Effectiveness of DOS (Dark-Object Subtraction) method and water index techniques to map wetlands in a rapidly urbanising megacity with Landsat 8 data

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Abstract

The objectives of this work were to examine the applicability of the Dark-Object Subtraction (DOS) atmospheric correction method and water-based index techniques to map wetlands in Dhaka megacity using Landsat 8 data. With the use of both raw data and DOS-corrected imagery, the analysis revealed that DOS-corrected images performed better in discriminating wetland areas. Furthermore, the Modified Normalised Water Index (MNDWI) was the most superior technique whilst the Normalised Difference Water Index (NDWI) was the least suitable in identifying the spatial locations of wetlands in a rapidly urbanising environment such as Dhaka.

Introduction

Wetlands comprise roughly 6–9 percent of the Earth's surface (Zedler and Kercher, 2005). The role of wetlands in maintaining environmental quality is well recognised (Ozesmi and Bauer, 2002), and includes the storage of global terrestrial carbon (Mitsch and Gosselink, 2007). In addition, their influence on many aspects of ecology, economy and human welfare has been well documented (Klemas, 2011; Ma et al. 2007). Furthermore, wetlands act as an oasis in an urban area which is important in the reduction of surrounding surface air temperature (Sun and Chen, 2012). Changes in the distribution of wetlands either by natural factors or anthropogenic activities could significantly affect the ecosystem services (Barducci et al. 2009) mentioned above. Although they are an important environmental resource, they are heavily abused due to a lack of understanding (Smardon, 2009), particularly in developing countries. Accurate mapping and precise area statistics are therefore of paramount importance in the prevention and management of wetlands and related ecosystem services (Klemas, 2011).

Satellite remote sensing data have extensively been used to delineate wetlands across the world with a wide range of techniques, including a per-pixel classifier (e.g. supervised classification), semi-automated (e.g. image segmentation) method and spectral water index (e.g. normalised difference water index) (Mwita et al. 2013; Sun et al. 2012; Song et al. 2012; Jiang et al. 2012; Lu et al. 2011; Zhou et al. 2010; Islam et al. 2008; Shanmugam et al. 2006; Lira, 2006; Ouma and Tateishi, 2006). Among these techniques, water-based indices including single-band density slicing (Knight et al. 2009; Frazier and Page, 2000) techniques and band ratios comprising of two reflective bands, are found to perform better in discriminating water features such as wetlands from non-water features (Sun et al. 2012; Xu, 2006). However, deciding the optimal threshold value in isolating wetlands from the surrounding urban and land features remains an inordinate challenge (Zhang et al. 2009). In addition to single-band and band ratio techniques, new automated water-based indices such as the Automated Water Extraction Index (AWEI) has been developed and tested with several sensors in different areas however its applicability to distinguishing wetland areas within a rapidly urbanizing environments has only undergone minor testing.

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Various methods have been developed to correct atmospheric influence on remote sensing data. Whilst absolute atmospheric correction methods require in-situ information, image base techniques known as relative scattering correction, on the other hand, are handy and relatively easier to subdue scattering problem in an image. A study by Song et al. (2000) suggests that atmospheric correction of remote sensing data is always not necessary and depends on the nature of the work. However, some researchers strongly favour reducing the effects of atmospheric scattering caused by light scattering (Weng, 2012), particularly in the visible region of the electromagnetic spectrum for all studies involving remotely sensed imagery.

The Dark Object Subtraction (DOS) method is an image-based technique to cancel out the haze component caused by additive scattering from remote sensing data (Chavez Jr, 1988). This method is found to be data dependent and well accepted by the geospatial community to correct light scattering in remote sensing data (Song et al. 2000). However, the DOS method has been developed for early generation Landsat sensors (e.g. TM) and may not work effectively for the new generation data such as Landsat 8 which started delivering data from early 2013. It may be noted that band composition according to electromagnetic energy of Landsat 8 differs from its predecessor Landsat sensors (e.g. TM/ETM+), hence little is known about the effectiveness of DOS method with respect to the scattering correction of the new Landsat 8 sensor. Since this new generation Landsat is expected to deliver data consistently over the next several years, research on the application of the DOS method in analysing Landsat 8 data deserves further examination.

