Depiction of Water Characteristics from Multispectral Imagery Using Image Processing

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DOI: http://doi.one/10.1729/Journal.24211

Abstract: **The evolution of remote sensing techniques enforces to acquire veracious and continual updates of surface water characteristic on Earth. To discernment water bodies from multispectral imagery one of the primarily employed techniques is Indices method with general threshold value. This general threshold value is fixed for most of the cases, but when minuscule water bodies surrounded by plenty of dense forests, clouds, shadows and constructed area, they convey results with some error. This study assesses the accomplishment of the primarily employed water indices techniques NDWI35, NDWI36, NDWI37 (Normalized Difference Water Index) and NWI (New Water Index) in Ayodhya region of Uttar Pradesh, India. The assessment result obtained from confusion matrix was not able to delineate surface water bodies with superior accuracy. To improve the accuracy in delineation of water bodies, enhanced water indices techniques were proposed with prime threshold and clustering algorithm. The results obtained from enhanced water indices techniques shows consequential enrichment in the overall accuracy and kappa coefficient. All the multispectral imagery data accumulated by Landsat-8 (OLI) satellite on 22nd March 2019 was used for obtaining results.**

Keywords: Remote Sensing; Indices Techniques; General Threshold; Prime Threshold; Discernment Water Bodies; Ayodhya; Landsat-8.

1. Introduction:

One of the cardinal elements to preserve an ecosystem's functioning and civilization of human being is water. Discernment of water bodies from multispectral imagery is become elementary with the employ of remote sensing. The remote sensing technique has so many advantages, as it provides accurate and real-time information about climate and environmental change on little cost. From the last two decades, numerous techniques have been evolved to discriminate minuscule water bodies which include canal, stream and ponds on the earth. To get accurate results, it is essential to eliminate the effect of the forest, clouds, shadow, and constructed area from input imagery [1].

Spectral characteristics index with general threshold is one of the highly conventional technique employed for discernment of water bodies. It exploits the dominance of difference in spectral reflectance of water and non-water objects in the visible and infrared regions. Generally, open water resources have feeble reflectivity of about 4% in the visible region compared to other ground entities like vegetation, soil, bare land and constructed area etc. Due to the extreme absorption power of open water resources, its reflectivity diminishes to around 2.5% in the near-infrared region, and it became easier to discriminate water resources from vegetation, soil, constructed area, and other ground entities. Fig.1 shows the spectral profile of water, constructed area, vegetation, bare land and soil for various bands of Landsat-8 satellite [1, 2, 3].

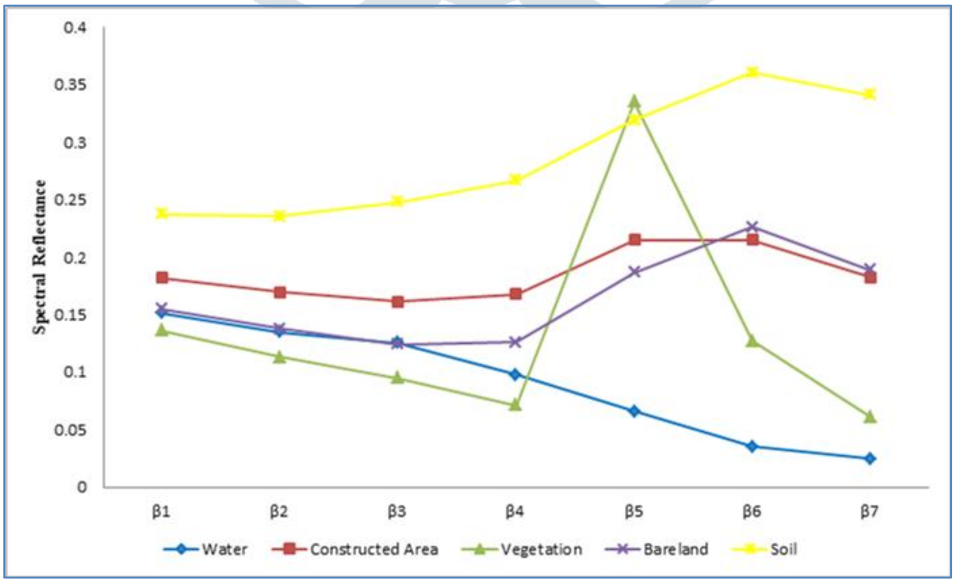


Fig.1: Spectral characteristics of five standard ground entities for the original seven bands of Landsat-8 Satellite

Spectral characteristics index with general threshold based water resource depiction techniques have experience a concatenation of transformation. In this paper the accomplishment of the primarily employed water indices techniques NDWI35, NDWI36, NDWI37

(Normalized Difference Water Index) and NWI (New Water Index) with general threshold and prime threshold employed to discriminate water resources from multispectral imagery data accumulated by Landsat-8 (OLI) satellite.. The objective of this paper is to delineate water resources present in Ayodhya region of Uttar Pradesh, India and compare the performance of general threshold & prime threshold with accuracy assessment.

