

SPECIFIC FEATURES OF NDVI, NDWI AND MNDWI AS REFLECTED IN LAND COVER CATEGORIES

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Abstract

The remote sensing techniques provide a great possibility to analyze the environmental processes in local or global scale. Landsat images with their 30 m resolution are suitable among others for land cover mapping and change monitoring. In this study three spectral indices (NDVI, NDWI, MNDWI) were investigated from the aspect of land cover types: water body (W); plough land (PL); forest (F); vineyard (V); grassland (GL) and built-up areas (BU) using Landsat-7 ETM+ data. The range, the dissimilarities and the correlation of spectral indices were examined. In BU – GL – F categories similar NDVI values were calculated, but the other land cover types differed significantly. The water related indices (NDWI, MNDWI) were more effective (especially the MNDWI) to enhance water features, but the values of other categories ranged from narrower interval. Weak correlation were found among the indices due to the differences caused by the water land cover class. Statistically, most land cover types differed from each other, but in several cases similarities can be found when delineating vegetation with various water content. MNDWI was found as the most effective in highlighting water bodies.

Keywords: Landsat, spectral index, land cover, Bodrogek

1. Introduction

Satellite images provide a wide range of possibilities of monitoring the environment in a fast way, especially on areas which are unavailable for a field survey due to the topography, dense vegetation or other local factors (Schowengerdt 2007; van Dessel et al. 2008; Lóki – Szabó 2011; Burai et al. 2014; Varga et al. 2015). There are lots of earth observation satellites with different spatial and spectral resolution can be used in these analyses (Singh et al. 2014; Srivastava et al. 2015). Accordingly, we have to consider the aims of the mapping to determine the scale of the investigation, i.e. different satellites provide images different purposes (Berke et al. 2013; Deák et al. 2013). A MODIS image with its 250–1000 m geometrical resolution

is appropriate for regional analyses and especially the NDVI composites are popular solutions for biomass monitoring (Ladányi et al. 2015). For local scale, at least 20–30 m geometric resolution is needed but there are very high resolution (HRV) images (e.g. WorldView, IKONOS) that makes possible detailed studies even in small areas (Taherzadeh – Shafri 2013). Since Landsat (USGS) and Sentinel (ESA) images, with 30 and 20 m geometric resolution, are available for free, this type of land cover mapping is cost effective and, considering the temporal resolution, the continuous observation of changes is ensured (Hansen – Loveland 2012). Their spectral resolution is also appropriate for land cover mapping providing three infrared bands beside the common RGB bands.

Land cover mapping uses satellite images and there are several classifier algorithms, Minimum Distance (Davies 2004), Maximum Likelihood (Wernick – Morris 1988), Support Vector Machine, Random Forest (Jin et al. 2005; Otukey – Blaschke 2010) etc., providing maps with acceptable thematic error. Another way of using the images is the application of spectral features: as all surface objects have a given and specific spectral profile, we can use it to determine measurable quantities (Kovács - Szabó 2016). A spectral band alone rarely corresponds with a measurable quantity, in conclusion band ratios are often used in remote sensing studies. The first published band ratio, the Normalized Difference vegetation Index (NDVI) became a popular tool of biomass estimation (Rousse et al. 1973). Later, lots of indices were developed for different purposes to identify e.g. water bodies (NDWI, McFeeters 1996); bare lands (BI, Zhao and Chen 2005; NDBal, Chen 2006) or to monitor the restoration of

abandoned quarries (LRI; Cutaia et al. 2004).

As coverages of spectral indices can be applied as input data for image classification, too (Olasz et al. 2015), it is important to know how they reflect the land cover types. Theoretically, and in case studies, these indices are investigated, but, if they really reflect the features of surface objects, they have to have values within a certain, non-overlapping, range with other land cover classes. Differences among forests, grasslands, water bodies, bare lands etc. can be enhanced; accordingly, they can increase the performance of the classifications, too.

