm to 2577nm</td>
<td>Tsai et al. (2007)</td>
</tr>
<tr>
<td>Salt cedars (Tamarix spp.)</td>
<td>California</td>
<td>Shrubby trees</td>
<td>Riparian</td>
<td>SOC 700 (hyperspectral)</td>
<td>0.5m</td>
<td>120 channels, 394-890nm</td>
<td>Hamada et al. (2007)</td>
</tr>
<tr>
<td>Tropical Ash (Fraxinus uhdei), Cattley guava (Psidium cattleianum), Faya (Myrica faya)</td>
<td>Hawaii</td>
<td>Trees</td>
<td>Rainforest</td>
<td>Carnegie Airborne Observatory (CAO) with 2 instruments: 1) High-fidelity Imaging Spectrometer (hyperspectral), 2) LiDAR hyperspectral = 3m, LiDAR = 1.5m</td>
<td>380-2510nm at 10nm channels</td>
<td>Asner et al. (2008)</td>
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<tr>
<td>Perennial pepperweed (Lepidium latifolium)</td>
<td>California</td>
<td>Herbaceous perennial, clonal reproduction via roots and root fragments</td>
<td>Wetlands, riparian areas</td>
<td>HyMap (hyperspectral)</td>
<td>3m</td>
<td>450-2500nm, 126 channels at 15-20nm each</td>
<td>Andrew and Ustin (2008)</td>
</tr>
<tr>
<td>Water caltrop (Trapa natans), Phragmites australis, and Purple loosestrife (Lythrum salicaria)</td>
<td>New York</td>
<td>Water caltrop - submerged stem, leaves floating on surface, Phragmites - large perennial grass, purple loosestrife - herbaceous</td>
<td>Wetland</td>
<td>Quickbird, photo interpretation of aerial photos (multispectral) Quickbird = 2.4m</td>
<td>450-890nm (non-continuous), 4 channels</td>
<td>Laba et al. (2008)</td>
<td></td>
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<tr>
<td>Salt cedars (Tamarix chinensis, T. ramosissima, and T. parvifolia)</td>
<td>Nevada</td>
<td>Shrubby trees</td>
<td>Riparian areas</td>
<td>CASI (hyperspectral, 3 dates)</td>
<td>1 - 2m, 2.3 - 1m</td>
<td>1 - 48channels at 11nm, 2 - 36 channels, 15nm 3 - 32 channels, 17nm</td>
<td>Pu et al. (2008)</td>
</tr>
<tr>
<td>Amur honeysuckle (Lonicera maackii)</td>
<td>Ohio</td>
<td>Tall shrub</td>
<td>Deciduous forest</td>
<td>Landsat 5 TM, Landsat 7 ETM+</td>
<td>30m</td>
<td>See Bradley and Mustard (2006) Wilfong et al. (2009)</td>
<td></td>
</tr>
<tr>
<td>Species of interest</td>
<td>Location</td>
<td>Life form</td>
<td>Ecosystems of interest</td>
<td>Remote sensing instrument</td>
<td>Spatial resolution</td>
<td>Spectral resolution</td>
<td>Citation</td>
</tr>
<tr>
<td>-----------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>Canada thistle (Cirsium arvense), Musk thistle (Carduus nutans), reed canary grass (Phalaris arundinacea), Russian olive (Elaegnus angustifolia), salt cedars (Tamarix spp.)</td>
<td>Nebraska</td>
<td>Canada thistle - herbaceous perennial, Musk thistle - perennial herb, reed canary grass - tall grass, Russian olive - thorny shrub, salt cedars - shrubby trees</td>
<td>Riparian areas</td>
<td>AISA Eagle (hyperspectral)</td>
<td>1.5m</td>
<td>62 channels, 392-982nm</td>
<td>Narumalani et al. (2009)</td>
</tr>
<tr>
<td>Cutleaf Teasel (Dipsacus laciniatus)</td>
<td>Missouri</td>
<td>Rosette</td>
<td>Along highways</td>
<td>AISA (hyperspectral)</td>
<td>1m</td>
<td>63 channels, 201-981nm</td>
<td>Bentivegna et al. (2012)</td>
</tr>
<tr>
<td>Bush honeysuckle (Lonicera maackii)</td>
<td>Kentucky</td>
<td>Tall deciduous shrub</td>
<td>Understory of urban forests</td>
<td>1) Aerial photograph, 2) Landsat 5 TM (both multispectral)</td>
<td>1) 0.3m, 2) 30m</td>
<td>1) RGB, 2) 7 channels</td>
<td>Shouse et al. (2013)</td>
</tr>
<tr>
<td>Common sea-buckthorn (Hippophae rhamnoides), Black pine (Pinus nigra), Black cherry (Prunus serotina), Japanese rose (Rosa rugosa), Creeping willow (Salix repens), Elder (Sambucus nigra)</td>
<td>Vlieland, the Netherlands</td>
<td>Shrubs and herbs</td>
<td>Coastal dunes, quasi-undisturbed</td>
<td>Imagery - Vexcel UltraCam-X camera, LiDAR - FLI-MAP LiDAR system</td>
<td>Imagery - 25cm, LIDAR - 0.18m point distribution</td>
<td>Imagery - NIR (700-805nm), red (635-675nm), green (455-580nm)</td>
<td>Hantson et al. (2012)</td>
</tr>
<tr>
<td>Late goldenrod (Solidago altissima)</td>
<td>Japan</td>
<td>Clonal growth, seed dispersal, highly competitive</td>
<td>Understory of moist tall grassland</td>
<td>AISA Eagle (hyperspectral)</td>
<td>1.5m</td>
<td>67 channels, 397nm to 983nm, 8.9nm each</td>
<td>Ishii and Washitani (2013)</td>
</tr>
<tr>
<td>Musk thistle (Carduus nutans)</td>
<td>Texas</td>
<td>Perennial herb</td>
<td>Grassland</td>
<td>AISA Eagle (hyperspectral)</td>
<td>1m</td>
<td>50 channels, 509-885nm</td>
<td>Mirik et al. (2013)</td>
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<tr>
<td>1) Australian blackwood (Acacia melanoxylon), 2) Bermuda buttercup (Oxalis pes-caprae), 3) Iceplant (Carpobatus edulis), 4) Elands Sourfig (Carpobatus acinaciformis)</td>
<td>Spain</td>
<td>1) Fast-growing tree species 2) Flowering herb 3) mat-forming succulent 4) mat-forming succulent</td>
<td>Coastal park</td>
<td>Custom (hyperspectral)</td>
<td>5-8 pixels/m²</td>
<td>200 channels, 380-1000nm</td>
<td>Calviño- Cancela et al. (2014)</td>
</tr>
<tr>
<td>Chinese privet (Ligustrum sinense)</td>
<td>North Carolina</td>
<td>Understory shrub</td>
<td>Urban forest</td>
<td>Optech ALTM Gemini 3100 LiDAR</td>
<td>1 point/m²</td>
<td>N/A</td>
<td>Singh et al. (2015)</td>
</tr>
</tbody>
</table>
1.5 Research objectives and thesis overview

The overall objectives of this research are to close the gaps presented in section 1.4, specifically, to provide wall-to-wall fine spatial resolution maps of invasive shrub invasion across an urban area. Remote sensing and field data from Surrey, British Columbia, Canada are used to accomplish the primary objective. Two main research questions, and four sub research questions are posed to address this objectives:

1) Can Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) be distinguished from each other, and from other common native and invasive species based on hyperspectral data?
   a) What are the spectral properties of Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*)?
   b) Which method(s) allow(s) distinction between the two species and others?

2) Can Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) be detected in Surrey, British Columbia using hyperspectral imagery and LiDAR data?
   a) Which LiDAR-derived variables are critical to determine the presence and absence of each species?
   b) How much area of Surrey is currently covered by the two species?
This thesis is structured such that the following chapters each address at least one of these questions and its sub-questions.

Chapter 2 introduces in detail the study area, species of interest, and the remote sensing data that subsequent chapters use.

Chapter 3 answers research question 1 and its sub research questions. Himalayan blackberry and English ivy are mapped in open areas in Surrey by using hyperspectral imagery to detect the plants and LiDAR data to mask closed and shaded areas. The ideal methods acquiring spectral data from the plants are discussed based in this chapter.

Chapter 4 builds upon the findings about spectral properties from Chapter 2, and extends the mapping process to the entire area of Surrey by including LiDAR-derived variables to detect Himalayan blackberry and English ivy in open and forested areas. The resulting maps are tested for accuracy and spatial analyses are conducted to discern some management implications yielded by the distributions of Himalayan blackberry and English ivy invasions in Surrey, British Columbia, Canada.

Chapter 5 concludes the thesis by discussing key results and innovations from Chapter 3 and Chapter 4, as well as the limitations of the findings and some recommendations for future studies.
Chapter 2

Study area, species, and data

2.1 Study area

Surrey, British Columbia, Canada (49°11’N, 122°51’W) is located in the greater Vancouver area and has an area of 316 km² (Figure 2.1). It is one of the fastest growing cities in Canada, with a population of 468 000 in 2011 and a projected population of 818 000 by 2046 (Statistics Canada 2011, City of Surrey 2016). One reason that Surrey is rapidly growing is due to the quality of life afforded by its expansive parks and natural areas system (Figure 2.1). This network of parks is over 30 km² and exists amongst the mosaic of urban and agricultural areas. Most of the parks and natural areas in Surrey contain vegetated areas with dense, shrubby and herbaceous understories, as are commonly found in the temperate climate characteristic of the area.

The parks and natural areas in Surrey have a high native plant biodiversity. However, managers of these areas also monitor 41 invasive plant species that threaten to decrease the abundance of native flora and fauna. These invasive plants are classified as highly or moderately invasive based on a number of criteria, including ecological impact, invasive potential, and eradication feasibility. Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) are two species that are of moderate or high concern for parks and natural areas managers. As such, eradication programs are in place to find and remove these two species.
Figure 2.2. Location of the Surrey, British Columbia, the parks and natural areas system across the city, and two example sites used throughout this thesis, Green Timbers and Crescent Beach.

2.2 Species

2.2.1 Himalayan blackberry

Himalayan blackberry (Rubus armeniacus; Figure 2.2) is shrub native to Eurasia, but now well-established across California, Oregon, Washington, and British Columbia (Boersma et al. 2006, Gaire et al. 2015). Himalayan blackberry plants were initially introduced to North America in the 19th century for fruit production, and by 1945 it had escaped cultivation and was growing outside of agricultural areas without human assistance (Hall 1990, Gaire et al. 2015).
Himalayan blackberry individuals prefer nutrient-rich, well-drained soils, but can grow in barren, dry soils to soils on the verge of flooding (Boersma et al. 2006, Caplan and Yeakley 2006, Gaire et al. 2015). It can also establish and grow in coarse-textured soils, which are often associated with anthropogenic activities (Caplan and Yeakley 2006). Accordingly, Himalayan blackberry thickets are frequently found in riparian areas near agriculture and residential neighbourhoods (Gaire et al. 2015). It is more frequently found in open forests or open lowlands than in dense forests, as it prefers sunlight (Caplan and Yeakley 2006). However, it is not entirely absent in forests with high canopy cover, suggesting that other factors determine its distribution as well (Caplan and Yeakley 2006, Gaire et al. 2015).

