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# Comparison of surface water extraction performances of different classic water indices using OLI and TM imageries in different situations

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Recently, water extraction based on the indices method has been documented in many studies using various remote sensing data sources. Among them, Landsat satellites data have certain advantages in spatial resolution and cost. After the successful launch of Landsat 8, the Operational Land Imager (OLI) data from the satellite are getting more and more attention because of its new improvements. In this study, we used the OLI imagery data source to study the water extraction performance based on the Normalized Difference Vegetation Index, Normalized Difference Water Index, Modified Normalized Water Index (MNDWI), and Automated Water Extraction Index (AWEI) and compared the results with the Thematic Mapper (TM) imagery data. Two test sites in Tianjin City of north China were selected as the study area to verify the applicability of OLI data and demonstrate its advantages over TM data. We found that the results of surface water extraction based on OLI data are slightly better than that based on TM in the two test sites, especially in the city site. The AWEI and MNDWI indices performs better than the other two indices, and the thresholds of water indices show more stability when using the OLI data. So, it is suitable to combine OLI imagery with other Landsat sensor data to study water changes for long periods of time.

Keywords: water extraction; operational land imager (OLI) data; threshold stability; water indices

## 1. Introduction

Water is an important feature of the Earth's dynamic system that is essential to human health, society, and environment. Studies on examining water extraction or changes have been a key area of research in land use/ cover (1). Remote sensing offers an efficient and reliable means to identify the properties, distribution, and changes of water bodies (2). A variety of remote sensing data, including Landsat, Systeme Probatoire d'Observation dela Terre (SPOT), Moderate-resolution Imaging Spectroradiometer (MODIS), have been used in water assessment, erosion, constituent concentrations, and outline extraction (3-5). Compared to other remote sensing data, Landsat imageries are widely used in surface water and other environment fields due to their advantages in spatial resolution and cost (6).

The methods used to extract surface water features using remote sensing data can be categorized into four types: thematic classification, linear immixing, singleband threshold, and two-band spectral indices (1). Liu and Zhang extracted water information using four different methods based on Landsat 5 Thematic Mapper (TM) imageries of Wu Lake in China, concluding that the spectral band relation model was perfect (7). Spectral indices have been widely used to extract water bodies in recent years. After the Normalized Difference Vegetation Index (NDVI) was introduced (8), many similar indices have been proposed. The Normalized Difference Water Index (NDWI) (9), which used the green and NIR bands, was proposed by McFeeters in 1996. McFeeters also proposed that the threshold 0 could distinguish the water from the background using NDWI (9). Xu (10, 11) noted that the threshold 0 was not an appropriate distinguishing feature and proposed the Modified Normalized Difference Water Index (MNDWI). He extracted water distributions in cities based on the MNDWI index using Landsat Enhanced Thematic Mapper Plus (ETM+) imageries, finding that the MNDWI was much better than NDWI in distinguishing water from shadow. Zhang et al. (12) and Yang et al. (13) compared the results of the indices and single-band threshold to find that NDWI and MNDWI were both capable of quickly extracting water information and obtained accurate water information using an appropriate threshold. The Automated Water Extraction Index (AWEI) was introduced to improve classification accuracy in areas including shadow and dark surfaces that other classification methods often failed to classify correctly (1).

The presence of shadows may lessen the accuracy of the surface water extraction, and the threshold definition to separate water from other land cover components is uncertain (1, 11). Many studies have paid attention to the threshold methods, such as the logical standard threshold, arbitrary thresholds determined by

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photo-interpretation or experimental trials (11, 14-16) and the maximum between-class variance method (the Ostu method) (17, 18). Campos et al. (19) selected the threshold based on the mean and standard deviation (SD) of different NDWI and the 12 monthly images to distinguish seasonal, permanent water, and non-water in the Sahara-Sahel zone. Surface water body is difficult to distinguish from shadow due to their similar spectral reflectance, especially in mountain and city areas. Zhang et al. (12) noted that the multi-band spectral relationship was the best way to remove shadow in mountain areas, while the MNDWI was the best way to remove shadow in city areas. Considering that the MNDWI uses the mid-infrared band (MIR), it is not available for sensor data without the MIR band (10). Landsat 8 was launched in 2013 with two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The number of bands and the band spectral range are different in OLI data compared to the previous Landsat missions. The Landsat 8 satellite provides the latest images for land science research. As most conclusions are based on the TM or ETM+ sensors, it is necessary to verify the availability and reliability of the new OLI Landsat satellite data for surface water information extraction. In our study, we analysed the extraction accuracy of surface water body distributions in city and village environments based on classic indices (NDVI, NDWI, MNDWI, and AWEI) and compared the result of Landsat 8 OLI imagery with that of Landsat 5 TM imagery.

