MODIFIED OPTIMIZATION WATER INDEX (MOWI) FOR LANDSAT-8 OLI/TIRS

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ABSTRACT:

Water is one of the most important resources that essential need for human life. Due to population growth and increasing need of human to water, proper management of water resources will be one of the serious challenges of next decades. Remote sensing data is the best way to the management of water resources due time and cost effectiveness over a greater range of temporal and spatial scales. Between many kinds of satellite data, from SAR to optic or from high resolution to low resolution, Landsat imagery is more interesting data for water detection and management of earth surface water. Landsat8 OLI/TIRS is the newest version of Landsat satellite series. In this paper, we investigated the full spectral potential of Landsat8 for water detection. It is developed many kinds of methods for this purpose that index based methods have some advantages than other methods. Pervious indices just use a limited number of spectral band. In this paper, Modified Optimization Water Index (MOWI) defined by consideration of a linear combination of bands that each coefficient of bands calculated by particle swarm algorithm. The result shows that modified optimization water index (MOWI) has a proper performance on different condition like cloud, cloud shadow and mountain shadow.

1. INTRODUCTION

Water is one of most important earth resources that about 71 percent of the Earth's surface is covered by water (Williams 2014). Rapid population increase and unplanned urbanization leading to decrease of water bodies. Monitoring and proper management of water resources such rivers, lakes as natural reservoirs and dams as a man-made reservoir are essential to human health, society, agriculture, global carbon cycle and climate variations (Brezonik, Menken et al. 2005, Prasad, Rajan et al. 2009). Remote sensing data has been widely used for water detection in last 3 decades rather than ground-based methods with the advent and development of remote sensing sensors and methods due to a time and cost effectiveness over a greater range of temporal and spatial scales (Wang, Ruan et al. 2011). Therefore, water detection is an interesting field of experts and researchers of remote sensing and photogrammetry.

Landsat imagery is one of the most wildly used remote sensing data that applied in most previous studies for water body detection or water change detection. The Landsat series of satellites have many sensor and generation. Multispectral Scanner System (MSS) for landsat-1 to landsat-3 (1972-1983), Thematic Mapper (TM) for landsat-4 to landsat-5 (1982-2012) and Enhanced Thematic Mapper Plus (ETM+) for landsat-7 (1999-now) have been used for many application especially water index and water body detection (McFeeters 1996, Xu 2006). The newest generation of Landsat series of satellites is landsat-8 that lunched on 2013. Operational Land Imager (OLI) sensor of landsat-8 has 12-bit pixel value rather than the 8-bit pixel value of ETM+ images that lead to higher quality and improve three times better signal to noise ratio (SNR) than ETM+ (Irons, Dwyer et al. 2012).

There are many kinds of algorithm have been adopted for water detection especially on Landsat data that categorized into four main groups: 1- classification and pattern recognition methods that include supervised (Tulbure and Broich 2013) and unsupervised methods (Ko, Kim et al. 2015), 2- spectral unmixing (Sethre, Rundquist et al. 2005), 3- single-band thresholding (Klein, Dietz et al. 2014), 4- the spectral water index (Ji, Zhang et al. 2009). Classification methods have a better performance than thresholding methods. If images consist of complex topologies such as mountain shadows, roads, and urban areas, high false classification rate may be achieved in water body detection process (Ko, Kim et al. 2015). Also, classification methods are highly dependent on human and have some difficulty (Ouma and Tateishi. 2006). Index-based methods can detect water body more accurately, quickly and easily than classification methods and does not need any prior knowledge (Li, Du et al. 2013), especially on low-resolution images and single-class (water) study.

There are many kinds of water indices in past studies. One of popular water index is the normalized difference water index (NDWI) (McFeeters 1996). The other one is the modified NDWI (Xu 2006) that introduced to overcome the inseparability of built up areas in NDWI. Automated water extraction index (AWEI) introduced for better result achieving in an area by shadow and dark surface on Landsat TM. AWEInsh and AWEIsh are used for an area by urban background and area by shadow respectively (Feyisa, Meilby et

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al. 2014).Water Ratio Index (WRI) is another widely used water index (Shen and Li 2010).