Himalayan blackberry (*Rubus armeniacus*) displaces native vegetation and birds in both disturbed and undisturbed areas (Amor 1973, Caplan and Yeakley 2006, Astley 2010), and alters successional patterns along streams, changing long-term ecosystem functioning in these forests (Fierke and Kauffman 2006). Himalayan blackberry individuals grow and reproduce quickly, produce large amounts of seeds, and outcompete native individuals (Schwartz et al. 1996, Caplan and Yeakley 2006). Plants also overgrow walking paths and roadways, creating a nuisance for city residents and managers. Despite the negative effects of Himalayan blackberry, its fruit is well-liked by many residents, and as such it may promote a greater connection to urban parks.

In Surrey, Himalayan blackberry is of moderate concern for city authorities as it has relatively moderate ecological impact and eradication feasibility. However, the invasive potential of Himalayan blackberry is high, thus stopping it from spreading is critical to its eradication strategy.
Figure 2.2. Himalayan blackberry in a forest in Surrey, British Columbia, Canada.
2.2.2 English ivy

English ivy (*Hedera helix*; Figure 2.3) is a woody vine native to areas across Europe (Metcalfe 2005). Its uses for architecture and horticulture motivated people to spread the species to temperate climates of North America (Bell et al. 2003). Since escaping cultivation, its distribution has been increasing in urban forests on the Pacific coast (Dlugosch 2005, Biggerstaff and Beck 2007).

English ivy is mostly a forest-dwelling species, but is often found in open areas as well (Clergeau 1992). In forested areas, it is generally associated with large trees as it able to climb on them better than smaller trees (Castagneri et al. 2013). In the absence of large trees, it can also form mats on the forest floor (Metcalfe 2005). It can establish itself under the shade of coniferous trees (Sack 2004). Additionally, English ivy is tolerant of most soils, sparing the most acidic, water-logged or dry soils (Metcalfe 2005).

English ivy may produce allergens (Jones et al. 2009, Paulsen et al. 2010), has competitive advantages over native plants (Thomas 1980, Dlugosch 2005), and endangers users of natural areas by weakening trees (Thomas 1980). It is challenging to control due to the many various life forms: herbaceous vines, climbers, herbs, woody shrubs, and sometimes small trees (Metcalfe 2005).

For managers in Surrey, English ivy is of high concern as it has large ecological impacts and invasion potential. Additionally, it is classified as easily eradicated, thus efforts to curb its invasions can be successful.
Figure 2.3. English ivy in a forest in Surrey, British Columbia, Canada.
2.3 Remote sensing data

2.3.1 LiDAR data

Between April 3 and April 11, 2013, airborne LiDAR data were acquired for the entire City of Surrey by Airborne Imaging (Calgary, Alberta, Canada). The Leica ALS70-HP (Leica Geosystems, Heerbrugg, Switzerland) system sent pulses with a wavelength of 1064 nm from an altitude of 1000 m with a view angle of 20° and a scan frequency of 53 kHz resulting in a point density of 25 points/m². TerraScan software (Terrasolid, Finland) classified points as ground or non-ground (Figure 2.4).

Figure 2.4. Classification of LiDAR points from an (a) aerial perspective and (b) cross-section subset in Surrey, British Columbia, Canada.
2.3.2 Hyperspectral imagery

The Compact Airborne Spectrographic Imagery (CASI) 1500 acquired hyperspectral imagery over Surrey on May 4, 2013 at a 1 m pixel resolution (Figure 2.5). The imagery consists of 72 spectral channels from 363 to 1051 nm with a channel width of 9.6 nm. Following the acquisition of the images, they were radiometrically corrected, georeferenced, and converted to reflectance imagery. To radiometrically correct the imagery, raw digital numbers, value representations of the contents of a pixel, were converted into spectral radiances for each spectral channel. ITRES Research (Calgary, Alberta, Canada) calibrated the radiance imagery to known lab calibration files and corrected for dark and electronic offsets. These corrected images were georeferenced to a 1 m digital elevation model (DEM) produced from the LiDAR data and ground-based global positioning data (GPS) data. Lastly, atmospheric conditions and topographic and bi-directional effects were corrected to produce reflectance imagery that ranges from 0 to 10000 using the ATCOR-4 procedure (Richter and Schlapfer 2016).

Figure 2.5. Radiometrically corrected CASI hyperspectral imagery (red=683 nm, green=588 nm, blue=482 nm) in Surrey, British Columbia, Canada.
2.3.3 Ground-based spectra

Spectral libraries of plants may be useful for identifying plants (see Andrew and Ustin 2006). As such, ground-based spectra were collected to be used for plant detection. Prior to collecting the spectra, growing degree days (GDDs) were used as a proxy for the growth stage of plants, to ensure that the plants were in similar growth stages between 2013, when the CASI imagery was acquired, and 2015 when the ground-based spectra were collected. A baseline temperature ($T_{base}$) of 5°C was used in Equation (2.1) where $T_{max}$ and $T_{min}$ are the daily maximum and minimum temperatures.

$$\text{GDD} = \frac{T_{max} + T_{min}}{2} - T_{base}$$  \hspace{1cm} (2.1)

By May 4, 2013, the imagery acquisition date, Surrey had 297 GDDs. In 2015, 297 GDDs occurred on April 2 in Surrey (2015 data; http://www.farmwest.com/climate/gd). The field campaign spanned from March 31, 2015 to April 10, 2015. During this time, some tree and plant species had new leaves growing, matching the leaf-on conditions of the imagery. Himalayan blackberry and English ivy plants that were encountered in the field did not have new leaf growth. Spectra from Himalayan blackberry, English ivy, and other common plant species in Surrey were collected using an Analytical Spectral Devices (ASD) full range (FR) spectrometer (Analytical Spectral Devices, Boulder, Colorado, USA) within ± two hours from solar noon. The spectrometer recorded the spectra from 350-2500 nm at a 3 nm channel resolution between 350 nm and 1000 nm, and at a 10 nm resolution between 1000 nm and 2500 nm. Preference was given to plants or objects in direct sunlight, however, this was not always possible due to clouds. To account for this variation in irradiance conditions, the spectrometer was calibrated before each collection using a Spectralon panel (Labsphere, North Sutton, New Hampshire, USA). During each collection the spectrometer was held approximately 10 cm from the object or plant being measured. Leaves were
stacked at least six leaves deep in order to achieve a standard optical depth (Datt 1998, Jones et al. 2010). Following spectra collection, ASD channels were converted to the 72 CASI channels by averaging the ASD reflectance values that corresponded to the appropriate CASI channels.
Chapter 3

Spectral properties and spectral detection of Himalayan blackberry and English ivy¹

3.1 Introduction

Due to the environmental and economic costs associated with invasive plant species, managers at all levels of governments implement and fund programs to eradicate and control them. In particular, managers of urban parks and natural areas are concerned about the spread of invasive plants, as areas near and within urban centres are most susceptible to invasions due to the high amount of human activity (Pysek 1998). Often, these urban areas serve as starting points for the spread of invasive species (Pimentel et al. 2000, Pysek and Hulme 2005), thus it is critical for managers to aim to maintain the integrity of these ecosystems. Removal of invasive plants first requires detection, which commonly involves deploying a field crew to undertake field surveys, followed by another crew to remove the plants.

Remote sensing and analysis of the spectral properties of invasive plants can augment the detection of these species, and if used across large areas, can produce maps of the distribution of invasive plants (Huang and Asner 2009, He et al. 2011). Hyperspectral remote sensing is an excellent technology for detecting individual plants due to the narrow spectral channel widths and high number of channels in the visible (400-700 nm) and near-infrared (NIR; 700-1350 nm) wavelengths (Adam et al. 2010). Multiple airborne hyperspectral sensors including HyMap, the Airborne Imaging Spectrometer for Applications (AISA), the Airborne Visible InfraRed Imaging Spectrometer (AVIRIS), and the Compact Airborne Spectrographic Imager (CASI) (see Andrew and Ustin, 2008; Gu et al., 2015; Hestir et al., 2008; Ishii and Washitani, 2013; Miao et al., 2006;...

¹A version of this chapter has been published. Chance, C.M., Coops, N.C., Crosby, K., and Aven, N. 2016. Spectral wavelength selection and detection of two invasive plant species in an urban area. Canadian Journal of Remote Sensing 42: 1-14
Underwood et al., 2003) have successfully detected invasive plants. The fine spatial resolution (often 1 m) of these sensors is a further advantage for detecting individual plants, as a single pixel is more likely to contain a single species, often called an endmember. Such fine spatial resolution allows researchers to choose from a variety of spectral matching algorithms for detection. Mundt et al. (2005) showed that the spectral angle mapper classification (SAM; Kruse et al. (1993)) performed best for detecting invasive species, as SAM assumes that each pixel has only one plant species.

Regardless of which hyperspectral instrument and spectral matching algorithm are used, a subset of spectral channels is often selected for analysis, as hyperspectral imagery includes redundancy, noise in some of the channels (Clark et al. 2005), and is computationally intensive when using all channels. Selection of certain spectral features potentially improves classification accuracies (Somers et al. 2010). However, choosing the best source for the spectra, be it from imagery or from ground-based spectra, is often overlooked. Some studies (Underwood et al. 2003, Mundt et al. 2005, Asner et al. 2008b, Andrew and Ustin 2008, Narumalani et al. 2009) successfully used aerial-obtained training spectra to detect invasive plant species. Fewer studies (see Williams and Hunt 2002, Andrew and Ustin 2006, Fernandes et al. 2013) have used ground-based spectra to detect or analyze the spectral properties of invasive plant species. Spectra are often collected from imagery to eliminate disparities between the conditions in which the imagery and ground-based data were collected, including atmospheric and phenological differences (Ghulam et al. 2014). However, ground-based spectra often capture signals from species without atmospheric or shading effects (Ghulam et al. 2014), rendering them ideal for detecting species or selecting spectral channels to distinguish between species.
One way to isolate uncontaminated spectra of understory plant species from imagery is to mask areas with taller vegetation or shade. Airborne light detection and ranging (LiDAR) data can be used to mask imagery based on forest structural metrics, such as height, as demonstrated in Asner et al. (2008). Additionally, shaded areas can be derived from LiDAR data using hillshade models (Tooke et al. 2009). Together, with LiDAR-derived cover models, these metrics can ensure that aerial-based spectra are unimpeded by other vegetation or objects.

