A novel built-up spectral index developed by using multiobjective particle-swarm-optimization technique

Maher Ibrahim Sameen and Biswajeet Pradhan
Department of Civil Engineering, Faculty of Engineering, University Putra Malaysia, 43400 Selangor, Malaysia
* Author to whom correspondence should be addressed; Tel: + 6(03)-8946-6383; Email: biswajeet24@gmail.com or biswajeet@lycos.com

Abstract. In this study, we propose a novel built-up spectral index which was developed by using particle-swarm-optimization (PSO) technique for Worldview-2 images. PSO was used to select the relevant bands from the eight (8) spectral bands of Worldview-2 image and then were used for index development. Multiobjective optimization was used to minimize the number of selected spectral bands and to maximize the classification accuracy. The results showed that the most important and relevant spectral bands among the eight (8) bands for built-up area extraction are band4 (yellow) and band7 (NIR1). Using those relevant spectral bands, the final spectral index was formulated by developing a normalized band ratio. The validation of the classification result using the proposed spectral index showed that our novel spectral index performs well compared to the existing WV-BI index. The accuracy assessment showed that the new proposed spectral index could extract built-up areas from Worldview-2 image with an area under curve (AUC) of (0.76) indicating the effectiveness of the developed spectral index. Further improvement could be done by using several datasets during the index development process to ensure the transferability of the index to other datasets and study areas.

1. Introduction

Recent advances in remote sensing and computing technology have created several new applications. There are numerous applications, which need information about urban features (i.e. buildings, paved roads) such as urban heat island [1], land use mapping [2], flood simulation and modelling [3-4], site suitability analysis [5] etc. Remote sensing data such as very high-resolution satellite images (e.g. Worldview-2) can be used to extract that information. One of the rapid and efficient method and data processing approach is the spectral indices developed and proposed by researchers to extract built-up areas from multispectral satellite images.

There are several studies proposed spectral indices for built-up area extraction from satellite images. Reference [6] proposed a new spectral index to extract built-up areas from Landsat OLI images. The spectral index developed by analyzing different band ratios using spectral and thermal bands. The developed index was compared with four previously used spectral indices; the Band Ratio for Built-up Area (BRBA), the Normalized Built-up Area Index (NBAI), the New Built-up Index (NBI) and the Normalized Built-up Index (NDBI). The results showed that the developed spectral index was superior as compared to ones of the other spectral indices.

In another paper, reference [7] developed a technique to extract urban built-up land features from Landsat imagery using three indices, NDBI, Modified Normalized Difference Water Index (MNDWI), and Soil Adjusted Vegetation Index (SAVI). The results indicated that the urban built-up lands were extracted with an overall accuracy ranging from 91.5 to 98.5 percent. In addition, reference [8] proposed a new spectral index for delineating built-up areas from satellite images. The new index combined three existing indices to derive a new improved index for rapid extraction of built-up areas from satellite images. Furthermore, reference [9] presented a new technique for extracting built-up areas from panchromatic images using texture information. The results...
showed that the method could detect built-up areas from panchromatic images with an overall accuracy of 86.7%.

The literature review revealed that most of the studies developed spectral indices for rapid extraction of built-up areas from various types of satellite images based on specific image data. Therefore, it is required to develop spectral indices for other types of satellite images, which is not investigated in literature. In addition, investigation more advanced and robust methods are required to be involved in the development of spectral indices. Therefore, this study proposes a novel spectral built-up index for rapid built-up extraction from Worldview-2 images. Most of the literature presented above used spectral analysis for the development of spectral indices while in this study we use optimization techniques to develop such indices. Optimization techniques provide best solution for several problems including the selection of relevant wavelengths and determining the best combination of spectral bands for the development of final spectral indices.

1.1 Study area and image data

The study area of this research is a subset of Universiti Putra Malaysia (UPM) campus located in the state of Selangor (ranged from upper left longitude 3°00′14.48′N and latitude 101°42′14.71′E, lower right longitude 3°00′00.71′N and latitude 101°42′44.12′E, of WGS84 coordinate system) (Figure 1). The study area is a mix of urban and vegetation features. Buildings are vary in terms of roofing materials, shape, size and spectral signatures which is very important to take into account when developing new methods or algorithms for feature extraction.

An eight-band pan-sharpened multispectral Worldview-2 standard image (resolution 0.5 m) was utilized to be cloud-free and to consist of different land-cover classes. The image was collected in March 2009. The data set has 1.81m spatial resolution with eight channels: Coastal, Blue, Green, Yellow, Red, Red Edge, Near-Infrared1 (NIR1) and Near-Infrared2 (NIR2), with center wavelengths at 425, 480, 545, 605, 660, 725, 835, and 950 nm, respectively. The radiometric resolution of the data set is 16bit.