Amare Sisay (2016), used NDWI for MSS image data due lacks mid-infrared band (MIR) and AWEI for TM, ETM+, and OLI_TIRS for change detection of central rift valley region of Ethiopia (Sisay 2016). DU et al. (2014), tested three NDWI models include $NDWI_{O5,3}$, $NDWI_{O6,3}$, $NDWI_{O7,3}$ based on reflectance value that result show the better accuracy of $NDWI_{O6,3}$ than two other models (Du, Li et al. 2014). Liu et al. (2016), indicated that $NDWI_{3,5}$ and $NDWI_{5,6}$ have better performance by reflectance images whereas $NDWI_{3,6}$ has better performance by DN value images (Liu, Yao et al. 2016). Blackmore (2016), showed the effectiveness of NDWI and MNDWI for open water and surface moisture detection. Also, results of this study indicated that NDWI is more sensitive to an area with vegetation (Blackmore 2016). Xie et al. (2016), studied about clear water, turbid water, and eutrophic water. The results indicated that AWEIsh, $NDWI_{4,7}$ and $NDWI_{3,7}$ with accuracies of 98.55%, 95.50%, and 96.61% have the highest accuracy to clear water, turbid water, and eutrophic water, respectively (Xie, Luo et al. 2016).

It should be noted that all of the above mentioned spectral indices only use a limited number of bands that may lead to the poor result for pixels that contaminated by ice, snow or cloud. In this paper, a modified optimization water index (MOWI) is proposed to use the full spectral potential of landsat-8 OLI/TIRS as the newest generation of Landsat series of satellites in water detection and reduce shadow effects, cloud effects and other disturbing factors. The proposed method can be considered as classification method or index-base method that we have an index-based view in this paper.

2. WATER INDICES

In this section, an overview of the water indices is presented. By considering high reflectance of green band and low reflectance of near infrared band for water, normalized difference water index (NDWI) defined as bellow (McFeeters 1996):

$$NDWI = \frac{b_{green} - b_{nir}}{b_{green} + b_{nir}} \qquad (1)$$

Modified normalized difference water index (MNDWI) is achieved with replacing infrared by shortwave infrared that its wavelength is [1.57-1.65] micrometers (SWIR1). MNDWI defined as bellow (Ji, Geng et al. 2015):

$$MNDWI = \frac{b_{green} - b_{swir1}}{b_{green} + b_{swir1}} \qquad (2)$$

Automated water extraction index (AWEI) use four bands unlike two bands of NDWI and MNDWI. This index defined as bellow (Ji, Geng et al. 2015):

$$\begin{aligned} AWEI_{nsh} &= 4\times(b_{green} - b_{swir1}) - (0.25\times b_{nir} + 2.75\times b_{swir2}) \\ AWEI_{sh} &= b_{blue} + 0.25\times b_{green} - 1.5\times(b_{nir} + b_{swir1}) - 0.25\times b_{swir2} \end{aligned} \qquad (3)$$

Water ratio index is another water index that defined as bellow (Rokni, Ahmad et al. 2014, Sisay 2016):

$$WRI = \frac{b_{green} + b_{red}}{b_{nir} + b_{mir}} \qquad (4)$$

3. THE PROPOSED METHOD

All of the previous indices calculated by the commentary of spectral curvature but in this paper, another approach has been adopted that use combination of bands for water detection under a linear combination of bands. The coefficient of each band is determined by the optimization algorithm. This linear combination defined as bellow:

$$MOWI = \sum_{i=1}^{N} a_i \times b_i \qquad (5)$$

N : number of bands
a_i : coefficient of band i, $a_i \in [-10,10]$
b_i : band i

Proposed method can be adopted at two strategies:

1- Classification-based: in this strategy, coefficients calculated by some test and some terrain pixel. Then water body or surface can be detected by applying these coefficients. These coefficients are proper just for this image.