Vegetated areas across Surrey, British Columbia, Canada harbour a variety of native and invasive plants. Throughout the entire area of the city, certain species are common including grasses (lawns and less commonly European beachgrass [Ammophila arenaria]), lamium (Lamium galeobdolon), Himalayan blackberry (Rubus armeniacus), and English ivy (Hedera helix). Himalayan blackberry and English ivy are two invasive species of special concern to city managers due to their detrimental impacts on biodiversity and residents and their potential to invade areas quickly.

The objective of this chapter is to determine how well two invasive plant species, Himalayan blackberry (Rubus armeniacus) and English ivy (Hedera helix), can be distinguished from other plant species in open areas using hyperspectral imagery and ground-based spectra. Spectral channels were selected and used to map the distributions of the two species in open areas. The accuracies of the maps are tested using field data. Lastly, urban park management implications of area covered by Himalayan blackberry and English ivy, and the detection accuracies are discussed.
3.2 Methods

3.2.1 Methods overview

The methods of this study followed a series of steps to detect Himalayan blackberry and English ivy in open areas (Figure 3.1). First, spectral channels were selected from aerial- and ground-based spectra. As much of the study area was covered with coniferous forests, LiDAR data was used to mask the imagery based on height, shade, and cover. Second, a SAM classification was performed on imagery using all channels and the subsets. Maps of the distribution of the two species were produced and the detection accuracies of Himalayan blackberry and English ivy in each classification scenario were compared.

![Flow diagram for using the LiDAR data, field plots, CASI imagery, and ground-based spectra for detecting Himalayan blackberry (Rubus armeniacus) and English ivy (Hedera helix). Rectangles](image)

Figure 3.1. Flow diagram for using the LiDAR data, field plots, CASI imagery, and ground-based spectra for detecting Himalayan blackberry (Rubus armeniacus) and English ivy (Hedera helix). Rectangles
represent data and ovals represent processes. CHM = canopy height model, ISI = instability index, SAM = spectral angle mapper.

### 3.2.2 Masking

As the first step in the methods (Figure 3.1), a LiDAR-derived height, cover, and shade mask was created to ensure that detection of Himalayan blackberry and English ivy was trained and validated using unshaded pixels in open areas. A 1 m resolution canopy height model (CHM) and a cover model were created in FUSION (Version 3.42, Seattle, Washington, USA). Pixels with a height above 2.5 m or without vegetation cover between 0 and 2.5 m were masked. Additionally, a shadow model was developed using the hillshade tool in ArcGIS (Version 10.3, Esri, Redlands, California, USA) based on the CHM and the solar position 2 hours past solar noon on May 4, 2013. Shaded pixels were also masked, creating a combined cover, shade, and height mask (Figure 3.2). As the focus of this study is about detecting invasive species in urban areas, agricultural areas were masked to avoid confusion between crops and Himalayan blackberry and English ivy. The mask was created from the Agricultural Land Reserves information from the Government of British Columbia (http://catalogue.data.gov.bc.ca/dataset/agricultural-land-reserve-alr-polygons). After applying the LiDAR and agriculture masks, the total unmasked area was 138.4 km².

### 3.2.3 Field plots

Vegetation plots were used for spectral channel selection, and the training and assessment of detection of Himalayan blackberry and English ivy. As the focus of this study was on detecting Himalayan blackberry and English ivy in open areas, only species commonly occurring in open areas were considered. As such, field plots were collected for Himalayan blackberry and English ivy, as well as two other common species in Surrey, lamium (Lamium galeondolon) and grasses
(lawn and European beachgrass [*Ammophila arenaria*]). Although other species were present in open areas, they were not abundant enough to reliably collect spectra from the imagery. Similar to Andrew and Ustin (2008), accessible, discrete patches of one species were used as plots. Forest edges, riparian areas, fields, edges to private property, and trails were surveyed in parks and natural areas from May to August 2013, and in July 2015. In 2015, only large, established patches were used as plots, as these patches would have been present in 2013. GPS locations of patches of plants were recorded. At each plot, a single 1 m by 1 m point was selected to extract the spectra from the CASI imagery. All points were screened against an orthophoto of the study area and points obviously incorrectly positioned removed. In total, there were 108 plots, comprised of 55 randomly selected training and 53 validation plots (Table 3.1). Using the 55 training plots, the mean and standard deviation of the spectra were obtained from the CASI imagery for each species (Figure 3.3).

![Figure 3.2. Example of CASI imagery (red=683 nm, green=588 nm, blue=482 nm) (a) unmasked, and (b) masked by LiDAR data according to height, cover, and shade in Surrey, British Columbia, Canada.](image-url)
Figure 3.3. Locations of the training (yellow) and validation (green) plots for the detection of Himalayan blackberry and English ivy with an orthophoto as a background in Surrey, British Columbia, Canada.
Table 3.2. Plants considered for spectral channel selection and detection in Surrey, British Columbia, Canada and their associated number of plots for training the spectra from the CASI imagery or validation.

<table>
<thead>
<tr>
<th>Species</th>
<th>Training plots</th>
<th>Validation plots</th>
<th>Total plots</th>
</tr>
</thead>
<tbody>
<tr>
<td>Himalayan blackberry (Rubus armeniacus)</td>
<td>23</td>
<td>20</td>
<td>43</td>
</tr>
<tr>
<td>English ivy (Hedera helix)</td>
<td>11</td>
<td>11</td>
<td>22</td>
</tr>
<tr>
<td>Lamium (Lamium galeobdolon)</td>
<td>11</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td>Grasses</td>
<td>10</td>
<td>9</td>
<td>19</td>
</tr>
<tr>
<td>All species</td>
<td>55</td>
<td>53</td>
<td>108</td>
</tr>
</tbody>
</table>

3.2.4 Spectral channel selection

Numerous spectral channel selection algorithms have been proposed, though none have been adopted as a standard (Somers et al. 2011). One recently developed selection technique is the instability index (ISI), which stems from a classification process called stable zone unmixing (SZU; Somers et al. 2010). Traditionally, SZU combines the ISI calculation with a spectral mixture analysis to determine the fractional cover of species per pixel. The ISI process indicates which spectral channels best separate species by minimizing the ratio between within-species and between-species variability. For two species at wavelength $i$, the ISI is calculated as:

$$ISI_i = \frac{\Delta_{within,i}}{\Delta_{between,i}} = \frac{1.96(\sigma_{1,i} + \sigma_{2,i})}{|R_{mean,1,i} - R_{mean,2,i}|}$$ (3.1)

where $R_{mean,1,i}$ and $R_{mean,2,i}$ are mean reflectance values for species 1 and 2, and $\sigma_{1,i}$ and $\sigma_{2,i}$ are the standard deviations of the reflectance values for species 1 and 2. Somers et al. (2010) also developed a multiple-species ISI formula, calculated as:

$$ISI_i = \frac{\Delta_{within,i}}{\Delta_{between,i}} = \frac{m}{m(m-1) \sum_{z=1}^{m-1} \sum_{j=z+1}^{m} 1.96(\sigma_{z,i} + \sigma_{j,i})}{|R_{mean,z,i} - R_{mean,j,i}|}$$ (3.2)
where \( m \) is the number of species, and \( z \) and \( j \) are the species under consideration when comparing more than 2. Somers et al. (2010), Somers and Asner (2013), and Peterson et al. (2015) found that using ISI-derived subsets consistently increased the accuracy of detection of species.

In this paper, the ISI method was applied to reduce the spectral dimensionality prior to the spectral angle mapper (SAM) classification. \( Z \) in Equation (3.2) was held constant as the target species, the species to which the others were compared. Each of the other four species was compared only to the target species. The ISI values were calculated twice; once using Himalayan blackberry as the target species, and once using English ivy. As described by Peterson et al. (2015), channels were selected based on the local minima ISI value. Spectral channels were selected for both the CASI-obtained (aerial-based) spectra and the ASD-resampled (ground-based) spectra, and the subsets were subsequently compared to each other. Spectral channels that were commonly selected by the ground- and aerial-spectra were grouped by proximity to infer responses to specific pigments or leaf structure. As certain wavelengths may be associated with responses to foliar chemistry (Curran 1989), adjacent hyperspectral channels are highly correlated to each other (Delalieux et al. 2007), and the channel width of the CASI imagery and resampled ASD is approximately 10 nm, spectral channels within ± 10 nm of each other are grouped here. This procedure aimed to encompass similar responses within groups.

### 3.2.5 Invasive species detection

The SAM classification (Kruse et al. 1993) is a widely accepted spectral matching algorithm that uses the angle between spectral vectors of a common root wavelength. Smaller differences represent closer spectra. One advantage of the SAM approach, compared to other spectral classification methods is the use of the shape of the spectra rather than the radiance or reflectance,
minimizing the effects of different illumination conditions between samples. Additionally, the user-determined threshold angle is an inherent error metric in SAM, and pixels that have a spectral angle greater than this threshold are unclassified.

The CASI imagery, training areas of the five species in open (unmasked) areas in Surrey, and a threshold spectral angle of 0.1 were inputs into a SAM classification using ENVI (version 5.1, Exelis, McLean, Virginia, USA). This process was run five times: one using all 72 CASI channels, one using the ISI-selected channels from CASI for Himalayan blackberry, one using the ISI-selected from ASD for Himalayan blackberry, one using the ISI-selected channels from CASI for English ivy, and one using the ISI-selected from ASD for English ivy (Figure 3.1).

The SAM classifications produced distribution maps of Himalayan blackberry and English ivy for unmasked areas. The amount of area covered by Himalayan blackberry and English ivy was analyzed by separating the map into areas of parks and non-parks. The accuracy of the maps were then assessed for either Himalayan blackberry or English ivy. A total of 53 validation plots were used (Table 3.1). As these plots are homogeneous within the 1 m CASI pixels, they can be used as presence/absences where a species is present in its associated plots, and absent in plots associated with the other four species. Himalayan blackberry had 20 present plots and 33 absent plots. English ivy had 11 present plots and 42 absent plots. False positive and false negative percentages were calculated from these data.
3.3 Results

3.3.1 Spectra and channel selection

The means of the spectra collected from the ASD in the ground-based protocol had higher reflectance values than the spectra collected from the CASI imagery in the aerial-based protocol, for all species for wavelengths longer than approximately 750 nm (Figure 3.4). Grass was the only species that had overlapping standard deviations between the ground- and aerial-based spectra above 750 nm (Figure 3.4). The ground-based spectra of Himalayan blackberry had a higher reflectance than all other species at wavelengths longer than 700 nm. The ground-based spectra of English ivy overlapped with two other species, and the aerial-based spectra of English ivy overlapped with all other species at wavelengths longer than 700 nm (Figure 3.4). At most of the wavelengths, the ranges of the aerial-based spectra of Himalayan blackberry, English ivy, and lamium overlap almost completely.

