A Novel Water Index for Extraction of Water Features using Landsat-8 Images in Prayagraj District, India

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Abstract

The satellite images can be categorized in three classes on the basis of the spectral bands, viz., panchromatic, multispectral and hyprspectral. The multispectral imageries are very useful in the feature extraction and enhancement, the combination of bands creates magical effect not only to delineate some features but also to eliminate the others. Several water indices on the basis of band combinations have been proposed by the researchers for the open surface water detection. In the present work a new index has been proposed for open surface water detection from landsat-8 satellite imagery. The proposed index can detect the water class more efficiently as compared to the existing indices which has been supported by the quantitative data. The results are validated in terms of the number of pixels of water class with an accuracy of 99.77%.

1 Introduction

The life is not even imagined in the absence of water, however; due to urbanization and global progression the water bodies are dwindling. Therefore, the assessment of water resources in terms of both quantity, e.g., surface area and quality, e.g., less turbid, is required for the survival of human. Since, the study of water, especially the open water is not possible by visiting the water sources manually; the satellite images are one of the best alternatives. With the help of satellite images, the large geographical areas including the open water can easily be covered and studied. However, the major challenge to extract the open water is that the spectral response of deep water varies with the depth whereas that of shallow water gets mixed with the neighboring vegetation and other classes, e.g., shadows of the buildings and trees [1].

Satellite imageries are available in three forms based on the number of division of the electromagnetic spectrum: Panchromatic; consists earth feature information in a single band, Multispectral; requires less than 15 bands and Hyper-spectral; varies from 100 to 1000 bands. Landsat-8, carrying a multispectral sensor, captures the images in 11 bands where the first 9 bands are due to OLI sensor whereas the last two bands are due to TIRS sensor. Band 1 is known as deep blue band, Band 2 is known as blue band, Band 3 is green band, Band 4 is red band, Band 5 is known as Near Infrared (NIR), Band 6 is known as short-waves Infrared (SWIR)-1, Band 7 is called SWIR-2, Band 8 is the Panchromatic band with 15 meter spatial resolution and Band 9 is referred as Cirrus band. The Band 10 and band 11 are known as Thermal Infrared Sensor-1 and 2 respectively with 100 meter spatial resolution. The spatial resolution of all other bands is 30 meters.

Table 1. Existing Water Indices [3–10]

Water Index	Bands Used	Formula	Proposed by
TCW	RED, GREEN, BLUE, NIR, SWIR1, SWIR2	0.1509×BLUE+0.2021×GREEN+0.3102×RED+0.1594×NIR−0.6806×SWIR1−0.6109×SWIR2	Crist (1984)
TCW_{Crist}	RED, GREEN, BLUE, NIR, SWIR1, SWIR2	0.0315×BLUE+0.1973×GREEN+0.3279×RED+0.3406×NIR−0.7112×SWIR1−0.4572×SWIR2	Crist (1985)
NDWI	GREEN, NIR	(GREEN−NIR)/(GREEN+NIR)	Mcfeeters (1996)
MNDWI	GREEN, SWIR	(GREEN−SWIR)/(GREEN+SWIR)	Xu (2006)
NDPI	SWIR, GREEN	(SWIR−GREEN)/(SWIR+GREEN)	Lacaux et al. (2007)
WRI	GREEN, RED, SWIR, NIR	(GREEN+RED)/(NIR+SWIR1)	Shen & Li (2010)
AWEIsh	BLUE, GREEN, NIR, SWIR1, SWIR2	BLUE+2.5×GREEN1.5×(NIR+SWIR1)−0.25×SWIR2	Feyisa et al. (2014)
AWEInsh	GREEN, NIR, SWIR1, SWIR2	4×(GREEN−SWIR1)−(0.25×NIR+2.75×SWIR2)	Feyisa et al. (2014)
WI2015	GREEN, RED, NIR, SWIR1, SWIR2	1.7204+171×GREEN+3×RED70×NIR−45×SWIR1−71×SWIR2	Fisher et al. (2016)