#### 2. Study area and data source

# 2.1. Test sites

The two test sites are the subsets of the imagery covering Tianjin city, which is located on the Bohai bay of northern China (Figure 1). The sites are specially selected so that the sub-scenes contain complex surface features, including shadow, built-up area and other dark features as background to the water. The first test site with area of 701 ha in Hexi district, Tianjin city, is located in the urban center with parks and reservoirs and is characterized by the presence of the vegetation, builtup area, and building shadows. The other test site with area of 2218 ha is located in Nanyang Pier Village. The water feature types of this test site include river (the Chaobai River) and some ponds. The land cover types of the second test site include water bodies (ponds and river), vegetation (grassland and farmland), and rural residential land. There is seldom shadow in the village site since its topography is predominantly flat and the tall buildings are rare.

#### 2.2. Image data

The Landsat imageries, including TM images of Landsat 5 and OLI images of Landsat 8, were chosen for this study. Landsat 5 TM sensor contains seven bands: blue,

green, red, NIR, TIR, and two TIR bands (Table 1). Compared with TM data, the OLI sensor has two new bands: a deep blue band (b1) for coastal and aerosol observation and a shortwave infrared (SWIR) band for cirrus detection. In addition, the spectral range of OLI sensor has been refined, particularly for the NIR band, which is reduced to  $0.845-0.885 \,\mu\text{m}$  when compared to Landsat TM/ETM+ ( $0.775-0.900 \,\mu\text{m}$ ). This change avoids the effect of water vapor absorption at  $0.825 \,\mu\text{m}$  and helps to obtain accurate surface reflectance (20).

The available data are two image scenes (P122, R33) of Landsat8 OLI (29 September 2013) and Landsat5 TM (30 August 2009), which are obtained from the United States Geological Survey (USGS) Earth Resources Observation and Science Data Centre (EROS) (http://eros.usgs.gov/). The images were selected at the same season and similar dates to eliminate sun illumination differences, and differences in vegetation and soil conditions (21). All the Landsat imageries used are of product-type L1T with a spatial resolution of 30 meters. The acquired imageries are all free of snow, ice, or clouds.

#### 2.3. Reference data

The surface water bodies can be easily visually distinguished from non-water using high-resolution imageries provided by Google Earth<sup>®</sup>. So, we digitized manually the boundary of water bodies from Google Earth<sup>®</sup> as the reference data (Figures 2 and 3). And, the reference data were used to assess the extraction accuracy of the different water indices based on OLI and TM images.

In this study, the high-resolution imageries, as shown in Table 2, were acquired close to the dates when the OLI and TM imageries were obtained to decrease the bias resulting from the temporal variation. For the city site, we selected the image acquired on 5 March 2012 as the reference data for OLI imagery because the only image in 2013 was covered with frozen water bodies. In 2009, we found that the features in city site changed a lot from September to November, from the Google Earth<sup>®</sup>, so we selected the image acquired on 5 May 2009 as the reference data for TM imagery.

# 3. Methods

# 3.1. Data pre-processing

For imagery analysis and visualization purpose, ENVI 5.1 software was applied in this study. The two obtained Landsat imageries were already geo-referenced at the Universal Transverse Mercator projection system (zone: 50° N, datum: WGS–84) and resampled to 30 m with cubic convolution. The L1T data products provide geo-metric accuracy by incorporating ground control points while employing a digital elevation model for topo-graphic accuracy. The imagery pre-processing included radiance calibration and atmosphere correction. The



Figure 1. Location of test sites: (I) village site; (II) city site.

Table 1. The differences in band range and resolution between the OLI sensor and TM sensor.

