Available online at www.humg.edu.vn

ESASGD 2016

GIS–IDEAS (2016)

Conference Title: International Conference on GeoInformatics for Spatial-Infrastructure Development in Earth & Allied Sciences (GIS-IDEAS)

Usage of indices for mapping built-up and open space areas from Landsat 8 OLI imagery: A case study of Da Nang city, Vietnam

Do Thi Viet Huong[a]*, Nguyen Hoang Khanh Linh[b], Truong Do Minh Phuong[b]

[a]*Hue University of Sciences, VietNam*
[b]*Hue University of Agriculture and Forestry*

Abstract

Mapping the built-up and open space land in urban areas plays a vital role because these types of land cover can be used as an indicator of urban expansion and environmental quality. This paper addresses the usage of index based model for automatic delineation of the built-up and open space features from Landsat 8 Multispectral OLI imagery covering the urban areas of Da Nang - one of the cities with the highest rate of urbanization in Vietnam. Index-based built-up index (IBI) can be efficiently calculated by taking three indices: SAVI (Soil Adjusted Vegetation Index), MNDWI (Modified Normalized Difference Water Index), and NDBI (Normalized Difference Built-up Index). The threshold value of IBI was defined from 0.05 to -0.13 for built-up land and from 0.05 to 0.41 for open space land. The threshold value of IBI was defined from 0.05 to -0.13 for built-up land and from 0.05 to 0.41 for open space land. The result of accuracy assessment indicates that IBI approach has much higher accuracy, at 95.62% (with overall kappa of 0.89) than the supervised classification method of maximum likelihood algorithm does, at 85.05% (with overall kappa of 0.67). For the built-up areas and the open space land from IBI image, the Kappa coefficients were extracted with good agreement, at 0,84 and 0.82, respectively. Therefore, this result provide an alternate, effective and more accurate technique for mapping built-up and open space land areas.

Keywords: IBI index, built-up and bare land mapping, Landsat-8 OLI, threshold, Da Nang city

1. Introduction

Recently, with an accelerated speed of urban population worldwide, urbanization has become a significant urban environmental and ecological concern, especially in most developing countries (Xu, 2007, Zhongchang Sun et al. 2014, Fransis Mwakapuja, 2013). Urban expansion leads to conversion of agriculture land, forest land, water body… into impervious built-up land and open space/bare land (land that can be bare for a certain period of time before being developed) (Yi Zhou et al. 2014, Xu, 2007). Mapping the built-up and open space land in urban areas plays a vital role because these types of land cover can be used as an indicator of urban expansion and environmental quality (As-syakur, Adnyana et al. 2012, Li and Chen 2014). Although expanded urban/urban sprawl provides the benefits to the community, the negative/detrimental consequences of urbanization to the urban environment, socio–economic issues, ecosystem, hydrologic system, climate change are widespread (Xu, 2007, Zhongchang Sun et al. 2014). Therefore, timely and accurate land use/land cover (LULC) maps in general and built-up land and open space land in particular are needed for urban planners and decision makers.

Optical satellite imageries with different spatial and spectral resolution has become a vital sources for extraction of LULC features in urban and peri-urban. In which, Landsat imagery data are widely have been utilizing for LULC classification in order to monitoring natural resources, environment as well as urban development (Akjol Djenaliev and O. Hellwich, 2014; Kantan T. et al., 2015, Y. Zha et al, 2003, Yi Zhou et al. 2014). The successful launch of Landsat 8 on February 11, 2012 has made possible and effective the creation and development of different methods, algorithm LULC features extraction. Various techniques are available to

* Corresponding author. Tel.: +84 914202 266;
E-mail address: nhanhuong1005@gmail.com.

extract meaningful information of LULC from remote sensing that can be grouped into two generic categories: (1) pixel and object based classification methods, (2) index base classification (Nitin K. T. and Saad S. B., 2014, Ankit Gupta, 2015). In which, indices methods can aid to extract feature automatically, rapidly and effectively in various studies (Li and Chen 2014, Xu, 2008, Nitin K. T. and Saad S. B., 2014). This paper adresses the usage of Index - based Built-up Index (IBI) as was first introduced by Xu (2008) for automatic delineation of the built-up and open space land features. This index is calculated by taking three known indices: SAVI (Soil Adjusted Vegetation Index), MNDWI (Modified Normalized Difference Water Index), and NDBI (Normalized Difference Built-up Index) derived from the from Landsat-8 multispectral OLI imagery covering the urban areas of Da Nang city of Vietnam. Finally, the result was conducted the accuracy assessment and compared with the pixel based classification result to explore their applicability of using indices for mapping built-up and open space land areas from Landsat 8 OLI imagery.