Dhaka megacity, the capital of the people's republic of Bangladesh, has evolved into a rapidly urbanizing mega city as it attempts to accommodate large numbers of people migrating from rural areas since the independence of the country in 1971 (Dewan and Corner, 2014). With a total population of more than 14 million people according to 2011 population and housing census, the city is facing severe environmental degradation, including the rapid decline in natural wetlands due to unplanned urban expansion and related socioeconomic development (Dewan and Yamaguchi, 2009). Studies for example, show that the rapid conversion of wetlands to urban areas aggravated flooding during the monsoon seanson(Dewan et al. 2012), thus increasing vulnerability of urban dwellers to severe floods. Although a number of studies on the mapping of wetlands in Dhaka have been conducted (Islam, 2009; Sultana et al. 2009), they all are based on a smaller study area. Moreover, none of the studies considered advanced techniques to accurately map wetlands in the megacity. Hence, this paper is expected to contribute significantly to the existing knowledge-base on the spatial locations of wetlands in the Dhaka Metropolitan Development Plan (DMDP) area which is a recently developed planning unit by the policy makers, enforcing local organisations to preserve remaining wetland ecosystems.

Considering the above facts, the objectives of the work are: (i) to understand the effect of DOS correction technique on Landsat 8 in estimating wetlands; and (ii) to analyse the suitability of water-based index in assessing the spatial locations of wetlands in a rapidly urbanising megacity.

Figure 1 Location map of the DMDP area (source: Google Earth)

Data and Image Pre-Processing

The imagery was sourced from the USGS Earth Explorer web service, with two images having a path-row of 137-43 and 137-44 required as the study area is split between them. The two images were mosaicked with the resultant image clipped to the study area. As this study examines the impact of the DOS algorithm (Chavez Jr., 1988) on Landsat 8 imagery, a copy of the raw imagery was made and underwent DOS correction. Song et al (2001) describes how the DOS algorithm assumes the existence of 'dark objects', which are pixels having zero to very small reflectance numbers, within a Landsat scene. Therefore the minimum DN (digital number) value in the histogram is considered to be the effect of atmospheric scattering and is subtracted from all pixels within the scene, thus creating ‘dark objects’ with a DN value of zero. Elexclis ENVI software was used for performing the DOS correction as it is an automated process which produces a corrected multispectral image. The two corrected images were then mosaicked and co-registered to the raw image was returning a RMSE of < 0.5 pixels which ensured that pixels from both images were positioned almost perfectly on top of each other.

Methodology

The preceding data preparation produced two images, the ‘raw’ image and DOS corrected image. Four indices were studied and compared in their ability to accurately classify wetland areas using this imagery. Once calculated, each index underwent dynamic threshold segmentation (Zhang and Wylie, 2009) in order to find the optimal water/non-water threshold value. This was then applied to produce a binary image with water areas having a value of one and all non-water areas a value of zero. A brief outline of each index applied in this study is given below:
The Normalized Difference Water Index (NDWI) was calculated using the formula proposed by McFeeters (1996):

$$\mathrm{NDWI} = \frac{\mathrm{Green\ Band} - \mathrm{NIR\ Band}}{\mathrm{Green\ Band} + \mathrm{NIR\ Band}}$$

Where, Green Band (0.52 – 0.60 µm) represents band 3 and the NIR Band (0.76 – 0.90 µm) represents band 5 for the OLI (Operational Land Imager) of Landsat 8.
The Modified Normalised Difference Water Index (MNDWI) was calculated using the formula proposed by Xu (2006):

$$\mathrm{MNDWI} = \frac{\mathrm{Green\ Band} - \mathrm{MIR\ Band}}{\mathrm{Green\ Band} + \mathrm{MIR\ Band}}$$

Where, Green Band (0.52 – 0.60 µm) represents band 3 and the MIR Band (1.55 – 1.75 µm) represents band 6 for the OLI (Operational Land Imager) of Landsat 8.
The Collective Indices classification was performed using a modified version of the formula developed by Lu et al. (2011). Firstly, the MNDWI was used in place of the NDWI as it performs better in extracting wetland areas in an urban dominated environment which was shown during the MNDWI’s development by Xu (2006). Secondly, the formula was reversed by subtracting the NDVI from the MNDWI. This was done because on the first use of the index it gave low negative values to wetland areas and moderate – high positive values to urban and vegetation dominated areas. However, by reversing the formula it was found that the values were reversed. The modified formula is:

$$\mathrm{Collective\ Indices} = \mathrm{MNDWI}\ - \mathrm{NDVI}$$

Where, NDVI is calculated using the formula first developed by Tucker (1979):

$$\mathrm{NDVI} = \frac{\mathrm{NIR\ Band} - \mathrm{Red\ Band}}{\mathrm{NIR\ Band} + \mathrm{Red\ Band}}$$

