Modification of urban built-up area extraction method based on the thematic index-derived bands

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Abstract. This research aims to develop new automatic and quicker spectral signature analysis tools to separate urban built-up area and determines urban area changes. Nowadays, researcher uses thematic index-derived bands for automatic urban data extraction. The extraction of urban built-up land can be automatically done with New Built-Up Index (NBUI) although it has a limitation on separating built-up land and water body. This study attempts to obtain the maximum accuracy of the extraction by merging several indices including Enhanced Built-Up and Bareness Index (EBBI), Soil Adjusted Vegetation Index (SAVI), Modified Normalized Difference Water Index (MNDWI), New Water Index (NWI) and Normalized Different Pond Index (NDPI) and compared its accuracy with NBUI. The results showed that merging EBBI, SAVI, MNDWI and NDPI produces the highest accuracy of 98.21% by addition and subtraction. The combined application of EBBI, SAVI and NWI also gives a good effect for extracting urban built-up areas and has 94.64% mapping accuracy.

1. Introduction

In recent years, scientists have struggled to develop automatic and quicker spectral signature analysis tools and different features index which are of the great achievements in the field of Geographical Information System (GIS) [1]. The remote sensing and GIS techniques are one of the most excellent tools for urban land use classification [2]. It is not only fast and automatic tools and also free from statistical assumption [3]. Zha et al. (2003) for the first time developed the Normalize Different Built-up Index (NDBI) algorithm to separate residential and non-residential area by using satellite imagery. This is one of the automatic mapping tools based on the arithmetic calculation of three bands: Red(R), Near Infrared (NIR) and Medium Infrared (MIR) [4]. He et al. (2010) improved and modified NDBI algorithms by utilizing the concept of original NDBI approach and proposed a revised version of NDBI algorithm. According to this research, original methodology suffers lots of errors of commission because it assumes that all positive values of Normalized Difference Vegetation Index (NDVI) and NDBI indicate vegetation and built-up regions. The revised version extracts built-up regions using the difference of the continuous images of NDBI and NDVI, and utilizes the thresholding algorithm which identifies more accurate outputs than the difference output generated from binary images [5]. Varshney (2013) improved this method by setting an optimal threshold value by allocating improved positive difference values of continuous NDBI and NDVI to built-up areas [6].
Xu (2008) utilized Soil Adjusted Vegetation Index (SAVI) and Modified Normalized Difference Water Index (MNDWI) values for eliminating the other land use/land cover classes, and proposed Index-based Built-up Index (IBI) approach to improve the output of built-up index [7]. Jieli et al. (2010) proposed New Built-up Index (NBI) by utilizing the R, NIR and MIR bands. The main concept behind this built-up index is that the R band’s spectral response of barren land is higher than built-up regions, the spectral response of which is in turn greater than the other land use/land cover classes [8]. As-syakur et al. (2012) developed the Enhanced Built-Up and Bareness Index (EBBI). The EBBI is able to map built-up and bare land areas using a single calculation. The EBBI is the first built-up and bare land index that applies NIR, Short Wave Infrared (SWIR), and Thermal Infrared (TIR) channels simultaneously. This new index was applied to distinguish built-up and bare land areas in Denpasar (Bali, Indonesia) and had a high accuracy level when compared to those of existing indices. The EBBI was more effective at discriminating built-up and bare land areas and due to this discriminating feature its accuracy is also high [9]. Sinha et al. (2016) developed a spectral signature analysis tools called New Built-up Index (NBUI). This tool is based on three thematic index-derived bands i.e., the EBBI, Soil Adjusted Vegetation Index (SAVI) and Modified Normalized Difference Water Index (MNDWI), to represent three major urban land-use classes: built-up and barren/bare land, open water body, and vegetation, respectively [10]. The SAVI tool was developed by Huete in 1988 at the University of Arizona, United States. The idea was to have a global model for monitoring soil and vegetation from remotely sensed data. SAVI is similar to NDVI because both are based on original image bands i.e, NIR and R but spectral indices may be calibrated in such a way that the variations of soils are normalized and do not influence measurements of the vegetation canopy. These enhancements to NDVI are useful because SAVI accounts for variations in soils [11]. Different water indexes have already been proposed in the past few decades. Specifically, McFeeters (1996) proposed the Normalized Difference Water Index (NDWI), using the Green (G) and NIR bands of remote sensing images based on the phenomenon that the water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. NDWI can enhance the water information effectively in most cases, but it is sensitive to built-up land and often results in over-estimated water bodies [12]. To overcome the shortcomings of NDWI, Xu (2006) developed the MNDWI that uses the SWIR band to replace the NIR band used in NDWI [13]. Many previous research works have demonstrated that MNDWI is more suitable to enhance water information and can extract water bodies with greater accuracy than NDWI [14,15,16,17]. Ding (2009) proposed The New Water Index (NWI) on the basis of further finding and analysis of water’s and other ground objects’ spectrum feature in the satellite imagery. The NWI is a representative method based on the fact that water has lower digital values in Blue (B), NIR, SWIR1 and SWIR2 than other land-cover types [18]. Lacaux et al. (2007) have developed the Normalized Difference Pond Index (NDPI) by using G and MIR bands [19]. These all tools are either based on original image bands or thematic index-derived bands.