The aim of this study is to investigate the ranges of three spectral indices from the aspect of land cover types. We compared the spectral ratios by land cover types and evaluated their efficiency in discriminating land cover classes.

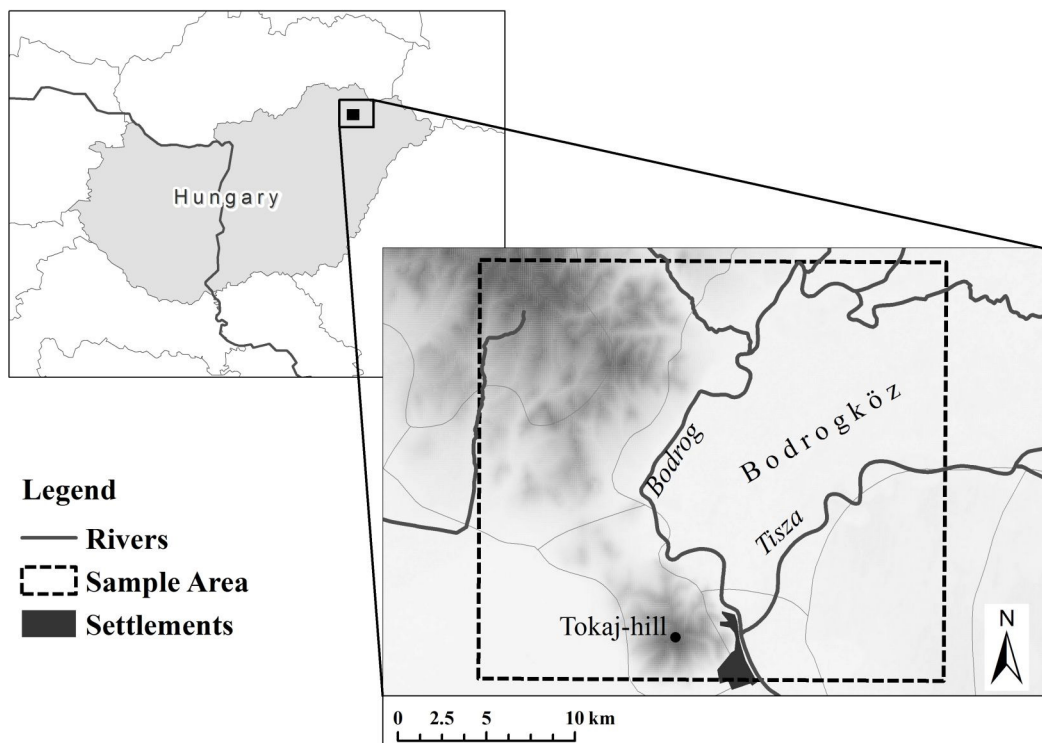


Fig. 1. Location of study area

2. Materials and methods

Study area

Our study site was a topographically diverse area in the border of four microregions (Fig. 1): Bodrogköz (floodplain), Tokaj-hill (mountain), Tokaj-hegyalja (mountain) and a part of the Central-Zemplén (mountain). The land cover also variegated with water bodies (Tisza and Bodrog Rivers, oxbows) wetlands (Bodrozug), forests (Central Zemplén and Tokaj-hill) or bare soil surfaces (plough lands and vineyards in the Hegyalja region). Mountainous regions and the floodplain with its oxbows and frequently flooded areas (Vass et al. 2010; Bertalan 2011; Szabó et al. 2012; Incze – Novák 2016).

Data and data extraction

A Landsat-7 ETM+ image was used in the analysis captured in 20th August 2000 (NASA Landsat Program, 2000). Although August is usually a warm and dry month in Hungary, this period was cooler and had more precipitation than the average according to the archive data resulting in relatively high water content in soils. First, we collected land cover data using ancillary data of previous field observations (several landscape elements did not change) and also aerial orthophotos and maps with the following land cover classes: water body (W); plough land (PL); forest (F); vineyard (V); grassland (GL) and built-up areas (BU). Next, we calculated three spectral indices (NDVI, NDWI and MNDWI). GIS operations were performed with QGIS R14.3 LTR (QGIS Development Team 2016) and IDRISI Selva (Clarklabs 2012).

