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RESEARCH PAPER

A novel spectral index to automatically extract road networks from WorldView-2 satellite imagery

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Abstract This research develops a spectral index to automatically extract asphalt road networks named road extraction index (REI). This index uses WorldView-2 (WV-2) imagery, which has high spatial resolution and is multispectral. To determine the best bands for WV-2, field spectral data using a field spectroradiometer were collected. These data were then analyzed statistically. The bands were selected through the methodology of stepwise discriminant analysis. The appropriate WV-2 bands were distinguished from one another as per significant wavelengths. The proposed index is based on this classification. By applying REI to WV-2 imagery, we can extract asphalt roads accurately. Results demonstrate that REI is automated, transferable, and efficient in asphalt road extraction from high-resolution satellite imagery.

1. Introduction

Remote sensing can monitor built-up areas because it can detect the growth and spatial distribution of urban built-up, such as roads. Furthermore, remote sensing images provide a synoptic view of land cover (Xu, 2008; Bhatta, 2009; Griffiths et al., 2010).

In remote sensing applications, road extraction is challenging. Moreover, information on road networks is important in urban planning and transportation engineering. Thus, this information must be accurate and updated (Rajeswari et al., 2011). Local communities must monitor urban road extraction in a timely and cost-effective manner (Xu, 2008). Through this monitoring process, the monitoring time of automatic road extraction can be reduced and the spatial databases of some applications can be updated. In applications requiring precision, developing fully automated algorithms to determine road network information is difficult (Tupin et al., 2002; Chaudhuri et al., 2012).

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To identify built-up land features through unsupervised classification, Masek et al. (2000) established a technique based on a normalized difference vegetation index (NDVI). To automate the mapping process of built-up areas and to accurately extract urban features, Zha et al. (2001) developed the novel normalised difference built-up index (NDBI). Moreover, Zha et al. (2003) automatically mapped urban built-up areas by arithmetically manipulating NDBI and NDVI. However, this method is ineffective because the extracted features did not differentiate built-up areas from bare land successfully. He et al. (2010) improved the accuracy of the original approach using the automatic segmentation method. Varshney (2013) enhanced this method further by setting an optimal threshold value. This value allocates the improved positive difference values of continuous NDBI and NDVI to built-up areas. To enhance the efficiency of the detection process of built-up change in both built-up and bare areas, a thresholding algorithm based on automated kernels is utilized. This algorithm also classifies the difference values of multi-temporal images. To map urban areas, Xu (2008) developed the index-based built-up index. This index is derived from three different indices, namely, the soil adjusted vegetation index, modified normalized built-up index, and NDBI. To detect asphalt and concrete surfaces, Mhangara et al. (2011) established a new spectral index called the built-up area index (BAI) for SPOT imagery. Furthermore, several previous studies focused on spectral indices for Landsat TM imagery. Despite the effectiveness of these indices on such data, they may be difficult to apply to novel imagery with high spatial resolution.

Several studies have attempted to develop fully automated procedures to extract roads from remotely sensed images with high resolution (Bacher and Mayer, 2005; Kirthika and Mookambiga, 2011; Karaman et al., 2012; Zarrinpanjeh et al., 2013). Given road map limitations such as time-consuming field surveys, accurate and timely road network information is detected using high resolution imagery (Resende et al., 2008; Hu et al., 2007; Valero et al., 2010; Das and Mirnalinee, 2011; Xinpeng et al., 2014). Hence, high spatial resolution satellites such as IKONOS and QuickBird mainly extract impervious surfaces (Cablk and Minor, 2003; Lu and Weng, 2009; Wu 2009).

Some methods integrate hyperspectral field spectroradiometry with multispectral imagery to extract roads and conditions simultaneously (Herold and Roberts, 2005; Kavzoglu et al., 2009; Mohammadi, 2012; Andreou et al., 2011). Road network information can be extracted from WorldView-2 (WV-2) satellite imagery (DigitalGlobe, 2009). Unlike other commercial satellites, the WV-2 satellite imagery contains eight bands with high spatial resolution. These new features can help to extract information more effectively than other images with high spatial resolution. Several indices have been developed for built-up areas; however, a lack of a suitable asphalt road extraction index as well as an automated method for road detection and extraction from WV-2 imagery is still a major setback.

