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Comparative Evaluation of Water Indices for Water Body Mapping from Sentinel 2 Imagery: A Thresholding and SVM-Based Accuracy Approach

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Abstract:

This study compares water body extraction techniques using Sentinel-2 images. It combines spectral index-based thresholding with a supervised machine learning approach. Four common water indices—NDWI, MNDWI, AWEI, and SWM—were analyzed using Otsu and Minimum thresholding methods. A Support Vector Machine (SVM) classifier assessed accuracy. The results show that the SVM classifier performed the best, achieving an overall accuracy of 99.79%, a Kappa coefficient of 0.9912, and an F1-score of 0.9901. This demonstrates outstanding precision and reliability. In contrast, thresholding methods were less effective, especially for indices like AWEI_nsh and AWEI_sh, revealing their sensitivity to data changes. The findings stress that while spectral indices effectively highlight water features, combining them with machine learning greatly enhances extraction accuracy. The study concludes that using Sentinel-2 images alongside SVM classification provides a strong method for accurate and efficient water body mapping.

Keyword: NDWI, MNDWI, AWEI, SWM, SVM

1. Introduction

For many environmental and hydrological applications, the accurate, efficient mapping of bodies is critical for a broad range of environmental and hydraulic applications: water resource management, flood monitoring, wetland assessment and climate change studies [1]. This data on spatial and temporal characteristics of surface water is a crucial basis for understanding hydrological processes and enabling sustainable management of freshwater resources. But, traditional field-based water monitoring methods are labor intensive, time consuming and spatially limited; they are not suitable for large-scale or frequent assessments and therefore will not work for small-scale or frequent monitoring [2].

In this way, remote sensing technologies have become indispensable tools for water resource analysis and management. They provide synoptic, repetitive, and multi-temporal observations over an innumerable area that can be used for continuous monitoring of surface water features [3]. With a growth in satellite research using the European Space Agency's Sentinel-2, which provides high-resolution multispectral

images from a much higher resolution and has recently been revisited, this has allowed us to better understand the dynamics of water bodies more effectively. Sentinel-2 flight has also provided spectral bands sensitive to visible, near-infrared (NIR) and shortwave infrared (SWIR) wavelengths which are good for distinguishing water from non-water surfaces [4].
While urbanization, agricultural water demand, and climate variability are growing environmental pressures, accurate water body detection has grown the need. These are also where water detection spectral indicators have become the main focus and analysis [5]. These indexes are more attractive to the contrast between water and surrounding land cover by exploiting the inherent absorption and reflectance properties of water in different spectral regions. Water absorbs radiation in the near-infrared and shortwave-infrared areas, reflecting in the visible spectrum, so algorithms can isolate water features successfully [6].

In addition, many water indices for surface water extraction have been proposed aimed at achieving the maximum distinction between water features and vegetation or building areas. Most commonly used is the Normalized Difference Water Index (NDWI), the Modified Normalized Difference Water Index (MNDWI), the Automated Water Extraction Index (AWEI), and the Sentinel Water Mask (SWM). These indices employ spectral combinations to improve water signal and reduce non-water reflectance. While they are widely used, each index has multiple characteristics, both surface conditions, atmospheric effects, and sensor characteristics, so comparative tests are needed to understand relative performances and reliability in different contexts [7].

It therefore presents a comparison of four prominent water indexes, NDWI, MNDWI, AWEI and SWM for surface water bodies using Sentinel-2 imagery. This is achieved by making optimal thresholds for each index objectively based on Otsu's and Minimum thresholding methods to generate binary water maps. The accuracy of the water map is then tested against a Support Vector Machine (SVM)-based classification to verify their accuracy. In this integrative approach, we aim to design an optimal and robust combination of water index and thresholding technique to extract automated water bodies from large scale water monitoring systems and provide valuable insights for future large-scale water monitoring applications. The following section consist of literature review followed with study area. Next section explains detailed methodology used for study followed with result and discussion and finally conclusion.

