SURFACE WATER CLASSIFICATION AND MONITORING USING POLARIMETRIC SYNTHETIC APERTURE RADAR

by

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Abstract

Surface water classification using synthetic aperture radar (SAR) is an established practice for monitoring flood hazards due to the high temporal and spatial resolution it provides. Surface water change is a dynamic process that varies both spatially and temporally, and can occur on various scales resulting in significant impacts on affected areas. Small-scale flooding hazards, caused by beaver dam failure, is an example of surface water change, which can impact nearby infrastructure and ecosystems. Assessing these hazards is essential to transportation and infrastructure maintenance. With current satellite missions operating in multiple polarizations, spatio-temporal resolutions, and frequencies, a comprehensive comparison between SAR products for surface water monitoring is necessary. In this thesis, surface water extent models derived from high resolution single-polarization TerraSAR-X (TSX) data, medium resolution dual-polarization TSX data and low resolution quad-polarization RADARSAT-2 (RS-2) data are compared. There exists a compromise between acquiring SAR data with a high resolution or high information content. Multipolarization data provides additional phase and intensity information, which makes it possible to better classify areas of flooded vegetation and wetlands. These locations are often where fluctuations in surface water occur and are essential for understanding dynamic underlying processes. However, often multipolarized data is acquired at a low resolution, which cannot image these zones effectively. High spatial resolution, single-polarization TSX data provides the best model of open water. However, these single-polarization observations have limited information content and are affected by shadow and layover errors. This often hinders the classification of other land cover types. The dual-polarization TSX data allows for the classification of flooded vegetation, but classification is less accurate compared to the quad-polarization RS-2 data. The RS-2 data allows for the discrimination of open water, marshes/fields and forested areas. However, the RS-2 data is less applicable to small scale surface water monitoring (e.g. beaver dam failure), due to its low spatial resolution. By understanding the strengths and weaknesses of available SAR technology, an appropriate product can be chosen for a specific target application involving surface water
change. This research benefits the eventual development of a space-based monitoring strategy over longer periods.
Co-Authorship

The thesis “Surface water classification and monitoring using polarimetric synthetic aperture radar” is a product of the research conducted solely by the author Katherine Irwin. Dr. Alexander Braun and Dr. Georgia Fotopoulos provided supervision, advice and editorial assistance. Dr. Alexander Braun and Dr. Georgia Fotopoulos are co-authors on all manuscripts listed below. Danielle Beaulne is a co-author on the first manuscript and Achim Roth (DLR) is a co-author on the second manuscript.

*Manuscripts published, under review and in preparation:*


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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
</tr>
<tr>
<td>PolSAR</td>
<td>Polarimetric Synthetic Aperture Radar</td>
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<tr>
<td>TSX</td>
<td>TerraSAR-X</td>
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<tr>
<td>RS-2</td>
<td>RADARSAT-2</td>
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<td>QUBS</td>
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<tr>
<td>WV-2</td>
<td>WorldView-2</td>
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<tr>
<td>SEASAT</td>
<td>Sea Surveillance Satellite</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
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<tr>
<td>HH</td>
<td>Horizontal linear transmission and Horizontal linear reception</td>
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<td>SLC</td>
<td>Single Look Complex</td>
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<td>Shuttle Radar Topography Mission</td>
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<td>Japanese Earth Resources Satellite</td>
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<td>Advanced Synthetic Aperture Radar</td>
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<td>ALOS</td>
<td>Advanced Land Observing Satellite</td>
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<td>PALSAR</td>
<td>Phased Array type L-band Synthetic Aperture Radar</td>
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<td>COSMO-SkyMed</td>
<td>Constellation of small Satellites for Mediterranean basin Observation</td>
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<td>Radar Imaging Satellite</td>
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<td>ALS</td>
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<td>Incidence angle</td>
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<td>R</td>
<td>Slant range</td>
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<td>( \overrightarrow{E}_S )</td>
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<td>( P_R )</td>
<td>Power received</td>
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<tr>
<td>Symbol</td>
<td>Definition</td>
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<tr>
<td>$P_T$</td>
<td>Power transmitted</td>
</tr>
<tr>
<td>$G_T$</td>
<td>Antenna gain</td>
</tr>
<tr>
<td>$A_{ER}$</td>
<td>Effective aperture of the receiving antenna</td>
</tr>
<tr>
<td>$r_T$</td>
<td>Distance between the transmitting system and the target</td>
</tr>
<tr>
<td>$r_R$</td>
<td>Distance between the target and the receiving system</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Elevation angle</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Radar cross section</td>
</tr>
<tr>
<td>$\sigma_0$</td>
<td>Scattering coefficient or “sigma-naught”</td>
</tr>
<tr>
<td>$A_0$</td>
<td>Area</td>
</tr>
<tr>
<td>$\varepsilon_r$</td>
<td>Dielectric constant</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Permittivity</td>
</tr>
<tr>
<td>$\varepsilon_0$</td>
<td>Free space permittivity</td>
</tr>
<tr>
<td>$AB$</td>
<td>Width of the layover zone</td>
</tr>
<tr>
<td>$CD$</td>
<td>Width of the shadow zone</td>
</tr>
<tr>
<td>$h_1$</td>
<td>Height of obstruction 1</td>
</tr>
<tr>
<td>$h_2$</td>
<td>Height of obstruction 2</td>
</tr>
<tr>
<td>$E_S$</td>
<td>Jones vectors of the scattered</td>
</tr>
<tr>
<td>$E_I$</td>
<td>Jones vectors of the incident waves</td>
</tr>
<tr>
<td>$e^{-jkr}$</td>
<td>Propagation affects term</td>
</tr>
<tr>
<td>$r$</td>
<td></td>
</tr>
<tr>
<td>$[S]$</td>
<td>Scattering matrix</td>
</tr>
<tr>
<td>$S_{HH}$</td>
<td>Complex scattering coefficient horizontal transmission and horizontal reception</td>
</tr>
<tr>
<td>$S_{HV}$</td>
<td>Complex scattering coefficient horizontal transmission and vertical reception</td>
</tr>
<tr>
<td>$S_{VH}$</td>
<td>Complex scattering coefficient vertical transmission and horizontal reception</td>
</tr>
<tr>
<td>$S_{VV}$</td>
<td>Complex scattering coefficient vertical transmission and vertical reception</td>
</tr>
<tr>
<td>$[T3]$</td>
<td>Coherency matrix</td>
</tr>
<tr>
<td>$[C3]$</td>
<td>Covariance matrix</td>
</tr>
<tr>
<td>$[K]$</td>
<td>Kennaugh matrix</td>
</tr>
<tr>
<td>$K_{0-9}$</td>
<td>Kennaugh elements</td>
</tr>
<tr>
<td>$k_{0-9}$</td>
<td>Normalized Kennaugh elements</td>
</tr>
</tbody>
</table>
A  Single or off bounce scattering (Pauli decomposition)
B  Volume scattering (Pauli decomposition)
C  Double or even bounce scattering (Pauli decomposition)
H  Entropy (H-Alpha Decomposition)
A  Alpha (H-Alpha Decomposition)
[T2]  Coherency matrix for dual-polarization data
Coastal  Band 1 of WorldView-2 band multispectral imagery
NIR2  Band 2 of WorldView-2 band multispectral imagery
Red  Band 8 of WorldView-2 band multispectral imagery
Chapter 1

Introduction

1.1 Motivation

Changes of surface water are a dynamic process affected by interactions in the Earth systems. Surface water can fluctuate in both time and space and at different scales. The change of surface water can affect local and global ecosystems, and can pose hazards to manmade infrastructure. For example, the outburst floods caused by failed beaver dams pose significant hazards to transportation corridors and infrastructure. In 1984 in Vermont, USA, the water released from the collapse of several beaver dams damaged a drainage culvert and railroad embankment. This damage resulted in a passenger train derailment killing five people and injuring 149. In 1994, an outburst flood in Alberta, Canada, produced a flood wave 3.5 times the maximum discharge recorded for that creek and resulted in the destruction of five hydrometric stations downstream (Butler and Malanson, 2005; Butler, 1989). More recently, in 2016, a two-metre high beaver dam collapse caused a 9 m section of the Cataraqui Trail in Ontario, Canada to be completely washed out. This trail was built and maintained on an old railway line, demonstrating the extent of damage such hazards can pose to critical infrastructure. Photos of the beaver dam, pond and trail, as well as a photogrammetry model of the trail failure, can be seen in Figure 1.1. Flooding hazards posed by dam failure are one example of a small-scale, quickly occurring change of surface water that can significantly impact local ecosystems and infrastructure.
Figure 1.1. Field investigation photos from April 2016 beaver dam collapse: (A) beaver dam; (B) pond where water was held; (C) washed out area of Cataraqui trail; (D) photogrammetry model of trail failure.

Due to fluctuating spatial and temporal changes of surface water, it is important to develop a monitoring strategy, which can be used to document changes. Besides the established in situ monitoring tools, remote sensing technologies, such as synthetic aperture radar (SAR), light detection and ranging (LiDAR) and optical imagery, can be used to monitor diverse surface targets of multiple scales with relatively homogeneous coverage and ever increasing spatial resolution. Each of the aforementioned technologies have unique strengths and weaknesses that must be considered before application. For monitoring surface water, polarimetric synthetic aperture radar (PolSAR) is a viable technology. Several studies have shown the ability of single-polarization SAR
to successfully classify open water (Giustarini et al., 2015; Imhoff et al., 1987; Kuenzer et al., 2013; Liu and Jezek, 2004; Martinis et al., 2015a, 2009; Mason et al., 2010, 2007; Matgen et al., 2007; Schlaffer et al., 2015; White et al., 2015, 2014). With the additional phase and intensity information acquired from dual-polarization data, surface water can be further classified into areas of open water and flooded vegetation (Moser et al., 2016; Schmitt and Brisco, 2013; Schmitt et al., 2012b). Finally, quad-polarization data can provide all four channels of polarimetric information which allows for the discrimination of scattering mechanism and the differentiation of marsh areas, fields, and open water (Gallant et al., 2014; S. H. Hong et al., 2015). With current SAR missions operating in multiple polarizations, spatio-temporal resolutions, and frequencies, a comparison between SAR products for surface water monitoring is necessary.

In this study, the feasibility of using SAR data to monitor water extent change for the purpose of small-scale flooding hazards is tested. Water bodies on the scale of tens to hundreds of metres are classified using two SAR acquisition systems, namely TerraSAR-X (TSX) and RADARSAT-2 (RS-2). Single, dual and quad-polarization SAR is used to classify surface water through time and multiple processing techniques are evaluated. Multispectral imagery, LiDAR and in situ field observations are also used to compare, enhance and validate the created surface water models. Surface water is monitored at two distinct locations, documenting the spatio-temporal change.

1.2 Study Area and Data Description

Two study areas were investigated in this thesis. The first study area, discussed in Chapters 3 and 5, is located at the Queen’s University Biological Station (QUBS) in Kingston, Ontario, Canada. QUBS was chosen due to the abundance of natural land cover including water bodies and marshland that vary in size and are seasonally flooded. Four different types of remote sensing data were acquired over QUBS: TSX single-polarization SAR data, RS-2 quad-polarization SAR data,
airborne LiDAR data and WorldView-2 (WV-2) multispectral imagery. This study area is a 2 km by 2 km square where these datasets overlap as seen in Figure 1.2.

Figure 1.2. Map showing the extent of TSX data (dark blue), RS-2 data (green), airborne LiDAR survey (red), WV-2 imagery (yellow), the study area (black), lakes (light blue) and land (white) mapped by the Ontario Ministry of Natural Resources, located north of Kingston, ON, Canada (black star).

The second study area, discussed in Chapter 4, is located south of Lac-Simon in Quebec, Canada. This area was chosen because it is a principally natural landscape with open water bodies, marshlands and streams. The 6 km by 12 km study area is centered on the Ruisseau Schryer, which floods during snow melt each year. Two different types of remote sensing data were acquired over
this study area: TSX dual-polarization SAR data and Landsat 8 multispectral imagery (Figure 1.3).

More details on the study areas and data acquired can be seen in Chapters 3 to 5.

![Map showing the extent of TSX data (blue), Landsat 8 imagery (yellow) and the study area (white), shown over Google Earth imagery, located north east of Ottawa, ON, Canada (white star).](image)

**Figure 1.3.** Map showing the extent of TSX data (blue), Landsat 8 imagery (yellow) and the study area (white), shown over Google Earth imagery, located north east of Ottawa, ON, Canada (white star).

**1.3 Thesis Objectives**

There are three main research objectives in this thesis, which aim to expose the capabilities and limitations of PolSAR as a small-scale surface water monitoring tool, namely:

1. Perform surface water classification using high resolution single-polarization TSX data and fuse with WV-2 multispectral imagery and airborne LiDAR models in order to understand the capabilities and limitations of each sensor’s data.
2. Perform surface water classification using medium resolution dual-polarization TSX data and compare to medium resolution single-polarization TSX data in order to understand the capabilities and limitations of each product and method.

3. Perform surface water classification using low resolution quad-polarization RS-2 data and compare to high resolution single-polarization TSX data in order to understand the capabilities and limitations of each product and method.

1.4 Thesis Outline

The first two chapters (Introduction and Literature Review) provide motivation and background information to better understand the content presented in Chapters 3 to 5. Chapters 3 to 5 are written in manuscript format, and each chapter exists as an independent study. Chapter 3 investigates the fusion of single-polarization SAR data with other remote sensing techniques (optical and LiDAR) for improved surface water classification, primarily addressing the first thesis objective. Chapter 4 provides a comparison of dual-polarization and single-polarization SAR for surface water classification focusing on the advantages and limitations, primarily addressing the second thesis objective. Chapter 5 investigates the use of quad-polarization SAR for surface water classification in comparison with single-polarization data, primarily addressing the third thesis objective. Finally, Chapter 6 summarizes the main conclusions as they pertain to the research objectives and outlines recommendations for future work. The manuscripts that Chapters 3 to 5 are based on are listed below.

Chapter 3: Fusion of SAR, Optical Imagery and Airborne LiDAR for Surface Water Detection.


Chapter 2

Literature Review

2.1 SAR Fundamentals

Radar imaging has been an established Earth remote sensing instrument since 1978, when the Sea Surveillance Satellite (SEASAT), the first civilian SAR satellite was launched. SAR is the only imaging radar technique to achieve high spatial resolution from spaceborne platforms (Skolnik, 1985; Tomiyasu, 1981). SAR uses a small antenna to generate an effectively long antenna by using the motion of the radar platform. In traditional radar systems, a long linear array of physical antennas is constructed, with multiple radiating elements to transmit and receive the signal. In SAR, only a single antenna is used and is moved to take up multiple positions along the line. A signal is transmitted at each location, and received signals are stored and processed to synthesize a long antenna array. SAR is an active remote sensing technique, meaning it provides its own source of illumination. It has the capability to penetrate cloud cover and image the Earth during the day and night (Barton, 1965; Curlander and McDonough, 1991; Elachi et al., 1982; Oliver and Quegan, 1998; Rosen and Hensley, 2000; Wiley, 1985).

The geometry of a spaceborne SAR system can be seen in Figure 2.1. The azimuth direction (y) is the direction in which the satellite is flying. Along the ground, perpendicular to the azimuth, is the ground range (x). The satellite’s look direction is perpendicular to the flight path, forming an angle called the incidence angle (θ) between the radar line of sight or slant range (r) and the normal of the satellite to the Earth surface or height of the satellite (H). R₀ is the distance between the satellite and the antenna footprint centre. SAR satellites fly with a velocity V_{SAR} and have an antenna length (L_Y) and width (L_X) which define the antenna footprint. The antenna footprint is defined by the range swath (ΔX) and the azimuth swath (ΔY). Most satellite systems fly a near-polar orbit (north to south) and have an imaging direction perpendicular to their flight path. Therefore, the SAR
satellite is often east-looking or right-looking or west-looking or left-looking. The satellite is on an ascending track if it is orbiting toward the north, or descending if it is orbiting toward the south (Lee and Pottier, 2009).

Figure 2.1. Example of basic geometry of a right-looking descending orbit (south-y and east-x) satellite SAR system showing: azimuth direction (y), ground range (x), incidence angle (θ), radar line of sight or slant range (r), height of the satellite (H), distance between the satellite and the antenna footprint centre (R₀), satellite velocity (V_{SAR}), antenna length (L_Y), antenna width (L_X), range swath (ΔX) and the azimuth swath (ΔY).

SAR systems transmit and receive an electromagnetic wave with a specific wavelength (λ) and frequency (f). When the incident wave interacts with the ground surface or target, part of the energy
is absorbed by the target and part of the energy is reflected and scattered. A fundamental form of
descrribing the interaction of a wave with a given target is the radar equation (Equation 2.1). This
equation describes the relationship between the power which the target receives from the incident
electromagnetic wave ($E_I$) and the power reradiated by the same target in the form of a scattered
wave ($E_S$).

$$P_R = \frac{P_T G_T(\theta, \phi)}{4\pi r_T^2} \sigma \frac{A_{ER}(\theta, \phi)}{4\pi r_R^2} \quad (2.1)$$

Where $P_R$ is the power detected at the receiving system, $P_T$ is the power transmitted, $G_T$ is the
antenna gain, $A_{ER}$ is the effective aperture of the receiving antenna, $r_T$ is the distance between the
transmitting system and the target, $r_R$ is the distance between the target and the receiving system,
and $\theta$ and $\phi$ are the spherical angles that define the direction of observation and correspond
respectively to the incidence and elevation angles. $\sigma$ is the radar cross section, which defines the
effects of the target of interest on the balance of powers in the radar equation (Equation 2.2).

$$\sigma = 4\pi^2 \frac{|E_S|^2}{|E_I|^2} \quad (2.2)$$

The radar cross section is a function of a large number of parameters which are difficult to isolate.
These include parameters connected to the imaging system such as wave frequency ($f$), wave
polarization, and image configuration ($\theta$ and $\phi$ in both the incident and scattering directions). Other
parameters are related to the target itself which include the objects geometrical structure
(topography, surface roughness and shape) and dielectric properties (surface material and moisture)
(Dobson et al., 1995; Mott, 1992). This equation is valid for targets of interest that are smaller than
the radar footprint, called point targets. However in situations where the target is larger than the
radar footprint, it is represented by an infinite collection of statistically identical point targets. This
creates a new term, “sigma-naught” ($\sigma_0$) which is the averaged radar cross section per unit area
(A_0), and is also called the scattering coefficient. The scattering coefficient is a dimensionless parameter and is seen in Equation 2.3.

\[
\sigma_0 = \frac{\sigma}{A_0} = \frac{4\pi r^2 |E_S|^2}{A_0 |E_I|^2}
\]  

(2.3)

The SAR image produced is a 2-D array of pixels, where each pixel represents an area on the Earth’s surface. A complex number representing the amplitude and the phase information, often called the backscatter, is stored in each pixel, and is associated with the radar scattering coefficient contained in the pixel. The magnitude or amplitude represents the characteristics of the ground surface detected by the SAR, whereas the phase represents the distance from the SAR system to the surface in fractions of the radar wavelength (Dobson et al., 1995).

Multiple different microwave wavelengths are used to transmit the electromagnetic energy in a SAR system (Figure 2.2). These different wavelengths (\(\lambda\)) are often called bands and image the surface in different ways. More penetration though Earth materials will occur in bands with longer wavelengths. The three most frequently used bands are the X, C and L-band, and each are used for numerous applications. The L-band (\(\lambda\sim15\) cm), used on the ALOS mission, is better for penetrating vegetation like forest canopy because of the large wavelength and is often used for subsurface imaging or biomass estimation. The C-band (\(\lambda\sim5.6\) cm), used on the RS-2 and SRTM mission, can penetrate some forest canopies but is often used for agriculture, ocean, ice or subsidence monitoring. The X-band (\(\lambda\sim3.1\) cm) can also be used for these applications but it is effected by smaller scatterers in vegetation. TSX uses X-band and exploits the higher spatial resolutions for various applications including snow and ice and elevation mapping (Moreira et al., 2013; Skolnik, 1985).
Figure 2.2. Commonly used bands for SAR systems showing their frequency, wavelength and application examples.