2. Related Works:

In neoteric decades, various image processing techniques have been established for the depiction of water characteristics from multispectral satellite imagery. The single band technique employs a selective general threshold to discriminate water resources. Although this method is one of the most effortless technique used for the discernment of water resources, but it cannot delineate minuscule water resources and remove shadows. In comparison with single band technique, the classification method acquire for the depiction of water characteristics furnish more veracious results. The multi-band technique employs the combination of spectral characteristic of various bands for enhanced water delineation [4].

McFeeters exploit the green and near infrared bands of Landsat satellite for amplified delineation of water characteristics and named it as NDWI (Normalized Difference Water Index). This technique select zero as a general threshold to segregate water resources with other ground entities. Xu recognized that the general threshold with zero value was inadequate to scatter water resources with constructed areas. So, he remodelled the NDWI by changing the near infrared band with the shortwave infrared band to eradicate the shortcoming of NDWI and named it as MNDWI (Modified Normalized Difference Water Index).MNDWI provides near-perfect results; but the elimination of shadows is not accomplished by this technique [5, 6].

Albeit fresh water indices acknowledged for the delineation of surface water resources were introduced quite recently. G.L. Feyisa recommends a new water extraction index using general threshold technique to further ameliorate the accuracy in the discernment of water resources from multispectral satellite imagery and named it as Automated Water Extraction Index (AWEI). In 2016 Fisher introduced Water Index (WI_{2015}) to facilitate the improved results for the delineation of surface water resources. According to the study disseminate by Fisher established on Landsat's 30 meter resolution imagery, it was concluded that none of the water indices accomplish the finest results for all water and non-water resources [7, 8].

3. Study Area and Data Acquisition:

A Landsat territory around Ayodhya, Uttar Pradesh, India Region was chosen for the measure of the water indices. Ayodhya is one of renowned city of Uttar Pradesh and is surrounded by Saryu River on its northern side. The test area is around 388.80 sq. Km which covers larger part of Saryu River and all most entire Ayodhya district which includes urban area, vegetation and minuscule water resources. True colour composite image of study area is shown in Fig.2.

Fig.2: True Colour Composite image of Study area

The principal water reservoir in Ayodhya comprises Saryu River and some canals which are flowing western side of the city. Saryu River originated from Sarmul, Uttrakhand and after passing through Bahraich, it flows towards Ayodhya, Uttar Pradesh, and finally flows into Ganga near Chhapra, Bihar. The river travels around 350 Km distance before merging into Ganga. The study area is situated between 82˚04'11.77" to 82˚18'41.36" eastern meridians and 26˚42'56.47" to 26˚51'42.89" northern parallels.

The multispectral imagery of study area obtained from Landsat-8 satellite. The satellite uses Operational Land Imager (OLI) sensors with 30 meter spatial resolution to acquire metadata of Ayodhya Region with path number 143 and row number 41. The imagery of study area was projected to a Universal Transverse Mercator (UTM) Zone 44 North coordinate system with the World Geodetic System (WGS)-84 datum. U.S. Geological Survey's remote pixel open source portal had been used for acquiring multispectral imagery with metadata. In adopting the remote sensing data, specific attention was given to images with no cloud or fog over the study area. All the multispectral imagery data accumulated by Landsat-8 (OLI) satellite on 22nd March 2019 was used for obtaining results.

4. Methodology:

The progress of this study includes: selection of test area, data collection, image pre-processing, and extraction of water indices, prime thresholding, combining, and clustering the test area for depiction of surface water. Each surface water map had been evaluated qualitatively and quantitatively based on validation points. All of the processing was done in Environment for Visualizing Images (ENVI) version 5.3 and MATLAB R2015. Detailed flow chart of methodology used for obtaining result is shown in Fig.3.