		OLI			TM/ETM+			
No.	Band	Range (µm)	Resolution (m)	No.	Band	Range (µm)	Resolution (m)	
1	Deep blue	0.433-0.453	30	1	Blue	0.450-0.515	30	
2	Blue	0.450-0.515	30	2	Green	0.525-0.605	30	
3	Green	0.525-0.600	30	3	Red	0.630-0.690	30	
4	Red	0.630-0.680	30	4	NIR	0.775-0.900	30	
5	NIR	0.845-0.885	30	5	MIR	1.550-1.750	30	
6	SWIR1	1.560-1.660	30	6	TIRS	10.40-12.50	60	
7	SWIR2	2.100-2.300	30	7	MIR	2.080-2.350	30	
8	Pan	0.500-0.680	15	8 (ETM+)	Pan	0.520-0.900	15	
9	Cirrus	1.360-1.390	30	- /				

Digital numbers (DNs) of the image are converted to Top-of-Atmosphere reflectance using the radiance calibration module in ENVI 5.1 (22). Atmospheric correction was applied to all images using the Fast Line-of-Sight Atmospheric Analysis of Spectral Hyper-cube (FLAASH) module in ENVI 5.1. The Equation (1) is as follows (23).

$$L = A \frac{\rho}{1 - S\rho_e} + B \frac{\rho_e}{1 - S\rho_e} + L_e \tag{1}$$

where *L* is the pixel spectral radiance,  $\rho$  is the pixel surface reflectance,  $\rho_e$  is the radiance backscattered by the atmosphere, the parameters *A*, *B*, *S*, and *L<sub>a</sub>* are calculated by the ENVI software.

Besides, the spectral radiance can be calculated by the raw quantized calibrated pixel values  $(Q_{cal})$  as shown in Equation (2).

$$L = M Q_{\rm cal} + A \tag{2}$$

where M is the band-specific multiplicative rescaling factor and A is the band-specific additive rescaling factor. M and A can be found in the OLI metadata file

#### 3.2. Spectral curves of typical features

Considering the changes in the band range of OLI sensor, it is essential to draw spectral curves of the typical features. Five features are considered: water bodies,



Figure 2. The reference data of water bodies for (a) OLI and (b) TM imagery of the city site from Google Earth<sup>®</sup>.



Figure 3. The reference data of water bodies for (a) OLI and (b) TM imagery of the village site from Google Earth®.

Table_2.	The	dates	of	the	referenced	images	from	Google
Earth <sup>®</sup> .								

	Da	te
Test site	For OLI	For TM
City Village	2012.03.11 2011.08.20.	2009.05.05 2011.08.20

built-up land, vegetation, bare land, and shadow. In order to draw the curves, we selected feature samples by pixel manually using multiple spectral bands and pan band.

As shown in Figure 4, the changes of OLI spectral curves are similar to that of TM. For different features,

the difference in visible bands is not obvious so that it is hard to distinguish different features, i.e. the values of shadow and bare land are close to that of the surface water in green band. There is an obvious difference in other bands for OLI, i.e. the NIR band and SWIR bands. The difference of spectral reflectance value for different features in the NIR band is distinct when compared with TM, such as built-up/bare land, and water/shadow.

#### 3.3. Water extraction indices

NDVI (8), as shown in Equation (3), is based on the fact that the reflectance of the vegetation in the NIR band is higher than that in the Red band. Thus, the vegetation



Figure 4. The wave spectrum for the typical features obtained from (a) OLI and (b) TM imagery.

can be easily distinguished from the background. Generally, the water body can be extracted when NDVI < 0 (12).

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$
(3)

The different reflectance values in the NIR band and green bands demonstrate the principle of the NDWI, as shown in Equation (4). As the water reflectance value is higher in the NIR band than in the green band, a negative value is more clearly compared with other features (3, 12, 19).

$$NDWI = \frac{\rho_{green} - \rho_{NIR}}{\rho_{green} + \rho_{NIR}}$$
(4)

In the infrared band, the water reflectance value is commonly close to zero, especially in the mid-infrared band (Landsat TM/ETM+ sensors). This provides the basis of the MNDWI index (11,12). As shown in Equation (5), for the Landsat 8 OLI sensor, the mid-infrared band in TM within the range of  $1.550-1.750 \mu m$  corresponds to the SWIR band within the range of  $1.560-1.660 \mu m$ .