There are massive studies on the development of tools to extract settlements areas using remote sensing data. However, there are still problems related to the classification result, particularly the mixing of built-up land with others results classification. A multispectral classification approach is developed through the method of combining the same pixel value for each land use/land cover class [20,21,22]. Although NDBI is already widely used for the extraction of urban built-up areas, it still has limitations. Therefore, it is necessary to develop new methods by combining some indices and improving the accuracy of built-up area maps [23,24]. Even researchers have tried to develop or modify numbers of tools for land use classification but there is still confusion to identify the objects [25]. Due to the lack of clear shape, texture characteristics, and abundant spectral or spatial information of urban objects, traditional per-/sub-pixel analysis and interpretation for moderate-resolution-remote sensing data are always confused by such shortcomings as dependence on special skills, requirements to a priori knowledge and training samples, complex process, time-consuming and subjective operations and so on, [26] Furthermore, the accuracy of extracting is affected by the phenomenon that the homogeneous objects have the different spectrum and the heterogeneous objects have the same spectrum. So that, every year scientists develop new methods and improve existing
methods across the world with high precision rate compared to the original method [27]. On this research, we try to develop automatic and quicker spectral signature analysis tools, with which we want to create a modified new built-up index that could provide the highest accuracy in comparison to others.

2. Material and methodology

2.1. Study area

The Pokhara city which is situated within the Pokhara-Lekhnath metropolitan city of Nepal at province number four and located between 83° 58' 30" to 84° 02' 03" east longitudes and 28°10' north to 28°16' north latitudes. This metropolitan city is made up of a combination of land use/land cover and completely bordered to the north by the Annapurna mountain region. Topographically it is the valley with few hillock areas. The city has a humid subtropical climate; however, the elevation keeps temperatures moderate. The altitude varies from 827 meters in the southern part to 1,740 meters in the north. Temperatures in summer average between 25 and 35 °C; in winter around -2 to 15 °C. Pokhara and nearby areas receive a high amount of precipitation. The total surface area of this metropolitan city is 464.24 km².

2.2. Image acquisition and pre-processing

Landsat 8(OLI & TIRS) data of March 2016 (path 142, row 41; cloud cover 1.80%) were acquired for built-up area extraction for the study. The Landsat 8(OLI & TIRS) has eight reflectance bands with a resolution of 30 m, one panchromatic band with 15 m and two thermal bands with a resolution of 100 m. The specifications of Landsat 8(OLI & TIRS) are shown in Tables 1. The raw data were analyzed using ArcGIS 10.3 software without atmospheric correction. In the current study; the images were geometrically referenced to the UTM Zone 44 N projection system.

Table 1. Landsat 8 (OLI & TIRS)

| Bands                          | Wavelength (micrometers) | Resolution (meters) |
|-------------------------------|--------------------------|---------------------|
| Band 1 - Ultra Blue (coastal/aerosol) | 0.435 - 0.451            | 30                  |
| Band 2 – Blue                  | 0.452 - 0.512            | 30                  |
| Band 3 – Green                 | 0.533 - 0.590            | 30                  |
| Band 4 – Red                   | 0.636 - 0.673            | 30                  |
| Band 5 - Near Infrared (NIR)   | 0.851 - 0.879            | 30                  |
| Band 6 - Shortwave Infrared (SWIR) 1 | 1.566 - 1.651          | 30                  |
| Band 7 - Shortwave Infrared (SWIR) 2 | 2.107 - 2.294          | 30                  |
| Band 8 – Panchromatic          | 0.503 - 0.676            | 15                  |
| Band 9 – Cirrus                | 1.363 - 1.384            | 30                  |
| Band 10 - Thermal Infrared (TIRS) 1 | 10.60 - 11.19           | 100 * (30)          |
| Band 11 - Thermal Infrared (TIRS) 2 | 11.50 - 12.51           | 100 * (30)          |

2.3. New Built-Up Index (NBUI)

Sinha et.al (2016) developed an NBUI. This built-up index based on five bands of satellite images i.e., NIR, SWIR1, TIRS1, R and G.

