Assessment of Multi-temporal RADARSAT-2 Polarimetric SAR Data for Crop Classification in an Urban/Rural Fringe Area

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Abstract—This paper investigated the potential of multi-temporal polarimetric RADARSAT-2 data for crop classification in urban/rural fringe area. Using five scenes of fine beam Quadpol RADARSAT-2 data acquired during the 2012 growing season, five main crop types (wheat, soybeans, corn, field peas, and forage) in the Southwestern Ontario, Canada have been identified. The potential of the RADARSAT-2 data for crop classification were assessed from the following four aspects: (1) the selection of classifier, (2) the effectiveness of polarimetric parameters, (3) the combination of multi-temporal data, and (4) post-classification processing methods. Pauli decomposition parameters proved to be effective in crop classification using Gaussian based Maximum Likelihood Classifier. With five dates of the images, the five crop types and other four non-crop types were classified at an overall accuracy of 91%. Satisfactory results with an overall accuracy of 87.8% were achieved by using three dates as long as the images acquired at the critical crop growth stages were included. Results demonstrate that polarimetric RADARSAT-2 data are suitable for accurate and economic crop mapping in urban/rural fringe areas.

Keywords—Remote Sensing, crop, classification, multi-temporal, polarimetric RADARSAT-2

I. INTRODUCTION

Crop type information is important for many applications, such as crop inventory, crop condition monitoring, biomass estimation, and crop yield prediction[1]. The emergence of urban/rural fringe zone caused by rapid urban expansion has led to serious environmental problems, such as the loss of agricultural lands, disturbance of natural ecological ecosystems, and so on[2]. Complete and timely crop information is required for both agricultural applications and for assessing the impacts of urban expansion on agriculture in the urban/rural fringe areas.

Remote Sensing has the characteristics of broad coverage and repetitive visits, and thus has been widely used in crop type information extraction. Some methods have been developed for crop inventory using Remote Sensing techniques, but are mainly used in rural areas[3]. Few studies have focused on the crop mapping in the urban/rural fringe areas. The dynamic land use and complex land use and land cover (LU/LC) classes in the urban/rural fringe zones have created challenges for the accurate crop mapping[4].

Currently, Synthetic Aperture Radar (SAR) sensors play an increasingly important role in crop classification because of their ability to obtain images day and night through cloud cover and haze. Also, SAR data are able to capture the dielectric properties and structure of the Earth’s surface materials, and thus provide complementary information for optical data[5]. Polarimetric SAR data provide additional information about land surface features compared with single polarization data[6]. Some recent study have proved that by integrating polarimetric data in crop mapping, the classification accuracy has been enhanced significantly [3]. However, the potential of multi-temporal RADARSAT-2 data in crop classification in the complex urban/rural fringe areas has not been fully explored yet.

The objective of this study is to investigate the potential of multi-temporal polarimetric RADARSAT-2 data for crop type mapping in urban/rural fringe areas.

II. STUDY AREA AND DATA DESCRIPTION

A. Study Area

The Study area is in the urban/rural fringe area northwest of London Ontario, one of the most agricultural productive regions in Canada. However, in the past few decades the urban area expanded rapidly, which results in the loss of agricultural lands in the fringe zone. In order to create a complete map for this area, four non-crop types (built-ups, construction sites, forest, and lawn) and five main crop types (corn, soybeans, wheat, field peas and forage) were classified.

B. Data

Five scenes of RADARSAT-2 wide fine beam Quadpol images were acquired in ascending orbits over the study area from May 4th to September 1st. Polarimetric information was recorded in HH, VV, HV, and VH bands, with a nominal pixel spacing of 4.7m in both the range and azimuth directions. The incidence angles for the five images from 24.9° to 28.3°. The
center frequency of the RADARSAT-2 data is C band 5.4 GHz at a wavelength of 5.6 cm.

