An effective modified water extraction method for Landsat-8 OLI imagery of mountainous plateau regions

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Abstract. Water body extraction from remote sensing imagery is an efficient way to investigate and monitor water resources. In the study area of this research, a mountainous plateau near Kashgar, China, sparse vegetation and seasonal rivers affect water body extraction. In order to extract water bodies, a modified water body extraction method is proposed in this paper and tested using Landsat-8 OLI imagery. Following this method, binary images are first generated using a classification, a Tasseled Cap transform, and a normalized difference water index, respectively, and then combined to yield a mask. Next, water bodies are delineated by masking the Landsat-8 OLI imagery and then refined by eliminating false areas using a supervised classification. It is demonstrated from the resulting water body maps that terrain related shadows in imagery were effectively eliminated and river tributaries and artificial ditches were precisely delineated, with accuracy up to 94%. Compared with several current water body extraction methods, the modified method yielded water body maps with better visualization and slightly improved accuracy.

1. Introduction
Monitoring water resources in general by using remote sensing data has been widely applied in last 30 years. With the ability of short period access and wide detection range, remote sensing technology is able to acquire water body information rapidly, repeatedly and accurately for monitoring surface water resources[1]. In optical remote sensing, there are mainly two categories of methods to extract water bodies: single band threshold and multi-band threshold[2].

Single band threshold methods determine the threshold according to reflectivity differences between water bodies and other surface features in order to extract water body information while filtering others. When using multi-band Landsat OLI imagery as a data source, OLI 5 near-infrared or OLI 6 mid-infrared bands are normally selected. Water has strong absorption in the near-infrared and mid-infrared spectral ranges, whereas vegetation and soil have strong reflection. Based on these characteristics, the most suitable threshold can be determined. However, such methods fail in mountainous areas, where terrain shadow effects are difficult to eliminate and small water bodies might be ignored during the information extraction process.

Multi-band threshold methods are widely used in water body extraction. These methods extract water bodies based on comprehensive consideration of each band, such as the Multi-band Spectral Relationship method, Normalized Difference Water Index (NDWI), and Tasseled Cap transformation. McFeeters [3] suggested that NDWI can improve the accuracy of water body extraction by suppressing non-water information. The Modified Normalized Difference Water Index (MNDWI)
method was proposed by Xu [4] in 2005 and achieved better results in urban areas. Yang [2] found that water bodies have a unique feature (TM2 + TM3) > (TM4 + TM5) in TM images. Ouma [5] proposed that the wetness component (TCW) of Tasseled Cap transformation can indicate water bodies. However, these methods have limitations with regard to shadow elimination and small water body extraction.

In order to accurately extract water bodies in mountainous areas, a modified water body extraction method combining several current methods based on Landsat-8 OLI Imagery is proposed in this study. It is demonstrated that this method can effectively eliminate mountain shadow and extract small water bodies, such as tributaries and artificial canals.

2. Study area and test data
Located in near the city of Kashgar, Xinjiang Uygur Autonomous Region, China, the study area (37°47’40”-38°15’40”N, 76°20’57”-77°12’39”W) including a mountainous area (A) and a relatively flat plateau area (B), were selected (figure 1). Water supplies of the two areas are mainly glacial water from rivers, most of which are seasonal. The rivers have fine and dense tributaries. Water consumption in the region has increased with the economic development of Kashgar, and artificial canals have been an essential part of the distribution of water resources in the downstream areas.

Drainage channels within the two areas in figure 1 are part of the Yarkant River system. The first area (A) reveals complicated geological structures and strong topographic relief at an altitude of more than 2000 m on average. The second area (B), further downstream, is part of the Yarkant River alluvial plain at an average altitude of more than 1000 m, with a dense network of channels, an elaborate artificial canal system, and irrigated farmland.

A Landsat-8 OLI image with processing level 1T of the study areas, acquired on September 19, 2014 has been geometrically corrected with reference to topography. This image contains eight multispectral bands with a spatial resolution of 30m and one 15-m panchromatic band. The radiometric resolution is 16 bits, which is an improvement over preceding Landsat sensors. The improvement of radiometric resolution can effectively avoid grayscale over-saturation in extreme dark region and facilitate discriminating subtle features of water bodies with extremely low reflectivity.

