THE EFFECT OF FOUR NEW MULTISPECTRAL BANDS OF WORLDVIEW2 ON IMPROVING URBAN LAND COVER CLASSIFICATION

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ABSTRACT

Conventional VHR imagery provides four multispectral (MS) bands. Built-up and traffic areas, however, are spectrally too similar to be distinguished using exclusively the spectral information of VHR imagery. The recently available WorldView2 (WV2) imagery introduces four new MS bands in addition to the four standard MS bands. This rich amount of spectral information together with the very high spatial resolution of WV2 imagery provides the potential for more robust and accurate discrimination between impervious land cover types. This paper aims to explore the contribution of the four newly added MS bands of WV2 imagery to increasing the class-pair separability of urban impervious land covers and consequently classification accuracy. For this, several object-based spectral and textural features of two data sets are extracted. The first data set consist of four standard MS bands, while the second one includes all eight MS bands of WV2. Then, a class-pair separability analysis is conducted to assess the contribution of new bands in discriminating different classes. Finally, the image is classified using each set of data separately. The effect of four new bands on land cover classification is evaluated by accuracy assessment of the results. Results demonstrate that the new four bands of WV increase the overall accuracy by 21.5 %. However, it is found that these new four bands will not have a significant effect on classification accuracy if additional textural and, specially, spectral feature of segmented image are utilized in the classification process.

KEYWORDS: WorldView-2, multispectral bands, urban land cover classification, separability analysis

INTRODUCTION

Land cover classification of urban areas using VHR satellite imagery is an extremely challenging task. This is mainly because of spectral similarity of impervious land covers such as buildings and traffic areas together with the limited number of spectral bands from VHR imagery. Traditional VHR imagery such as that of IKONOS, QuickBird and GeoEye-1satellites possess four multispectral bands in blue, green, red, and near infra red regions of electromagnetic spectrum. When utilized in traditional pixel-based classification approaches, these four spectral bands are not sufficient for distinguishing spectrally similar land covers in a complex urban environment (Herold et al. 2003, Salehi et al. 2011).

The newly launched WV-2 satellite carries a panchromatic (Pan) and two multispectral (MS1 and MS2) sensors onboard. The MS1 provides four traditional multispectral bands with the wavelength centered at 480, 545, 660, and 835 nm for blue (B), green (G), red (R) and near infrared-1(N1) respectively. The MS2 gives four new multispectral bands, namely, coastal (C), yellow (Y), red edge (RE) and near infrared-2 (N2) with the wavelength centred at 425, 605, 725, and 950 nm respectively (WorldView-2, 2009). These new multispectral bands increase the opportunity for more accurate mapping of complex urban environment with spectrally similar land cover types. Marchisio et al. (2010) applied four data mining methods as a comparative framework to the multispectral bands of WV2. They concluded that the additional spectral bands in WV2 improve the classification accuracy by 5-20% over the case when only the four traditional spectral bands of VHR imagery are utilized.

This study aims to explore the effect of newly added multispectral bands (i.e. MS2) of WV2 on classification accuracy of urban land covers. For this, two data sets (images) were created, and further analysis was carried out on each data set independently. The first image includes those four bands of WV2 which are available in other VHR imagery (i.e. B, G, R, and N1) and the second image contains all eight bands of WV2. In order to exploit the full spectral and spatial potentials of the image, each image was first segmented using a multiresolution segmentation algorithm, and then several spectral and textural features of objects were extracted. These new features were stacked to the original bands of each image forming two several-band data sets. For each data set the class separability analysis was performed and best features (bands) were selected for the final Maximum Likelihood classification. Finally the accuracy assessment of the classification results for each data set with different band combination was performed.

STUDY AREA AND IMAGE DATA

The study area is a part of the City of Moncton in New Brunswick, Canada. The area contains five major land cover types including buildings, parking lots, roads, vegetation, and river. The classification of the area is very challenging. Buildings in the area have different sizes and roofs' color and they are very diverse in terms of spectral properties. Some parking lots contain cars while some others are empty. This makes the spectral properties of parking lots very diverse. The river in the area also contains dissolved materials which is far different than the pure water. Also road segments with cars have very different spectral properties than those of the empty segments.