Optical data were used as reference data, which included geometrically corrected RapidEye imagery and air photos. The RapidEye images have five multispectral bands (from 440 nm to 850 nm) at 6.5m spatial resolution. The air photos used in the study were taken in April, 2011 with 15cm spatial resolution (Provided by city of London, Ontario).

Field work was conducted to collect ground truth for both training the supervised classifier and testing the classification results. 190 crop lands, which includes forage, wheat, field peas, soybeans, and corn, were surveyed in the entire study area. In order to facilitate the interpretation of the SAR data, hourly weather information (precipitation, temperature and wind speed) were also recorded on each image acquisition day.

III. METHODOLOGY

The methodology for this research includes RADARSAT-2 image processing, classification, post classification processing, and accuracy assessment (Fig. 1).

A. Preprocessing

Crop classification using polarimetric SAR data usually requires the integration of images from multi-temporal acquisitions as well as polarimetric information from various decomposition parameters. In the preprocessing, polarimetric information in each RADARSAT-2 image was firstly extracted from the original scattering matrix \( S \), (see equation 1). Speckles in all the images were then reduced using the Gaussian filter at the window size of 5. Finally, the multi-temporal data were geometrically corrected and orthorectified using the platform ephemeris information, the ground control points (GCPs), and the digital elevation models (DEM).

The polarimetric information is sensitive to the geometric structure and physical characteristic of the ground targets. A target decomposition theorem expresses the average mechanism of the independent elements in order to be associated with a physical mechanism with each component. The components from different decomposition methods can be used for the classification or target recognition [6]. To fully explore the polarimetric information from the RADARSAT-2 data, the coherency matrix \( T(3) \) was firstly extracted from the \( S \) matrix, (see equation 2). Three decomposition methods (Pauli, Freeman-Durden, and H/Alpha/A) have been used to derive decomposition parameters from the \( T(3) \) matrix.

Pauli is a well-known decomposition method. The method separates the backscattering signal into three simple mechanisms, single, double, and volume scattering. The Pauli decomposition parameters are derived from the three diagonal elements of the coherency matrix, and are often employed to present full polarimetric information [2].

\[
S = \begin{bmatrix}
S_{hh} & S_{hv} \\
S_{hv} & S_{vv}
\end{bmatrix}
\] (1)

\[
T(3) = (K \cdot K^\top) =
\begin{bmatrix}
|S_{hh} + S_{vv}|^2 & (S_{hh} + S_{vv})(S_{hh} - S_{vv})^* & 2(S_{hh} + S_{vv})S_{hv}^* \\
(S_{hh} - S_{vv})(S_{hh} + S_{vv})^* & |S_{hh} - S_{vv}|^2 & 2(S_{hh} - S_{vv})S_{hv}^* \\
2S_{hv}(S_{hh} + S_{vv})^* & 2S_{hv}(S_{hh} - S_{vv})^* & 4|S_{hv}|^2
\end{bmatrix}
\] (2)

Where \( K = \frac{1}{\sqrt{2}}[S_{hh} + S_{vv}] \begin{bmatrix} S_{hh} - S_{vv} \\ S_{hv} \end{bmatrix}^T \)

H/Alpha/A decomposition is an approach proposed by Cloude and Pottier for extracting average parameters from experimental data using a smoothing algorithm based on second-order statistics [7]. The decomposition parameters are generated from an eigenvector analysis of the coherency matrix \( T(3) \). The eigenvectors describe different scattering processes, and the eigenvalues indicate their relative magnitudes. Among all the parameters, the averaged Alpha angle \( \alpha \) relates directly to underlying average physical scattering mechanisms. Entropy \( (H) \) describes the randomness of the scatter. The anisotropy \( (A) \) corresponds to the relative power of the second and third eigenvectors [7].

The Freeman-Durden decomposition is a method for fitting a physically based model with three-component scattering mechanisms to polarimetric SAR observations, particularly for wetland and forest. The three-component scattering mechanisms include surface, double-bounce and volume scattering mechanisms [7]. This approach can be used to determine the dominant scattering mechanism and help to distinguish between different surface cover types.