2- Index-based: in this strategy, coefficients calculated on one image by test and obtained water index. Then we can apply this index to other images.

In this study, the index-based strategy has been used for water detection that used all bands instead of using a limited number of bands. The flowchart of the proposed method is presented in Figure 1.

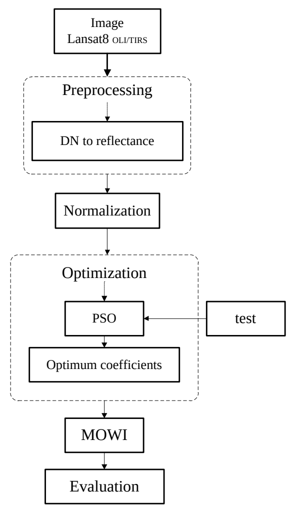


Figure 1. Schema of the proposed method

3.1 Study area and Data source

Landsat-8 is the newest generation of Landsat series of satellites that is the most interesting source for water detection studies. In order to reach the final aim of this study, four Landsat 8 OLI/TIRS images were collected from the US Geological Survey (USGS) Global Visualization Viewer (collection 1 level-1). All of these four case studies are in Iran and includes Zarivar Lake, Kazemi Dam, Gotvand Dam and Karun-1 Dam. These images have a different condition like cloud and shadow that are disturbing factor for water detection. In this paper, we wanted to use all potential of spectral space for water index definition. So, 10 bands of landsat-8 had been used to determined water index. Table 1 presents the specifications of Landsat 8 OLI/TIRS images (Rokni, Ahmad et al. 2014, Sisay 2016).

Table 1. Landsat-8 bands information

Wavelength (μm)	Band	This paper
Band 1: 0.43 - 0.45	Coastal aerosol	b1
Band 2: 0.45 - 0.51	Blue	b2
Band 3: 0.53 - 0.59	Green	b3
Band 4: 0.64 - 0.67	Red	b4
Band 5: 0.85 - 0.88	Near IR	b5
Band 6: 1.57 - 1.65	SWIR 1	b6
Band 7: 2.11 - 2.29	SWIR 2 (MIR)	b7
Band 8: 0.50 - 0.68	Panchromatic	-
Band 9: 1.36 - 1.38	Cirrus	b10
Band 10:10.60 - 11.19	Thermal Infrared (TIRS) 1	b8
Band 11: 11.50 - 12.51	Thermal Infrared (TIRS) 2	b9

3.2 Preprocessing

Preprocessing is one of the most important steps for each photogrammetry and remote sensing analysis. In this paper, the original DN values had to be converted into radiance and then into reflectance.

3.3 Normalization

Reflectance values normalized between [0, 1] by equation 6.

$$Nb_i = \frac{b_i - \min(\min(b_i))}{\max(\max(b_i)) - \min(\min(b_i))} \tag{6}$$

3.4 Optimization

Particle swarm optimization (PSO) is a population based metaheuristic algorithm that has a simple programming, high run speed and high convergence rate that proposed in 1995 by Kennedy and Eberhart (Eberhart and Kennedy 1995). Here, PSO is used to find optimum coefficients for each band for have a proper water index. The overall accuracy is considered as objective function and variables (coefficients) domain is considered in [-10, 10]. The coefficients of the index (modified optimization water index (MOWI)) are calculated on Karun-1 Dam due to having water, shadow, and cloud.

3.5 Evaluation

After calculated coefficients and modified optimization water index on Karun-1 Dam, MOWI evaluated on three other case studies by the recall, Precision (P), f-score, overall accuracy (OA) and kappa coefficient (K).

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

Coefficients of each band that calculated by particle swarm optimization are as bellow.

