Multitemporal Spaceborne Polarimetric SAR Data for Urban Land Cover Mapping

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ABSTRACT

Urban represents one of the most dynamic areas in the global change context. To support rational policies for sustainable urban development, remote sensing technologies such as Synthetic Aperture Radar (SAR) enjoy increasing popularity for collecting up-to-date and reliable information such as urban land cover/land-use. With the launch of advanced spaceborne SAR sensors such as RADARSAT-2, multitemporal fully polarimetric SAR data in high-resolution become increasingly available. Therefore, development of new methodologies to analyze such data for detailed and accurate urban mapping is in demand.

This research investigated multitemporal fine resolution spaceborne polarimetric SAR (PolSAR) data for detailed urban land cover mapping. To this end, the north and northwest parts of the Greater Toronto Area (GTA), Ontario, Canada were selected as the study area. Six-date C-band RADARSAT-2 fine-beam full polarimetric SAR data were acquired during June to September in 2008. Detailed urban land covers and various natural classes were focused in this study.

Both object-based and pixel-based classification schemes were investigated for detailed urban land cover mapping. For the object-based approaches, Support Vector Machine (SVM) and rule-based classification method were combined to evaluate the classification capacities of various polarimetric features. Classification efficiencies of various multitemporal data combination forms were assessed. For the pixel-based approach, a temporal-spatial Stochastic Expectation-Maximization (SEM) algorithm was proposed. With an adaptive Markov Random Field (MRF) analysis and multitemporal mixture models, contextual information was explored in the classification process. Moreover, the fitness of alternative data distribution assumptions of multi-look PolSAR data were compared for detailed urban mapping by this algorithm.

Both the object-based and pixel-based classifications could produce the finer urban structures with high accuracy. The superiority of SVM was demonstrated by comparison with the Nearest Neighbor (NN) classifier in object-based cases. Efficient polarimetric parameters such as Pauli parameters and processing approaches such as logarithmically scaling of the data were found to be useful to improve the classification results. Combination of both the ascending and descending data with appropriate temporal span are suitable for urban land cover mapping. The SEM algorithm could preserve the detailed urban features with high
classification accuracy while simultaneously overcoming the speckles. Additionally the fitness of the $G_p^u$ and $K_p$ distribution assumptions were demonstrated better than the Wishart one.

**Keywords:** RADARSAT-2, Spaceborne, Polarimetric SAR, Urban Landcover, Object-based, Pixel-based, Classification, Support Vector Machines, Stochastic Expectation-Maximization.
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1. INTRODUCTION

Urbanization is one of the most dynamic processes in this world. According to the 2009 Revision of the UN World Urbanization Prospects report (UN Department of Economic and Social Affairs, 2009), more than half of the world’s population is living in the urban area by 2009. And the global proportion of urban population is expected to be 60 percent by 2030. Alongside the fast expansion of the urban area, various socioeconomic and environmental problems arise, such as resource wasting, environment disruption and ecological crisis (Benfield, 1999; Cieslewicz, 2002).

To prevent such negative consequences in the development, effective management policies require updated and detailed information representing the current urban status. Therefore, effective techniques collecting accurate and detailed urban land cover/land-use information through remote sensing are essential for urban planners (Gao and Liu, 2001). Among various remote sensing systems, Synthetic Aperture Radar (SAR) has been increasingly used for land-cover/land-use mapping, since it is less affected by weather conditions and solar illumination in comparison to the optical sensors (Hayes and Gough, 2009).

Among various SAR features, the usefulness of the polarization diversity has long been recognized as providing additional information of the observed targets such as the physical characteristics, geometry, shape and orientation (Dong et al., 1997; Ainsworth, 2009). However, considerable progress in land-cover/land-use applications using polarimetric SAR techniques has not been made until the last 20 years. The fast progress in current years is credited to the available access of high quality polarimetric SAR data offered by the practical polarimetric SAR sensors these years (Corr et al., 2003a). Currently, it has been an attractive data source and has been successfully used in various applications including agriculture, sea-ice, forestry, hydrology, oceans, etc. (e.g. Lee and Pottier, 2009a; Lee et al., 2004b; Henderson and Xia, 1997).

Since the launch of advanced SAR sensors such as TerraSAR-X and RADARSAT-2, the golden age of polarimetric SAR imaging has arrived. Currently, frequent observations in full polarizations with high resolutions become available. Meanwhile, there is a strong need for interpretation of such advanced polarimetric SAR data. New research topics have emerged when sufficient data are provided for studying the SAR polarimetric properties of the observed classes such as the behaviors
in various electromagnetic spectrums, the responses in the time series, and the effects in high resolution situations.

The potential of polarimetric SAR data for urban applications has been demonstrated in previous researches (Dell’Acqua and Gamba, 2003; Boehm and Schenkel, 2003; Pellizzeri et al., 2003a, 2003b; Gao and Ban, 2008 and 2009; Simonetto and Malak, 2009). Nevertheless, few studies have focused on the mapping of the finer structures of urban areas. Most of the works are limited in mapping the urban footprints or extracting some specific man-made features. The difficulties of using polarimetric SAR data for urban mapping lie in several places. The complex context of urban areas, which is mixed by various natural and man-made objects with wide diversities of materials, orientation, size, etc., makes the SAR image interpretation complicated (Franceschetti et al., 2002). Problems also arise from the complicated natures of the polarimetric SAR data features such as speckle inherited from SAR systems. Moreover, the efficiencies of various polarimetric features for detailed urban mapping have not yet been fully assessed.

Regarding the methodology for land-cover/land-use mapping, novel methods have been put forward such as object-based analyses and advanced pattern recognition techniques. In comparison to traditional pixel-based methods, object-based analyses could integrate the object characters such as shape and inner statistics into classification process. Moreover, in high resolution data, problems caused by increased variance of pixels within a class could be better handled by object-based analysis. Thus the object-based analysis currently enjoy growing popularity in processing remote sensing data with ever increasing spatial resolution (Blaschke, 2010). For exploration of the spatial-temporal information implied in the available data sets, many novel techniques have been proposed in the remote sensing field these years. For example, the Artificial Neuro-Network (ANN) and Support Vector Machine (SVM) have successfully been employed in multitemporal or multi-source data analyses (Jain et al., 2000; Hu, 2010). The Markov Random Field (MRF) (Wu et al., 2008) is well applied to explore contextual information. However, for detailed urban mapping using fine resolution polarimetric SAR data, effective algorithms are still required.

Therefore, there is a strong need to develop efficient classification methods exploring fine resolution multitemporal polarimetric SAR data and evaluating the efficiencies of the polarimetric features for the detailed urban mapping.
1.1 Research Objectives

This research investigates multitemporal fine-resolution polarimetric SAR data for detailed urban land-cover/land-use mapping. The specific research objectives are:

1. Develop efficient methods for classification of multitemporal fine-resolution polarimetric SAR data, such as object-based SVM and temporal-spatial SEM.
2. Assess the fitness of various data distribution assumptions of urban classes, and develop effective rules to describe the classes' properties.
3. Evaluate different polarimetric features and multitemporal data combinations for the classification efficiency.

To this end, RADARSAT-2 polarimetric SAR data is evaluated with regards to the above objectives.

1.2 Organization of the Thesis

This thesis is organized as follows. Chapter 1 introduces the research background and objectives. Chapter 2 reviews the polarimetric SAR principles and current status of polarimetric SAR applications in the urban area. Chapter 3 describes the study area and data used in this research. Chapter 4 proposes the methodologies for mapping urban land cover using polarimetric SAR images. Chapter 5 evaluates the classification results and discusses the effects and relative issues of the suggested approaches. Conclusions and future works are presented in Chapter 6.

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.


