IMPROVING URBAN IMPERVIOUS SURFACE CLASSIFICATION BY COMBINING LANDSAT AND POLSAR IMAGES: A CASE STUDY IN KITCHENER-WATERLOO, ONTARIO, CANADA

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ABSTRACT

Urban impervious surface mapping using moderate-resolution optical images such as Landsat images could be challenging due to the complexity of urban land cover. The study aims to combine optical and PolSAR images to improve accuracy of impervious surface classification. A scene of Landsat-5 TM image and a scene of RADARSAT-2 full-polarized imagery of Kitchener-Waterloo were used. The classification accuracies of Landsat image with the combination of different polarizations were compared. The results demonstrated the improvement of impervious surface classification with the combination of RADARSAT-2 PolSAR imagery with Landsat imagery. The major improvement was distinguishing between dark and bright impervious surface. In addition, generally more polarizations generated better results, and HV had the most contributions compared to the rest three polarizations. The results of the study may serve as a reference for further application for combining PolSAR and optical images.

Index Terms— Polarimetric synthetic aperture radar (PolSAR), image classification, land surface, remote sensing

1. INTRODUCTION

The impervious surfaces have emerged not only as a key indicator of urbanization, but also a measurement of environmental and habitat quality in urban areas [1], [2]. Landsat images, as a data source with accessibility at low cost, have been widely used in urban impervious surface studies [3]. However, because of the heterogeneity of urban land cover, accurate mapping using Landsat images could be limited due to the medium spatial resolution and limited radiometric wavelength coverage. Synthetic aperture radar (SAR) images have been demonstrated effective in land cover classification with the integration of optical images to overcome some limitations [3]. The effectiveness of image fusion of SAR and optical images is considered to be limited because of the weak correlation between optical reflectance and SAR backscattering [4], so that a combination method could be used to improve classification accuracy [4], [5]. However, few studies have been found taking advantage of multiple polarizations, which may have different sensitivity to different land cover types [6], to improve optical image classification accuracy. Therefore, the study aims to improve urban impervious surface classification accuracy with the combination of RADARSAT-2 full polarization (PolSAR) and Landsat images, as well as to compare different effectiveness of polarizations.

2. METHOD

One scene of Landsat-5 TM image at 30m-resolution, and one scene of RADARSAT-2 PolSAR imagery at 8m-resolution in Kitchener-Waterloo were used in this study. In addition, one digital elevation model (DEM) at 10m-resolution was used for orthorectification, and two orthoimages at 12cm-resolution, were used as ground truth. After radiometric correction and orthorectification, the RADARSAT-2 PolSAR imagery was co-registered to the Landsat images and the orthoimages. An enhanced Frost filter was applied to reduce speckle noise in the RADARSAT-2 PolSAR imagery [7]. A combination approach was adopted from previous research [4], [5] to improve land cover classification, which allows more than one PolSAR bands to integrate with Landsat images. Texture features were demonstrated more effective in SAR image processing comparing to pixel-based classification because of the speckle noise, but no consensus has been made on the most significant texture features in classification [5], [8]. Eight texture features, including mean, variance, homogeneity, contrast, dissimilarity, second angular moment, entropy and correlation, were calculated using grey level co-occurrence matrix at a window size of 7*7 [8] for both images. Random forest classifier is considered to be an efficient machine learning classifier [9], and it could reduce the potential problem of over fit [10] with the large number of input variables. Therefore, a total of 90 variables, (6 optical bands + 4 polarizations)*(8 textures + 1 original value), were put into the classifier.

Five classes: water, vegetation, bright impervious surface (concrete, rooftops, metal), dark impervious surface (asphalt, parking lots) and bare ground, were used as the classification scheme. Training samples were manually selected by comparing to the orthoimages, taking possible time difference into consideration. Two major variables, number of trees (T) and number of variables (m) were determined as $T=20$ and $m = \sqrt{M} + 1$ (M is the total number of variables) according to previous research [4]. In order to compare the effectiveness of different polarizations, eight cases were tested corresponding to the RADARSAT-2 products that could be purchased. The cases were listed in **Table 1**. In order to reduce the problem of coincidence because of the random selection process in the classifier, five rounds of results were produced for each case. 500 random points were selected on the orthoimages and the classes were determined manually to assess classification accuracy. The workflow is illustrated in **Fig. 1**.

