

Enhancing Water Body Detection in Satellite Imagery: A Novel Hybrid Approach Exploiting Spectral and Reflectance Characteristics

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Abstract: Water body mapping using satellite data is necessary for environmental assessment and proper allocation and utilization of water resources. Existing methods for extracting water from Sentinel-2 data using water indices often produce mixed, misleading results because of mixed pixels, spectral ambiguity, atmospheric changes, and optical distortions such as shadows and glare. In contrast, while the colour image is rich in hue detail, it lacks the spectral data needed to classify water. This work aims to develop a combined water fusion approach that uses RGB reflectance and Sentinel-2 bands, along with water indices such as NDWI and MNDWI, to produce multidimensional features for both spectral and spatial aspects. This approach leverages both spectral and RGB data, improving discrimination of water features and enhancing the reliability of water extraction under different conditions. To demonstrate the method's effectiveness, researchers tested it on Indian water bodies using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Mean Absolute Error (MAE). These indicators assess result reliability across regions. This hybrid framework shows how remote sensing can support sustainable water resource management at scale.

Keywords: Remote Sensing; Water Resource Management; Mean Absolute Error (MAE); Mean Squared Error (MSE); Spatial Aspects; Environmental Assessment; Spectral Ambiguity.

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1. Introduction

Studying Earth's water bodies with space-based sensors is fundamental to many applications, including hydrological management and environmental protection. Using state-of-the-art satellite imaging and remote sensing techniques, researchers can now observe and monitor aqueous systems, including lakes, rivers, and oceans, with greater precision [1]. This technology is an important component of many fields, including navigation, disaster management, agriculture, city planning, and water resource management [2]. Extracting water-related information through remote sensing, such as detection, volumetric assessment, and quality assessment, is highly beneficial for various purposes [3]. These include monitoring water supplies,

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assessing ecosystem status, determining water extremes, improving farm irrigation, planning infrastructure development, monitoring climate disturbances, and enhancing navigation and disaster mitigation [4]. In fact, remote sensing's ability to detect water bodies has revolutionized how researchers perceive and manage this important resource without damaging the environment. Sentinel-2 L1C band images are very important for our research [5]. They provide abundant spectral data needed to represent land cover types [6] accurately.

These images are vital for demarcating water environments from other surface cover materials through careful analysis of selected band combinations and spectral unmixing techniques. These techniques help process mixed pixels and reduce misclassification risk caused by similar spectra in moist soils or lush vegetation cover [8]. Spectral unmixing faces several challenges, including end-member selection, assumptions of spectral linearity, constraints imposed by spectral variability, vulnerability to noise, and the peculiarities of subpixel diversity. To address these issues, this research proposes a novel methodology that combines the reflective capabilities of RGB imagery with Sentinel-2 L1C spectral data [9]. This technique creates a unique feature vector with two water indices and optical distortion correction.

This enables much higher-accuracy classification of water bodies. Additionally, our research considers the qualitative value of RGB imagery, as it allows us to perceive water bodies by their unique chromatic composition. This combination of methodologies improves spectral band analysis by addressing the issues mentioned above. Our goal is to make water body identification through remote sensing much easier.

2. Related Work

In water body detection using remote sensing techniques, the literature offers many methods. Sun et al. [1] introduced a new approach to extract water bodies from remote sensing images by employing both entropy-based thresholding and morphological operators. This technique is considerably more accurate and uses significantly fewer computational resources. Zhao et al. [2] proposed applying Classification and Regression Tree (CART) models to detect polluted water bodies, and they demonstrated the method's efficiency using sensor network data. Jin et al. [3] did the same, combining multiscale segmentation with SVMs for the same purpose. Significant advances have also improved feature extraction. For instance, Jagruth et al. [19] developed a model that integrates feature pyramid grouping with multiscale feature extraction. The model has proven highly effective for identifying water bodies and is also highly efficient. Researchers recommend using deep learning to improve these approaches further. In addition, Li et al. [4] used a U-Net model that integrates CNNs with an attention mechanism, achieving significant gains in accuracy and efficiency over conventional models. This has the potential to improve environmental and water resource management.

Moreover, Markert et al. [13] demonstrated that an improved FCN can precisely identify water bodies. Ahmed et al. [5] proposed a deep learning model that uses contextual data to improve water body detection in remote sensing images by incorporating a CNN and a context module. This approach has opened the door to better research in hydrology and land cover. Qiao et al. [6] also proposed a growth-based region approach for extracting water bodies, which can help with various environmental and land classification tasks. Gao et al. [7] provided a detailed analysis of SegNet compared with other segmentation approaches. Buma et al. [8] demonstrated the accuracy of multispectral sensors in determining surface-water depth, while Bijesh et al. [9] showed that dual-channel CNN architectures perform more effectively in image super-resolution tasks. Miao et al. [10] presented the accuracy of classification and regression tree models that depend on sensor network data. Globally, Feng et al. [11] compiled an extensive dataset of inland waters, which is important for global ecological and climate models. Qiao et al. [6] advocated integrating remote sensing data and field surveys because of the growing need for integrated water resources management. Hollstein et al. [20] developed algorithms to identify pixels in Sentinel-2 MSI imagery. They improve workflows in environmental studies.