A subset of geometrically corrected WV-2 imagery, acquired on October 2010, was used in this study. WV-2, launched on October 8, 2009, is the first VHR satellite that possesses 8 multispectral bands and a panchromatic band with the spatial resolution of 1.84m and 0.46 m at nadir, respectively (WorldView-2 2009). As the pre-processing step, the 8 multispectral bands were fused with the panchromatic band using UNB-Pansharp algorithm (Zhang 2004) to generate 8 pan-sharpened bands with the spatial resolution of the panchromatic band. Figure 1 shows the true color composite of the Pan-sharpened image used in this study.

Figure 1. Pan-sharpened WV2 image of the study area.

OBJECT-BASED FEATURE EXTRACTION

In order to exploit the full potential of WV2 bands, the image was first segmented into image objects and several spectral and textural feature of object were extracted to use in the subsequent classification. Due to the presence of land cover with different sizes and shapes, the multiresolution segmentation algorithm, available in eCognition software, were used for segmenting the image. Each image (i.e. the four-band image and the eight-band image) were segmented into 4 levels of segmentation. Based on our experience (Salehi et al. 2011), the scale parameters were set 20, 54, 90, 142 for the first (L1), second (L2), third (L3), and fourth (L4) levels, respectively.

Having segmented the image, several textural and spectral features of objects were extracted. Textural features include the GLCM-based angular second moment (ASM) and entropy (ENT) for all bands in three levels of segmentations (L2, L3, and L4) forming 24 features for the four-band image and 48 features for the eight-band image. Spectral features include the mean value of objects and the ratios of all bands (eCognition 2010) as well as the NDVI indices (for the eight-band image two NDVIs were extracted using the N1 and N2 bands) for the three levels of segmentation forming 27 and 54 features for the eight-band and four-band WV2 images. Having extracted the spectral and textural features for each image, they were stacked to the original bands of each WV2 image forming two multiple-band images. The first image contains 55 bands including 4 original bands, 27 spectral, and 24 textural bands. Similarly, the second image contains 110 bands including 8 original, 54 spectral, and 48 textural bands.

SEPARABILITY ANALYSIS AND CLASSIFICATION

The conventional stochastic classification approaches such as maximum likelihood (ML) does not give promising result when applied to the high dimensional data sets because of the curse of dimensionality (Bellman, 1961). In order to mitigate the problem of high dimensionality, a class pair separability analysis were conducted on each data sets to determine the best bands in terms of separating different classes. Due to the special characteristics of Bhattacharyya distance such as having a nearly linear and nearly one-to one relationship with the classification accuracy (Landgrebe 2003), this distance was used to measure the class separability of different band combinations. When the distribution function of classes is normal, The Bhattacharyya distance (BD) is computed as (Fakunaga 1990, Landgrebe 2003):

$$B_{ij} = \frac{1}{8}(\mathrm{M_i} - \mathrm{M_j})^T \left[\frac{\sum_i + \sum_j}{2}\right]^{-1}(\mathrm{M_i} - \mathrm{M_j}) + \frac{1}{2}\ln \frac{\left|\frac{1}{2}\left[\sum_i + \sum_j\right]\right|}{\sqrt{\left|\sum_i\right|\left|\sum_j\right|}}$$

where $\mathrm{M_i}$ and $\mathrm{M_j}$ are the means of classes i and j and $\mathrm{S_i}$ and $\mathrm{S_j}$ are the covariance matrices of those classes. $\mathrm{B_{ij}}$ is the Bhattacharyya distance between the two classes. For our case where the number of classes is more than two, the minimum Bhattacharyya distance among the classes is used. The BD is calculated for different bands combination and then the ML classification is applied to that combination which represents the highest minimum BD among the classes.

RESULTS AND DISCUSSION

The BDs for different band combinations for each data set (i.e. the 55-band image and 110-band image) were calculated and the classification accuracies of best bands were determined. Surprisingly, the results show that the aforementioned spectral and textural features of only fourth level of segmentation (L4) have the maximum contribution in increasing the classification accuracy. In fact the features from other levels of segmentation have no effect or very less effect in increasing the classification accuracy. This can be explained by the fact that objects in L4 are more meaningful for large size classes such as buildings, parking lots, and roads which are spectrally similar. For this reason, the total number of features (spectral and textural features) was reduced to features in L4 only. Therefore, for the 4-band image, only 9 spectral and 8 textural features were used in the subsequent feature selection and classification processes. Similarly, for the 8-band image, 18 spectral and 16 textural features were used.