Table 1. Number of variables input in random forest classifier

Case	Images	Number of bands	Number of textures	*M*	*m*
Case 1	Landsat	6	48	54	8
Case 2	Landsat+ quad pol	10	80	90	11
Case 3-6	Landsat+ single pol	7	56	63	9
Case 7-8	Landsat+ dual pol	9	72	81	10

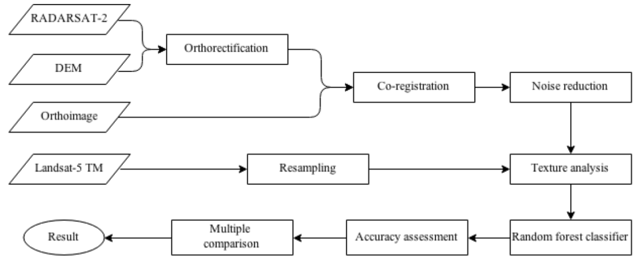

Fig. 1. Workflow chart

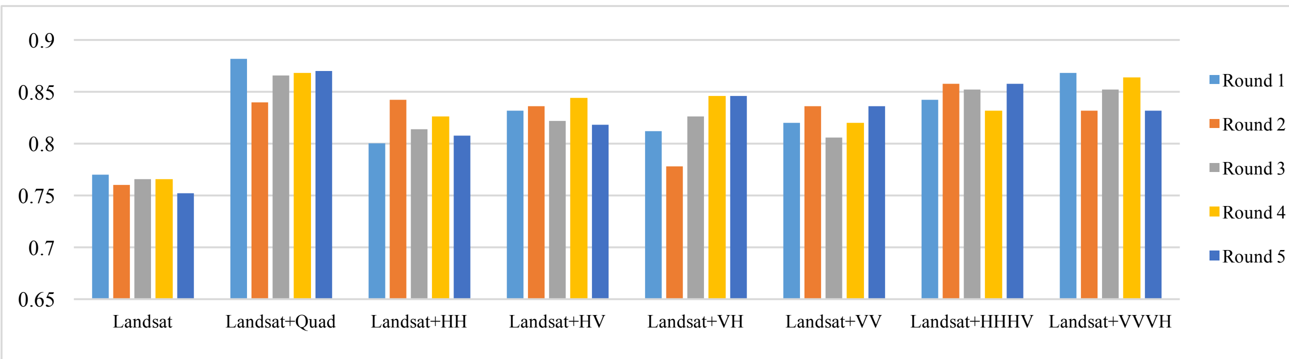

Fig. 2. Overall accuracy of land cover classification

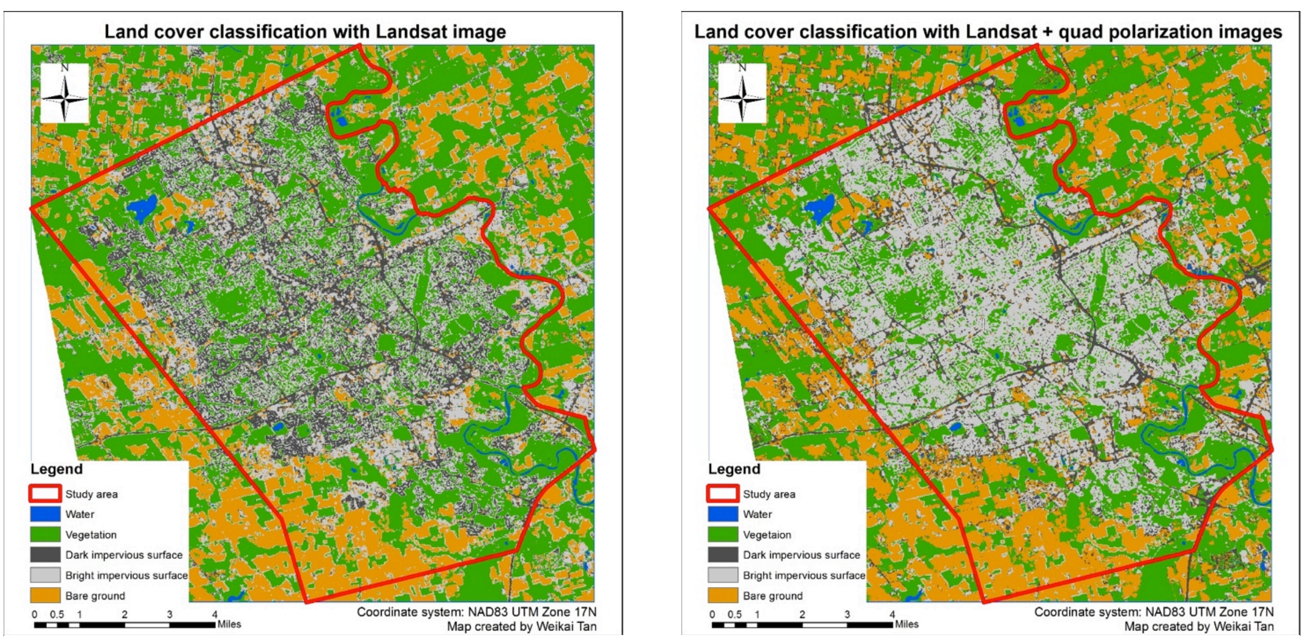

Fig. 3. Land cover classification maps

3. RESULTS AND DISCUSSION

Five rounds of classification for all 8 cases were processed, and classification maps, as well as classification confusion matrices were produced. Because of the random selection of variables in random forest classifier, the five rounds generated different results in each case, and the classification accuracies are shown in **Fig. 2**. There are some differences in each case but general trends could be found. In order to have a quantitative comparison, the rounds, which generated median overall classification accuracy, were selected for further analysis. Furthermore, statistical multiple comparisons were done to assess the results in different cases.

Table 2. Comparison of classification confusion matrices

Landsat							Landsat + Four Polarizations					
	Wat	VG	DIS	BIS	BG	UA	Wat	VG	DIS	BIS	BG	UA
Wat	5	0	0	0	0	100%	6	0	0	0	0	100%
VG	2	163	3	10	3	90.1%	1	156	3	8	1	92.3%
DIS	0	1	56	51	4	50%	0	0	61	6	3	87.1%
BIS	0	1	24	88	14	69.3%	0	6	18	136	13	78.6%
BG	0	0	1	3	71	94.7%	0	3	2	2	75	91.5%
PA	71.4%	98.8%	66.7%	57.9%	77.1%	**76.6%**	85.7%	94.5%	72.6%	89.5%	81.5%	**86.8%**

(Wat: water; VG: vegetation; DIS: dark impervious surface; BIS: bright impervious surface; BG: bare ground. UA: user's accuracy; PA: producer's accuracy)

Table 3. Result of pairwise *t* test between polarizations

Case	1	2	3	4	5	6	7
2	**1.70E-11**	-	-	-	-	-	-
3	**5.30E-06**	**5.30E-05**	-	-	-	-	-
4	**1.50E-07**	**0.00164**	0.22942	-	-	-	-
5	**1.90E-06**	**0.00015**	0.72438	0.39103	-	-	-