The material and conditions of the ground surface impact the dielectric constant ($\varepsilon_r$) which is a ratio of the permittivity of a medium ($\varepsilon$) to the permittivity of empty space ($\varepsilon_0$) (Equation 2.4). The permittivity is defined as the ability of the substance to store electrical energy in an electric field. Therefore, the dielectric constant of a medium can describe the ability for a medium to transmit, absorb and scatter energy (Dobson et al., 1995).

$$\varepsilon_r = \frac{\varepsilon}{\varepsilon_0}$$  \hspace{1cm} (2.4)

The dielectric constant is always greater than 1 since the permittivity of a medium is always assumed to be greater or equal to that of free space. Water, for example, has a high dielectric constant (~80) tends to absorb the energy well with low backscatter. Low values generally appear dark in SAR imagery. Ice, which has a dielectric constant of approximately 3 and a brighter return than water, can appear similar to vegetation or wavy water which can have a dielectric constant of approximately 3 to 6. The dielectric constant of vegetation is proportional to its moisture content which can vary daily, seasonally, and between vegetation type (Dobson et al., 1995; Martinez et al., 2001; White et al., 2015). Table 2.1 displays bulk dielectric constants of common Earth materials.
Table 2.1. Dielectric constants of common earth materials (Dobson et al., 1995; Martinez et al., 2001; White et al., 2015).

<table>
<thead>
<tr>
<th>Material</th>
<th>Dielectric Constant ($\varepsilon_r$) (unitless)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air</td>
<td>1</td>
</tr>
<tr>
<td>Water</td>
<td>80</td>
</tr>
<tr>
<td>Fresh water ice</td>
<td>3-4</td>
</tr>
<tr>
<td>Sea water ice</td>
<td>4-8</td>
</tr>
<tr>
<td>Snow</td>
<td>8-12</td>
</tr>
<tr>
<td>Dry sand/soil</td>
<td>3-6</td>
</tr>
<tr>
<td>Wet sand/soil</td>
<td>10-30</td>
</tr>
</tbody>
</table>

The geometrical structure of the target surface also plays a large role in how the electromagnetic wave scatters. The type of scattering is often defined by four main types as seen in Figure 2.3. Smooth surface scattering or specular scattering is a mirror-like reflection of the waves, where each incident ray is reflected having the same angle to the surface normal as the incident ray away from the sensor. Because SAR is side-looking, this often occurs over calm water and results in almost no energy being returned to the antenna, resulting in low backscatter values and dark areas on SAR imagery. Rough surface scattering results in the incident wave being scattered in all directions and often occurs over low vegetation, rough soil surfaces, and wavy water. The rougher the surface, the higher the backscatter intensity, and therefore these areas will appear brighter in SAR imagery. Double bounce scattering occurs when the incident angle hits two surfaces and bounces back to the radar antenna resulting in a high backscatter response. This often occurs in urban environments between buildings, and in flooded vegetation between the water and the vegetation interface. Finally, volume scattering is caused by randomly oriented scatterers such as tall vegetation and forest canopy. It occurs when the incident waves penetrate the vegetation layer and can be partially
scattered back to the radar antenna and partially distributed throughout the randomly oriented vegetation (White et al., 2015). A target is not limited to one type of scattering mechanism, and can often present combinations of all four. For example, ice can be represented by rough surface scattering (if ice is rough), smooth surface scattering (if there are pools of water), and volume scattering (if the wave can penetrate the ice partially and interact with the structure inside) (Dabboor et al., 2013b; Geldsetzer et al., 2007; Howell et al., 2005; Mermoz et al., 2014, 2008). Any interface between natural targets also presents differing scattering mechanisms. For example, as water transitions to vegetation on land, the effects of surface scattering and double bounce scattering can both play a role. Through time, as vegetation grows in and over water bodies, scattering mechanisms can change and misclassification can occur. The varying state of natural materials and the effect of moisture, temperature, wind and time can have on the structure of these targets make understanding the types of scattering mechanisms complicated (White et al., 2015). However, the knowledge of the different backscattering mechanisms often leads to new classification algorithms particularly when multi-polarization SAR is available (Dabboor et al., 2013a; Schmitt et al., 2015).

![Scattering mechanisms in natural environment](image)

**Figure 2.3.** Scattering mechanisms in natural environment: (a) smooth surface scattering; (b) rough surface scattering; (c) double bounce scattering; (d) volume scattering. Satellite is right-looking and ascending (flight path into page) with a height of H and an incidence angle of θ.
The side-looking geometry of a SAR system can cause significant distortions due to height differences perpendicular to the flight path (x). These errors caused by undulated terrain are well studied and are known as shadow and layover zones (Curlander and McDonough, 1991; Gelautz et al., 1998; Henderson and Lewis, 1998; Loew and Mauser, 2007; Schreier, 1993). A radar shadow zone is produced when the signal is blocked from reaching the ground surface resulting in a lower than expected backscatter value. Since water also appears dark in SAR imagery, shadow errors can often result in false positives for water (errors of commission). In a layover region, objects located at different positions along the height of the obstruction will have the same distance to the sensor thus their backscatter value will appear brighter than anticipated. These error zones are often modelled and calculated using Digital Elevation Models (DEM) and the satellite geometry (incidence angle). Other studies have used DEMs to calculate occlusion areas caused by shadow and layover of tall vegetation and infrastructure (Mason et al., 2010; Soergel et al., 2003). The width of these regions can be estimated using Equations 2.4 and 2.5 which correspond to Figure 2.4, where AB represents the width of the layover zone, CD represents the width of the shadow zone, $h_1$ and $h_2$ correspond to heights, in metres, of the obstructions and $\theta$ represents the satellites incidence angle in degrees (Mason et al., 2010).

\[
AB = h_1 \cot \theta 
\]

\[
CD = h_2 \tan \theta 
\]
Figure 2.4. Layover (AB) and shadow (CD) regions between obstructions of heights \( h_1 \) and \( h_2 \). Satellite is right-looking and descending (flight path out of page) with a height of \( H \) and incidence angle of \( \theta \).

2.2 PolSAR Principles

Polarimetric Synthetic Aperture Radar (PolSAR) is the science of acquiring, processing and analyzing the polarization state of an electromagnetic field transmitted and received by SAR systems (Boerner et al., 1997). Antennas on the SAR platform are designed to transmit incident electromagnetic waves \( \vec{E}_I \) and receive scattered electromagnetic waves \( \vec{E}_S \) with a specific polarization direction. The most common polarizations in SAR are the horizontal linear and the vertical linear as seen in Figure 2.5. When a horizontally polarized wave interacts with a target, the backscattered wave can have contributions in both the horizontal and vertical polarizations. The same applies to a vertically polarized incident wave. Systems that use both H and V polarization can have four possible channels: HH - horizontal linear transmission and horizontal linear reception; HV - horizontal linear transmission and vertical linear reception; VH - vertical linear transmission and horizontal linear reception; VV - vertical linear transmission and vertical linear reception.
Figure 2.5. Spatial evolution of linearly polarized wave, showing horizontal polarized wave and vertically polarized wave.

Co-polarized data refers to the combinations that use the same polarization in transmission and reception (HH and VV), whereas cross-polarized data uses transmitted and received polarizations that are orthogonal to one another (HV and VH). A SAR system can also be classified based on the level of polarization complexity. When a data set is only transmitted and received in one polarization, it is called single-polarization and can be HH, VV, HV, or VH imagery. Dual-polarized systems transmit a horizontally or vertically polarized waveform and measure both received polarization signals (HH and HV, VV and VH, HH and VV). Finally, full-polarization or quad-polarization refer to when H and V polarized waveforms are alternated during transmission and both H and V are received giving HH, HV, VH and VV imagery (Ulaby and Elachi, 1990).

The polarization of the incident and scattered electromagnetic wave can be represented by the Jones vector (Boerner et al., 1997) and are related as shown by Equation 2.6.

\[
E_s = \frac{e^{-jkr}}{r} [S] E_i
\]  

(2.6)
Where \( \mathbf{E}_S \) and \( \mathbf{E}_I \) are the Jones vectors of the scattered and incident waves respectively, \( [S] \) represents the scattering matrix and the term \( e^{-jk_r}r \) takes into account the propagation affects both in amplitude and phase. Since a wave can be linearly polarized in the horizontal or vertical plane, Equation 2.6 can be rewritten as Equation 2.7

\[
\frac{E_{Sx}}{E_{Sy}} = e^{-jk_r}r [S] \frac{E_{Ix}}{E_{Iy}}
\]

(2.7)

Where \( E_{Sx} \) and \( E_{Ix} \) are scattered and incident waves in the horizontal direction, and \( E_{Sy} \) and \( E_{Iy} \) are scattered and incident waves in the vertical direction. The scattering matrix \( [S] \) (Boerner et al., 1997) is an array of four complex scattering coefficients \( (S_{XX}, S_{VH}, S_{XV}, S_{VV}) \) that describe the transformation of the polarization of a wave as it interacts with the target (Equation 2.8).

\[
S = \begin{bmatrix}
S_{XX} & S_{VH} \\
S_{XV} & S_{VV}
\end{bmatrix}
= \begin{bmatrix}
S_{HH} & S_{HV} \\
S_{VH} & S_{VV}
\end{bmatrix}
\]

(2.8)

The horizontal and vertical components form a complete basis set to describe the electromagnetic wave, therefore the backscattering properties of the target can be completely described by a scattering matrix. However, there are two different types of scattering; incoherent and coherent. Coherent scatters can be completely described by the scattering matrix. This assumes that targets are completely polarized, pure and independent of each other. However, for most applications, this is not true. Incoherent scattering is a combination of distributed scatterers which are partially polarized and cannot be fully described by the scattering matrix or vectors. Most natural targets are not fixed with time, and can be affected by wind, temperature, pressure, clouds, water droplets and animals. Therefore to understand the incoherent scatterers and the state of the wave, the second order moments of the fluctuations can be extracted from the polarimetric coherency \([T3]\) and covariance \([C3]\) matrices (Equation 2.9 and 2.10). These matrices are generated from the outer
product of the scattering vectors (vector forms of the scattering matrix) and its conjugate transpose
(Boerner et al., 1997; Luneburg, 1999; Tragl et al., 1991).

\[
[C_3] = \begin{bmatrix}
S_{HH}S_{HH}^* & \sqrt{2}S_{HH}S_{HV}^* & S_{HH}S_{VV}^*
S_{HV}S_{HH}^* & 2S_{HV}S_{HV}^* & \sqrt{2}S_{HV}S_{VV}^*
S_{VV}S_{HH}^* & \sqrt{2}S_{VV}S_{HV}^* & S_{VV}S_{VV}^*
\end{bmatrix}
\] (2.9)

\[
[T_3] = \frac{1}{2} \begin{bmatrix}
|S_{HH} + S_{VV}|^2 & (S_{HH} + S_{VV})(S_{HH} - S_{VV})^* & 2(S_{HH} + S_{VV})S_{HV}^*
(S_{HH} - S_{VV})(S_{HH} + S_{VV})^* & |S_{HH} - S_{VV}|^2 & 2(S_{HH} - S_{VV})S_{HV}^*
2S_{HV}(S_{HH} + S_{VV})^* & 2S_{HV}(S_{HH} - S_{VV})^* & 4|S_{HV}|^2
\end{bmatrix}
\] (2.10)

Another way to represent the scattering matrix is in terms of power or real quantities, called the Stokes vector. Unlike the Jones vector which represents the polarization state of an electric field by two complex quantities, the amplitude and phase, this Stokes vector eliminates the absolute phase from the target, representing only the measurable power-related parameters. This is beneficial as it allows the parameters to become incoherently additive (Boerner et al., 1997). The Kennaugh Matrix \([K]\) is a linear transformation of the four-dimensional Stokes vector. The normalized Kennaugh elements divide the Kennaugh Matrix by the total intensity \((K_0)\) (Equation 2.11) (Schmitt et al., 2015). This allows for all Kennaugh elements to be described in the same scale, which is an advantage to other polarimetric descriptors where units cannot be compared. The matrix contains ten elements defined in Equations 2.12 to 2.21 (Schmitt et al., 2015).

\[
[K] = \begin{bmatrix}
K_0 & K_4 & K_5 & K_6
K_4 & K_1 & K_9 & K_8
K_5 & K_9 & K_2 & K_7
K_6 & K_8 & K_7 & K_3
\end{bmatrix} = K_0 \begin{bmatrix}
1 & k_4 & k_5 & k_6
k_4 & k_1 & k_9 & k_8
k_5 & k_9 & k_2 & k_7
k_6 & k_8 & k_7 & k_3
\end{bmatrix}
\] (2.11)

\[
K_0 = \frac{1}{2}(|S_{HH}|^2 + |S_{HV}|^2 + |S_{VH}|^2 + |S_{VV}|^2)
\] (2.12)

\[
K_1 = \frac{1}{2}(|S_{HH}|^2 - |S_{HV}|^2 - |S_{VH}|^2 - |S_{VV}|^2)
\] (2.13)

\[
K_2 = \frac{1}{2}(|S_{HV}|^2 + |S_{VH}|^2) + \text{Re} (S_{HH}S_{VV}^*)
\] (2.14)
The scattering matrix [S], coherency matrix [T3], covariance matrix [C3], and Kennaugh matrix [K] are essential tools to describe the polarization of an electromagnetic wave, and how that polarization changes when it interacts with the target. By introducing these matrices and parameters, PolSAR can be used to understand the type of scattering mechanism occurring at the target and classify the Earth’s surface.

2.3 Data Processing

2.3.1 Original Data Products – SAR Modes

In this study, SLC (Single Look Complex) products were obtained. Each image pixel is represented by a complex magnitude value, and the coordinates are given in radar slant range (r) rather than ground range (x). This means that the range pixel spacing and range resolution are measured along a slant path perpendicular to flight path (y) as seen in Figure 2.1. Pixel spacing is determined by the radar range sampling rate and pulse repetition frequency, which vary with beam and altitude.

For dual and quad polarization SLC products, the images for different polarization channels are co-registered. Co-registration is the act of geometrically aligning two or more data sets to integrate or fuse corresponding pixels that represent the same objects (Airbus Defence and Space, 2014).
RS-2 fine quad (FQ) resolution beam mode is a single beam strip-map SAR mode in which the beam elevation and profile are maintained constant throughout the data collection period (Figure 2.6). FQ beam mode provides full polarimetric imaging with a nominal ground swath of 25 km and a nominal resolution (slant range x azimuth) of 5.2 m x 7.6 m. It can be obtained from an incidence angle of 18 degrees to 49 degrees (Brisco et al., 2008; Livingstone et al., 2006).

TSX staring spotlight (ST) mode is a single beam spotlight SAR mode which has azimuth steering that points the antenna pattern to a rotation center within the imaged scene (Figure 2.6). This mode provides unprecedented azimuth resolution of up to 0.24 m and slant range resolution of 0.6 m. It also has a much smaller nominal scene extent of 4.2 km (azimuth) and 8 km (ground) depending on the angle of steering (usually between 20 degrees and 60 degrees). ST mode can be obtained from an incidence angle of 20 degrees to 45 degrees in single (HH or VV) polarization (Airbus Defence and Space, 2014; Mittermayer et al., 2012; Werninghaus and Buckreuss, 2010).

TSX stripmap mode (SM) is the basic SAR imaging mode similar to RS-2. It is available in both single and dual-polarization. The dual-polarization data has a slant range resolution of 1.2 m and azimuth resolution of 6.6 m. The scene extent is 15 km by 50 km and can be acquired at incidence angles between 20 and 45 degrees (Airbus Defence and Space, 2014; Werninghaus and Buckreuss, 2010).
Figure 2.6. Diagram of staring spotlight and stripmap SAR acquisition modes, showing velocity of satellite ($V_{SAR}$), the flight path of the satellite ($y$) and the direction of imaging or ground range ($x$). The black circle represents the rotation centre for the staring spotlight imaging mode.

2.3.2 Radiometric Calibration

The objective of SAR calibration is to provide imagery in which the complex pixel value can be directly related to the radar backscatter of the scene. Once calibration has occurred, SAR images acquired using different sensors, times, modes, or processing techniques can be compared. Both RS-2 and TSX use absolute calibration which takes into account all the contributions in the radiometric values that are not due to the target characteristics, such as incidence angle, ascending-descending geometries and look directions. These corrections can be found in the metadata of the product provided. This does not take into account terrain fluctuations (as it assumes that the Earth’s surface is an ellipsoid at a constant base elevation), and does not include instrument noise (Small and Schubert, 2008).

2.3.3 Geometric Terrain Correction

SAR data is right-looking and therefore is imaged at an angle. Data that is acquired not directly under the sensor’s Nadir location will have geometric distortion. Topography can distort the
geolocation information of the pixel as the sensor assumes a flat target. Therefore, terrain corrections are essential to fix the geometry of topographical distortions. The Range Doppler Terrain Correction uses radar timing annotations, the slant to ground range conversion parameters, a reference DEM, and available orbit information to precisely locate the satellite's position. This information can be found in the metadata of the product or externally acquired (Small and Schubert, 2008; Small, 2011). The main contributions to the pixel localization accuracy are the orbit determination and the vertical accuracy of the DEM. For TerraSAR-X data, there are three types of orbits used for basic product processing: the predicted, rapid and science orbit. The science orbit provides the highest orbit accuracy at ± 20 cm and can result in a pixel location accuracy of better than ± 1 m. However, the vertical accuracy of the DEM used has been shown to contribute the most error to the pixel localization accuracy, especially at low incidence angles. The vertical accuracy using the 30 m grid size Shuttle Radar Topography Mission (SRTM) DEM product ranges from ±15 m (Farr et al., 2007). However, some studies have found that the error is ±4-5 m depending on vegetation and terrain (Bhang et al., 2007; Braun and Fotopoulos, 2007; Carabajal and Harding, 2005). It was found by Nonaka et al. (2008) that in flat areas the SAR pixel localization accuracy was approximately ± 5 m, but in mountainous areas, the accuracy degraded to ± 10 m due to the DEM height error. Therefore it is important to use the highest quality DEM available to minimize pixel location error (Airbus Defence and Space, 2014; Nonaka et al., 2008). There have been several DEMs created, however, in this study the 30 m resolution SRTM (version 4) is used as it is currently the highest quality publicly available global DEM (Jarvis et al., 2016). The DEM resampling and image resampling method used is the bilinear interpolation technique. This technique has been shown to be superior to the nearest neighbor technique (Small and Schubert, 2008; Small, 2011). The latest global DEM was released in September 2016, and was produced by the TanDEM-X mission. The DEM has a spatial resolution of 12 m with an estimated accuracy of 1-2 m vertically (Brautigam et al., 2014).
2.3.4 Speckle Filter

SAR images also have an inherent, multiplicative error called speckle which is a pixel-to-pixel variation in intensity that causes a granular noise pattern in the images (Figure 2.7a). This is due to the coherent interference (constructive and destructive) of waves reflected from many elementary scatterers which have a size similar to the radar wavelength. Speckle can complicate the image interpretation and analyses and reduces the ability to classify the image. Speckle filters can be applied to single and polarimetric SAR data to help reduce the noise but can affect the inherent scattering characteristics of polarimetric SAR data and degrade the resolution and sharp edges of features in the image. The goal of speckle filtering is to reduce the speckle noise level without sacrificing the information content. Speckle filtering can use multiple window sizes (for example, 5×5, 7×7, and 9×9 pixels). Larger windows provide more speckle smoothing, and smaller windows provide better texture preservation (Figure 2.7). For single polarization data several filters exist. The more simple filters like the mean and median filter, which take the mean or median of the surrounding pixels and replaces the centre pixel with that value, are often used. However, a main deficiency of this filter is that speckle noise near strong edges is not adequately filtered. More advanced filters, such as the Refined Lee filter were developed to compensate for this problem. This filter is able to detect the edge direction and apply filtering to pixels in an edge-aligned window (Goodman, 1976; Lee et al., 1994).

Polarimetric speckle filtering algorithms also exist which aim to preserve polarimetric properties, process all channels independently, and preserve scattering characteristics. The Refined Lee PolSAR speckle filter was developed which uses an edge-aligned non-square window and applies the minimum mean square error filter. This polarimetric filter uses the span image which is an average of the HH, VH+HV, VV intensities, instead of using the individual channels which may have different scattering characteristics. This filter first chooses the edge-aligned window, then computes the filtering weight applied to the span image, and then filters the covariance matrix [T3]
Figure 2.7. Example of effect different window sizes have on SAR data using RADARSAT-2 SAR scene from April 13, 2017 and a polarimetric Refined Lee speckle filter: (a) SAR intensity image with no speckle filter applied; (b) Window size of 5×5 applied; (c) Window size of 7×7 applied; (d) Window size of 9×9.