Hence, we develop an automated technique based on spectral index, using a field spectroradiometer to identify the significant bands. These bands are selected through stepwise discriminant analysis (DA). This method distinguishes useful bands for asphalt road extraction. The selected significant bands are matched on the WV-2 range to establish a new spectral index and assess asphalt road extraction.

2. Materials and methods

2.1. Study area

The selected study area is a section of Universiti Putra Malaysia (UPM) in Serdang, Selangor. This area is located between 3°00′34.05″N,101°43′19.77″E and 3°00′01.21″N, 101°42′35.63″E (Fig. 1a) and is surrounded by approximately 10 km^2 of residences and nature. The study area is also bordered by numerous tall trees and various buildings, as well as pervious and impervious surface materials.

2.2. Data acquisition

The information obtained by the field spectroradiometer were used as spectral reflectance. Data were obtained by an ASD hand-held spectroradiometer (Fig. 2a), which detects reflectance within the wavelength range of 350–2500 nm. Sampling was conducted in clear weather when illumination was stable. To determine the exact location of roads on the images, a Garmin handheld global positioning system (GPS) device was used during field observation (Fig. 2b).

In this study, we utilized a WV-2 satellite image. This satellite was launched in October 2009 as the first multispectral high-resolution system with eight bands. WV-2 has eight spectral sensors in the visible to near-infrared regions and provides 1.85 m and 46 cm multispectral and panchromatic resolutions, respectively. The high spatial resolution discriminates between various fine details, and the spectral resolution provides details on road surface quality, as shown in Fig. 1c and d.

2.3. Data pre-processing

To generate accurate results with WV-2 images, the data were preprocessed. The geometries were corrected based on points collected from Google Earth. The images were selected to generate a spectral index for road extraction using WV-2 images. To refine the results and maintain the sharpness of the images, the data were passed through Lee filters (Taherzadeh and Shafri, 2011).

2.4. Data processing and analysis

Significant data bands were identified using the band selection method. This method can extract asphalt roads and quality. The selected bands are then compared to discriminate the important ones on WV-2. To develop the new index, we identified significant bands through stepwise DA.

Stepwise DA was mainly applied to examine the differences between groups. It effectively discriminates among classes and generates the quantitative variable that reduces data dimensionality. Subsequently, different parts of the image are validated under the novel spectral index based on WV-2 imagery to assess its accuracy. The stepwise DA method was applied to the reflectance given a significance level of 0.05. This band selection method was also used by Fung et al. (2003), Clark et al. (2005), Debba et al. (2009), and Pu et al. (2011).

In DA, all independent variables can be simultaneously entered into the equation. Moreover, stepwise DA can eliminate insignificant independent variables when the number of