For both Himalayan blackberry and English ivy, the ISI spectral channel selection process selected fewer channels from the aerial-based spectra than for the ground-based spectra (Figure 3.5). Five of the 72 channels were selected using the aerial-based spectra, and ten channels were selected using the ground-based spectra for Himalayan blackberry (Figure 3.5). For English ivy, five of the 72 channels were selected using the aerial-based spectra, and eight channels were selected using the ground-based spectra. Within species and between the ground- and aerial-based spectra, there are common selected channels. Himalayan blackberry had four similar channel groups – a common channel at 511 nm, a group of two channels at 559 nm and 569 nm, a group of two channels at 654 nm and 673 nm, and a group of three channels at 1017 nm, 1027 nm, and 1036 nm (Figure 3.5). English ivy also had four channel groups – a common channel at 569 nm,
three channels at 588 nm, 597 nm, and 607 nm, two channels at 683 nm and 693 nm, and two channels at 845 nm and 855 nm (Figure 3.5).

### 3.3.2 Invasive species detection

The SAM classification detected English ivy more accurately than Himalayan blackberry in all spectral channel combinations of the CASI imagery (Table 3.2). For Himalayan blackberry, the highest detection accuracy of 76.4% was achieved when all channels and the ground-based subset were used (Table 3.2). When all channels and the ground-based subset were used, the false positive error was 26.3% and the false negative error was 17.6% (Table 3.2). The aerial-based spectral channel subset decreased the overall accuracy to 61.8%, and increased the false positive error to 46.2% and the false negative error to 32.5% (Table 3.2). For English ivy, the ground-based subset produced the most accurate detection with an accuracy of 80.0% (Table 3.2). Detection using all channels and the aerial-based subset followed at 76.4% and 72.3% respectively (Table 3.2). English ivy had higher false positive rates, but lower false negative rates than Himalayan blackberry for all channel subsets (Table 3.2). Both Himalayan blackberry and English ivy covered a larger proportion of area outside of parks than inside parks for all channel subsets (Table 3.3).
Figure 3.4. Ground-based (ASD) and aerial-based (CASI) means and ±1 standard deviation of spectra, in the spectral resolution of CASI, of the four species used for analysis.
Table 3.2. Species detection accuracies, error rates for Himalayan blackberry (HB; *Rubus armeniacus*) and English ivy (EI; *Hedera helix*) detection in Surrey, British Columbia, Canada for ground-based spectra (ASD) subsets, and aerial-based subsets (CASI).

<table>
<thead>
<tr>
<th>Channel subset</th>
<th>Species</th>
<th>Overall BB accuracy</th>
<th>Overall ivy accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All channels</td>
<td>HB (n=53)</td>
<td>Observed</td>
<td>76.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td></td>
<td>26.3</td>
<td>17.6</td>
</tr>
<tr>
<td></td>
<td>EI (n=53)</td>
<td>Observed</td>
<td>76.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>39</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>17.0</td>
<td>17.0</td>
</tr>
<tr>
<td>HB CASI</td>
<td>HB (n=53)</td>
<td>Observed</td>
<td>61.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>46.2</td>
<td>32.5</td>
</tr>
<tr>
<td>HB ASD</td>
<td>HB (n=53)</td>
<td>Observed</td>
<td>76.4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>26.3</td>
<td>17.6</td>
</tr>
<tr>
<td>EI CASI</td>
<td>EI (n=53)</td>
<td>Observed</td>
<td>72.3%</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>37</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td></td>
<td>62.5</td>
<td>17.8</td>
</tr>
<tr>
<td>EI ASD</td>
<td>EI (n=53)</td>
<td>Observed</td>
<td>80.0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td></td>
<td>% Error</td>
<td>% Error</td>
</tr>
<tr>
<td>Detected</td>
<td></td>
<td>5</td>
<td>5</td>
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<tr>
<td></td>
<td></td>
<td>39</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>37.5</td>
<td>13.3</td>
</tr>
</tbody>
</table>
Table 3.3. Area and proportion of area invaded by Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) in Surrey British Columbia, according to the results of the spectral angle mapper (SAM) classification using all channels, and the aerial- (CASI) and ground-based (ASD) subsets.

<table>
<thead>
<tr>
<th>Species</th>
<th>Himalayan blackberry</th>
<th>English ivy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All channels</td>
<td>CASI</td>
</tr>
<tr>
<td>Proportion of total</td>
<td></td>
<td></td>
</tr>
<tr>
<td>unmasked area invaded</td>
<td>0.06</td>
<td>0.02</td>
</tr>
<tr>
<td>Proportion of area</td>
<td></td>
<td></td>
</tr>
<tr>
<td>invaded in parks</td>
<td>0.02</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Proportion of area</td>
<td></td>
<td></td>
</tr>
<tr>
<td>invaded outside of parks</td>
<td>0.06</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Figure 3.5. Wavelengths corresponding to CASI channels selected through the ISI selection process from the resampled Analytical Spectral Devices (ASD) spectrometer and from the CASI imagery for Himalayan blackberry (*Rubus Armeniacus*) and English ivy (*Hedera helix*) as target species.
3.4 Discussion and conclusions

3.4.1 Spectra and channel selection

The ISI spectral channel selection process is still nascent compared to other spectral channel selection processes (Somers et al. 2011). To our knowledge, only four studies, the introduction of the ISI (Somers et al. 2010) and three others (Somers et al. 2011, Somers and Asner 2013, Peterson et al. 2015) have used the ISI process. Each of these four studies used the ISI process in conjunction with a spectral mixture analysis, a classification in which pixels can be classified as more than one endmember (Goodwin et al. 2005). We first used the ISI algorithm as a standalone spectral channel selection process.

Figure 3.6. Examples of detection of Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) using all channels at two sites, Green Timbers and Crescent Beach, in Surrey, British Columbia, Canada.
selection process, and then applied the selected channels to a SAM classification, utilizing the spectral channel selection in a novel way.

The ISI process selected some similar channel groups between both the aerial- and ground-based spectra (Figure 3.5), each of which may correspond to a similar chemical response. Mutanga et al. (2004) observed the relationships between concentrations of nitrogen, phosphorus, potassium, magnesium, and calcium—all common nutrients in plant tissue—and spectral responses. According to the results of Mutanga et al. (2004), the Himalayan blackberry spectral group at 511 nm could be a response to nitrogen, phosphorus, potassium, or a combination thereof. Also, according to these results, the Himalayan blackberry and English ivy groups between 559 nm and 569 nm could be responses to a lack of nitrogen or potassium. The Himalayan blackberry group at approximately 660 nm may be an electron transition response to Chlorophyll a (Curran 1989). This may additionally be a response to mark the beginning of the red edge. The next channel selected by the ISI for the ground-based Himalayan blackberry spectra is at 712 nm, followed by one at 750 nm (Figure 3.5), the latter of which marks near the end of the red edge and may help differentiate the species (Vaiphasa et al. 2007). The same phenomenon occurs in the English ivy ground-based spectra, as a channel at 693 nm is selected, followed by one at 740 nm (Figure 3.5). For both Himalayan blackberry and English ivy, the aerial-based spectra only has one channel selected immediately before the red edge, and no channels selected immediately after (Figure 3.5). Lastly, the Himalayan blackberry group around 1020 nm may be a response to water, cellulose, starch, or lignin in the plant (Curran 1989). These responses to biophysical properties, which appear to occur more from the ground-based subsets than the aerial-based subsets, are critical in spectral channel selection to ensure the transferability of the channels for future hyperspectral imaging studies of these species.
Despite the fact that the aerial-based spectra has less separation between species compared to the ground-based spectra, fewer spectral channels are selected by the ISI algorithm. Because the channels are selected using the local minimums of the ISI values, this signals a lack of representative channels in certain areas of the aerial-based spectra, especially between 700 and 1000 nm for Himalayan blackberry, and above 850 nm for English ivy (Figure 3.5), which are areas that respond to the internal structure of a leaf (Curran 1989). This indicates that structure between the studied plants may be quite similar or that there are no specific aspects of the structure that invoke a reflectance response causing higher variability between species. The LiDAR-derived cover-shade-height mask applied to the hyperspectral imagery eliminated coarse shading effects and focused the study area to open sites. Additionally, only pure plots of Himalayan blackberry and English ivy are considered for spectra acquisition. Even with these constraints on the data, individual plants in the aerial-based sampling protocol were subject to reflectance variations (Bousquet et al. 2005). Calibration protocol differences between hyperspectral imagery and the ground-based sampling may be responsible for the differences in the spectra between sampling methods within species. The imagery was calibrated using the entire area, whereas the ground-based spectra were calibrated at each site. As discussed here, the source of data for spectral channel selection has some implications on its results. While spectral channel selection greatly reduced the number of channels across the two data sources, the ground-based spectra resulted in the selection of more channels for both Himalayan blackberry and English ivy. As the ground-based subset resulted in higher detection accuracies, this may imply that the aerial-based channel selection reduced the dimensionality of the data to the point that information was removed. As the use of hyperspectral data increases, spectral channel selection will gain popularity. Conditions surrounding its use, such as the data source, need to be tested.
Invasive species detection

Our study extends the use of the ISI algorithm beyond spectral mixture analyses to classification algorithms that predict only one species per pixel, such as SAM. The SAM classification may be advantageous for processing high spatial resolution imagery, including CASI, as many individual plants or clusters of plants encompass at least 1.0 m² in area. Consistent with previous research, the ISI spectral channel selection maintained, or improved, detection accuracy (Somers et al. 2011). However, in our study the results only improved in certain cases. For both Himalayan blackberry and English ivy, the ground-based spectra had more selected channels and detected the species with the same or greater accuracy compared to when all channels were used (Table 3.2). In fact, the aerial-based spectra resulted in lower detection rates than when all channels were used (Table 3.2). These differences in detection accuracy manifested in a range of areas predicted to have Himalayan blackberry and English ivy. The aerial-based subset for Himalayan blackberry resulted in the highest false positive rate (Table 3.2), and also detected the least amount of invasion (Table 3.3), meaning that the areas detected as Himalayan blackberry may be more erroneous than the detection accuracy of 61% suggests. Using all channels and the ground-based subset provided the same accuracies and error rates (Table 3.2) as well as similar areas covered by Himalayan blackberry (Table 3.3), indicating that these results may be more reliable. The fact that for English ivy, the ground-based subset resulted in both the highest false positive rate (Table 3.2) and area detected (Table 3.3), is consistent with more pixels being misclassified as English ivy. More complicated is that using all channels for English ivy detection derived the second highest false positive rate (Table 3.2), but smallest area detected (Table 3.3). This may be reconciled by the higher false negative rate that using all channels produced compared to when the ground-based subset was used (Table 3.2). Beyond the detection accuracies and overall detection areas, the
locations of the invasions have operational considerations. For example, in this paper, differences in the areas invaded between areas inside and outside of parks were investigated. The proportion of area covered by Himalayan blackberry and English ivy outside of parks was consistently higher than that within park boundaries (Table 3.3), likely due to previous eradication efforts on city land but not private property.