2.4 Polarimetric Decomposition

In order to physically interpret PolSAR data to allow for classification and analysis of the target, the scattering matrix [S], coherency matrix [T3], covariance matrix [C3], and Kennaugh matrix [K] must be decomposed to understand the scattering mechanisms involved.
Several decomposition methods have been developed. These decomposition methods can be grouped into four main types (Lee and Pottier, 2009):

1. Those that use the coherent decomposition of the scattering matrix \([S]\). Example: Pauli Decomposition

2. The model-based decomposition of the coherency matrix \([T3]\) or covariance matrix \([C3]\). Example: Freeman-Durden Decomposition

3. Those that use the eigenvectors and eigenvalues of the coherency matrix \([T3]\) or covariance matrix \([C3]\). Example: H-Alpha Decomposition

4. Those based on the dichotomy of the Kennaugh matrix \([K]\). Example: Kennaugh element framework

**2.4.1 Pauli Decomposition**

The Pauli Decomposition is a coherent decomposition which expresses the scattering matrix \([S]\) as the complex sum of the Pauli matrices, where an elementary scattering mechanism is associated for each basis matrix. It assumes pure polarimetric scattering and is effective in urban environments. The Pauli decomposition can only be used on quad-polarization data. Equations 2.22 to 2.24 show the three polarimetric parameters generated where: \(a\) represents the single or off bounce scattering, \(b\) represents the volume scattering, and \(c\) represents the double or even bounce scattering. These parameters are displayed as decibel intensity values and are usually represented by approximately -40 to 0 db. \(S_{HH}\), \(S_{VV}\), \(S_{HV}\) and \(S_{VH}\) are the four complex scattering coefficients described by the scattering matrix \((S)\) in Equation 2.8 (Cloude and Pottier, 1996; Dabboor et al., 2010).

\[
a = \frac{S_{HH} + S_{VV}}{\sqrt{2}} \quad (2.22)
\]
\[
b = \frac{S_{HH} - S_{VV}}{\sqrt{2}} \tag{2.23}
\]
\[
c = \frac{S_{HV} + S_{VH}}{\sqrt{2}} \tag{2.24}
\]

### 2.4.2 Freeman-Durden Decomposition

The incoherent Freeman-Durden decomposition fits a physically based, three component scattering mechanism model to the covariance matrix \([T3]\), without utilizing ground truth data. It is designed for natural environments and can characterize distributed scatterers. Because this decomposition is applied to the coherency matrix, there is an inherit loss of resolution, as a large window size is required to maintain stability. The Freeman-Durden decomposition can only be used on quad-polarization data. Three different scattering mechanisms are modelled and three different polarimetric parameters are produced (Freeman and Durden, 1998).

- **Double-bounce Scattering**: modelled and occurs when two perpendicular planes are imaged and therefore the wave is reflected twice before it is received. This rarely occurs in natural environments, but often occurs over flooded vegetation.

- **Volume Scattering**: modelled and occurs when the target has a large number of disordered dipoles and causes purely diffuse backscattering behaviour, often occurring within the tree canopy

- **Rough Surface scattering**: modelled and occurs when a single bounce returns from surfaces like rough water and small shrubs

### 2.4.3 H-Alpha Decomposition

The H-Alpha decomposition is a method for extracting parameters from experimental data using a smoothing algorithm based on second-order statistics. An eigenvector analysis of the coherency \([T3]\) matrix is used since it separates the parameters into scattering processes (the eigenvectors)
and their relative magnitudes (the eigenvalues). The two key parameters that can be calculated from the eigenvalues and one from the eigenvectors, are the entropy (H) and alpha (\(\alpha\)). Entropy is calculated from the eigenvalue information, represents the degree of randomness in the scattering and lies between 0 and 1. Alpha is calculated from the eigenvectors, represents a rotation and can indicate the type of scattering mechanism, and ranges from 0 to 90 degrees. For example, calm water has low values of both entropy and alpha, whereas forest canopies usually have high values of entropy and medium values of alpha. This decomposition can characterize distributed scatterers and works well in natural environments (Cloude and Pottier, 1996). It also has an inherit loss of resolution similar to the Freeman-Durden decomposition which can reduce speckle but also reduce detail. The H-Alpha decomposition was developed for quad-polarization data but has also been adapted for dual-polarization data that uses the \([T2]\) coherency matrix (Cloude and Pottier, 1996).

### 2.4.4 Kennaugh Element Framework

The Kennaugh element framework (Schmitt et al., 2015) uses the normalized Kennaugh elements to represent different combinations of scattering mechanisms. This matrix can be used to compute the Kennaugh elements for single, dual or quad polarization data. Four modified normalized Kennaugh elements can be computed for dual-polarization HH/VV data (Equations 2.25 to 2.28). \(K_0\) is the total intensity as a sum of HH plus VV, \(K_3\) is the intensity ratio between double bounce and surface intensity, \(K_4\) is the ratio between HH and VV intensity and \(K_7\) is the phase shift between double-bounce and surface scattering (Moser et al., 2016b; Schmitt et al., 2015). These parameters can be displayed as decibel intensity values and are usually represented by approximately -40 to 0 db (Moser et al., 2016; Schmitt et al., 2015). \(S_{HH}\), \(S_{VV}\), \(S_{HV}\) and \(S_{VH}\) are the four complex scattering coefficients described by the scattering matrix \((S)\) in Equation 2.8.

\[
K_0 = \frac{1}{2}(|S_{HH}|^2 + |S_{VV}|^2) \tag{2.25}
\]

\[
K_3 = -\text{Re} (S_{HH}S_{VV}) \tag{2.26}
\]
\[ K_4 = \frac{1}{2} (|S_{HH}|^2 - |S_{VV}|^2) \]  

\[ K_7 = \text{Im} (S_{HH} S_{VV}) \]  

Nine normalized Kennaugh elements can be computed using quad polarization data (Equations 2.15 to 2.24). \( K_0 \) is the total intensity as a sum of the four channels. The meaning of each channel of the other elements is less intuitive and less studied (Schmitt et al., 2015). In this study, different combinations of Kennaugh elements were tested in an unsupervised classification technique.

**2.5 PolSAR Classification**

One of the most important applications for PolSAR is terrain and land cover classification. Algorithms have been developed for supervised and unsupervised terrain classification. Supervised classification involves using a training dataset for each class based on another data set that provides ground truth. Ground truth data is not always available, therefore unsupervised classification can also be used. Unsupervised classification classifies the image automatically by finding clusters of pixels based on a certain criterion. The interpretation of the segmented classes however may have to be done manually (Lim et al., 1989). Due to the changeability of surface water with time and the remote locations that flooding events often occur in, ground truth data is often unavailable in the correct spatial or temporal scale. Therefore in this study, all SAR data was classified using unsupervised techniques.

Two different clustering algorithms were used in this study to classify the polarimetric SAR data. The k-means clustering algorithm is one of the simplest forms of clustering techniques which aims at minimizing the Euclidean distance between points. The algorithm randomly defines \( k \) number of pixels as the initial cluster centres. It then assigns each pixel to the nearest cluster centre as defined by the Euclidean distance. Finally, it recalculates the cluster centres as the arithmetic mean of all the samples from all pixels in a cluster and iteratively adjusts cluster centres until it converges.
on the best solution (Figure 2.8). The number of clusters and number of iterations can be pre-defined.

**Figure 2.8.** K-means clustering algorithm showing four steps: (a) The algorithm randomly defines initial cluster centres (stars); (b) Assigns each observation (circles) to the nearest cluster centre (stars) as defined by the Euclidean distance (lines); (c) Recalculates and iteratively adjusts the cluster centres based on minimizing the Euclidean distance to observations; (d) Converges on the best solution.

The advantages of this technique is that it is fast and robust and therefore works well when applied to large data sets (Kanungo et al., 2002; Ortega et al., 2009). The algorithm works well for linear
data sets such as the Pauli and Kennaugh Element decompositions, but cannot be applied to non-linear datasets such as the Freeman-Durden and H-Alpha decompositions. K-means clustering does not handle noisy data well, but by applying speckle filtering to SAR data, multiplicative noise can be reduced (Kanungo et al., 2002; Ortega et al., 2009). The Wishart distance classification is similar to the K-Means algorithm in that it aims at minimizing a distance between points. However, this method uses a non-linear distance measure derived from the Wishart distribution and complex Wishart probability function. The Wishart distribution is a multi-variant, two parameter continuous probability function, which is a generalization of the gamma distribution. The polarimetric covariance matrix \([T3]\) has a complex Wishart distribution, and therefore this classification algorithm can be used for PolSAR decomposition techniques which use the \([T3]\) matrix, such as the Freeman-Durden decomposition and the H-Alpha decomposition. The advantages of this method is that it is robust and can be assigned to any type of PolSAR data (single, dual, quad) (Dabboor et al., 2013a; Lee et al., 2004, 1999; Olivié, 2015; Ouarzeddine et al., 2007).

### 2.6 PolSAR Systems

There are several satellite missions with polarimetric SAR capabilities that can be used for long-term monitoring or near-real time monitoring. Relevant past and present missions and their characteristics are described in Table 2.2. SAR missions continue to develop with over 25 missions being planned for 2018-2025 (CEOS, 2016; Moreira et al., 2013). Each satellite has a repeat period (RP), which is the time it takes the satellite to return to the same location on Earth. Depending on the satellite this time can vary between 11 and 46 days. Each sensor also has multiple beam modes with varying resolutions and spatial extents. These characteristics along with the desired polarization complexity are important when choosing a monitoring strategy for a specific application. For small scale flood hazard monitoring, a short repeat period with high resolution data is desirable, however, acquisition conflicts between different users as well as different acquisition modes do not always allow for an optimal sampling of a specific target.
Table 2.2. Overview of past and present spaceborne SAR sensors and their main characteristics (CEOS, 2016; Moreira et al., 2013; Zhou et al., 2009).

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Operation</th>
<th>RP (Days)</th>
<th>Band</th>
<th>Polarization</th>
<th>Institution</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEASAT</td>
<td>1978</td>
<td>17</td>
<td>L</td>
<td>Single (HH)</td>
<td>NASA/JPL</td>
</tr>
<tr>
<td>ERS-1</td>
<td>1991-2000</td>
<td>35</td>
<td>C</td>
<td>Single (VV)</td>
<td>ESA</td>
</tr>
<tr>
<td>ERS-2</td>
<td>1995-2011</td>
<td>35</td>
<td>C</td>
<td>Single (VV)</td>
<td>ESA</td>
</tr>
<tr>
<td>JERS-1</td>
<td>1992-1998</td>
<td>44</td>
<td>L</td>
<td>Single (HH)</td>
<td>JAXA</td>
</tr>
<tr>
<td>SIR-C/X-SAR</td>
<td>1994</td>
<td>-</td>
<td>L &amp; C</td>
<td>Quad</td>
<td>NASA/JPL, DLR, ASI</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>Single (VV)</td>
<td></td>
</tr>
<tr>
<td>RADARSAT-1</td>
<td>1995-2008</td>
<td>24</td>
<td>C</td>
<td>Single (HH)</td>
<td>CSA</td>
</tr>
<tr>
<td>RADARSAT-2</td>
<td>2007-present</td>
<td>24</td>
<td>C</td>
<td>Quad</td>
<td>CSA</td>
</tr>
<tr>
<td>SRTM</td>
<td>2000</td>
<td>-</td>
<td>C</td>
<td>Single (HH + VV)</td>
<td>NASA/JPL, DLR, ASI</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>Single (VV)</td>
<td></td>
</tr>
<tr>
<td>ENVISAT/ASAR</td>
<td>2002-2012</td>
<td>35</td>
<td>C</td>
<td>Dual</td>
<td>ESA</td>
</tr>
<tr>
<td>ALOS-PALSAR</td>
<td>2006-2011</td>
<td>46</td>
<td>L</td>
<td>Quad</td>
<td>JAXA</td>
</tr>
<tr>
<td>ALOS-2</td>
<td>2014-present</td>
<td>14</td>
<td>L</td>
<td>Quad</td>
<td>JAXA</td>
</tr>
<tr>
<td>TerraSAR-X</td>
<td>2007-present</td>
<td>11</td>
<td>X</td>
<td>Quad</td>
<td>DLR</td>
</tr>
<tr>
<td>TanDEM-X</td>
<td>2010-present</td>
<td>11</td>
<td>X</td>
<td>Quad</td>
<td>DLR</td>
</tr>
<tr>
<td>COSMO-SkyMed-1</td>
<td>2007-present</td>
<td>16</td>
<td>X</td>
<td>Dual</td>
<td>ASI</td>
</tr>
<tr>
<td>COSMO-SkyMed-2</td>
<td>2007-present</td>
<td>16</td>
<td>X</td>
<td>Dual</td>
<td>ASI</td>
</tr>
<tr>
<td>COSMO-SkyMed-3</td>
<td>2008-present</td>
<td>16</td>
<td>X</td>
<td>Dual</td>
<td>ASI</td>
</tr>
<tr>
<td>COSMO-SkyMed-4</td>
<td>2010-present</td>
<td>16</td>
<td>X</td>
<td>Dual</td>
<td>ASI</td>
</tr>
<tr>
<td>RISAT-1</td>
<td>2012-present</td>
<td>12</td>
<td>C</td>
<td>Quad</td>
<td>ISRO</td>
</tr>
<tr>
<td>SENTINEL-1A</td>
<td>2014-present</td>
<td>12</td>
<td>C</td>
<td>Dual</td>
<td>ESA</td>
</tr>
<tr>
<td>SENTINEL-1B</td>
<td>2016-present</td>
<td>14</td>
<td>C</td>
<td>Dual</td>
<td>ESA</td>
</tr>
</tbody>
</table>
The two satellites used in this study are TerraSAR-X (TSX) and RADARSAT-2 (RS-2). TSX was developed by DLR and Astrium and launched in June 2007 equipped with an X-band sensor which operates in different modes and therefore different resolutions. The mission objectives are to provide high-quality SAR data for scientific research and commercial applications. TSX is considered a low earth orbiter, orbiting the Earth at an elevation of 514 km in a near-polar orbit. TSX has a nominal lifespan of seven years, although it has surpassed this time period and is still operational. TSX provides single and dual polarized data, and on an experimental basis it is able to offer quad polarization data. An almost identical twin satellite, TanDEM-X (TDX) flying in close formation to TSX was launched in June 2010 which generated a consistent global Digital Elevation Model (DEM) with unprecedented resolution of 12 m (Brautigam et al., 2014). Both offer SAR imagery with a resolution of up to 0.25 m and a repeat period of 11 days (Krieger et al., 2007; Wermuth et al., 2014; Yoon et al., 2009; Zhou et al., 2009).

In 2007, RS-2 was launched due to the need for effective monitoring of Canada’s icy waterways. It is a collaboration between the government (CSA-Canadian Space Agency) and industry (MDA-MacDonald, Dettwiler and Associates Ltd). RS-2 is also a low earth orbiter that flies at 798 km above the Earth in a sun-synchronous near-polar orbit, and has a design life of 7.25 years. Similar to TSX, RS-2 has surpassed this time period, and is still operational. RS-2 operates in C-band and offers single and dual polarization channels with at 24 day repeat period and a resolution of 3 to 100 m. It is also the first commercial space-borne satellite to offer quad-polarization capabilities (Brisco et al., 2008; Livingstone et al., 2006; Morena et al., 2004)
Chapter 3

Fusion of SAR, Optical Imagery and Airborne LiDAR for Surface Water Detection


3.1 Abstract
The detection and monitoring of surface water and its extent are critical for understanding floodwater hazards. Flooding and undermining caused by surface water flow can result in damage to critical infrastructure and changes in ecosystems. Along major transportation corridors, such as railways, even small bodies of water can pose significant hazards resulting in eroded or washed out tracks. In this study, heterogeneous data from synthetic aperture radar (SAR) satellite missions, optical satellite-based imagery and airborne light detection and ranging (LiDAR) were fused for surface water detection. Each dataset was independently classified for surface water and then fused classification models of the three datasets were created. A multi-level decision tree was developed to create an optimal water mask by minimizing the differences between models originating from single datasets. Results show a water classification uncertainty of 4–9% using the final fused models compared to 17–23% uncertainty using single polarization SAR. Of note is the use of a high resolution LiDAR digital elevation model (DEM) to remove shadow and layover effects in the SAR observations, which reduces overestimation of surface water with growing vegetation. Overall, the results highlight the advantages of fusing multiple heterogeneous remote sensing techniques to detect surface water in a predominantly natural landscape.
3.2 Introduction

Synthetic aperture radar (SAR), light detection and ranging (LiDAR) and multispectral imaging are established remote sensing techniques for use in land cover classification models (Höfle et al., 2009; Jiang et al., 2012; White et al., 2015). Many studies assess the ability to integrate two remote sensing techniques to detect wetlands (Bourgeau-Chavez et al., 2009; Corcoran et al., 2012; S. Hong et al., 2015; Huang et al., 2014; Joshi et al., 2016; Millard and Richardson, 2013; Na et al., 2013; Parent et al., 2015; Rebelo, 2010). However, fewer studies discuss the ability to integrate all three (Gala and Melesse, 2012; Vanderhoof et al., 2017). A number of studies assess the ability of an integrated model to detect wetlands, e.g. in Gala and Melesse (2012), the focus is on prairie grasslands and LiDAR is used to correct terrain effects in the SAR models. The objectives of this study are to (1) develop a synergistic water classification model by integrating models derived from SAR, optical, and LiDAR data, (2) compare the integrated models to those derived from individual remote sensing techniques, and (3) investigate discrepancies in land cover classification between the individual techniques and the integrated models, with a focus on surface water.

SAR detects differences in the dielectric and geometric properties of target surfaces, which affects the intensity of the backscatter signal. Water has a high dielectric constant and generally acts as a specular reflector, thus it is differentiable in SAR imagery appearing dark with low backscatter. Misclassification errors of omission can occur due to wind (which creates waves on the water surface), flooding of vegetated areas, or ice cover (White et al., 2015). Several studies demonstrate the utility of single polarization SAR data for analyzing surface water extent and changes. SAR observations can also penetrate vegetation, to varying degrees, depending on the wavelength, vegetation type and canopy conditions. However, due to the side looking nature of SAR, some areas on the ground surface may be misclassified when terrain, urban agglomerates, or vegetation create regions of radar shadow (commission error) and layover (omission error) (Mason et al., 2010). Regional studies including RADARSAT-1, RADARSAT-2 and TerraSAR-X (TSX) data
for mapping open water can be found in (Brisco et al., 2009; Martinis et al., 2015a; White et al., 2014). For the purpose of flood mapping, single polarization SAR imagery is used to create time series of water changes (Kuenzer et al., 2013; Schlaffer et al., 2015) and fully automated processing chains using TSX and ENVISAT SAR (Gstaiger et al., 2012; Martinis et al., 2015a). Processing techniques applied to SAR in order to map surface water include multi-temporal interferometric SAR coherence, active contour modelling, and texture-based classification. The most commonly used approach, also used herein, is grey-level thresholding (Gstaiger et al., 2012; White et al., 2015).

Airborne LiDAR scanning (ALS) surveys use laser pulses to collect both positional and intensity information for each reflector point (Wehr and Lohr, 1999). Associated with each data point is an intensity value, which is a measure of the strength of the backscattered signal. This intensity value is influenced by the spectral characteristics of the material at the wavelength used by the LiDAR instrument. As an active remote sensing technique, data can be acquired during the day or night. Although surveys should be performed in cloud- and fog-free conditions, the survey can often be flown beneath the cloud ceiling for land cover classification studies. Other environmental variables, such as wind, can affect the collected data (Leigh and Hale, 2005). An advantage of ALS surveys is their customizability. Spatial coverage and resolution of the data can be controlled, and is mainly dependent on the height of the LiDAR platform, aircraft speed, scanning frequency and pulse repetition frequency of the instrument, and swath width (Saylam, 2009). The ability to record more than one return signal per emitted pulse also enables LiDAR to generate a 3-dimensional model of the landscape. In temperate forests, the signal is able to penetrate through the tree canopy and provide information about the forest floor. This creates the potential for LiDAR to detect inundation below a forest canopy (Lang and McCarty, 2009). Water is typically characterized by (i) having a low elevation when compared to the immediately neighbouring landscape, (ii) low elevation variability, (iii) a low intensity signature at high incidence angles (Lutz et al., 2003) and (iv) a high
intensity signature at low scan angles (Lutz et al., 2003), both related to the specular nature of calm water (Brzank and Heipke, 2005), (v) a high incidence of laser point ‘dropouts’ which occur when the return signal is too weak to detect (Höfle et al., 2009), and (vi) as a result of the high rate of dropouts, water bodies tend to have a lower point density (Höfle et al., 2009). Misclassifications can arise from the variability in the intensity signature which lead to portions of water bodies being misclassified as fields or similar land cover classes. Flat areas including roads and agricultural land cover that have similarly low intensity signatures can also be misclassified as water.