Where, the NIR Band (0.76 – 0.90 µm) represents band 5 and the Red Band (0.63 – 0.69 µm) represents band 4 for the OLI (Operational Land Imager) of Landsat 8.
The Automated Water Extraction Index (AWEI) was calculated using a modified version of the non-shadow formula developed by Feyisa et al. (2014). The original formula had band designations based on Landsat 7 which were updated to the band designations of Landsat 8. The modified formula is:

$$\mathrm{AWEI_{nsh}} = 4 \times (\ \mathrm{BAND\ 3} - \mathrm{BAND\ 6}\ ) - (\ 0.25\ \times \mathrm{BAND\ 5} + 2.75 \times \mathrm{BAND\ 7}\ )$$

Where, Band 3 (Green Band) is 0.53 – 0.59 µm, Band 5 (NIR Band) is 0.85 – 0.88 µm, Band 6 (SWIR1 Band) is 1.57 – 1.65 µm and Band 7 (SWIR2 Band) is 2.11 – 2.29 µm. The non-shadow formula was selected over the shadow formula as the study area is gently sloping to the south-east with no mountainous areas that would produce large shadows. When calculated using the raw Landsat 8 imagery, the indexes DN values ranged between -58555.5 and 60796.5, and was therefore normalized which reduced the range of DN values to between 0 and 53.3, making the thresholding process more manageable. The DOS AWEI was not required to be normalized which is most likely due to the DOS image consisting of reflectance values.
The overall accuracy, producers’ accuracy, users’ accuracy and kappa were calculated for each index based on the binary map produced using the optimal threshold. As there was no wetland based ground truth data available from the study area, the data was built in the form of 700 random points generated by ArcMap and classifying them as either water or non-water based on the raw imagery using the band combination 7,5,3 (Red, Green, Blue). This combination represented water as blue – black, urban and agricultural areas as pink and vegetation areas as shades of green. In instances, where the points lay within Dhaka’s urban centre, historical Geoeye imagery of 2010 was also used as a reference. The 1989 SPOT imagery was also used sparingly when points lay in wetland areas to the north of the study area as these areas have changed significantly throughout the last 24 years. In total 200 points were classified as water and 500 as non-water. Finally, the total wetland area was calculated by multiplying the number of pixels with the value of one from the binary map by 90 m^2, as each pixel is 30m x 30m.

Results and Discussion

The MNDWI was the best performing index with raw/DOS overall accuracies of 97.28/98% and kappa values greater than 0.9 (Table 1). It was able to effectively distinguish wetland areas within the urban centre and also in the marshy areas to the north-east in Dhaka megacity. The optimal thresholds were 0.055 for the raw image and 0.15 for the DOS image indicating that the index was correctly giving wetland area pixels positive values.

Table 1 Accuracy assessment on the indices. OA refers to overall accuracy, PA refers to producers' accuracy and UA refers to users' accuracy

		OA	PA-Wetland	PA-Other	UA-Wetland	UA-Other	Kappa
RAW	NDWI	92.7%	98.4%	71.8%	92.8%	92.2%	0.76
	MNDWI	97.3%	98.2%	94.0%	98.4%	93.3%	0.92
	COLLECTIVE	96.6%	98.4%	89.9%	97.3%	93.7%	0.90
	AWEI	94.9%	96.9%	87.3%	96.6%	88.4%	0.85
DOS	NDWI	92.9%	98.2%	73.3%	93.1%	91.7%	0.77
	MNDWI	98.0%	98.9%	94.7%	98.6%	96.0%	0.94
	COLLECTIVE	97.9%	98.7%	94.7%	98.6%	95.3%	0.94
	AWEI	96.9%	98.6%	90.7%	97.5%	94.4%	0.91

The Collective Indices method was the second best performer with raw/DOS overall accuracies of 96.57/97.86% and kappa values greater than 0.89. It was able to correctly extract majority of the marshy wetland areas however misclassified some pixels within the urban area meaning that it may be overestimating the total wetland area. The optimal thresholds were -0.055 for the raw image and -0.1 for the DOS corrected image.

The AWEI was the third best performing index with raw/DOS overall accuracies of 94.85/96.86% and kappa values greater than 0.84. It struggled to accurately extract marshy wetland areas and misclassified several urban areas as wetlands. This is because while the index gives high positive values to clear water, it appears to give marshy wetland and urban areas the same DN values which made it difficult to decide an optimal threshold value. The optimal thresholds were 36.6 for the raw image and -0.725 for the dos corrected image.