Spectral indices

We determined three spectral indices using the bands of the Landsat image. NDVI (Normalized Difference Vegetation Index) is developed by Rouse et al. (1973) to estimate the amount of biomass. It takes into consideration the red (RED) and the near infrared bands (NIR), in case of Landsat-7 it was the band#3 and band#4, respectively:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

NDWI (Normalized Difference Water Index) is developed by McFeeters (1996) to enhance the water related features of the landscapes. This index uses the near infrared (NIR) and the short wave infra red (SWIR) bands, in case of Landsat-7 it was band#4 and band#5, respectively:

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR}$$

MNDWI (Modification of Normalized Difference Water Index) is also a water-index and is developed by Xu (2005). It uses the green (GREEN) and the short wave infrared (SWIR) bands, in case of Landsat-7 it was band#2 and band#5, respectively:

$$MNDWI = \frac{GREEN - SWIR}{GREEN + SWIR}$$

Statistical analysis

According to the Shapiro-Wilk test spectral indices did not follow the normal distribution, therefore, we applied non-parametric statistical tests. Null hypothesis testing (Kruskal-Wallis test combined with Bonferroni correction) and correlation analysis was conducted in R 3.3.1 software (R Core Team 2016) with the coin (Hothorn 2006) and the ggplot2 (Wickham 2009) packages. Land cover type was used as target variable and NDVI, NDWI and MNDWI as explanatory variables. Beside correlation, we analysed the relationship of the variables visually, in 2D scatterplots indicating the data distribution by land cover types with 95% ellipses (assuming bivariate normal distribution and determine the region where 95% of observations are expected to fall).

3. Results

General description of spectral indices

NDVI and MNDWI highlighted the water and dense vegetation visually, but NDWI, as a water index, was not appropriate to

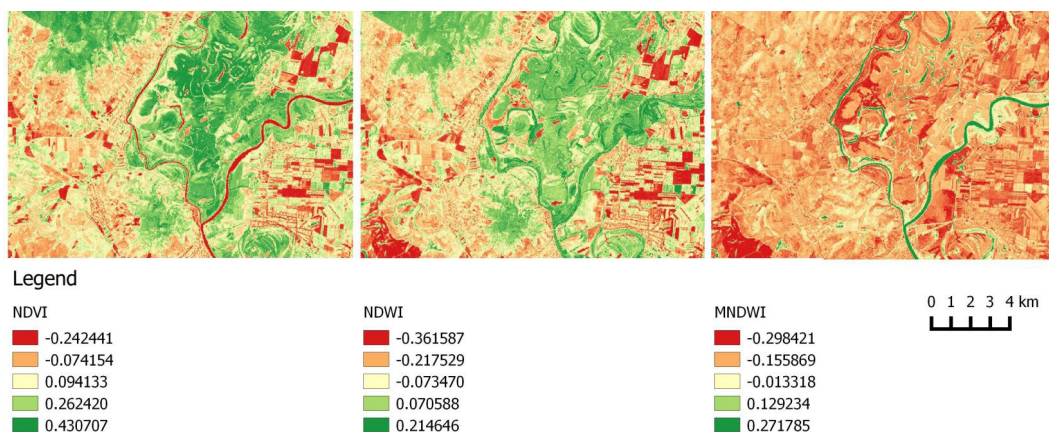


Fig. 2. NDVI, NDWI and MNDWI coverages of the study area

discriminate water itself (Fig. 2). For NDWI, water had the same pixel value as forests and grasslands. MNDWI enhanced water bodies (rivers, oxbows, ponds) but all the other land cover classes did not seem to be discriminated. Next step we analyzed the pixel values by land cover classes and justified the visual observations.