Much progress has been made in using LiDAR intensity data to classify land cover from the first proof of concept study performed by (Song et al., 2002). This study uses a pixel-based decision tree classification system which incorporates parameters derived from both the positional and intensity data to identify bodies of water (Crasto et al., 2015; Höfle et al., 2009). Both intensity and positional data were used as inputs to the model to capitalize on the wealth of data provided by LiDAR surveys.

Since the launch of Landsat in 1972, multispectral imagery has been the principle data type for land cover classification studies (Joshi et al., 2016). Current multispectral satellite missions include up to 8 spectral bands in the visible-to-near infrared (NIR) wavelengths, an average revisit period of 1.1 days, and a spatial resolution reaching 0.3-0.5 metres (Nouri et al., 2013). Water is characterized in multispectral imagery as having a low reflectance, especially in the NIR wavelengths. For this reason, some land cover classification studies use the NIR band to separate water from land (Lu et al., 2011); others use band ratios to extract water bodies (Jawak and Luis, 2013; Jones, 2015; McFeeters, 1996) and supervised classification techniques (Wang et al., 2004). However, these techniques can be confounded by shadows, which can be misclassified as water (Franklin and Wulder, 2002; Sawaya et al., 2003; Zhang et al., 2014). Optical imaging is unable to penetrate vegetative cover, which results in challenges with detecting areas of inundation below
forest canopies. While some of these limitations may affect the ability of optical imagery to correctly classify all bodies of water, in a cloud-free scene optical imagery has proved to classify open bodies of water successfully.

In this study, TSX scenes were combined with airborne LiDAR and optical imagery using a pixel based decision tree analysis to classify areas of water and non-water and identify areas where the classification was uncertain. TSX has a repeat period of 11 days and a resolution of up to 0.24 m in staring spotlight beam mode (Eineder et al., 2009; Mittermayer et al., 2012), allowing for frequent monitoring of small water bodies. The methodology, processing techniques and decision tree analysis used to exploit the strengths of each sensor are described in the following sections. The fused water models are visualized, analyzed and compared to the single sensor models in order to identify discrepancies. Ultimately, the percent of water and uncertainty of each model is determined in order to understand the influence of using multiple data sets to classify surface water.

3.3 Materials and Methods

3.3.1 Study Area and Data Description

The study area is located at the Queen’s University Biological Station (QUBS) in Kingston, Ontario, Canada, approximately 50 km north of the eastern end of Lake Ontario. QUBS was chosen due to the abundance of water bodies that vary in size from small inundated forests to large open bodies of water. The 2 km x 2 km square area where the SAR, LiDAR and optical data sets overlap is shown in Figure 3.1.
Figure 3.1. Map showing the extent of SAR scenes (dark blue), LiDAR airborne survey (red), optical imagery (yellow), the study area (black), lakes (blue) and land (white) mapped by the Ontario Ministry of Natural Resources.

Five TSX staring spotlight mode scenes were acquired over QUBS from April to September 2016. These scenes represent single look slant range (SLC) products of descending path, single polarization (HH), right looking with an incidence angle of 44°. They have a slant range and azimuth resolution of up to 0.6 m and 0.24 m, respectively. The LiDAR data were acquired using an Optech Gemini ALTM, which is a small-footprint, single wavelength, discrete return system.
The survey was flown on June 2015 at an altitude of 1200 m, and resulted in a spatial resolution of 1 pt/m². WorldView-2 imagery was acquired in August of 2016 consisting of 8-band multispectral optical images with a resolution of 2 m. Table 3.1 outlines the data sets used in this study.

**Table 3.1.** Summary of TSX, airborne LiDAR and satellite-based optical imagery data used in this study

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Date Acquired</th>
<th>Platform/Mission Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optical</td>
<td>August 26, 2016</td>
<td>WorldView-2 multispectral imagery (8-band)</td>
</tr>
<tr>
<td>LiDAR</td>
<td>June 10/11, 2015</td>
<td>Airborne LiDAR</td>
</tr>
<tr>
<td>SAR 1</td>
<td>April 2, 2016</td>
<td>TSX staring spotlight mode</td>
</tr>
<tr>
<td>SAR 2</td>
<td>April 24, 2016</td>
<td>TSX staring spotlight mode</td>
</tr>
<tr>
<td>SAR 3</td>
<td>May 5, 2016</td>
<td>TSX staring spotlight mode</td>
</tr>
<tr>
<td>SAR 4</td>
<td>July 10, 2016</td>
<td>TSX staring spotlight mode</td>
</tr>
<tr>
<td>SAR 5</td>
<td>September 3, 2016</td>
<td>TSX staring spotlight mode</td>
</tr>
<tr>
<td>Field Investigation 1</td>
<td>April 2, 2016</td>
<td>Photographs and GPS coordinates</td>
</tr>
<tr>
<td>Field Investigation 2</td>
<td>May 5, 2016</td>
<td>Photographs and GPS coordinates</td>
</tr>
<tr>
<td>Field Investigation 3</td>
<td>July 10, 2016</td>
<td>Photographs and GPS coordinates</td>
</tr>
</tbody>
</table>

In situ field investigations were performed on three different occasions, which overlap with three of the five SAR acquisition dates. During these field investigations to five chosen study locations, GPS coordinates were recorded as well as water and site conditions, including the presence of open water, flooded vegetation, and the dominant vegetation type such as reeds, shrubs or forest. The five sites were chosen for having different environmental and surface water conditions as follows:

A. *Poole Lake* - A large, open body of water bordered by wetlands and mixed forest.
B. *Marsh A* - A dense cattail marsh connected to a small lake, with the potential to be flooded during parts of the year. A small stream runs along the periphery of the marsh.

C. *Inundated Forest* - A small area of observed inundation beneath a mixed forest canopy with some emergent shrubbery. Depth of water in April was approximately 1 meters.

D. *Marsh B* - A small pond bordered by a sparse cattail marsh, which immediately backs onto a flat field to one side and a forest to the other side. The forested side is beyond the chosen study area. Water level was observed to be highest in the spring and receded throughout summer.

E. *Vegetated Lake* - A wetland composed of a central pond/marsh, transitioning into a dense cattail marsh along the periphery. In the central pond/marsh, there are sparse cattails and the remnant trucks of dead trees. A central stream cuts through the marsh, connected to peripheral streams throughout the marsh.

The locations of these sub-areas are shown in Figure 3.2.
3.3.2 SAR Processing

The single-polarization TSX staring spotlight mode scenes were processed to create five SAR water masks that each contain five different classes. The TSX intensity data were calibrated and speckle filtered using a Refined Lee 7 × 7 speckle filter three times to optimally reduce speckle while maintaining edges and histogram form (Dabboor et al., 2011). A Range-Doppler Terrain correction was applied to geometrically correct the TSX data using STRM DEM (Jarvis et al., 2016), producing a processed SAR intensity image (Figure 3.3a).

Grey-level thresholding was used to classify the image into water, uncertain and non-water. This technique classifies all pixels with a value less than this threshold as water. The histogram of the

Figure 3.2. Five in situ field work locations in study area: (A) Poole Lake; (B) Marsh A; (C) Inundated Forest; (D) Marsh B; (E) Vegetated Lake.
backscatter intensity data from each SAR scene was used to calculate the threshold values. The histogram is bimodal, with one mode largely representing water and the other representing dry land. The local minimum between the two modes represents the area of transition between water and non-water. Using this approach, two thresholds were chosen which could separate classes of water and uncertain, and uncertain and non-water. Three normal distribution curves were fit to the histogram data. Since the left mode (representing water) was skewed to the left, two normal distribution curves were fit to this, one using the variance and one using the mean. Where these two curves intersected with the right mode’s normal distribution fitted curve, represents the two threshold values. Intensity values in-between the two thresholds were marked as the class “uncertain”. Values greater than the thresholds were classified as “non-water” and values less than were classified as “water”. Figure 3.3b displays the SAR threshold water mask.

The next step in SAR processing involved determining the shadow and layover zones, which exist in the SAR scenes and can confound classification using intensity values. Areas of shadow occur where the radar wave is blocked from reaching the ground surface. This creates areas of false positives for water (error of commission). Layover zones occur where the returns from two surfaces with equal distances to the sensor are received together, creating errors of omission. The approach to shadow and layover zones used in this study were adapted from Mason et al. (2010). This includes the traditional shadow and layover zones created by terrain geometry, but also includes occlusion areas caused by tall vegetation (Mason et al., 2010). Due to the varying degrees of canopy (density, growth state) throughout the SAR scenes, and the ability for the leaves to cause signal attenuation, the assumption is made that the tree canopy is impenetrable, similar to urban infrastructure and terrain. Therefore, a shadow and layover mask was generated using the satellites geometric parameters (incidence angle and azimuth) and a LiDAR digital elevation model (DEM), combining the affects from both the terrain elevation and vegetation height. It is noted that, if LiDAR surveys are conducted in concert with the SAR scenes, further vegetative parameters such
as density derived from the intensity and positional data from the surveys can be used to further refine the shadow and layover mask. However, due to the disparate acquisition dates of these data, and the seasonality of vegetation cover in the study area, only the parameter of vegetation height, integrated in the DEM, was considered. Figure 3.3c shows the error mask delineated into three classes: shadow region (blue), layover region (red), no error (white).

Finally, the SAR classified water mask and the error mask were combined to create a final SAR water mask for five different classes with each class representing the estimated probability that the pixel is water. The estimated probability values were assigned as 0, 25, 50, 75 and 100 to represent the five different classes evenly distributed between zero and 100%. Figure 3.4 outlines the decision tree used to classify each pixel in the SAR model. For instance, pixels in the uncertain zone between thresholds that were also within a shadow error of commission zone were assigned a probability of 25% water (highlighted in Figure 3.4). Five final SAR water masks were created; one for each acquisition date. Figure 3.3d shows the final SAR water mask for the April 2, 2016 TSX acquisition.
Figure 3.3. Example of masks created using TSX data for April 2, 2016: (a) Processed SAR intensity image, greyscale with black representing low intensity values (-25 dB) and white representing high intensity values (0 dB); (b) SAR threshold water mask showing three classes-water (blue), uncertain (black), and non-water (white); (c) Error mask showing three classes; shadow commission zones in blue, layover omission zones in red, and no error in white; (d) Final SAR water mask showing five classes representing the probability that a pixel is water.
Figure 3.4. Decision tree analysis performed to create the final SAR water mask by combining the SAR threshold water mask with the shadow and layover zones within text example highlighted in grey.

3.3.3 LiDAR Processing

As noted in Table 3.1, airborne LiDAR data was acquired over QUBS in June 2016 using an Optech Gemini ALTM, which is a small footprint, discrete return LiDAR instrument capable of recording 4 return pulses per emitted pulse, each with an associated intensity value. The LiDAR data provided was filtered for outliers and ground classified. The original point cloud was rasterized into 3m x 3m pixels for further processing. Rasterization was performed for each input parameter individually. A tiered decision tree classifier (adapted after (Crasto et al., 2015)), was used to classify water in the study area using both the positional and intensity data available in the LiDAR dataset.
The six input parameters used for this study are: 1) point density, 2) intensity, 3) scan angle, 4) standard deviation of intensity, 5) standard deviation of elevation, and 6) pulse density of only ground classified points; these parameters are illustrated in Figure 3.5. Subsets of these parameters were combined into 4 intermediate water masks as illustrated in Figure 3.6:

The Density Mask (Mask DEN) was generated using only point density; due to the specular reflection of water, open bodies of water have a high rate of point dropouts and thus a low point density (Höfle et al., 2009). This is contrasted with forested areas which commonly have more than one return signal per emitted signal, and open fields which do not generally produce point dropouts.

The Scan Angle/Intensity Mask (Mask SCI) was generated using scan angle and intensity data; because of its properties as a specular reflector, open water bodies typically have low intensity at high incidence angles and high intensity beneath the nadir of the platform and at smaller incidence angles.

The Standard Deviation Mask (Mask STD) incorporates the standard deviations of intensity and elevation; open bodies of water are by definition flat, and so have a low variation in elevation. They are also characterized as having a low standard deviation of intensity at moderate scan angles because of the consistent reflection of the laser signal away from the receiver and subsequent low intensity returns and dropouts, and a high standard deviation of intensity at low scan angles because of the contrasting high intensity returns beneath the nadir of the plane and low intensity returns from the neighbouring flight strips due to the effects of flight strip overlap (Crasto et al., 2015; Höfle et al., 2009).

The Inundation Mask (Mask IND) was generated to highlight forested areas that have the potential to be inundated and was generated by integrating the pulse density of ground points, elevation standard deviation, and intensity; this mask was made by visually inspecting the raster of each
individual parameter to identify patterns in the study area. A region of moderately low intensity within a forested area was noted. The low intensity could be indicative of water cover beneath the forest canopy, which would lower the average intensity of the returns from that area. Pulse density was used to identify areas where the LiDAR signal was routinely able to penetrate the forest canopy and correctly classify ground points. A forest which is flooded for a significant portion of the year is likely to be unhealthier than the surrounding forest, allowing more laser pulses to reach the ground surface beneath the canopy (Kozlowski, 2002).

Finally, once the inundated forest model was created, it was checked visually against optical imagery of the area and a DEM created from the LiDAR data. Visual inspection of the optical imagery did not reveal any indication of the forest being flooded. However, on inspection of the DEM it was observed that the area of inundation is flat, occurs in a local elevation minima, and most notably it appears to connect the lakes in the study area with Lake Opinicon, a larger lake east of the study area. Along with connecting those water bodies, the elevation of the area suspected of inundation is intermediate between that of the lakes in the study area and Lake Opinicon.
Figure 3.5. Flow chart illustrating the tiered decision tree methodology used for classifying water using LiDAR data.

Figure 3.6. Input parameters derived from LiDAR data to generate intermediate water masks: (a) Point density; (b) Intensity; (c) Scan angle; (d) Standard deviation of intensity; (e) Standard deviation of elevation; (f) Pulse density of classified ground returns. Low values are in black, high values are in white.

The final water mask was generated through a decision tree using each of the intermediate water masks as inputs (Figure 3.7). Due to the fact that water does not have one distinctive elevation, intensity, or point density signature, each of the intermediate water masks were developed to isolate one or more sections of the water body. Each of the masks were optimized to minimize noise and errors of commission (false positives). Therefore, when generating the final water mask, a pixel was classified as 100% water if either the SCI mask or the STD mask classified it as water. Due to
artifacts introduced into the density mask from the variations in airplane orientation throughout the flight, and through a miscalculation in flight trajectory, the density mask could not be directly input into the final mask. Instead, the DEN mask was filtered to only classify pixels as water if they had both a low standard deviation of elevation and had a low point density. Pixels that were identified as being potentially inundated were assigned a value of 50% in the final LiDAR water mask.

Figure 3.7. Intermediate water masks derived from the input parameters using a decision tree, and the final water mask generated using LiDAR data: (a) Density water mask; (b) Intensity and Scan Angle water mask; (c) Standard Deviation water mask; (d) Inundation water mask; (e) Final water mask classified using a decision tree with the intermediate water masks as input.

3.3.4 Optical Imagery Processing

WorldView-2 8-band multispectral imagery was used to create a water mask using the Normalized Difference Water Index (NDWI) and the Normalized Difference Vegetation Index (NDVI) seen in Equation 3.1 and 3.2, respectively.

\[
\text{NDWI} = \frac{\text{Coastal} - \text{NIR2}}{\text{Coastal} + \text{NIR2}} \quad (3.1)
\]
\[
\text{NDVI} = \frac{\text{NIR2} - \text{Red}}{\text{NIR2} + \text{Red}}
\] (3.2)

These equations utilize the coastal and NIR2 bands unique to WorldView-2, which provide a larger difference in wavelength, resulting in a more discrete threshold for detecting water and vegetation (Maglione et al., 2014; Nouri et al., 2013; Wolf, 2012). The NDWI is used to identify areas of water, which is characterized by high values, since the coastal band maximized the reflectance of water and the NIR2 band minimizes the reflectance of water (Figure 3.8a). The NDVI is used to identify vegetation, where higher values characterize healthier growth (Figure 3.8c). The red band is traditionally used as it is absorbed by chlorophyll in healthy plant materials, and again the NIR2 band is used, as it is strongly absorbed by water and reflected by terrestrial vegetation and soil (McFeeters, 1996; Rokni et al., 2014; Wolf, 2012; Xu, 2006). The histograms of both the NDWI and the NDVI are bimodal and range from -1 to +1, where the higher value mode represents water and healthy vegetation, respectively. A threshold value was chosen to segment the indices into two classes by fitting a normal distribution curve to the mode and choosing the value where the slope of the mode becomes zero. The threshold for the NDWI was 0.58, where pixels greater than the threshold were classified as water, and pixels below were marked as non-water (Figure 3.8b). The NDVI was used to create an error mask, where a threshold of 0.54 was used to classify areas of canopy (above) and areas of non-canopy (below). This error mask represents the areas where the signal from optical remote sensing would be obstructed and water on the ground surface under vegetation could not be detected (Figure 3.8d).

Finally, the optical water mask and the optical error mask were combined to create a final optical water mask with three classes. Pixels were assigned a probability of that pixel being water. Areas where non-water were classified and where no tree canopy exists were marked as 0% probability water. Pixels within the error zone were assigned a 50% probability of being water due to the inability of the instrumentation to correctly classify land cover type beneath the canopy. The
remaining pixels, representing where water was classified with no error, were given a value of 100% water. The final optical water mask can be seen in Figure 3.8e.

**Figure 3.8.** Masks created using 8-band multispectral WorldView-2 imagery from August 26, 2016: (a) NDWI (Low values are in black, high values are in white); (b) Optical water mask showing two classes; water (blue), non-water (white); (c) NDVI (Low values are in black, high values are in white); (d) Error mask showing two classes; error/canopy zones in black, and no error in white; (e) Final optical water mask showing three classes representing the probability that a pixel is water.

### 3.3.5 Fused Water Model

The final water masks created from all three datasets result in a fused water model that exploits the strengths and compensate for the weaknesses of SAR, airborne LiDAR and optical imagery. Since there were five different SAR acquisitions and water masks, each of these were combined with LiDAR and optical to create five different fused water models, each representing a different point in time. This fused model classifies pixels based on the agreement of the sensors at each pixel. As
a measure of agreement, each of the masks generated from the different remote sensing techniques were differenced from each other. The absolute value of these differences were used in a decision tree analysis (Figure 3.9) to determine the value of the pixel in the final fused water model.

| $|P_{\text{LIDAR}} - P_{\text{Optical}}|$ | $|P_{\text{SAR}} - P_{\text{Optical}}|$ | $|P_{\text{SAR}} - P_{\text{LIDAR}}|$ | Fused Water Model |
|-------------------------------|-------------------------------|-------------------------------|------------------|
| ≤ 25                          | > 25                          | ≤ 25                          | All Agree        |
| > 25                          | > 25                          | ≤ 25                          | $P_S = P_O = P_L$|
| ≤ 25                          | > 25                          | > 25                          | SAR Disagree     |
| > 25                          | ≤ 25                          | ≤ 25                          | $P_L = P_S = P_O$|
| > 25                          | > 25                          | > 25                          | LIDAR Disagree   |
| > 25                          | ≤ 25                          | > 25                          | Optical Disagree |
| > 25                          | > 25                          | > 25                          | All Disagree     |

**Figure 3.9.** Decision tree classifier used to create five fused water models from each of the SAR water masks combined with the LiDAR and optical water masks. The absolute differences at the pixel value of each water mask ($P_S$, $P_L$ and $P_O$) were calculated, and used to create eight different outcomes of which five occurred (white) and three did not occur (grey).

