Monitoring and Extracting of Surface Water Area from Landsat Imagery Using Water Indices

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Abstract

Taung-Tha-Man Lake (TTM) is the major fresh water body providing Amarapura with this water used for various purposes. One of the main challenges faced by the sustainable development of TTM is the need for better water management. The purpose of this study is to extract water area and detect changes in TTM Lake from Landsat imagery. NDWI, Modified NDWI, WRI and AWEI are used for extraction of surface water. The accuracies of the water indices are tested using the error matrix. Among them, MNDWI is the highest accuracy in extract water body compared to other indices. The results illustrate that average accuracy of the water indices method is 90%. Experimental results indicate very small change (0.4032 km^2 in 2000-2010 and -0.2484 km^2 between 2010 and 2017) in TTM Lake. This study can be used as guidance to protect the lake and manage water resources.

Keywords: *Change Detection, NDWI, MNDWI, WRI, AWEI, Surface Water Extraction*

1. Introduction

Surface water is one of the irreplaceable strategic resources of human survival and social development [18]. It is also necessary for humans, food crops, and ecosystems [10]. There are numerous resources of the consumable water which include the rainfall, groundwater and the various surface water bodies such as ponds, rivers, lakes, etc. [15].

Consequently, accurate extraction of surface water areas of water body of lake is crucial [5]. Accurate mapping of surface water to describe its spatial and temporal distributions is essential for both academic research and policy-making [16].

Detection of water level changes is usually done by extracting water features individually from multiple satellite images, before making comparison to detect their changes [3].

A recently developed approach for change detection of water bodies is water indices. Index-based methods can detect water more accurately, quickly and easily than classification methods and do not require prior knowledge [9]. There are many types of water indices in previous studies. From among, these water indices: normalized-difference water index (NDWI) [12] has achieved high reflectance of green band and low reflectance of near infrared band for water. Modified NDWI (MNDWI) [23] gave to overcome the inseparability of built up areas in NDWI which replaced near infrared band with mid infrared. Automated Water Extraction (AWEI) [6] performed to improve a better result in an area of shadows and darkness on Landsat surface.

Taung-Tha-Man Lake is fresher water lake and a big source of fish production in Amarapura Township. Moreover it has also become people attraction to U Bein Bridge. Nevertheless, the lake has been in a critical situation in recent year due to increasing water in 2004 and in 2016, entering forsaken water from Factory in 2017 and the number of dead fish found in 2015. One of the major challenges facing sustainable development in TTM Lake is the need for better development and management of freshwater resources. Therefore, water surface extraction and monitoring of TTM Lake is critical to understand the human impact on the lake and to manage it more effectively.

The specific objectives of this study are to extract water body from time series Landsat images using the appropriate water index and evaluate the lake-water extent changes over the 17 years period, 2000-2017.

2. Related Works

Water body extraction is an important task in different disciplines, such as lake coastal zone management and coastline changes, and erosion monitoring, flood prediction and evaluation of water resources [24]. The real-time monitoring of water bodies on the Earth's surface is an essential work to control surface water pollution and protect ecological environments. Due to the advantages of fast information update and the ability to produce near real-time observations over large geographic areas, remote sensing has been widely applied in investigating and monitoring surface water resources in the past two decades [12, 23, 8, 19].

At present, the methods for extracting surface water bodies are prominently based on spectral index or multiband techniques. McFeeters [12] proposed the normalized difference water index (NDWI) in 1996 using Near Infrared (NIR) and green channels of Landsat that can delineate and enhance open water features. As a result, the extracted features could be a mixture of water and built-up land noises. Based on the NDWI, Xu [23] proposed a modified normalized difference water index (MNDWI) in 2006, and made a change by replacing the NIR band with the shortwave-infrared (SWIR) band, which helped to remove the disturbances from built-up lands. Automated Water Extraction Index (AWEI) was developed by Feyisa et al. [6] to extract surface water with improved accuracy, and the coefficients that were used and the combinations of the chosen bands were determined based on critical examination of the reflectance properties of various land cover types. The most important ones can be presented as follows: Muala [14] concluded that the NDWI gave accurate results than the MNDWI for delineating the Roseires reservoir area that is located on the Blur Nile. Rokni [19] illustrated that NDWI indicated higher performance as compared with other indexes for the extraction of surface water area from Landsat data. These indices have also previously been tested in several applications, including surface water mapping [4, 6], land use land cover analysis [2] and environmental research [17].

3. Study Area and Data Collection

Taung-Tha-Man Lake is located between latitudes 21°53′09″ *N* and 096°03′16″ *E* long in the southeast of Amarapura Township, Mandalay region as shown in Figure 1. Total geographical area is approximately 231.73 acres. During monsoon the area is affected by widespread flooding. On the other hand, some parts of this area suffer from water logging problem during dry season.

