

Water Body Extraction Using Images From Two Different Satellites Over Chilika Lake

B. Chandrababu Naik¹, Prof. B. Anuradha¹¹

¹ Research Scholar, Dept. of Electronics and Communication, SVU College of Engineering, SV University, Tirupathi, Andhra Pradesh, India.

¹¹ Professor, Dept. of Electronics and Communication, SVU College of Engineering, SV University, Tirupathi, Andhra Pradesh, India.

Abstract: Remote sensing data used for extraction of water bodies in the earth and it also plays a vital role in the accuracy of the extracted water features. Two different satellite data are used for extraction of water bodies such as Landsat-8 (OLI) and Sentinel-2A over a Chilika Lake in the period of January, 2018 and it was located in Odisha state, India. The spatial, spectral and multi-temporal water index including the Normalized Water Difference Index (NDWI), Modified Normalized Water Difference Index (MNDWI), Automated Water Extraction Index (AWEI), and Principle Component of Analysis (PCA) are used to the extraction of water bodies. The PCA and MNDWI water index methods provide better results as compared to other water index methods in two different satellite images (Landsat-8 and Sentinel-2A). The maximum extracted water area of Chilika Lake was about 394.026 Sq. miles in the Landsat-8 image, and 385.422 Sq. miles in Sentinel-2A image by using PCA method. The ISODATA unsupervised classification is used for accuracy assessment analysis. The maximum overall classification accuracy of 94.74%, overall kappa statistics is 0.8869 achieved in Landsat-8 data and the maximum overall classification accuracy of 92.11%, overall kappa statistics is 0.8364 achieved in Sentinel-2A data. The results obtained in Landsat-8 are better when compared to Sentinel-2A satellite data.

Keywords: water index, NDWI, MNDWI, AWEI, PCA, Landsat-8, Sentinel-2A, ISODATA unsupervised algorithm.

1. Introduction

The spatial, spectral and multi-temporal satellite data are widely used in remote sensing applications, such as land use land cover change [1,2], flood mappings, environment monitoring [5-8], forest and vegetation change [3,4] and detection and extraction of surface water bodies [9-15]. Identification of water bodies using either field surveying or remote sensing techniques [21]. The remote sensing techniques having more advantages over the field surveying techniques, because it is low cost and time effective. The multi-temporal remote sensing techniques are applied to the extraction of water bodies such as lakes, Reservoirs, rivers, sea ice, and icebergs [22].

Several image processing techniques have introduced the extraction of water bodies in recent decades such as water index methods including Normalized Water Difference Index (NDWI), Modified Normalized Water Difference Index (MNDWI), Automated Water Extraction Index (AWEI), and Principle Component of Analysis (PCA). Two different satellite data are used for extraction of water bodies such as, Landsat-8 (OLI) and Sentinel-2A over a Chilika Lake in the period of January, 2018 and it was located in Odisha state, India. These Landsat-8 and Sentinel-2A data are freely available in USGS portal and Global Visualization Viewer. The Landsat-8 data consist of 11 bands and its resolution is 30m. Sentinel-2A data consist of 12 bands and its resolution is 20m. In some of the remote sensing applications, the Sentinel-2A data does not provide good results, especially for detecting and extraction of water bodies and flood mapping areas.

The spectral bands of Landsat-8 and Sentinel-2A satellite data are especially the Near-Infra-Red, Middle-Infra-Red, and Short-Wavelength Infra-Red bands provide information about extraction of water bodies [21]. The PCA and MNDWI water indexing methods performed better results for acquired satellite data and AWEI water indexing methods give poor performance for evaluation of water extraction. The ISODATA unsupervised classification is used for accuracy assessment analysis. Therefore, the accuracy assessment analysis for the water body extraction work gives better results in Landsat-8 as compared to Sentinel-2A satellite data.