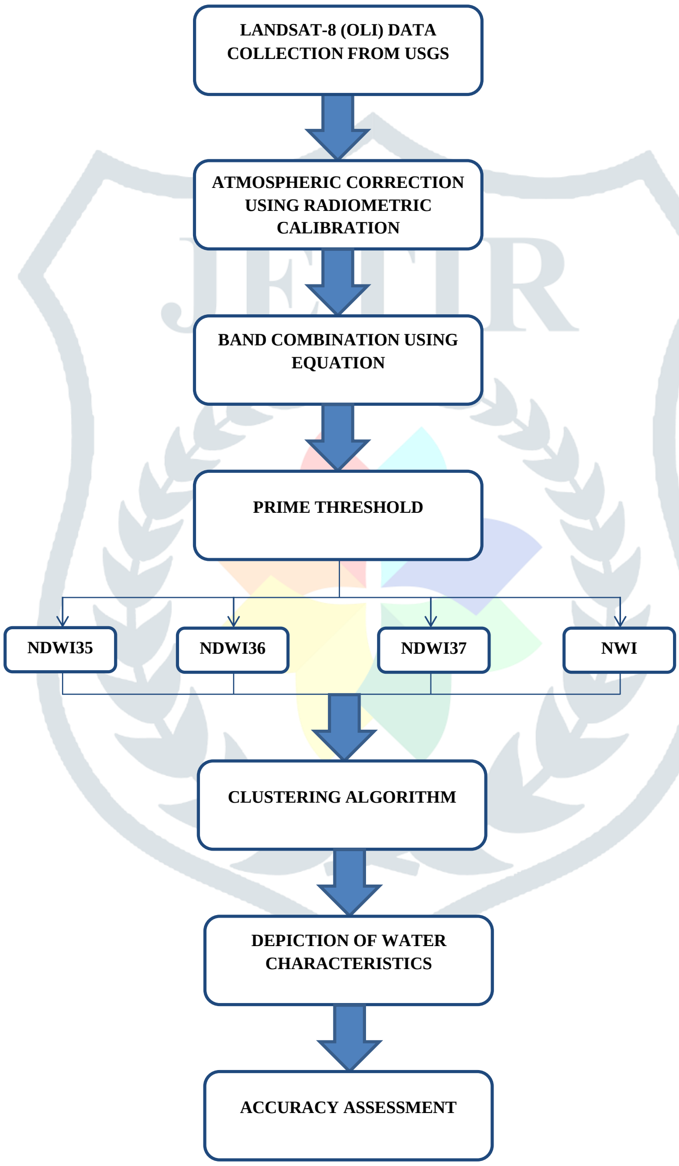


Fig.3: Flow Chart of Methodology used for obtaining result

4.1 Pre-Processing of Image:

After obtaining multispectral satellite images of the study area, we need to perform pre-processing of the imagery. In the operation of pre-processing the following steps were executed: radiometric calibration, atmospheric correction and Dark Object Subtraction (DOS). Radiometric calibration and atmospheric correction was executed using ENVI (Environment for Visualizing Images) tool. An essential pre-processing step in evaluating images of surface reflectance is to remove the influence of the atmosphere. To achieve the desired result, the acquired images were converted to top of atmosphere (TOA) radiance using radiometric calibration tool in ENVI. After conversion to top of atmosphere (TOA) radiance, each image was converted to top of atmosphere (TOA) reflectance. All the required information including the Data Acquisition Date and Sun Elevation etc. was obtained from the Landsat metadata files. Final step for pre-processing of image was executed by converting top of atmosphere (TOA) reflectance in to surface reflectance for full absolute correction. This desired result was achieved by using Dark Object Subtraction (DOS) method.

4.2 Spectral Water Indices:
Spectral Water indices is one of the most broadly used techniques for the depiction of water resources. It employs mathematical representation for enrichment of water resources from a given pixel in the images obtained from visible, near-infrared and other scanning sensors. These mathematical representations are normally calculated from blue, green, NIR, SWIR1 and SWIR2 regions of the spectrum.

McFeeters (1996) recommended ratio based water index method for depiction of water bodies from multispectral imagery. The water bodies manifest high percentage of spectral reflectance in green band in distinction to the NIR, SWIR1 and SWIR2 bands. Combinations of these bands are used to intensify vegetation and other ground entities and suppress the water bodies. So it is tranquil for depiction of water resources by using the appropriate threshold value from processed imagery. General threshold of water is always greater than zero for normalized difference water index. The ratio of difference between green band and NIR band to the sum of these bands gives the NDWI35. Based on Landsat-8 imagery, the general equation to calculate NDWI35 is as follows;

$$NDWI35 = (\beta_3 - \beta_5) / (\beta_3 + \beta_5)$$

Where β_3 signifies the reflectance on the green band in the visible region, and β_5 signifies the reflectance on the NIR band in the infrared region.

A modified version of normalized difference water index uses the ratio of difference between green band and SWIR1 band to the sum of these bands. In this index, the NIR band used in NDWI was replaced by the SWIR1 band of Landsat-8 imagery. The general equation to calculate NDWI36 is as follows;

$$NDWI36 = (\beta_3 - \beta_6) / (\beta_3 + \beta_6)$$

Where β_3 signifies the reflectance on the green band in the visible region, and β_6 signifies the reflectance on the SWIR1 band in the infrared region.