Table 2. Optimized coefficients of each band

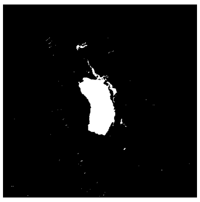
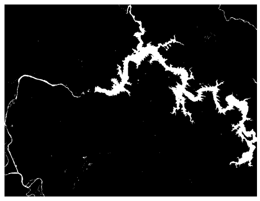
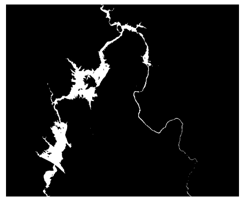
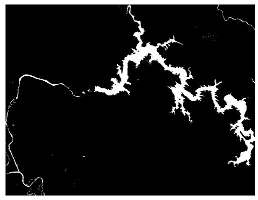
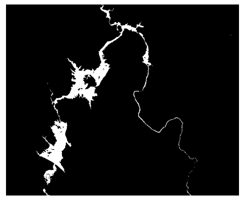
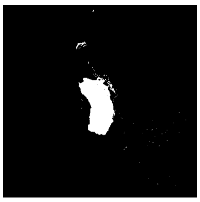
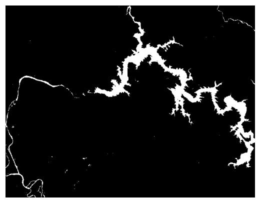
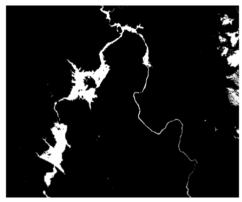
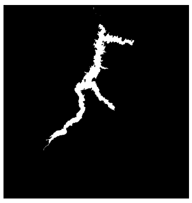
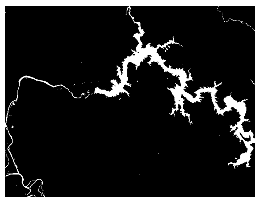
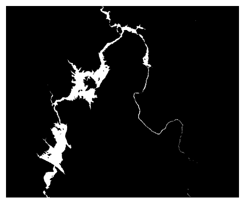
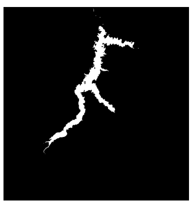
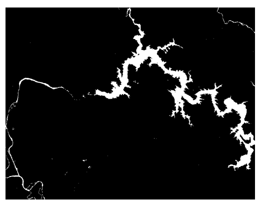
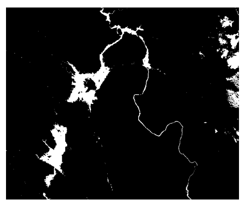
Band	Coefficient
b1: Coastal aerosol	-0.969616734045172
b2: Blue	2.19807138881102
b3: Green	5.85814134568662
b4: Red	0.370296018291466
b5: Near IR	-8.72362757074720
b6: SWIR 1	-4.33503214968681
b7: SWIR2	2.64552671963812
b8: Thermal Infrared (TIRS) 1	1.51971484483010
b9: Thermal Infrared (TIRS) 2	0.593968608786066
b10: Cirrus	-0.906978774853697

Table 3 show the statistical results of MOWI and other indices for water detection. Also, table 4 show the maps of water indices on each case study.