6	**1.10E-06**	**0.00026**	0.58387	0.50646	0.84459	-	-
7	**1.20E-09**	0.10668	**0.00514**	0.08481	**0.01246**	**0.01991**	-
8	**8.40E-10**	0.13304	**0.00379**	0.06686	**0.00933**	**0.01506**	0.90635

Table 4. Results of MRT

Case	Means of Accuracy	Level
2 Landsat+Quad	0.8652	A
8 Landsat+VVVH	0.8496	AB
7 Landsat+HHHV	0.8484	AB
4 Landsat+HV	0.8304	BC
6 Landsat+VV	0.8236	C
5 Landsat+VH	0.8216	C
3 Landsat+HH	0.8180	C
1 Landsat	0.7628	D

Table 5. Confusion matrix of pervious-impervious classification

	Landsat			Landsat+quad		
	IS	PS	UA	IS	PS	UA
IS	219	20	91.6%	221	22	91.0%
PS	17	244	93.5%	15	242	94.2%
PA	92.8%	92.4%	**92.6%**	93.6%	91.7%	**92.6%**

(IS: impervious surface; PS: pervious surface; UA: user's accuracy; PA: producer's accuracy)

There are majorly three findings from the classification result analysis. First of all, impervious surface classification accuracy could be improved by combining RADARSAT-2 image with Landsat-5 TM image, and the improvement could be found in **Fig. 3**. In **Fig. 3**, major difference in bright and dark impervious surface could be found through visual interpretation. In the classification using the Landsat image only, dark impervious surface is obviously overestimated. The detailed classification differences are provided in **Table 2**. As **Table 2** shows, the overall accuracy of land cover classification increases from 76.6% to 86.8% adding the RADARSAT-2 full polarization image. It demonstrates that the most significant improvement was in distinguishing between dark and bright impervious surfaces by comparing the user's and producer's accuracy. The user's accuracy of dark impervious surface improved from 50% to 87.1%, while the producer's accuracy of bright impervious surface improved from 57.9% to 89.5%. This means that some bright impervious surfaces were misclassified into dark impervious surface with Landsat image only, which corresponded to the visual interpretation of the classification maps. The sensitivity to geometry of SAR could have contributed to the improvement.