The NDWI was the worst performing index with raw/dos accuracies of 92.7/92.86% and kappa values greater than 0.7. While it effectively extracted clear water, it performed poorly in separating marshy areas of urban areas with large sections of the southern part of Dhaka misclassified. The optimal thresholds were -0.035 for the raw image and -0.075 for the dos indicating that the index is giving some wetland pixels negative values leading to misclassification.

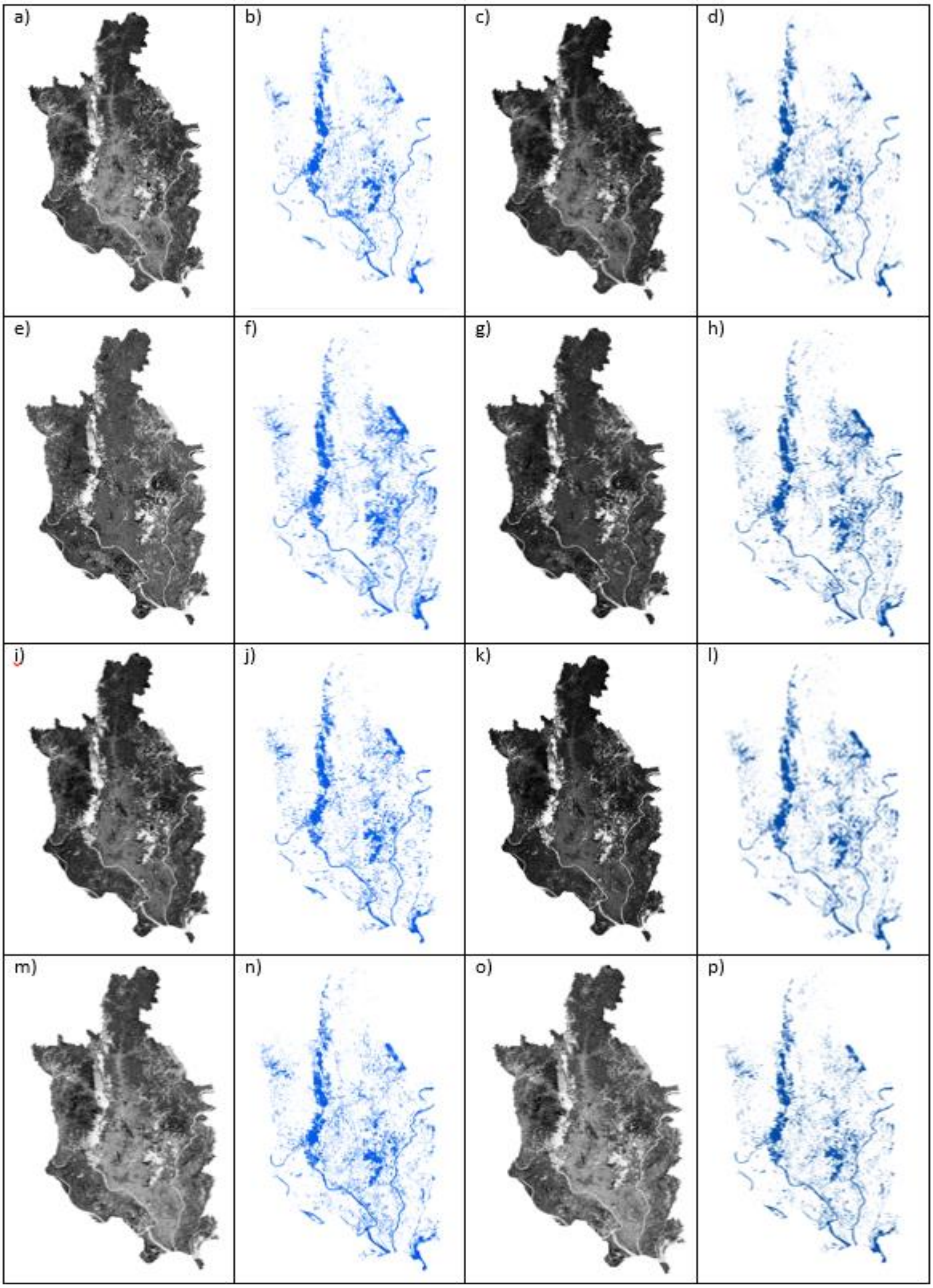

Figure 2 Spatial locations of wetlands using different band ratio techniques; (a) The NDWI produced from the raw imagery (b) Classified NDWI using the optimal threshold (c) The NDWI produced from the DOS imagery (d) Classified DOS NDWI using the optimal threshold (e) The MNDWI produced from the raw imagery (f) Classified MNDWI using the optimal threshold (g) The MNDWI produced from the DOS imagery (h) Classified DOS MNDWI using the optimal threshold (i) The Collective Indices method produced from the raw imagery (j) Classified Collective Indices method using the optimal threshold (k) The Collective Indices method produced from the DOS imagery (l) Classified DOS Collective Indices method using the optimal threshold (m) The AWEI produced from the raw imagery (n) Classified AWEI using the optimal threshold (o) The AWEI produced from the DOS imagery (p) Classified DOS Collective Indices using the optimal threshold