Paper I brought forward an object-based multitemporal classification scheme for detailed urban land cover mapping. Rules are developed to extract specific land use/land cover classes and improve the mapping result. Those rules will serve the further object-based approaches in paper II and paper III.

Paper II proposed an object-based SVM and rules combined classification method for mapping urban details. Various polarimetric SAR parameters are compared in the ascending data set. The efficiency of employing SVM classifier is demonstrated by comparison with the results using a Nearest Neighbor (NN) classifier.

Paper III extended the comparisons in paper II taking into account both the polarimetric parameters and processing effects on those parameters. Alternative multitemporal data combinations are assessed as well. The efficiencies of the parameters are confirmed on both ascending and descending data sets. Significance of the complement of orbital modes and the temporal relationship of the data are demonstrated in multitemporal comparisons.

Paper IV put forward a novel pixel-based classification algorithm for detailed urban mapping using fine-resolution polarimetric SAR data in comparison to the objet-based approaches in paper I, II, III. Employing an adaptive MRF analysis and multitemporal mixture models, an enhanced Stochastic Expectation-Maximization (SEM) algorithm is devised to map homogenous urban land covers with high accuracy. Various polarimetric SAR data distributions are compared by that method for fitness of detailed urban mapping.
2. LITERATURE REVIEW

It was in the late 1950s and early 1960s when SAR systems were first applied for civilian geoscience researches. Nevertheless, less attention has been received for urban applications in the past time (Henderson and Xia, 1998). Since the launch of the advanced spaceborne SAR sensors, polarimetric SAR data become increasingly available. That contributes to the development of the polarimetric SAR processing techniques to a great extent. With the arrival of high resolution SAR data, the investigations of SAR for urban applications have becoming more visible. In the following three sections, the principles of polarimetric SAR imaging (section 2.1), urban mapping using SAR data (section 2.2) including the SAR data properties on urban area, approaches for various polarization data, and some state-of-the-art methods are reviewed. Those further highlight the rationale of this study.

2.1 Principle of Polarimetric SAR Imaging

In this section, the principle of polarimetric SAR imaging is briefly introduced, including the polarimetry fundamentals, the decomposition theorem and the speckle statistics.

2.1.1 SAR Polarimetry Fundamentals

SAR polarimetry is concerned with exploring the target properties from the behaviors of backscattered polarized electromagnetic waves. The effects of the interactions between the electromagnetic waves and the observed targets are associated with imaging systems such as wave frequency, polarization, incident angle and scattering directions and target characteristics such as geometrical structure and dielectric properties.

In the polarimetric SAR system, the antennas for transmitting and receiving electromagnetic waves are configured in different polarization states. Thus the scattering properties of the observed targets can be revealed in the alternative polarimetric combinations providing more information with contrast to the single polarization systems.

For modeling the interactions of the polarized waves with nature, the trace of electric filed $E$ of a monochromatic wave are projected as the so called polarization ellipse (Boerner, 1990) on a fixed plane perpendicular
to the propagation direction. And that ellipse can be further described as a linear combination of two polarization states \( E_m \) and \( E_n \) under two basis vectors \( \{u_m, u_n\} \) (e.g. the linear horizontal and vertical polarization basis: \{H, V\}) as follow:

\[
E = u_mE_m + u_nE_n
\]  

(1).

Given the specific basis \( \{u_m, u_n\} \), we can define the Jones vector (Boerner et al., 1998) as the electric field representation:

\[
E_{mn} = \begin{bmatrix} E_m \\ E_n \end{bmatrix} = \begin{bmatrix} |E_m|e^{i\theta_m} \\ |E_n|e^{i\theta_n} \end{bmatrix}
\]  

(2).

Therefore, the backscattering properties of the observed targets can be represented through the scattering matrix \( S \) which records the response from the alternative polarization combinations of the transmitted and received electromagnetic waves (Van Zyl et al., 1987). In the case of the linear horizontal and vertical polarization basis (and in the following illustrations, the linear horizontal and vertical polarization basis is always assumed), that relation can be formulated as follow:

\[
\begin{bmatrix} E_h \\ E_v \end{bmatrix}_{\text{rec}} = \frac{e^{ikr}}{kr} S \begin{bmatrix} E_h \\ E_v \end{bmatrix}_{\text{trans}} = \frac{e^{ikr}}{kr} \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} \begin{bmatrix} E_h \\ E_v \end{bmatrix}_{\text{trans}}
\]  

(3).

The values of the scattering matrix \( S \) depends on the coordinates used to define the polarizations of the incident and scattered waves, e.g., FSA (“forward scatter alignment”) and BSA (“backscatter alignment”) conventions. In the MSA case (when the receiver and transmitter are co-located, or to say mono-static), the scattering matrix is called the Sinclair matrix. Further, with the reciprocal medium assumption, the Sinclair matrix is symmetric, i.e. \( S_{hh} = S_{vv} \). (Boerner et al., 1998) The SAR cross section can be related with the elements of the scattering matrix by the following equation:

\[
\sigma_{qp} = 4\pi |S_{qp}|^2
\]  

(4).

It is necessary to introduce the conception of the “distributed scatters” and the “pure single scatters”, since those target conceptions will determine the way in which we describe them. Most natural targets which have varying properties are regarded as distributed scatters, while most of the man-made objects which represent the stationary properties will be observed as pure single scatters. According to those assumptions, the pure single targets could be directly characterized by the single scattering matrix. However for the distributed scatters, the SAR system will receive the backscattering sums from various single targets. In this case, the polarimetric features can be analyzed more precisely by the spatial and temporal statistic process. Therefore, the second order Hermitian average covariance \( C \) and the coherency \( T \) matrices are introduced (Boerner et al.,
The covariance or coherency matrices are derived from the polarimetric target vectors, namely the ‘Lexicographic Feature vector’

\[
\mathbf{f}_{4L} = \begin{bmatrix} S_{hh} & S_{hv} & S_{vh} & S_{vv} \end{bmatrix}^T
\]

and the ‘Pauli Feature vector’

\[
\mathbf{f}_{4P} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh} + S_{vv} & S_{hv} - S_{hh} & S_{hv} + S_{vh} & j(S_{hv} - S_{vh}) \end{bmatrix}^T
\]

Then the lexicographic and pauli-based covariance and coherency matrices can be defined as:

\[
\mathbf{C}_4 = \langle \mathbf{f}_{4L} \cdot \mathbf{f}_{4L}^T \rangle
\]

and

\[
\mathbf{T}_4 = \langle \mathbf{f}_{4P} \cdot \mathbf{f}_{4P}^T \rangle
\]

where the \( \langle \ldots \rangle \) indicate the spatial or temporal averaging. The coherency matrix \( \mathbf{T} \) and covariance matrix \( \mathbf{C} \) are similar matrices. One can be calculated from the other. And either contains all the polarimetric information measured from the observed targets.

For the monostatic case, where \( S_{vh} = S_{hv} \), we define the corresponding 3-D vectors as:

the ‘Lexicographic Feature vector’

\[
\mathbf{f}_{3L} = \begin{bmatrix} S_{hh} & \sqrt{2} S_{hv} & S_{vv} \end{bmatrix}^T
\]

and the ‘Pauli Feature vector’

\[
\mathbf{f}_{3P} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh} + S_{vv} & S_{hv} - S_{hh} & 2 S_{hv} \end{bmatrix}^T
\]

Thus, the corresponding covariance and coherency matrices are defined as:

\[
\mathbf{C}_3 = \langle \mathbf{f}_{3L} \cdot \mathbf{f}_{3L}^* \rangle
\]

and

\[
\mathbf{T}_3 = \langle \mathbf{f}_{3P} \cdot \mathbf{f}_{3P}^\ast \rangle
\]

### 2.1.2 Polarimetric Decompositions

The purpose of the polarimetric decomposition is to provide interpretations in the physical aspects, such as the scattering mechanisms or the polarimetric properties. The parameters acquired from the
decomposition methods are popular in the polarimetric SAR classifications, since they present direct explanations and efficient mapping features. According to the assumptions of the target types, the decomposition methods, therefore, are divided into two major categories, namely the coherent decompositions for the “pure single scatters” type and the incoherent decompositions for the “distributed scatters”.