Figure 1. The Geographical Location of Taung-Tha-Man Lake

3.1. Landsat Imagery

In this study, Landsat (C1 Level-1) TM and OLI/TIRS images were downloaded from EarthExplorer (http://earthexplorer.usgs.gov/). All images were pre-georeferenced to Universal Transverse Mercator (UTM) zone 47 North projection using WGS-84 datum.

All image processing and lake water extraction and analyses were performed using ArcGIS 10.1 (Environmental Systems Research Institute, Redlands, CA, USA) and QGIS 3.2 software.

4. Methodology

This study establishes Landsat imagery based water body mapping and monitoring system using Landsat 5 TM and Landsat 8 OLT/TIRS time series satellite images of three different years i.e. 2000, 2010 and 2017. To achieve the aim of this paper, the following tasks were performed: data collection, image preprocessing, computation of the spectral water indices, extraction of the lake surface area, accuracy assessment and change detection of the extracted water areas. Figure 2 shows the general methods adopted in this study for detecting changes in the lake surface area.

4.1. Image Preprocessing

Landsat imagery from United States Geological Survey (USGS) provides L1T data in GeoTIFF format which were then geometrically corrected and referenced to UTM (zone 47 N) coordinate system (WGS 84 datum and Spheroid) [7]. These images (all of the individual bands) were originally obtained raw DN (digital-number) values.

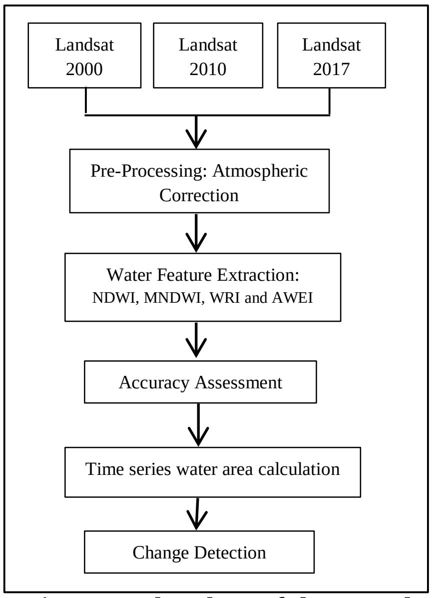

Figure 2. Flowchart of the procedures

Atmospheric correction was needed to modify atmospheric scattering and absorption effects caused by ozone, water vapor, aerosols and other particles, and Rayleigh scattering [11]. Thus, Dark Object Subtraction method was used to convert the reflectance on the satellite to surface reflectance for complete absolute correction. This was important step in extracting the water surface with better accuracy.

Sub-images containing the lakes area were extracted using the ArcGIS Desktop software. After preprocessing, NDWI, MNDWI, WRI and AWEI were investigated for the extraction of surface water from Landsat imagery.

4.2. Water Index Methods

Spectral water indexes have been developed to extract water bodies from remotely sensed imagery, usually by calculating the normalized difference between two image bands and then applying an appropriate threshold to segment the results into two classes (water and non-water features). In this study, NDWI, MNDWI, WRI and AWEI are used to extract lake water bodies from TM and ETM images [20].

4.2.1. Normalized Difference Water Index (NDWI)

The NDWI proposed by McFeeters (1996) [12] is expressed the equation shown below:

$$NDWI = \frac{Green - NIR}{Green + NIR} \qquad (1)$$

where Green is a green band such as TM band 2, OLI/TIRS band 3 and NIR is a near infrared band such as TM band 4, OLI/TIRS band 5.

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.

In this result, water features have positive values and vegetation and soils features usually have zero or negative values.

4.2.2. Modified Normalized Difference Water Index

The modified NDWI (MNDWI) by Xu, H., 2006 [23], expressed as follows:

$$MNDWI = \frac{Green - MIR}{Green + MIR} \qquad (2)$$

where Green is green band such as TM band 2, OLI/TIRS band 3 and MIR is a middle infrared band such as TM band 5, OLI/TIRS band 6.

The computation of the MNDWI will produce three results: (1) water has greater positive values than in the NDWI as it absorbs more MIR light than NIR light; (2) built-up land have negative values as mentioned above; and (3) soil and vegetation have negative values as soil reflects MIR light more than NIR light and the vegetation reflects MIR light still more than green light.

4.2.3. Water Ratio Index (WRI)

The WRI proposed by Shen, L. and Li, C., 2010 [21], is expressed the equation shown below.

$$WRI = \frac{Green + \mathrm{Re}\,d}{NIR + MIR} \qquad (3)$$

where Green is a green band such as TM band 2, OLI/TIRS band 3, red is red band such as TM band 3, OLI/TIRS band 4, NIR is a near infrared band such as TM band 4, OLI/TIRS band 5, MIR is a mid-infrared band such as TM band 5, OLT/TIRS band 6, and SWIR is a short wave infrared band such as TM band 7, OLI/TIRS band 8.