Researchers used the multispectral data in two ways to delineate open surface water feature on the earth. The first is single band analysis method [2], e.g., NIR band which has a strong absorption by water and high reflectance by soil and vegetation [3]. The second is the use of band images from different spectra and their combinations to generate some empirical relation among the bands. A number of water indices are proposed by the researchers till date, e.g., Tasseled Cap Wetness (TCW and TCW_{Crist}) [4, 5], Normalized Difference Water Index (NDWI) [3], Modified Normalized Difference Water Index (MNDWI) [6], Normalized Difference Pond Index (NDPI) [7], Water Ratio Index (WRI) [8], Automated Water Extraction Index with shadow (AWEIsh) and with no shadow (AWEInsh) [9], and Water Index (WI2015) [10]. Table 1 summarizes the existing water indices described above in a chronological order.

2 Study Area and Data Set

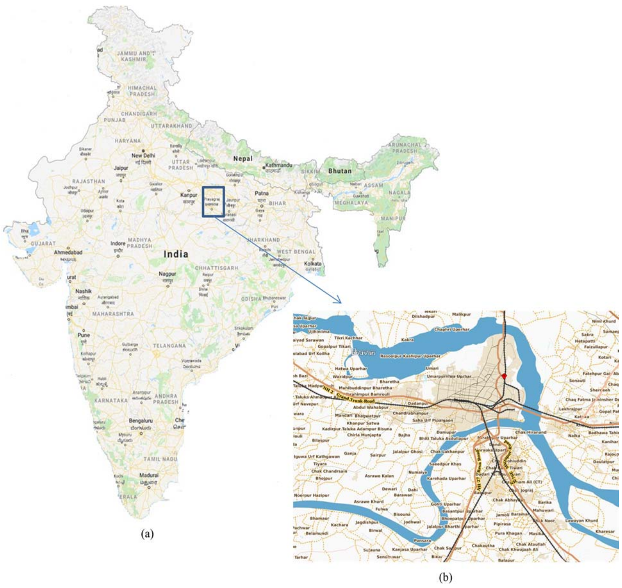


Figure 1. Study Area (a) India (b) Prayagaraj.

The study area is located in Prayagraj district of Uttar Pradesh state in India. The geographical coordinates of the top left and bottom right points of the study area are (25˚31′21.55″N, 81˚39′17.30″E) and (25˚17′22.08″N, 81˚57′39.17″E) respectively. Fig. 1 shows the study area in detail. The initial 7 bands of Landsat-8 of the year 2018 have been selected for the identification of open surface water in the study area.

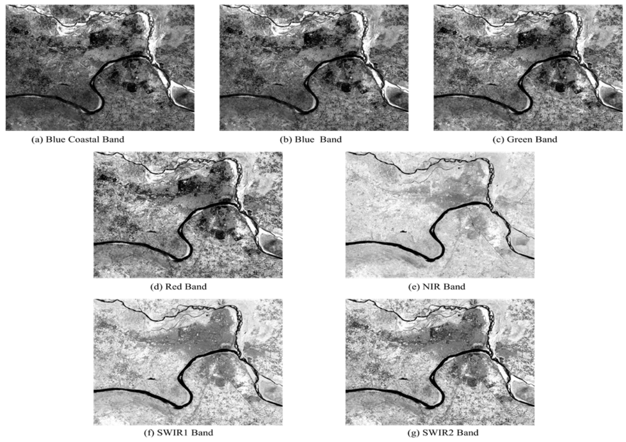


Figure 2. Band 1 to Band 7 Images of Landsat-8 from May, 2018.

3 The Proposed Water Index

The spectral response of water in NIR band and SWIR band is lower as compare to the visible spectrum because the water strongly absorbs the NIR and SWIR energy and reflects very less, just opposite scenario is observed for the soil and other terrestrial features. Table 2 shows the variation of spectral response of various land features with respect to the available bands of Landsat-8. The study area is comprised of the water, sand, land, vegetation and built-up land covers for which two samples have been shown with the spectral response in the specified band. It is observed that the spectral response of water in NIR, SWIR1 and SWIR2 is lesser than that of visible spectrum whereas it is larger for other land features. The graph in figure 3 depicts the variation of spectral response of land features. The x-axis represents the bands (Band 1- Band 7) and the y-axis represents the spectral response.

