Water Feature Extraction, Enhancement and Change Detection of Multi-Temporal Satellite Images using MNDWI2-PCA

M Hemalatha
ECE department, Chadalawada Ramanamma Engineering College, Tirupati, A.P, India. maddihemalatha@gmail.com

Abstract- Water feature extraction is a challenging task in remote sensing. In this research work, a new water index is implemented for easy identification of water pixels. The Area of interest is extracted with desired shape file. Here water bodies from kalahasti region are extracted, which is in Chittoor district. The Water indices are used to identify water pixels from Landsat-8 image, which has high spectral resolution. This image is multi-spectral image comprising of eleven bands. Interactive supervised classification is implemented for segmenting the satellite image. The image is classified into two categories i.e. water bodies and non-water bodies. Then MNDWI2-PC (Normalized Difference Water Index2 -Principal Component) is applied to LANDSAT-8 image. Then this image is segmented into water bodies and non-water bodies. Finally accuracy assessment is carried out by confusion or error matrix. Quantitative parameters such as Overall Accuracy (OA), Kappa Coefficient (KC), Overall Kappa Coefficient (OKC) User’s accuracy (UA), Producer’s Accuracy (PA), and F1score (F-Measure) are calculated for this multi-spectral satellite imagery. The algorithm reduced misclassification of water pixels with urban pixels, vegetation and other land covers. The algorithm outperforms in terms of quantitative performance metrics.

Keywords –Normalized Difference Water Index –Principal Component, Modified Normalized Difference Water Index -Principal Component, error matrix, and accuracy assessment.

1. Introduction

Many water indices have been used for water feature Extraction. McFeeters proposed Normalized Difference water index (NDWI) to extract ponds and lakes related to wetlands [1]. Xu proposed modified normalized difference water index (MNDWI) for identifying water pixels. Ji proposed a new method where he replaced band 4 with band 5 in MNDWI and suggested that, this method was more stable [2]. Automated Water Extraction Index with no shadow (AWEI_{nh}) and Automated Water Extraction Index with shadow (AWEI_{sh}) are the two WI’s (Water Indices) proposed by Feyisa [3]. Water pixels are mixed up with background noise and According to time and location of image acquired, the threshold values are varied [4]. PCA has two merits one is dimensions of data set are reduced and second is noise is reduced. Without PCA (Principal Component Analysis), the author in [5] calculated WI’s. Change detection with NDWI-PC has got good accuracies, proposed by Komeil Rokni [6]. Fusion of remote sensing indices gave good results for water pixel extraction [7]. The Proposed method gave better results in water feature extraction and qualitative performance metrics.

2. Materials And Methods

Kalahasti area from Chittoor district in Andhra pradesh is used for water bodies’ detection and analysis. To analyze water bodies from satellite images, ArcGIS 10.3 software is used. The total image Resolution is 7631×7801. The satellite images are pre-processed by nearest neighbor interpolation algorithm. Area of Interest (AOI) is extracted from 143/50 (row/path). Here, AOI is kalahasti, which is extracted from Chittoor district. Geo-processing clip is applied for shape file. Then Raster clip is applied for satellite image and shape file, to extract desired area.
The PCA algorithm is used to achieve uncorrelated data set. In satellite imagery each band corresponds to different wavelengths. With PCA, the bands are reduced to give unique information. The merits of principal component analysis are to reduce the dimensionality and to reduce the noise. The PCA is also used for enhancement of satellite images. Finally, Interactive supervised classification is used for identifying land-covers. All the evaluation performance metrics are calculated with the help of confusion matrix.

For validating satellite data, 25 ground truth points (GTP) or tie points in each class are selected in satellite data. Total 50 tie points are selected two land covers. Shape file is created for these two classes with 50 tie points. Then, shape file is converted into raster. This resultant image is combined with classified data. Finally pivot table is generated, which gives confusion matrix for classified data and reference data. While creating shape file, the input satellite data and shape file data should be in same coordinate system. Otherwise pixels in the satellite data are misclassified. Quantitative performance metrics such as OA, KC, OKC, PA, UA, and F1Score are calculated. The algorithm for water extraction and enhancement is shown in Figure 1.

Water features are easily identified by Modified Normalized Difference Water Index 2 -Principal Component (MNDW2-PC). The misclassified with this algorithm are minimized. The edges are detected well and the image is enhanced with the PC.

![Flow chart for water feature extraction](image)

**Figure 1.** Flow chart for water feature extraction

### 2.1 Data set

The data set is downloaded from USGS (United States Geological Survey) earth explorer. These images are collected from satellite LANDSAT-8 OLI (Operational Land Imager). Table 1 describes Landsat-8 OLI characteristics. Table 2 presents various bands of Landsat-8 OLI. In this research letter, extraction of water is main scenario. So band 2, band 4, band 5, and band 7 are selected for water feature extraction. They gave better results compared to other spectral bands.