**Coherent decompositions**

The coherent decompositions are carried on the scattering matrix $S$, since the single scattering matrix can be used to represent the polarimetric properties of the “pure single scatters”. In this case, the scattering matrix $S$ is expressed as the combination of the scattering responses of typical object models

$$S = \sum_{i=1}^{k} c_i S_i$$

(13),

in which $S_i$ stands for the response of simple objects, $c_i$ serves as the weight. The objective of this kind is to interpret the physical properties through the analysis of the simple object models $S_i$. Followed are the brief descriptions of the most used ones:

**Pauli decomposition:** The scattering matrix $S$ is interpreted in terms of four scattering mechanisms, namely sphere surface, dihedral, di-plane oriented at 45 degrees and helix related. They are modeled respectively in the following Pauli basis:

$$[S]_a = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

(14),

$$[S]_b = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

(15),

$$[S]_c = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

(16),

$$[S]_d = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

(17).

In the situation that the reciprocity is assumed in the monostatic system, where $S_{vh} = S_{hv}$, the Pauli basis can be reduced to \{[S]_a, [S]_b, [S]_c\}. Thus, the scattering matrix can be decomposed as follow:

$$[S] = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} = \alpha[S]_a + \beta[S]_b + \gamma[S]_c$$

(18),

where
\[ \alpha = \frac{S_{hh} + S_{vv}}{\sqrt{2}} \]  
\[ \beta = \frac{S_{hh} - S_{vv}}{\sqrt{2}} \]  
\[ \gamma = \sqrt{2}S_{hv} \]  

The Pauli decomposition result is often used to illustrate the whole polarimetric info in a single color image.

**Krogager decomposition:** In this, the S is represented as the combination of a sphere, a di-plane and a helix. And the last two components are depicted with the angle \( \theta \).

**Cameron decomposition:** This decomposition first factors the S matrix into the non reciprocal part \([S_{nr}]\) and reciprocal part \([S_{rec}]\), then the latter one will be further parted into the max symmetric component \([S_{max}]_{sym}\) and min symmetric one \([S_{min}]_{sym}\). And the max symmetric part will be used to compare the referenced measures to match the identical objects.

**Incoherent decompositions**

In case of the decomposition of the incoherent targets, the second order descriptors: covariance and coherency matrices are employed. These decompositions can be expressed as

\[ C = \sum_{i=1}^{k} p_i C_i \]  
or
\[ T = \sum_{i=1}^{k} q_i T_i \]  

And those factors \( C_i \) or \( T_i \) represent the easier physical interpretation. The most popular decomposition schemes of this kind will be concisely depicted as below:

**The Model-based Freeman Decomposition:** The freeman decomposition is based on the modeling which takes the covariance matrix as the combination of three scattering mechanisms, namely “Volume scattering” (i.e. forest canopy), “Double-bounce scattering” (i.e. dihedral corner reflector) and “Surface or single-bounce scattering” (i.e. first-order Bragg surface scatterer). In the reciprocal monostatic situation, the models of the above mechanisms are described respectively as follow:
Thus the covariance matrix \([C_3]\) can be expressed as follow:
\[
[C_3] = [C_1] + [C_2] + [C_3]
\] (27).

**Phenomenological Huynen Decomposition:** The Huynen decomposition tries to divide the coherency matrix \(T\) into two parts which are the pure target \(T_0\) and the distributed N-target \(T_N\). Thus, for the man-made areas, there will be strong response from the pure target part \(T_0\), whereas for the natural scenes, the noise component \(T_N\) will become dominant.

**Eigenvector-Eigenvalue based Decomposition:** This decomposition utilizes the products from the eigen decomposition of the coherency matrix \(T\), in the reciprocal mono-static assumption, that eigen decomposition can be illustrated as
\[
T_3 = \sum_{i=1}^{3} \lambda_i \mu_i^{T} \tag{28}
\]
Here \(\lambda_i\) and \(\mu_i\) denote the eigenvalue and eigenvector of \(T\) respectively. And the eigenvector can be formulated as
\[
\mu_i = [\cos \alpha_i, \sin \alpha_i, \cos \beta e^{i\delta}, \sin \alpha_i, \cos \beta e^{i\gamma}]^T \tag{29}
\]
Then, 3 parameters can be defined as
**Entropy:** \(H = -\sum_{i=1}^{3} p_i \log_3 (p_i) \tag{30}\)

where
\[
p_i = \frac{\lambda_i}{\sum_{k=1}^{3} \lambda_k} \tag{31}
\]
**Anisotropy:** \(A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \tag{32}\).
Mean alpha angle: \( \alpha = \sum_{i=1}^{3} p_i \alpha_i \) \( (33) \).

This eigen decomposition of the coherency matrix is also known as \( H/A/\alpha \) decomposition or Cloude Pottier decomposition. In which the mean alpha angle \( \alpha \) represents the main scattering mechanism (single-bounce scattering, volume scattering or double-bounce scattering, etc). The entropy \( H \) measures the degree of the randomness of the scattering process, for which \( H \to 0 \) corresponds to a pure target, whereas \( H \to 1 \) means the target is a distributed one. The anisotropy \( A \) gives the relative importance of the second and the third eigenvalues. But it is most meaningfully used while \( H>0.7 \). Lee et al. (2008) evaluated the bias on Entropy/Alpha/Anisotropy and developed a bias removal method for land mapping.

2.1.3 Polarimetric SAR Speckle Statistics

Speckle is inherent in SAR system due to the interference phenomenon of the coherent waves from many elements in the same resolution cell (Goodman, 1976). The sum of the waves is carried out as vector sum in the complex plane. That causes a pixel-to-pixel variation which represent as a granular noise pattern in SAR image. Understanding SAR speckle statistics is essential for analysis and process of the SAR data. For the polarimetric SAR system, the situation become complicated since the statistics of the phase difference and coherences between polarizations are of extreme significance. The following sections will discuss the polarimetric SAR speckle statistics and the derivation of various PDFs (probability density function) for polarimetric SAR parameters.

Speckle noise and multiplicative model

It has been verified (Oliver and Quegan, 1998; Frery et al., 1995; Arsenault and April, 1976) that in many situations the multiplicative model is proper to represent the statistical properties of SAR data. In this framework, the observation \( Z \) is the product of two independent random variables: \( X \) for the backscatter and \( Y \) for the noise. Thus the model can be stated as:
\[ Z = X \cdot Y \] \( (34) \).

Polarimetric SAR speckle statistics

Under the reciprocal medium assumption, where \( S_{vh} = S_{hv} \), the complex scattering vector can be written as:
By employing the multiplicative model, the single-look complex scattering matrix holds:
\[ Z = X^{1/2}Y \tag{36} \]
In this model, \( X \) is assumed a positive random variable with \( E(X) = 1 \). \( Y \) accordingly follows a zero mean complex Gaussian distribution. That means the mean value of the scatters is assigned to \( Y \) which not only represents the variety of noise but also contains the mean values of the observed targets from each channel. However, this assumption does not change the distribution of \( Y \).