2. Literature Review

The evaluation of water indices for mapping water bodies using Sentinel-2 imagery involves assessing various indices to determine their effectiveness in accurately identifying and mapping water features. Sentinel-2's high spatial resolution and multispectral capabilities make it a valuable tool for this purpose. Different indices have been tested for their accuracy and applicability in various environments, each offering unique advantages and limitations. The following sections detail the performance and suitability of these indices based on recent studies.

One of the study evaluates three water extraction indices—Water Ratio Index (WRI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Water Index (NDWI)—using Sentinel-2 imagery across eight sites in Ethiopia. The WRI demonstrated the highest producer accuracy (97.98%) and user accuracy (88.78%), making it ideal for areas with minimal vegetation. On the contrary, NDWI is better for regions with moderate vegetation, while MNDWI helps distinguish water bodies from built-up areas. Establishing optimal thresholds is crucial for effective monitoring [8]. Another study evaluates three water indices—MNDWI, AWEIsh, and WI2015—using Sentinel-2 imagery for water body mapping. All indices demonstrated satisfactory extraction capabilities, with kappa coefficients above 0.8. The WI2015, combined with the Gram–Schmidt downscaling method, yielded the best performance, achieving a kappa coefficient of 0.897. MNDWI showed the highest user accuracy, while WI2015 had the highest producer accuracy, indicating its effectiveness in urban water body extraction, particularly for river water bodies [9].

Another author evaluates seven water indices for mapping surface water using Sentinel-2 data in Ethiopia. It finds that the Water Index (WI) and Automatic Water Extraction Index with Shadow (AWEIsh) are the most accurate, achieving kappa coefficients of 0.96 and 0.95, respectively, with an overall accuracy of 0.98. The spatial coverage of surface waters was similar, with WI covering 82,650 km² and AWEIsh covering 86,530 km², demonstrating their effectiveness in water body mapping [10]. In different study evaluates six water indices, including 10-m NDWI, 20-m MNDWI, and 10-m MNDWI produced by four pan-sharpening algorithms (PCA, IHS, HPF, ATWT) for water body mapping using Sentinel-2 imagery. Results indicate that 10-m MNDWI enhances water bodies and suppresses built-up features more effectively than NDWI and 20-m MNDWI. Among the algorithms, ATWT yielded the best water body mapping results, despite HPF producing more accurate sharpened images and MNDWI images [11]. Another study evaluated three water indices: Modified Normalized Difference Water Index, Normalized Difference Pond Index (NDPI), and Normalized Difference Turbidity Index (NDTI) for mapping water bodies using Sentinel-2 imagery. MNDWI provided the best distinguishability for water bodies, while NDPI and NDTI showed poorer results. The combination of these indices in a false color composite significantly improved the recognition of flooding in wetland areas, demonstrating the effectiveness of using Sentinel-2 data for water body mapping [12].

3. Study Area

For research we choose,jaykwadi dam which is located in the Godavari river basin in the Paithan of th Maharashtra state in Chhatrapati Sambhajinagar district. The reservoir's waters spread across the districts of Chhatrapati Sambhajinagar, Ahmednagar, and Jalna. The area has one of the state's largest irrigation schemes consisting of a large freshwater reservoir commonly known as the Nath Sagar. The research site was selected specifically to preserve the water surface below the surface year-round. The reservoir has relatively shallow and deeper freshwater lakes, with the deeper portions generally being near the dam wall and the shallow parts extending outward, especially in the larger northern and eastern areas.