The results demonstrate that using a spectral channel subset derived from ground-based spectra is more appropriate for detection of Himalayan blackberry and English ivy. This may be due to limited samples from the aerial-based data, varying atmospheric effects present in the aerial-based data and not the ground based, or both. Limited opportunities for training and validation plots in open areas, particularly for Himalayan blackberry and English ivy, may also restrict some studies to use spectra from ground-based surveys only. Training areas using ground-based spectra can include forested areas so long as each collection is calibrated, increasing the number of plants available for data collection. However, validation data is still limited as these areas should occur in open areas when detecting plants using their spectral properties. While this study is limited to open sites in parks and natural areas, the results highlight important considerations when detecting species based on their spectra. Additionally, the training data can be used to create a city-wide distribution map of Himalayan blackberry and English ivy. This enables park managers to enact preventative measures to ensure that invasive plants are kept out of parks by targeting specific areas across the city. Other municipal departments may have jurisdiction over some of the land and thus can remove plants as well. Future avenues of research could advance the use of LiDAR data to detect Himalayan blackberry and English ivy using structural or habitat characteristics (Andrew and Ustin 2009, Singh et al. 2015). This could potentially increase the detection accuracy while enlarging the study area beyond the unmasked area used in this research. This approach may
work particularly well for English ivy, as individuals often occur in areas of dense vegetation canopies (Clergeau 1992), and thus can increase the amount of available data.
Chapter 4

Detecting Himalayan blackberry and English ivy with LiDAR data and hyperspectral imagery²

4.1 Introduction

Due to the detrimental impacts of invasive plant species, city authorities are required to coordinate programs to control or eradicate the plants. Notably, managers in urban areas are particularly interested controlling invasive species encroachment as human activity is positively related to plant invasions (Pysek 1998, Pimentel et al. 2000, Pysek and Hulme 2005). Specifically, novel habitats and increased habitat disturbance in urban areas provide areas where certain invasive species can thrive (Gundale et al. 2008, Lampinen et al. 2015, Hawthorne et al. 2015). In addition to being the centre for many plant invasions, urban areas are often the most affected by them. As more people migrate to urban areas and existing urban areas are densified, the ecosystem services that urban forests and other urban natural areas provide, namely recreational values, will become increasingly important (Hough 2014). It is therefore critical that the integrity of these urban natural areas is maintained, partially by controlling the spread of invasive plant species.

Detecting invasive species is typically undertaken using field surveys when field crews are available, which may be costly and have inconsistent methodologies over space and time. Additionally, field crews cannot survey large areas enough to develop an accurate map of invasion location. As such, different approaches are needed to monitor and map the distributions of invasive species. Remote sensing technology, specifically, light detection and ranging (LiDAR) data and

²A version of this chapter has been submitted for publication. Chance, C.M., Coops, N.C., Plowright, A.A., Tooke, T.R., Christen, A., Aven, N. 2016. Invasive shrub mapping in an urban environment from hyperspectral and LiDAR-derived attributes.
hyperspectral imagery, can produce maps of the distribution of invasive plant species, augmenting previous detection approaches.

LiDAR alone has been used for species habitat modelling and detection. Andrew and Ustin (2009) used LiDAR data to create wall-to-wall habitat suitability models of an invasive shrub in wetland areas. This study combined LiDAR-derived metrics such as surface elevation, slope, aspect, and curvature with training field plots to produce the suitability models. Singh et al. (2015) mapped the distribution of an understory invasive species in urban forests using various LiDAR-derived topographical predictors as well as LiDAR-derived forest structural characteristics, such as return height variance, standard deviation, and mean to gather information about the various height strata in a stand. Some of these vegetation characteristics were found to be predictors of invasive species presence. While LiDAR data allows for mapping distribution via habitat suitability, it lacks the ability to directly differentiate between species that may occupy similar habitats due to an absence of spectral information.

Hyperspectral imagery excels where LiDAR data is often hindered, by offering a number of spectral channels in the visible (400-700 nm) and near-infrared (700-1350 nm) wavelengths, and narrow spectral channel widths (Adam et al. 2010). Early studies investigating hyperspectral detection of invasive plant species were restricted to mapping with large (up to 20 m²) pixels or to mapping communities of invasive shrubs rather than specific plants (Parker Williams and Hunt 2002, Underwood et al. 2003). More recently Underwood et al. (2006) built upon this previous research and used hyperspectral imagery with an increased spatial resolution to detect individual plants in a scrubland delta in California, USA. Hyperspectral imagery also has also been applied for invasive species in forested areas. Asner and Vitousek (2005) mapped tree invasions by analyzing hyperspectral imagery for nitrogen concentration and relating this concentration to
invasive species presence across their study area in tropical forests of Hawaii. While these studies have shown success, Andrew and Ustin (2008) suggest that environmental context is important when detecting species with hyperspectral imagery, as some species may have similar spectral signatures, but different habitat requirements.

Fusion of LiDAR and hyperspectral technologies has also been successful in mapping invasive species, as when combined they can be used to mask certain areas or provide additional contextual environmental information. Asner et al. (2008) used hyperspectral imagery to identity and map tree species in species-rich Hawaiian rainforests and masked shaded pixels using LiDAR data. Chapter 3 undertook a similar approach by masking densely forested and shaded areas with LiDAR to map the distributions of two understory invasive shrub species on high spatial resolution hyperspectral images. Gu et al. (2015) incorporated environmental information, and mapped gradients of species composition, including invasive species, in urban-rural gradients using hyperspectral imagery and LiDAR-derived structural variables, however, locations of individual species were not mapped.

Despite these advances in modelling and mapping invasive plant species distributions, the use of LiDAR data been restricted to masks or structural and topographic variables when combined with hyperspectral imagery. Techniques developed for modelling direct and diffuse light regimes from LiDAR data in urban areas (see Tooke et al. 2012) may increase model accuracy by providing high resolution, relevant environmental context.

The aim of this chapter is to analyze the use of a combination of LiDAR data and hyperspectral imagery to map the distributions of two invasive plant species, Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*), in the urban area of Surrey, British Columbia, Canada. First, LiDAR data was utilized to map the local solar irradiance conditions
during the growing season in vegetated areas across the city. Second, a spectral classification of the hyperspectral imagery was performed across open areas of the city to map the likely locations of the two species based on their spectral properties. Lastly, a random forest (RF) model was created with LiDAR-derived environmental variables and the results of the spectral classification as inputs to predict the presence and absence of Himalayan blackberry and English ivy. The accuracies of the models were assessed, the importance of model variables and spatial information were analyzed, and implications were discussed.

4.2 Methods

4.2.1 Methods overview

Field plots of Himalayan blackberry and English ivy and other common plants in Surrey were combined with LiDAR data and hyperspectral imagery to map the distribution of Himalayan blackberry and English ivy. Spectral detection of the hyperspectral imagery was conducted producing rule images, indicating the degree to which each pixel matched the target spectra of Himalayan blackberry or English ivy. Multiple layers of environmental variables were then created as input into a binary detection model, including a land cover classification, irradiance model, and other LiDAR-derived variables. Lastly, combinations of the spectral detection results and the environmental variables were used as inputs into the binary detection model to map the distributions Himalayan blackberry and English ivy across the Surrey. The methods are detailed below and illustrated in Figure 4.1.
4.2.2 Field measurements

The presence and absence of Himalayan blackberry, English ivy, and other common plant species in Surrey were recorded by field crews throughout 2012 and 2013 in parks and natural areas. The municipal government sent experts to locate invasive species across the city according to a stratified design that targeted areas known to be susceptible to invasions first. These initial surveyed areas included forest edges, riparian areas, fields, edges to developed properties, and trails. Following the survey of these selected sites, other locations in parks and natural areas across the city were surveyed for invasions. Single points in large, discrete, established patches of pure species separated by least 10 m from another plot were recorded as having either a presence or absence of the two species. After the field survey, plots were randomly categorized as either training or validation, creating 646 training plots (108 Himalayan blackberry, 123 English ivy, and 415 of other species), and 496 validation (160 Himalayan blackberry, 114 English ivy, and 222 of other species) which were used for detection models.

4.2.3 Creation of model variables

4.2.3.1 LiDAR-derived variables

As topography and forest structural characteristics may partially drive understory plant invasions (Royo and Carson 2006), numerous topographic and forest attribute layers were created. Summaries of the vertical LiDAR data distribution were produced across the entire extent of the city, at 1.0 m pixel resolution: a digital elevation model (DEM) of the elevation of the ground, a digital surface model (DSM) of the elevation of the first returns including trees and buildings, 75th (P75), 90th (P90), and 95th (P95) height percentiles, kurtosis of height, skewness of height, coefficient of variation of height, canopy cover and penetration above 2.5 metres, and cover below
2.5 metres (Table 4.1). For cover and penetration, 2.5 m was chosen as a threshold as Himalayan blackberry and English ivy plants that are not vines on trees mostly occur below this height in Surrey.

Slope and aspect were calculated from the DEM. A cosine transformation was applied to aspect to convert the value range from -1 to 1, 1 being north (360º), and -1 being south (180º). Curvature rasters, which describe the concaveness of a surface, were created from the DEM. From the penetration layer, and a measure of distance to open areas was created for each pixel. Pixels with penetration values above 90 % were classified as open areas. Distances to these areas were calculated using Euclidean Distance.

Figure 4.1. Flow diagram showing the use of the LiDAR data, hyperspectral imagery, and field data to detect Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*).
Table 4.1. Variables used as inputs to the random forest models to detect Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) in Surrey, British Columbia, Canada.