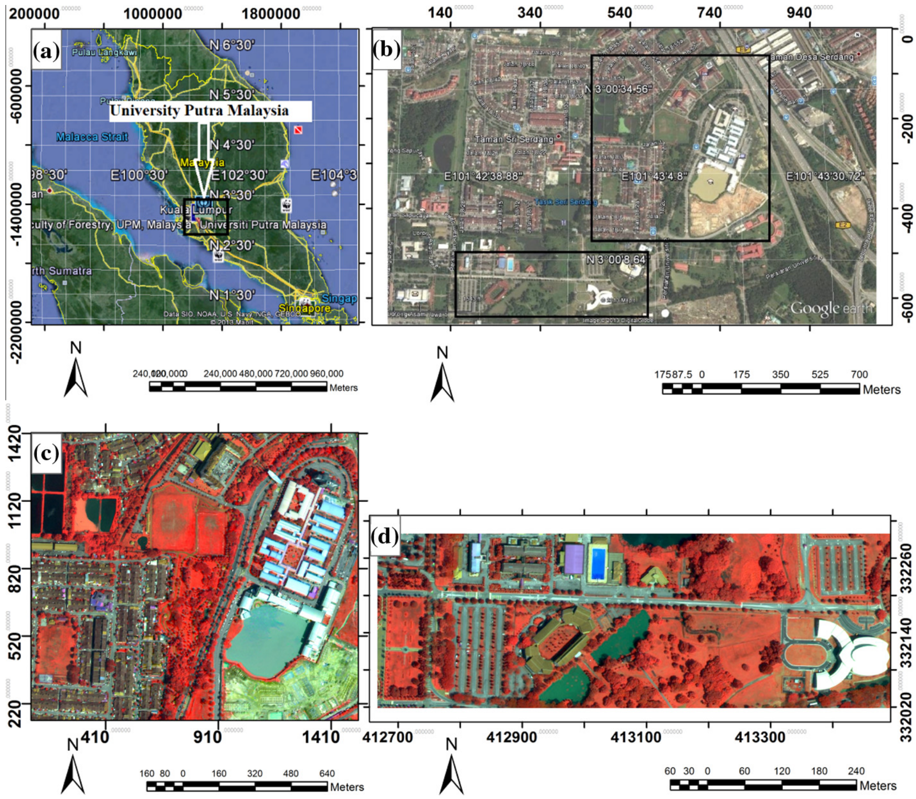

Figure 1 Location of UPM in Malaysia (a); location of the study area (b); the main study area (c); and validation area (d).

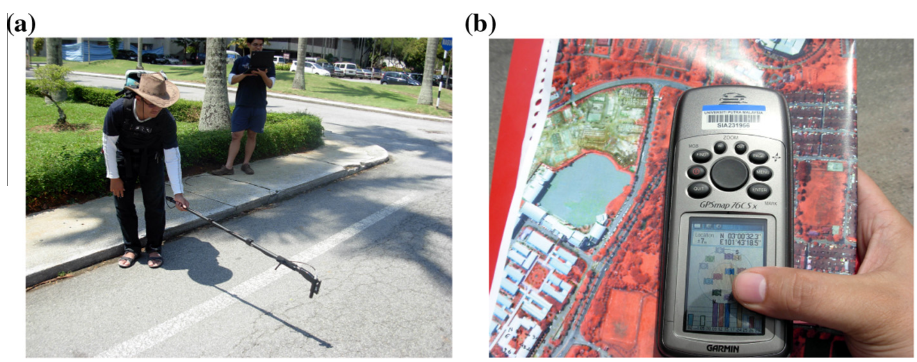

Figure 2 Field spectroradiometer measurement (a) and field observation by hand-held GPS (b).

potential discriminating variables must be reduced (Morrison, 2011). The spectral range of the WV-2 image (from 400 nm to 1040 nm) was utilized in spectral field measurement. In accordance with the focus of the current study on developing an automatic method of asphalt road extraction, we establish a new, spectral asphalt road extraction index (REI) that is fully automated.

2.5. Assessment and validation of accuracy

To assess the accuracy of the results, we conducted a field survey to gather ground-truth data (Fig. 2a). As shown in Fig. 1c and d, we validated the new index in different parts of the main study area (Fig. 1b) to evaluate its potential use in WV-2 imagery. We utilize a confusion matrix to compute the precision of the REI (Fig. 3).

2.6. Band selection

With respect to road extraction from WV-2 imagery, the stepwise DA determined the significant bands (Table 1). These bands are located at wavelengths 450–510 nm, 510–580 nm, 630–690 nm, and 860–1040 nm.

In Table 1, tolerance is the proportion of the variance of a variable that is not considered by other independent variables in the equation. A variable with very low tolerance contributes little information and causes computational problems.

F to Remove values describe the effect of removing a variable from the current model (given that the other variables are retained).