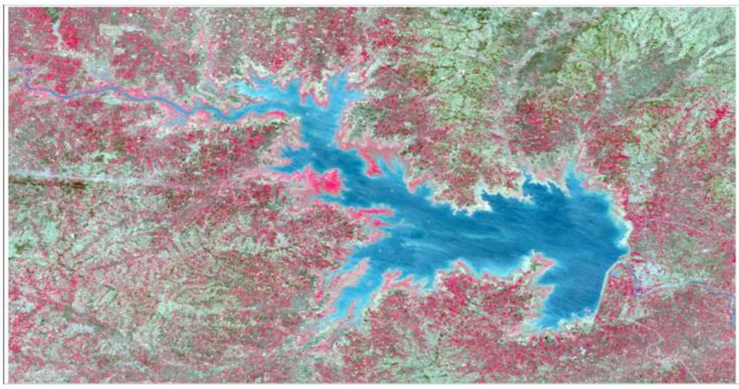

Figure 1: Study Area

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4. Methodology

This section explains the methodology as shown in Figure 2, it uses Sentinel-2B imagery for water body extraction and classification into water and non-water area using the thresholding technique. Initially, bands B8A, B11, and B12 are resampled to 10 meters for enhancing the accuracy, followed by layer stacking and clipping to the area of interest (AOI). Water indices NDWI, MNDWI, Sentinel Water Mask, AWEI_nsh, and AWEI_sh were calculated to highlight water features. Thresholding techniques, Otsu and Minimum Thresholding methods, are applied to classify indices images into water and non-water areas. Simultaneously, a Support Vector Machine (SVM) classifier is trained using selected training samples to perform supervised classification. SVM classified image accuracy is assessed, and finally, using the SVM classified image as a reference, the accuracy of thresholded images is assessed. Finally, the classified outputs are compared and analyzed, followed by a result discussion and conclusion.