Feature Selection Results

Table 1 and Table 2 show best features, in terms of BD, for different combinations of spectral features and textural features of the 4-band image, respectively. Overall classification accuracy (OA) and its corresponding kappa coefficient (KC), reported in these tables, were the classification results of the combination of the selected features and 4 original bands of the image. As seen in Table 1 (bold text), 7 spectral features (out of 9 features) gives the maximum classification accuracy. These features are RatioR, RatioN, RatioG, NDVI, MeanR, MeanN, and MeanG. The contribution of textural feature however is less than spectral feature. Six textural features, as shown in Table 2, give the maximum classification accuracy. Similar to Tables 1 and 2, Table 3 & 4 show the feature selection and classification result of spectral and textural feature selection. For spectral features, 9 features (out of 18 features) result the maximum classification accuracy. These features are shown in bold in Table 3. For textural features, however, only four features achieved the best results, as shown in Table 4.

Table 1: Feature selection results for different combinations of 9 spectral features of objects in L4 for the 4-band WV2 image

# of best bands	Bands name	M.B.D[1]	A.B.D[2]	O.A[3]	K.C[4]
1	RR[5]	0.06	1.07	66.9	57.3
2	RR,MN[6]	0.17	1.99	74.5	67.0
3	RN,MN,MG	0.56	6.19	68.2	58.7
4	RN,MN,MG,MB	0.76	8.78	70.7	61.5
5	RR,RN,MR,MN,MB	1.03	11.89	80.8	74.6
6	RR,RN,NDVI,MR,MN,MB	1.26	14.92	81.0	74.9
7	**RR,RN,RG,NDVI,MR,MN,MG**	**1.45**	**16.47**	**82.9**	**77.2**
8	RR,RN,RG,NDVI,MR,MN,MG,MB	1.55	19.49	82.7	77.0

[1] minimum Bhattacharyya distance; [2] average Bhattacharyya distance; [3] overall accuracy; [4] kappa coefficient.
[5] Ratio of band R; [6] Mean of band N.

Table 2: Feature selection results for different combinations of 8 textural features of objects in L4 for the 4-band WV2 image.

# of best bands	Bands name	M.B.D	A.B.D	O.A	K.C
1	ENTN	0.08	0.91	68.7	59.7
2	ASMN, ENTG	0.53	2.54	76.3	69.3
3	ENTR, ENTG, ENTB	0.99	3.05	66.5	57.5
4	ASMR,ENTR, ENTG, ENTB	1.36	4.79	72.8	65.1
5	ASMR, ASMG,ENTR,ENTN,ENTG	1.75	7.19	74.7	67.4
6	**ASMR, ASMG,ENTR,ENTN,ENTG, ENTB**	**2.16**	**8.60**	**78.4**	**67.5**
7	ASMR,ASMN,ASMG,ENTR,ENTN,ENTG,ENTB	2.55	10.47	75.7	68.7
8	ASMR,ASMN,ASMG,ASMB,ENTR,ENTN,ENTG,ENTB	2.55	10.47	77.3	70.6

Table 3: Feature selection results for different combinations of 18 spectral features of objects in L4 for the 8-band WV2 image

# of best bands	Bands name	M.B.D	A.B.D	O.A	K.C
1	RC	0.10	0.35	81.2	75.2
2	MN2, MN1	0.38	3.66	81.7	75.5
3	RRE, RC, RB	0.71	6.41	84.9	80.5
4	RRE, RB, MN2, MN1	1.11	8.79	83.8	78.3
5	RRE, RN2,NDVI1,MG,MB	1.34	10.58	89.1	85.4
6	RN2,RC,NDVI1,MRE, MG,MC	1.81	18.65	87.3	83.1
7	RRE, RN2,RC,NDVI1,MN2,MG,MB	2.36	21.10	88.0	84.0
8	RRE, RN2,RC,NDVI1,MN2,MN1,MG,MB	2.70	23.55	89.3	85.6
9	**RRE, RN2,RC,NDVI1,MY,MR,MN2,MG,MC**	**3.13**	**28.05**	**90.0**	**86.6**
10	RR, RN2, RC,NDVI1,MY,MR,MN2,MN1,MG,MC	3.54	29.90	89.8	86.3

Table 4: Feature selection results for different combinations of 16 textural features of objects in L4 for the 8-band WV2 image