Land cover types had similar features considering the NDVI values of BU – GL – F; and GL – F. All other land cover classes had significant differences (Fig. 3; Table 1). An interesting result was that BU values were similar to the most natural classes (F and GL) but built in areas of the study area are usually mean rural environment (Tokaj and Tarcál); therefore, beside the artificial objects (roads, houses) relevant amount of green surface was also found (gardens, orchards which spectral profiles are similar to grasslands and forests). Accordingly, BI's interquartile range (IQR) was wide (Fig. 2). GL's and W's IQR were also wide: water bodies are biased by the forests along the rivers, and grasslands also varied in their biomass.

NDWI and MNDWI, as water related indices, reflected water better in their values; however, MNDWI seemed a more reliable indicator as this index was the only one out of the three indices that could enhance the water surfaces. Both the Tisza River and the lakes (ponds and oxbows) had a unique range which did not overlap with other land cover

classes. Although MNDWI's values of the other land cover classes were in a narrower range (between -0.4 and 0.0), only BU and F values had not significant differences (Table 2). NDWI's differences were similar to that we experienced in case of NDVI's (Table 3).

Correlation of the indices

Correlation was weak among the indices, and its reason was the water land cover class; all three pairs' (NDVI – NDWI; NDVI

Table 1. Differences among the land cover classes regarding the NDVI values (p-values; **p<0.05**; Kruskal-Wallis test with Bonferroni correction)

NDVI	W	BI	PL	F	GL
V	<0.001	<0.001	<0.001	<0.001	<0.001
W		<0.001	<0.001	<0.001	<0.001
BI			<0.001	1	1
PL				<0.001	<0.001
F					1

Table 2. Differences among the land cover classes regarding the NDWI values (p-values; **p<0.05**; Kruskal-Wallis test with Bonferroni correction)

NDWI	W	BI	PL	F	GL
V	<0.001	<0.001	<0.001	<0.001	<0.001
W		<0.001	<0.001	<0.001	<0.001
BI			<0.001	1	0.092
PL				<0.001	<0.001
F					0.001

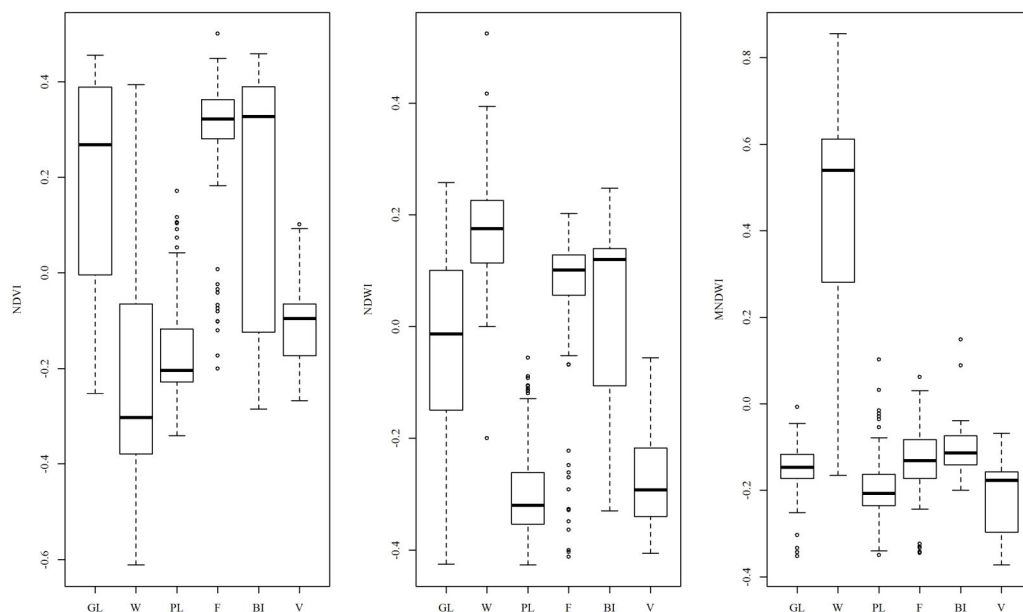


Fig. 3. NDVI, NDWI and MNDWI coverages of the study area

Table 3. Differences among the land cover classes regarding the MNDWI values (p-values; $p < 0.05$; Kruskal-Wallis test with Bonferroni correction)