In the decision tree classifier, if the absolute difference between two sensors exceeded 25%, then the sensors did not agree on their classifications; for example, one sensor classified water and the other sensor did not. If the absolute difference between two sensors was less than 25%, the two sensors agreed and classified the pixel similarly (ex. Both sensors classified water). The value of 25% was chosen as it is the difference between classes in the individual water masks. Using this principle, there were eight different possible outcomes, of which five occurred. If all sensors agreed
(all differences were less than 25%), then the median values of the pixels were used in the fused water model. Similarly, if all sensors disagreed (all differences were greater than 25%), then the median values of the pixels were used. Finally, if only a single sensor disagreed, then the mask generated from that sensor was disregarded and the average of the two remaining sensors was used. When a shadow or layover zone in SAR overlapped with the tree canopy in the optical mask, both the optical and SAR were within an error zone. In this case, the LiDAR mask was used for classification in the final fused water model since it would be the most reliable sensor in that situation.

3.4 Results

A fused model was developed by exploiting the strengths of three unique remote sensing techniques. Five different fused water models were created, representing the timeline during which the SAR scenes were acquired. These five models can be seen in Figure 3.10. Pixels shown in blue represent water, gray represents uncertain areas, and white pixels show non-water.
Figure 3.10. Five fused water models created for the five SAR acquisition dates: April 2, April 24, May 5, July 10, September 3, 2016. The three classes shown are non-water (white), uncertain (grey), water (blue). Rectangles outline the five study sub-areas.

Photographs from the in situ field investigations in April, May and July 2016 can be seen in Figure 3.11. Observations made from the three field investigations were used to correlate the temporal changes in the fused models to seasonal changes. Seasonal changes from Spring to Summer in the study area are representative for a mid-continental climate and characterized by increasing temperature and vegetation cover, a decrease in precipitation, and a consequent recession of shorelines. All five monitored locations observed a decrease in surface water extent from April to July. From April through May to July, the tree canopy was observed to be bare, budding, and in full bloom, respectively. These seasonal changes are mirrored in the classification of pixels in the fused models. The number of uncertain pixels in the fused models increases from 6% to 9% from April to September. This could be due to the increase in tree canopy through the season, causing an increase in false positives for water. The percent of water classified in the fused models is seen to decrease from 18% to 17% from April to September, which is also corroborated by the field investigations. Specifically, Poole Lake remained relatively unchanged throughout the season since it is a relatively large, deep body of water with steep shorelines (Yellow box in Figure 3.10). Similarly, water levels at Marsh A remained low throughout the season, although in some areas the mud was observed to be wet (Red box in Figure 3.10). The classification of Inundated Forest is also unchanged throughout the season (Green box in Figure 3.10), although this is because of the fact that LiDAR was only captured once for the study area, and in areas which are both covered by canopy and in shadow, the fused model defers to the LiDAR model. Marsh B receded through time with the shoreline transitioning from muddy and wet to hard and dry, a recession which is also seen in the fused models (Purple box in Figure 3.10). The Vegetated Lake also becomes drier through time which is observed in the field investigations and in the fused models (Blue box in Figure 3.10).
Figure 3.12 and Figure 3.13 represent each of the five outcomes of the decision tree classifier, as well as the areas where the conditional LiDAR mask was applied when both optical and SAR are in shadow. These figures highlight the areas over which each of the outcomes occur, indicating whether all sensors agree, all sensors disagree, and where either SAR or LiDAR or optical disagree with the other two techniques. Figure 3.12 shows the sensor agreement models for the first acquisition date (April 2016) and Figure 3.13 shows the sensor agreement models for the last acquisition date (September 2016). In each of these models, the black pixels represent the areas in which the labeled outcome occurred and the white areas represent where it did not.

All sensors agreed in areas with open bodies of water and fields. Disagreement was most common along shorelines, shallow bodies of water and over wetlands since these areas are the most changeable seasonally. These areas are also important indications of flooding events and water extent change. Areas over which the SAR classification disagreed, but LiDAR and optical agreed were concentrated around shorelines and within shadow and layover zones. Optical disagreed under tree cover, over flooded vegetation and over the wetlands surrounding Poole Lake, which may be shallow or have a thin vegetative covering. LiDAR disagreed in a few areas where classification of water was confounded by a systematic error introduced by the swaying of the aircraft during data acquisition, compounded with the variable intensity signature of water.
Figure 3.11. Photographs from in situ fieldwork performed on three of the five SAR acquisition dates: in April, May and July 2016: (A) Poole Lake; (B) Marsh A; (C) Inundated Forest; (D) Marsh B; and (E) Vegetated Lake. This location was first observed on 5 May and also shows a photogrammetric model created using images captured from UAV.
Figure 3.12. Five outcomes from the decision tree classifier and the LiDAR only additional statement showing the spatial extent of the sensor agreement from April 2, 2016. Black pixels represent areas where outcome occurred, white pixels represent areas where outcome did not occur: (a) All agree; (b) All disagree; (c) SAR disagree; (d) Optical disagree; (e) LiDAR disagree; (f) LiDAR only.
**Figure 3.13.** Five outcomes from the decision tree classifier and the LiDAR only additional statement showing the spatial extent of the sensor agreement from September 3, 2016. Black pixels represent areas where outcome occurred, white pixels represent areas where outcome did not occur: (a) All agree; (b) All disagree; (c) SAR disagree; (d) Optical disagree; (e) LiDAR disagree; (f) LiDAR only.

The graph in Figure 3.14 displays the percent of pixels of the five different outcomes and LiDAR only areas from the sensor agreement models plotted through time. Several trends were noticed. The areas where all sensors agree, mainly open water bodies and fields, remains stable through time; this is expected because these areas experience little to no seasonal fluctuation in water extent. Pixels at which all sensors disagree, principally along shorelines and over wetlands, increase through time which relates to the increase in tree canopy causing a shadow and layover error. Optical disagreement lessens as it converges upon its August acquisition date. Similarly, LiDAR disagreement increases as it diverges from its June acquisition date. SAR disagreement remains
stable which is expected due to the increasing disagreement with LiDAR, but increasing agreement with optical. Finally, LiDAR only increases as the number of commission error of water increases from the growing tree canopy throughout the season.

Figure 3.14. Percent of pixels of the five outcomes from the sensor agreement models and the LiDAR only additional statement through time of SAR acquisition dates, also showing LiDAR acquisition month (June) and optical acquisition month (August).

Table 3.2 outlines the percentages of water, uncertainty, and non-water comparing each of the input water masks from the individual remote sensing techniques, and the five fused models. By fusing the three sensors together, the uncertainty within the individual SAR models was decreased from 17-23% to 4-9%. The uncertainty in the optical data was originally 75%, but by combining with LiDAR and SAR, the uncertainty in the fused models is reduced. Although the single LiDAR model uncertainty was 4%, which is lower than the fused models uncertainty, by combining the SAR and optical with the LiDAR, the artefacts in the LiDAR model (such as the incorrectly identified strips over open bodies of water) were corrected for.
Table 3.2. Percent of water, uncertainty and non-water of all models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Percent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100% water</td>
</tr>
<tr>
<td>1 Single: SAR April 2</td>
<td>19</td>
</tr>
<tr>
<td>2 Single: SAR April 24</td>
<td>18</td>
</tr>
<tr>
<td>3 Single: SAR May 5</td>
<td>18</td>
</tr>
<tr>
<td>4 Single: SAR July 10</td>
<td>19</td>
</tr>
<tr>
<td>5 Single: SAR Sept 3</td>
<td>20</td>
</tr>
<tr>
<td>6 Single: LiDAR</td>
<td>20</td>
</tr>
<tr>
<td>7 Single: Optical</td>
<td>11</td>
</tr>
<tr>
<td>8 Fused (April 2)</td>
<td>18</td>
</tr>
<tr>
<td>9 Fused (April 24)</td>
<td>18</td>
</tr>
<tr>
<td>10 Fused (May 5)</td>
<td>18</td>
</tr>
<tr>
<td>11 Fused (July 10)</td>
<td>18</td>
</tr>
<tr>
<td>12 Fused (Sept 3)</td>
<td>17</td>
</tr>
</tbody>
</table>

3.5 Discussion

The fused classification models indicate a decline in the extent of surface water throughout the study period, which is consistent with seasonal changes observed during field investigations. However, the uncertainty rate also increases, which could be due to the increase in tree canopy through the season, causing an increase in false positives for water, an interpretation which is corroborated by the field investigations. This ability of the fused models to correctly interpret seasonal trends in water extent fluctuations highlights its applicability for flood hazard monitoring. The models also worked over wetlands and water bodies of differing depths and types of flooded vegetation.
The disagreement of the individual remote sensing techniques over wetlands and at the shorelines of larger water bodies highlights the weaknesses of each technique and the advantage of integrating SAR, LiDAR and optical remote sensing into a fused water classification model. Considering that wetlands are important indicators for flooding events and water extent change, they are one of the most relevant areas when planning a flood monitoring strategy. While the SAR only models disagreed largely in zones of shadow or layover, the disagreement of the optical models along the edge of Poole Lake may be due to those areas being shallow or having a thin vegetation cover. The ability of LiDAR to penetrate tree canopy further improves this model by being able to identify potential areas of inundated forests, and the artifacts introduced from flight conditions during data acquisition can be corrected by SAR and optical data. When comparing the spatial extent of the sensor agreement models from April (Figure 3.12) to September (Figure 3.13), the main changes seen are due to seasonal variations in the models and are located in areas where there are significant fluctuations in surface water extent due to shallow water bodies and wetlands.

The agreement between sensors over the course of the study period can mostly be explained by the dissimilar seasons in which each of the remote sensing data were acquired (Figure 3.14). Since LiDAR was acquired in June, LiDAR disagreement increases as it diverges from its June acquisition date. Similarly, Optical disagreement decreases as the study period progresses and converges upon its August acquisition date. SAR disagreement remains stable which is expected due to the increasing disagreement with LiDAR, but increasing agreement with optical. While temporal disagreements between sensors could be mitigated by acquiring all remote sensing data coincidently, this study demonstrates that it is not necessary for all data to be collected concurrently in order to exploit their synergies and integrate these data into a fused water extent model. This is important to note as most remote sensing project will not have access to all three remote sensing observation types acquired at the same time.
Ultimately, the fused model benefitted from all individual sensor and their synergies. The increase in water from 19% to 20% through time seen in the individual SAR scenes does not correlate to seasonal effects that were observed at the individual study sites, which were characterized by a progressive recession of the shallow water bodies. This increase in classifying water pixels in the SAR masks is theorized to correspond to the increase in tree canopy cover which would increase the number and extent of shadow zones, which can be misclassified as water. In the fused models, percentage of classified water decreases from 18% to 17%, which agrees better with seasonal trends.

3.6 Conclusions

In this study, TSX scenes were combined with airborne LiDAR and optical images using a pixel based decision tree analysis to classify areas of water and non-water and identify areas where the classification remains uncertain. This fusion technique exploits the strengths and weaknesses of each sensor and allows for an optimized fused water extent classifier which decreases the uncertainty. It was found that although the optical, SAR and LiDAR data were collected in different seasons, the uncertainty of the fused model was lower than the uncertainty of any single technique. The uncertainty in the final fused models was between 4% and 9%, compared to 17–23% from the single polarization SAR classified water models. The development of a SAR only time series of water coverage is hindered by processes including vegetation growth (leading to different errors of commission due to shadow and omission due to layover zones over time) and land cover changes which change the backscatter (and threshold per scene). Optical and LiDAR data can enhance a time series by removing some of these competing processes. In addition, the water model could be enhanced by using multi-polarization SAR to better classify areas of different scattering mechanisms, including flooded vegetation. A monitoring strategy for surface water thus needs to analyze the spatio-temporal processes of land cover change first, and then design an acquisition plan which includes optical and LiDAR acquisitions and continuous SAR acquisitions. The benefit
of having access to three independent observation types was demonstrated herein, and will be used to create a flooding hazard monitoring strategy in the future.
Chapter 4

Assessing Single-Polarization and Dual-Polarization TerraSAR-X Data for Surface Water Monitoring


4.1 Abstract

Three SAR data classification methodologies were used to assess the ability of single-polarization and dual-polarization TerraSAR-X (TSX) data to classify surface water including open water, ice and flooded vegetation. Multi-polarization SAR observations contain more information than single-polarization SAR, but the availability of multi-polarization data is much lower which limits the temporal monitoring capabilities. The study area is a principally natural landscape centered on a seasonally flooding river, in which four TSX dual-co-polarized images were acquired between the months of April and June 2016. Previous studies have shown that single polarization SAR is useful for analyzing surface water extent and change using grey-level thresholding. The H-Alpha-Wishart decomposition adapted to dual-polarization data and the Kennaugh Element Framework were used to classify areas of water and flooded vegetation. Although, grey-level thresholding was able to identify areas of water and non-water, the percentage of seasonal change was limited indicating an increase in water area from 8% to 10%. The dual-polarization methods show a decrease in water over the season and indicate a decrease in flooded vegetation, which agrees with expected seasonal variations. When comparing the two dual-polarization methods a clear benefit to the Kennaugh Elements is the ability to classify change in the transition zones of ice to open water, open water to marsh, and flooded vegetation to land using the differential Kennaugh technique. The H-Alpha-Wishart classifier was not able to classify ice, and misclassified fields and
ice as water. Although single-polarization SAR was effective in classifying open water, the findings of this study confirm the advantages of having dual-polarization observations, with the Kennaugh Element Framework being the best performing classification framework.

4.2 Introduction

Synthetic Aperture Radar (SAR) is an active remote sensing technique and can penetrate cloud cover and operate during the day or night. Often flood events occur during unfavourable weather conditions when optical visibility is low, which allows SAR to be a useful sensor for surface water classification (Lee and Pottier, 2009). SAR missions and products vary in polarization, frequency and resolution, which allows the user to select the most suitable SAR observations to the application at hand, which in this case is the classification of surface water and its varying states. Currently, there exists a trade-off between spatio-temporal coverage and information content with respect to single-polarization and multi-polarization SAR data. While multi-polarization contains more information about the scattering mechanism of the target, the temporal coverage over a single target is limited and prohibits monitoring over regional scales. Many studies addressed the use of single or multi-polarization SAR individually using diverse classification algorithms, but few addressed the comparison of single- and multi-polarization SAR data for surface water monitoring (Brisco et al., 2008; Lee and Pottier, 2009; Lee et al., 2001; White et al., 2015). These comparative studies mainly address single-polarization and quad-polarization processing methods, or address which dual-polarization channels are most effective for surface water monitoring, but lack discussion of the dual-polarization processing methods. In this study, there are three main objectives. The first is to create classified models of surface water using both single and dual-polarization TSX data. The second is to compare these models to better understand the extent of the limitations of single-polarization data and to what extent they are aided by dual-polarization data. The third objective is to create a surface water extent time series from the initial snow melt period and into spring to demonstrate the feasibility for near-continuous surface water monitoring from space. The current
fleet of ~10 civil SAR missions in orbit and the planned missions up to 2020 provide and will continue to provide an unprecedented amount of observations in the X-, C-, and L-band, mostly in single-polarization mode, which will lead to near-continuous monitoring capabilities.

Previous studies have shown that single polarization SAR data is a viable technology for analyzing surface water extent and spatio-temporal change (Giustarini et al., 2015; Imhoff et al., 1987; Irwin et al., 2017; Kuenzer et al., 2013; Liu and Jezek, 2004; Martinis et al., 2015a, 2009; Mason et al., 2010, 2007; Matgen et al., 2007; Schlaffer et al., 2015; White et al., 2015, 2014). Single polarization SAR provides one channel of intensity data in either HH (horizontal linear transmission and horizontal linear reception), HV (horizontal linear transmission and vertical linear reception), VH (vertical linear transmission and horizontal linear reception) or VV (vertical linear transmission and vertical linear reception). One of the most common and effective classification techniques is grey-level thresholding which can be applied to differentiate areas of water and non-water (Gstaiger et al., 2012; White et al., 2015). This has proved successful to delineate open water bodies, but limitations arise with more heterogeneous targets such as ice covered water bodies and surface water beneath vegetation, which are abundant in Canada, with approximately 14% of the Canadian landscape being covered in wetlands (White et al., 2015). Vegetation cover leads to misclassification due to shadow and layover effects and ice can often be misclassified due to the similar backscatter response to rough surface water (Mason et al., 2010; White et al., 2015). Wind effects can also lead to misclassification causing water to be mistaken as land rough vegetation or ice (White et al., 2015). Multi-temporal SAR acquisitions often occur during ice-off conditions to avoid misclassification. However it is important to document the initial stages of snowmelt and spring flooding, because the subsequent hydrological conditions rely on this initial process (White et al., 2015). The limitations of single-polarization SAR could be aided by the use of dual-polarization SAR which provides two channels of intensity and phase information (HH/HV, VV/VH, or HH/VV). Having two channels of intensity and phase information allows for discerning
among scattering mechanisms, such as surface scattering, double bounce and volume scattering. Dual-polarization SAR data can be used to distinguish ice, and vegetated areas from open water, while those land cover types often lead to misclassification in single-polarization data (Mermoz et al., 2014; Schmitt and Brisco, 2013; White et al., 2015). Several studies have identified the significant double-bounce component originating from flooded vegetation and hence, quad-polarization SAR must often be used for classification (Brisco et al., 2011; Gallant et al., 2014; S. Hong et al., 2015; White et al., 2015). Quad-polarization data is often not available, while dual-polarization has been demonstrated to be sufficient (Betbeder et al., 2015; Dabboor et al., 2015; Moser et al., 2016; Schmitt and Brisco, 2013; Schmitt et al., 2012b).

4.3 Data Description and Methodology

4.3.1 Study Area and Data Description

The ~ 6 km x 12 km study area is located south of Lac-Simon in Quebec, Canada (Figure 4.1). This area was chosen because it is a principally natural landscape with open bodies of water, marshland and forested areas. Most importantly, the Ruisseau Schryer which flows from A (Lac-Schryer) to B (Baie-de-l’Ours in Lac-Simon) in Figure 4.1 which is flooded during snow melt each year. This could affect the urban areas located near the river, including the town of Montpellier located on the North side of the stream. Montpellier experienced flooding due to seasonally high water levels, and overflowing rivers in April of 2017. These events threatened and damaged multiple homes and a state of emergency was declared in towns near to Montpellier. The orange box in Figure 4.1 zooms in on the river entering Baie-de-l’Ours showing a distinct flood plain surrounding both sides of the meandering river.
Figure 4.1. Map of study area showing town of Montpellier, southern extent of Lac-Simon, and stream (Ruisseau Schryer) flowing from A (Lac-Schryer) to B (Baie-de-l’Ours). Base map is provided by the Quebec Ministry of Energy and Natural Resources (MERN) showing urban areas (grey), water (blue), forest (green), low vegetation (tan) and marshlands (blue horizontal lines). Zoomed in orange box of Google Earth imagery from July 2017 shows a flood plain surrounding the stream entering Lac-Simon at B.

Four TSX dual-co-polarization (HH/VV) stripmap mode scenes were acquired through the spring and summer of 2016. Each scene has an areal extent of 15 km by 50 km and a slant range and azimuth resolution of 1.2 m and 6.6 m, respectively. Details of each product are provided in Table 4.1.

Table 4.1. Specifications of the four dual-polarization TerraSAR-X scenes used for this study

<table>
<thead>
<tr>
<th>ID</th>
<th>Date (2016)</th>
<th>Mode</th>
<th>Polarization</th>
<th>Product</th>
<th>Look Direction</th>
<th>Path</th>
<th>Incidence Angle (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>April 2</td>
<td>Stripmap</td>
<td>HH/VV</td>
<td>SSC</td>
<td>Right</td>
<td>Descending</td>
<td>39</td>
</tr>
<tr>
<td>2</td>
<td>April 24</td>
<td>Stripmap</td>
<td>HH/VV</td>
<td>SSC</td>
<td>Right</td>
<td>Descending</td>
<td>39</td>
</tr>
<tr>
<td>3</td>
<td>May 5</td>
<td>Stripmap</td>
<td>HH/VV</td>
<td>SSC</td>
<td>Right</td>
<td>Descending</td>
<td>39</td>
</tr>
<tr>
<td>4</td>
<td>June 18</td>
<td>Stripmap</td>
<td>HH/VV</td>
<td>SSC</td>
<td>Right</td>
<td>Descending</td>
<td>39</td>
</tr>
</tbody>
</table>
Three 8-band multispectral Landsat 8 images from April 13, April 29 and June 16, 2016 with a resolution of 30 m were used to aid in visual comparison and validation of the TSX data (Figure 4.2). It is important to note the change in ice cover between the April 13th scene and the April 29th scenes. By the June 16th scene the vegetation canopy is fully developed, shown in green. In the April 29th scene, cloud cover can be noticed, which is a clear limitation of optical imagery.