\[ \text{NBUI} = \text{EBBI} - (\text{SAVI} + \text{MNDWI}) \]  ..........................................................(1)

Where,
\[ \text{EBBI} = \frac{(\text{SWIR1-NIR})}{10\sqrt{\text{SWIR1+TIRS1}}} \]
SAVI = 1.5*(NIR-R)/(NIR+R+0.5)  
MNDWI = (G-NIR)/(G+NIR)  

2.4. Built-Up extraction method  
The NBUI extract built-up area by merging EBBI, SAVI and MNDWI through addition and subtraction. But our assumption was that there may be still some prone to error due to presences of water bodies. In this research, we followed the steps of developing the NBUI by Sinchaet al (2016) and tried to modify the extraction method of urban built-up area based on thematic index-derived bands. The Principle Component Analysis (PCA) was used to combine the NWI and NDPI to find the best combination rather than NBUI combination bands. We developed two PCA equations based on thematic index-derived bands as follows:  

PC1 = EBBI - (SAVI + NWI) ...........................................(2)  
Where,  
NWI = [Blue-(NIR + SWIR1 + SWIR2)]/[Blue+(NIR + SWIR1 + SWIR2)]  
PC2 = EBBI - (SAVI + MNDWI + NDPI)  ...................................(3)  
Where,  
NDPI = SWIR1-G)/(SWIR1+G)  

The equation (2) utilized seven bands of satellite images i.e., NIR, SWIR2, SWIR1, TIRSI, Red, Green and Blue. Likewise, equation (3) also utilized same five bands of the satellite images which used on NBUI but combination of indices bands are different.  

2.5. Accuracies assessment  
The worldview-3 image of year 2016 of Pokhara-Lekhnath metropolitan city of Nepal was used to assess the accuracy. A random sampling technique was applied to collect sample pixels to compare the accuracies from different indices and to evaluate the difference between them. The mapping accuracies were reported in the form of user accuracy (UA), producer accuracy (PA) overall accuracy (OA) and kappa coefficient (κ) [28].  

3. Results and discussions  

![Figure 1. NBUI.](image-url)
Figure 2. PC1.

Figure 3. PC2.

Table 2. Accuracy assessment of extracted Built-up Area (2016)

| Built-up Index 2016 | Value     | Count | Area (km²) | UA  | PA  | OA  | κ   |
|---------------------|-----------|-------|------------|-----|-----|-----|-----|
| PC1                 | -0.4 to 0.1 | 22687 | 20.42      | 93.86 | 95.54 | 94.64 | 89.29 |
| PC2                 | 0.15 to 0.7  | 23525 | 21.2       | 95.83 | 96.64 | 98.21 | 96.25 |
| NBUI                | -0.33 to 0.19 | 21614 | 19.45      | 92.37 | 94.78 | 95.54 | 90.65 |
The accuracy of NBUI (Figure 1), PC1 (Figure 2) and PC2 (Figure 3) were 95.54, 94.64 and 98.21 percent respectively. It was found that PC2 have the highest accuracy with comparisons to NBUI and PC1. Even accuracy of PC1 also acceptable but there was low accuracy with a comparison to NBUI and PC2. Although PC1, PC2 and NBUI were acceptable automatic and quicker spectral signature analysis tools, the value range was not same. With comparison to NBUI and PC1, it was found that PC2 was a suitable tool to extract urban built-up area by separating water index from EBBI. The image analysis result showed that the pixels counts of NBUI, PC1 and PC2 were 21614, 22687 and 23525 respectively. Similarly, the modified extraction method of urban built-up area by PC1 and PC2 based on thematic index-derived bands EBBI, SAVI, MNDWI, NWI and NDPI able to extract built-up area 20.42 and 21.2 square kilometers respectively and these results were similar to the area (19.45 km²) extracted by NBUI. The full data are shown in Tables 2. The combination of SAVI, MNDWI, NDPI with EBBI, can remove the disturbance of water. The merging of these various indices is expected to improve the accuracy of the research.

4. Conclusions
Researchers have developed two new automatic and quicker spectral signature analysis tools to separate urban built-up area from the non-built-up area of Pokhara-Lekhnath Metropolitan City of Nepal. The PC2 gives a superior outcome in terms of accuracy as compared to NDBI and PC1. This study also concludes that remotely sensed datasets can be used efficiently in index modeling techniques in order to study the urban growth, sprawl, agglomeration, and conurbation of any growing area. To provide better information about land use pattern and behavior, this technique needs high level of interpretation and spectral identification. Digital image processing techniques can bring huge achievement to this work by improving image quality for analysis. Good advice/suggestion from GIS & Image analyst, urban planner & remote sensing experts can improve this type of study further and increase the possibility of fine results.

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