2. Study Area and Collection of Data Set

The study area of the Chilika Lake is biggest brackish water Lake in India. This Lake was Located in Odisha state, but it attached to a bay of Bengal in the east coast of India. It is also one of bird sanctuary reserved. The Latitudes and Longitudes of this Lake is $19^{\circ}46'30.37''$ N and $85^{\circ}25'4.85''$ E respectively as shown in Fig. 1 and 2.

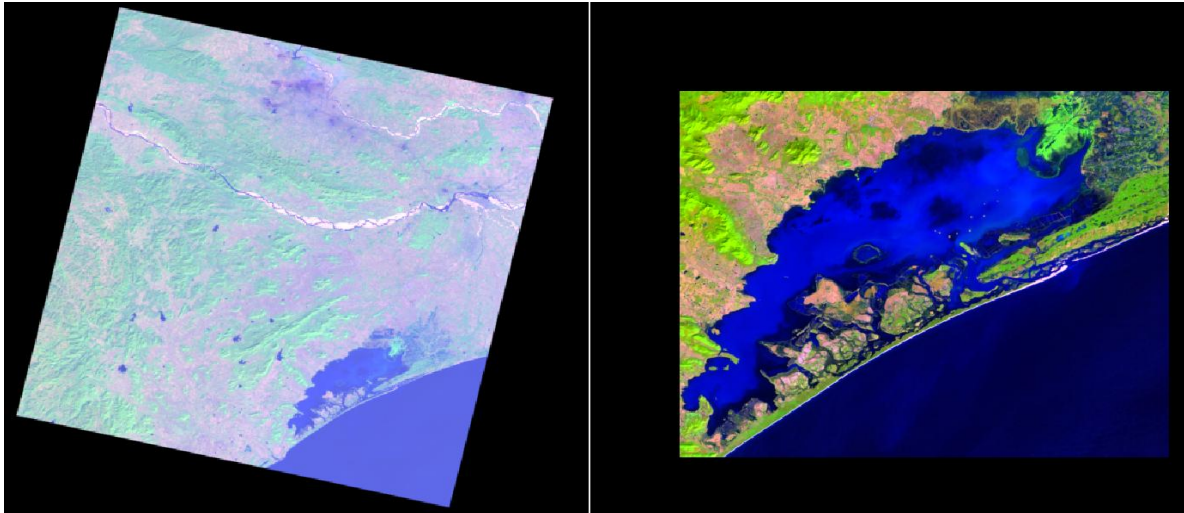


Fig.1. Location of Chilika Lake from Landsat-8 (OLI) satellite image in January, 2018.

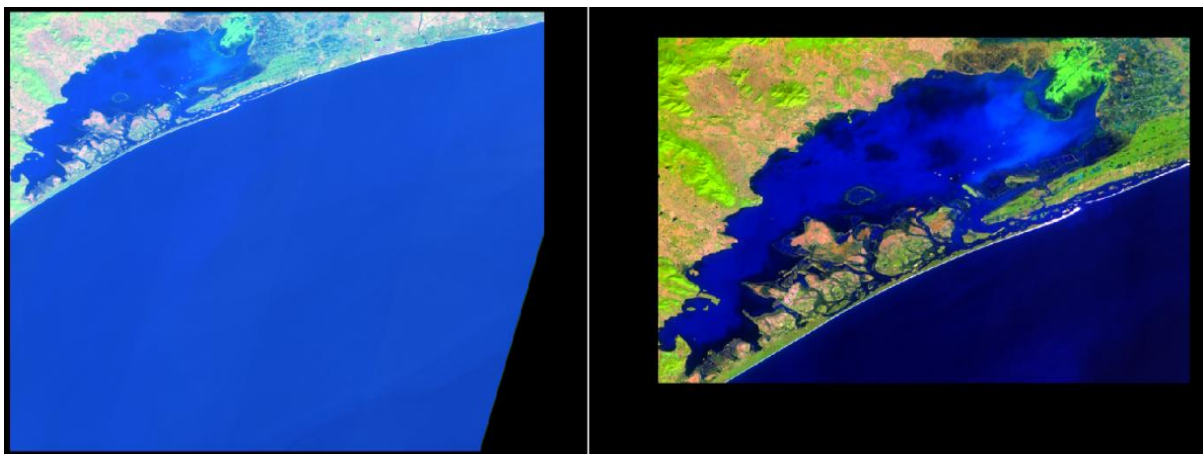


Fig.2. Location of Chilika Lake from Sentinel-2A satellite image in January, 2018.