WRI method showed convincing results for values greater than 1 as it enhanced water while the cloud shadows, roads and vegetation remained suppressed.

4.2.4. Automated Water Extraction Index (AWEI)

The AWEI proposed by Feyisa.G., 2014 [6], is expressed as equation below.

$$AWEI = 4 \times (Green - MIR) - (0.25 \times NIR + 2.75 \times SWIR) \quad (4)$$

where Green is a green band such as TM band 2, OLI/TIRS band 3, NIR is a near infrared band such as TM band 4, OLI/TIRS band 5, MIR is a mid-infrared band such as TM band 5, OLT/TIRS band 6, and SWIR is a short wave infrared band such as TM band 7, OLI/TIRS band 8.

The main aim of the AWEI is to maximize the separability of water and non-water pixels using band differencing, addition and application of different coefficients. This method is formulated to effectively eliminate non-water pixels, including dark, built-up surfaces in areas with urban backgrounds and shadow pixels and extract surface water with improved accuracy.

4.2.5. Extraction of Surface Water

Surface water body for TTM Lake was extracted by using NDWI, MNDWI, WRI and AWEI. The calculated water indices were then further reclassified into two different classes where by positive values were identified as water bodies and negative values as non-water (land surfaces) [22]. Calculating the area of water and non-water was carried out on raster calculator for 2000, 2010 and 2017.

4.2.6. Generation of the Reference Map

The reference map is generated lake surface boundaries in Landsat imagery using TM such as band 4 and OLT such as band 5. Band 4 and band 5 represent near infrared band (NIR) which is usually preferred for visual interpretation of water bodies; because NIR is strongly absorbed by water and is strongly reflected by terrestrial vegetation and dry soil. Therefore, NIR is selected in this study due to its higher ability to discriminate water and land area [19].

4.2.7. Accuracy Assessment

In this study, accuracy assessment is performed on two images between the results from the water indices method and the reference water body image. For this purpose, 55 random points have been generated on the reference image, which are then exported into "kml" file for viewing on the "Google Earth". Each of these points is examined to identify whether it belongs to "water" or "non-water" class. Finally, the accuracy of the output has been reported in percentage [1].

Overall Accuracy, user's accuracy, producer's accuracy, and Kappa Coefficient were calculated to support the accuracy of the results. The following formulas are measured for each water index methods [13].

$$\text{Overall Accuracy} = \frac{\text{Total number of correctly classified pixels(diagonal)}}{\text{Total numbet of reference pixels}} \quad (5)$$

$$\text{User Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total numbet of classified pixels in that category(row total)}} \quad (6)$$

$$\text{Producer Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total numbet of classified pixels in that category(column total)}} \quad (7)$$

$$\text{Kappa coefficient} = \frac{(TS*TCS) - \sum(\text{col.tol}*\text{row.tol})}{TS^2 - \sum(\text{col.tol}*\text{row.tol})} \quad (8)$$

5. Results and Discussion

After pre-processing (RGB-432 for Landsat TM and RGB-543 for Landsat 8, false color composite), the following images obtained from Landsat imagery as shown in Figure 3.

Figure 3. Landsat images in 2000 (a); in 2010 (b); in 2017 (c)

Firstly, the water index images were generated from Landsat images using equation 1-4 (see Figure 4). In Figure 4, the water feature pixels have high value, and the other features pixels have low value.

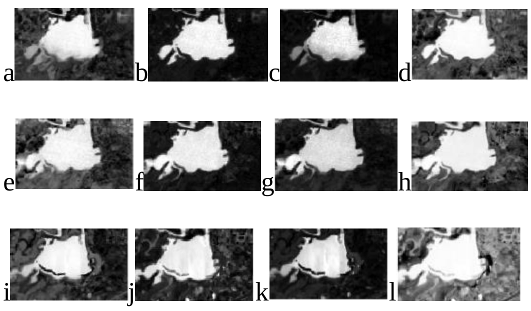

Figure 4. Difference Water Index images generated from Landsat; NDWI: a, MNDWI: b, WRI: c, AWEI: d in 2000; NDWI: e, MNDWI: f, WRI: g, AWEI: h in 2010; NDWI: i, MNDWI: j, WRI: k, AWEI: l in 2017

Secondly, these images are reclassified into water (i.e., lake) and non-water (i.e., building land, vegetation, crop land, bare land). For each of water index methods, the water features were extracted from the water index image using the thresholding method. After the water surface and number of pixels extracted from data of 2000 and 2017, it is calculated the area of water and non-water as shown in Table 1. TTM Lake is slightly changed in shape and spatial coverage for each study year (see Figure 5).