### Table 1. Landsat-8 OLI main characteristics

| Acquired images dates | 19/03/2019 |
|-----------------------|------------|
| Path/Row              | 143/50     |
Datum: WGS 84
Projection: UTM
Spatial Resolution: 30m
File Format of Acquired images: Geo-Tiff

| Total number of bands | 11 |
|-----------------------|----|
| Type of Sensor        | OLI|
| Radiometric Resolution| 16 bits |
| Temporal Resolution   | 16 days |
| Swath                 | 190 km |

Table 2: Landsat-8 bands description

| Bands | Wavelength (µm) | Resolution (m) |
|-------|----------------|----------------|
| Band 1| 0.43-0.45      | 30             |
| Band 2| 0.45-0.51      | 30             |
| Band 3| 0.53-0.59      | 30             |
| Band 4| 0.64-0.67      | 30             |
| Band 5| 0.85-0.88      | 30             |
| Band 6| 1.57-1.65      | 30             |
| Band 7| 2.11-2.29      | 30             |
| Band 8| 0.50-0.68      | 30             |
| Band 9| 1.36-1.38      | 30             |
| Band 10| 10.6-11.19   | 100            |
| Band 11| 11.5-12.51    | 100            |

Here, band 1 is coastal aerosol, band 2 is Blue, band 3 is Green (G), band 4 is Red (R), band 5 is Infra Red, band 6 is SWIR1 (Short Wave Infra Red), band 7 is SWIR2, band 8 is panchromatic, band 9 is Cirrus, band 10 is TIRS1 (Thermal Infra red), and band 11 is TIRS2. In this research work, the bands R, NIR, G, and SWIR are used for water feature extraction. The formulas for NDWI [6], MNDWI [6], and MNDWI2 are shown in equations 1, 2, and 3 respectively.

\[
\text{NDWI}_{L8} = \frac{G_{L8} - \text{NIR}_{L8}}{G_{L8} + \text{NIR}_{L8}} \tag{1}
\]

\[
\text{MNDWI}_{L8} = \frac{\text{NIR2}_{L8} + R_{L8}}{\text{NIR2}_{L8} + R_{L8}} \tag{2}
\]

\[
\text{MNDWI2}_{L8} = \frac{G_{L8} - \text{SWIR1}_{L8}}{G_{L8} + \text{SWIR1}_{L8}} \tag{3}
\]

PCA is calculated with Eigen value decomposition of data covariance matrix or singular value decomposition of data matrix.

PCA is dire necessary to decrease satellite image dimensions without any distortion. It eliminates noise in satellite imagery. The PCA is also used for feature extraction and enhancement of multispectral satellite images.

2.2 Study Area

The proposed water feature extraction algorithm is implemented on kalahasti region in Chittoor. Chittoor district is in Andhra Pradesh (India). It has longitude of 79°10’03” and latitude of 13°21’72”. It belongs to Rayalaseema region of AP.

3. Results And Discussions

The False color image (FCC) is shown in Figure 2. This image is the resultant of adding 4, 3, and 2 bands. Figure 3 explains NDWI-PC classification after applying principal component to NDWI (2014). Figure 4 explains MNDWI-PC classification after applying principal component to MNDWI.
(2014). Figure 5 describes MNDWI2-PC classification after applying principal component to MNDWI2 (2014).

The False color image (FCC) for 2018 is shown in Figure 6 and NDWI-PC classification after applying principal component to NDWI (2018) is depicted in Figure 7. Figure 8 describes MNDWI-PC classification after applying principal component to MNDWI (2018). Figure 9 explains MNDWI2-PC classification after applying principal component to MNDWI2 (2018).

Table 3 describes about surface area calculation for kalahasti image (2014). The area calculated for proposed method has got better value i.e. 52.21km². The same is validated with google earth reference pixels. Table 3 also describes about surface area calculation for kalahasti image (2018). The area calculated for proposed method has got better value i.e. 50.21km². The same is validated with google earth reference pixels.

Table 4 explains about accuracy assessment of kalahasti image in 2014. With this method, OKC is improved to 0.933 and KC is improved to 0.954. The method has got UA of 96.67 percent, PA of 96.67 percent and F1Measure value is 0.949. OA is same with all the three methods. Table 5 explains about accuracy assessment of kalahasti image in 2018. With proposed method, OKC is improved to 0.933 and KC is improved to 0.932. The method has got UA of 96.67 percent, PA of 93.35 percent and F1Measure value is 0.951. OA is 95 percent with proposed algorithm in 2018.