$$MNDWI = \frac{\rho_{green} - \rho_{swir1}}{\rho_{green} + \rho_{swir1}}$$
(5)

AWEI was created to maximize the reparability of water and non-water pixels through the differentiation and addition of bands and the application of different coefficients. Therefore, two equations based on Landsat 5 TM were proposed to effectively eliminate non-water pixels and extract surface water bodies with improved accuracy. The AWEI<sub>nsh</sub>, as shown in Equation (6), is

suited for situations where shadows are not major problems, while the AWEI<sub>sh</sub>, as shown in Equation (7), is intended to effectively eliminate shadows or other dark surfaces. The coefficients are empirical results determined based on reflectance patterns observed across the data-set of pure pixels for various land cover types. The coefficient choices also aimed to stabilize the threshold to distinguish water from non-water by forcing non-water pixels below 0 and water pixels above 0 (1).

$$AWEI_{nsh} = \rho_{green} + \rho_{blue} \times 0.25 - 1.5 \times (\rho_{nir} + \rho_{swir1}) \\ - 0.25 \times \rho_{swir2}$$
(6)

$$AWEI_{sh} = 4 \times (\rho_{green} - \rho_{swir1}) - (0.25 \times \rho_{nir} + 2.75 \times \rho_{swir2})$$
(7)

## 3.4. Threshold selection

The threshold values applied to distinguish water from non-water were unstable and varied with scene and location (24), the sample points method was used to select the thresholds in this study. First, drawing the spectral curves of typical feature based on the imageries of NDVI, NDWI, and MNDWI; second, calculating the data range of feature samples based on different indices to select the endpoint values (or values closing to the endpoints) or the logical values, i.e. water > 0 (9, 11); third, comparing the result imageries of each alternative visually to find the better one. As for the AWEI, according to Reference (1), we choose the AWEI<sub>nsh</sub> for the village water, and both AWEI<sub>sh</sub> and AWEI<sub>nsh</sub> for the city site in this study. Because the village site satisfied the condition that shadows were not a major problem, and the city site satisfied the condition that both high albedo surfaces and shadow/ dark surfaces were found. The value 0 was used to be the alternative threshold for AWEI imagery.

#### 3.5. Accuracy estimation

We calculated the confusion matrix between referenced water bodies and extraction results using the water indices to evaluate the accuracy. Table 3 shows the principle of the confusion matrix.

In Table 3, a is the number of correct prediction that an instance is negative, b is the number of incorrect predictions that an instance is positive, c is the number of incorrect of prediction that an instance negative, and d is the number of corrections that an instance is positive (25). The accuracy indices include the overall accuracy, kappa coefficient, the product accuracy, and the user accuracy. In this study, the overall accuracy and kappa coefficient are used to evaluate the results.

#### 4. Results

#### 4.1. Optimal threshold and extraction results

The mean of five typical features based on NDVI, NDWI, and MNDWI obtained from OLI and TM imagery was shown in Figure 5. The comparison shows that the mean of water bodies is positive in both MNDWI and NDWI. Conversely, the mean of water features in NDVI is below 0. Therefore, the 0 was to be the dividing point. Figure 6 shows the data range of each feature samples based on the imagery of NDVI, NDWI, and MNDWI, respectively. It shows the ability of three indices in correctly classifying the features with mean values in OLI and TM. It clearly appears that the data range of

Table 3. The principle of the confusion matrix.

		Predi	icted
		Negative	Positive
Actual	Negative	а	b
	Positive	С	d

water at different sensors exhibits large overlapping part when compared to other features. For the OLI, the data range of water has overlap with shadow, especially the range of water in MNDWI; it merges slightly with shadow when compared with other indices (Figure 6(a)–(c)). Except for MNDWI, the overlap between water, built-up lands, and shadow in TM makes it hard to distinguish water from other features (Figure 6(d)–(f)).

According to the above-mentioned methods to choose the threshold value, we got the optimal thresholds for each index (Table 4), and the extraction results of four indices were presented in Figures 7 and 8. For the village site, the value 0 is the most general threshold based on both OLI and TM sensor. For the city site, the threshold of NDVI is negative while others are positive. The thresholds of NDVI, NDWI, and MNDWI are -0.1, 0.05, and 0.2, respectively, in OLI. The thresholds of NDWI and MNDWI in TM are 0.15 and 0.31 which are bigger than that in OLI.