Multi-look processing is frequently taken for polarimetric SAR data. Thus, the \( n \)-looks complex covariance matrix is obtained from the averaging of the samples (Lee et al., 1995):
\[ Z^{(n)} = \frac{1}{n} \sum_{l=1}^{n} Z(l)(Z^*(l))^\dagger = \frac{1}{n} \sum_{l=1}^{n} X(l)Y(l)(Y^*(l))^\dagger \tag{37} \]
Since \( X(l) \) is assumed not to vary for the multi-look samples in the resolution cell, i.e. \( X(l) = X \) for every \( l \). Thus the equation can be written as:
\[ Z^{(n)} = \frac{X}{n} \sum_{l=1}^{n} Y(l)(Y^*(l))^\dagger = XY^{(n)} \tag{38} \]
Where \( Y^{(n)} \) follows a multivariate complex Wishart distribution (Goodman, 1963; Lee et al., 1994; Srivastava, 1965).

**Complex multi-look covariance matrix models**

As discussed in the above section, the distribution of the speckle variable \( Y^{(n)} \) is decided. Therefore the distribution of the multi-look covariance matrix \( Z^{(n)} \) only depends on the distribution of the scatter variable \( X \). For the homogeneous area, where \( X \) is constantly equal to 1, \( Z^{(n)} \) follows a complex Wishart distribution given by Lee et al. (1994):
\[ f_{Z^{(n)}}(z) = \frac{n^{mn}}{h(n,m)} |z|^{m-m} \exp(-nTr(C^{-1}z)) \tag{39} \]
Where \( h(n,m) \) is the scaling function and is given by \( h(n,m) = \pi^{(m-n)/2} \Gamma(n) \cdots \Gamma(n-m+1) \), \( \Gamma(\cdot) \) is Gamma function and \( C = E(ZZ^*) \). \( m \) is the dimension of the vector \( Z \), \( n \) is the number of looks.

\[ Z = \begin{bmatrix} S_{hh} & S_{hv} & S_{vv} \end{bmatrix}^T \tag{35} \]
By using a Gamma distribution for $X$, $K_p$ model is proposed (Jakeman and Pusey, 1976). This model is suitable for the heterogeneous area. Assuming $X$ follows generalized inverse Gaussian distribution, Freitas et al. (2005) proposed a $G_0^\alpha$ distribution which is capable of describing both heterogeneous and homogeneous areas by the following equation:

$$f_{Z^{(\alpha)}}(z) = \frac{n^{mn}|z|^{mn-\alpha} \Gamma(mn-\alpha)}{h(n,m)|C_{z,z}|^{\alpha} \Gamma(-\alpha)\Gamma(-\alpha-1)^{\alpha}} \Phi(nTr(C^{-1}z) - \alpha - 1)^{\alpha-mn}, \alpha < -1 \quad (40),$$

where $\alpha$ is the roughness parameter that describes the properties of the observed area. The big value of $\alpha$ indicates a heterogeneous area whereas the small value indicates a homogeneous one.

The models of the other polarimetric parameters like intensity or amplitude also have their distinctive forms and character with contrast to that of single-polarization SAR data (Lee and Potter, 2009b). Knowing those models is essential to develop effective algorithm for polarimetric SAR imaging processing.

### 2.2 Urban Land-Cover/Land-use Mapping Using SAR

Applications of urban land-cover/land-use mapping using SAR systems have been carried on for decades. Since the imaging SAR became commercialized in 1969, the potential of SAR systems for urban applications has been reported in several studies. However, most of the studies on the urban area are limited in only mapping or detection of the settlement regions. The detailed urban structures are less investigated. Due to the complicated environment, urban classification is one of the most challenging works in the land-cover/land-use field. In this section, the characters of urban SAR imaging are reviewed as well as the state-of-the-art classification methods. Comparison of using single, dual and full polarization SAR data for urban mapping are included in this section as well.

#### 2.2.1 SAR Features of Urban Areas

The urban area is a complicated region in which man-made objects are blended with natural targets. Therefore, particular phenomena in the SAR images should be noted.

High buildings introduce considerable geometrical distortion in SAR images. Due to the short distance of the roof towards the sensor
comparing with the walls facing the looking direction or the ground in front of the buildings, the positions of those targets will be reversed in the SAR image. That is called the “layover” phenomenon (Soergel et al., 2002). This phenomenon make it difficult to georeference and co-register data, especially for SAR image from different orbit mode, since the form of the layovers vary due to the different looking directions and angles.

The backscattering from urban area is complex. Dong et al. (1997) examined the backscattering mechanisms in the urban area and concluded that the dominant scattering types are single bounce from roofs, and double bounce from ground-wall structures. However, the backscattering always consists of many scattering mechanisms from heterogeneous elements in the same resolution cells. For example the wide roads through the building blocks will contain both the single and double bounce scatterings. The low density area is observed from the mixture waves composed of volume scattering from vegetations and double-bounce from buildings.

The looking directions greatly influence the SAR signatures of the urban area. The so-called cardinal effect occurs when man-made structures are laid out orthogonal to the illumination directions (Raney, 1998). In such case, significantly larger returns will be recorded. This effect is even enhanced for longer wavelength SAR.

One of the first studies of polarization characters in urban area was made by Lewis (1969). He argued that the cross-polarization enhance the ability to identify the commercial and industrial areas. The delineation of vegetated areas was more successful with HH-polarized images. Henderson (1979) noted that the HV polarization responses are less affected by the cardinal effects with contrast to the HH polarization and provide more details in the urban area. Moreover urban areas usually demonstrate medium polarimetric entropy (which indicates the degree of polarization) with multiple scattering mechanisms (Cloude and Pottier, 1997).

The textural differences exist not only between the urban and non-urban area, but also appear within intra-urban categories (Henderson and Xia, 1998). The urban area appears smoother than other places, especially in commercial or industry area. As intentionally organized and planned area with regular man-made objects, urban areas have unique patterns reflected in SAR images. Along with the shape, those patterns may assist the interpretation of the diversity of the urban functions of different areas (Geile, 1986).
2.2.2 Methodology on SAR Imagery for Urban Mapping

**Single-polarization SAR data for urban mapping**
Using only single-polarization SAR data for urban mapping, previous work focused on the interpretation of the backscattering behaviors under specific conditions for different various land use/land cover types. The mapping capacity is often limited to only separating urban from non-urban areas. Through studies on the SEASAT L-band HH polarization images, Fasler (1980) first employed texture analyses in urban applications. Henderson (1982) examined the utility of various scales for single polarization image urban mapping. He later examined the effects of various filter windows for urban detection (1983). Wu (1980) merged the SEASAT HH data with a LANDSAT MSS scene. Three urban categories could be mapped by an unsupervised classification. However, only one “urban class” could be identified using the single polarized data alone. Henderson and Anuta (1980) employed X-band, Ka-band and SEASAT HH SAR images of various scales in order to examine the influence of SAR wavelengths, looking directions and image scales for urban area detection. Brisco et al. (1983) compared urban area detection efficiencies with ascending and descending data and studied the effects of data fusion sets, where the incident angle influence for mapping accuracy and the importance of the complement orbital mode fusion are demonstrated. Li and Bryan (1983) examined the effects of resolution, sample bits and number of multi-looks for urban areas. Sieber and Hartl (1986) reported that the incident angle has more influence on the urban detection than the look angle. However, since the wide use of advanced polarimetric SAR data, research about single-polarization data mapping for urban areas has been less reported nowadays.

**Dual-polarization SAR data for urban mapping**
Dual-polarization SAR data enhances urban analyses not only by providing two alternative polarization channels but also introducing their phase difference information. The studies based on only dual-polarization images can be traced back decades ago. Actually, most of the earlier urban polarization studies are limited to the HH and HV channels due to the configuration of widely used SAR systems that time (Henderson and Xia, 1998). Moore (1969) used the Ka-band HH and HV imagery to study the urban patterns in Chicago. Dowman and Morris (1983) conducted a detailed study on the urban area using X-band HH and HV imagery. Behaviors of various man-made structure types on the dual-polarization images are observed. Henderson and Mogilski (1987) studied the
separability of many man-made cultural features and the natural terrain features under the two polarizations by measuring grey tone values. However, those studies only focus on the responses on the separated two polarizations while the relation between the channels is less explored. Unlike applications for forest or crop mapping, like- and cross-polarization ratios like HH/HV (Nguyen et al., 2009) or the phase difference (Ulaby et al., 1987) are found to be less applied on the studies on the urban area using dual-polarization data.