![Figure 4.2](image_url)

**Figure 4.2.** Time series of Landsat 8 true colour optical images (RGB: 4-3-2) from: (a) April 13, 2016; (b) April 29, 2016; (c) June 16, 2016.
4.3.2 Classification Methods

Each TSX scene was processed using three different methods: Grey-level thresholding applied to single-polarization data (HH), the Kennaugh Element Framework (Schmitt et al., 2015) applied to dual-polarization data (HH, VV), and H-Alpha-Dual-Polarization decomposition (HH, VV). The processing workflow for each method can be seen in Figure 4.3.

**Figure 4.3.** Processing workflow for single and dual-polarization data to create three final modes for each TSX scene.

The HH band of the TSX data was used to simulate single polarization data. HH polarization tends to be used over HV or VV because the difference in backscatter response between land and water are greatest for HH polarization (Bourgeau-Chavez et al., 2001; Gstaiger et al., 2012; Hess et al., 1995; Manjusree et al., 2012; Townsend, 2002; White et al., 2015). Grey-level thresholding was used to classify each SAR scene because it is a simple and effective way to map surface water (Brisco et al., 2009; White et al., 2014). Since the histogram of the intensity data is bimodal, a value in-between the two modes can be chosen in which everything below this threshold is classified as water and everything above is classified as non-water. In this study, the threshold value used was the minimum between the two modes. This method was applied to all four TSX images producing
four models each with two classes (water and other). The processing work flow for this method is shown in Figure 4.3.

Studies have shown successful results using dual-co-polarization HH/VV data for flooded vegetation mapping (Brisco et al., 2011; Kasischke et al., 1997; Schmitt and Brisco, 2013). Several common decomposition types exist to break down the data into polarimetric parameters, but there are few that are adapted for dual-polarization data. In this study, two dual-polarization decompositions will be used to classify water and flooded vegetation. The first is the H-Alpha decomposition which was developed in 2007 and modified for dual-polarization data (Cloude, 2007). The second method is the Kennaugh Element Framework developed by Schmitt et al. (2015). A few studies have researched the use of this technique for mapping wetlands and have proved it successful (Moser et al., 2016; Schmitt and Brisco, 2013; Schmitt et al., 2012b).

The H-Alpha decomposition for dual-polarization data uses an eigenvector analysis off the coherency matrix \([T2]\) which separates the parameters into scattering processes (the eigenvectors) and their relative magnitudes (the eigenvalues) (Cloude, 2007). There are two parameters outputted from the H-Alpha decomposition, entropy (H) and alpha (\(\alpha\)). Entropy is calculated from the eigenvalue information and represents the degree of randomness in the scattering. Alpha (\(\alpha\)) is calculated from the eigenvectors and represents a rotation which can indicate the type of scattering mechanism (Figure 4.4) (Cloude and Pottier, 1996). The quad-polarization decomposition of H-Alpha has shown to work well in natural environments, since this method is an incoherent decomposition which can characterize distributed targets (Lee and Pottier, 2009). However, the modified dual-polarized H-Alpha decomposition is less well studied. The unsupervised Wishart distribution clustering algorithm is applied to the H-Alpha decomposition as the coherency matrix can be modelled by this. The Wishart distribution is robust and can be applied to any type of polarimetric SAR data, so it is often applied to the H-Alpha decompositions (dual or quad) (Lee
and Pottier, 2009). Nine different classes were created using the Wishart classifier on the H-Alpha decomposition. These classes were visually inspected to determine which classes could be re-clustered to represent the desired three classes i) open water, ii) flooded vegetation, and iii) other. This processing method was applied to all four TSX images producing four models each with three classes. The processing work flow for this method is shown in Figure 4.3.

**Figure 4.4.** Images of parameters entropy (A) and alpha (B) for the TerraSAR-X scene from April 2, 2016.

The Kennaugh element framework was developed by Schmitt et al. (2015). This technique linearly transforms the four-dimensional Stokes vector into a four-by-four scattering matrix, called the Kennaugh matrix [K]. Four normalized Kennaugh elements from this matrix K can be computed.
using dual-co-polarization data. In the case of HH/VV data the elements are $K_0, K_3, K_4$, and $K_7$. $K_0$ represents the total intensity as a sum of HH and VV intensity, $K_3$ represents the difference between double bounce and surface intensity, $K_4$ represents the difference between HH and VV intensity, and $K_7$ represents the phase shift between double-bounce and surface scattering mechanisms. These four elements have shown to be very useful for identifying flooded vegetation. A study by Moser et al. (2016) has demonstrated that open water has low values of $K_0$, due to the specular scattering nature of calm water causing a low backscatter signature. These areas generally form clusters that can be distinctly separated from the other classes. Flooded vegetation is characterized by high values of $K_4$, medium values of $K_3$ and lower values of $K_0$. Another study identified the significant difference between HH and VV intensity over flooded areas and inundated forests, emphasizing the importance of $K_4$ (Zalite et al., 2014). Using a pre-process Kennaugh chain, the Kennaugh elements were geocoded, calibrated and enhanced using a multi-scale and multi-looking technique developed by Schmitt (2016) (Figure 4.3). An example of the four Kennaugh elements produced for the April 2, 2016 scene can be seen in Figure 4.5. This scene was selected as it exhibits open water, ice cover, inundated vegetation and other land cover. Open water is represented by the lowest values of $K_0$ (dark blue in Figure 4.5A) and medium values of $K_3$ (grey in Figure 4.5B). Flooded vegetation is represented by medium values of $K_3$ (grey and yellow in Figure 4.5B) and high values of $K_4$ (red and yellow in Figure 4.5C). Also $K_7$ (Figure 4.5D), representing the phase shift between double bounce and surface scattering, shows sensitivity to inundated vegetation, although not as strong as $K_4$, which was already found by Zalite et al. 2014. Ice cover is represented by low values of $K_0$ (light blue in Figure 4.5A) and low values of $K_3$ (dark blue in Figure 4.5B). These elements were processed using an unsupervised k-means classifier. The k-means clustering algorithm is one of the simplest forms of clustering techniques which aims at minimizing the Euclidean distance between points. The advantages of this technique is that it is fast and robust and therefore works well when applied to large, linear data sets such as the Kennaugh elements. The k-means classifier
produced 11 classes which were then visualized and analyzed to determine which classes represented i) open water, ii) flooded vegetation and iii) other. This processing method was applied to all four TSX images producing four models each with three classes.
**Figure 4.5.** Four Kennaugh elements derived from the dual-pol TerraSAR-X image from April 2, 2016. (a) K0- the total intensity sum of HH plus VV; (b) K3- difference double-bounce minus surface scattering; (c) K4- difference HH minus VV intensity; (d) K7- phase shift between double-bounce and surface scattering mechanisms. Open water is represented by dark blue in A and grey in B. Flooded vegetation is represented by grey and yellow in B and red and yellow in C. Ice cover is represented by light blue in A and dark blue in B. Inundated vegetation is shown in yellow/red in C and cyan in D.

**4.4 Results and Discussion**

**4.4.1 Single-Polarization Classification**

The four water classification models created using grey-level thresholding can be seen in Figure 4.6. Areas of black represent water and grey areas represent non-water. Table 4.2 outlines the percentages of the two classes through time as well as the threshold value used. Water classification changes from 8% to 10% throughout the four scenes disagreeing with seasonal trends, which should show an increase in temperature causing a decrease in water. However, several other processes are occurring to account for this change. Ice can be seen in only the first scene (Blue box in Figure 4.6a) as it is classified as both other and water, and decreases the amount of total water classified. The marsh land shown in the red box in Figure 4.6 is flooded in the first scene (A), but dried out by the last scene (D). This change agrees with seasonal change despite the overall trend of water classification showing an increase. Counteracting this seasonal drying is an increase in overall misclassification in the first scene (A) due to ice and snow and last scene (D) due to vegetation growth (shown in the yellow box in Figure 4.6). Although, the single-polarization methodology was able to see seasonal changes in some wetlands, flooded vegetation was not classified, and misclassification errors occurred due to ice and tall vegetation causing an incorrect interpretation of the total surface water change in the area, a clear limitation of using single-polarization data only.
Figure 4.6. Grey-level thresholding classified models showing water (black) and other (grey) for (a) April 2, 2016; (b) April 24, 2016; (c) May 5, 2016; (d) June 18, 2016. Coloured boxes indicate example areas of temporal change: blue- ice melting; red- marshland dries out; yellow- areas of misclassification due to ice (A) and vegetation (C).

Table 4.2. Percentages of each class and threshold values for each TSX scene using grey-level thresholding.

<table>
<thead>
<tr>
<th>Date (2016)</th>
<th>Threshold Value (dB)</th>
<th>Water (%)</th>
<th>Other (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 2</td>
<td>-17.38</td>
<td>8</td>
<td>92</td>
</tr>
<tr>
<td>April 24</td>
<td>-19.68</td>
<td>9</td>
<td>91</td>
</tr>
<tr>
<td>May 5</td>
<td>-18.56</td>
<td>10</td>
<td>90</td>
</tr>
<tr>
<td>June 18</td>
<td>-18.87</td>
<td>10</td>
<td>90</td>
</tr>
</tbody>
</table>
4.4.2 Dual-Polarization Classification: H-Alpha-Wishart

The water classification models created using the unsupervised H-Alpha-Wishart classification can be seen in Figure 4.7 showing three classes: water (black), flooded vegetation (blue) and other (grey). Of the original nine classes, each model consistently identified Class 3 (blue) as flooded vegetation and Class 7 (black) as open water.

Table 4.3 display the results for each scene classified using the H-Alpha-Wishart method. The percent of water classified gradually decreases from the first scene until the last scene. This is expected as the seasonal changes from wet to dry occur during the study time period. However, some areas are misclassified as water, including a golf course located south of the Baie-de-l’Ours present in the optical imagery (blue box in Figure 4.7). Some fields identifiable in the optical imagery are classified as water as well (black areas in yellow box in Figure 4.7). The percent of flooded vegetation stays around approximately 5% which is inconsistent with season trends. However, in the April scenes (A and B) there is flooded vegetation centered on the river, where as this disappears in the later scenes (yellow box Figure 4.7). The marsh area seen in the red box is shown to dry up in the final scene (D) which is consistent with the single-polarization SAR observations. Ice is not differentiable from open water in the first scene. The sum of water and flooded vegetation (total surface water) decreases and is consistent with the expected seasonal change. Some areas (yellow box in Figure 4.7) which are classified as water on May 5 (C) are classified as flooded vegetation on June 18 (D). This is an indication that vegetation changes may lead to a change in class, but not a change from water to non-water. Hence, the classification of total surface water seems more robust than the discrimination of open water and flooded vegetation. As the vegetation starts developing in May and are fully developed in June, the change in class could be a consequence of that.
Figure 4.7. H-Alpha-Wishart classified models showing water (black), flooded vegetation (blue) and other (grey) for (a) April 2, 2016; (b) April 24, 2016; (c) May 5, 2016; (d) June 18, 2016. Coloured boxes indicate example areas of change: blue - golf course misclassified as water; red - marshland dries out; yellow - flooded vegetation decreases, and misclassification of fields.

Table 4.3. Percentages of each class identified for each H-Alpha-Wishart model through time.

<table>
<thead>
<tr>
<th>Date (2016)</th>
<th>Water (%)</th>
<th>Flooded Vegetation (%)</th>
<th>Other (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 2</td>
<td>17</td>
<td>5</td>
<td>78</td>
</tr>
<tr>
<td>April 24</td>
<td>15</td>
<td>6</td>
<td>79</td>
</tr>
<tr>
<td>May 5</td>
<td>16</td>
<td>2</td>
<td>82</td>
</tr>
<tr>
<td>June 18</td>
<td>12</td>
<td>6</td>
<td>82</td>
</tr>
</tbody>
</table>

4.4.3 Dual-Polarization Classification: Kennaugh Element Framework

A time series of the four false colour composites of the processed Kennaugh elements, K3-K0-K4, are shown in Figure 4.8. Colours are used to clearly differentiate four classes. Bright pink represents open water; white/light pink colour represents flooded vegetation; green and blue represent the ‘other’ class which includes forest, urban areas, agricultural land or other classifications of land.
The dark purple colour seen in the April 2nd scene represents ice, which corresponds to the optical imagery.

The Kennough element technique agrees with the optical imagery. The ice can be seen to disappear by the end of April and the water bodies are consistent. The Kennough elements were able to observe the flooded vegetation during melting, especially in the first two scenes, which the optical imagery was not able to identify.

**Figure 4.8.** False colour composites of the processed Kennough elements, K3-K0-K4, from April 2, April 24, May 5, and June 18, 2016. Open water appears in pink, ice in dark purple, flooded vegetation in white/light pink, and ‘other’ in green and blue.

The Kennough elements were then classified using an unsupervised k-means classifier. This developed 11 classes for each scene. The average of each class of each Kennough element was analyzed and results are shown in Figure 4.9. It shows three plots, $K_0$ vs $K_4$, $K_3$ vs $K_4$, and $K_0$ vs $K_3$, for each of the four scenes. Using this technique, each point was assigned one class of three possible classes, open water, flooded vegetation, and other. It can be seen that the points assigned
as water were consistently the lowest value of $K_0$. Flooded vegetation was consistently identified as the highest value in $K_4$. These findings are consistent with (Moser et al., 2016).

**Figure 4.9.** Graphs of the average of each class for the Kennaugh elements used to classify water (red), flooded vegetation (yellow) and other (black). (a) April 2, 2016; (b) April 24, 2016; (c) May 5, 2016; (d) June 18, 2016.
The water classification models for each of the four scenes can be seen in Figure 4.10. Table 4.4 outlines the percentages of each class identified through time. The black areas represents open water and are shown to decrease from the first scene to the last scene from 16% to approximately 12%. However in the first scene (Green box in Figure 4.10a), the water is distributed, and lakes are classified as both other and water indicating the presence of ice. The flooded vegetation (blue) decreases from 13% to 5% with time. This corresponds well to the seasonal melt that would occur in the first two scenes in early spring, and the seasonal drying that could occur during late spring and early summer of the last two scenes. Similar to H-Alpha-Wishart, misclassification of flooded vegetation can be seen distributed throughout the scene. However, the flooding around the river is evident in the first two scenes and not the last two (yellow box in Figure 4.10). A golf course south of Baie-de-l’Ours is misclassified as water, which is not seen in the optical imagery (Blue box in Figure 4.10). Finally, the marsh area seen in the red box shows a drying out in the last scene similar to the other two classification methodologies.

Figure 4.10. Kennaugh Element models classified showing water (black), flooded vegetation (blue) and other (grey) for (a) April 2, 2016; (b) April 24, 2016; (c) May 5, 2016; (d) June 18, 2016. Coloured boxes indicate example areas of change: blue - golf course misclassified as water; red -
marshland dries with time; yellow - flooded vegetation decrease, and misclassification of field areas; green – ice melting.

Table 4.4. Percentages of each class identified for each Kennaugh Element model through time.

<table>
<thead>
<tr>
<th>Date (2016)</th>
<th>Water (%)</th>
<th>Flooded Vegetation (%)</th>
<th>Other (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 2</td>
<td>16</td>
<td>13</td>
<td>72</td>
</tr>
<tr>
<td>April 24</td>
<td>12</td>
<td>13</td>
<td>75</td>
</tr>
<tr>
<td>May 5</td>
<td>13</td>
<td>5</td>
<td>82</td>
</tr>
<tr>
<td>June 18</td>
<td>12</td>
<td>5</td>
<td>83</td>
</tr>
</tbody>
</table>

Differential Kennaugh elements (Schmitt et al., 2012b) use the differences between the Kennaugh elements of two scenes to understand how the landscape has changed with time. This technique was applied to the first (April 2) and last (June 18) scene and can be seen in Figure 4.11. Each colour represents a type of change. Green represents the change from ice to open water which is mainly a reflected as a change in $K_0$ showing a decrease in total intensity. Dark red represents the change from flooded vegetation to land and accounts for a decrease in the difference between double bounce and surface scattering or $K_3$. Yellow represents the change from open water to flooded vegetation, which is shown as an increase in $K_3$. This technique proves extremely useful, especially when comparing open water and flooded vegetation, since a clear distinction can be seen. The ability to identify change from ice over to open water is also important as it can indicate when the first seasonal melt and flooding occurs.
Figure 4.11. False colour composite of the differential Kennough elements, $K_0-K_4$, differenced between the June 18, 2016 scene and the April 2, 2016 scene. Red represents the change from flooded vegetation to land. Green represents the change from ice to open water. Yellow represents the change from open water to marshland.

4.4.4 Summary of Classification Methods

A comparison of the three methods, k-means performed on the Kennough elements, unsupervised H-Alpha-Wishart classification, and grey-level thresholding, can be seen in Figure 4.12. All methods were able to classify open water, however, the dual-polarization methods consistently classified more water than the grey-level thresholding technique. This was unexpected as the single-polarization data often have errors of commission from shadow zones classified as water. However, more misclassification occurred in the dual-polarization methods including classifying fields and golf greens as water. Both of the dual-polarization methods show the correct decreasing trend of water over the study period from April to June 2016 that one would expect to see including seasonal melting. Results from thresholding disagree with this and show a slight increases over time from 8% to 10%. No classification method was able to classify ice in a single class in the April 2 scene, however grey-level thresholding and Kennough Element k-means classifier were able to
classify some portion of the ice covered lakes as other. Both dual-polarization methods were able to identify flooded vegetation. However, the Kennaugh elements classifier sees a decrease in flooded vegetation with time, which agrees better with seasonal trends. Both methods were able to classify the river flooding in the April scenes and no flooding occurring in the later scenes. The single-polarization method was unable to classify flooded vegetation and instead classified it as other or non-water.

**Figure 4.12.** Graphs showing percent of water and percent of flooded vegetation classified through time for each of the classification methods. Lines: Blue diamond – Unsupervised k-means classification on Kennaugh Elements, Orange square – H-Alpha-Wishart unsupervised classification and grey triangle - grey-level thresholding.
4.5 Conclusions

In this study, three different SAR classification methods were used to identify areas of water, ice and flooded vegetation in four TSX scenes over a principally natural landscape. A river which is seasonally flooded in the centre of the study area serves as a test bed for these methodologies. Single-polarization grey-level thresholding is an established technique for surface water monitoring and has the capability to classify areas of water and non-water. Using the techniques of H-Alpha-Wishart and the Kennaugh Element Framework applied to dual polarization data, the ability to analyze scattering mechanisms and classify water and flooded vegetation was tested and compared to the single-polarization method.

The H-Alpha-Wishart unsupervised classification for dual-polarization data was able to classify areas of open water and flooded vegetation. Flooded vegetation was classified surrounding the river in the first two scenes, acquired in April, and not in the last two scenes acquired in May and June. This corresponds with optical imagery of the same time period. This classifier was not able to distinguish areas of ice in the first scene, and misclassified them as open water.

The Kennaugh Element framework was able to classify areas of open water, flooded vegetation, and ice. K4 was used to distinguish areas of flooded vegetation and K0 was used to identify areas of open water. Similar conclusions were found by Moser et al. (2016). The differential Kennaugh analysis on all four elements, looking at the difference from the first scene to the last scene, was able to indicate where changes occurred but also what changes occurred. The change between ice and open water, open water and marshland, and flooded vegetation and land, were clearly identified using this method. Applying the k-means classifier allowed for the classification of open water and flooded vegetation which agreed with seasonality, but the areas of ice cover are less well defined.

Finally, the single-polarization grey-level thresholding method proved to identify open-water well. Part of the lakes were classified as other in the first scene, which indicates an ability to classify ice
(or rather not misclassify water). However, the total surface water in each scene shows little change and no seasonal variation. Compared to the Kennaugh Element framework which shows a decrease in flooded vegetation from 12% to 5% indicating a seasonal change from flooding to drying. These conclusions could not have been drawn from the single-polarization data and, therefore, a clear advantage to dual-polarization data is the ability to show seasonal fluctuations. In addition, dual-polarization is able to distinguish open water and flooded vegetation.