Area Results and Comparison Between Raw and DOS Corrected Imagery

The indices produced from the DOS images outperformed the indices run on the raw images in every single accuracy statistic (Figure 3) with the greatest difference being in the overall accuracies and kappa coefficients. The difference in the measured overall accuracy's ranged from a minor 0.16% increase seen in the NDWI, up to a significant 1.3% increase seen in the Collective Index. Despite the accuracy differences, there was only a small amount of variation in the area calculated between the raw and dos indices (Figure 4). On average, there was only a 1.54% difference in the wetland area calculated.

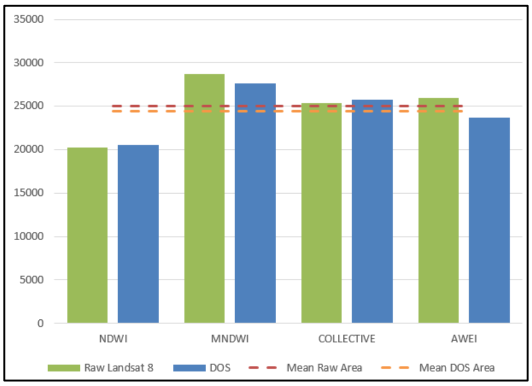

Figure 3 Calculated wetland area in hectares for each index produced from the raw (green) and DOS-corrected (blue) images. The mean calculated area is shown for the raw (red dashed) and DOS (orange dashed) imagery

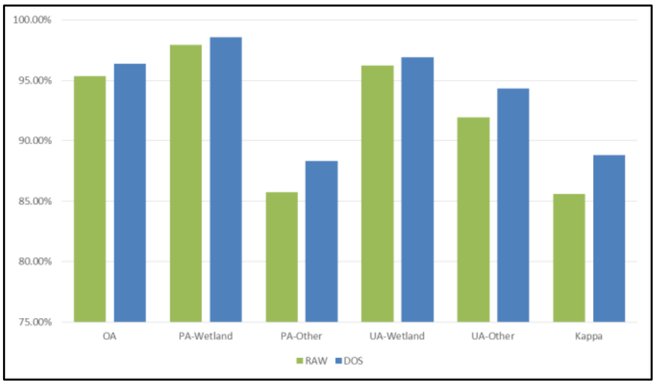

Figure 4 Mean values for area statistics produced from the raw (green) and DOS-corrected (blue) image. OA refers to overall accuracy, PA refers to producers' accuracy and UA refers to users' accuracy

As shown in Figure 2, the DOS-corrected image was consistently sharper in the contrast between wetland and non-wetland areas except for the AWEI. This suggests that maybe a pixel variance based thresholding method such as the Otsu method might be more applicable when classifying wetland areas on DOS-corrected imagery. While the raw imagery had 11 bands, the corrected DOS image produced from ENVI returned only 7, with the Panchromatic, Cirrus, TIRS 1 and TIRS 2 bands missing, however all the major bands required for classifications were included. This makes current atmospheric correction methods still applicable in wetland extraction from remotely sensed images such as from Landsat 8.

Conclusions

This study assesses the applicability of the widely-used dark-object subtraction method and water-based index techniques in assessing the locations of wetlands in the DMDP area of Bangladesh using new Landsat 8 multispectral data. The study reveals that atmospheric scattering effects should be removed prior to analysis in order to extract land cover information efficiently from Landsat 8 data. As far as water-based index approaches are concerned, the modified normalised difference water index (MNDWI) was found to be the suitable index to accurately determine the spatial locations of wetlands within the DMDP area, followed by the collective indices method. Note that the normalised difference water index (NDWI) was found to be the least suitable method in discriminating wetlands from non-water features which may have stemmed from the noisy characteristics of the urban dominated environment. A multitemporal work is currently underway to study the effectiveness of these methods between early and new generation Landsat sensors which is expected to advance the current knowledge-base.

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