<table>
<thead>
<tr>
<th>Variable type</th>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topographic</td>
<td>Digital elevation model (DEM)</td>
<td>Ground height from LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Digital surface model (DEM)</td>
<td>Surface heights from LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Aspect</td>
<td>“Northness,” 1 being north and -1 being south of a pixel on the DEM</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>Slope of a pixel on the DEM</td>
</tr>
<tr>
<td></td>
<td>Curvature</td>
<td>Degree of concavity of a pixel on the DEM</td>
</tr>
<tr>
<td></td>
<td>Plan curvature</td>
<td>Degree of concavity perpendicular to the maximum slope</td>
</tr>
<tr>
<td></td>
<td>Profile curvature</td>
<td>Degree of concavity parallel to the maximum slope</td>
</tr>
<tr>
<td>Vegetation</td>
<td>95th percentile height (P95)</td>
<td>Height of the 95th percentile of LiDAR returns</td>
</tr>
<tr>
<td>attributes and derivatives</td>
<td>90th percentile height (P90)</td>
<td>Height of the 90th percentile of LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>75th percentile height (P75)</td>
<td>Height of the 75th percentile of LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Kurtosis</td>
<td>Kurtosis of the height of LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Skewness</td>
<td>Skewness of the height of LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Coefficient of variation</td>
<td>Coefficient of variation of height of LiDAR returns</td>
</tr>
<tr>
<td></td>
<td>Penetration above 2.5 metres</td>
<td>Proportion of total LiDAR returns in a pixel above 2.5 metres</td>
</tr>
<tr>
<td></td>
<td>Cover below 2.5 metres</td>
<td>Proportion of total LiDAR returns in a pixel below 2.5 metres that are also above ground</td>
</tr>
<tr>
<td></td>
<td>Distance to open area</td>
<td>Distance to area with less than 10% canopy cover</td>
</tr>
<tr>
<td>Spectral</td>
<td>Himalayan blackberry rule image (all channels)</td>
<td>SAM rule image of Himalayan blackberry using all spectral channels</td>
</tr>
<tr>
<td></td>
<td>Himalayan blackberry rule image (channel subset)</td>
<td>SAM rule image of Himalayan blackberry using a subset of spectral channels</td>
</tr>
<tr>
<td></td>
<td>English ivy rule image (all channels)</td>
<td>SAM rule image of English ivy using all spectral channels</td>
</tr>
<tr>
<td></td>
<td>English ivy rule image (channel subset)</td>
<td>SAM rule image of English ivy using a subset of spectral channels</td>
</tr>
<tr>
<td>Land cover classification and derivatives</td>
<td>Land cover classification</td>
<td>7 class land cover classification from the LiDAR data and hyperspectral imagery</td>
</tr>
<tr>
<td></td>
<td>Distance to impervious</td>
<td>Distance to grass as determined by the land cover classification</td>
</tr>
<tr>
<td></td>
<td>Distance to grass</td>
<td>Distance to impervious surfaces as determined by the land cover classification</td>
</tr>
<tr>
<td>Irradiance layers</td>
<td>Direct irradiance</td>
<td>Average daily direct irradiance from the 15th day of each month of the growing season at 3 m by 3m resolution across Surrey</td>
</tr>
<tr>
<td></td>
<td>Diffuse irradiance</td>
<td>Average daily diffuse irradiance from the 15th day of each month of the growing season at 3 m by 3m resolution across Surrey</td>
</tr>
</tbody>
</table>
4.2.3.2 Invasive species and land cover classifications

Hyperspectral imagery was classified for Himalayan blackberry and English ivy presence and absence in open areas (all areas with less than 20% canopy cover above 2.5 m) using a spectral angle mapper classification (SAM; Kruse et al. 1993) rule images with ground-based spectra used as training data. SAM classifications are well-established spectral matching algorithms that classify pixels based on the angle between spectral vectors. Rule images indicate the degree to which the spectral signature of a pixel matches the spectral signature of the target object. Smaller differences between angles represent more closely aligned spectra. As hyperspectral imagery can be processing intensive and contain redundancy in the spectral signals between channels (Clark et al. 2005), a spectral channel selection was applied to test whether or not all channels were needed for accurate classification. The instability index (ISI) channel selection, which maximizes the variation between spectral signals of species and minimizes the variation within them was applied to the ground-based spectra according to Chapter 3. Prior to producing SAM rule images, forested areas were omitted by eliminating pixels with more than 20% cover above 2.5 metres according to the LiDAR-derived canopy cover layer. SAM rule images were produced by classifying the hyperspectral imagery using both the channel subsets and all channels of the ground-based spectra for Himalayan blackberry and English ivy across the open areas of the city completed in ENVI software (version 5.1, Exelis, McLean, Virginia, USA).

As land cover type may an indicator for plant invasions (see Roy et al. 1999, Pearson et al. 2004), a land cover map of Surrey derived by Plowright et al. (2016) was used as a categorical input in the detection models (Figure 4.2). Seven classes, coniferous forest, deciduous forest, grass, bare earth, paved areas, buildings, and water were classified at a 1 m pixel resolution using LiDAR data and hyperspectral imagery. The overall accuracy of this land cover classification was 88.6%
The total surface area of pervious surfaces (coniferous forest, deciduous forest, grass, and bare earth) was 215 km$^2$, 68% of the total area of Surrey.

Figure 4.2. Location of the Surrey, British Columbia, Canada, the land cover classification from Plowright et al. (2016), and the parks and natural areas system across the city.

### 4.2.3.3 Irradiance model

An irradiance model (Figure 4.3) indicating the light regime across the city was applied according to the methods of Tooke et al. (2012) at 3 m by 3 m pixel resolution. In this procedure, the LiDAR returns, the DSM, and the DEM were used in conjunction with solar angles and typical atmospheric conditions to calculate direct and diffuse irradiance on the 15th day of each month between March and October in 2013. Direct irradiance at each hour from 5 am to 10 pm local time was calculated according to the following three steps: atmospheric transmission, viewshed calculation, and
vegetation transmission. Prior to taking these steps, the solar position was calculated according to the ENEA solar position algorithm (Grena 2008) for each time interval.

The atmospheric transmission step calculates the irradiance that penetrates the atmosphere, a function of turbidity and cloud cover. Monthly broad scale (50 km) global turbidity maps were obtained from the National Oceanic and Atmospheric Administration website and the values over Surrey were used as inputs into the model. A clearness index Hammer et al. (2003) describing light transmission through clouds of 0.5 was applied to the model based on values obtained in Tooke et al. (2012) from a nearby weather station.

Second, a viewshed of the effective horizon from the point 2.5 m above the DEM was produced for 36 viewing azimuths. At each pixel and azimuth, the angle of the tallest obstruction within 100 m, whether tree, building, or otherwise, was obtained from the DSM, relative to the orientation and slope of the pixel. This information was used to calculate the sky view factor (SVF), a measure of the directly visible proportion of the sky.

Within vegetated pixels, an extinction coefficient, calculated from the proportion of LiDAR returns at regular height intervals, was determined. A two-parameter Weibull distribution function, previously shown to be capable of characterizing vegetation structure from LiDAR returns (Coops et al. 2007, Tooke et al. 2012), was produced using a vertical scaling parameter, a shape parameter, and the extinction coefficient as inputs.

The diffuse irradiance component was calculated using the diffuse transmissivity function and solar altitude function from Hofierka et al. (2002), which depends on atmospheric turbidity and solar elevation, in conjunction with the SVF (see Tooke et al. (2012) Eq. 9). The two output
layers were the average daily diffuse and direct irradiance during the growing season from March to October with units of MJ m\(^{-2}\) day\(^{-1}\).

Figure 4.3. Average daily direct and diffuse irradiance during the growing season in Green Timbers Urban Forest in Surrey, British Columbia, Canada.

4.2.4 Detection model

4.2.4.1 Development

Two binary random forest (RF) detection models were developed for each species. One model detected species in open areas using SAM rule images and LiDAR-derived variables relevant to open areas, and the second model detected species in areas of canopy cover using only LiDAR-derived variables. RF models create multiple trees using a randomized subset of predictor variables and samples (Breiman 2001). They have been shown to be useful for ecological predictions as they are designed to avoid overfitting data (Breiman 2001, Prasad et al. 2006). In this research, the
model development processes were iterative, as initially all relevant remote sensing predictor variables (Table 4.1) were considered. Using the field plots, correlated and unimportant variables were iteratively removed until only uncorrelated variables with high predictive power remained.

Prior to applying the model to data, two masks were created. Pixels with less than 10% cover below 2.5 m were omitted and dirt, paved areas/rock, buildings, and water were masked using the land cover classification. The RF models were applied to the unmasked areas.

RF classifications do not require independent accuracy assessments as some training data is inherently used as validation data to produce unbiased error estimates (Breiman 2001). However, using this implicit error estimate may inflate the accuracy of the classification in some cases (Millard and Richardson 2015). For detecting Himalayan blackberry and English ivy, the validation data from field plots were used to conduct an independent accuracy assessment. A minimum mapping unit (MMU) of 3 m radius around the validation plots was established since the two irradiance layers had pixels of 3 m resolution. Detection of the species of interest, either Himalayan blackberry or English ivy, within one of these plots counted as a presence in the accuracy assessment, indicating a true positive. Detection in an absence plot was recorded as a presence, and thus a false positive. The same logic applied for true and false negatives.

### 4.2.4.2 Analysis

The RF model results were used to quantify the distributions of Himalayan blackberry and English across the extent of the city and within parks. To examine the coverage of the species across the city, a 10 m by 10 m grid was created and the total area covered by each species as well as the number of grid cells containing the species tabulated. For analyzing the distribution of the species across the parks system, the total area of the species in parks as well as the number of parks
containing the species were tabulated. Additionally, RF classifications provide a probability at each pixel of the output class being correct. To determine Himalayan blackberry and English ivy responses to environmental variables, values for the environmental variables were sampled at locations in the top 2.5% most confidently predicted pixels.

As the distribution of invasions across the city has management implications, clusters and outliers of Himalayan blackberry and English ivy were identified using Anselin Local Moran’s I. Moran’s I is an indicator used to quantify spatial autocorrelation (Moran 1950, Anselin 1995). Anselin Local Moran’s I, which measures local autocorrelation, has proven to be an effective indicator of spatial clustering in ecological studies (see Fu et al. 2014, Swetnam et al. 2015). This metric ranks the abundance of species in each cell of a grid and determines which areas are significantly clustered or separated. At each cell of the 100 m by 100 m grid, the number of pixels with Himalayan blackberry or English ivy invasion was tabulated, creating a measure of abundance. Anselin Local Moran’s I was calculated across the city with $\alpha = 0.05$ for both Himalayan blackberry and English ivy.

4.3 Results

4.3.1 Models

The overall accuracies of the invasive species detection models ranged from 77.8% to 87.8% (Table 4.2). Himalayan blackberry in open areas was detected best, followed by English ivy in open areas (areas with canopy cover less than 20% above 2.5 m), English ivy in closed areas (areas with greater than 20% canopy cover above 2.5 m), and Himalayan blackberry in closed areas (Table 4.2). In open areas, the SAM rule images were ranked as highly important for both Himalayan blackberry and English ivy (Figure 4.4). For both species, the SAM rule image
produced using the subset of spectral channels was chosen over the SAM rule image from all spectral channels (Figure 4.4). Direct irradiance was more important to English ivy detection than to Himalayan blackberry detection in open areas (Figure 4.4). In closed areas, the most important predictor variables - 75th and 95th percentile height, skewness, and the coefficient of variation of height - were concerned with forest structural characteristics (Figure 4.4). Aspect was an important variable in both open and closed areas for both species (Figure 4.4). Land cover classification was ranked as the least important variable in all classifications, however its derivative, distance to impervious surface, was ranked highly for detecting Himalayan blackberry in open areas (Figure 4.4). Figure 4.5 shows the final classification results and Figure 4.6 shows the results at two subsets also highlighted in Chapter 3.

Table 4.2. Accuracy of the random forest models for detecting Himalayan blackberry (Rubus armeniacus) and English ivy (Hedera helix) in open and closed forested areas in Surrey, British Columbia, Canada. Presence and absence data are in number of points collected.