Figure 1. Image map indicating the location of study areas A and B on the Yarkant River in western China (Source of imagery: USGS)
3. Method
By analysing and discerning spectral features, water body extraction can distinguish water and non-water information by different algorithms [6], using the separation degree and extraction accuracy as main evaluation criteria. In the visible part of the spectrum, the albedo of water bodies is lower than 10%; it diminishes gradually with the increase of wavelength. The reflection of water primarily concentrates in the blue and green bands (0.45-0.52μm, 0.52-0.60μm) and has low values in other bands, especially near-infrared band, where light is almost entirely absorbed by water. Therefore, rivers and land display differently in remote sensing imagery, as indicated in figure 2.

3.1 Multi-band Spectral Relationship method
According to the analysis of the spectral curves, water has a unique feature in that the sum of Digital Numbers (DNs) of the green band and red band is greater than near-infrared (NIR) band and middle-infrared (MIR) band. On this basis, Chen et al. [7] proposed to extract the water information by the model: (Green+Red)-(NIR+MIR) > T, where T is a threshold to extract water bodies while suppressing non-water information. Experimental results indicate that this method has the ability to extract more water body related information, but it also mistakenly extracts some small shadow, which presents a limitation for the extraction of small water bodies.

3.2 Normalized difference water index
The Normalized Difference Water Index (NDWI) method is a common approach to detect water bodies. Its formula is as follows:

\[ NDWI = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \]

As a ratio combining two different bands, the NDWI index enhances water spectral signals by contrasting the reflectance between different wavelengths and removing a large portion of noise components in different wavelength regions [8]. With the increase of wavelength, water has a lower reflectance. In the NIR range, water has a strong absorption capacity, unlike vegetation. Therefore, NDWI can effectively distinguish water and vegetation and extract water bodies. Conversely, some small water bodies remain unclassified in this study, showing up as discontinuous water channels.
Figure 3. Illustration of different methodological results in area A (top, ~15 km x 10 km) and area B (bottom, ~20 km x 15 km), showing (a) OLI false composite (bands 5, 6, and 4 in red, green, and blue channels, respectively); (b) binary map of multi-band spectral relationships; (c) binary map using NDWI; and (d) binary map using TCW. (Source of Landsat-8 OLI image: USGS)
3.3 TCW method
The Tasseled Cap transform turns original, highly covariant data into three uncorrelated indices called brightness, greenness, and wetness. The three components capture 98 per cent of the information within the original bands. The wetness component (TCW) can characterize the outline of wet regions effectively so that rivers can be extracted integrally. However, this index fails to suppress mountain shadow and wetland areas. Hence TCW is not a satisfactory approach for final water body mapping.

3.4 The New Modified method
Image classification typically divides pixels into different classes according to their spectral brightness, spatial structure, and other information in diverse wavelengths by rules or algorithms[9]. Therefore, the mechanism of inaccurate extraction between classification and the current methods above is dissimilar, which may lead to inconsistent surface feature extraction. Consequently, it is efficient to remove non-water features from their binary maps. The procedure is shown in figure 4.

![Figure 4. Processing flow chart of the modified method.](image)

The classification method proposed in this study consists of four steps: (i) K-means classification, which performs an unsupervised classification of the study area and extracts initial water information; (ii) refinement (clipping), which uses the results of the K-means classification as the mask, clips the raw image to eliminate most non-water information; (iii) likelihood classification, which performs the supervised classification to the clipped image and extracts the water information precisely from the classification results; and (iv) image binarization of the extraction result, designated as B1. Images from the process of classification are shown in figure 5.

On the other hand, the raw imagery is disposed with the NDWI and TCW method. The optimal threshold of NDWI and the upper limit threshold of TCW are determined through visual interpretation and the enhanced spectral histogram. The corresponding binary images were designated as B2 and B3. Finally, three binary images are produced using the operation \((B_2 \cup B_3) \cap B_1\).