The Landsat-8 (OLI) and Sentinel-2A satellite data acquired is for the period of January 2018. These Landsat-8 and Sentinel-2A data were taken from the USGS portal, and all collected satellite data were cloud free data only. The specification of bands and its wavelengths for Landsat-8 and Sentinel-2A data are as shown in Table 1.

Table 1. The Specification of Landsat-8 and Sentinel-2A satellite data.

Satellite	Year	Path/Row/ Tile Number	Resolution (m)	Wavelengths (μm)
Landsat-8 OLI	January- 2018	140/46	30	Band1:0.433-0.453 Band2:0.450-0.515 Band3:0.525-0.600 Band4:0.630-0.680 Band5:0.845-0.885 Band6:1.560-1.660 Band7:2.100-2.300 Band9:1.360-1.390
Sentilen-2A	January- 2018	T45QUB	20	Band1:0.433 Band2:0.490 Band3:0.560 Band4:0.665 Band8:0.842 Band9:0.945 Band11:1.610 Band12:2.190

3. Methodology

The acquired Landsat-8 and Sentinel-2A satellite data in the period of January 2018 is considered. The performances of different satellite-multiband water indexes are evaluated, the Normalized Difference Water Index (NDWI) [10], and Modified Normalized Difference Water Index (MNDWI) [16], and Automated Water Extraction Index (AWEI) [17] (Table 2) were used for detecting and extraction of surface water bodies from two different satellite imagery. Table 2. Represent the Landsat-8 data, indexes used for water feature extraction (Band 3 = Green, Band 4 = Red, Band 5 = Near Infra Red, Band 6 = Middle Infra Red, Band 7 = Short wavelength Infra Red). Similarly, in Sentinel-2A data (Band 3 = Green, Band 4 = Red, Band 8 = Near Infra Red, Band 11 = Middle Infra Red, Band 12 = Shortwave Infra Red).

Table 2. Satellite-multi-band indexes used for water feature extraction.

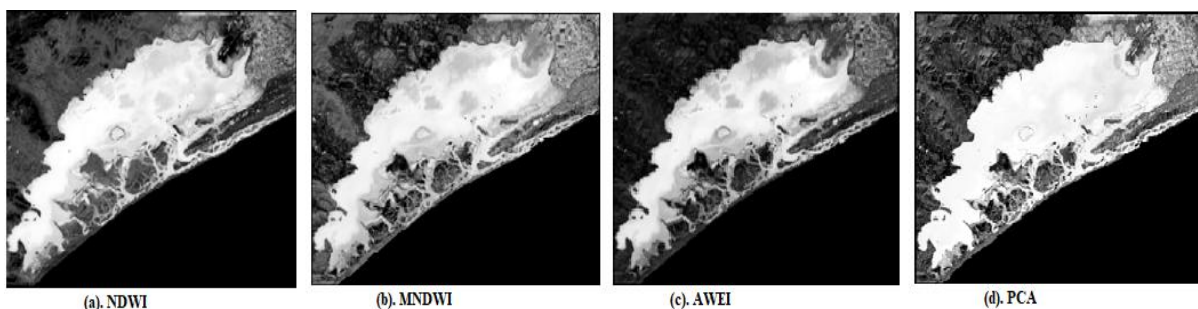
Water Index Method	Equation	Remark	Reference
Normalized Difference Water Index	$NDWI = \frac{Green - NIR}{Green + NIR}$	Water would be a positive value	[10]
Modified Normalized Difference Water Index	$MNDWI = \frac{Green - MIR}{Green + MIR}$	Water would be a positive value	[16]
Automated Water Extraction Index	$AWEI = 4 \times (Green - MIR) - (0.25 \times NIR + 2.75 \times SWIR)$	Water would be a positive value	[17]