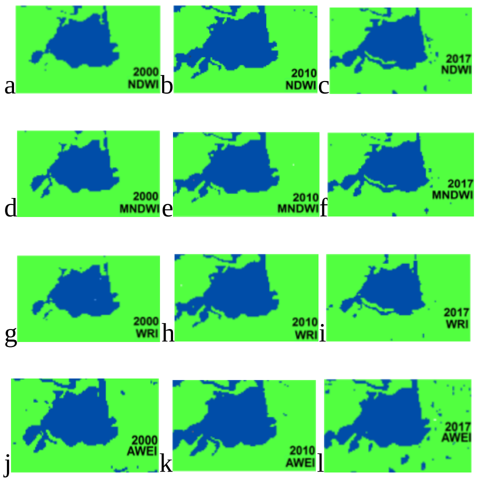

Figure 5. Extract water surface derived from water index image (NDWI, MNDWI, WRI, AWEI) in 2000, 2010, 2017 ; NDWI: a-c, MNDWI: d-f, WRI: g-h, AWEI: j-l

The change of surface water area in TTM Lake during 2000-2017 is shown in Table 2. It was observed that water area in TTM Lake increased 0.062314% km^2 during 2000-2010. Between 2010 and 2017, there was a decrease in 0.03834% km^2 of water area on TTM Lake.

Table 1. Estimated Area and pixels from each index

Water Index	2000 km^2(pixels)	2010 km^2(pixels)	2017 km^2(pixels)
NDWI	1.5075 (1675)	2.0178 (2242)	1.7127 (1903)
MNDWI	1.4724 (1636)	1.8756 (2084)	1.6272 (1808)
WRI	1.4058 (1562)	1.9287 (2143)	1.3851 (1539)
AWEI	1.8675 (2075)	2.1582 (2398)	2.0277 (2253)

Table 2. Surface Water Area Changes

km^2	NDWI(%)	MNDWI(%)	WRI	AWEI
Change in 2000-2010	0.078816	0.062314	0.080762	0.044898
Change in 2010-2017	-0.04712	-0.03834	-0.08396	-0.02007
Change in 2000-2017	0.031693	0.023978	-0.0032	0.02483

The performance of the different water index methods was evaluated their respective absolute errors, overall accuracy and kappa coefficient. Pixel-by-pixel comparison was used to generate error matrixes. The accuracy of each water index methods was indicated in Table 3.

Table 3. Accuracy Assessment Analysis

Period	Accuracy	NDWI	MNDWI	WRI	AWEI
2000	Overall	0.93220	0.96667	0.88	0.91428
	Kappa	0.86499	0.87461	0.75229	0.82744
2010	Overall	0.90769	0.92727	0.86	0.88
	Kappa	0.82353	0.85430	0.74414	0.76
2017	Overall	0.89014	0.90891	0.85251	0.873015
	Kappa	0.78085	0.81551	0.74	0.76254

According to the results of error matrix and water indexing; MNDWI performed better compared to other indices for extracting water pixels from Landsat data. The water information from the MNDWI reaches an overall accuracy between 91% and 97% and a Kappa value of 0.8 because no built-up land patches were mixed with enhanced water features. MNDWI and NDWI had kappa coefficients greater than 0.78. WRI were able to separate the water bodies well along with some errors in the vegetation and crop area. Therefore, WRI had overall accuracy about 85% AWEI had an average overall accuracy of 88.9% with the smallest kappa coefficient of 0.76. The kappa coefficient from the four indices is in the range of 0.7–0.87. It can be seen that result obtained from 2017 are less accurate compare to that of 2000, this is due to cloud coverage of 2017 Landsat image was high.

Results of four subsets show that WRI and AWEI have the problem by built-up and its shadow, and AEWI has a little problem for water detection. MNDWI has the best result in the case study and has the little difference by the best results of three other case study results.

6. Conclusion

This paper proposes water indices and Geographic Information System (GIS) for monitoring changes in the water resource using multi-temporal Landsat images. This study detects and analyzes for the spatial and quantify of the water area changes of TTM Lake. Generally, the end results show that MNDWI is the most suitable and easiest technique for the extracting and mapping of water resources.

The results of the analysis reveal that TTM Lake has shown very little changes in their surface area coverage over the past decades. This lake has shown very erratic changes in its area coverage by climbing up 0.4032 km^2 in 2000-2010 and then by losing almost 0.2484 km^2 between 2010 and 2017. Thus, gradually increasing and decreasing along with history makes TTM inclined in seventeen years. This study shows feasibility estimate lake water satellite data available. Specifically, it can be concluded that water indices method, and remote sensing based datasets provide great potential for the mapping and monitoring of water resources in arid environment.

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