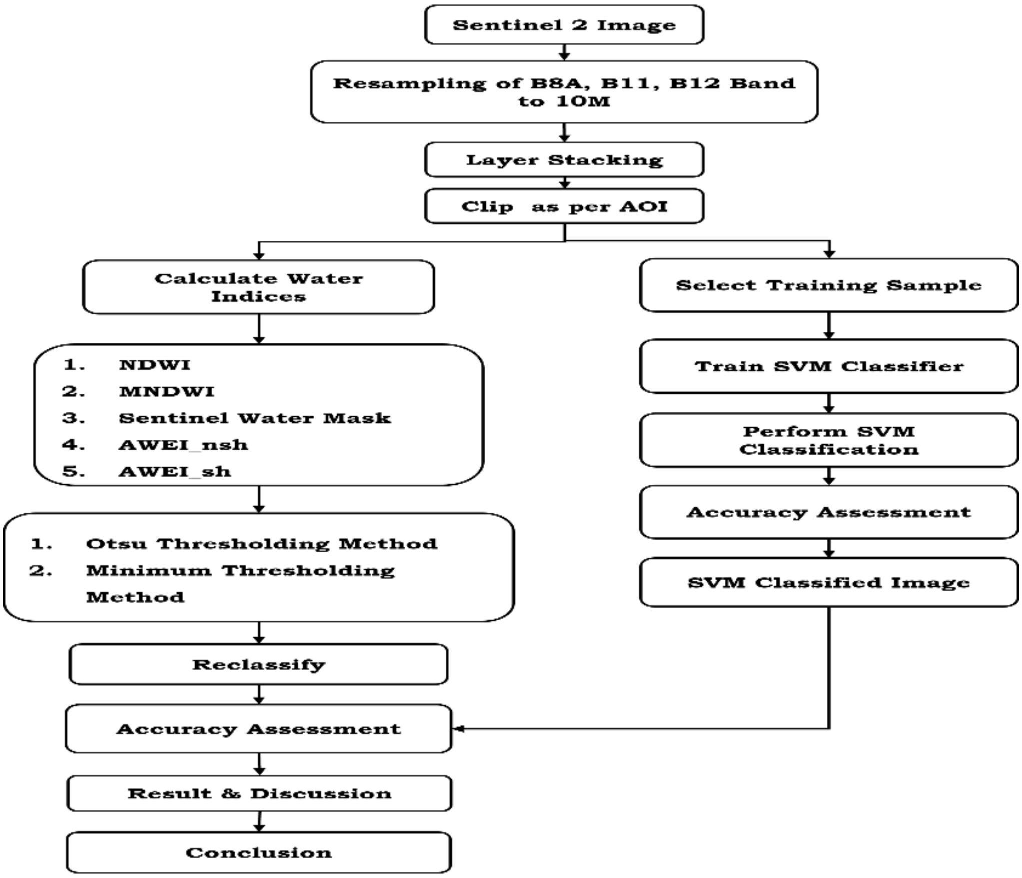

Figure 2: Proposed Methodology

4.1. Dataset

Study carried by Sentinel-2, the Multi Spectral Instrument (MSI) spans the visible, near-infrared, and SWIR wavelength ranges across 13 bands. Three 60 m coastal aerosol, water vapor, and SWIR-Cirrus bands; six 20 m vegetation red edge and short-wave infrared bands; and four ten meters visible and near-infrared bands. Analysis is based on the Sentinel-2B picture shot on May 28, 2024. The great spatial, spectral, and temporal resolution of Sentinel-2 data offers several benefits that raise both the precision and effectiveness of water body monitoring and detection.

4.2. Preprocessing

The groundwork for precise and effective examination of water bodies using remote sensing methods is provided by the data preparation phase. Because of its great spatial resolution (10–60 meters) and availability of several bands, Sentinel-2 imagery is used as the main source of data in this study. Spectral bands, especially helpful for studies involving water. The images are acquired from a dependable source such as Google Earth Engine of the Copernicus Open Access Hub.

4.2.1. Resampling

One of the crucial preprocessing procedures involves resampling bands B8A (Near Infrared), B11 (Shortwave Infrared 1), and B12 (Shortwave Infrared 2) to a spatial resolution of 10 meters. Originally having a resolution of 20 meters, these bands' sharing a common resolution of 10 meters guarantees spatial consistency across all bands. This is critical for correct multi-band operations including index computation and classification [13].

4.2.2. Layer Stacking

After resampling, layers are piled one upon another. Merging the separate spectral bands into one composite image—which gathers all the needed spectral information into one dataset—is this approach. Layer stacking makes it possible to simultaneously access several bands during analysis, hence simplifying the computation of water indexes or the carrying out of classification [14].

4.2.3. AOI Clipping

At last, the composite picture is trimmed to the Area of Interest (AOI), which is the particular geographical area under investigation. Clipping lowers the processing demand by deleting extraneous surrounding information, thereby enabling the attention to remain entirely on the targeted terrain. Particularly in region-specific water body evaluations, this local approach boosts both processing efficiency and interpretability of results [15].

4.3. Water Indices

Spectral reflectance investigations of several land surface characteristics have shown that high reflectance in the green part of the spectrum usually belongs to turbid or algae-laden water. Spectral reflectance of water approaches practically zero beyond the near-infrared (NIR) area (wavelengths > 0.9 µm), which is visible spectrum compared with other visible wavelengths. Conversely, soil and plants keep strong reflectance in the infrared bands. These unique spectral properties of water have inspired the creation of numerous spectral indices that improve the visibility of water features while minimizing non-water backgrounds in satellite data [16].

Among three commonly used surface water boundary measures are the Normalized Difference Water Index (NDWI), the Modified Normalized Difference Water Index (MNDWI), and the Automated Water Extraction Index (AWEI). To separate water from land and constructed locations, these indices use reflectance variations between the green, NIR, and shortwave infrared (SWIR) bands as depicted in figure 3.

