

### **International Journal of Remote Sensing**



ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: https://www.tandfonline.com/loi/tres20

# Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery

#### Hanqiu Xu

**To cite this article:** Hanqiu Xu (2006) Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery, International Journal of Remote Sensing, 27:14, 3025-3033, DOI: 10.1080/01431160600589179

To link to this article: <a href="https://doi.org/10.1080/01431160600589179">https://doi.org/10.1080/01431160600589179</a>





## Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery

#### HANOIU XU

College of Environment and Resources, Fuzhou University; Key Laboratory of Data Mining and Sharing, China's Ministry of Education; Fuzhou, Fujian 350002, China

(Received 24 July 2005; in final form 22 January 2006)

The normalized difference water index (NDWI) of McFeeters (1996) was modified by substitution of a middle infrared band such as Landsat TM band 5 for the near infrared band used in the NDWI. The modified NDWI (MNDWI) can enhance open water features while efficiently suppressing and even removing built-up land noise as well as vegetation and soil noise. The enhanced water information using the NDWI is often mixed with built-up land noise and the area of extracted water is thus overestimated. Accordingly, the MNDWI is more suitable for enhancing and extracting water information for a water region with a background dominated by built-up land areas because of its advantage in reducing and even removing built-up land noise over the NDWI.

#### 1. Introduction

Remotely sensed imagery has long been used in water resources assessment and coastal management. These applications have involved the delineation of open water using thematic information extraction techniques. There are various methods for the extraction of water information from remote sensing imagery, which, according to the number of bands used, are generally divided into two categories, i.e. single-band and multi-band methods. The single-band method usually involves choosing a band from a multispectral image to extract open water information (Rundquist et al. 1987). A threshold is then determined for the band to discriminate water form land. However, the subjective selection of the threshold value may lead to an over- or under-estimation of open water area and the extracted water information is often mixed with shadow noise. The multi-band method takes advantage of reflective differences of each involved band. There are two ways to extract water information using the multi-band method. One is through analysing signature features of each ground target among different spectral bands, finding out the signature differences between water and other targets based on the analysis, and then using an if-then-else logic tree to delineate land from open water (Yu et al. 1998, Xu 2002). The other one is a band-ratio approach using two multispectral bands. One is taken from visible wavelengths and is divided by the other usually from near infrared (NIR) wavelengths. As a result, vegetation and land presences are suppressed while water features are enhanced. However, the method can suppress non-water features but not remove them, and therefore the normalized difference water index (NDWI) was proposed by McFeeters (1996) to achieve this goal. Nevertheless, the NDWI cannot efficiently suppress the signal from built-up land so that enhanced or extracted water

features are still mixed with built-up land noise. Therefore, improvement of the index is necessary and the NDWI is modified here to remedy this problem.

#### 2. NDWI and MNDWI

The NDWI is expressed as follows (McFeeters 1996):

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

where *Green* is a green band such as TM band 2, and *NIR* is a near infrared band such as TM band 4.

This index is designed to (1) maximize reflectance of water by using green wavelengths; (2) minimize the low reflectance of NIR by water features; and (3) take advantage of the high reflectance of NIR by vegetation and soil features. As a result, water features have positive values and thus are enhanced, while vegetation and soil usually have zero or negative values and therefore are suppressed (McFeeters 1996). However, the application of the NDWI in water regions with a built-up land background does not achieve its goal as expected. The extracted water information in those regions was often mixed with built-up land noise. This means that many built-up land features also have positive values in the NDWI image.

To remove the built-up land noise, its signature features need to be examined. Figure 1 depicts the spectral reflectance patterns of three land cover types, i.e. water, vegetation and built-up land, from one of the test areas of this study. The reflectance pattern of built-up land in the green band (TM 2) and NIR band (TM 4) is similar with that of water, i.e. they both reflect green light more than they reflect near infrared light. As a result, the computation of the NDWI also produces a positive value for built-up land just as for water. This is why the enhanced water presence in

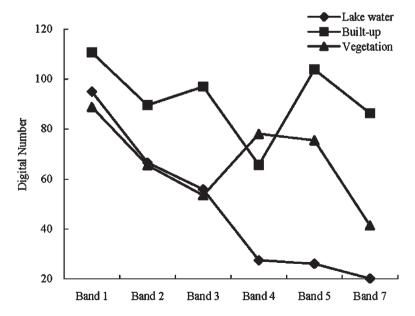


Figure 1. Spectral reflectance patterns of lake water, vegetation and built-up land in the raw Landsat image of Fuzhou City.