# of best bands	Bands name	M.B.D	A.B.D	O.A	K.C
1	ENTY	0.06	0.68	81.7	75.8
2	ENTG,ASMN1	0.59	2.10	82.7	77.1
3	ENTY,ENTR,ASMN1	1.10	2.95	74.4	67.1
4	**ENTN1,ENTG, ASMN1, ASMG**	**1.47**	**4.62**	**78.4**	**71.9**
5	ENTY, ENTR, ENTN1,ENTG, ASMN1	2.07	6.00	73.0	65.3
6	ENTY, ENTR, ENTN2,ENTN1,ENTG, ENTB	2.58	6.02	67.5	58.2
7	ENTY, ENTR, ENTN1, ENTG, ENTB, ASMN1, ASMB	3.07	11.39	73.4	65.6
8	ENTY, ENTN2,ENTN1, ENTG, ASMY, ASMN2, ASMN1,ASMG	3.77	10.15	77.8	71.0
9	ENTY,ENTR,ENTN2,ENTN1,ENTG,ASMY,ASMN2,ASMN1,ASMG	4.43	11.82	76.8	69.7
10	ENTY,ENTR,ENTN2,ENTN1,ENTG,ENTB,ASMY,ASMN2,ASMN1, ASMG	4.98	13.62	76.1	68.7

Classification Results

Having determined the best spectral and textural features, they were combined together for the subsequent classification. Three accuracy assessments were conducted for each data set. The first one is using only the original bands of the image. The next one is using the original bands together with the best spectral features selected in the previous step. Finally, the third accuracy assessment was conducted using the original bands and the best spectral and textural features. The result of each method is reported in Table 5. The thematic classification results for different methods were also depicted in figure 2. The OA for the 4-band image is 59.2%, while it is 80.7% for the 8-band image. It shows that the new four bands in WV2 increase the OA by 21.5% over the case when only four traditional bands are used. Adding spectral feature to either 4-band image or 8-band image greatly increases the classification accuracies, particularly for impervious land cover types. Spectral features of the 4-band image increases the OA by 23.7%, while for the 8-band image, the spectral features of the image increase the OA by 9.3%. Adding both the spectral and textural features improves the OA by only 3.4% over the case when only spectral feature are added for the 4-band image. For the 8-band image, textural features have almost no effect in increasing the OA (only 0.5% improvement).

The best classification results for the 4-band image were achieved when the original bands, the best spectral features, and the best textural features are were utilized in classification for both data sets (Fig. 2(e) and 2(f)). However, the difference between the best classification results of the two images is not significant (4.2% for OA and 5.7% for KC). This result demonstrates that if additional spectral and spatial (e.g. textural) features of the image are utilized in the classification process, the classification results of 4-band image and 8-band image are very close. In other words, the new spectral bands of WV2 (i.e. C, Y, RE, N2) does not have significant effect on increasing the classification accuracy of urban land covers if additional spectral and spatial features of the image are utilized in the classification process.

Table 5. Classification accuracies for different data sets

Class name	**4-band WV2 image**						**8-band WV2 image**					
	4 band		4band+7S		4band+7S+6T		8 band		8band+ 9S		8band+9S+4T	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Building	69.8	22.8	79.9	79.8	81.2	83.4	87.9	62.1	84.4	94.2	83.8	94.1
Parking lot	41.9	27.8	77.6	72.3	79.1	85.4	65.8	79.5	91.4	82.7	91.5	85.9
Road	24.6	90.4	56.9	84.4	76.2	82.5	55.5	68.4	71.6	84.5	76.2	84.5
Vegetation	97.4	98.6	98.6	96.6	98.8	96.7	98.1	98.4	98.5	97.7	98.6	97.6
Water	95.6	82.0	99.8	67.6	99.5	53.7	99.8	83.0	100	75.2	100	69.6
OA	59.2		82.9		86.3		80.7		90.0		90.5	
KC	48.1		77.2		81.6		74.1		86.6		87.3	

S: Spectral features, T: Textural features, PA: producer's accuracy, UA: user's accuracy, OA: overall accuracy, KC: kappa coefficient