<table>
<thead>
<tr>
<th></th>
<th>Open</th>
<th></th>
<th>Closed</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Himalayan</td>
<td>English ivy</td>
<td>Himalayan</td>
<td>English ivy</td>
</tr>
<tr>
<td></td>
<td>blackberry</td>
<td></td>
<td>blackberry</td>
<td></td>
</tr>
<tr>
<td>Observed</td>
<td>Presence</td>
<td>Absence</td>
<td>Presence</td>
<td>Absence</td>
</tr>
<tr>
<td>Predicted</td>
<td>42</td>
<td>12</td>
<td>81</td>
<td>21</td>
</tr>
<tr>
<td>Presence</td>
<td>3</td>
<td>66</td>
<td>16</td>
<td>78</td>
</tr>
<tr>
<td>Absence</td>
<td>23</td>
<td>6</td>
<td>34</td>
<td>112</td>
</tr>
<tr>
<td>Producer’s</td>
<td>93.3</td>
<td>95.6</td>
<td>70.4</td>
<td>84.2</td>
</tr>
<tr>
<td>accuracy (%)</td>
<td></td>
<td></td>
<td>54.7</td>
<td>93.6</td>
</tr>
<tr>
<td>User’s</td>
<td>77.7</td>
<td>84.6</td>
<td>79.4</td>
<td>76.7</td>
</tr>
<tr>
<td>accuracy (%)</td>
<td></td>
<td></td>
<td>78.8</td>
<td>82.6</td>
</tr>
<tr>
<td>Overall</td>
<td>87.8</td>
<td>80.5</td>
<td>77.8</td>
<td>81.9</td>
</tr>
<tr>
<td>accuracy (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 4.4. Variable importance as expressed by mean decrease accuracy (%) for random forest classifications of Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) distributions in open and closed areas across Surrey, British Columbia, Canada.
Figure 4.5. Detected locations of Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) across Surrey, British Columbia Canada displayed with a 7 m filter and subsets with actual detected areas.
### 4.3.2 Distribution of invasive species

Across the city, Himalayan blackberry covered 1.18 km$^2$ and English ivy covered 1.51 km$^2$ of plan surfaces, corresponding to 0.5\% and 0.7\% of the pervious areas (Table 4.3) and 0.004\% and 0.005\% of the total plan area respectively. Himalayan blackberry was also present in fewer 10 m by 10 m cells than English ivy (Table 4.3). Anselin Local Moran’s I results showed that Himalayan blackberry and English ivy were similarly clustered, with 98.5\% and 99.3\% of 100 m by 100 m grid cells containing either of the species located in clusters (Table 4.4). 1.5\% of grid cells with Himalayan blackberry and 0.7\% of grid cells with English ivy were spatial outliers (Table 4.4). Within parks, Himalayan blackberry covered 0.16 km$^2$ and English ivy covered 0.35 km$^2$, corresponding to 0.8\% and 1.8\% of the pervious surface respectively (Table 4.3). Although the area covered by English ivy was greater than Himalayan blackberry in parks, Himalayan blackberry was present in more parks (Table 4.3).
Figure 4.6. Detected Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) in Green Timbers Urban Forest and at Crescent Beach in Surrey, British Columbia, Canada.

In addition to differing in their spread across the city and parks systems, Himalayan blackberry and English ivy invasions differed in their relationships to forest types, irradiance, and roads. Himalayan blackberry was found more often in deciduous closed areas than in coniferous closed areas (Figure 4.8). The opposite was true of English ivy. In both open and closed areas, Himalayan blackberry did not have a strong relationship to direct irradiance, whereas English ivy occurred at areas with less direct irradiance (Figure 4.7). Himalayan blackberry and English ivy in open areas occurred mostly on sites with low slope values (Figure 4.7). Himalayan blackberry and English ivy in closed areas occurred most at areas of low slope or high slope, with relatively less proportional area covered between slopes of 15° and 30° for English ivy and between 25° and 45° for Himalayan blackberry (Figure 4.7). The high rate of occurrences of English ivy and Himalayan blackberry at low profile curvature values indicates that the species prefer areas with high convexity (Figure 4.7). However, English ivy in closed areas has a second peak at high profile curvature values (Figure 4.7). English ivy occurred sites that faced south, whereas Himalayan blackberry occurrence differed in open and closed areas, with more occurrences in northerly aspects in closed areas and no strong relationship to aspect in open areas (Figure 4.7). The absolute amount of Himalayan blackberry and English ivy decreased as the distance from roads increased, yet when this area was considered proportionally to the area, there were no relationships between invasive species occurrence and the distance to a road at areas less than 500 m from a road (Figure 4.9). Areas further than 500 m away from road had proportionally higher rates of invasion than areas within 500 m of a road (Figure 4.9).
Table 4.3. Total area covered across the parks system and the city, and number of parks and 10 m by 10 m cells covered by English ivy (*Hedera helix*) and Himalayan blackberry (*Rubus armeniacus*) in Surrey, British Columbia, Canada. Number of cells (N) = 1179195 for Himalayan blackberry and N = 1507252 for English ivy.

<table>
<thead>
<tr>
<th></th>
<th>Himalayan blackberry</th>
<th>English ivy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parks</td>
<td>Total area (km²)</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Proportion of parks with occurrence</td>
<td>90.8</td>
</tr>
<tr>
<td>City</td>
<td>Total area (km²)</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>Proportion of cells with occurrence</td>
<td>85.0</td>
</tr>
</tbody>
</table>

### 4.4 Discussion and conclusions

Few studies have mapped the distribution of invasive shrub species in complex urban areas using remotely sensed products. In one of these studies, Singh et al. (2015) mapped an invasive shrub in Charlotte, North Carolina at a 5 m by 5 m resolution using LiDAR data and a RF classifier and achieved overall accuracies between 81% and 89%. The results of this study were similar to those found in Singh et al. (2015) with overall classification accuracies of 77.8% and 87.8% (Table 4.2). However, the current study mapped invasions at a 1 m pixel resolution, indicating that highly accurate invasion maps can be produced at fine spatial resolutions.

Table 4.4. Percent of area invaded by Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) in significant clusters and outliers as determined by Anselin’s Local Moran’s I in Surrey, British Columbia, Canada.

<table>
<thead>
<tr>
<th>Percent of invaded area</th>
<th>Himalayan blackberry</th>
<th>English ivy</th>
</tr>
</thead>
<tbody>
<tr>
<td>In clusters</td>
<td>98.5</td>
<td>99.3</td>
</tr>
<tr>
<td>In outliers</td>
<td>1.5</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Figure 4.7. Histogram of proportion of pervious surface covered at values of topographic wetness index, slope, cosine of aspect (“northness”), direct radiation, and profile curvature at locations where Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) occur in open and closed areas of Surrey, British Columbia, Canada.
Figure 4.8. Percent of area covered by Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) in deciduous and coniferous forests in Surrey, British Columbia, Canada. Number of cells (N) = 1179195 for Himalayan blackberry and N = 1507252 for English ivy.

Open areas were classified with higher accuracies than closed areas for both Himalayan blackberry and English ivy. This is likely due to the inclusion of the rule images from the hyperspectral imagery in the model. The SAM rule images provided a continuous variable on which the RF model could base decisions. Other SAM classifications, such as that classifying Himalayan blackberry and English ivy in Chapter 3 transform the continuous rule image into a binary classification image by defining a threshold SAM value, below which is classified as presence and above which is classified as absence. By keeping the classification results as continuous, the RF model had greater flexibility in defining this threshold based on the values of the other predictor variables.

For both Himalayan blackberry and English ivy, the SAM rule images were highly ranked as important (Figure 4.4). More specifically, the SAM rule images produced from the subset of
spectral channels were chosen for the final models rather than those produced with all channels as they were ranked as more important. This is consistent with previous results comparing detection accuracies of different channel selections. For example, Chapter 3 found that a subset of spectral channels performed better in some cases than using all channels to map Himalayan blackberry and English ivy.

Figure 4.9. Proportion and area covered by Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*) related to the distance from roads in Surrey, British Columbia, Canada.
Direct irradiance was more highly ranked than diffuse irradiance, hence it being included in the final models. Direct irradiance was also highly ranked for English ivy detection in open areas (Figure 4.4). Consistent with the known habitat preferences of the species of cooler, shaded areas for English ivy and open areas for Himalayan blackberry (Clergeau 1992, Gaire et al. 2015), Himalayan blackberry preferred areas with more direct irradiance than English ivy (Figure 4.7), indicating that when in open areas, English ivy still established in shaded locations. Direct irradiance was likely important for determining the areas of English ivy in open areas due to the limited sites at which direct irradiance conditions suit English ivy in open areas.

Forest structural characteristics were most important in closed areas for both species (Figure 4.4). This contrasts Singh et al. (2015), which found topographic variables to be the most important predictors. While Himalayan blackberry and English ivy distributions may be more related to forest structural characteristics than topographic ones, the different pixel resolutions between the two studies may account for this. Furthermore, Gu et al. (2015) used a pixel size of 20 m to map forest composition with LiDAR-derived forest structural variables and hyperspectral imagery, and found that the imagery was more important for their purposes, perhaps due to the limitations caused by the large pixel size. The finer resolution used in this study may permit detecting the influence that Himalayan blackberry and English ivy have on forest structure.

As English ivy covered more areas in parks and across the city than Himalayan blackberry, but was present in a proportionately smaller number of parks and grid cells (Table 4.3), English ivy was likely more clustered than Himalayan blackberry. Anselin Local Moran’s I results did not corroborate this however as the number of 50 m by 50 m grid cells that were considered parts of Himalayan blackberry or English ivy clusters were similar for the two species (Table 4.4). It is logical that English ivy is clustered when considering its habitat preferences. As English ivy
prefers coniferous forests (Clergeau 1992; Figure 4.6), its potential range is limited to a few patches across the city.

The land cover classification was ranked as the variable with the lowest importance in all models (Figure 4.4). Because water, paved areas, and buildings were masked, only coniferous forests, deciduous forests, and areas of grass were considered in the RF model. The spatial breadth of these classes may have contributed to the low importance of the land cover classification, as other variables could likely better explain the distributions of the invasions. However, analysis of the locations of the invasions found that Himalayan blackberry and English ivy differed in abundance between deciduous and coniferous forests (Figure 4.8), with Himalayan blackberry showing a preference for deciduous forests and English ivy for coniferous forests, consistent with the habitat preferences of the two species (Clergeau 1992, Gaire et al. 2015).

Analysis of the distance between roads and invasion showed that both absolute coverage of Himalayan blackberry and English ivy was inversely related to the distance from roads (Figure 4.9). These results have management implications, as they indicate target areas for city managers to direct resources towards curbing the spread of invasion. Additionally, targeting areas near roads may be relatively low effort as field crews can access invasion patches without travelling far into urban natural areas. However, when considered proportionally, the area covered by Himalayan blackberry and English ivy was not related to the distances from roads (Figure 4.9). This contradicts previous research corroborates, which shows positive relationships between Himalayan blackberry and English ivy presence and roads in urban and suburban areas (Clarke et al. 2006, Gaire et al. 2015). The differences may be due to the study systems, as Surrey does contain many parks where both species can invade using ways other than roads.
Chapter 5

Conclusions

5.1 Overview

As more people move into urban areas, maintaining the integrity of urban greenspaces will become increasingly important. Invasive plant species may decrease both biodiversity and the well-being of users of these areas. As such, city authorities must control invasive plants effectively and efficiently. Remote sensing technologies, specifically light detection and ranging (LiDAR) data and hyperspectral imagery provide an opportunity to map plant invasions at a fine spatial resolution across a large area. Despite the history of success of mapping plant invasions using these technologies, mapping understory plant invasions in urban areas is largely unexplored. This thesis combined these two technologies to successfully map two invasive plant species, Himalayan blackberry (*Rubus armeniacus*) and English ivy (*Hedera helix*), across Surrey, British Columbia, Canada at a 1 m pixel size. The results of this study may contribute to management decisions about removing invasive plants. Key findings of the four guiding research questions were:

1) Can Himalayan blackberry and English ivy be distinguished from each other, and from other common native and invasive species based on hyperspectral data?
   a) What are the spectral properties of Himalayan blackberry and English ivy?