Since the prevalence of full-polarization data at present, the research focus has shifted towards applications using full-polarization data. Therefore, fewer studies are found using only dual-polarization data, especially for mapping urban areas these days. Comparing with full-polarization data, Cloude (2007) proposed a dual-polarization entropy/alpha decomposition and studied the properties of urban scattering. Trianni et al. (2005) compared the potential of full and dual polarizations data for urban mapping. He argued that, for a pixel-based analysis, the result from dual-polarization data is satisfactory and the spatial contextual information is the most essential factor. To explore the spatial information, Wu et al. (2008) proposed a MRF-based classification method to map the built-up area for dual-polarization data. Ainsworth et al. (2009) compared the classification result of urban areas between the dual-polarization imagery and the pseudo-quad-polarization data derived from full-polarization scattering models, where the same overall classification accuracy is recorded. Although the employment of only the dual-polarization data on urban area are rare in recent, the techniques for dual-polarization data could be directly applied in the full-polarization case. The experience on dual-polarization data is essential for fully exploring the potential of the available data.

**Full-polarization SAR data for urban mapping**

Studies on urban areas using full-polarization SAR data could be found since late 1950s (Lewis et al., 1969; Moore, 1969). However, it is in the recent 20 years that the polarimetric SAR technique has made rapid progress due to the successful launch of many advanced polarimetric SAR sensors. Full-polarization SAR data could provide useful polarimetric parameters, that are used to estimate the targets’ properties. Those parameters have unique statistical characters and physical explanations compared to the normal single polarization data.

To study the polarimetric properties of urban areas, Rao et al. (2008) conducted a study on polarimetric properties of various features. Kimura (2008) analyzed the SAR polarization orientation shifts in built-up areas.
Mittal and Singh (2008) studied the relationship between the polarizations of linear and circular basis and various scattering mechanisms. Different polarization combinations for urban mapping are compared. Leducq et al. (2005) and Ferro-Famil et al. (2008) used the time frequency diversity to analyze the man-made environments through polarimetric SAR data.

By employing the polarimetric parameters, Pellizzeri (2003b) mapped the suburban areas using Cloude-Pottier decomposition and joint annealed segmentation. Lee et al. (2004a) developed an unsupervised classification method by Freeman decomposition followed by Wishart classifier. Lumsdon et al. (2005) have applied and compared the Freeman decomposition followed by Wishart classifier with the Cloude-Pottier decomposition. Park and Moon (2007) used the fuzzy logic on the Entropy/Alpha plane to improve the Cloude-Pottier unsupervised classification. Alberga (2007, 2008) compared various polarimetric parameters for land-cover/land-use classification. Zhang et al. (2008) extended the scattering model decomposition method by adding the helix and wire scattering models for urban area. Horta et al. (2008a; 2008b) devised a Stochastic Expectation Maximization (SEM) algorithm to mapping the full-polarization data using $G_P^0$ mixture model of the covariance matrix. Harant et al. (2009) used the KummerU PDF to model the covariance matrix of high resolution PolSAR.


For fusion of the polarimetric SAR data with other data source, Jouan and Allard (2004) fused the polarimetric SAR features with the Hyperspectral imagery for land cover mapping. Griffiths et al. (2010) mapped the megacity growth through combining multi-sensor data by SVM.

However, few of those studies focus on the finer structures of urban areas, and applications by using object-based methods are less reported.

2.2.3 State-of-the-Art SAR Urban Classification Methods

Successful classification schemes depend not only on exploring the knowledge of the SAR data but also relate to the classification techniques. Some popular concepts introduced into the SAR urban classification fields are demonstrated in the following sections. It must be pointed out that these methods can be used on either the single-polarization images or the multi-polarized images.

Object-based vs. Pixel-based approach

Traditionally, the classification schemes are devised on a pixel-by-pixel basis. The pixel-based approaches classify the individual pixels through analysis of their statistical characters. Those methods works well on the relatively coarse spatial resolution images before. However, in the case of high resolution images, the expected improvement of the classification results is hindered by the increase of the spectral variance within a class (Shaban and Dikshit, 2001). The “Salt and Peper” effect generally appears on pixel-based classification results in high resolution images. Current research has demonstrated that pixel-based methods are not fit for classification of very-high-resolution image (Scheiewe et al., 2001), since the high spatial resolution increases the spectral variability, which may decrease the classification results using pixel-based method. Object-based methods, on the other hand, make use of spatial information that is present only in meaningful image objects and their mutual relationships but not in single pixels. Object-based methods have been increasingly used in the urban mapping with reasonable successful (Ban et al. 2010, Hu and Ban 2008), since more information such as the object features and spatial relationships could be explored in the analysis. Successful segmentation of meaningful objects is therefore essential for the object-based classification approaches. Among many segmentation
algorithms, the multi-resolution segmentation (Baatz and Schape, 2000) is the most popular one. However, segmentation of SAR data is particularly difficult in comparison to optical data due to the disturbance of speckle.

Since the pixel-based approaches were explored extensively in most of the previous works, only object-based methods are considered in the current urban mapping research. Among those studies, Benz and Pottier (2001) separated the man-made objects and forest and vegetation types on the polarimetric SAR data through analyzing the object-based natures of the Cloude-Pottier decomposition parameters. Corr et al. (2003b) incorporated the polarimetric and interferometric SAR data into the object-based classification of urban areas. Shape, size and other object properties are proved to be useful in reducing the ambiguities among alternative classes. (Esch et al., 2005) developed a robust object-oriented approach to detect built-up areas on E-SAR data of three complete flight tracks, and he further (Esch et al., 2010) developed object-oriented approach to delineate the urban footprints from TerraSAR-X data. Thiel et al. (2008) also applied the speckle statistic analysis to detect urban areas on TerraSAR-X data by an object-based approach. However, most of those studies only focused on separating the built-up from non built-up area. Detailed descriptions of different urban categories are less analyzed.

Techniques on exploring contextual information
The spatial temporal context implies useful information for classifying various land-cover/land-use types. The neighboring pixels tend to be associated with the same class, especially in the high spatial resolution image. Different land-cover/land-use types have various temporal characters in the time series. Thus, exploring the spatial or temporal information is very likely to improve the mapping result.

One technique exploring the contextual information for remote sensing image classification is Markov Random Fields (MRF) which assumes that the classification result of a unit is related to the results of its local neighbors. Several cases using MRF models for urban mapping on SAR data could be found in previous studies. Solberg et al. (1996) developed a MRF-based classification algorithm for SAR data. Significant accuracy increase was obtained by using such an MRF-based algorithm in contrast to other approaches. By employing a hierarchical classification method combing MRF models, Crawford and Ricard (1998) successfully suppressed the speckle effect on the classification result. There are also many researches concerning classification accuracy improvement through fusion of multi-source data by MRF (Tso and Mather, 1999; Nishii,
To map multitemporal or multi-frequency data with high accuracies, many advanced model independent classifiers are introduced into the remote sensing imagery analyses, such as artificial neural networks (ANN) and support vector machine (SVM). Successful applications of those classifiers are reported in many studies. In comparison to the other traditional classifiers, SVM is increasingly be used by remote sensing researchers (Pal and Mather, 2005). Tzotsos (2006) has introduced SVM into object-based analyses. However, only few researches have been done concerning mapping SAR data using SVM for urban areas. Lehureau et al. (2009) mapped urban areas by combined SAR and optical features using SVM. Griffiths et al. (2010) fused multi-source data by SVM for megacity growth mapping. Tuia et al. (2010) proposed multisource composite kernels for urban classification.