3.1 Principle Component of Analysis (PCA)

The Principal Component Analysis (PCA) is a numerical method used to reduce a set of correlated multivariate measurements to a smaller setting where the quality are uncorrelated to each other. PCA extensively used to improve an image in the land-cover classification, remote sensing applications, and multispectral satellite images. It is an imperative tool for high-resolution multi-temporal analysis and precisely establishes a new set of variables, which explain the variation in the original dataset. The main principle of using a PCA is to decrease the dimensionality of the data, in this case the number of original bands, to maximize the quantity of in sequence from the original bands into the smallest amount number of principal components. A set of correlated variables (original bands) is transformed in other uncorrelated variables (principal components) which include the maximum unique in sequence with an objective meaning that wants to be explored. This analysis has been applied in the Landsat-8 and Sentinel-2A images and also first three principal components may include more than 90 percent of the information in the original seven bands [18]. These statistical parameter analyses have been extensively used in remote sensing applications to classify the land surface [19] and detect changes [20]. Therefore, the PCA can be used in image classification and to improve the accuracy.

4. Results and Discussions

Sentinel-2A satellite data and Landsat-8 satellite data is freely available data in USGS portal. The spatial and spectral resolution of Landsat-8 (30m) is less as compared to Sentinel data (20m). But for detecting and extraction of the water bodies the Sentinel-2A satellite data does not provide good results as compared to Landsat-8 data in some of water feature extraction applications (Fig. 3 and 4). The Lake water surface area and its statistical parameters (such as min, max thresholds, mean and standard deviation) were evaluated using water index methods including NDWI, MNDWI, AWEI and PCA for acquired two different satellite images in the period of January, 2018. The Results of water bodies extraction using water index methods (NDWI, MNDWI, AWEI, and PCA) for Landsat-8 and Sentinel-2A images are shown in Fig. 3 and 4.



(a). NDWI

(b). MNDWI

(c). AWEI

(d). PCA

Fig. 3. Results of water bodies extraction using water index methods (NDWI, MNDWI, AWEI, and PCA) for the Landsat-8 image.

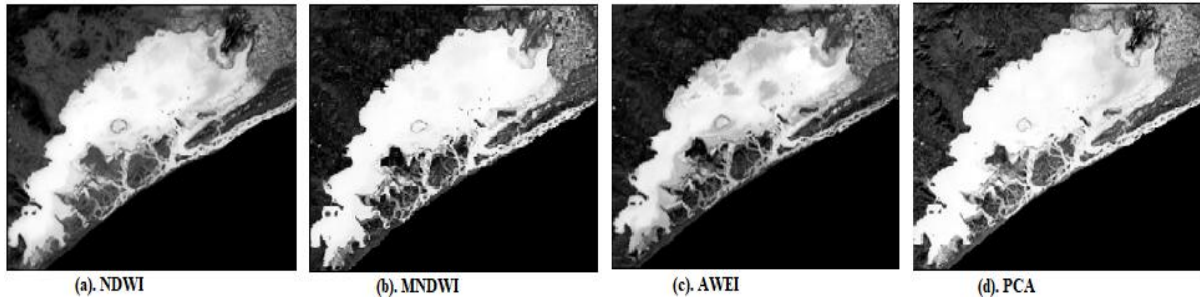


Fig. 4. Results of water bodies extraction using water index methods (NDWI, MNDWI, AWEI, and PCA) for Sentinel-2A image.