Table 2. Spectral Response of terrestrial features in different bands of Landsat-8.

Band	Water		Sand		Land		Vegetation		Built-up	
	25°25'16.30"N 81°50'33.67"E	25°29'31.89"N, 81°50'20.41"E	25°26'51.83"N, 81°53'27.27"E	25°28'12.75"N, 81°44'45.74"E	25°26'21.98"N, 81°52'22.61"E	25°30'28.84"N, 81°54'43.02"E	25°26'2.45"N, 81°52'27.83"E	25°28'17.23"N, 81°51'53.36"E	25°27'9.84"N, 81°52'10.06"E	25°27'52.19"N, 81°51'0.54"E
Band 1 (Coastal Blue)	12090	12469	15562	15880	13235	13961	12160	12324	13570	13515
Band 2 (Blue)	11196	11570	15504	15992	12729	13877	11316	11469	13101	13082
Band 3 (Green)	10546	10645	16107	16775	12776	14528	10833	10953	12961	12964
Band 4 (Red)	9500	10205	17001	17763	13481	15952	10280	10306	13394	13348
Band 5 (NIR)	9722	10751	19500	20630	16906	20162	17933	18451	15791	16829
Band 6 (SWIR1)	8464	9634	21796	23689	18811	22241	13939	13884	15853	16370
Band 7 (SWIR2)	7473	8366	20276	22204	16242	18754	10176	10744	14004	14153

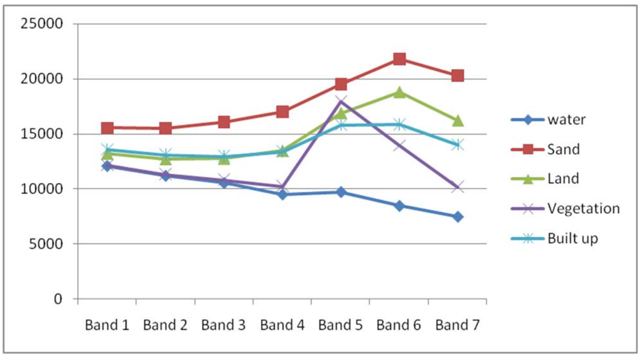


Figure 3. Spectral Responses of different features in different bands of Landsat-8.

The proposed water index uses four bands of Landsat-8, viz., green band, NIR, SWIR1 and SWIR2. The Eq. 1 depicts the index named as Mishra and Pant's Water Index (MPWI1):

$$MPWI1 = \frac{Green - (NIR + SWIR1 + SWIR2)/2}{Green + (NIR + SWIR1 + SWIR2)/2} \quad (1)$$