The above analyses have shown that NDWI is good at eliminating the mountain shadow but weak in extracting small water body, while TCW can extract more complete water body but so do the shadow (figure 3). The result from a series of classifications reveals moderate shadow control and complete water information. The calculation is based on the water information from the classification, with the addition of the results from the previous methods; it combines the advantages of the three methods while suppressing their disadvantages, obtaining improved water extraction results.

4. Results and evaluation
Compared with several current water information extraction methods, the modified method yielded water information maps with better visualization and improved accuracy, as shown in Figure 6. Terrain shadow effects are largely excluded, while tributaries and artificial canals for local irrigation schemes have been precisely delineated. The extraction of non-water information using the modified method is an improvement over the TCW method and the classification. The outlines of the river tributaries and artificial canal network are more continuous and inclusive than the NDWI method.
Figure 5. Image processing and classification results for study area A (~15 km x 10 km): (a) K-means classification; (b) Mask of water; (c) Likelihood classification; (d) Binary image (B$_1$).

Figure 6. Binary images of the modified method for study area A (left, ~15 km x 10 km) and study area B (right, ~ 20 km x 15 km).
Table 1. Accuracy evaluation of three water extraction methods.

| Methods    | Real point | Truth point | False point | Relative accuracy /% |
|------------|------------|-------------|-------------|-----------------------|
| NDWI       | 550        | 504         | 46          | 91.63                 |
| TCW        | 550        | 492         | 58          | 89.45                 |
| Modified method | 550      | 518         | 32          | 94.18                 |

Referring to 1:25,000 vector maps and very high-resolution imagery of Google Earth, this study randomly selected 550 sample points for “water” by means of visual interpretation to evaluate the results of the three methods above. The modified method improved classification accuracy by 3.64% on average (table 1) over the TCW and NDWI methods.

5. Discussions and conclusion
In view of the inaccurate extraction of mountain shadow and missed extraction of small river segments, this study has introduced a high precision automatic water body extraction model, modifying previously proven automatic water extraction methods. Landsat-8 OLI images are validated with this modified method; water bodies associated with artificial irrigation canals within the alluvial plain of the Yarkant River and the river tributaries originating from the Karakoram Mountains have been extracted successfully. In practice, the advantages of each water body extraction method are utilized effectively in combination, and the accuracy of extraction results is better than the result from the individual method. In addition, the main water body information is obtained by the modified classification method without the artificial selection of thresholds. Limitations of the modified method are associated with fact that it relies only on spectral feature analysis; terrain shadows with spectral characteristics extremely similar to those of water cannot be eliminated completely. In addition, the inherent spatial resolution of the Landsat-8 OLI imagery prevents detection and extraction of very small water bodies.

6. References
[1] Du Y and Zhou C 1998 Automatically extraction remote sensing information for water bodies. *J of Remote Sensing* 2 264-269.
[2] Yang, C and Xu M 1998 Study on the water-body extraction methods of remote sensing information mechanism. *Geographic Research* 17 86-89
[3] 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* 17 1425 1432.
[4] Pasolli E, Melgani F, Tuia D, Pacifici F and Emery W J 2014 SVM active learning approach for image classification using spatial information *IEEE Trans. Geosc. Remote Sens.* 52 2217-2233
[5] Xu, H Q 2006 Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing* 27 3025-3033.
[6] Liu J and Dai C 1996 The application of TM image in large reservoir storehouse sentiment monitors management application. *Remote Sensing of Environment* 11 53-58.
[7] Chen F, Wang J and Chen Z 2004 Comparison of water extraction methods in mountainous plateau region from TM image. *Remote Sensing Technology and Application* 19 479-484.
[8] Gao B C 1996 NDWI - a Normalized Difference Water Index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58 257 266.
[9] Du J K, Huang Y S, Fenx X and WANG Z L 2001 Study on water bodies extraction and classification from SPOT image *Journal of Remote Sensing* 5 (3) 214-219, 2001.

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