Wilks's Lambda determines significant differences between groups. Values are between 0 and 1. When the value is close to

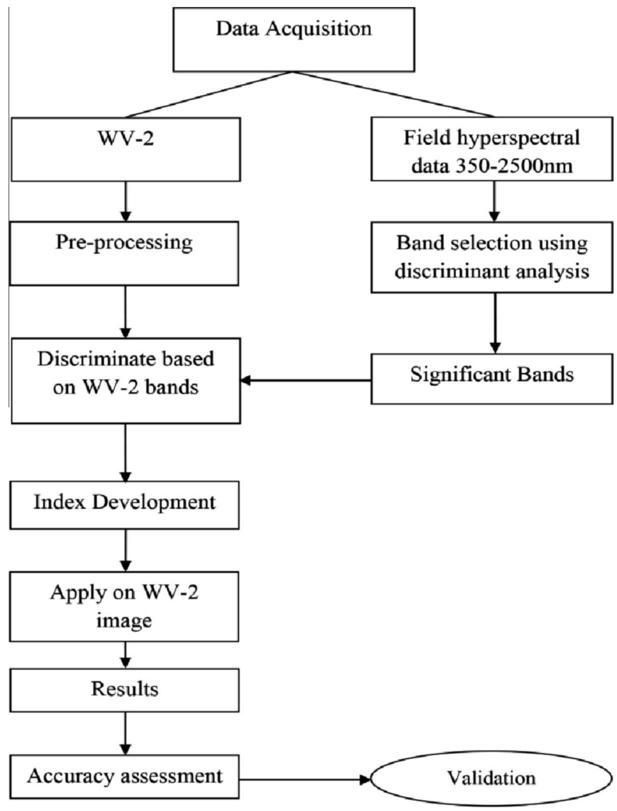

Figure 3 Flowchart of the research methodology.

Table 1 Results of band selection through stepwise DA.

Step	Tolerance	*F* to Remove	Wilks's Lambda
466	.985	60.252	.452
519	.965	53.134	.411
520	.960	56.139	.118
668	.879	37.134	.024
984	.970	46.792	.051

Table 2 Significant bands based on stepwise DA.

Spectral range	Wavelength (nm)	Significant stepwise DA (nm)
Blue	450–510	466
Green	510–580	519
Green	510–580	520
Red	630–690	668
NIR2	860–1040	984

1, the groups are similar, whereas small values indicate variation among groups.

Table 1 depicts the ideal bands that can distinguish among different classes of asphalt in WV-2. The result shown in Table 2 suggests that these significant bands are blue, green, red, and near-infrared2 (NIR2).

2.7. Index development

In order to develop the index, significant bands were used that best describe the asphalt road network. One of the most successful indices is NDVI which is useful to extract information from remotely sensed data, therefore; the theoretical foundation of the newly-developed index is based on NDVI. Since the oxidation process and exposure of rocky component is displayed by the appearance of iron-oxide absorption features at 520 and 870 nm (Herold et al., 2004), two significant bands in the Blue and NIR wavelengths which are close to these particular wavelengths are selected. Furthermore, it is multiplied by the NIR2 band to eliminate the water-body effect.

The WV-2 image was investigated under 16 different indices through the band math in ENVI software. Among the various bands, the best results were obtained with the NIR2 and blue bands (Table 3).The new index can thus be computed using Eq. (2). To evaluate the accuracy and effectiveness of REI through comparison, the BAI developed by Mhangara et al. (2011) is computed using Eq. (1).

$$\mathrm{BAI} = B - \mathrm{NIR}/B + \mathrm{NIR} \quad (1)$$

$$\mathrm{REI} = \mathrm{NIR2} - B/\mathrm{NIR2} + B \times \mathrm{NIR2} \quad (2)$$

Therefore, stepwise DA is used in this study to find the best combination of a pair of bands that can be used for asphalt road network extraction.

3. Results and discussion

3.1. Results

The proposed method is applied in our study area over UPM. The results on the REI are shown in Fig. 4.

REI extracted asphalt roads from the main study and validation areas at accuracies of 88% and 86%, respectively. Table 4 presents the accuracy assessment of the REI.

In this study area, the result of BAI is compared with that of REI given built-up areas, especially with respect to road extraction. The BAI can detect asphalt and concrete in urban areas. The efficiencies of these two indices were compared with regard to the extraction of impervious pixels of urban roads, as exhibited in Fig. 5.

Based on the confusion matrix, the accuracies of both indices are assessed in the same study area. Therefore, similar ground-truth data is used in the quantitative assessment on BAI. The evaluation results are shown in (Table 5).

3.2. Discussion

In this research, we generate the new REI in two steps as follows.