B. Supervised Classification Using Multi-temporal Polarimetric SAR Data

The purpose of this research is to assess the potential of multi-temporal polarimetric RADARSAT-2 data in crop type mapping. To achieve the purpose, the most commonly used supervised Maximum Likelihood classification (MLC) method was adopted. MLC is based on the mean, variance or covariance statistics of class signal responses, and uses a Bayesian Probability Function calculated from the training samples for each class. Each pixel is then classified to the
class to which it most probably belongs [8]. In this study, MLC based on two different probability functions, i.e. Gaussian and Wishart distributions, were applied to find the better classification method.

Gaussian distribution based MLC classification algorithm is widely used in the optical image classification, but rarely in SAR image classification. Due to the speckle effects, the radar responses in SAR image do not follow Gaussian distribution. However, some researchers recently have proved that when the number of look is large enough, the Gaussian probability density distribution is a valid approximation of multi-look SAR data [9]. In this study, we found the distributions of logarithm Pauli decomposition parameters are approximated to Gaussian distribution. For example, experiments in corn fields show that the histograms of the log transformed PauliT11, T22, and T33 are well-matched with the corresponding Gaussian distribution (See Fig. 2). Same results were also observed in the fields of wheat, soybeans.

Complex Wishart distribution (Wishart) MLC is an algorithm proposed by Lee to deal with LU/LC classification using the polarimetric SAR data[10]. This method have been widely used in polarimetric SAR classification. The Wishart distribution was adopted to describe the probability density functions of coherency or covariance matrix of polarimetric SAR data.

The application of Wishart MLC on multi-temporal polarimetric SAR data classification is based on the assumption that those multi-temporal data are uncorrelated. Thus, the Wishart probability measure for multi-temporal polarimetric SAR classification can be expressed as:

\[
D(Z, w_m) = \sum_{j=1}^{J} n \left[ \text{Tr}(C_m^{-1}(j)Z(j)) + \ln|C_m(j)| \right] - \ln \left[ P(w_m) \right]
\]

(3)

Where J is the total number of images, n is the number of looks, \(C_m(j)\) is the average covariance matrix of the \(m\)th class in the \(j\)th image, \(Z(j)\) is the pixel’s covariance matrix from the \(j\)th image [9].

C. Classification and Comparison Procedure

To find an appropriate classification procedure for the multi-temporal polarimetric RADARSAT-2 data, four aspects of the classifications have been assessed and compared in this study. They are the selection of the classifiers, the polarimetric parameters, different multi-temporal data combinations, and the post-classification processing methods.

From each raw RADARSAT-2 image, four sets of polarimetric parameters were generated. These parameters include the coherency matrix T3, Pauli (T11, T22, T33), Freeman-Durden (Surface, Double-bounced, and Volume Scattering), and H/Alpha/A (Entropy, Alpha, and Anisotropy) decomposition parameters. The multi-temporal T3 matrix data were input to the Wishart MLC Classifier. The other three sets of polarimetric parameters were input to the Gaussian MLC classifier.

The classification results giving by different classifiers and polarization datasets were compared and assessed. The best procedure was used for multi-temporal data classification with various combinations of images.

Finally, the original pixel-based SAR image classification results were generated with some unavoidable “noise”. In order to reduce the “noise” in the classification results, two post-processing methods have been used respectively. One is sieve filter, which merges polygons smaller than a user specified threshold with the largest neighboring polygon[11]. The other method implemented the segmentation algorithm in the eCognition software. The original SAR images were firstly segmented into spectrally similar and spatial contiguous objects, and then assigned the majority class in the classification results to each object.

D. Classification Accuracy Assessment

To assess the classification results, 700 testing samples were randomly generated. Most of the class types of those points have been confirmed and then over 500 clusters of testing samples with more than 7000 pixels were selected around those points as the testing samples. The same testing samples were used to evaluate different classification results.