If the NIR band used in NDWI was replaced by the SWIR2 band of Landsat-8 imagery. It generates another modified version of normalized difference water index .The ratio of difference between green band and SWIR2 band to the sum of these bands gives the NDWI37 The general equation to calculate NDWI37 is as follows;

$$NDWI37 = (\beta_3 - \beta_7) / (\beta_3 + \beta_7)$$

Where β_3 signifies the reflectance on the green band in the visible region, and β_7 signifies the reflectance on the SWIR2 band in the infrared region.

The new water index uses multiple bands from visible & infrared region at the same time. The blue band of the visible region and NIR, SWIR1, SWIR2 bands of the infrared region is used to evaluate NWI. The general equation to calculate NWI is as follow;

$$NWI = [\beta_2 - (\beta_5 + \beta_6 + \beta_7)] / [\beta_2 + (\beta_5 + \beta_6 + \beta_7)]$$

Where β_2 signifies the reflectance on the blue band of the visible region and β_5, β_6, β_7 signify the reflectance on NIR, SWIR1 & SWIR2 bands of the infrared region.

4.3 Prime Threshold:
Histogram based method is one of the highly productive technique used for selecting threshold. First of all binary classification was supervised with the general threshold value for each spot of the image. Then after that prime thresholds were selected on the basis of the highest overall accuracy (OA) and kappa coefficient for the validation dataset. The trial and error technique were used for selection of prime threshold. For the trial and error technique, first of all we used two-decimal thresholds of a 0.05 interval between -1 and +1 for the validation data to obtain the highest overall accuracy (OA) and kappa coefficient. Once the two-decimal threshold was manifested, a smaller interval threshold of 0.0005 was used between ±0.05 of the previously selected two-decimal threshold value. Similarly, once the four- decimal threshold was decided, a smaller interval threshold of 0.000005 was used between ±0.0005 of the previous selected four-decimal threshold value. The final six-decimal threshold was chosen for the closest real value in the validation data. This algorithm generates near perfect threshold value for depiction of water resources.

4.4 Clustering Algorithm:
Clustering is one of the most common investigative data analysis method employed for measurable information examination and utilized as a segment of various domains, including machine learning. It is defined as the assignment of collection an arrangement of articles in such a path to the point that questions in the same gathering (called a group) are more comparative (in some sense or another) to one another than to those in different gatherings (bunches). K means clustering algorithm is a frequentative algorithm that endeavours to partition the dataset into *K* pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs

to only one group. It endeavours to construct the intra-cluster data points as similar as possible while besides keeping the clusters as different (far) as possible. It employed distance-based estimation to simulate the closeness between data points.

4.5 Accuracy Assessment:
Evaluation of the results obtaining from clustering algorithm is performed by using accuracy assessment. In this process effectiveness and exactness of water bodies executed from multispectral imagery is tested. To do so, a confusion matrix-based approach is employed in this study. On comparing the extracted water bodies and non-water bodies with reference data, the outcomes are classified into four types of pixels:

i. True Positive (TP): The number of correctly extracted water pixels;
ii. False Negative (FN): The number of undetected water pixels;
iii. False Positive (FP): The number of incorrectly extracted water pixels; and
iv. True Negative (TN): The number of correctly rejected non-water pixels.

On the basis of these four outcomes the overall accuracy (OA) and kappa coefficient were employed for the assessment of the accuracy of the produced results with different water indices. These can be calculated as:

$$Producer's\ Accuracy = \frac{TP}{TP + FN}$$

$$User's\ Accuracy = \frac{TP}{TP + FP}$$

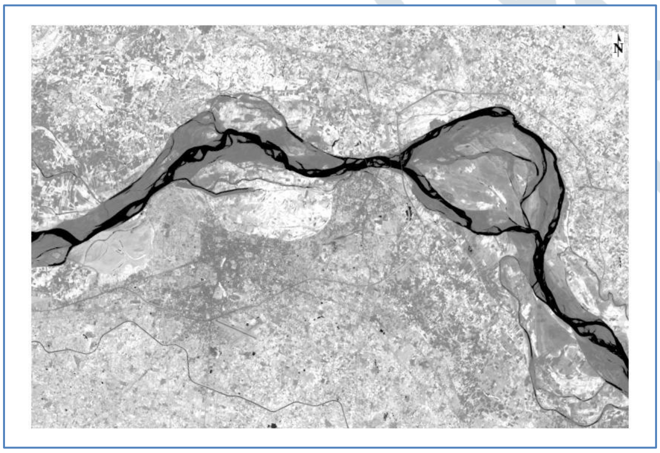
$$Overall\ Accuracy = \frac{TP + TN}{T}$$