The findings of this study confirm the expected advantages of dual-polarization observations, however, single-polarization observations are still useful in classifying water, albeit not sufficiently for identifying seasonal changes in vegetated areas. The applicability of single-polarization SAR for landscape dynamics is thus limited. Considering potential applications in Earth system monitoring and process understanding, where not only the land cover type, but also the spatio-temporal transition from one type to another is highly relevant, the use of dual-polarization (or multi-polarization) SAR data is a necessity.
Chapter 5

Comparing Low Resolution Quad-Polarization RADARSAT-2 Data and High Resolution Single-Polarization TerraSAR-X Data for Surface Water Classification


5.1 Abstract

The performance of high resolution single-polarization TerraSAR-X (TSX) staring spotlight mode data and lower resolution quad-polarization RADARSAT-2 (RS-2) data is compared to classify a principally natural landscape into water, marsh/field and forested areas. Six different methodologies are tested, including grey-level thresholding on the HH band of the TSX and RS-2 data, as well as four decomposition techniques on the quad-polarization RS-2 data. The four decomposition and classification techniques were found to have similar performance, however they differ spatially and exhibit strengths and weaknesses. The Freeman-Durden decomposition had the highest Overall Accuracy (OA) at 84%, however it has an inherit loss of resolution and underestimates the water extent. The Pauli decomposition and Kennaugh element framework classified water the best, having a Producer’s Accuracy (PA) of 89% and 79%, respectively. The H-Alpha decomposition had the highest PA for marsh/field at 74%. By combining the best class from each decomposition, an optimized model was created which increased the OA to 89%, which achieves a similar accuracy as the high resolution single-polarization TSX model, which had an OA of 88%. A time series of water extent change using fourteen SAR scenes demonstrate the ability to observe seasonal variations using both TSX and RS-2 data. Overall, the results highlight the

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advantages of using both types of data, but suggest scenarios when high resolution data in single-polarization or low resolution quad-polarization would be more suitable.

5.2 Introduction
In recent years, SAR has become an established method for Earth surface monitoring. The current fleet of operational SAR missions offers SAR data in various modes, frequencies and spatio-temporal resolutions to monitor diverse Earth systems (CEOS, 2016; Moreira et al., 2013; Zhou et al., 2009). For example, the SAR mission TerraSAR-X (TSX) can monitor the same location every 11 days, covering a swath of approximately 16 km² at 0.25 m azimuth resolution using its staring spotlight mode (Eineder et al., 2009; Mittermayer et al., 2012). Among other products, RADARSAT-2 (RS-2) provides quad-polarization data with a repeat cycle of 24 days and a swath size of approximately 25 km² with an 8 m resolution (Livingstone et al., 2006). Depending on the target size and complexity, the right product needs to be identified, considering the competing parameters of spatio-temporal resolution and information content. In this study, the main target is surface water, both open water and inundated vegetation.

Understanding the SAR products available today, including their strengths and weaknesses is essential to developing an optimized surface water monitoring strategy. Because water has a high dielectric constant and generally acts as a specular reflector, water is easily differentiable in single-polarization SAR and generally causes low intensity backscatter. Previous studies demonstrate that single-polarization SAR data is a viable technology for analyzing surface water extent (Giustarini et al., 2015; Imhoff et al., 1987; Liu and Jezek, 2004; Martinis et al., 2015b, 2009; Mason et al., 2010, 2007; Matgen et al., 2007; White et al., 2015, 2014). However, misclassification errors can occur due to wind, flooded areas of vegetation, and shadow or layover zones (Mason et al., 2007; White et al., 2015).
Quad-polarization SAR data provides all four channels of intensity and phase information (HH, HV, VH and VV) which can be very helpful for classifying surface water and discriminating errors caused by wind, flooded vegetation and shadow and layover zones exploiting their differing scattering mechanisms (Touzi et al., 2004; White et al., 2014). Along with surface water classification, it has been demonstrated to be effective at classifying wetlands, specifically, discriminating between vegetation types (Brisco et al., 2011; S. H. Hong et al., 2015; Schmitt et al., 2012a; Touzi et al., 2007; White et al., 2015, 2014). There are multiple techniques developed to decompose and classify quad-polarization data. Each technique produces different polarimetric parameters which lead to different surface water models.

There are three main objectives to this study. The first is to create multiple water classification models from single-polarization SAR data and quad-polarization SAR data, respectively. The second is to assess the performance of surface water models obtained from single-polarization TSX staring spotlight data and quad-polarization RS-2 data. Finally, the third is to create a water extent time series to observe seasonal and incidental change for floodwater hazard monitoring.

5.3 Data Description and Methodology

5.3.1 Study Area and Data Description

The study area is located at the Queen’s University Biological Station (QUBS) in Kingston, Ontario, Canada. QUBS was chosen due to the abundance of natural land cover including water bodies that vary in size and marshland that can be seasonally flooded. The study area is a 2 km by 2 km square where the SAR data and multispectral imagery used for validation overlap (Figure 5.1).
Figure 5.1. Map showing the extent of RADARSAT-2 (RS-2) scenes (red), TerraSAR-X (TSX) scenes (blue), WorldView-2 (WV-2) imagery (yellow), the study area (black), and lakes (blue). Water mask data provided by the Ontario Ministry of Natural Resources.

Fourteen SAR scenes were acquired between November 2016 and May 2017. Of the fourteen, eight were TSX staring spotlight mode scenes using X-band in the HH polarization in staring spotlight mode. The remaining six were RS-2 fine quad-polarization beam mode scenes in C-band with a slant range and azimuth resolution of 5.2 m and 7.6 m, swath with of 25 km and revisit period of 24 days. The RS-2 scenes and TSX scenes were acquired with similar acquisition dates to allow for comparison. Multispectral imagery used for validation was acquired from the WorldView-2 (WV-2) satellite with a 2 m resolution (cropped to the study area in Figure 5.1). Table 5.1 outlines the details of the data used in this study.
Table 5.1. Summary of satellite and in situ data acquired over QUBS and used in this study.

<table>
<thead>
<tr>
<th>Scene #</th>
<th>Data type</th>
<th>Date Acquired</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>WV-2 Multispectral Imagery</td>
<td>April 23, 2017</td>
</tr>
<tr>
<td>-</td>
<td>Field Investigation</td>
<td>May 4, 2017</td>
</tr>
<tr>
<td>1</td>
<td>TSX Single-Polarization</td>
<td>November 19, 2016</td>
</tr>
<tr>
<td>2</td>
<td>TSX Single-Polarization</td>
<td>November 30, 2016</td>
</tr>
<tr>
<td>3</td>
<td>TSX Single-Polarization</td>
<td>December 22, 2016</td>
</tr>
<tr>
<td>4</td>
<td>TSX Single-Polarization</td>
<td>February 4, 2017</td>
</tr>
<tr>
<td>5</td>
<td>TSX Single-Polarization</td>
<td>February 15, 2017</td>
</tr>
<tr>
<td>6</td>
<td>TSX Single-Polarization</td>
<td>April 22, 2017</td>
</tr>
<tr>
<td>7</td>
<td>TSX Single-Polarization</td>
<td>May 3, 2017</td>
</tr>
<tr>
<td>8</td>
<td>TSX Single-Polarization</td>
<td>May 14, 2017</td>
</tr>
<tr>
<td>1</td>
<td>RS-2 Quad-Polarization</td>
<td>November 5, 2016</td>
</tr>
<tr>
<td>2</td>
<td>RS-2 Quad-Polarization</td>
<td>November 29, 2016</td>
</tr>
<tr>
<td>3</td>
<td>RS-2 Quad-Polarization</td>
<td>December 23, 2016</td>
</tr>
<tr>
<td>4</td>
<td>RS-2 Quad-Polarization</td>
<td>January 16, 2017</td>
</tr>
<tr>
<td>5</td>
<td>RS-2 Quad-Polarization</td>
<td>February 9, 2017</td>
</tr>
<tr>
<td>6</td>
<td>RS-2 Quad-Polarization</td>
<td>April 13, 2017</td>
</tr>
</tbody>
</table>

5.3.2 SAR Processing

Initial water model creation and comparison was performed on the April 2017 SAR data due to the leaf off and ice free conditions and the availability of optical imagery with a similar acquisition date for validation. Field work was performed on May 4, 2017 to create in situ environmental observations of the site conditions, including the presence of open water, flooded vegetation, and the dominant vegetation type such as reeds, shrubs or forest. Field photos were tagged with GNSS...
positions at selected sites (Figure 5.7 and Figure 5.8). Figure 5.2 shows an overview of the methodology used to produce seven different water classification models. It should be noted that the Kennaugh elements were processed at the German Aerospace Center (DLR) and used an image enhancing multi-scale multi-looking filter (Schmitt, 2016; Schmitt et al., 2015). The other three decompositions were processed by the author and were enhanced using a 9 by 9 Refined Lee polarimetric speckle filter.

**Figure 5.2.** Flowchart of processing chain used on April 2017 SAR data to produce seven water models.

The single-polarization TSX HH band and the RS-2 HH band were used to compare to the RS-2 quad-polarization data. The single-polarization intensity data was classified using a grey-level thresholding. This technique is one of the most common approaches applied to SAR single-polarization data for classifying open water bodies (Gstaiger et al., 2012; White et al., 2015). Since the intensity data of the HH band is bimodal, a threshold value between the two modes can be chosen, in which everything below this threshold is classified as water. Everything above this threshold is considered non-water, but in this study, non-water was synonymous with forest to
allow for comparison of quad-polarization models that classified forest. The threshold value was chosen as the minimum value between the two modes (Figure 5.3). The final water models are labelled ‘Model 1’ and ‘Model 2’ for the TSX and RS-2 HH bands in Figure 5.2, respectively, and can be seen in Figure 5.4(1-2).

**Figure 5.3.** Histograms of HH band intensity for both the TSX and RS-2 April 2017 scenes with threshold values shown (left of threshold – water, right of threshold – non-water).

The RS-2 quad-polarization data was processed using several decomposition techniques which aim to generate polarimetric parameters that are used for analysis, interpretation and classification of the radar scattering mechanisms. These decompositions can be classified into four main types as seen in Table 5.2 (Lee and Pottier, 2009). In this study, the Pauli decomposition, Kennaugh element framework, Freeman-Durden decomposition and H-Alpha decomposition were compared.

**Table 5.2.** Description of four decomposition types and the specific decomposition used in this study.

<table>
<thead>
<tr>
<th>Decomposition Type</th>
<th>Decomposition Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coherent decomposition of the scattering matrix [S]</td>
<td>Pauli Decomposition</td>
</tr>
<tr>
<td>Dichotomy of the Kennaugh Matrix [K]</td>
<td>Kennaugh Element Framework</td>
</tr>
</tbody>
</table>
Model-based decomposition of the covariance matrix [C3] or the coherency matrix [T3]

Freeman-Durden Decomposition

Eigenvector or eigenvalue analysis of the covariance matrix [C3] or the coherency matrix [T3]

H-Alpha Decomposition

The Pauli decomposition expresses the scattering matrix [S] as the complex sum of the Pauli matrices, where an elementary scattering mechanism is associated for each basis matrix. The output of the decomposition is three parameters seen in Figure 5.4(3): a – single or odd bounce scattering, b – volume scattering, and c – double or even bounce scattering. The Pauli decomposition is relatively simple, therefore it is fast to compute. It works well in low-entropy scattering environments like urban areas, since it is designed for pure targets without external disturbances (Cloude and Pottier, 1996).

The Kennaugh element framework was developed by Schmitt et al., (2015) and processed at DLR. This technique linearly transforms the four-dimensional Stokes vector into a four-by-four scattering matrix, called the Kennaugh matrix [K]. This matrix contains ten different Kennaugh elements, in which K0 represents the total intensity seen in Figure 5.4(4). The remaining Kennaugh elements represent independent linear coefficients of the transformation and can represent different combinations of scattering mechanisms (Schmitt et al., 2015). K0 can be used to detect surface water and K2 and K4 have been shown to indicate flooded vegetation (Schmitt and Brisco, 2013). This method can be used for single, dual or quad polarization data and uses minimal computational effort. It works well in urban environments but can also process distributed targets (Schmitt et al., 2015).

The Freeman-Durden decomposition fits a physically based, three-component scattering mechanism model to the polarimetric SAR observations, without utilizing ground truth data. The mechanisms modelled are a canopy scatter from a cloud of randomly oriented dipoles, even or
double bounce scattering from a pair of orthogonal surfaces with different dielectric constants and a Bragg scatter from a moderately rough surface. This decomposition outputs three parameters see in Figure 5.4(5), each representing one of the modelled mechanisms. This method was designed to handle distributed targets and therefore works well in natural environments. It requires higher computation effort and has reduced resolution (Freeman and Durden, 1998).

Cloude and Pottier (1996) proposed the H-Alpha decomposition for extracting parameters from experimental data using a smoothing algorithm based on second-order statistics. An eigenvector analysis off the coherency matrix [T3] is used since it separates the parameters into scattering processes (the eigenvectors) and their relative magnitudes (the eigenvalues). There are two parameters outputted from the H-Alpha decomposition seen in Figure 5.4(6): Entropy (H) – calculated from the eigenvalue information and represents the degree of randomness in the scattering, Alpha (α) – calculated from the eigenvectors and represents a rotation which can indicate the type of scattering mechanism (Cloude and Pottier, 1996). This method is good at characterizing distributed targets and therefore works well in natural environments. It also has reduced resolution and requires higher computational effort (Lee and Pottier, 2009).
Figure 5.4. Intensity data and decompositions used as input for classification. (1) TSX HH intensity where blue-low, red-high; (2) RS-2 HH intensity where blue-low, red-high; (3) RGB composite of Pauli decomposition where Red: single or odd bounce scattering, Green: volume scattering, and Blue: double or even bounce scattering; (4) Total Intensity (K0) of Kennaugh element framework where blue-low, red-high; (5) RGB composite of Freeman-Durden decomposition with Red: double bounce scattering, Green: volume scattering, and Blue: surface scattering; (6) RG composite of H-Alpha decomposition where Red: entropy and Green: alpha.

After the decompositions were performed, unsupervised classification was used to create the final water models. The k-means clustering algorithm is one of the most common clustering techniques which aims at minimizing the Euclidean distance between points. An advantage of this technique is that it has fast processing speeds and therefore works well when applied to large data sets. The algorithm can be applied to linear data sets such as the Pauli and Kennaugh Element decompositions, but cannot be applied to non-linear datasets such as the Freeman-Durden and H-Alpha decompositions. K-means clustering does not handle noisy data well, but by applying
Speckle filtering to SAR data, multiplicative noise can be reduced (Kanungo et al., 2002; Ortega et al., 2009). Therefore, this algorithm was used on the Pauli decomposition and the Kennaugh element framework after speckle filtering to create nine different classes. The histograms of each class for each polarimetric parameter were then plotted to reveal their distribution. Each histograms distribution and shape was observed, and based on overlap or similar spatial distribution, the nine classes were re-clustered into three main classes (Figure 5.5). The final water models are labelled ‘Model 3’ and ‘Model 4’ for the Pauli decomposition and Kennaugh element framework, respectively, showing three classes: water, marsh/field and forest (Figure 5.2). Both marshes and fields contain low vegetation and are relatively dry compared to open water, so they both give a similar single bounce return and are classified together. This class is important because it incorporates areas that could be flooded seasonally, hence would show up in the time series of water change.

![Histograms of nine classes for Pauli Decomposition and Kennaugh element framework](image)

**Figure 5.5.** Example histograms of nine classes shown for the b parameter of Pauli Decomposition and K0 parameter of Kennaugh element framework. Dashed boxes outline classes that were clustered together to form three main classes: water (black), marsh/field (blue), and forest (grey).

The Wishart distribution clustering algorithm is similar to the k-means algorithm in that it aims at minimizing a distance between points. However, this method uses a distance measure derived from the Wishart distribution and complex Wishart probability function, as the covariance matrix of the
PolSAR data can be modelled by this. The advantages of this method is that it is robust and can be assigned to any type of PolSAR data (single, dual, quad) or decomposition (Lee and Pottier, 2009; Lee et al., 1999; Ouarzeddine et al., 2007). This method is often used to classify the H-Alpha or the Freeman-Durden scattering mechanisms and therefore was used to classify nine different classes from each decomposition in this study. The classes were visually inspected and re-clustered into three main classes: water, marsh/field and forest. The final water models are labelled ‘Model 5’ and ‘Model 6’ for the Freeman-Durden and H-Alpha Decomposition, respectively (Figure 5.2). Models 1 through 6 can be seen in Figure 5.6.

Figure 5.6. Six final water classification models: (1) Single-polarization TSX; (2) Single-polarization RS-2; (3) Pauli decomposition; (4) Kennaugh element framework; (5) Freeman-Durden decomposition; (6) H-Alpha decomposition.
5.4 Results and Discussion

5.4.1 Accuracy Assessment

WV-2 high resolution multispectral imagery was used to create a reference raster containing three classes: water, marsh/field and forest to compare with the models created from the SAR data (Figure 5.7). An object based image analysis using Felzenszwalb segmentation and Random Forest classification was used on all eight bands and the NDWI and NDVI indices, totaling 10 variables (Duro et al., 2012; Felzenszwalb and Huttenlocher, 2004; Malinowski et al., 2015; Pal, 2005; Richards, 2013). NDWI and NDVI indices were adapted from Maglione et al., (2014).

Approximately 10% of the data was split into training and testing polygons in which the number of points for each class was proportional to the expected size of that class (Olofsson et al., 2014). Maximum Likelihood and Support Vector Machine were also tested, but Random Forest combined with Felzenswalb was found to model the environment the best, with the highest overall accuracy of 97% using the testing polygons. Figure 5.7 also shows a true colour image of the study area showing a sun glint affect over open water (Kay et al., 2009). This did not affect the classification accuracy but should be noted as to why the water appears lighter than usual. In situ field work was also performed to validate the classification models and to better understand how each class appears naturally (Figure 5.8).
Figure 5.7. WV-2 multispectral imagery from April 23, 2017 over the study area: (a) NDWI where black-low, white-high; (b) NDVI where black-low, white-high; (c) True colour image RGB: 5, 3, 2; (d) Classified optical model used as a reference model in accuracy assessment where water-black, marsh/field-blue and forest-grey.

Figure 5.8. In situ field work photos from May 4, 2017 showing three main environments labeled: water, marsh/field and forest. Red numbers correspond to photo locations shown in Figure 5.7D.
An accuracy assessment was performed using a confusion matrix (Congalton, 1991; Jensen, 1996; Olofsson et al., 2014). The classified raster created from the WV-2 imagery was used as a reference raster to compare against the six water models created from the SAR data. The reference data was resampled to the resolution of the SAR models and 10% of the pixels were selected by stratified random sampling to use in the accuracy assessment. This created six confusion matrixes which can be seen in Table 5.3 to Table 5.8. The ratio between the amount of correctly classified pixels to the total number of pixels, also called the Overall Accuracy (OA), is bolded in each table. Errors of omission are shown by the Producer’s Accuracy (PA) and errors of commission are shown by the User’s Accuracy (UA) for each class in each model. Table 5.9 summarizes the OA and PA for each model.

Table 5.3. Confusion matrix for single-polarization TSX model (1).

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>2155</td>
<td>212</td>
<td>395</td>
<td>2762</td>
<td>78%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Forest</td>
<td>250</td>
<td>619</td>
<td>8409</td>
<td>9278</td>
<td>91%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
</tbody>
</table>

PA 90% 0% 96% - 88%

Table 5.4. Confusion matrix for single-polarization RS-2 model (2).

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1625</td>
<td>14</td>
<td>18</td>
<td>1657</td>
<td>98%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Forest</td>
<td>780</td>
<td>817</td>
<td>8786</td>
<td>10383</td>
<td>85%</td>
</tr>
<tr>
<td>--------</td>
<td>-----</td>
<td>-----</td>
<td>------</td>
<td>-------</td>
<td>-----</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
</tbody>
</table>

**PA** | 68% | 0% | 100% | -     | **86%** |

**Table 5.5.** Confusion matrix for quad-polarization RS-2 model (3) using Pauli decomposition.

(3) Pauli

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>2137</td>
<td>73</td>
<td>118</td>
<td>2328</td>
<td>92%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>234</td>
<td>597</td>
<td>1804</td>
<td>2635</td>
<td>23%</td>
</tr>
<tr>
<td>Forest</td>
<td>34</td>
<td>161</td>
<td>6882</td>
<td>7077</td>
<td>97%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
</tbody>
</table>

**PA** | 89% | 72% | 78% | - | **80%** |

**Table 5.6.** Confusion matrix for quad-polarization RS-2 model (4) using Kennaugh element framework.

(4) Kennaugh Element Framework

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1909</td>
<td>43</td>
<td>23</td>
<td>1975</td>
<td>97%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>399</td>
<td>511</td>
<td>1309</td>
<td>2219</td>
<td>23%</td>
</tr>
<tr>
<td>Forest</td>
<td>97</td>
<td>277</td>
<td>7472</td>
<td>7846</td>
<td>95%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
</tbody>
</table>

**PA** | 79% | 61% | 85% | - | **82%** |
Table 5.7. Confusion matrix for quad-polarization RS-2 model (5) using Freeman-Durden decomposition.