Compared with OLI, it is relatively difficult to choose appropriate alternative thresholds for TM. For example, the NDVI value of the city site is easy to misclassify water bodies with shadow and built-up area because they overlap with each other (Figure 6). According to the results, the threshold 0 of AWEI can achieve a better result than that of NDVI and NDWI (Figures 7 and 8). The threshold based on the OLI is more stable, especially using MNDWI, which has little intersection between shadow and other features (Figure 6).



Figure 5. The mean of three water indices for five typical features obtained from OLI and TM imagery: (a) NDVI; (b) NDWI; (c) MNDWI.



Figure 6. The variation ranges in each index value obtained from TM imagery: (a) NDVI, (b) NDWI, (c) MNDWI obtaining from OLI imagery, (d) NDVI, (e) NDWI, (f) MNDWI.

# 4.2. Comparison of indices

Based on the city water results obtained from OLI and TM imageries, AWEI was the best index to distinguish shadow and water, followed by MNDWI (Table 5). In particular, the kappa coefficient for AWEI result based on OLI data is up to 0.68 with an overall accuracy of 97.61%. However, the shadow created by the high buildings of the city is easily confused with water bodies, which reduced the extraction accuracy of surface water bodies in urban environment.

For the rural water bodies, MNDWI and AWEI extraction results are better than NDVI at preserving the completeness of the water bodies, especially for river and pond areas (Figure 8). The MNDWI is slightly better than AWEI, and the kappa coefficients are 0.90 and 0.89, respectively. Also, NDVI extraction results obtained from OLI imagery show better accuracy in village environment.

## 4.3. Comparison of OLI and TM

We compared the extraction results of surface water bodies obtained from the OLI and TM sensor imageries. For village situation, the river water is extracted perfectly by both OLI and TM (Figure 9), but the OLI data are slightly better at extracting small water bodies compared to TM. Details of accuracy assessment including overall accuracy and kappa coefficient are shown in Table 6. According to the confusion matrix, the OLI kappa coefficient is 0.89, and that of TM is 0.90. For city water, it is difficult to distinguish shadows completely from water bodies based on OLI and TM images. Some water bodies are excluded by eliminating shadow resulting from the edge effects (Figure 9). The kappa coefficients for OLI and TM are 0.68 and 0.63, respectively.

Table 4. The optimal thresholds chosen for each index based on OLI and TM imagery.

	C	DLI	TM		
Optimal threshold	City	Village	City	Village	
NDVI	-0.10	0	-0.09	0.20	
NDWI	0.05	0	0.15	0	
MNDWI	0.20	0.07	0.31	0	
AWEI	0	0	0	0	



Figure 7. The optimal results maps from each index for the city site based on OLI imagery: (b) NDVI, (c) NDWI, (d) MNDWI, and (e) AWEI; and based on TM imagery: (g) NDVI, (h) NDWI, (i) MNDWI, and (j) AWEI. The other two figures show false color images for the city site: (a) OLI and (f) TM.

Therefore, in the urban situation, the extraction results based on the OLI data are much better than that of TM.

# 5. Discussion

Landsat8 OLI sensor has greatly improved center wavelength and wavelength range compared to previous Landsat missions, especially in the non-visible light bands (20). The OLI data are better than the TM/ETM+ data in the visible band, especially for the NIR band (20), which has an effect on NDVI and NDWI. The thresholds of NDVI and NDWI are more stable in OLI than that in TM as shown in Figure 6. The results of the two test sites as shown in Figure 7 and 8, the indices of NDVI and NDWI in OLI are better than that in TM, especially in the village site. The optimal index was different for the same test sites based on OLI and TM imageries. Both OLI and TM failed to distinguish fine



Figure 8. The optimal results maps from each index for the village site based on OLI imagery: (b) NDVI, (c) NDWI, (d) MNDWI, and (e) AWEI; and based on TM imagery: (g) NDVI, (h) NDWI, (i) MNDWI, and (j) AWEI. The other two figures show false color images for the village site: (a) OLI and (f) TM.