However, there is a lack of detailed urban analysis in the previous studies using such advanced classifiers.
3. STUDY AREA AND DATA DESCRIPTION

3.1 Study Area

As one of the most populous metropolitan areas in Canada, the Greater Toronto Area (GTA) has rapidly expanded towards the Oak Ridges Moraine in recent years. The area is enclosed by Lake Ontario to the south, Kawartha Lakes to the east, the Niagara Escarpment to the west, and Lake Simcoe to the north. A unique natural ecosystem known as the Greater Toronto Bioregion is identified here (Furberg and Ban, 2008). However, significant environmental changes are occurring there due to the rapid urban sprawl.

The study area covers the town of Vaughan, Richmond Hill, Aurora, Bolton, the west part of Markham, the southern part of Newmarket, and the east part of Brampton in the Greater Toronto Area (Figure 3.1). In recent years, those regions such as Vaughan and northern Richmond Hill have undergone dramatic changes. Continuously incoming immigrants accelerate the urbanization process.

![Study Area: Rural-urban Fringe of GTA, ON, Canada. Left: Map of Canada; Right: GTA Area Map](image)

**Figure 3.1** Study Area: Rural-urban Fringe of GTA, ON, Canada. Left: Map of Canada; Right: GTA Area Map

The major land-cover/land-use classes can be summarized as man-made classes including high-density residential areas, low-density residential areas, industry and commercial areas, construction sites, wide roads, streets, parks and golf courses, and natural classes including forests, pasture, water and several types of agricultural crops.
3.2 Data Description

The data used in this study can be divided into three categories according to their functions for the research. They are as follows:

2. Orthorectification auxiliary data: DEM
3. Georeference data: NTDB vector data
4. Reference data: Quickbird (2009) and Field data.

3.2.1 RADARSAT-2 Fine Beam Quad-Polarimetric SAR Data

The data used for the classification study consist of six-date RADARSAT-2 fine-beam quad-polarimetric SAR (PolSAR) images featuring four linear polarization channels namely: HH, HV, VH and VV. The centre frequency at this beam mode is 5.4GHz, i.e., C-band and the spatial resolution is 4.7 meters in range direction and 5.1 meters in azimuth direction. The detailed descriptions of these imageries are given in Table 3.1.

<table>
<thead>
<tr>
<th>Data</th>
<th>Orbit</th>
<th>Incident angle range (degree)</th>
</tr>
</thead>
<tbody>
<tr>
<td>June 11 2008</td>
<td>Ascending</td>
<td>40.179~ 41.594</td>
</tr>
<tr>
<td>June 19 2008</td>
<td>Ascending</td>
<td>40.215~ 41.619</td>
</tr>
<tr>
<td>July 05 2008</td>
<td>Ascending</td>
<td>40.182~ 41.597</td>
</tr>
<tr>
<td>August 06 2008</td>
<td>Ascending</td>
<td>40.197~ 41.612</td>
</tr>
<tr>
<td>August 22 2008</td>
<td>Ascending</td>
<td>40.174~ 41.590</td>
</tr>
<tr>
<td>September 15 2008</td>
<td>Ascending</td>
<td>40.173~ 41.588</td>
</tr>
</tbody>
</table>

3.2.2 Other Datasets

The National Topographic DataBase (NTDB) vectors of 1:50,000 were used to georeference the RADARSAT-2 images and verify the classification result of certain land-cover/land-use classes. The database includes vectors such as roads, water bodies, forest, built-up areas and etc.
The DEM issued by DMTI Spatial Inc was used for orthorectification of the RADARSAT-2 images with a resolution of 30 meters. And for both the DEM and NTDB, the projection is UTM, with the NAD83 datum.

Quickbird data from 2009 was used as reference source. Field data was collected during the satellite overpass. Soil conditions, vegetation heights, and ground-types are recorded alongside photographs.
4. METHODOLOGY

For mapping of detailed urban land cover classes using fine resolution multitemporal polarimetric SAR data, both object-based and pixel-based classification schemes are proposed. For object-based analysis, specific rules and schemes are developed to extract specific land use/land cover types and refine the mapping results. An object-based SVM is introduced into the polarimetric SAR classification collaborating with the developed rules in the first approach. The object-based classification performances of various polarimetric SAR features are compared and efficiencies of multitemporal data combinations are evaluated. For comparison with the object-based approaches, a pixel-based algorithm exploring the spatial-temporal contextual information of the polarimetric SAR data is devised.

4.1 Selection of Polarimetric SAR Parameter Sets

The performance of various polarimetric SAR parameters on detailed urban mapping is the concerns in this study. Thus, comparison of various polarimetric SAR parameters is conducted which consider the following aspects:

1. Various polarimetric parameters: Freeman, Pottier, Pauli, Intensity, Coherency matrix.
2. Part and Whole: Raw Pauli data and Coherence matrix.
3. Logarithm and non logarithm: log Intensity and Intensity as well as log Pauli and raw Pauli
5. Filtered and unfiltered: Compressed log filtered Pauli and Compressed log Pauli.

To this end, typical polarimetric SAR parameters are generated through various decomposition methods and data processing approaches as illustrated in table 4.1. Detailed descriptions about those parameters are given in paper III.
Table 4.1 Selected feature sets for comparisons

<table>
<thead>
<tr>
<th>Parameter Set (Code)</th>
<th>Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensity (I)</td>
<td>$</td>
</tr>
<tr>
<td>Logarithmic Intensity (L I)</td>
<td>$\log$ (Intensity)</td>
</tr>
<tr>
<td>Coherency Matrix (T)</td>
<td>$T$</td>
</tr>
<tr>
<td>Raw Pauli (R P)</td>
<td>$T_{11}, T_{22}, T_{33}$</td>
</tr>
<tr>
<td>Logarithmic Pauli (L P)</td>
<td>$\log$ (Raw Pauli)$_{16\text{-bit}}$</td>
</tr>
<tr>
<td>Compressed Logarithmic Pauli (CL P)</td>
<td>$(\log$ (Raw Pauli))$_{8\text{-bit}}$</td>
</tr>
<tr>
<td>Compressed Logarithmic Filtered Pauli (CLF P)</td>
<td>$(\log$ (Filtered Pauli))$_{8\text{-bit}}$</td>
</tr>
<tr>
<td>Freeman (Freeman)</td>
<td>D, O, V</td>
</tr>
<tr>
<td>Cloude-Pottier (Pottier)</td>
<td>H, A, a</td>
</tr>
</tbody>
</table>

4.2 Object-Based Rules for Multitemporal SAR Classification

By employing the object-based approach, specific rules are developed to map the urban details. Those rules concern not only the polarimetric features but also the shape of the objects and the spatial relationships between the classes. To implement such classification schemes, the multitemporal polarimetric data are first orthorectified and georeferenced. A multi-scale segmentation hierarchy is constructed on the multitemporal data stack, since particular segmentation scales are suitable for some specific land-cover features. Contextual information for classification is explored from the relationships between super and sub segmentation scale layers. The multiresolution segmentation algorithm in eCognition is selected as the segmentation method (Baatz and Schape, 2000). However, one difficulty of using object-based analysis for SAR data is to successfully segment out the meaningful objects from the speckled SAR images. To this end, processed Pauli (Cloude and Pottier, 1996) parameters which are the logarithmic filtered Pauli parameters truncated to 8-bit by linear scaling are proposed as the polarimetric features for segmentation. The image is filtered by the refined Lee filter (Lee, 1981) before the actual segmentation. The necessity of applying such filtered parameters for segmentation could be observed from the comparison of the segmentation results with that of using the raw data in figure 4.1.
Figure 4.1 Segmentation results on the raw Pauli data (left) and processed Pauli data (right)

Based on the multi-scale segmentation, a hierarchical multitemporal land use/land cover extraction and a fusion scheme are performed as illustrated in figure 4.2. Various land-cover/land use types were extracted into different type layers. The multitemporal class extraction schemes have two aspects: 1. The layer of many class types such as various built-up areas and natural classes are the classification results by the advanced classifier (such as SVM or NN) on the stacked multi-date data. 2. Any of the other class layers, such as road or street, is the fusion result of multi single-date classification results of that specific class. Those layers are then hierarchically combined according to the features’ properties and classification accuracy. The red arrow in figure 4.2 specifies the fusion order. Finally post-processing is applied to refine the results.