the NDWI-image is often mixed with built-up land noise. However, detailed examination of the signatures of the figure reveals that the average digital number of TM band 5, representing middle infrared (MIR) radiation, is much greater than that of TM band 2 (green band). Therefore, if a MIR band is used instead of the NIR band in the NDWI, the built-up land should have negative values. Based on this assumption, the NDWI is modified by substituting the MIR band for the NIR band. The modified NDWI (MNDWI) can be expressed as follows:

$$MNDWI = \frac{Green - MIR}{Green + MIR} \tag{2}$$

where MIR is a middle infrared band such as TM band 5.

The computation of the MNDWI will produce three results: (1) water will have greater positive values than in the NDWI as it absorbs more MIR light than NIR light; (2) built-up land will have negative values as mentioned above; and (3) soil and vegetation will still have negative values as soil reflects MIR light more than NIR light (Jensen 2004) and the vegetation reflects MIR light still more than green light. Consequently, compared with the NDWI, the contrast between water and built-up land of the MNDWI will be considerably enlarged owing to increasing values of water feature and decreasing values of built-up land from positive down to negative. The greater enhancement of water in the MNDWI-image will result in more accurate extraction of open water features as the built-up land, soil and vegetation all negative values and thus are notably suppressed and even removed.

It is worth to mention here that Gao (1996) also named a NDWI for remote sensing of vegetation liquid water but used a different band composite:

$$NDWI_{GAO} = \frac{NIR - MIR}{NIR + MIR} \tag{3}$$

Wilson *et al.* (2002) proposed a Normalized Difference Moisture Index (NDMI), which had an identical band composite with Gao's NDWI. Both Gao's NDWI and Wilson's NDMI are all for the detection of vegetation water liquid and thus are different from McFeeters' NDWI. For clarity and to avoid confusion between Gao's NDWI and McFeeters' NDWI, the former might be renamed as NDMI of Wilson.

#### 3. Method to validate the MNDWI

The MNDWI was tested with three major open water types, i.e. ocean, lake and river. Two Landsat images were employed to do the validation. One is a TM image, acquired on 15 June 1989, with Xiamen City inside and the other is an ETM+ scene, dated on 4 May 2000, with Fuzhou City included. The two cities are both located in Fujian Province, SE China. Three test subscenes representing the above three water types were further picked from the two images.

The three subscenes were all processed using equations (1) and (2) to produce both NDWI and MNDWI imagery. The results were quantitatively evaluated by the comparison between the MNDWI and NDWI images using the following equation:

$$C = \bar{F} - \bar{B} \tag{4}$$

where C is a contrast value,  $\bar{F}$  is the mean of a foreground target, here denoting the mean of water in the index-derived image,  $\bar{B}$  is the mean of a background target, here referring to the mean of a non-water feature in the image. In addition, once the indexes were thresholded, the results were also evaluated using the confusion

matrixes produced with pixel-by-pixel comparison between the predicted and reference images.

#### 4. Results and discussions

#### 4.1 Lake water enhancement

The Bayi Lake, also a reservoir for Fuzhou City, was selected from the ETM+ image for the test. The background of the subscene was built-up land and vegetation (figure 2(a)). The MNDWI and NDWI images of the subscene (figures 2(b-c)) both clearly show open water features as the result of enhancement. Nevertheless, visual inspection can find that the built-up lands also present in the NDWI image in a medium grey tone (figure 2(b)), suggesting having a positive brightness value. These built-up lands can be seen as noise mixed with water features. However, the built-up lands in the MNDWI image take a black tone and have a large contrast with the water features (figure 2(c)), suggesting that the noise is notably suppressed or even removed.

Table 1 lists the statistical results of the subscene. The most noticeable characteristic is that the built-up land in the NDWI image has a positive mean value (0.15). This is because it reflects more green light than NIR light, just as water does (figure 1). Therefore, its mean value in band 2 (89.61) is greater than that in band 4 (65.71), resulting in the positive mean value of the NDWI calculated using equation (1). Consequently, the contrast value between the built-up land and water is only 0.27. It is the positive mean value and low contrast with water that directly results in the presence of the built-up land in the NDWI image as noise.