Figure 1. Location of the study area used to develop and validate the new proposed spectral index for built-up area extraction from worldview-2 image.
2. Methods

Figure 2 shows the steps followed to develop the new spectral built-up index based on Worldview-2 satellite image. First, we applied the standard preprocessing steps on the data to reduce the present noises in the dataset. Radiometric calibration was applied to convert the digital numbers of the satellite image pixels into physical units (radiance). Then the radiance values were converted into reflectance to get at surface reflectance signature for the objects found in the image subset. After that, IARR atmospheric correction was applied due to the lack of reference and field data.

The next step was the collection of endmembers of built-up objects as well as the other classes found in the Worldview-2 image. These endmembers were collected directly from the image for both built-up and other classes. For each class, 200 randomly selected samples were collected to ensure accurate index development. Once the training samples (end-members) are selected, the next step was to select the relevant (useful) spectral bands from the available eight (8) bands of Worldview-2 image. These relevant (useful) bands were assumed to best separate the classes and extract the built-up areas from the image. Particle swarm optimization (PSO) technique was used to select those relevant bands.

Once the relevant and useful spectral bands selected, the new spectral index can be developed. Band ratio is one of the most common spectral indices developed and widely used to extract features from satellite images. Therefore, we selected such type of index for the new built-up index aimed to be developed in this study. In order to find the best band ratio that could separate the other classes from the built-up class, an optimization technique should be applied. In this study, the same optimization technique (PSO) which was used for feature selection is used to find the best band ratio.

Finally, when the new spectral built-up index is developed, it was used to classify the Worldview-2 image and extract the built-up areas. Then the results were validated and compared with the existing spectral NDBI index to measure its accuracy and performance. The subsequent sections describe the details of those steps followed to develop the new index for built-up area extraction from Worldview-2 image.

![Figure 2. Overall methodology applied to develop the new spectral index for built-up area extraction from worldview-2 image.](image)
2.1 Image processing

Original Worldview-2 satellite image contains variety types of noises and it is important to reduce those noises before the actual processing. First, the digital number of the image pixels were converted to radiance to reduce the sun illumination and some of the sensor related noises. After that, the radiance values of image pixels were converted into reflectance values to reduce the other types of noises such as atmospheric effects. In order to get the surface reflectance signatures, it was important to apply atmospheric correction models to reduce the effect of atmospheric layers on the object reflectance signatures. In this study, IARR model was used because this type of atmospheric correction requires no input data. After that, it was important to apply pan sharpening to the original image to improve the spatial resolution of the multispectral image by fusing the panchromatic band (0.5 cm) due to complexity of the urban environment.

2.2 Feature selection by multiobjective particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) is one of the successful algorithms [10] reported in literature. PSO has been accepted to be effective in a wide variety of applications, being able to produce very good results at a very low computational cost [11]. A multi-objective extension, the Non-dominated Sorting Particle Swarm Optimizer (NSPSO), was proposed in [12] to cover multi-objective problems. The algorithm initializes the population and evaluates the initial particles using the fitness functions. The solutions are organized into fronts called Pareto fronts, and the non-dominated solutions construct the first Pareto front. Once the population is ranked, the nondominated solutions are identified and ranked using one niching method (e.g. crowding distance). The population is then evolved using velocities calculated with regards to the sorted list of the non-dominated solutions.

The fitness function is shown in Equation (1) which is used to minimize the classification error rate obtained by the selected features during the evolutionary training process and the number of selected features [13].

\[
F = \begin{cases} 
    w \times \text{Train}_{ER_s} + (1-w) \times \text{Test}_{ER_s} \\
    \alpha \times \frac{\#\text{Features}}{\#\text{All Features}} + (1-\alpha) \times \frac{ER_s}{ER_{all}} 
\end{cases} 
\]

(1)

where \( w \) is a constant number (weight of classification error rate obtained from training data) and \( w \in [0,1] \), \( \text{Train}_{ER_s} \) is the classification error rate obtained by the selected feature subset and training subset data, \( \text{Test}_{ER_s} \) is the classification error rate obtained by the selected feature subset and testing subset data, \( \alpha \) is a constant number (weight of number of selected features), \( \#\text{Features} \) stands for number of selected features, \( \#\text{All Features} \) represents the total number of features available for classification, \( ER_s \) is the classification error rate obtained by the selected features, \( ER_{all} \) is the classification error rate obtained by all the available features. Error rate of classification results can be calculated using Equation (2) [14].

\[
\text{Error Rate (ER)} = \frac{FP + FN}{TP + TN + FP + FN} 
\]

(2)

where \( TP \), \( TN \), \( FP \), and \( FN \) stand for true positives, true negatives, false positives, and false negatives, respectively.
2.3 Index development

Once the relevant spectral bands are selected, the next step is to put them in a mathematical form to be used for rapid built-up area extraction. The most common practice technique for formulating such mathematical equations from a set of variables is to use band ratios which best classifies a set of testing data. In this study, trial-and-error approach is replaced with a method that is more efficient. PSO optimization is used to find the best band ratio from the relevant spectral bands that could classify the image data.