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1641</td>
<td>10</td>
<td>10</td>
<td>1661</td>
<td>99%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>695</td>
<td>547</td>
<td>901</td>
<td>2143</td>
<td>26%</td>
</tr>
<tr>
<td>Forest</td>
<td>69</td>
<td>274</td>
<td>7893</td>
<td>8236</td>
<td>96%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
<tr>
<td>PA</td>
<td>68%</td>
<td>66%</td>
<td>90%</td>
<td>-</td>
<td>84%</td>
</tr>
</tbody>
</table>

Table 5.8. Confusion matrix for quad-polarization RS-2 model (6) using H-Alpha decomposition.

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1493</td>
<td>5</td>
<td>2</td>
<td>1500</td>
<td>100%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>866</td>
<td>618</td>
<td>1305</td>
<td>2789</td>
<td>22%</td>
</tr>
<tr>
<td>Forest</td>
<td>46</td>
<td>208</td>
<td>7497</td>
<td>7751</td>
<td>97%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
<tr>
<td>PA</td>
<td>62%</td>
<td>74%</td>
<td>85%</td>
<td>-</td>
<td>80%</td>
</tr>
</tbody>
</table>

Table 5.9. Summary table of Overall Accuracy (OA) for all six models, and Producer’s Accuracy (PA) for each class in each model). Kennaugh element framework (KEF), Freeman-Durden (FD), and H-Alpha (HA).

<table>
<thead>
<tr>
<th></th>
<th>(1) TSX</th>
<th>(2) RS-2</th>
<th>(3) Pauli</th>
<th>(4) KEF</th>
<th>(5) FD</th>
<th>(6) HA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
When comparing all six models visually and using the accuracy assessment, several observations can be made. The single-polarization model created using the TSX data has the highest overall accuracy at 88%. This is expected as it has a much higher resolution than the other models, so it is able to delineate small water bodies and their extent similarly to the high resolution optical imagery. Because of the high resolution of TSX, it is more affected by shadow and layover errors, which are apparent in Model 1. However, previous studies have shown that by combining single-polarization SAR with airborne LiDAR, this error can be compensated for, increasing the OA (Chapter 3). The single-polarization RS-2 model has the second highest OA at 86%. However, it underestimates the water class with a PA of 68%. Both single-polarization models were limited in that they could not classify marsh/field, which leads to higher PA compared to the 3 class models.

When comparing the quad-polarization models, the Pauli decomposition has the highest PA for water at 89%. Both the Freeman-Durden and H-Alpha models underestimate the amount of water and tend to classify it as marsh/field instead. This could be due to their inherit loss of resolution in their decomposition as a large window size is required to maintain stability. However, H-Alpha has the highest PA for marsh/field at 74%. The Pauli decomposition and Kennaugh element framework produce more false positives for marsh/field as these methods are more affected by speckle/noise. This effect is reduced in the H-Alpha and Freeman-Durden decompositions because of their lower resolution and smoothing. Finally, Freeman-Durden has the highest PA for forest at 90%. Freeman-Durden decomposition is a model based method developed for forested areas and volume scattering, and tend to favour volume scattering over other scattering mechanisms. The highest OA

<table>
<thead>
<tr>
<th></th>
<th>Water</th>
<th>March/Field</th>
<th>Forest</th>
<th>OA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>90</td>
<td>0</td>
<td>96</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>68</td>
<td>0</td>
<td>100</td>
<td>86</td>
</tr>
<tr>
<td></td>
<td>89</td>
<td>72</td>
<td>78</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>79</td>
<td>61</td>
<td>85</td>
<td>82</td>
</tr>
<tr>
<td></td>
<td>68</td>
<td>66</td>
<td>90</td>
<td>84</td>
</tr>
<tr>
<td></td>
<td>62</td>
<td>74</td>
<td>85</td>
<td>80</td>
</tr>
</tbody>
</table>
achieved by the quad-polarization models was 84% by the Freeman-Durden decomposition. However, all decompositions fell within 4% of each other, and Kennaugh elements was the second best at 82%. When visually inspecting Model 4 created by the Kennaugh element framework, it is clear that this decomposition preserved the resolution and detail the best.

Despite Freeman-Durden having the highest OA, the other decomposition methods have their strengths and weaknesses and performed better for specific classes. It also must be considered that the validation data is obtained from optical imagery, which has limitations as well, foremost in the areas of inundated vegetation, which often remains undetected. In order to exploit the strength of each model, an optimized quad-polarization model was created using the best performing class from each model 3 to 6. The water class was used from the Pauli decomposition and the forest class was taken from the Freeman-Durden decomposition. Although H-Alpha had the best PA for marsh/field, the Kennaugh element framework provides better resolution. Therefore, the H-Alpha and Kennaugh elements were combined to reduce the noise using H-Alpha but preserve detail using the Kennaugh elements. The optimized model can be seen in Figure 5.9, and the confusion matrix created to access the accuracy can be seen in Table 5.10.
Figure 5.9. Optimized RS-2 quad-polarization model (Model 7) (right) compared to reference data from WV-2 multispectral imagery (left).

Table 5.10. Confusion matrix for quad-polarization RS-2 optimized model using all four decompositions (Model 7).

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Marsh/Field</th>
<th>Forest</th>
<th>Total</th>
<th>UA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>2134</td>
<td>71</td>
<td>115</td>
<td>2320</td>
<td>92%</td>
</tr>
<tr>
<td>Marsh/Field</td>
<td>152</td>
<td>413</td>
<td>533</td>
<td>1098</td>
<td>38%</td>
</tr>
<tr>
<td>Forest</td>
<td>119</td>
<td>347</td>
<td>8156</td>
<td>8622</td>
<td>95%</td>
</tr>
<tr>
<td>Total</td>
<td>2405</td>
<td>831</td>
<td>8804</td>
<td>12040</td>
<td>-</td>
</tr>
<tr>
<td>PA</td>
<td>89%</td>
<td>50%</td>
<td>93%</td>
<td>-</td>
<td>89%</td>
</tr>
</tbody>
</table>

By combining the four decompositions from the RS-2 data, the OA was increased from 80%-84% to 89% which is higher than all individual quad-polarization models and higher than the TSX high resolution model. The noise seen in the Pauli and Kennaugh decompositions is removed, but more detail is preserved than in the H-Alpha and Freeman-Durden decompositions. The water class PA
is maintained at 89% and the forest PA is increased from 90% to 92%. The marsh/field class PA was reduced to 50% from 74%, however, the UA was significantly increased from 22-26% for individual models to 38% which implies a more balanced classification with less false positives.

For the purpose of water classification and flood monitoring higher resolution data is preferred, especially when the water bodies are small-scale. The optimized scenario would be to acquire high resolution quad-polarization data so that water extent could be delineated at high resolution, while maintaining the ability to classify all relevant land cover types. However, based on the data availability used in this study, high resolution single-polarization data processed using grey-level thresholding, is comparable in performance to lower resolution quad-polarization methods, especially when the decomposition methods are combined optimally. However, the number of classes is reduced to two, which does not allow for the detection of marsh/fields or inundated vegetation, which presents a significant limitation for flood assessment. The additional information content in the quad-polarization data is exploited by different decomposition methods, and could in principle, be combined to improve performance. The performance of each of the quad-polarization methods cannot be objectively evaluated as the reference data from WV-2 is not objective either. Hence, all methods should always be used to evaluate their performance before combining the best classes for a fused model.

5.4.2 Surface Water Time Series

Using all SAR scenes acquired over the study area, a timeline of surface water change was created to demonstrate the monitoring capabilities. Eight TSX scenes were processed using grey-level thresholding outlined in Figure 5.2 creating eight models of two classes: water (black) and non-water (grey) (Figure 5.10). All TSX models have areas of shadow present being falsely classified as water. In TSX models 3-5 in Figure 5.10, taken in the winter months when the open water was covered in ice, the only classified water is the shadow zones created from topography.
Six RS-2 scenes were processed using the four decomposition methods outlined in Figure 5.2, creating 24 models of three classes; water (black), marsh/field (blue), and forest (grey) (Figure 5.11). For the RS-2 winter scenes (models 3-5 in Figure 5.11), the open water was completely frozen over. Since the ice was probably covered in snow, all decompositions and classifications could not isolate ice from field areas covered with snow (with no forest). Therefore the marsh/field class shown in blue in these models can also be interpreted as open areas with snow. No decomposition does well at classifying data from the winter months, however, for the purpose of flood hazard monitoring, floods are not possible in these months and so this would not be an issue (Grey shaded months in Figure 5.12).

**Figure 5.10.** Time series of water models for eight TSX scenes showing water (black) and non-water (grey): (1) November 19, 2016; (2) November 30, 2016; (3) December 22, 2016; (4) February 4, 2017; (5) February 15, 2017; (6) April 22, 2017; (7) May 3, 2017; (8) May 14, 2017; (9) June 5, 2017; (10) June 27, 2017.
Figure 5.11. Time series of water models for six RS-2 scenes and four decomposition methods showing water (black), marsh/field/open area (blue), and forest (grey): (A) Pauli decomposition; (B) Kennaugh element framework; (C) Freeman-Durden decomposition; (D) H-Alpha decomposition; (1) November 5, 2016; (2) November 29, 2016; (3) December 23, 2016; (4) January 16, 2017; (5) February 9, 2017; (6) April 13, 2017.

Figure 5.12 shows the change in water and marsh/field through time for all four decomposition methods and TSX single-polarization data. Each decomposition model shows similar general trends of seasonal water loss, absence through the winter months and gain in April. The high resolution TSX model consistently identifies the most water, with the Pauli decomposition model reaching similar values. The other three decomposition methods fluctuate through time as to which method classifies the most water. When comparing the amount of marsh/field classified through time using the decomposition methods, there is no method which consistently identifies the most or least areas.
This is consistent with the conclusion that optimized surface water models would need to be created independently at each acquisition in time to obtain the best results.

**Figure 5.12.** Graphs showing percent of water and marsh/field classified through time for each of the classification methods. Lines: yellow square – Pauli decomposition, blue diamond – Kennaugh element framework, orange square – Freeman-Durden decomposition, grey triangle – H-Alpha decomposition, and green triangle – TSX single-polarization. Grey shaded area represents ice covered months where interpretation of surface water was impossible.
5.5 Conclusions

In this study, six different methodologies were applied to SAR data to better understand the water classification abilities of single-polarization and quad-polarization data over a principally natural environment. These methodologies were tested on TSX and RS-2 data, originally comparing scenes acquired in April 2017, and then creating a water extent time series using all fourteen available SAR scenes to model seasonal variations in water extent. Grey-level thresholding applied to the TSX data was seen to be an effective way at classifying open water bodies with the highest overall accuracy of 88%, although it is limited to only classifying water and non-water and has areas of misclassification due to shadow. The four decomposition and classification techniques applied to the RS-2 quad polarization data were found to have similar performance, however they differed spatially. The Freeman-Durden decomposition had the highest OA at 84%, however it has an inherit loss of resolution and underestimates the water class. The Pauli decomposition and Kennaugh element framework classified water the best, having a PA of 89% and 79%. The H-Alpha decomposition had the highest PA for marsh/field at 74%. By combining the best class from each decomposition, an optimized model was created which increased the OA to 89%, which reflects a similar accuracy to the high resolution TSX model.

High resolution SAR data is advantageous in locations and applications where extracting small open bodies of water bodies is needed. However, it is affected by shadow and layover zones caused by tall vegetation due to its high resolution. These zones often occur along the shorelines of water bodies where the tree canopy meets the water’s edge. Low resolution quad-polarization SAR data has the capability to classify different land cover types, including the location of marshes and fields, open water and forest. However, the low resolution data creates misclassification errors in transition zones between water and marsh/field, and marsh/field and forest. These areas are often the most important surface water classification zones, as the seasonal fluctuations of water extent occur within them. Although a low resolution optimized water model was created which mirrors the open
water accuracies of the high resolution single-polarization data, the available spatial detail shown in single-polarization data is necessary for applications of local small-scale water bodies. For studies which focus on regional surface water and marshland classification, low quad-polarization data surpasses high resolution single-polarization data due to its land cover classification capability. Although, high resolution data is readily available in single-polarization modes, future satellite missions should be designed to acquire high resolution quad-polarization data, to receive the benefits of both data types.
Chapter 6
Conclusions and Future Work

6.1 Conclusions

In this thesis, the use of PolSAR as a tool for surface water monitoring was investigated. Single, dual and quad-polarization SAR data was used to classify and compare various surface water models in order to better understand their strengths and limitations. Airborne LiDAR and satellite-based optical imagery, were compared and fused with single-polarization SAR data to create an optimized surface water time series. SAR products with differing spatial and temporal resolutions were processed and analyzed, allowing for a better understanding of the appropriate applications for each data set.

In Chapter 3, a methodology for the fusion of TSX scenes with airborne LiDAR and optical imagery using a pixel based decision tree analysis was developed. It was observed that even though the optical, SAR and LiDAR data were collected in different seasons, the uncertainty of the fused model incorporating all three techniques was lower than the uncertainty of any single technique. The development of a SAR only time series of water coverage is hindered by processes including vegetation growth (leading to different shadow and layover zones over time) and land cover changes which affect the backscatter (and threshold per scene). Optical and LiDAR data can enhance a time series by removing some of these competing processes. It was concluded that one LiDAR acquisition is very useful to correct a series of high resolution single-polarization SAR acquisitions for shadow and layover effects.

In Chapter 4, single-polarization SAR data was compared to dual-polarization SAR data using three different classification methods. The findings of this study confirm the expected advantages of dual-polarization observations. While the applicability of single-polarization SAR for landscape
dynamics is limited, single-polarization SAR was found to be a viable technology for classification of open water. However, monitoring the spatio-temporal transition from one type of land cover to another can only be effectively performed using dual-polarization (or multi-polarization) SAR data.

In Chapter 5, high resolution single-polarization TSX data and low resolution quad-polarization RS-2 data were compared using six different classification methodologies. It was found that high resolution SAR data is advantageous in locations and applications where extracting small open bodies of water bodies is needed, as it classifies open water with the highest accuracy. However, the high resolution data is strongly affected by shadow and layover zones caused by tall vegetation. Low resolution quad-polarization SAR data has the capability to classify marshes, fields, open water and forest. However, the low resolution data creates misclassification errors in transition zones between water and marsh/field, and marsh/field and forest. The errors posed by both high resolution single-polarization and low resolution quad-polarization data often occur at the edge of water bodies. These areas are important surface water classification zones, as the seasonal fluctuations of water extent occur within them.

Overall, PolSAR presents a viable technology for surface water monitoring. Similar to other data collection methods, there exists a compromise between acquiring SAR data with a high resolution or high information content. For studies which focus on regional surface water and marshland classification, low resolution quad-polarization or dual-polarization data surpasses high resolution single-polarization data due to its land cover classification capability. For example, regional wetland and fresh water monitoring is an important application of SAR data in Canada. Currently, there is no ongoing or completed wetland inventory or monitoring program in place in Canada. Canada contains approximately 25% of the world’s wetlands, and 20% of the world’s fresh water (White et al., 2015). Due to the vast landscape of Canada and the dynamic change and interaction of these natural resources with humans, the use of PolSAR for regional wetland and surface water
monitoring is essential. Low resolution quad-polarization RS-2 data would allow for the discrimination between wetlands and open water, and it has a larger swath width to allow for efficient imaging of the entire country. This application does not need high resolution, due to the size of the target, and therefore the low resolution of the RS-2 data would not hinder these results. For regions in Canada which require higher resolution wetland mapping, medium resolution dual-polarization SAR data could be used. For example, mapping and monitoring the Prairie pothole regions of Canada and the US could also be enhanced by the use of dual polarization data (Bhang et al., 2007; Bolanos et al., 2016). This provincial size region is considered one of the largest wetland complexes in the world and is affected by severe flooding after snowmelt each year. These potholes range in size from 1 m to 100 km. Because of the varying size of potholes and the need to monitor wetlands and open water, the use of a medium resolution dual-polarization TSX data would present a viable option for this application.

However, for small-scale surface water monitoring strategies, high resolution single-polarization SAR data is desirable to allow for the differentiation of small rivers and ponds, and potentially the hazard itself. For example, near real time flood detection is an extremely useful application of high resolution single-polarization TSX data (Martinis et al., 2015a). Local scale flooding events are common throughout the world and require quick response time and high resolution data. An advantage to single-polarization data is the high availability of data due to the abundance of satellite missions offering this product. Specifically, TSX has a short repeat period of 11 days, which enables frequent imaging. With several missions in orbit, the observation options will be even more frequent. Because this type of application is for local flood management, the major concern is determining the extent of flooding, therefore classification of other land cover types is not as relevant. For flooding hazards posed by beaver dam failures, high resolution, single-polarization TSX data is appropriate. This data type allows for the differentiation of small ponds and rivers on the scale of 10s of metres, and can identify, measure, and monitor the dam itself.
When applying PolSAR to surface water monitoring, it is essential to understand the characteristics of the target, including size, shape, land cover type, and how that target changes with time (including seasonal features such as snow, ice and leaf-on-off cycles). It is also important to understand the SAR products available and their strengths and weaknesses, as demonstrated in this study. No remote sensing technology is perfect, but certain products are more effective for specific applications.

6.2 Future Work
As new SAR missions develop, the availability of polarimetric data products will diversify and increase. Higher resolution quad-polarization data would be ideal for small-scale surface water classification. Classification methodologies of multi-polarized data should be further researched, as the application of different clustering algorithms to various decomposition techniques could improve classification results. Quad-polarization decompositions are well developed, whereas dual-polarization decomposition methods for surface water and wetland mapping are relatively understudied (Moser et al., 2016). The frequency/band of each SAR product could be specifically studied and compared, to understand the impact of surface water classification. Acquiring L-band data could assist in canopy cover penetration, and aid in shadow and layover removal.

An important next step to this study would be to acquire SAR data over an active beaver dam hazard and apply a SAR monitoring strategy. This could provide a case study of a small-scale hazard that would be directly comparable using current in situ monitoring methods and could demonstrate the benefit of integrating SAR into surface water and flood hazard assessments.
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doi:10.1080/10106049009354274


### Appendix A

**Table A1.** Description of software used to process, manipulate and visualize data.

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<thead>
<tr>
<th>Software</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentinel</td>
<td>Processing of SAR data (All chapters)</td>
</tr>
<tr>
<td>Application</td>
<td>- Radiometric calibration</td>
</tr>
<tr>
<td>Platform (SNAP)</td>
<td>- Terrain correction</td>
</tr>
<tr>
<td></td>
<td>- Speckle filtering</td>
</tr>
<tr>
<td></td>
<td>- Decomposition</td>
</tr>
<tr>
<td></td>
<td>- Classification</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Matrix Laboratory (MATLAB)</th>
<th>Classification of data sets (Chapter 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>- SAR curve fitting and thresholding (sar_classification_irwin.m)</td>
</tr>
<tr>
<td></td>
<td>- LiDAR decision tree (lidar_classification_irwin.m)</td>
</tr>
<tr>
<td></td>
<td>- Optical curve fitting and thresholding (optical_classification_irwin.m)</td>
</tr>
<tr>
<td></td>
<td>- Fused decision tree (fused_classification_irwin.m)</td>
</tr>
</tbody>
</table>

| ArcGIS                  | Visualization and comparison of models (All chapters)                         |
|                        | SAR shadow and layover removal (Chapter 3)                                    |
|                        | Accuracy assessment and optimized model creation (Chapter 5)                  |

| Python                  | Object based image classification (Chapter 5)                                 |
|                        | (optical_classification_irwin.py)                                            |