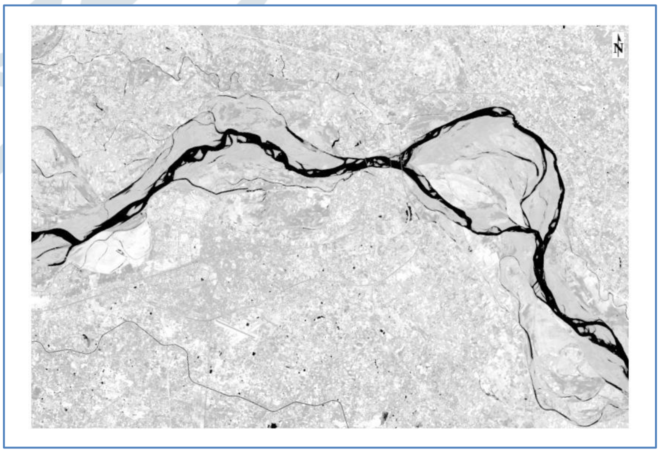
$$Kappa\ Coefficient = \frac{T(TP + TN) - CA}{T^2 - CA}$$

Where CA is the chance accuracy represented by (TP + FP) (TP + FN) + (FN + TN) (FP + TN), and T is the total number of pixels in accuracy assessment.

5. Results and Discussion:

The accomplishment of the numerous water indices for the depiction of surface water resources for the entire study area is estimated in this segment. First of all we have supervised the estimation of every water index with general threshold and after that the evaluation of water indices with prime threshold for entire study area has been performed. A detailed analysis and comparison of numerous water indices has been conducted to estimate the achievement by each technique. We have performed the binary classification of study area with general threshold. For each four water index zero is treated as conventional value of threshold. Fig.4 shows the result of images obtained for numerous water indices with general threshold.

(a)


(b)


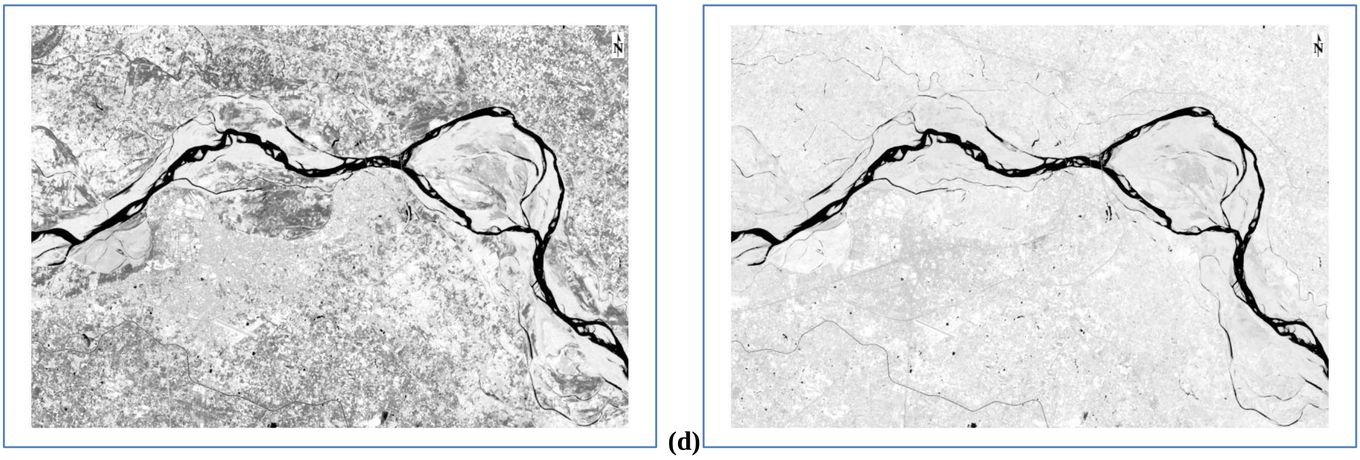

(c) (d)