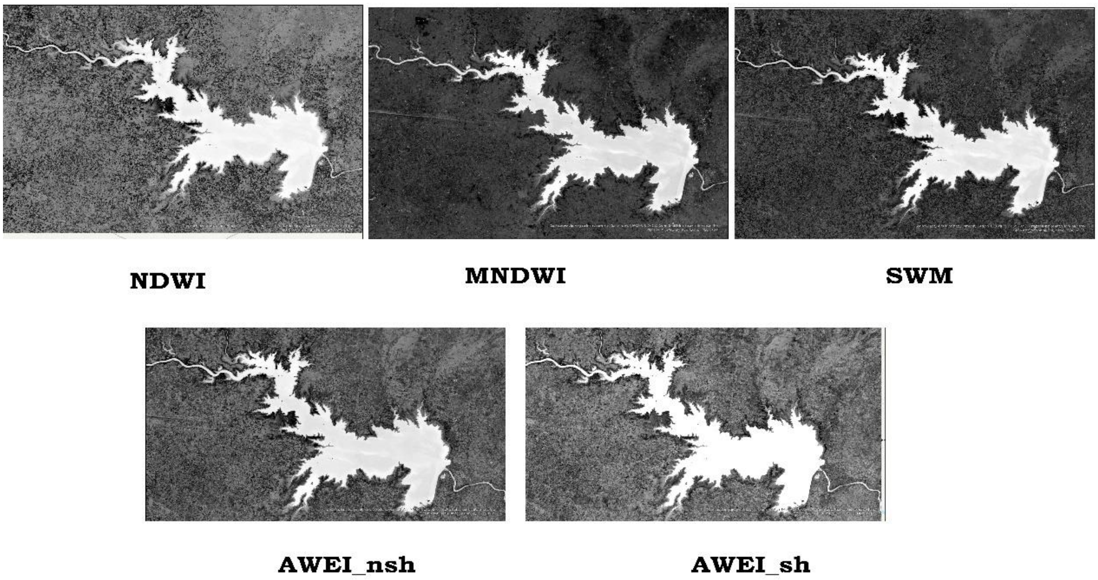

Figure 3: Water Indices

The NDWI is determined using the reflectance in the green and near-infrared spectral bands, where GREEN and NIR correspond to the reflectance values in the green and near-infrared bands, correspondingly. Although this index enhances open water features well, its similar spectral response in the NIR band sometimes causes built-up areas to be incorrectly categorized [17]. To get around this constraint, the Modified Normalized Difference Water Index (MNDWI) was created by swapping the shortwave-infrared (SWIR) band for the NIR band, therefore better inhibits signals coming from developed and planted areas [17][18]. Here SWIR1 is the initial shortwave-infrared band (about 1.55–1.75 µm). An alternate form called Using the second shortwave-infrared band (SWIR2, roughly 2.09–2.35 µm), MNDWI is calculated. Although these have been better, shadows cast by topography, vegetation, or infrastructure—which may display spectral characteristics comparable to water—can still influence water extraction precision. To solve this problem, the Automated Water Extraction Index (AWEI) was developed using several spectral bands—blue, green, NIR, SWIR1, and SWIR2—to minimize shadow- and bright-surface-created uncertainty. Different AWEI formulas can be applied depending on the properties of the scene to manage shaded, bright, or mixed-surface environments [19].

Table 1: Water Indices

Index	Index Name	Equation
NDWI	Normalized Difference Water Index	$\text{NDWI} = \dfrac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}}$
MNDWI	Modified Normalized Difference Water Index	$\text{MNDWI} = \dfrac{\text{Green} - \text{SWIR}}{\text{Green} + \text{SWIR}}$
SWM	Sentinel Water Mask	$\text{SWM} = \dfrac{(\text{Blue} + \text{Green})}{(\text{NIR} + \text{SWIR1})}$
AWEI_nsh	Automated Water Extraction Index non-shadow	$4 \times (\text{Green} - \text{SWIR1}) - (0.25 \times \text{NIR} + 2.75 \times \text{SWIR2})$

AWEI_sh	Automated Water Extraction Index non-shadow	$Blue + 2.5 \times Green - 1.5 \times (NIR + SWIR1) - 0.25 \times SWIR2$

For surface water mapping, all three indices as represented table 1 —NDWI, MNDWI (including MNDWI2), and AWEI—were used in this research to Sentinel-2 multispectral images. Thresholding methods were used to improve the created water maps even further, and Support Vector Machine (SVM)-based classification was applied to confirm the most precise and effective one. Index for automatically delineated water body.

4.4. Thresholding Methods

Otsu Thresholding and Minimum Thresholding, two automated thresholding techniques, were used to find the best separation of water and non-water pixels from the calculated index pictures. extraction cutoff thresholds for water bodies.