# 40 *K. ZHAI* et al.

		0	LI		Т	М		
	City		Village		City		Village	
	Overall accuracy(%)	Kappa						
NDVI NDWI	97.07 96.50	0.61 0.59	94.78 92.72	0.86 0.80	95.88 96.60	0.37 0.53	85.94 89.45	0.59 0.70
MNDWI AWEI	97.28 97.61	0.64 0.68	96.86 95.34	0.89 0.88	96.94 97.10	0.60 0.63	96.03 96.83	0.90 0.89

Table 5. The accuracy evaluation results of water body extraction using different indices based on OLI and TM imageries.



Figure 9. The optimal result maps for the city site: (a) OLI and (b) TM; and for the village site: (c) OLI and (d) TM.

water with minority pixels resulting from the mixed pixels.

The optimal thresholds for the water indices vary depending on the proportions of sub-pixel water/non-water components (24). Because of instability, it is difficult to decide which value should be used in classification trees. According to our results, AWEI has a stable

threshold of 0 that can achieve a better result than other indices. For other three indices, the threshold based on the OLI is more stable, especially using MNDWI, which has little intersection between shadow and other features (Figure 6). The data range of water indices based on the TM imagery has a larger intersection with shadow, builtup area, and other features. Thus, it is hard to choose the

Table 6. The comparison of extraction accuracy of the surface water body between OLI and TM imagery.

	OLI		TM		
	Overall accuracy (%)	Kappa	Overall accuracy (%)	Kappa	
Village situation	96.86	0.89	96.03	0.90	
City situation	97.61	0.68	97.10	0.63	

alternative threshold from the background in TM imagery. In addition, different regional conditions have different difficulties related to threshold selection. For the village site, which is covered by simple features, the threshold 0 is frequently selected in the water extraction processing (Table 4). For the city site, more analysis is needed to select the optimal threshold due to the influence of the shadow or other dark features.

According to previous research, the optimal index depends on the environmental characteristics of the study area including topography and shadows. Similarly, our study demonstrates that the AWEI and MNDWI indices performed better for distinguishing water from shadow in the city site. In particular, AWEI can distinguish water bodies from shadows and high albedo features better than other indices. In the village region, MNDWI are more appropriate to distinguish water bodies, and NDVI shows better results based on OLI imagery.

For the city site, the fine river cannot be distinguished by any index because the size of the water body is just one or two pixels, which are affected by building shadow. Based on the Google Earth<sup>®</sup> imagery from different time, the urban landscape at the study site has changed significantly since 2009, resulting in uncertainty in the water body extraction and differences with the referenced data. These are the reasons why the kappa coefficients for the city site are low. In addition, the size of the test site also affects the extraction accuracy evaluation. Because a land use classification map is lacking, the existence of mixed pixels and the imagery date from Google Earth<sup>®</sup> is not the same as the OLI and TM imagery. Thus, the evaluation mechanism is not perfect.

Seasonal and daily variation in the angle of the sun, atmospheric composition, and changes in the biophysical and chemical properties of water bodies may influence the reflectance of water (26). It is thus necessary to study the applicability of OLI data in other environmental conditions such as mountain areas and polluted water to verify the advantage of OLI in extracting water bodies. In future work, we will pay more attention to the effect of diverse test sites and sample sizes on extraction accuracy. In summary, the OLI sensor data show some advantages in water extraction in the two test sites, primarily its stable thresholds.

#### 6. Conclusion

This study investigated the applicability of OLI imagery from Landsat 8 satellite to detect surface water bodies in urban and rural situation using different water indices, and made a comparison with TM imagery. The results showed that the overall accuracy of water extraction from OLI imagery for both city and village sites is slightly better than TM, especially in the urban environment. By comparing the extraction results from different indices under different conditions, we found that MNDWI and AWEI indices were better than both NDVI and NDWI for water extraction in the two test site of this study, which were consistent with those in previous studies (1, 7, 13). Significantly, our study showed that the OLI data has an advantage of threshold selection for water indices. Compared with TM imagery, it is easier to find an appropriate threshold value and the changes of the optimal threshold values in different situation and using different water indices is relatively stable.