MNDWI	W	BI	PL	F	GL
V	<0.001	<0.001	<0.001	<0.001	<0.001
W		<0.001	<0.001	<0.001	<0.001
BI			<0.001	0.086	<0.001
PL				<0.001	<0.001
F					0.041

– MNDWI; NDWI – MNDWI) correlation was influenced by the water itself. Water seemed like an outlier group in the scatter plots (Fig. 4) and biased the strength of the relationships. Plough lands and vineyards had similar values, thus, their 95% ellipses covered each other. Furthermore, grasslands and built-up areas also had similar features in these bivariate approach, too; i.e. their appearance in the diagrams were similar. Forests differed from BU and V classes but not significantly, it is due to the narrower range of their values.

4. Discussion

NDVI's aim is to assess the biomass quantity, while NDWI was developed to identify water bodies and saturated water. Previous studies found that NDVI was appropriate to reveal soil moisture and NDWI did not give substantial advantage to that (Gu et al. 2008). However, in other studies, NDVI and NDWI seemed useful variables in assessing urban heat island according to Ogashawara and Bastos (2012). They analyzed the correlation of the spectral indices by land use/land cover types and found that $r_{NDVI-NDWI}$ varied between 0.74–1.00 (lowest was in case water bodies and largest was in case of urban cover pattern). NDVI and NDWI also were successfully applied in the study of Chen et al. (2006) in analyzing urban heat island and land cover change. Spectral indices were predictor variables and temperature was the target variable, the gained outcome were $R^2=0.98-0.99$ determination coefficients; however, the relationship was not obvious, they