Figure 4.2 Flow chart of the knowledge-based multitemporal classification schemes

The developed rules and the extracted class layers, such as the road and street layers, could be further employed in the subsequent analyses. Details of such rules and schemes for class layer extraction and data fusion are described in paper I.
4.3 Combined SVM and Rules for Detailed Urban Land Cover Mapping

The superiority of SVM comparing with many other traditional classifiers has been currently demonstrated in many remote sensing image mapping applications (Pal and Mather, 2005). SVM is especially suitable for classifying the multitemporal or multi-source data since no distribution assumption is required. However, the effect of using the object-based SVM in comparison with the rule-based methods on the multitemporal polarimetric SAR data for detailed urban mapping are less reported.

Therefore, an object-based SVM classification frame is developed as shown in figure 4.3. The procedure mainly consists of two sections which are the object-based SVM classification for the major land use/land cover classes on the multitemporal data stack, and rule-based road and street extraction with subsequent mapping refinement. Rules developed in paper I are employed for that purpose. The actual input classification vector of the SVM classifier consists of the multi-date stack of the mean and standard deviation of one specific polarimetric parameter set within the object. An example of using Pauli parameters on multitemporal data stack is shown in figure 4.4. Detailed descriptions about this SVM and rules combined object-based classification for detailed urban mapping are introduced in paper II.
Performances of the polarimetric SAR parameters selected in table 4.1 are compared by such SVM and rules combined object-based classification method. Instead of using the SVM classifier, those comparisons are also conducted using Nearest Neighbor (NN) classifier to evaluate the efficiency of SVM in the object-based classification and confirm the parameters’ capabilities.

In order to select efficient date and orbital mode combinations for urban observation in such local regions, the significance of the temporal relationship and orbital complement information among the data are studied. To this end, alternative temporal and orbital mode combinations are compared using the verified best polarimetric parameters. Details of the above polarimetric parameter and multitemporal combination comparisons by such object-based SVM are described in paper III.

### 4.4 Pixel-Based Spatial-Temporal SEM algorithm

Although the object-based methods could generate homogeneous mapping results, the success of such approaches depends on the segmentation of the meaningful objects, which is usually difficult within SAR images that contain speckle. On the other hand, pixel-based methods often suffer from the “pepper-salt” results. Moreover, the contextual information is relatively hard to be explored. Therefore, a supervised
Stochastic Expectation-Maximization (SEM) algorithm (Horta et al., 2008) exploring the spatial-temporal contextual information for pixel-based classification is proposed in order to compare it to the object-based approaches addressed in paper I, II and III. In this algorithm, a multitemporal mixture model considering the statistical characters of each selected day and the local condition distribution is devised. The local condition is modelled by an adaptive Markov Random Field (MRF) (Wu et al., 2008) in which the homogeneity and the form of the neighborhood is concerned. By employing the SEM algorithm, parameters representing the class’ characters will be estimated during the iterations until they converge. The framework of this algorithm is illustrated in figure 4.5.

![Flow chart of the pixel-based spatial-temporal SEM algorithm](image)

**Figure 4.5** Flow chart of the pixel-based spatial-temporal SEM algorithm

To test the efficiency of this algorithm on mapping urban details, various multi-look polarimetric SAR data distributions are compared by a mixture model. Those distributions (Frery et al., 2007) include the Wishart distribution which is able to describe homogeneous areas, $K_p$ distribution which is suitable for describing the heterogeneous areas and
distribution which is proposed to model extremely heterogeneous areas as well as homogeneous areas. Details of such pixel-based algorithm are presented in paper IV.
5. RESULTS

5.1 Object-Based Rules and Hierarchical Fusion Scheme

In paper I, by applying the rule-based class layer extraction and hierarchical multitemporal fusion approaches, 11 land use/land cover classes are mapped with an overall classification accuracy of 82.1% and Kappa coefficient 0.80. Besides, the wide roads (80.76%) and streets (80.63%) could be modeled accurately enough to outline the finer urban structures. Examples of part of the road network and the street are illustrated in figure 5.1. However, since the mapping and fusion rules for those man-made functional classes are defined in a stricter way than the other types, the commission error of them is relatively low. Therefore, higher user’s accuracies could be achieved for those strict defined man-made classes, such as golf and parks.

![Figure 5.1](image)

**Figure 5.1** Part of the wide road structure (left) and street layer (right) extracted by the rules

Some characteristics of this proposed multitemporal classification scheme could be noted in the following way: 1. The detailed urban structures are extracted through the mapping of many urban functional classes. 2. Specific classes are extracted separately with high accuracies. Therefore, some rules for specific classes could be reused for the further studies, as we use the road and street extractions in the SVM and rules combined method in paper I and II.

5.2 SVM and Rules Combined Multitemporal Classification

In paper II, the SVM and rules combined mapping approach...
demonstrated obvious improvement for 14 land use/land cover classes with an overall accuracy of 86.79% and a Kappa value of 0.85 using the processed Pauli parameters (the truncated 8-bit filtered logarithmic Pauli parameters). The superiority of using Support Vector Machine (SVM) is also demonstrated by comparing it to the Nearest Neighbor (NN) classifier with which overall accuracy of 82.13% and Kappa 0.8 could be achieved under the same conditions. The obvious superiority of SVM to NN could be observed on urban categories such as industry, high density and low density areas. The enhanced capability of differentiating between the low scattering types such as golf, pastures and water is evident. Selected examples of the SVM and rules combined method using the processed Pauli parameters are given in figure 5.2.

High mapping accuracy could be achieved for most of the natural classes such as water, forest, and various crops. The urban categories could be well identified, and detailed urban structures extracted. With regards to the confusion source, industrial and commercial areas are easily confused with high density built-up areas due to the similar polarimetric properties in particular situations, e.g. specific orientations. Besides forest, low density built-up areas are also confused with high density built-up areas due to the uncertain definition of the transitional density area. The omission errors of the street and road classes to the urban categories are mostly due to the incomplete segmentation from urban area. Although the results might be different with alternative polarimetric parameters, those above mentioned phenomena could still be observed in the following comparisons.
Multitemporal Spaceborne Polarimetric SAR Data for Urban Land Cover Mapping

Figure 5.2 Selected examples of the SVM and rules combined mapping results on processed Pauli parameters, compared with the Quick-bird image

5.3 Comparison of Polarimetric Features and Multitemporal Efficiency

In paper III, performances of using various polarimetric SAR parameter sets and the efficiencies of alternative date combinations are compared by the SVM and rules combined classification scheme which is described in paper II. Paper III extended the polarimetric comparisons of paper II in the following way: 1. More polarimetric parameter forms are considered. 2. The capabilities of those parameters are confirmed both on the ascending and descending data stack with SVM and NN classifiers. 3. The temporal relationship and orbital mode complement among the data for multitemporal mapping are investigated. Results are given in the following sections.