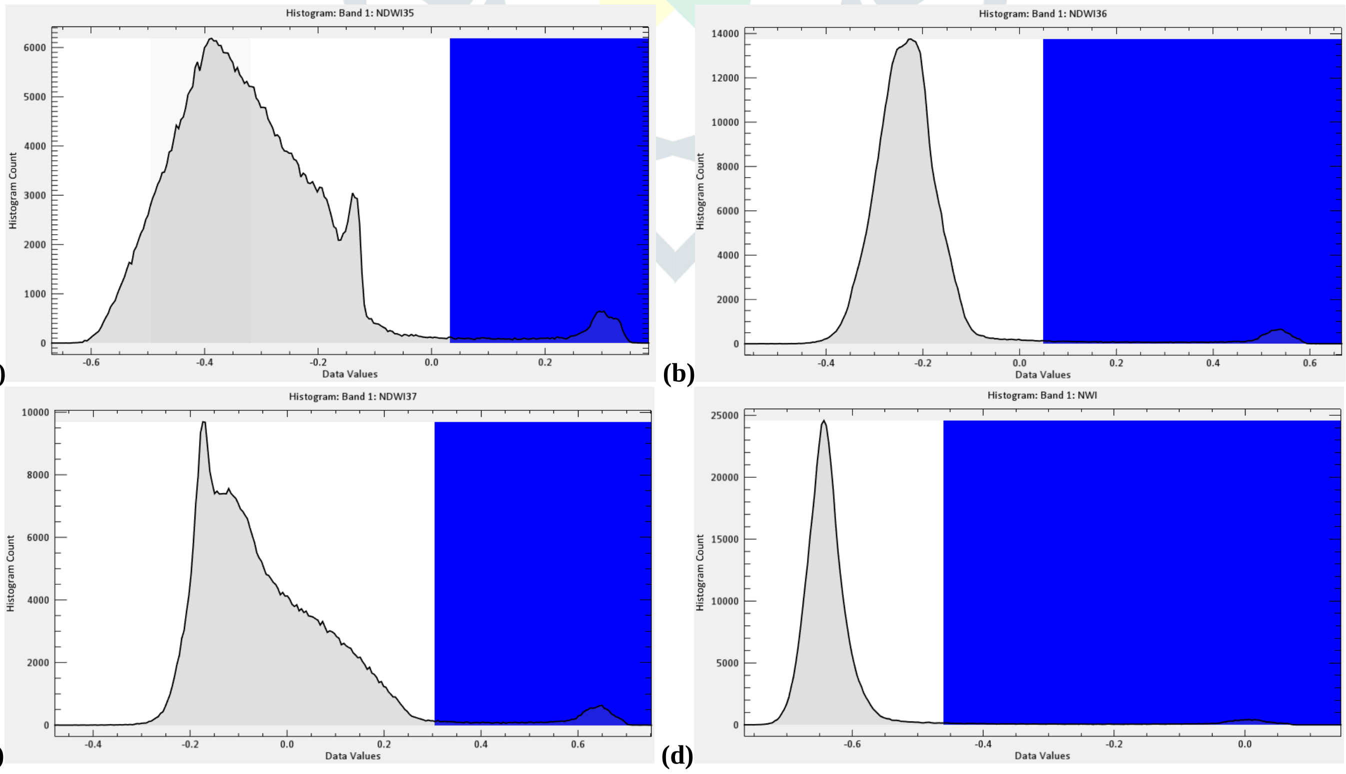
Fig.4: Result of images obtained using General Threshold (a) NDWI35, (b) NDWI36, (c) NDWI37 and (d) NWI

The assessment result obtained from confusion matrix is shown in Table1. It is clearly visible that these results were not able to delineate surface water bodies with superior accuracy. In spite of overall accuracy for all water indices shows balanced results, none of the water indices showed kappa coefficient above 0.90. The highest overall accuracy achieved by NDWI37 with 96.0040% and highest value for kappa coefficient was obtained by NWI with 0.8799.

Table1: Accuracy Assessment of numerous water indices with General Threshold

	Overall Accuracy	Kappa Coefficient
NDWI35	94.2284%	0.8785
NDWI36	90.0967%	0.8087
NDWI37	96.0040%	0.8467
NWI	94.5290%	0.8799

To improve the accuracy in depiction of water bodies enhanced water indices techniques were employed with prime threshold. The trial and error technique were used for selection of prime threshold. In this technique, first of all we used two-decimal thresholds of a 0.05 interval between -1 and +1 for the validation data to obtain the highest overall accuracy (OA) and kappa coefficient. Similar process was used for obtaining four decimal thresholds and six decimal thresholds. The final six-decimal threshold was chosen for the closest real value in the validation data. Fig.5 shows histogram for numerous water indices with Prime Threshold.



(a) (b) (c) (d)

Fig.5: Histogram for numerous water indices with Prime Threshold (a) NDWI35, (b) NDWI36, (c) NDWI37 and (d) NWI

After selecting prime threshold and performing clustering algorithm on the image of study area, we had obtained better result images for numerous water indices. Fig.6 shows the result of images obtained for numerous water indices with prime threshold.