However, the built-up land noise is considerably suppressed in the MNDWI image (figure 2(c)) owing to having a negative mean value of -0.08. The characteristic of higher reflectance of MIR energy by the built-up land (figure 1) results in a negative MNDWI value due to a greater band 5 value (103.89) and a smaller band 2 value (89.61). The decrease of built-up land's mean from 0.15 in NDWI image to -0.08 in MNDWI image and the increase of water' mean from 0.42 in NDWI image to 0.44 in NDWI image results in the enlargement of the contrast between them with a C value of 0.52, nearly twice as much as that in the NDWI image (0.27). The increase of the contrast leads to the considerable suppression of the built-up land noise.

A threshold value of zero was further applied to extract water features from both the NDWI and MNDWI images. The extracted water information from the MNDWI achieves an overall accuracy of 99.85% and a Kappa value of 0.9927 because no built-up land patches were mixed with enhanced water features (figure 2(e), table 2). The underestimation of the water area is only 1.29%. However, the extracted water patches from the NDWI image were mixed with many built-up land patches with positive values (figure 2(d), table 2). This results in the overestimation of the water area and a low accuracy of 77.25%. Manual adjustment of the threshold value to 0.243 can achieve the best overall accuracy and Kappa value for the NDWI image but causes an underestimation of 21% of the water area (table 2).

#### 4.2 Sea water enhancement

Coastal area around Xiamen City from the Landsat image was chosen for the test (figure 2(f)). The ocean areas are highlighted in the NDWI and MNDWI images

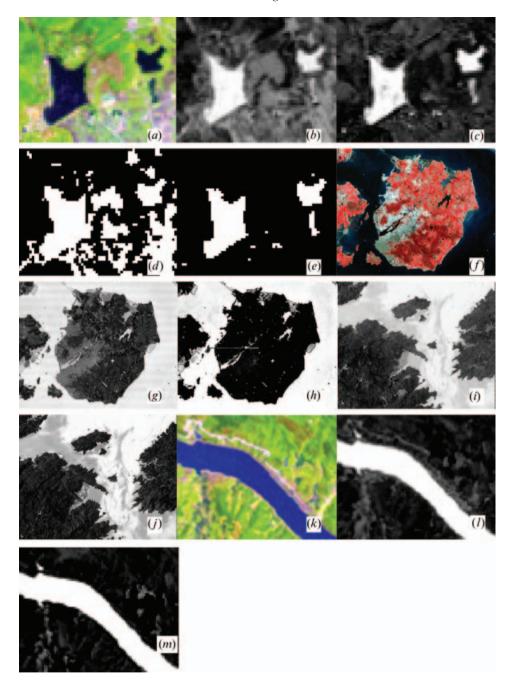


Figure 2. Various NDWI and MNDWI images. (a) Bayi Lake image (RGB:541); (b) NDWI image of the lake; (c) MNDWI image of the lake; (d) extracted water bodies from NDWI image; (e) extracted water bodies from MNDWI image; (f) Xiamen City image (RGB:432); (g) NDWI image of the city; (h) MNDWI image of the city; (i) NDWI image of outlet of Luoyuan Bay; (j) MNDWI image of the bay. (k) image of a middle-portion of Min River (RGB:541); (l) NDWI image of the river; m) MNDWI image of the river.

| Toble 1  | Moon and Cyalua  | a of these maior land | l agreem trimag of the three | tost subscense  |
|----------|------------------|-----------------------|------------------------------|-----------------|
| rable 1. | Mean and C value | s of three major land | l cover types of the three   | test subscenes. |