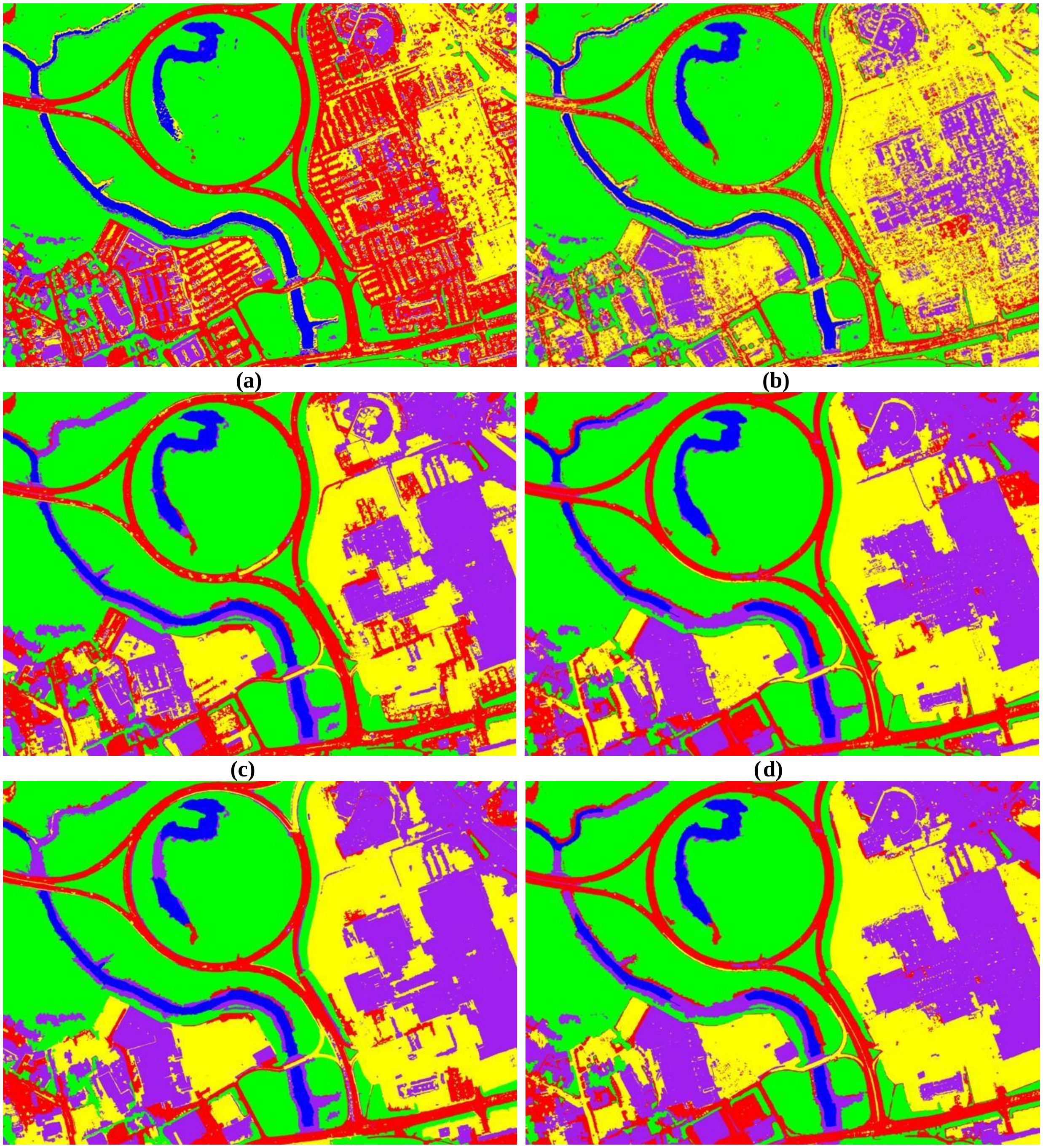

Figure2: Thematic map of the classification results for different sets of data. Buildings (purple), parking lots (yellow), roads (red), vegetation (green), and water (blue). a) using four traditional bands of WV2, b) using all 8 bands of WV2, c) using 4 bands and 7 best spectral features extracted from the segmentation of 4-b image, d) using 8 bands and 9 best spectral features extracted from the segmentation of 8-band image, e) using 4 bands,7 best spectral, and 6 best textural features extracted from the segmentation of 4-band image, f) using 8 bands, 9best spectral, and 4 best textural features extracted from the segmentation of 8-band image.

CONCLUSION

This study shows that the new four bands in WV2 increase the classification accuracy of land covers in a complex urban environment by 21.5% over the case when only four traditional bands are utilized. However, these new four bands will only make marginal improvements to the classification accuracy when additional spectral and textural features, obtained from image segmentation process, are utilized in the classification process. In addition, regardless of the number of bands, spectral features have greater contribution in improving the classification accuracy than textural features.

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