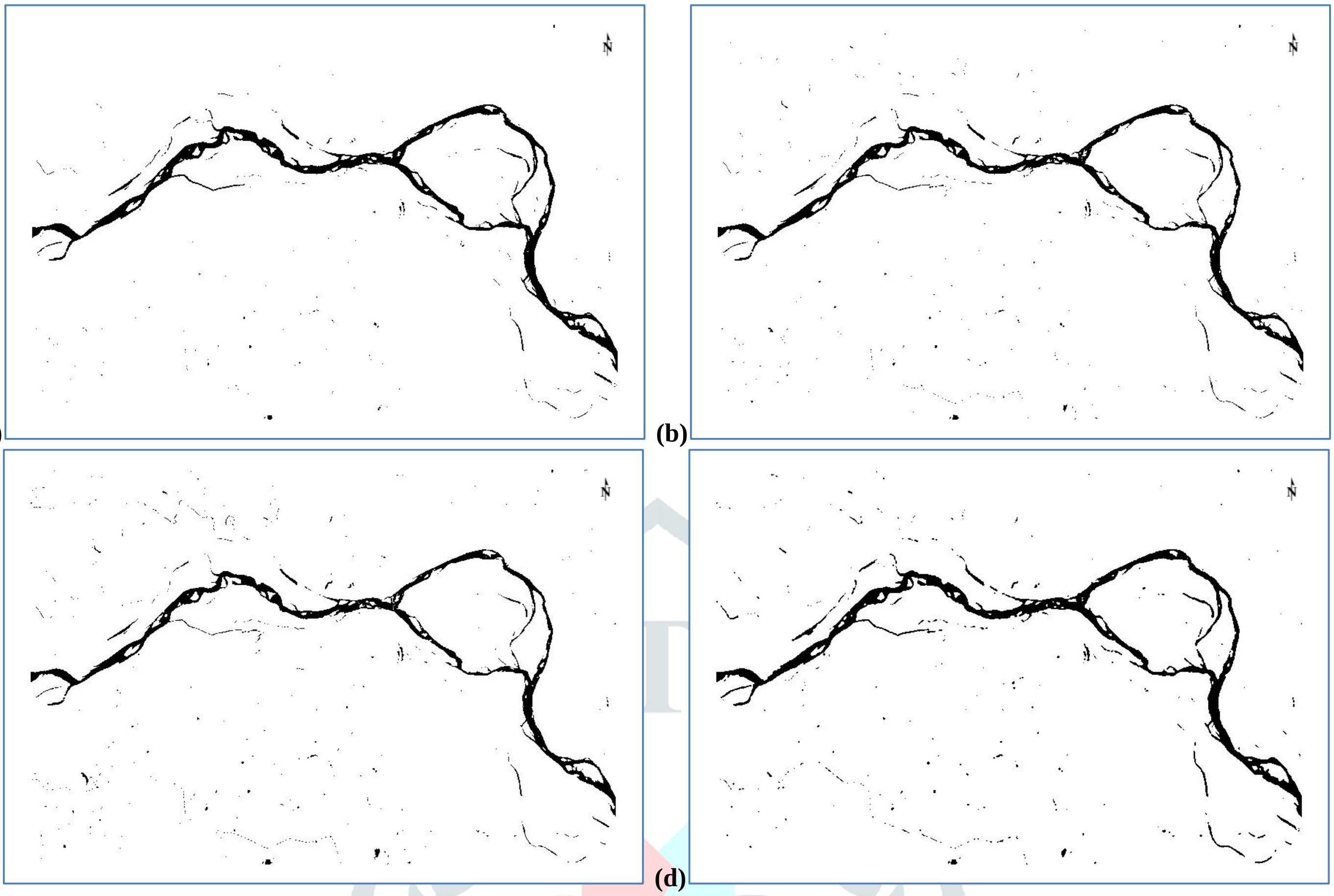

(a) (b) (c) (d)

Fig.6: Result of images obtained using Prime Threshold (a) Enhanced NDWI35, (b) Enhanced NDWI36, (c) Enhanced NDWI37 and (d) Enhanced NWI

The accuracy assessment results were obtained using confusion matrix technique and it is shown in Table2. Accuracy assessment obtained by enhanced water indices was accomplished superior results. Enhanced NDWI35 and enhanced NWI shows premier results in terms of producer's accuracy with 85.94% and 92.67%. But in case of user's accuracy these indices showed low performance. Enhanced NDWI36 and enhanced NDWI37 accomplished higher results in exhibition of user's accuracy with 99.80% and 97.70%. Every water indices manifested more than 99% in exhibition of overall accuracy and enhanced NDWI35 placed on top of all other water indices with 99.2777%. These excellent outcomes show the impact of prime threshold. In terms of kappa coefficient enhanced NDWI35 and enhanced NWI generate superior outcome as comparison to other two water indices. Enhanced NDWI37 accomplished below par outcome in kappa coefficient with 0.8648, while the highest outcome for kappa coefficient was attained by enhanced NWI with 0.9079. Estimated area of surface water resources is also mentioned in Table2.