5.3.1 Comparisons of Various Polarimetric Feature Sets

The performances of various polarimetric SAR parameters for object-based detailed urban mapping are confirmed by the comparisons on the ascending data stack and comparisons on the descending data stack. By comparing the overall accuracy and Kappa coefficient, the following facts could be observed: 1. The best classification results are produced by the processed Pauli (P Pauli) parameters. 2. The lowest mapping accuracy is reported by using Cloude-Pottier parameters. 3. The performance of logarithmic data demonstrated better results than the raw data. 4. The difference between the usage of raw Pauli parameters as the diagonal elements of the coherency matrix (T) and the usage of all the matrix elements is not remarkable. 5. The Freeman parameters perform equally well as the logarithmic intensity parameters. 6. The compressed data could generate approximately similar mapping results as when using raw data. 7. Based on the segmentation of the compressed logarithmic filtered Pauli, the mapping result of using that is similar to that of using the compressed logarithmic Pauli. 8. The Pauli parameters yield better results than intensity data. Those above phenomena are confirmed by results from the classification of using SVM or NN classifier alone and the results by the rule and classifier combined classification. Figure 5.3 and 5.4 illustrate comparisons of some polarimetric SAR parameters on the
ascending data stack in a local region. Details of those comparisons are described in paper III.

Figure 5.3 The multitemporal SVM and rules combined classification result of parameter sets 1: Compressed logarithmic filtered Pauli (top-left); Compressed logarithmic filtered Processed Pauli but using NN classifier instead (top-right); Coherence matrix (bottom-left); Raw Pauli (bottom-right)

5.3.2 Comparisons of Multitemporal Data Combinations

The efficiencies of multitemporal data mapping are evaluated in two aspects: 1. The efficiency of each single date data mapping. 2. The efficiency of various data combinations of selected dates.

By comparing the single date data mapping results, it was found that the ascending images perform better than the descending ones. Within the ascending data, the images from July, 5th and August, 22nd are evidently more efficient, indicating a better observation time span for this area.
By studying the performance of some selected data combinations as illustrated in figure 5.5 (For convenient description, A and D stand for Ascending and Descending. A1, 2, 3, 4 stand for 11th June, 5th July, 22nd August and 15th September, D1, 2 stand for 19th June and 6th August.), the significance of the complement information from ascending and descending orbital modes are evident. Although ascending data perform better than descending data in this single date data mapping study, the combination of 4 dates ascending data is even not as good as the 3 dates combination which has 2 descending images and 1 ascending image. We can also observe that the combination of ascending image with D2 is better than that with D1, which shows the better complement effect of date D2 (6th August) rather than D1 (19th June). Combinations of ascending data with D12 are better than those with only D1 or D2. These phenomena could be observed by the comparison examples such as A1+D1, A1+D2, A1+D12 and A12+D1, A12+D2, A12+D12. It could be
found that adding one more image from another date improves overall classification accuracy. However, this trend grows slow after the orbital complement of 1 ascending data with 2 descending data. Nevertheless, the best results could be obtained for the complete data stack which is A1234+D12.

![Graph showing performance of selected multitemporal date combinations](image)

**Figure 5.5** The performances of selected multitemporal date combinations

### 5.4 Spatial-Temporal SEM for Detailed Urban Mapping

In paper IV, the performance of the spatial-temporal SEM algorithm is tested on the four ascending images from the 11th of June, 5th of July, 22nd
of August and 15\textsuperscript{th} of September. Regarding the multitemporal fusion effect, improvement of the mapping accuracy could be observed with an increasing number of selected images. Due to the MRF analysis, the class centers could be kept stable during the changes in the iterations. Moreover, homogenous and detailed mapping results could be achieved in comparison to the traditional pixel-based classification.

Figure 5.6 The temporal-spatial SEM classification results assuming various polarimetric SAR data distributions: 4-looked Pauli image of date 5\textsuperscript{th} July (top-left); $G^0_p$ distribution (top-right); Wishart distribution (bottom-left); $K_p$ distribution (bottom-right)

Effects of applying Wishart, $G^0_p$ and $K_p$ multi-look polarimetric SAR data distribution assumptions on the detailed urban mapping are
compared as illustrated in figure 5.6. The $G_p^0$ and $K_p$ models could generate more accurate results than the ones by the Wishart models especially for urban categories. The results of $G_p^0$ and $K_p$ models are close. However, due to the complex Bessel function involved in the $K_p$ model, it is much more time consuming than the other two models in the classification process. Regarding the multi-look effect, evident improvement could be observed for all the distribution models by increasing the multi-look windows size from 2x2 to 4x4. Such an increase in window size has a significant impact on the urban categories. For example the low density area will be more distinctive in comparison to the forest, since the increased window size covers more typical objects representing those areas. However, there is a balance between keeping the feature details and mapping accuracy, when increasing the multi-look window size.
6. CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusions

Throughout this study, the potential of using RADARSAT-2 fine-beam polarimetric SAR data for urban land cover mapping is evaluated. Both object-based and pixel-based methods exploring the multitemporal polarimetric SAR parameters have proven effective in mapping detailed urban structures.

By developing a rule-based multitemporal classification scheme, finer urban structures could be mapped with high accuracy. The rules and fusion scheme can effectively extract the functional urban types such as parks, streets and major roads, and residential areas could be successfully divided further into low- and high-density built-up areas. The rules defined independently for each specific type could be transferred to the further developed object-based algorithms (Paper I).

Combining the rule-based method and object-based SVM, detailed urban mapping could be achieved with high accuracy on the multitemporal polarimetric SAR data stack. The superiority of using SVM for multitemporal object-based classification is verified by comparing it with the nearest neighbor classifier. (Paper II).

Through the comparison of various polarimetric SAR parameters using the combined SVM and rules classification scheme, the efficiency of using the Pauli parameters as diagonal elements of the coherence matrix is proven, and the necessity of the logarithm and compression of the data to improve the classification results is validated. Efficiency of various polarimetric features such as intensity, Freeman decomposition parameters, Cloude-Pottier decomposition parameters etc. are compared for the object-based approach as well. The significance of incorporating complement information of the alternative orbital modes in the multitemporal classification is validated (Paper III).

Exploring the potential of the pixel-based methods for detailed urban mapping, a temporal-spatial SEM algorithm is proposed for classification of polarimetric SAR data. By analyzing the temporal-spatial contextual information, a homogenous mapping result with high accuracy could be achieved while keeping the feature details. $G_p^0$ and $K_p$ distributions are demonstrated to be more effective for detailed urban mapping in
comparison to the Wishart distribution. A larger multi-look window size is validated to be able to improve the urban mapping accuracy (Paper IV).

6.2 Future Research

Accurate and detailed urban mapping using polarimetric SAR data relies on the correct knowledge about the polarimetric properties of various land use/land cover classes and the proper classification method to efficiently make use of polarimetric SAR imagery. According to the current progress, the following topics will be focused on in the future research.

The first is to analyze the SAR polarimetric properties of specific land use/land cover classes. Efficient polarimetric SAR features for discriminating particular classes will be explored. Relationships between the polarimetric features and varying scattering conditions such as the directions and the orientations of the man made structures will be studied.

The second is to explore effective fusion methods for analysis of multitemporal, multi-resolution and multi-sensor data. The efficiency of employing the spatial-temporal context information will be also compared to various polarimetric features.

The third is to integrate object-based and pixel-based methods to improve the mapping accuracy. Thus the polarimetric behavior of the pixels and objects for specific land-cover/land-use type will be studied. Various statistical models for pattern recognition of urban categories will be analyzed. Fusion method of the analyzed results from pixels and objects will be developed.
7. REFERENCES


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