2. Study area

Da Nang city is located in the middle of Vietnam, between the range of $15^0 55'15"$ - $16^0 13'15"$ North latitude and $107^0 49'05"$-$108^0 20'18"$ East longitude. Da Nang, one of the five direct-controlled municipalities under central government, is strategically chosen as a key economic growth pole and supposed to function as such for the Central region of Vietnam with its international airport, deep-water seaport and National Highway 1. The city has an area of 1,283.42 km^2 with a population of 1.028.838 people (2015) including 6 urban districts, one rural district and one island district (Fig.1). Da Nang has an early history of urban development with its city growth of 2.6% per annum (higher than other class 1 cities of Vietnam 1.2%) that will grow to play as pivotal a role in the national urban system (World Bank, 2011).

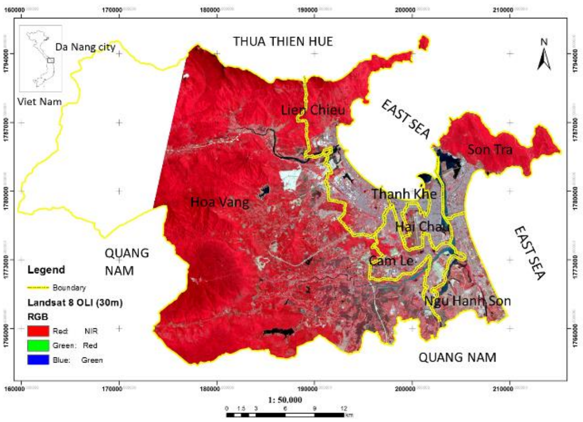


Fig.1. Location of study area

3. Data and methods

3.1. Data and processing

The remote sensing data covers the whole Da Nang city including two scenes in path 124, 125 and Row 49, in which the majority area belongs to the path 124 and Row 49 (occupied 80.20% total of territory area). This study focuses on automatic clarifying the built-up and bare land features that mainly present in the scene of path 124 and row 49. Therefore, the authors limited the study area within the territory areas of that scene (Fig.1). The Landsat 8 OLI data were acquired on 10 June 2015 (Path 124 and Row 49) with scene cloud cover of 0.55% (download address: http://landsatlook.usgs.gov/viewer.html). The data are a standard Landsat Level 1T (L1T) product in the format of 16-bit unsigned integer providing systematic radiometric accuracy and geometric accuracy. The acquired scene quality value is 9 which referring to a perfect scene with no detected errors. Pre-processing was done by converting the Digital Numbers (DNs) to the reflectance values (Top of Atmosphere (TOA) using reflectance scaling coefficients provided in the product metadata file (MTL file). The spatial data image was projected in to the UTM Zone 48 N (WSG 84) coordinate system using topographic sheet and Google Earth. Finally, the Landsat OLI sub-scene was derived by clipping with the administrative boundary of study area.