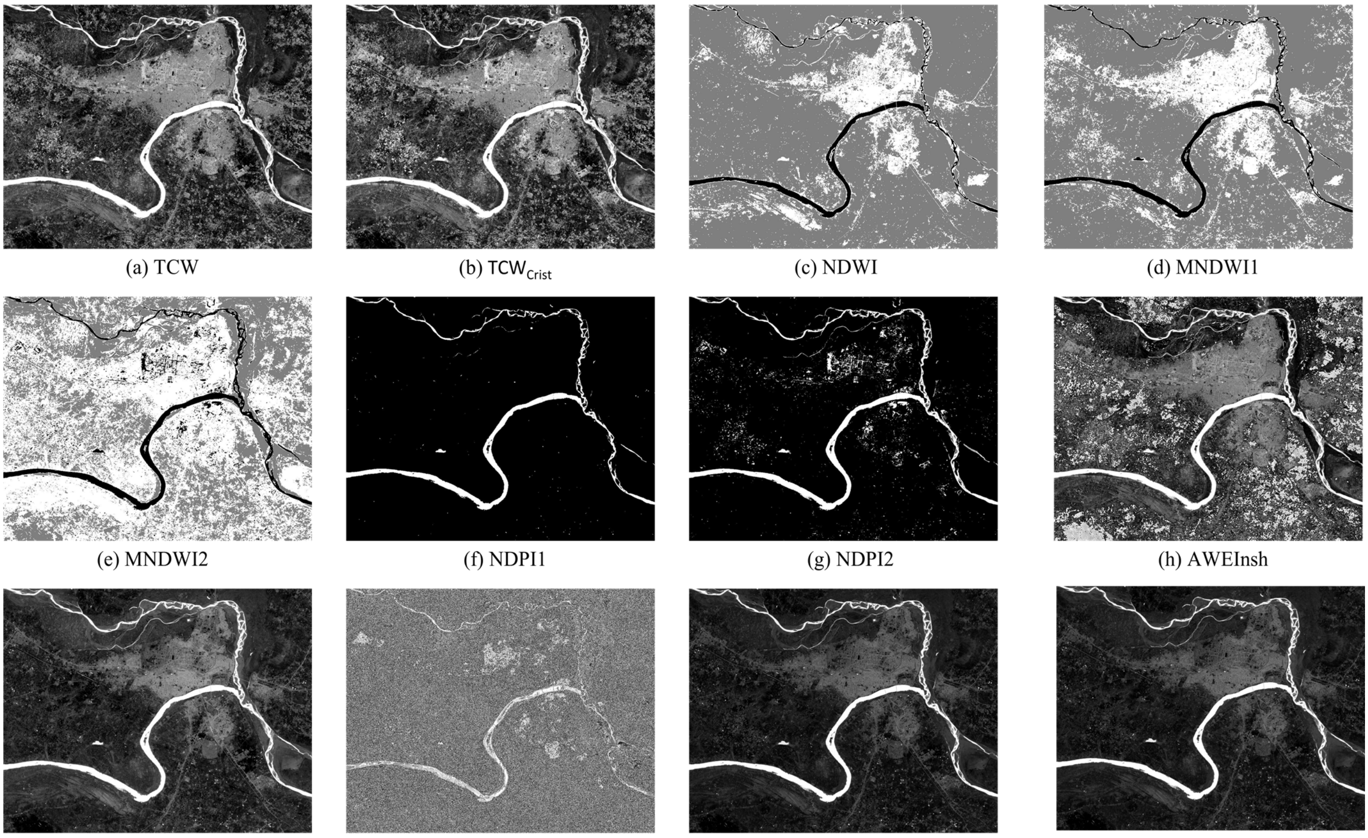
The result of this index is in the range of negative values only. Further, the open water features have all the values near to zero and the remaining values belong to non-water features. In order to find out the values in positive range, a new formula, named as MPWI2, has been proposed and given in Eq. 2.

$$MPWI2 = \frac{Green - (NIR + SWIR1 + SWIR2)/3}{Green + (NIR + SWIR1 + SWIR2)/3} \quad (2)$$

The result of Eq. 2 is in the range of positive values for water class and negative values for other classes. Due to higher reflectance in NIR, SWIR1 and SWIR2 as compared to Green band, the terrestrial features, viz., land, sand, vegetation and built-up, the values of MPWI2 are negative. On the other hand, due to low reflectance in these three bands as compared to Green band the values of MPWI2 are positive for water. This effect enhances the open surface water feature in the study area and eliminates the non-water features. Thus, the shortcoming of Eq. 1 is overcome by the Eq. 2.

4 Results

The existing water indices are implemented on the data set of figure 2, and the corresponding visual results are shown in figure 4. The proposed indices MPWI1 and MPWI2 represented by the Eq. 1 and Eq. 2 are also evaluated and corresponding images are depicted in figure 4(k), 4(l).