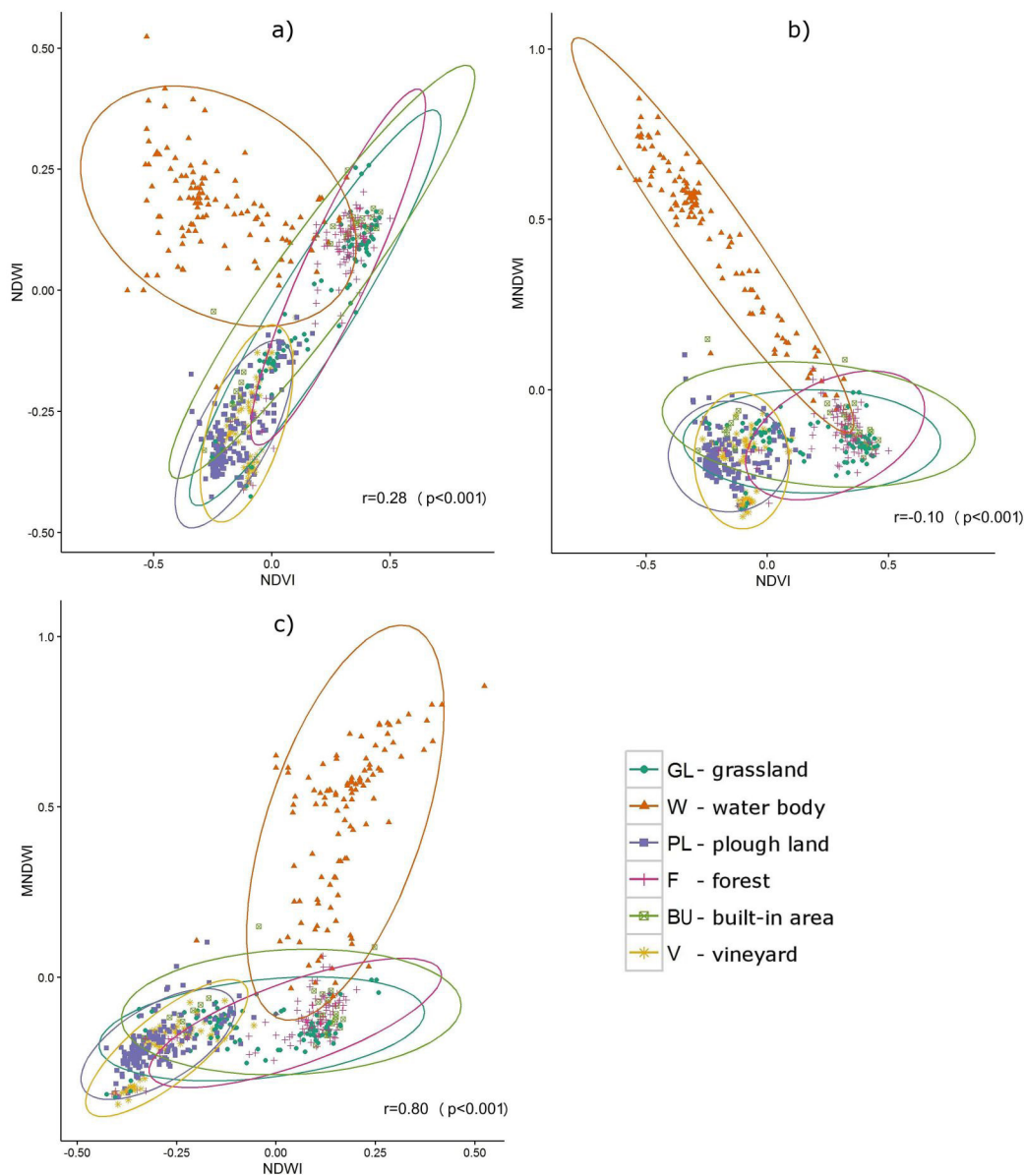


Fig. 4 Scatterplots of spectral index pairs
(a: NDVI-NDWI, b: NDVI-MNDWI, c: NDWI-MNDWI)

had to apply a threshold value with two curve fitting to reach this result. There are relevantly less experience with MNDWI, nevertheless it has favorable capability for water detection according to our results; studies found both NDVI and MNDWI useful indicators in environment monitoring (Liu et al. 2009; Bakar et al. 2016;). Xu (2007) found MNDWI (and SAVI and NDBI) effective

in mapping built-up areas related to the application of NDVI and NDWI or even to the Principal Component Analysis of the original bands of a Landsat ETM+ image. Bhatti et al. (2014) found NDVI as better predictor of vegetation than MNDWI. We agree with its result as the latter index was developed for other purpose and had good performance in the identification of water, i.e. if they not

correlate, they have unique values making them appropriate to fulfill the aims they were developed.

Although, in a statistical perspective, most of the land cover types differed from each other, e.g. NDWI's efficiency in the identification of water, saturated soil or different water content of the vegetation can lead to misclassification. Our plan is to continue this research with supervised classification of the land cover involving the spectral indices and compare their efficiency with the method based on original bands.

5. Conclusions

We revealed that spectral indices can enhance the landscape features, however, in several cases, they can have similar values for different land cover classes. In general, they are able to discriminate land cover classes but ranges have considerable overlap with other classes. In case of NDVI and NDWI grasslands and built-up areas did not differ from each other due to the rural like appearance of the settlements (e.g. Tokaj, Tarcál), and orchards and gardens biased the reflectance of artificial surfaces. MNDWI was the most efficient in enhancing water-related features, values of water bodies never mixed with other land cover types. Generally, MNDWI performed best in discriminating all land cover classes.

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