3.2. Imagery indices determination

The main analysis performed throughout this study was an application of the Index-based Built - up Index (IBI) for mapping built - up and open space land areas using Landsat 8 OLI. The development of the IBI approach for automatic extracting built-up was first proposed by Xu (2008) with Landsat TM and then was successful applied for various cases using Landsat TM and Landsat 8 OLI (Linh 2011, Francis Mwakapuja1 2013, Fajar Yulianto, Boedi Tjahjono et al. 2014, Gupta, Swain et al. 2015). IBI approach is made using a combination of three thematic index-derived images, namely: Normalized Different Built-up Index (NDBI), Soil Adjusted Vegetation Index (SAVI), and Modified Normalized Different Water Index (MNDWI) corresponded to the three main urban land cover classes, built-up and open space, vegetation and water body, respectively. The built-up and open space areas were extracted by using NDBI of Zha et al. (2003) based on theirs spectral response that have higher reflectance in the middle infrared (MIR) wavelength range than in the near infrared (NIR) in equation (1). However, extraction of built-up and open space area information using only NDBI is often mixed with plant and water noise. Therefore, NDBI was combined with SAVI and MNDWI to extract the built-up land features (Xu, 2007, 2008). NDVI is effective used for extraction of vegetation feature in the dense vegetation area (plant cover >30%), but due to its insensitive in detecting the vegetation in low plant covers areas which are normally seen in urban areas (plant cover <15%). Therefore, SAVI was used to extract the vegetation features using NIR and Red wavelength range following the equation (2) proposed by Huete (1988). The water body was extracted by using MNDWI introduced by Xu (2005). This index can enhance water body features while effectively suppressing and even removing built-up and open space land, vegetation and soil noise (Francis et al. 2013) by using Green and MIR wavelength range as equation (3). From the result of IBI calculation approach, built-up and open space land areas will appear and have the enhanced values when compared with other land cover classes (Xu 2007, Fajar Yulianto, Boedi Tjahjono et al. 2014, Gupta, Swain et al. 2015). The threshold for separation built-up and open space land then was defined by examining the IBI range of values in compare with three thematic index-derived images false color composed of NDBI, SAVI, MNDWI as well as the correlations of those index images. Finally, the results of extraction were evaluate by conducting the accuracy assessment by visualizing the Google Earth Image near the time of acquiring Landsat 8 OLI (28/06/2015). In addition, this result was also tested with the supervised classification of seven multispeatrals band image for enhancing the accuracy. Formulas of the IBI approach and the three thematic index-derived images can be presented in equation 1 to 4 (Xu 2007, Fajar Yulianto, Boedi Tjahjono et al. 2014, Gupta, Swain et al. 2015, Huete, 1988).

$$NDBI = (MIR - NIR)/(MIR + NIR) \quad (1)$$

$$SAVI = \{(NIR - Red)\,(1 + l)\}/(NIR + Red + l) \quad (2)$$

$$MNDWI = (Green - MIR)/(Green + MIR) \quad (3)$$

$$\text{IBI} = [\text{NDBI-(SAVI-MNDWI)/2}]/[\text{NDBI+(SAVI-MNDWI)/2}] \quad (4)$$

Where: NIR is a near infrared band: OLI_5, Red is a red band: OLI_4, Green is a green band: OLI_3, MIR is a middle infrared band: OLI_6; and l is a correction factor whose value ranges from 0 – 1, depends upon the plant densities. If there is very high plant densities then value of l will be zero and vice versa.

In this study, Erdas Imagine 2014 with Model Maker was used for image processing and calculation indices image, whereas ArcGIS desktop was used for editing the result. The procedure of study was clearly showed in Fig.2.

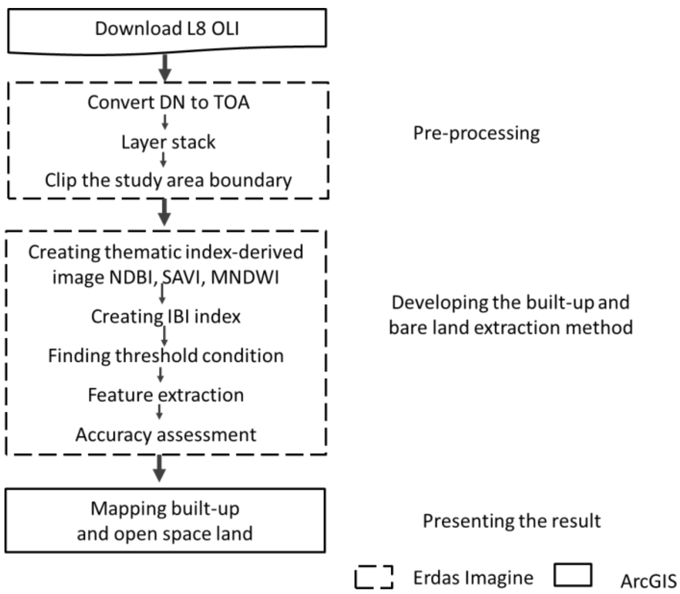


Fig.2. Procedure of the study

4. Result and discussion

4.1. Thematic index-derived images of NDBI, SAVI and MNDW

The calculation of NDBI, SAVI and MNDBI was done by drawing the model in Model Maker tool palette following the above equation. The single band images result was declared as float with the Nearest Neighbor Interpolation method showing in Fig.3a, Fig.3b and Fig.3c, respectively. Some strange values might exit in the output indices image of NDVI, SAVI, and MNDWI, therefore they were recalculated by using condition statement that only contains values between -1 and 1. From the calculation of NDBI index (Fig.3a), the open space land object look bright white tends to be high positive, while built–up objects looks bright grey tones with a bit lower value than the open space land object. The densely vegetation areas are showed dark tone whereas the less dense vegetation and water are showed in bright dark tone and they tend to be negative value.