(a) TCW (b) TCW_{Crist} (c) NDWI (d) MNDWI1
(e) MNDWI2 (f) NDPI1 (g) NDPI2 (h) AWEInsh
(i) AWEIsh (j) WI2015 (k) MPWI1 (l) MPWI2

Figure 4.(a-j) The existing Water Indices and their visual results, (k-l) the Proposed Water Index.

Table 3. Classification results of existing and proposed water indices in binary class, i.e., water and non-water and corresponding accuracy.

Water Index	Water class	Non-water class	Overall Accuracy (%)
TCW	46961	837287	98.85
TCW_{Crist}	52777	831471	97.93
NDWI	27567	856681	83.18
MNDWI1	32439	851809	94.23
MNDWI2	59873	824375	98.16
NDPI1	32418	851830	93.77
NDPI2	59511	824737	93.78
AWEInsh	155750	728498	89.17
AWEIsh	38583	845665	99.53
WI2015	NA	NA	NA
MPWI1	38418	845830	99.77
MPWI2	38476	845772	99.77

5 Validation of Results

For validation of results the NIR band is used as it is strongly absorbed by water. The NIR band is classified into two classes, i.e., water and non-water and corresponding pixels are counted. It is observed that 37745 pixels belong to water class while 846503 pixels belong to non-water class out of 884,248 pixels in the study area. The results obtained by proposed indices shown in Table 3 are compared with the above data for validation. The index WI2015 is not able to classify the image into water and non-water classes which is indicated by NA in Table 3. It is observed that the proposed water indices match closely to the validation data with highest accuracy of 99.77%.

6 Conclusion

The water sources are found in different forms, viz., ocean, river, pond, lake, stagnant water etc. throughout the globe. For delineation of such sources of water, a number of water indices are proposed and used by researchers in past. In the presented work the existing indices are implemented and the water sources are delineated. Two water indices MPWI1 and MPWI2 are proposed and implemented which successfully enhance the water features by suppressing the non-water features. The water pixels are slightly more in number for MPWI2 as compared with MPWI1 whereas the accuracy and visual appearance is same for both. These results are validated and found outperforming other indices with an accuracy of 99.77% in the selected study area.

7 References

1. N. Yagmur, N. Musaoglu, and G. Taskin. "Detection of Shallow Water Area with Machine Learning Algorithms." International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, **42**, 2, 2019, pp. 1269–1273.

2. V. K. Mishra and T. Pant, "Application of Classification Techniques for Identification of Water Region in Multiple Sources using Landsat-8 OLI Imagery." In 2019 URSI Asia-Pacific Radio Science Conference (AP-RASC), pp. 1–4. IEEE, 2019.

3. S. K. McFeeters, "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features." International journal of remote sensing, **17**, 7, 1996, pp. 1425–1432.

4. E. P. Crist, and Richard C. Cicone. "A physically-based transformation of Thematic Mapper data-The TM Tasseled Cap." IEEE Transactions on Geoscience and Remote sensing, 3, 1984, pp. 256–263.

5. E. P. Crist, "A TM tasseled cap equivalent transformation for reflectance factor data." Remote Sensing of Environment, **17**, 3, 1985, pp. 301–306.

6. H. Xu, "Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery." International journal of remote sensing, **27**, 14, 2006, pp. 3025–3033.

7. J. P. Lacaux, Y. M. Tourre, Cecile Vignolles, J. A. Ndione, and M. Lafaye. "Classification of ponds from high-spatial resolution remote sensing: Application to Rift Valley Fever epidemics in Senegal." Remote Sensing of Environment, **106**, 1, 2007, pp. 66–74.

8. L. Shen, and C. Li. "Water body extraction from Landsat ETM+ imagery using adaboost algorithm." In 2010 18th International Conference on Geoinformatics, IEEE, 2010, pp. 1–4.

9. 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 Sensing of Environment, **140**, 2014, pp. 23–35.

10. A. Fisher, N. Flood, and T. Danaher. "Comparing Landsat water index methods for automated water classification in eastern Australia." Remote Sensing of Environment, **175**, 2016, pp. 167–182.