Table 3. Statistical results of indices

Case study	indices	Recall		P		f-score	OA	K
		No water	water	No water	water			
Karun-1 Dam	MOWI	99.4186	100	100	99.9207	99.7085	99.9301	0.9967
	NDWI	89.4057	99.9603	99.6759	98.5733	94.2619	98.6921	0.9353
	MNDWI	98.1116	95.3407	72.0530	99.7581	83.0870	95.6430	0.8065
	AWEIsh	98.9664	99.9956	99.9674	99.8590	99.4644	99.8719	0.9939
	WRI	86.1575	94.8535	67.2103	98.2446	75.5135	93.9050	0.7209
Gotvand Dam	MOWI	99.9822	99.9966	99.9941	99.9898	99.9881	99.9914	0.9998
	NDWI	99.9881	99.9898	99.9822	99.9932	99.9852	99.9892	0.9998
	MNDWI	99.9704	100	100	99.9830	99.9852	99.9892	0.9998
	AWEIsh	100	99.9966	99.9940	100	99.9970	99.9978	0.9999
	WRI	99.9466	99.9966	99.9941	99.9695	99.9703	99.9784	0.9995
Kazemi Dam	MOWI	99.9854	100	100	99.9872	99.9927	99.9932	0.9999
	NDWI	99.9854	100	100	99.9872	99.9927	99.9932	0.9999
	MNDWI	100	100	100	100	100	100	1
	AWEIsh	99.9709	99.9872	99.9854	99.9743	99.9781	99.9795	0.9996
	WRI	100	100	100	100	100	100	1
Zarivar Lake	MOWI	93.1862	99.9658	99.8971	97.6314	96.4250	98.1862	0.9521
	NDWI	83.1574	100	100	94.3442	90.8043	95.5788	0.8793
	MNDWI	83.2054	99.9317	99.7699	94.3557	90.7378	95.5410	0.8783
	AWEIsh	92.5624	100	100	97.4210	96.1376	98.0476	0.9483
	WRI	81.8618	100	100	93.9355	90.0264	95.2387	0.8694

Table 4. Result of each index on each case study

Study area	Zarivar Lake	Kazemi Dam	Gotvand Dam	Karoon-1 Dam
false colour (432)	 2016-11-23	 2016-11-23	 2016-04-08	 2016-04-08
MOWI				
NDWI				
MNDWI				
AWEIsh				
WRI				

In the case study of Karun-1 Dam, MOWI has the best performance by 99.7085, 99.9301 and 0.9967 for f-score, overall accuracy, and kappa coefficient respectively. The result of this case study shows the problem of MNDWI and WRI by cloud and its shadow. Also, AWEIsh has a little problem for narrow water detection especially at down-right and NDWI has a little weak result in water detection at down-left.

In the case study of Gotvand Dam, AWEIsh has the best performance by 99.9970, 99.9978 and 0.9999 for f-score, overall accuracy, and kappa coefficient respectively. However, this index has less noise than other indices but has a little problem for narrow water detection at middle-top and middle-left. After AWEIsh, MOWI has the best performance in this case study by 99.9881, 99.9914 and 0.9998 for f-score, overall accuracy, and kappa coefficient respectively that has a little difference by AWEIsh.

In the case study of Kazemi Dam, MNDWI and WRI have the best result but MOWI and NDWI performance have the little

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difference by MNDWI and WRI. Also, AWEIsh has the lowest accuracy.

Results of Zarivar Lake show the better performance of MOWI by 96.4250, 98.1862 and 0.9521 for f-score, overall accuracy, and kappa coefficient respectively. Also, WRI has the poor result on this case study.

Results of four subsets show that MNDWI and WRI have the problem by cloud and its shadow, and AEWI has a little problem for narrow water detection. MOWI has the best result in two case study and has the little difference by best results of two other case study result. Totally, MOWI uses all potential of landsat-8 images for water detection that has the desirable results on the different case study by different condition such as cloud, its shadow and mountain shadow.

5. CONCLUSION

Water is one of the important resources that should be managed properly for needs of human life in future. One of best tools for water resource management is remote sensing data and techniques. Also, water detection is one of interest subjects of photogrammetry and remote sensing researcher. Between many kinds of satellite data, Landsat imagery is the more interesting data for water detection especially Landsat8 OLI/TIRS that is the newest version of Landsat satellite series. In this paper, we investigated the full spectral potential of Landsat8 to calculate the water index by consideration of the linear combination of bands. Particle swarm optimization had been sued for calculation of each band coefficient. The result showed that modified optimization water index (MOWI) has a proper performance on different condition like cloud, cloud shadow and mountain shadow.

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