4.4.1. Otsu Thresholding Method

Otsu proposed a nonparametric and unsupervised method to compute the optimal threshold value. In Otsu's method, the optimal threshold value is calculated with regard to discriminant analysis, and the method maximizes the "between-class variance" $\sigma_B^2(t)$ of the gray-level histogram to ideally separate the classes. The pixels of a definite image are presented in L gray levels $[0,1,2,\ldots,L-1]$. Here, $n(i)$ is the number of pixels at level i, and N is the total number of pixels. The gray-level histogram is normalized and treated as a probability distribution, where the occurrence probability of each gray level $p(i)$ is given by [20]:

$$p(i) = \frac{n(i)}{N} \qquad (1)$$

For a given threshold t, the image is divided into two classes: C_0 (pixels with intensities $[0,t]$) and C_1 (pixels with intensities $[t+1, L-1]$). The probabilities of the two classes are:

$$\omega_0(t) = \sum_{i=0}^{t} p(i), \qquad (2)$$

$$\omega_1(t) = \sum_{i=t+1}^{L-1} p(i) = 1 - \omega_0(t) \qquad (3)$$

The mean intensities of the two classes are:

$$\mu_0(t) = \frac{\sum_{i=0}^{t} i \cdot p(i)}{\omega_0(t)} \qquad (4)$$

$$\mu_1(t) = \frac{\sum_{i=t+1}^{L-1} i \cdot p(i)}{\omega_1(t)} \qquad (5)$$

The total mean intensity of the image is:

$$\mu_T = \sum_{i=0}^{L-1} i \cdot p(i). \qquad (6)$$

The between-class variance is calculated as:

$$\sigma_B^2(t) = \omega_0(t) \cdot \omega_1(t) \cdot (\mu_0(t) - \mu_1(t))^2 \quad (7)$$

The optimal threshold t^* is determined by maximizing the between-class variance:

$$t^* = \arg\max_{0 \le t < L} \sigma_B^2(t) \quad (8)$$

4.4.2. Minimum Thresholding Method

The Minimum thresholding algorithm is an iterative method that minimizes the intra-class variance[22]. The intra-class variance is defined as [21]:

$$\sigma_W^2(t) = \omega_0(t) \cdot \sigma_0^2(t) + \omega_1(t) \cdot \sigma_1^2(t) \quad (9)$$

where $\sigma_0^2(t)$ and $\sigma_1^2(t)$ are the variances of the two classes. The optimal threshold t^* is found by minimizing the intra-class variance:

$$t^* = \arg\min_{0 \le t < L} \sigma_W^2(t) \quad (10)$$

4.5. Accuracy Assessment

To evaluate the performance of the thresholding methods, a comprehensive accuracy assessment was conducted as shown in table 2. A confusion matrix was generated to quantify the agreement and disagreement between the classified water bodies and the reference data. by using confusion matrix, other key metrics were calculated i.e. overall accuracy, it represents the proportion of correctly classified pixels; Kappa coefficient, a measure for agreement that accounts for chance; precision, which indicate the proportion of correctly identified water pixels among all pixels classified as water; recall, quantifying the proportion of correctly identified water pixels out of all actual water pixels; and the F1-score, the harmonic mean of precision and recall, providing a balanced measure of accuracy. These metrics are helpful for objectively comparing the effectiveness of different thresholding techniques, ensuring a robust and reliable assessment of water body delineation accuracy. By using this suite of metrics, we aimed to provide a complete understanding of the strengths and limitations of each thresholding method, thereby informing the selection of the most suitable approach for accurate water resource monitoring and extracting water surface area for further analysis [22]. Following section discuss the all equation used for accuracy assessment.

Table 2: Performance Metrics

Performance Metrics	Equation
ConfusionMatrix	$\begin{bmatrix} \text{TruePositives(TP)} & \text{FalsePositives(FP)} \\ \text{FalseNegatives(FN)} & \text{TrueNegatives(TN)} \end{bmatrix}$
Overall Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Kappa	$\frac{\text{Accuracy} - \text{ExpectedAccuracy}}{1 - \text{ExpectedAccuracy}}$
ExpectedAccuracy	$\frac{(TP + FP) \cdot (TP + FN) + (TN + FP) \cdot (TN + FN)}{(TP + TN + FP + FN)^2}$

Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1Score	$2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$

4.5.1. Reference Data

For reference data researchers mainly use the high-resolution image from google earth and manually digitize the water bodies; however reference image and test image must have close acquisition dates, which is very difficult to get. Some uses in situ sampling data which is labor intensive and costly; to address this issue some researchers used SVM classified image is as reference for comparison since SVM has high accuracy in water body discriminations. Therefore, for the purpose of this investigation, a supervised support vector machine (SVM) classification algorithm was used to the Sentinel-2 image, and a two-class image, consisting of water and non-water imagery, was generated for the purposes for reference and comparison.

SVM-classified image as a reference for water body identification is used due to its high accuracy in discriminating water. For reference data different kinds of data is used in remote sensing, mainly high resolution Google Earth imagery is used. However, Google earth image date and test data date should have nearby acquisition dates, this situation is one of the drawbacks, for Google earth High resolution image is used as reference. SVM classification has the high accuracy in water body discrimination and is used as reference data in this research, SVM classified image has Overall accuracy of 99.4% and Kappa coefficient of 0.988.

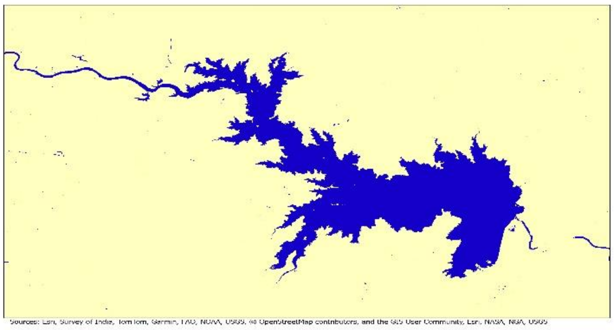

Figure 4: SVM Classified Image

5. Result and Discussion

The table presents a thorough analysis of the findings from several water body extraction techniques based on Sentinel-2 images. The most dependable and precise results came from the Support Vector Machine (SVM) classifier among all of the approaches. With an F1 score of 0.9901, a Kappa coefficient of 0.9912, and an overall accuracy of 99.79%, it clearly shows a very high degree of concordance with reference data and great classifying results. Because of its capacity to process complicated data patterns, the SVM model was exceptionally successful at discriminating between water and non-water pixels.

By contrast, thresholding-based approaches—especially Otsu Thresholding and Minimum Thresholding—generated inconsistent results. Both techniques were used throughout several water indices including AWEI_nsh, AWEI_sh, MNDWI, NDWI, and Sentinel Water Mask. But only when applied to MNDWI, where both thresholding approaches produced the same Overall Accuracy of 99.79%, were meaningful results noted. Although they matched the SVM in terms of accuracy, these methods produced invalid Kappa and F1 numbers, suggesting possible problems with class imbalance, inadequate Inability to produce a full confusion matrix known as classification variability.

Table 3: Result of Accuracy Assessment

Water Indice	Method	Threshold Value	Overall Accuracy	Precision (Water)	Recall (Water)	F1- Score (Water)	Producer Accuracy (Water)	User's Accuracy (Water)	Producer's Accuracy (Non-Water)	User's Accuracy (Non-Water)	Kappa Coeficent
NDWI	Otsu Thresholding Method	-0.0786	99.45	95.78	99.69	0.977	99.69	95.78	99.42	99.96	0.9739
NDWI	Minimum Thresholding Method	-0.0438	99.63	98.22	98.63	0.9843	98.63	98.22	99.76	99.82	0.9822
MNDWI	Otsu Thresholding Method	-0.0519	99.54	96.4	99.76	0.9805	99.76	96.4	99.51	99.97	0.9779
MNDWI	Minimum Thresholding Method	-0.007	**99.79**	98.75	99.5	**0.9912**	99.5	98.75	99.83	99.93	**0.9901**
Sentinel Water Mask	Otsu Thresholding Method	0.8687	99.68	97.54	99.74	0.9863	99.74	97.54	99.67	99.97	0.9844
Sentinel Water Mask	Minimum Thresholding Method	0.9595	**99.79**	99.66	98.57	0.9911	98.57	99.66	99.96	99.81	0.9899
AWEI_nsh	Otsu Thresholding Method	-992.4219	99.38	95.09	99.79	0.9739	99.79	95.09	99.32	99.97	0.9703
AWEI_sh	Otsu Thresholding Method	-3132.6016	99.39	95.14	99.9	0.9746	99.9	95.14	99.33	99.99	0.9712
AWEI_sh	Minimum Thresholding Method	6180.0234	**No Result , Invalid**								
AWEI_nsh	Minimum Thresholding Method	27741.4844	**No Result , Invalid**								