Future work will involve more tests under different environmental conditions such as mountainous areas, polluted water, and coastal areas. The results of this study are valuable for developing applications of the new sensor based on the water index model in the field of water detection. The results also demonstrate that it is suitable to combine OLI imagery with other Landsat sensor data to study water changes for long periods of time.

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#### References

- Feyisa, G.L.; Meilby, H.; Fensholt, R.; Proud, S.R. Remote Sens. Environ. 2014, 140, 23–35.
- (2) Giardino, C.; Candiani, G.; Bresciani, M.; Lee, Z.; Gagliano, S.; Monica, P. Comput. Geosci. 2012, 45, 313–318.
- (3) Mcfeeters, S.K. *Remote Sens.* **2013**, *5*, 3544–3561.
- (4) Santini, F.; Alberotanza, L.; Cavalli, R.M.; Pignatti, S. Remote Sens. Environ. 2010, 114, 887–898.
- (5) Vrieling, A. Catena 2006, 65, 2-18.

# 42 *K. ZHAI* et al.

- (6) Prishchepov, A.V.; Radeloff, V.C.; Dubinin, M. Remote Sens. Environ. 2012, 126, 195–209.
- (7) Liu, G.; Zhang, L. J. Univ. Chinese Acad. Sci. 2013, 30, 644–650.
- (8) Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. Monitoring vegetation systems in the great plains with ERTS; *The 3rd ERTS Symposium, NASA*, Washington, DC, 1973; pp 309–317.
- (9) Mcfeeters, S.K. Int. J. Remote Sens. 1996, 17, 1425-1432.
- (10) Xu, H. J. Remote Sens. 2005, 9, 589–595.
- (11) Xu, H.Q. Int. J. Remote Sens. 2006, 27, 3025-3033.
- (12) Zhang, F.; Zhang, B.; Li, J.; Shen, Q.; Wu, Y.; Song, Y. Proc. Environ. Sci. 2011, 11, 1482–1487.
- (13) Yang, H.; Wang, Z.; Zhao, H.; Guo, Y. . *Proc. Environ. Sci.* **2011**, *10*, 2619–2624.
- (14) Gao, B. Remote Sens. Environ. 1996, 58, 257–266.
- (15) Chipman, J.W.; Iillesand, T.M. Int. J. Remote Sens. 2006, 28, 4365–4379.
- (16) Lacaux, J.P.; Tourre, Y.M.; Vignolles, C.; Ndione, J.A.; Lafaye, M. *Remote Sens. Environ.* **2007**, *106*, 66–74.
- (17) Foody, G.M. Remote Sens. Environ. 2002, 80, 185-201.
- (18) Li, W.B.; Du, Z.Q.; Ling, F.; Zhou, D.B.; Wang, H.L.; Gui, Y.M.; Sun, B.Y.; Zhang, X.M. *Remote Sens.* **2013**, *5*, 5530–5549.

- (19) Campos, J.C.; Sillero, N.; Brito, J.C. J. Hydrol. 2012, 464–465, 438–446.
- (20) Jia, K.; Wei, X.; Gu, X.; Yao, Y.; Xie, X.; Bin, L. Geocarto Int. 2014, 29, 941–951.
- (21) Kolios, S.; Stylios, C.D. Identification of land cover/land use changes in the greater area of the Preveza peninsula in Greece using Landsat satellite data. *Appl. Geogr.* 2013, 40, 150–160.
- (22) Chander, G.; Markham, B.L.; Helder, D.L. Remote Sens. Environ. 2009, 113, 893–903.
- (23) Du, Z.Q.; Li, W.B.; Zhou, D.B.; Ling, F.; Wang, H.L.; Gui, Y.M.; Sun, B.Y. *Remote Sens. Lett.* **2014**, *5*, 672– 681.
- (24) Ji, L.; Zhang, L.; Wylie, B. Photogramm. Eng. Remote Sens. 2009, 75, 1307–1317.
- (25) Provost, F.; Fawcett, T.; Kohavi, R. The case against accuracy estimation for comparing induction algorithms. In *Proceedings of the fifteenth International Conference* on Machine Learning (ICML), Madision, 1998.
- (26) Zhang, Y.; Feng, L.; Li, J.; Luo, L.; Yin, Y.; Liu, M.; Li, Y. J. Plankton Res. 2010, 32, 1023–1037.