In the first step, bands are selected according to the field data obtained by the spectroradiometer. In the second step, the new spectral index is developed. The results of band selection agree with those obtained by Herold et al. (2004).The

Table 3 Significant wavelengths for the new REI from WV-2 images.

Bands	Spectrum region	Wavelength (nm)
2	Blue	450–510
3	Green	510–580
5	Red	630–690
8	NIR2	860–1040

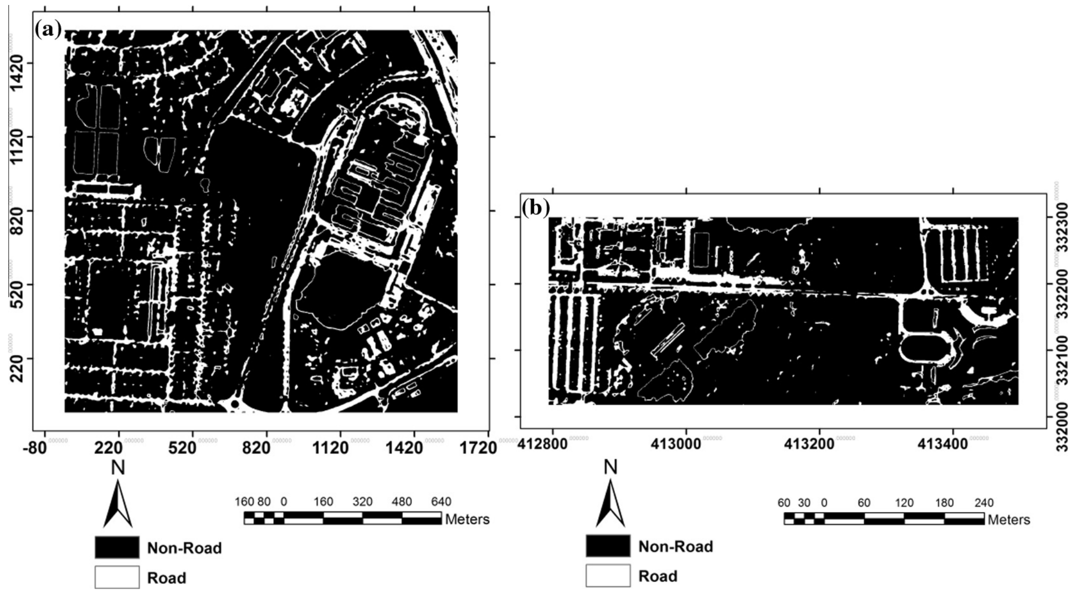

Figure 4 Extraction of the UPM road network (a) and validation of the road network extraction (b).

Table 4 Accuracy assessment based on the confusion matrix.

Main area		Road	Non-road	Total	User's accuracy
	Road	351	40	391	89.77%
	Non-road	57	373	430	86.74%
	Total	408	413	821	
	Producer's accuracy	86.03%	90.31%		
	Overall accuracy	88.18%		Kappa	0.7636
Validation area		Road	Non-road	Total	User's accuracy
	Road	104	30	134	77.61%
	Non-road	1	93	94	98.94%
	Total	105	123	228	
	Producer's accuracy	99.05%	75.61%		
	Overall accuracy	86.40%		Kappa	0.7318