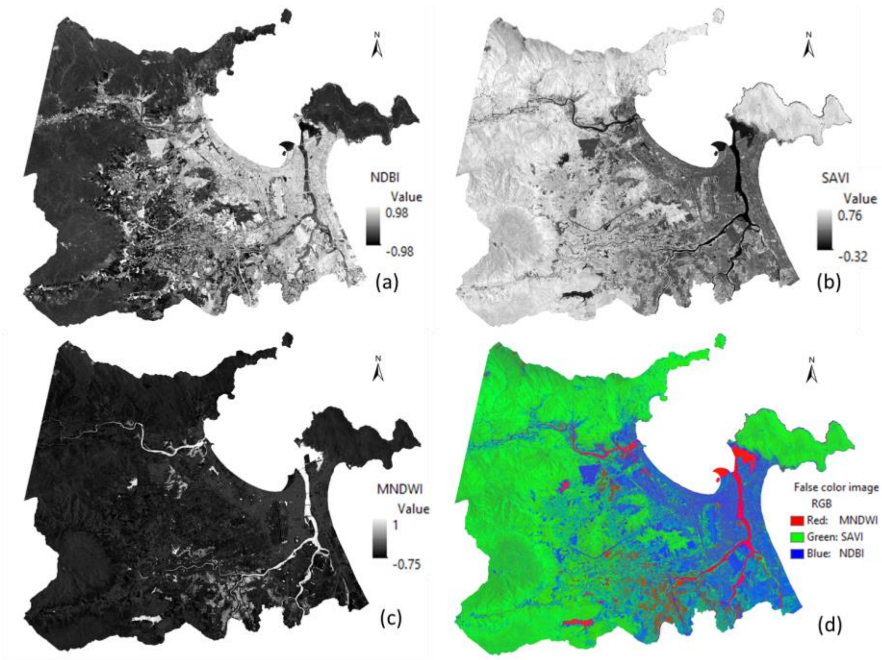


Fig.3. Thematic index-derived images of NDBI (a), SAVI (b), MNDWI (c) and its false color composition (d)

However, the built-up feature extraction from this index image is still mixed with plant and water noise, hence it is needed to filter by using SAVI and MNDWI image. From the SAVI image (Fig.3b), it shows a high separation between vegetation and non-vegetation. In which, the pixels with white and grey tone indicate vegetation (with high positive value), moderate grey to dark grey indicate other land cover (built-up, open space land…) (with relative low positive value), and black pixels show water (with negative value). From the MNDWI illustrating in the Fig.3c, water object appears bright white and tend to be positive value, while areas with dense vegetation appear black and dark. The built - up and open space land appear to dark grey and tend to be negative value. From the false color image composing of the three thematic index-derived images MNDWI, SAVI, NDBI (Red, Green, Blue) (Fig.3d), the major urban land cover as vegetation, water body, built-up and open space land are well discriminated. In addition, the scatterplots delivering from analyzing those major urban land cover signatures in Fig.4 (a, b, c) also indicates a clear separation. Therefore these indices images can be utilized for further processing for built-up and open space extraction.