The classification accuracy assessment is performed by referencing to the testing samples. The overall accuracy (OA), Kappa statistic (Kappa), producer’s accuracy (PA) and user’s accuracy (UA) are derived from the error matrix to access the mapping accuracies[12].

IV. RESULTS ANALYSIS AND DISCUSSIONS

A. Classification Results Using the Gaussian and Wishart Classifier

Both Gaussian and Wishart-based methods were effective in identifying crop types using multi-temporal RADARSAT-2 data. Overall, using three-date images, accuracies higher than 75% were achieved by either Wishart or Gaussian based MLC.
The Gaussian based MLC is more effective in polarimetric SAR data classification. For example, using the same three-date images, the classification results given by Gaussian MLC using the Log transformed Pauli decomposition parameters is 86.3% (OA) and 0.83 (Kappa), while those given by Wishart MLC is 78.4% (OA) and 0.73 (Kappa). Current implementation of Wishart MLC is designed mainly for the coherency or covariance polarimetric SAR classification. Gaussian based MLC is applicable for various polarimetric parameters, therefore, the comparison between different polarimetric parameters were conducted using Gaussian based MLC.

B. Classification Results Using Different Polarization Parameters

Polarimetric parameters, synthesized from the complex polarimetric SAR data, are able to describe the relative strength and purity of microwave scattering. Compared with the linear polarization data, more information can be exploited from polarimetric data, and thus higher classification accuracies can be achieved. However, parameters generated from different decomposition methods have different contributions in improving the classification accuracies. In this study, the performances of the classification results based on four sets of polarimetric parameters were assessed and compared.

Log transformed Pauli decomposition parameters (Pauli) achieved the highest accuracy. Pauli decomposition parameters only include part of the polarimetric information in T3, but gave the higher accuracy than T3. For example, using the same four-date datasets, the overall accuracy given by Pauli was 89% and those by T3 coherency was merely 84.8%. Specifically, for most crops (hay, wheat, and peas) and other vegetation types, such as forest, the Pauli3 gives higher accuracy than T3 in either producer’s or user’s accuracy.

H/Alpha/A decomposition parameters are less useful in crop type classification than Pauli decomposition parameters, but are much better than Freeman-Durden decomposition parameters. Using the same four-date images, the OA generated by H/Alpha/A was 84.1% at 0.79 (Kappa), while those results from Freeman-Durden were as low as 76.9% (OA) at 0.71 (Kappa).

An analysis of these scattering parameters might assist in interpreting the contributions of these parameters to the crop discrimination. The responses of Pauli polarimetric parameters (T11, T22, and T33) to six crop types at different images are presented in the Fig. 3.

PauliT11 represents surface scattering from scatterers such as soil surface and harvested fields. As Fig.3 (a) shows, the major difference among crops were observed in the images taken on June 21st and July 15th. The mean PauliT11 values of the field peas and the wheat land peaked at July 15th, because most of them were cut in the mid-July. Oppositely, the PauliT11 of the soybeans and the corn decreased from June to July because of the increase of the plant biomass.

PauliT33 is indicative of volume scattering from the scatterers. Usually, the plants with large biomass and random surface will have high PauliT33 value. Significant differences in PauliT33 among crop types can be observed from the images taken on May 28th and September 1st. On May 28th, the mean PauliT33 value from field peas was -7 dB, from wheat and hay was around -13 dB, while that from soybeans and corn was lower than -15 dB. The variation of PauliT33 in the same image is because of different growing conditions and stages of different crops. In the end of May, soybeans and corn started to emerge, while the seeds of wheat and field peas have already begun to develop. On September 1st, wheat, hay and field peas were harvested, but soybeans and corn were not. Also on September 1st, the average PauliT33 value from soybeans was slightly higher than that from corn. It might be because soybean canopy was rougher than corn in early September.

Entropy parameter from H/Alpha/A decomposition characterizes the randomness of scattering occurring within a target. Although Entropy is similar to PauliT33, the variation among different crops in Entropy is less significant than that from PauliT33, thus is less useful in classification.