To find the best band ratio using the relevant spectral bands, an optimization problem were formulated as shown below,

Find optimal values of $a, b, c, d$ in the Equation (3), which minimizes the function ($f$) presented in Equation (4)

$$BSI = \frac{a \times Band1 + b \times Band2}{c \times Band1 + d \times Band2} \quad (3)$$

where $Band1, Band2$ are the two most significant spectral bands selected by PSO.

$$f = Error \ Rate \ (ER) = \frac{FP + FN}{TP + TN + FP + FN} \quad (4)$$

The above optimization problem can be solved with any optimization techniques and in this research; PSO was used for its efficiency. The optimization is implemented in Matlab 2015 software and the best solutions were determined. The algorithm tries to find the best solution for the coefficient values in Equation (3) which minimizes the error rate to achieve the high the possible classification accuracy. Finally, the spectral index for built-up area extraction was produced.

3. Results and discussion

This section presents the results obtained from the data processing and optimization solutions applied as discussed above.

3.1 Results of feature selection

The worldview-2 image has eight (8) spectral bands; however, not all of them are useful for built-up area extraction. Therefore, PSO was applied to select the best bands that can achieve similar and better classification results than using all the available spectral bands. An optimization problem was formulated as discussed in the methods section and solved by using Matlab software.
In the first iteration, PSO found that the bands (7, 4) are the best bands for built-up area extraction based on the classification error rate values. Following the other 19 iterations, it was found that the same bands (7, 4) remained the best for built-up area extraction. These bands in worldview-2 image are Near Infrared 1 (NIR1, 770 - 895 nm), Yellow (585 - 625 nm).

3.2 Results of index development

Based on the best spectral bands selected by PSO, the second optimization problem was solved to find the best mathematical function which best classifies the image data. The second optimization was applied and the optimum values for the coefficients \((a, b, c, d)\) were found. Table 1 shows the values for the coefficients in Equation (3) which formulate the final spectral index (BSI) developed for rapid built-up area extraction from worldview-2 images.

Table 1. Best values of coefficients in BSI found by PSO.

| Coefficient | Best value found by PSO | Approximated value |
|-------------|-------------------------|-------------------|
| \(a\)       | 1.33                    | 1                 |
| \(b\)       | -2.46                   | -2                |
| \(c\)       | 1.07                    | 1                 |
| \(d\)       | 1.77                    | 2                 |
The final spectral index (BSI) is formulated as presented in Equation (5) and Equation (6),

\[ BSI = \frac{\text{Band}4 - 2 \times \text{Band}7}{\text{Band}4 + 2 \times \text{Band}7} \]  

(5)

\[ BSI = \frac{\text{Yellow} - 2 \times \text{NIR1}}{\text{Yellow} + 2 \times \text{NIR1}} \]  

(6)

3.3 Results of image classification by the proposed index

The developed spectral index can be used in band math available in ENVI software to classify the Worldview-2 image into built-up and non-built-up classes. The following results were produced by applying the proposed and existing Worldview-2 spectral indices.

![Results of proposed and existing spectral indices](image)

Figure 4. Results of the proposed (a) and existing (b) spectral indices of built-up area extraction applied in ENVI's band math.

The existing worldview-2 built-up area index based on band1 (coastal) and band6 (red edge) spectral bands, while in our approach, PSO found that band4 (yellow) and band7 (NIR1) are the most suitable bands to extract the built-up areas from the worldview-2 image. However, this study limited on using only one dataset for the development of spectral index for built-up area extraction and this could affect the transferability of the index for other study areas.

In order to extract the built-up areas from the above raster images, a threshold needs to be determined. In this study, we determined the suitable thresholds by visual interpretation of the images. The results obtained from the application of the selected thresholds are represented in Figure 5.
3.4 Validation

Testing data was generated in ArcGIS software based on the original Worldview-2 image for validation purposes. Using the testing data and classified images, ROC curves were generated in Matlab software (Figure 6). After that, area under curve (AUC) was calculated for both ROC curves indicating the accuracy of the detected built-up areas. The AUC values were calculated for the proposed spectral index (BSI) and the existing index (WV-BI) and they found to be equal to 0.76 and 0.69 respectively.

![ROC curves](image)

Figure 6. Area under curve and ROC curve of detected built-up areas, (a) the proposed spectral index (BSI), (b) the existing Worldview index (WV-BI).
Conclusion

This study proposed a new spectral built-up index for Worldview-2 data. The proposed index was developed by using multi-objective particle swarm optimization. The optimization technique applied selected the most two significant bands for built-up area extraction. Then it was applied in this research for the second time to develop the final index in mathematical form by using band ratio strategy. The two significant bands selected were band4 (yellow) and band7 (NIR1). The results of built-up area extraction were then compared with an existing built-up index proposed by Digital Globe called WV-BI. The accuracy assessment showed that our index outperforms the existing spectral index quantitatively and qualitatively. However, the validation is only applied on the image that we used for the index development and it was tested for its transferability. Therefore, it is recommended for other researchers for further improvements on the index and develop more indices for various purposes using optimization techniques.

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