The results show that the Lake surface water area about 394.026 Sq. miles in PCA method and 387.434 Sq. miles in MNDWI method by using Landsat-8 data (Table 3). Similarly the Lake surface water area about 385.422 Sq. miles in PCA method and 364.127 Sq. miles in MNDWI method by using Sentinel-2A data (Table 4). The AWEI water index method performed poor results as compared to other water index methods. Therefore, the summarized results show that the PCA and MNDWI water index methods provide better results for water extraction in both acquired Landsat-8 and Sentinel-2A satellite images. The performance and evaluation of water extraction results for Landsat-8 and Sentinel-2A multi-band satellites are shown in Table 3 and 4.

Table 3. The Performance evaluation of the Landsat-8 multi-band indexes used for water extraction.

Methods	Min Threshold	Max Threshold	Mean	Standard Deviation	Area (Sq. miles)
NDWI	0.538	0.994	0.620	0.264	347.794
MNDWI	0.587	0.982	0.791	0.124	387.434
AWEI	0.554	0.966	0.534	0.256	356.242
PCA	-17108.786	-14055.478	-18840.815	4242.687	394.026

Table 4. The Performance evaluation of the Sentinel-2A multi-band indexes used for water extraction.

Methods	Min Threshold	Max Threshold	Mean	Standard Deviation	Area (Sq. miles)
NDWI	0.652	0.972	0.569	0.282	336.642
MNDWI	0.666	0.983	0.642	0.286	364.127
AWEI	0.452	0.922	0.362	0.323	306.735
PCA	-2889.783	-1110.691	-3070.330	1652.585	385.422

The performance of water feature extraction based ISODATA unsupervised classification provide good results for both Landsat-8 and Sentinel-2A satellite data (Fig. 5 and 6). By using ISODATA unsupervised classification the accuracy assessment performed easily. Considered possible ten iterations for classification of ISODATA unsupervised algorithm for getting accurate results in both satellite images. The results of ISODATA unsupervised classification for Landsat-8 and Sentinel-2A as shown in Fig.5 and 6.

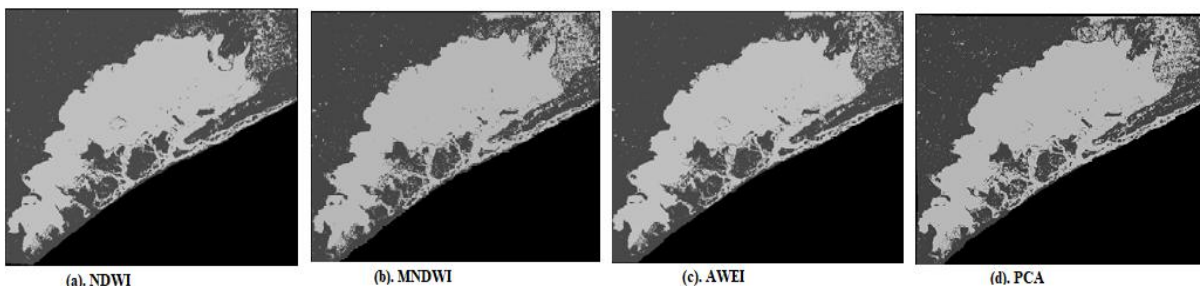


Fig. 5. ISODATA unsupervised classification results for the Landsat-8 image.

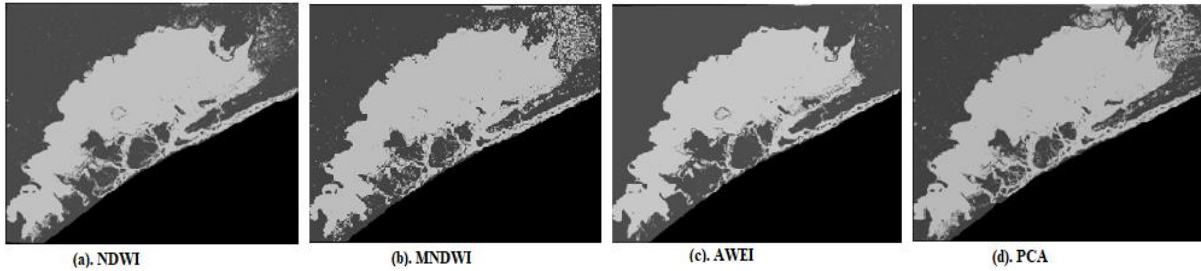


Fig. 6. ISODATA unsupervised classification results for Sentinel-2A image.