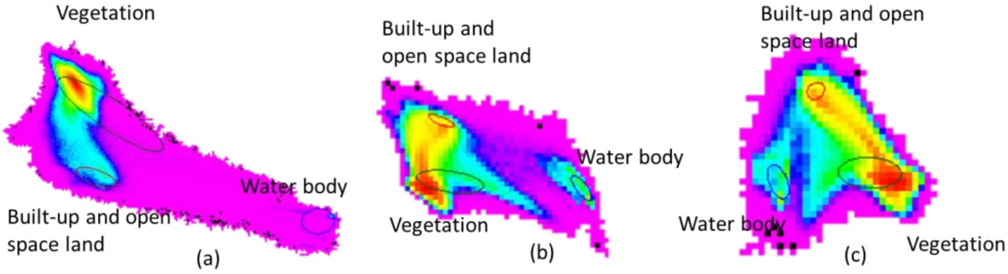
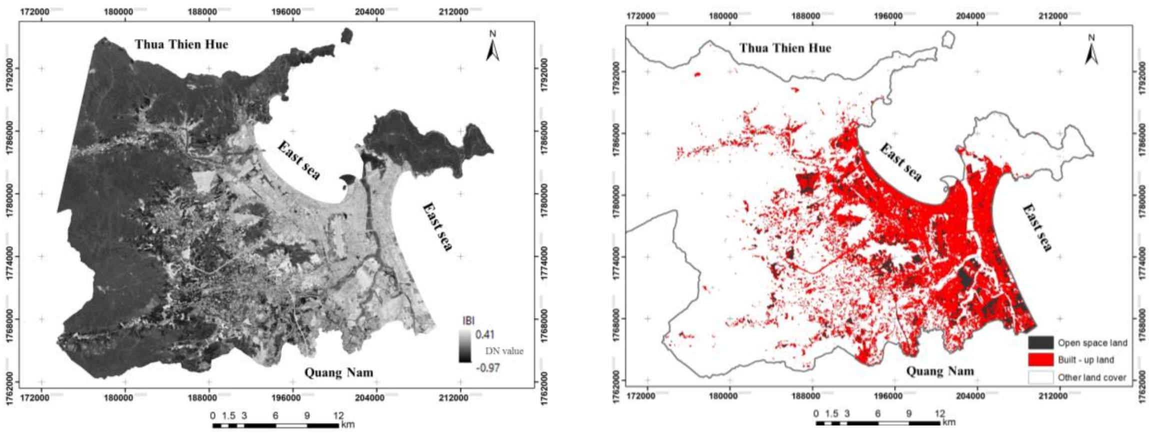


Fig. 4. Scatterplot of spectral feature space of the two new three-thematic index-derived images of Da Nang city (a) MNDWI (x-axis) - SAVI (y-axis); (b) MNDWI (x-axis) - NDBI (y-axis); (c) SAVI (x-axis) - NDBI (y-axis).

4.2. Mapping of built-up and bare land features from IBI image

A continuous raster of IBI image obtaining from the equation 4 through Model Maker of MNDWI, SAVI, and NDBI images (Fig.5a). This index enhanced to distinguish the built-up and open land feature from the other land covers. In which the built-up and open land feature appear with a white, bright grey and light grey tone while vegetation and water body are considerably suppressed as background noise with a dark grey and black tone. The value of IBI image ranges from -0.97 to 0.41. To extract the built-up and open space land features from the IBI images, a threshold was manually determined for each land cover type. The result indicates that the pixels with values greater than 0.05 are open space land and assigned a value of 0, while the pixels ranges from 0.05 to -0.13 are built-up land and assigned a value of 1. The other land cover types are the remained pixels and assigned a value of 3 (Fig.5b). Finally, the classification result including three types of land cover as built up, open space land and other land cover was obtained by using thematic recode tool.



(a) (b)

Fig.5. Continuous IBI raster image (a) and its Built-up and Open space land extraction in Da Nang city

4.3. Accuracy assessment of result

The accuracy of Landsat image classification through IBI index approach was assessed using "ground truth" data and Da Nang land use status map in 2015 provided by the Da Nang's Land Registration Office. For an evaluation, a grid point with 1 km grid spacing was created and convert to .kml file that included 776 points. Subsequently, each individual point was trained by visual interpretation of the land use status map of 2015. The code grid points were then overlaid by the IBI image classification in order to compare the accuracy of result. In addition, to compare the extraction of built-up and open space land features, the study also conducted the accuracy assessment for the supervised classification result of the TOA seven-band Landsat 8 OLI image (maximum likelihood algorithm method). The result shows that the built-up and open spaces areas extraction from the TOA seven-band Landsat 8 OLI image larger than the IBI image. In which, the misclassification between built-up and open space pixels is indicated higher in supervised classification method than in IBI method. Therefore, the IBI approach has much higher accuracy, at 95.62% (with overall kappa of 0.89) than the supervised classification method of maximum likelihood algorithm does, at 85.50% (with overall kappa of 0.67) (Tab 1). For the built-up areas and the open space land extraction from IBI method, the Kappa coefficients were extracted with good agreement, at 0,84 and 0.82, respectively. Therefore, this result provide an alternate, effective and more accurate technique for mapping built-up and open space land areas.