For other indices—NDWI, Sentinel Water Mask, AWEI_nsh, and AWEI_sh—both Otsu and Minimum Thresholding failed entirely, as indicated by “No Result; Invalid” in the table. This failure likely resulted from the inability of these algorithms to identify a meaningful threshold in the pixel value distribution, particularly where the distinction between water and non-water classes was not well defined. In summary, while MNDWI showed some promise with both supervised and unsupervised methods, the SVM classifier consistently outperformed all thresholding approaches, providing valid and highly accurate results. This highlights the strength of machine learning techniques over basic thresholding methods, particularly when applied to complex and diverse remote sensing data for water body extraction.

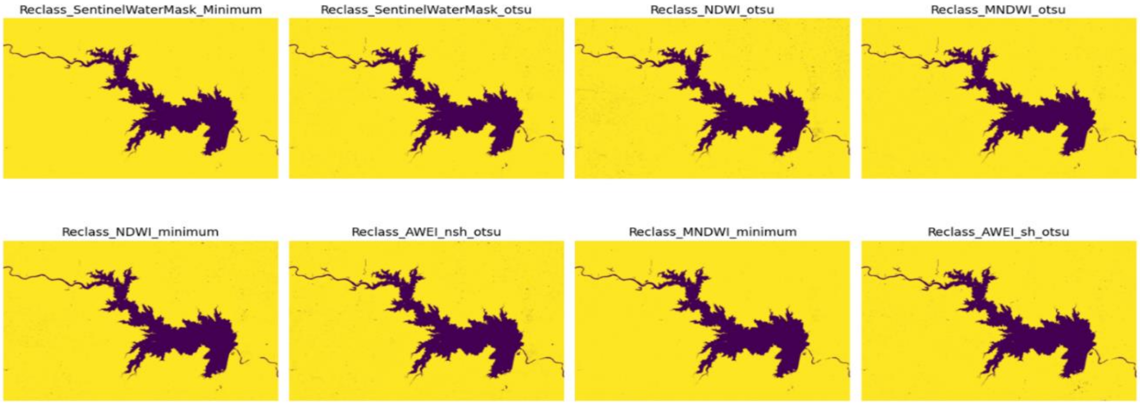

Figure 5: Reclassified Water Indices

6. Conclusion

In this study, we used Sentinel-2 images to extract water bodies, trying out both spectral index-based thresholding and a supervised machine learning method—the Support Vector Machine (SVM) classifier. SVM really stood out. Pinpointed in an overall accuracy of 99.79%, F1-score of 0.9901 and a Kappa of 0.9912. So, it's safe to say it's precise and reliable for classifying water. The thresholding methods, like Otsu and Minimum thresholding, stumbled. They didn't give valid results for some indices, especially AWEI_nsh and AWEI_sh. That just shows that while spectral indices help highlight water, using thresholding alone can be tricky. It's sensitive to local differences and how the data changes from place to place. So, if you want solid, accurate water extraction from remote sensing data, it makes sense to bring machine learning into the mix—especially SVM. Comparing water indices like NDWI, MNDWI, AWEI, and SWM, it's clear that traditional indices still matter for mapping water bodies. But advanced methods that use machine learning take things up a notch. Combining Sentinel-2 imagery with these indices gives us a strong setup for tracking water resources accurately. Looking ahead, it's worth digging deeper into how different indices and machine learning can work together to make water body mapping even better and more efficient.

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