Table2: Accuracy Assessment of numerous water indices with Prime Threshold and Estimated Area

	Producer's Accuracy	User's Accuracy	Overall Accuracy	Kappa Coefficient	Estimated Area
Enhanced NDWI35	**85.94%**	**96.31%**	**99.2777%**	**0.9042**	**14.4894 Km^2**
Enhanced NDWI36	**81.49%**	**99.80%**	**99.2228%**	**0.8932**	**13.2570 Km^2**
Enhanced NDWI37	**78.38%**	**97.70%**	**99.0234%**	**0.8648**	**13.0248 Km^2**
Enhanced NWI	**92.67%**	**89.73%**	**99.2532%**	**0.9079**	**16.7670 Km^2**

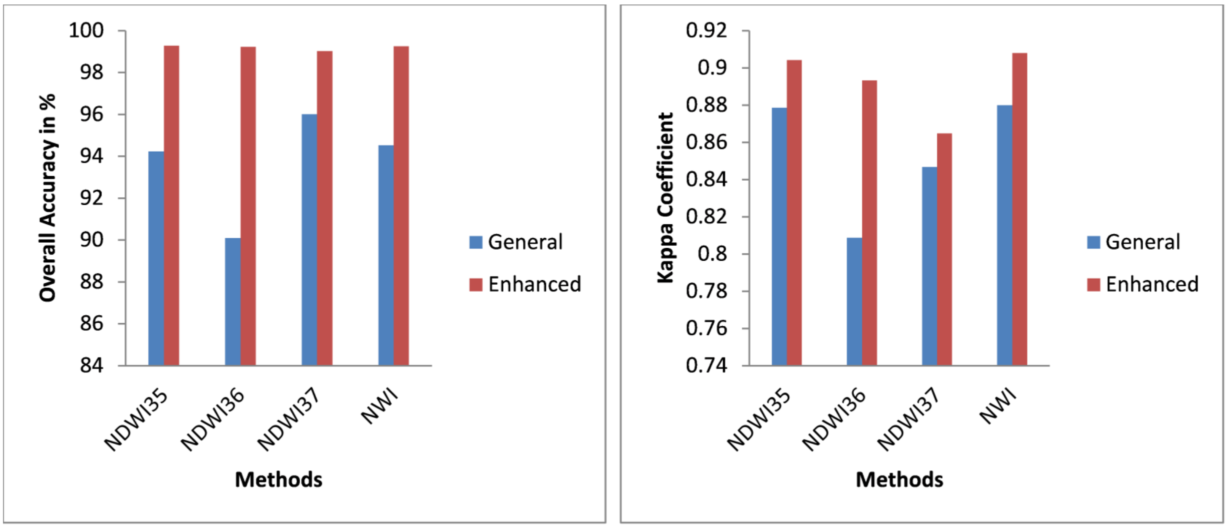


Fig.7: Comparison of performance for numerous water indices with general threshold (General) and prime threshold (Enhanced)

As seen from chat in Fig.7, it has been clearly visible that all water indices with prime threshold accomplished superior outcome in overall accuracy and kappa coefficient than with general threshold technique. NDWI36 shows maximum amplification in overall accuracy and kappa coefficient with enhanced method (prime threshold technique).

6. Conclusion:

Generally numerous kind of surface water resources associated with environmental noise is available in the multispectral imagery of Landsat-8 satellite. Minuscule water resources present in urban area is the best example of surface water resources associated with environmental noise. In this study we have evaluated the accomplishment of numerous water indices: NDWI35, NDWI36, NDWI37 and NWI with general threshold and proposed the enhanced technique by using prime threshold & clustering algorithm. The outcome for numerous water indices with general threshold was compared with prime threshold under validation values. The comparative analysis was accomplished with the outcome of data set of a confusion matrix. The employ of general threshold with numerous water indices was suited for the depiction of normal and large surface water resources. But in general they also contained pixels of non-water entities. The assessment result obtained from confusion matrix was not able to delineate surface water bodies with superior accuracy. The prime threshold enhanced the depiction of minuscule surface water resources with excellent overall accuracy and superior kappa coefficient. The highest overall accuracy was achieved by enhanced NDWI35 with 99.2777% while maximum value of kappa coefficient was attained by enhanced NWI with 0.9079. This analysis manifested that the depiction of surface water resources can be further amplified by the employment of prime threshold and clustering algorithm. In addition to this, it is highly recommended to employ a smaller interval with adequate to the validation data set. These proposal and findings further will be employed to analyse on numerous segment of remote sensing.

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