The overall accuracy for both satellite data and it from 88.89% to 94.74% and overall kappa statistics from 0.7662 to 0.8869. The Maximum overall accuracy of 94.74% in PCA and 92.59% in MNDWI and overall kappa statistics 0.8869 in PCA and 0.8508 in MNDWI for the Landsat-8 image (Table 5). Similarly, the Maximum overall accuracy of 92.11% in PCA and 91.84% in MNDWI and overall kappa statistics 0.8278 in PCA and 0.8364 in MNDWI for Sentilen-2A image (Table 5). The NDWI and AWEI water index method does not provide accurate results as compared to PCA and MNDWI water index methods. Therefore, the PCA and MNDWI provide better results in accuracy assessment analysis using ISODATA unsupervised classification. The statistical parameters of accuracy assessment result for Landsat-8 and Sentinel-2A data is as shown in Table. 5.

Table 5. Statistical parameters of accuracy assessment results for Landsat-8 and Sentinel-2A satellite data.

Satellite	Methods	Overall Classification Accuracy (%)	Overall Kappa Statistics
Landsat-8	NDWI	91.18	0.8211
	MNDWI	92.59	0.8508
	AWEI	91.84	0.8322
	PCA	94.74	0.8869
Sentinel-2A	NDWI	89.47	0.7662
	MNDWI	91.84	0.8364
	AWEI	88.89	0.7761
	PCA	92.11	0.8278

5. Conclusions

The main aim of this paper is to compared two different satellite images such as Landsat-8 and Sentinel-2A for feature extraction of water bodies using different water index methods using NDWI, MNDWI, AWEI, and PCA. The performance of water feature extraction based ISODATA unsupervised classification provide good results for both the Landsat-8 and Sentinel-2A satellite data. The maximum surface water area of Lake was about 394.026 Sq. miles in PCA method and 387.434 Sq. miles in MNDWI method for Landsat-8 image. The maximum overall classification accuracy of 94.74% and overall kappa statistics is 0.8869 achieved in two different satellite images. The PCA and MNDWI water index methods provide better results in accuracy assessment analysis using ISODATA unsupervised classification. The most of water body extraction enhancement indexes gives 1.01% better results in Landsat-8 as compared to Sentinel-2A satellite data.

References

- [1] Salmon, B.P.; Kleynhans, W.; van Den Bergh, F.; Olivier, J.C.; Grobler, T.L.; Wessels, K.J. Land cover change detection using the internal covariance matrix of the extended Kalman filter over multiple spectral bands. *IEEE J. Sel. Topics Appl. Earth Observations Remote Sens.* 2013, 6, 1079–1085.
- [2] Demir, B.; Bovolo, F.; Bruzzone, L. Updating land-cover maps by classification of image time series: A novel change-detection-driven transfer learning approach. *IEEE Trans. Geosci. Remote Sens.* 2013, 51, 300–312.
- [3] Kaliraj, S.; Muthu Meenakshi, S.; Malar, V.K. Application of remote sensing in detection of forest cover changes using geo-statistical change detection matrices—A case study of devanampatti reserve forest, tamilnadu, India. *Nat. Environ. Polluti. Technol.* 2012, 11, 261–269.
- [4] Markogianni, V.; Dimitriou, E.; Kalivas, D.P. Land-use and vegetation change detection in plastira artificial lake catchment (Greece) by using remote-sensing and GIS techniques. *Int. J. Remote Sens.* 2013, 34, 1265–1281.
- [5] Desmet, P.J.J.; Govers, G. A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. *J. Soil Water Conserv.* 1996, 51, 427–433.