|                  | Band 2           | Band 4 | Band 5 | NDWI  | MNDWI |
|------------------|------------------|--------|--------|-------|-------|
| Bayi Lake        |                  |        |        |       |       |
| Lake water       | 66.57            | 27.47  | 26.09  | 0.42  | 0.44  |
| Built-up land    | 89.61            | 65.71  | 103.89 | 0.15  | -0.08 |
| Vegetation       | 65.53            | 78.13  | 75.51  | -0.09 | -0.07 |
| C (lake water v  | s. built-up land | d)     |        | 0.27  | 0.52  |
| C (lake water v  | s. vegetation)   |        |        | 0.51  | 0.51  |
| Xiamen           |                  |        |        |       |       |
| Sea water        | 26.95            | 6.65   | 2.44   | 0.60  | 0.75  |
| Built-up land    | 58.97            | 51.80  | 99.47  | 0.06  | -0.21 |
| Vegetation       | 28.17            | 87.20  | 58.44  | -0.51 | -0.47 |
| C (sea water vs. | built-up land    | )      |        | 0.54  | 0.96  |
| C (sea water vs. | vegetation)      |        |        | 1.11  | 1.11  |
| Min River        |                  |        |        |       |       |
| River water      | 80.22            | 20.34  | 16.26  | 0.60  | 0.66  |
| Built-up land    | 69.78            | 60.00  | 69.95  | 0.08  | 0.00  |
| Vegetation       | 61.56            | 89.32  | 79.05  | -0.18 | -0.12 |
| C (river water v | s. built-up lan  | d)     |        | 0.52  | 0.66  |
| C (river water v | s. vegetation)   | •      |        | 0.78  | 0.78  |

(figures 2(g-h)). Again, many built-up land areas in a grey tone are present as noise in the NDWI image, especially in western island (figure 2(g)). However, the noise was largely reduced in the MNDWI image (figure 2(h)). This is due largely to the decreases of mean value of built-up land from a positive value in the NDWI image down to a negative value in the MNDWI image along with the increase of mean value of water in the MNDWI image (table 1). This obviously leads to a large increase in contrast between water and built-up land. A threshold value of 0.09 can achieve the best water extraction result for the MNDWI image, with 0.43% of overestimation of water area. The best extraction result was achieved for the NDWI image with a threshold of 0.337 but with much more confusion between water and non-water classes, compared with the MNDWI image (table 2).

#### 4.3 River water enhancement

A middle portion of the Min River selected from the Landsat ETM + image was used for the validation (figure 2(k)). The background of the subscene is dominated by vegetation with rare built-up land areas. Therefore, visual inspection found no major difference between the MNDWI and NDWI images except a small road still visible in the NDWI image due to having positive values (figure 2(l)). However, the confusion matrix in table 2 still reveals a better extraction result of the MNDWI over the NDWI.

McFeeters (1996) pointed out that the NDWI could be used for detecting water turbidity. This study has also confirmed this but found the MNDWI revealed the water turbidity more clearly, which is very useful in the detection of subtle variation of water. Figures 2(i) and 2(j) are the NDWI and MNDWI images revealing a turbid water body in the Luoyuan Bay from the Landsat ETM+ image. However, the MNDWI image shows more details than the NDWI image. In addition, the MNDWI image of the Bayi Lake also shows some subtle water features in the centre of the lake, but this is not seen in the NDWI image. The following three reasons may help to interpret this phenomenon: (1) the MNDWI has a larger standard deviation

Table 2. Confusion matrixes of three subscenes.

|                  | MNDWI          |             |                |           |                 |        |           |               |        |
|------------------|----------------|-------------|----------------|-----------|-----------------|--------|-----------|---------------|--------|
|                  | Non-water      | Water       | Total          | Non-water | Water           | Total  | Non-water | Water         | Total  |
| Bayi Reservoir   |                | Threshold=0 |                |           | Threshold=0     |        | T         | hreshold=0.24 | .3     |
| Non-water        | 2925           | 5           | 2930           | 2171      | 0               | 2171   | 2916      | 81            | 2997   |
| Water            | 0              | 385         | 385            | 754       | 390             | 1144   | 9         | 309           | 318    |
| Total            | 2925           | 390         | 3315           | 2925      | 390             | 3315   | 2925      | 390           | 3315   |
| Overall accuracy | 99.85          |             |                | 77.25     |                 |        | 97.30     |               |        |
| Kappa            | 0.9927         |             |                | 0.4040    |                 |        | 0.8579    |               |        |
| Xiamen           | Threshold=0.09 |             | Threshold=0.09 |           | Threshold=0.337 |        |           |               |        |
| Non-water        | 151518         | 0           | 151518         | 107082    | 0               | 107082 | 149555    | 4522          | 152077 |
| Water            | 639            | 147573      | 148212         | 45075     | 147573          | 192648 | 2602      | 143051        | 147653 |
| Total            | 152157         | 147573      | 299730         | 152157    | 147573          | 299730 | 152157    | 147573        | 299730 |
| Overall accuracy | 99.79          |             |                | 84.96     |                 |        | 97.62     |               |        |
| Kappa            | 0.9957         |             |                | 0.7005    |                 |        | 0.9524    |               |        |
| Min River        | Threshold=0.07 |             | Threshold=0.07 |           | Threshold=0.19  |        |           |               |        |
| Non-water        | 19901          | 10          | 19911          | 19067     | 515             | 19582  | 19812     | 855           | 20667  |
| Water            | 8              | 6250        | 6258           | 842       | 5745            | 6587   | 97        | 5405          | 5502   |
| Total            | 19909          | 6260        | 26169          | 19909     | 6260            | 26169  | 19909     | 6260          | 26169  |
| Overall accuracy | 99.93          |             |                | 94.81     |                 |        | 96.36     |               |        |
| Kappa            | 0.9981         |             |                | 0.8600    |                 |        | 0.8957    |               |        |