Secondly, as **Fig. 3** shows, generally more polarizations generated higher classification accuracy. In order to take all the five rounds into consideration, a pairwise *t* test was conducted. In **Table 3**, a value smaller than 0.05 represents that the difference is significant. The results showed that the RADARSAT-2 PolSAR imagery significantly improved classification accuracy regardless of what combination of polarizations. All polarizations provided the best improvement, and the two dual-polarizations provided second best results but no significant difference between the two polarizations was found. In addition, the results of two dual-polarizations did not show significant differences with full polarizations, and Case 4, which is HV only, showed less difference with dual-polarizations compared to the other three single polarizations. The Duncan's multiple range test (MRT) showed similar results in **Table 4** and HV showed larger contribution to accuracy compared to the rest three single polarizations. By comparing the importance of variables in random forest classifier, HV showed special contribution comparing to other polarizations. By further investigation on confusion matrices in all 8 cases, it could be found that HV best distinguished bright impervious surface among the four single polarizations, which could be the reason for providing higher classification accuracy.

Thirdly, the combination of RADARSAT-2 PolSAR imagery may not improve general impervious-pervious surface mapping using Landsat image only, because major improvement was within the

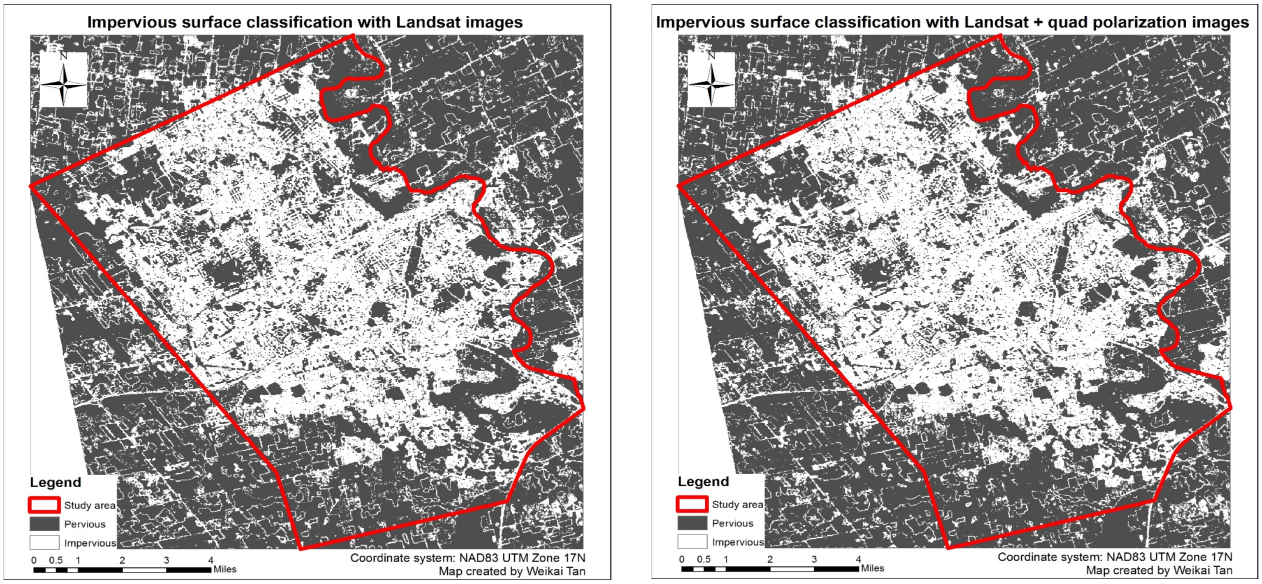

Fig. 4. Impervious-pervious classification maps

impervious surface class. From **Fig. 4**, no significant difference could be found between the two classification maps. According to **Table 5**, after combining the five classes into impervious (dark and bright impervious surface) and pervious surface (water, vegetation, bare ground), the overall accuracy both reached 92.6% for Landsat image only and Landsat with RADARSAT-2 PolSAR imagery, and the user's and producer's accuracy for both class showed no significant differences. Therefore, RADARSAT-2 PolSAR imagery may not have advantage in distinguishing impervious and pervious surface when combined with optical images.

4. CONCLUSION

The results of the study demonstrated the effectiveness of RADARSAT-2 PolSAR images in improving urban impervious surface classification with the combination of Landsat images. The classification accuracy increased to 86.8% with the combination method from 76.6% with Landsat image only. In addition, more polarizations generally provided better classification result, and HV contributed most among the four single polarizations in this study. The different contribution of polarizations could be implicated to achieve better classification results with limited budget. However, more scenarios are needed to further test the effectiveness of the combination method. The selection of window size in texture analysis and the comparison between random forest classifier and other methods shall be assessed in further studies.

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