- [6] Zhou, W.; Wu, B. Assessment of soil erosion and sediment delivery ratio using remote sensing and GIS: A case study of upstream chaobaihe river catchment, north China. *Int. J. Sediment Res.* 2008, 23, 167–173.
- [7] Du, Z.; Linghu, B.; Ling, F.; Li, W.; Tian, W.; Wang, H.; Gui, Y.; Sun, B.; Zhang, X. Estimating surface water area changes using time-series Landsat data in the qingjiang river basin, China. *J. Appl. Remote Sens.* 2012, 6, doi:10.1117/1.JRS.6.063609.
- [8] Sun, F.; Sun, W.; Chen, J.; Gong, P. Comparison and improvement of methods for identifying waterbodies in remotely sensed imagery. *Int. J. Remote Sens.* 2012, 33, 6854–6875.
- [9] Water Body Extraction from Multi-Source Satellite Images. Available online: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.301.8033&rep=rep1&type=pdf> (accessed on 21 June 2003).
- [10] Xu, H. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *Int. J. Remote Sens.* 2006, 27, 3025–3033.
- [11] Water Body Extraction And Change Detection Based on Multi-Temporal SAR Images. Available online: <http://adsabs.harvard.edu/abs/2009SPIE.7498E..96Z> (accessed on 21 January 2014).
- [12] Zhou, H.; Hong, J.; Huang, Q. Landscape and water quality change detection in urban wetland: A post-classification comparison method with IKONOS data. *Procedia Environ. Sci.* 2011, 10, 1726–1731.
- [13] Tang, Z.; Ou, W.; Dai, Y.; Xin, Y. Extraction of water body based on Landsat TM5 imagery—A case study in the Yangtze river. *Adv. Inf. Comm. Technol.* 2013, 393, 416–420.
- [14] Li, W.; Du, Z.; Ling, F.; Zhou, D.; Wang, H.; Gui, Y.; Sun, B.; Zhang, X. A comparison of land surface water mapping using the normalized difference water index from TM, ETM+ and ALI. *Remote Sens.* 2013, 5, 5530–5549.
- [15] McFeeters, S.K. Using the normalized difference water index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. *Remote Sens.* 2013, 5, 3544–3561.
- [16] Lu, S.; Wu, B.; Yan, N.; Wang, H. Water body mapping method with HJ-1A/B satellite imagery. *Int. J. Appl. Earth Obs. Geoinf.* 2011, 13, 428–434.
- [17] Feyisa, G.L.; Meilby, H.; Fensholt, R.; Proud, S.R. Automated water extraction index: A new technique for surface water mapping using Landsat imagery. *Remote Sens. Environ.* 2014, 140, 23–35.
- [18] Fundamentals of Remote Sensing. Canada Centre for Remote Sensing. Accessed 23th October 2012. <http://www.nrcan.gc.ca/earth-sciences/geography/boundary/remotesensing/fundamentals/1814>.
- [19] X. Jia, J. A. Richards. Segmented Principal Components Transformation for Efficient Hyperspectral Remote-Sensing Image Display and Classification. *IEEE Transactions on Geoscience and Remote Sensing.* 37(1). pp. 538{542. (1999).
- [20] J. R. Eastman, M. Filk. Long sequence time series evaluation using standardized principal components. *Photogrammetric Engineering and Remote Sensing.* 59(6) 991-996. (1993).
- [21] Yang, X., Zhao, S., Qin, X., Zhao, N., & Liang, L. (2017). Mapping of Urban Surface Water Bodies from Sentinel-2 MSI Imagery at 10 m Resolution via NDWI-Based Image Sharpening. *Remote Sensing*, 9, 569. <https://doi.org/10.3390/rs9060596>.
- [22] Jawak, S. D., Kulkarni, K., & Luis, A. J. (2015). A Review on Extraction of Lakes from Remotely Sensed Optical Satellite Data with a Special Focus on Cryospheric Lakes. *Advances in Remote Sensing*, 4, 196-213. <https://doi.org/10.1016/j.aqpro.2015.02.018>.