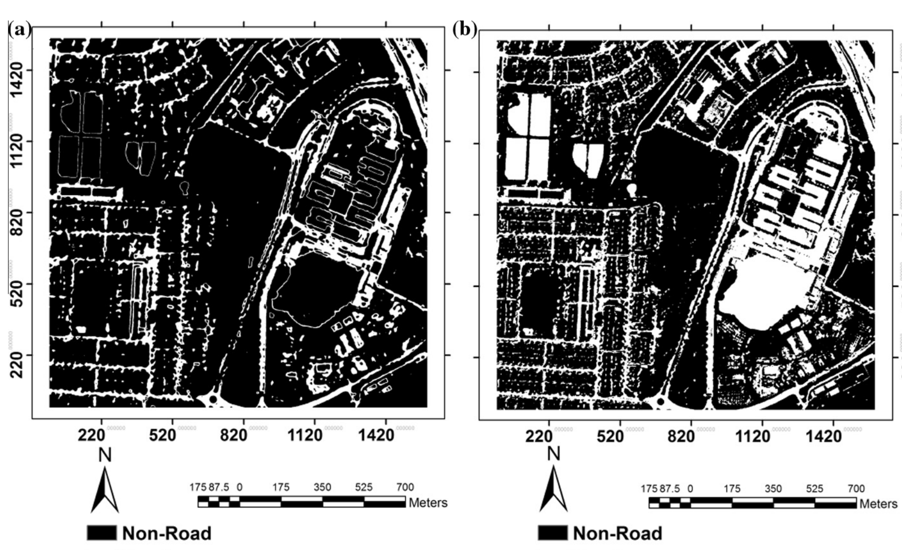

Figure 5 Road network of UPM based on REI (a) and the extracted UPM road network based on BAI (b).

Table 5 Accuracy assessment based on the confusion matrix.

BAI	Road	Non-Road	Total	User's accuracy
Road	362	98	41	78.74%
Non-road	45	315	360	87.50%
Total	408	413	821	
Producer's accuracy	88.97%	76.27%		
Overall accuracy	82.58%		Kappa	0.6519

wavelengths from the visible and near-infrared regions are used to develop the REI given their significant variation with respect to the amount of iron oxide absorbed (Herold et al., 2004; Kavzoglu et al., 2009).

Through band selection, we can determine the significant band and reduce the time consumed by index development. We obtained ground-truth data for accuracy assessment through in situ observation. To evaluate the proposed REI, two road extraction experiments are conducted on the WV-2 image. In the first experiment, the REI is used to extract asphalt roads. The road map is thus constructed using the two selected bands (blue and NIR2). The road positions were accurately and reliably extracted (Fig. 4). However, the REI also misclassified a building boundary as a road, and it did not extract areas under occlusion by trees or shadows properly. Nonetheless, other pixel-based methods experience similar issues (Valero et al., 2010). Hence, the obtained accuracy of road extraction is acceptable.

To assess the REI, we compared it with another experimental index. The proposed algorithm is applied to the same study area and detects asphalt roads effectively. However, BAI greatly misclassified major sections of water bodies as road networks, although it extracted the roads accurately (Fig. 5). This misclassification must be addressed because it results in an inaccurate assessment.

With the REI, the roads extracted from the main and validation study areas were accurate at 88% and 86%, respectively. The accuracy of road extraction from the main study area was higher than that obtained with BAI (82%). This finding is attributed to the fact that the NIR2 band is multiplied to eliminate the effect of water bodies on the new REI. Thus, this index can be used in automatic asphalt road extraction. Moreover, the REI can extract asphalt roads without any training data, unlike other classification methods. Therefore, it saves on time.

4. Conclusion

In this research, we presented an automatic and quick approach for asphalt road extraction from WV-2 imagery. The proposed method is based on the new spectral index, which can extract asphalt roads automatically. In our approach, we utilized a full-range spectroradiometer and WV-2 images. This study mainly aims to develop the new index called REI, which is based on WV-2 bands that can be employed to extract the asphalt roads automatically. To discriminate significant and efficient bands on WV-2 for automatic road extraction, we select bands according to hyperspectral data.

The experimental results demonstrate that the proposed method can extract the asphalt road network accurately. Furthermore, the significant bands can differentiate road and non-road areas. In this procedure, the blue and NIR2 bands are ideal for the REI, as indicated in Fig. 4. Nonetheless, the proposed method failed to extract some asphalt roads and areas under occlusion by trees or shadows. In addition, this spectral index misclassified a building boundary. Despite these limitations, the results are generally accurate. The proposed method is confirmed to be effective by extensive tests using all of the data from WV-2 imagery and the field observations. Moreover, it achieved a steady minimum accuracy rate of 86% in asphalt road extraction. To assess the accuracy of our REI, we compared it with the BAI. The comparison of results demonstrates that the REI misclassifies roads less than the BAI (Fig. 5).

Future research can test this index using different sensors and enhance its capability to classify and map road conditions. Furthermore, new techniques can be developed to improve its performance.

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