The capability of Freeman-Durden decomposition parameters in crop identification is relatively poor. The standard deviations of Freeman-Durden decomposition parameters are very high even within the same crop type,
which make it even harder to separate crop types using those parameters.

C. Classification Results Using Different Time Combinations

Dataset with high temporal resolution are preferable for crop type identification. However, due to the limitation of the budget for data purchasing, and limitation of image processing abilities, it is especially valuable to accurately classify crops with the least scenes of images.

To achieve this goal, a variety of data combinations using one to five images from different dates were tested. Those multi-temporal classification results were assessed and compared using the same classification procedure.

Generally, the classification accuracy increases as more dates of images are included in the classification, as shown in TABLE 1. The highest accuracy was achieved by using all the five-date dataset at 91% (OA) and 0.888 (Kappa). The best classification results generated by four-date dataset was 90.1% (OA) and 0.877 (Kappa), which was very close to that given by five-date one. The classification results given by three-date and two-date datasets are less satisfactory, with the highest OA of 87.8% and 83.3% respectively. The best result generated by one-date data was as low as 62.4% (OA).

The most significant enhancement of classification accuracies (over 20%) is observed from one-date datasets to two-date ones. Less than 1% increase in OA is observes from the four-date datasets to five-date one, which indicates that well-selected four-date datasets are able to generate the classification results almost as accurate as the five-date one.

For crop identification, images obtained in early and middle growing seasons (May to July) are relatively more useful than those in the late seasons. For example, the OA given by the three-date dataset from May 4th, May 28th, and July 15th is 3.8% higher than that given by June 21th, July 15th, and September 1st. In the early growing seasons, non-crop land use, such as the urban and the forest can be easily separated from crop fields because most of the fields have not been covered by plants yet. Also, some crop types planted early in the growing season, such as the wheat and field peas, are more likely to be distinguished from others. While in the late growing season, most crop types are either harvested or senescent, so the crop plants are similar to each other. In addition, some dry plants might be easily confused with plants residues, which also increase the difficulty in crop identification.

D. Classification Results Using Different Post-classification Processing

In general, both sieve filter and segmentation post-classification processing methods are effective in enhancing the classification accuracy. For example, the overall accuracy of five-date MLC results was 87% before any post-classification processing. The OA increased to 91% and 92% after using sieve filter and segmentation method respectively.

A detailed analysis reveals that both methods are effective for most classes, but also induced some omission errors in the classification of LU/LC classes with small and fragmented patches. For example, after using segmentation processing, the producer’s accuracy for the forage class decreased by 40%. The decrease is due to the small areas of the forage field. Those small polygons of forage fields were reassigned to their neighboring classes in the segmentation.

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V. CONCLUSIONS

This study demonstrates that multi-temporal polarimetric RADARSAT-2 data have the potential for crop classification in urban/rural fringe areas. Most crop types can be identified using the multi-temporal datasets. Also, the study assessed the capabilities of these RADARSAT-2 data in crop classifications from four aspects. The major findings are as follows.

1) Gaussian based MLC is an effective classifier for crop identification in urban/rural fringe areas. Using the Gaussian based MLC, the overall accuracy of 89% has been achieved with four-date RADARSAT-2 data.

2) An appropriate decomposition method is essential for polarimetric RADARSAT-2 classification. Using log transformed Pauli decomposition parameters, the overall accuracy increased by 12% than that using Freeman-Durden decomposition parameters.

3) The classification accuracy can be significantly improved through carefully selecting and combining multi-date images. Overall accuracy of 91% was achieved by using five-data images. Satisfactory classification accuracies (over 87%) can also be achieved using images from three dates, as long as the images at the key crop growing dates were included.

4) The polarimetric SAR classification results can also be improved by using appropriate post-classification processing methods.
The classification procedure provided in this study might have applications both in annual crop inventory, and in assessing the urban expansion on the agriculture, particularly in the urban/rural fringe areas.

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