Table 1. Accuracy assessment result of built-up and open space land extraction derived from IBI method and supervised classification

Extraction method		Reference Land use map 2015			Overall accuracy & Overall Kappa	Use's accuracy	Kappa
		Built-up	Open space	Other lands			
IBI method (Combination of NDBI, MNDWI, SAVI image)	Built-up	**148**	13	8	**95.62%** **0.89**	87.57%	0.84
	Open space	5	**25**	0		83.33%	0.82
	Other lands	6	2	**569**		98.61%	0.95
Supervised classification method TOA 7-band Landsat 8 OLI	Built-up	**111**	10	26	**85.50%** **0.67**	75.59%	0.69
	Open space	40	**33**	2		48.00%	0.40
	Other lands	31	7	**544**		98.74%	0.79

5. Conclusions

This study presented the methodological approach of classification satellite image of Landsat 8 OLI through using threshold condition from the indices image. The new IBI image comprised of three thematic index-derived images, the MNDWI, the SAVI, and the NDBI can greatly enhance to distinguish the built-up and open land features from the other land covers by suppressing the background noise. The proposed IBI image is more successful support for built-up and open space land features extraction than conventional supervised classification of multispectral Landsat 8 image with the high overall accuracy 95.62% (overall kappa statistics of 0.89). This technique will be helpful in automatic addressing the built-up and open space land areas for studying urban growth, sprawl and its trend of any growing urban areas.

References

As-syakur, A. R., et al.,2012. Enhanced Built-Up and Bareness Index (EBBI) for Mapping Built-Up and Bare Land in an Urban Area. Remote Sensing of Environmen, Vol. 4, pp.2957-2970.

Fajar Yulianto, et al., 2014. Detection Settlements and Population Distribution Using GIS And Remotely Sensed Data, In The Surrounding Area of Merapi Volcano, Central Java, Indonesia. International Journal of Emerging Technology and Advanced Engineering, Vol. 4, No.3, pp. 1-10.

Francis Mwakapuja1, E. L., Japhet Kashaigili, 2013. "Usage of Indices for Extraction of Built-up Areas and Vegetation Features from Landsat TM Image: A Case of Dar Es Salaam and Kisarawe Peri-Urban Areas, Tanzania." International Journal of Agriculture and Forestry, Vol 3, No.7, pp. 273-283.

Guntenspergen, G. R., 2014. Application of Threshold Concepts in Natural Resource Decision Making. USA, Springer.

Gupta, A., et al., 2014. "Urban Growth Trend Analysis of Indore city (2005 - 2014) Through Index Based Models". 15th ESRI India User Conference 2014, pp. 1-7.

Gupta, A., et al., 2015. "A geoinformatic approach to study urban agglomeration of Bhubaneswar city (Odisha)". 16th Esri India User Conference 2015, pp. 1-7.

Huete, A. R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, Vol.25, pp. 295-309.

Li, S. and X. Chen, 2014. "A new bare-soil index for rapid mapping developing areas using Landsat 8 data." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XL, No. 4, pp. 139-144.

Linh, N. H. K., 2011. "Thành lập tự động bản đồ phân bố đất đô thị bằng chỉ số ibi từ ảnh landsat TM: Trường hợp nghiên cứu tại thành phố huế - tỉnh Thừa Thiên Huế." Hội thảo ứng dụng GIS toàn quốc 2011.

McFeeters, S. K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, Vol. 17, No.7, pp. 1425-1432.

USGS, 2016. Landsat 8 (L8) Data Users Handbook - Version 2. EROS, Sioux Falls, South Dakota.

Xu, H., 2006. Modification of Normalized Difference Water Index (NDWI) to Enhance Open Water Features in Remotely Sensed Imagery. Journal of Remote Sensing, Vol. 27, No.14, pp. 3025–3033.

Xu, H., 2007. Extraction of Urban Built-up Land Features from Landsat Imagery Using a Thematicoriented Index Combination Technique. Photogrammetric Engineering & Remote Sensing, Vol. 73, No.12, pp. 1381–1391.

Zha, Y., et al., 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing, Vol. 24, No. 3, pp. 583-594.

World Bank, 2011. Vietnam urbanization review - technical asisstance report, World Bank in Vietnam, Ha Noi, Vietnam.