Chapter 3 addressed the spectral characteristics of Himalayan blackberry and English ivy by using an ISI spectral channel selection to select key wavelengths that differentiate the two species from
each other and other species in Surrey. Additionally, the spectral curves obtained from both ground-based (ASD) and aerial-based (CASI) sources were compared.

Both Himalayan blackberry and English had distinct sets of wavelengths selected from either the ground-based spectra or the aerial-based spectra. These spectra are related to physiological properties of the plants. For example, the wavelengths selected around 511 nm for Himalayan blackberry is likely a response to nitrogen, phosphorous, potassium, or any combination. The responses from both species at wavelengths just smaller than 750 nm were likely related to the changes in chlorophyll absorption and leaf structure.

Analyses of the spectral curves of the species showed that ground-based spectra had, on average, higher reflectance values than the aerial-based spectra for both species. Additionally, analyses showed that the ground-based spectra produced less overlap between species than the aerial-based spectra.

1) Can Himalayan blackberry and English ivy be distinguished from each other, and from other common native and invasive species based on hyperspectral data?

b) Which method(s) allow(s) distinction between the two species and others?

Chapter 3 also addressed and compared methods of detecting and mapping Himalayan blackberry and English ivy using hyperspectral imagery. LiDAR data was used to omit forested and shaded areas from analyses, allowing only spectra from open, sunlit areas to be considered. This ensured that training data for the mapping exercise was not contaminated with spectra from taller shrubs or trees, and was in as uniform lighting conditions as possible. Next, reflectance values from the
wavelengths in the spectral channel subsets obtained in the previous research question were extracted from the hyperspectral imagery. These spectra were used as target spectra for a spectral angle mapper (SAM) classification. The SAM classification classified each unmasked pixel of the hyperspectral imagery as Himalayan blackberry and English ivy presence or absence depending on how closely its spectra matched the target spectra of the two species. This process determined good practices for distinguishing and identifying the two species on the hyperspectral data.

The overall classification accuracies ranged from 61.8% to 76.4% for Himalayan blackberry and from 72.3% to 80.0% for English ivy. For both species, the subset of spectral channels from the ground-based spectra performed best. The resulting map showed that for both species a larger proportion of area was invaded outside of parks than inside parks. The map also showed that Himalayan blackberry and English ivy covered 0.02% to 0.06% and 0.02% to 0.04% of open, unshaded areas respectively.

2) Can Himalayan blackberry and English ivy be detected in Surrey, British Columbia using hyperspectral imagery and LiDAR data?

   a) Which LiDAR-derived variables are critical to determine the presence and absence of each species?

Chapter 4 mapped Himalayan blackberry and English ivy across the entire city, both in forested and open areas. Hyperspectral imagery and LiDAR-derived variables, such as slope, aspect, curvature, topographic wetness, and irradiance were used as inputs into random forest models that classified each as pixel as present or absent for both Himalayan blackberry and English ivy.
Separate models were created for forested and open areas. The RF models ranked the importance of each variable. Additionally, this study analyzed the responses to the most important variables.

The important variables differed between species and open and forested areas. Slope was more important to Himalayan blackberry than it was to English ivy, and aspect was important to both species. For both Himalayan blackberry and English ivy in forested areas, metrics of height and height variation were important. Direct irradiance was important to English ivy in open areas, likely because it prefers darker sites which are seldom in open areas, restricting its potential habitat in these areas.

2) Can Himalayan blackberry and English ivy be detected in Surrey, British Columbia using hyperspectral imagery and LiDAR data?

b) How much area of Surrey is currently covered by the two species?

The RF models created in Chapter 4 mapped Himalayan blackberry and English ivy across the entire city. The total areas covered by these two species was calculated and the distributions of the areas were analyzed.

Himalayan blackberry covered 1.18 km$^2$ and English ivy covered 1.51 km$^2$ of the plan area of the city, corresponding to 0.004% and 0.005% respectively. The addition of the LiDAR data decreased the relative area in which the two invasive species were detected when compared to detection using only the hyperspectral imagery. English ivy covered more area in parks than Himalayan blackberry. Despite the smaller area covered, Himalayan blackberry was found in more parks than English ivy. Anselin Local Moran’s I analysis showed that the abundances of both
species were significantly auto-correlated throughout most of the area they covered. Lastly, the areas covered by both species decreased as the distance from a road increased.

5.2 Research innovations

This thesis provided multiple innovations for detecting plant invasions:

- The instability index (ISI) spectral channel selection, a recently developed method, was used to select spectral channels that best distinguished invasive plants from each other and other species in Chapter 3. Spectral channel selections from ground-based spectra and from aerial-based spectra were compared to determine which was most suitable for mapping plant invasions.

- An irradiance model was created and applied within an invasive species detection model in Chapter 4.

- Hyperspectral imagery and a spectral classification were combined with LiDAR data in Chapter 4 at a fine spatial resolution to map invasive shrub species.

- Understory plant invasions were mapped at 1 m pixel resolution across an entire city in open and forested areas using novel modelling approaches and remote sensing fusion in Chapter 4. The resulting maps from Chapter 4 were analyzed to demonstrate spatial relationships between environmental variables and invasive species distribution. These analyses showed the capabilities of LiDAR-derived variables to advance our understanding of plant invasions.
5.3 Limitations

While the results are accurate, they may not be accurate for all occurrences of Himalayan blackberry and English ivy in Surrey. First, training areas for both spectral detection in Chapter 3 and combined LiDAR and hyperspectral models in Chapter 4 consisted of established, mature, plants in relatively large patches. Consequently, juvenile and recently-established plants, which may have a different spectral signature than mature plants (Hoflacher and Bauer 1982), may not be detected as well. Additionally, plants that cover less than 1 m² may not be detected. One solution to the latter issue is to use spectral unmixing analyses which can determine the fraction of a pixel covered by a species. However, this approach may require a spectral library of all plants in Surrey that could be in the same pixel as Himalayan blackberry or English ivy.

A second limitation relates to the spatial extent of the results. As all training points for both Chapter 3 and Chapter 4 were collected on public parks and natural areas, there is a data gap on private lands. While the spectra of the plants is unlikely to change between publicly and privately managed areas, the human component of plant invasions will (see Roura-Pascual et al. 2009). Plant invasions on public lands are monitored and removed strategically, whereas plants may be removed any time on private lands. As the training data for the environmental variables was from publicly managed areas, the accuracy of the maps may not be as high in privately managed forests.

Lastly, LiDAR-derived variables used were based on knowledge of niches of Himalayan blackberry and English ivy. As such, potentially important habitat predicates may have been omitted from the study due to the potentially limited extent of knowledge about the habitats of the two species. This study is not meant to discover new habitat preferences for Himalayan blackberry and English ivy, but future studies could attempt that by using LiDAR-derived variables that are not known to be important in determining the habitats of the species.
5.4 Directions for future work

Benefits of using a fusion of LiDAR data and hyperspectral imagery to detect plant invasions in urban areas are evident from this thesis, and there is potential to expand upon this research. In addition to exploring more LiDAR-derived variables, other future studies should focus efforts on closing the aforementioned research gaps as well as expanding on the data sources available.

To locate juvenile invasive plants, researchers could collect species location data and include a class relating to the life stage of the plant. Separate models could be created to detect mature species and juvenile species, providing a more complete representation of where plant invasions occur on the landscape. To map species at an even higher specificity, researchers, in conjunction with city employees, can collect spectral signatures of many different plant species. This would allow for spectral unmixing approaches, facilitating detection of extremely small plant invasions.

The hyperspectral imagery in this study was taken when some deciduous trees had leaves. Acquiring hyperspectral imagery during leaf-off conditions would allow researchers to use spectral analyses to detect understory plants in deciduous forests. Additionally, collecting LiDAR data in leaf-off conditions may allow patches of understory shrubs to be better discriminated (Hill and Broughton 2009). This type of analysis has not yet been undertaken for understory plant invasions.

Providing accurate maps of plant invasions on privately-owned and -managed lands is critical to predicting where future invasions may occur. It is recommended that researchers strive to acquire as much data possible in these areas about the locations, patch size, and age of invasive
species. Asking residents for permission to collect data on their land is one way to accomplish this. Another is to crowdsource the data. Hawthorne et al. (2015) demonstrated the feasibility of using smartphone and tablet programs to crowdsource data collection about invasive plants in urban areas. The next step is to integrate this data with remotely-sensed data to provide wall-to-wall maps of plant invasions in a novel manner.
**References**


Appendix 1

A MAP OF HIMALAYAN BLACKBERRY AND ENGLISH IVY PRODUCED FROM REMOTELY SENSED DATA FOR THE CITY OF SURREY

A city wide map of Himalayan blackberry and English ivy was produced using LIDAR (light detection and ranging) data and hyperspectral imagery from 2013. The process involved using existing field plots to develop a model that predicted 1 metre pixels as having either Himalayan blackberry, English ivy, or neither.

METHODS

LIDAR variables:
- Aspect
- Slope
- Landscape shape
- Landscape moisture
- Vegetation height
- Height distribution
- Cover
- Sunlight

Hyperspectral variables:
- Reflectance

RESULTS AND MANAGEMENT

The accuracies for Himalayan blackberry were 87.8% in open areas, 77.8% in forested areas, and 81.1% across the entire city. The accuracies for English ivy were 82.1% in open areas, 81.9% in forested areas, and 81.9% overall.

The 1 by 1 m grid is a fine-scale resolution that may not be necessary for invasive species management purposes. The results could be scaled to a 5 by 5 m pixel resolution and still be useful for invasive species managers. However, it is important that the process outlined here is undertaken at a 1 m pixel resolution to ensure that hyperspectral signal is 'pure' (i.e. not mixed with other species) and that LIDAR data is meaningful for such fine-scale modelling.

MORE INFORMATION AND CONCLUSIONS

LIDAR data and hyperspectral imagery can accurately map the occurrence of Himalayan blackberry and English ivy across Surrey. This map allows managers to focus field campaigns to areas of occurrence, visit areas where invasive species do not occur less often, and provides statistics about location and environmental context of occurrence.

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