Table 5 describes graph for Change detection of water pixels for SriKalahasti in between 2014 and 2018. Change detection is performed by taking pixels difference in 2014 and 2018.
**Figure 4.** MNDWI-PC classification (2014)

**Figure 5.** MNDWI2-PC classification (2014)

**Figure 6.** FCC for Sri kalahasti image (2018)

**Figure 7.** NDWI-PC classification (2018)
Figure 8. MNDWI-PC classification (2018)

Figure 9. MNDW12-PC classification (2018)

Table 3. Surface Area calculation of Srikalahasti in 2014 and 2018

| Remote sensing indices | Pixel count | Spatial Resolution (m) | Area (Km²) |
|------------------------|-------------|------------------------|------------|
| NDWI-PC(2014)          | 59016       | 30                     | 53.31      |
| MNDWI -PC(2014)        | 62909       | 30                     | 56.67      |
| MNDWI2-PC (2014)       | 58006       | 30                     | 52.21      |
| NDWI-PC (2018)         | 58079       | 30                     | 52.27      |
| MNDWI-PC (2018)        | 62567       | 30                     | 56.31      |
| MNDWI2-PC (2018)       | 55797       | 30                     | 50.21      |

Table 4. Accuracy assessment of Srikalahasti in 2014

| Method            | Area (Km²) | Over All Kappa Coefficient (OKC) | Over All Accuracy (OA in %) | Kappa Coefficient (KC) | UA (%) | PA (%) | F-Measure |
|-------------------|------------|----------------------------------|----------------------------|------------------------|--------|--------|-----------|
| NDWI-PC           | 53.31      | 0.90                             | 96.67                      | 0.935                  | 96.56  | 93.33  | 0.571     |
|                   | 56.67      |                                   |                            |                        |        |        |           |
| MNDWI-PC          | 93.1       | 96.67                            | 0.954                      | 93.75                  | 96.77  | 0.956  |
| MNDWI2-PC         | 52.21      | 0.933                            | 96.67                      | 0.956                  | 96.67  |        | 0.949     |

Google earth reference data- 52.76 km²

Table 5. Accuracy assessment of Srikalahasti in 2018

| Method | Area (Km²) | Over All Kappa Coefficient (OKC) | Over All Accuracy (OA in %) | Kappa Coefficient (KC) | UA (%) | PA (%) | F-Measure |
|--------|------------|----------------------------------|----------------------------|------------------------|--------|--------|-----------|
| NDWI-PC| 52.27      | 0.844                            | 91.67                      | 0.892                  | 93.1   | 96.43  | 0.948     |
4. Conclusion

A novel algorithm is used to extract water from satellite imagery. With this method water bodies are identified properly. MNDWI2-PC is applied to the resultant image. Supervised classification is performed. Finally accuracy assessment has been performed with error matrix or confusion matrix. The proposed algorithm gave better results in terms of qualitative parameters such as OA, KC, OKC, UA, PA, and F-Measure. The method is able to extract water bodies in multi-spectral satellite imagery. Change detection has been performed with difference of four years.

Acknowledgement

The authors appreciate USGS for providing LANDSAT-8 ETM+ images. The authors would also like to express their appreciation to S. V. University, C.O.E (centre of excellence) laboratory, Tirupati, for providing all facilities and assistantship and necessary software’s for our research.

References

[1] S. McFeeters, “The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features”, Int. J. Remote Sens., Vol. 5, pp. 1425–1432, 1996.
[2] H. Xu, “Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery” Int. J. Remote Sens. Vol. 27, No. 14 pp. 3025–3033, 2006.
[3] G.L. Feyisa, H. Meilby, R. Fensholt, and S.R. Proud, “Automated water extraction index: A new technique for surface water mapping using Landsat imagery”, Remote Sens. Environ., Vol.140, 23–35, 2014.
[4] L. Ji, L. Zhang, and B. Wylie, “Analysis of dynamic thresholds for the normalised difference water index”, Photogramm. Eng. Remote Sens., Vol. 75, No. 11, pp.1307–1317, 2009.
[5] L. Yongxue, S. Chao, “Automated Extraction and Mapping for Desert Wadis from Landsat Imagery in Arid West Asia”, Remote Sens., Vol.8, No.246, pp.1-23, 2016.
[6] Komeil Rokni, Anuar Ahmad, Ali Selamat, and Sharifeh Hazini, “Water feature extraction and change detection using multi temporal landsat imagery”, Remote Sens., Vol.6, 4173–4189, 2014.
[7] M.Hema Latha, S.Varadarajan, “Feature enhancement of multispectral images Using vegetation, water, and soil Indices Image Fusion, ISMAC-CVB, Springer Conference, May 2018.”