|                    | NDWI   | MNDWI  |
|--------------------|--------|--------|
| minimum            | 0.00   | 0.00   |
| maximum            | 255.00 | 255.00 |
| mean               | 123.16 | 151.33 |
| standard deviation | 71.61  | 77.32  |

Table 3. Statistics of NDWI, and MNDWI images of the Luoyuan Bay subscene.

Note that both NDWI and MNDWI images have been rescaled within 0-255.

and thus contains more information (table 3); (2) water's greater mean MNDWI value and stronger contrast with background targets (table 1) will allow it to be enhanced more efficiently and more details of water to be revealed; and (3) as shown in figure 3, the spectral response of water is more sensitive in MIR than in NIR. This would be helpful for showing more subtle water features in the MNDWI image computed using MIR.

In addition, owing to the normalization algorithm, the MNDWI can reduce shadow noise without using sophisticated procedures (figure 2), which is otherwise difficult to be removed.

#### 5. Conclusions

The modification of the NDWI using a MIR band instead of a NIR band can considerably improve the enhancement of open water features. It can quickly and accurately discriminate water from non-water features. The MNDWI is more suitable for enhancement of water with many built-up land areas in the background than the NDWI because it can efficiently reduce and even remove built-up land noise. The threshold values for the MNDWI to achieve best water extraction result are usually much less than those of the NDWI, suggesting using zero as a default threshold value can produce better water extraction accuracy for the MNDWI than for the NDWI. This would be very useful for the MNDWI to be automated. Furthermore, the MNDWI can reveal more detail of the open water than the NDWI. This is useful for the detection of subtle differences in water quality.

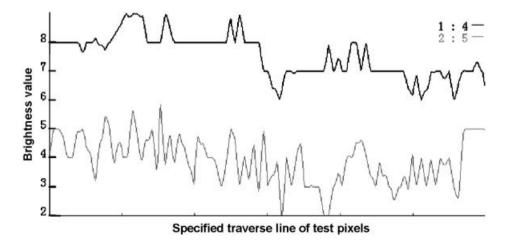


Figure 3. Spectral responses of water in NIR wavelengths (ETM + band 4, upper curve) and MIR wavelengths (ETM + band 5, lower curve).

#### Acknowledgement

This study was supported by the National Natural Science Foundation of China (40371107).

#### References

- GAO, B.C., 1996, (NDWI—a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, **58**, pp. 257–266.
- JENSEN, J.R., 2004, *Introductory digital image processing: A remote sensing perspective*, 3rd edition (NJ: Prentice Hall Logicon Geodynamics, Inc).
- McFeeters, S.K., 1996, The use of normalized difference water index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, **17**, pp. 1425–1432.
- RUNDQUIST, D., LAWSON, M., QUEEN, L. and CERVENY, R., 1987, The Relationship between the Timing of Summer-Season Rainfall Events and Lake-Surface Area. *Water Resources Bulletin*, **23**, pp. 493–508.
- WILSON, E.H. and SADER, S.A., 2002, Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*, **80**, pp. 385–396.
- Xu, Hanqiu, 2002, Spatial expansion of urban/town in Fuqing of China and its driving force analysis. *Remote Sensing Technology and Application*, **17**, pp. 86–92 [in Chinese].
- Yu, J., Huang, Y. and Feng, X., 2001, Study on water bodies extraction and classification from SPOT image. *Journal of Remote Sensing*, **5**, pp. 214–219 [in Chinese].