In the meantime, Meng et al. [12] demonstrated an automatic perceptron-based technique for identification of water features in Landsat imagery. Markert et al. [13] merged spectral data with radar backscatter, improving surface water map accuracy. Pekel et al. [14] developed high-resolution mapping using Landsat data to monitor worldwide changes in surface water, underscoring the importance of satellite imagery in environmental management. Moreover, Wang et al. [15] evaluated MD-DenseNet's accuracy in detecting water bodies in high-resolution images, while Wieland et al. [16] demonstrated the value of multispectral data for automating flood monitoring.

However, the strategies mentioned above by Acharya et al. [17], Halder et al. [18], and Zhao et al. [2] have weaknesses, particularly noise interference. In addition, studies such as Jagruth et al. [19], Pekel et al. [14], and Wang et al. [15] that focus on RGB components ignore the value of multispectral data. Hybrid approaches that combine machine learning techniques should be developed to fill this gap. By combining the advantages of different spectral data with computational power, these techniques will enhance satellite-based water-body detection.

3. Methodology

This work presents an automated technique to detect and segment water bodies in satellite images. The methodology uses Sentinel-2 Level-1C imagery and a hybrid fusion technique that combines NDWI, MNDWI, and RGB. This approach improves interpretability of the water body environment while increasing detection accuracy. The proposed methodology relies on a novel hybrid machine learning algorithm (Algorithm 1) that captures complex interactions between multispectral bands and RGB colours. To ensure robust, reliable water body detection, the researchers defined empirical thresholds for NDWI and MNDWI. Namely, water bodies are detected when $NDWI > 0.3$ and $MNDWI > 0.2$. Researchers derived these thresholds by validating the algorithm on the dataset to ensure consistent segmentation across different environmental conditions. As a result, the improved algorithm integrates this threshold-based feature extraction, making classification more efficient. The high segmentation accuracy achieved with the proposed model demonstrates its ability to learn from the complexities of remote sensing data. Figure 1 shows the proposed model structure, presenting its elements and their interactions to illustrate how machine learning can be effectively combined with spectral and image data. This combination of approaches significantly improves remote sensing.

Algorithm 1: Hybrid Water Detection Model Using NDWI, MNDWI, and RGB Markers:

- **Require:** Sentinel imagery with water bodies
- **Ensure:** Accurate water detection in images

```
1: Initialize the Random Forest model with 10 estimators
2: for each training image do
3:   Compute  $NDWI = \frac{B_{green} - B_{nir}}{B_{green} + B_{nir}}$ 
4:   Compute  $MNDWI = \frac{B_{green} - B_{swir}}{B_{green} + B_{swir}}$ 
5:   if  $NDWI > 0.3$  then
6:     Extract NDWI feature for water detection
7:   end if
8:   if  $MNDWI > 0.2$  then
9:     Extract MNDWI feature for water detection
10:  end if
11:  Employ an RGB-based model to detect water and generate RGB markers
12:  Combine extracted NDWI, MNDWI, and RGB markers into feature vector F
13: end for
14: Train the hybrid model using the feature vector F on training images
15: Assess the hybrid model on a separate set of test images
16: for each test image do
17:   Compute  $NDWI$  and  $MNDWI$ 
18:   if  $NDWI > 0.3$  then
19:     Extract NDWI feature
20:   end if
21:   if  $MNDWI > 0.2$  then
22:     Extract MNDWI feature
23:   end if
24:   Generate RGB water markers
25:   Combine extracted features into test feature vector  $F_{test}$ 
26:   Input  $F_{test}$  into the trained hybrid model
27:   Predict the presence of water using  $\hat{y} = RF(F_{test})$ 
28:   Record the prediction accuracy
29: end for
30: Calculate overall model accuracy and efficacy
```

3.1. Dataset Description

Our research used a dual dataset approach to develop a hybrid water fusion model. The primary dataset from Kaggle includes 1500 annotated RGB images for RGB marker extraction. The secondary dataset consists of 50 multispectral Sentinel-2 L1C images from SentinelHub, representing various water bodies in India, to derive water indices. These images enable the computation of water indices such as NDWI and MNDWI, improving the accuracy of water body detection. Researchers meticulously generated ground-truth labels and validated them against Google Maps annotations. The training set comprises

35 images, with the remaining 15 designated for testing. This fusion of RGB markers and spectral data underpins our proposed model's enhanced ability to detect water bodies.

3.2. Platforms and Software Utilized for Analysis

For this analysis, researchers used cloud-based platforms and Python-based tools. Researchers used Google Earth Engine (GEE) for large-scale geospatial data processing, while Sentinel Hub handled automatic Sentinel-2 image retrieval and processing. Researchers used multiple Python libraries, including the Sentinel Hub Python API for data acquisition, GDAL and Rasterio for geospatial data processing and transformation, Scikit-learn to implement a Random Forest Tree (RFT) classifier, and OpenCV and NumPy for image pre-processing and feature extraction. Obtaining Sentinel-2 L1C multispectral imagery from Sentinel Hub entails a systematic process. First, create a Sentinel Hub account. Second, obtain API credentials by creating an instance ID in Configuration Utility and a new OAuth client in User Settings, which provides the Client ID and Secret; store these securely for API use. Third, demarcate the AOI by drawing a bounding box on the Sentinel Hub dashboard to obtain the latitude and longitude coordinates. After establishing the AOI, request Sentinel-2 imagery with the required spectral bands (RGB, NIR and SWIR) and the most appropriate acquisition time. Finally, Sentinel-2 imagery, along with its metadata and spectral bands, is acquired.

3.3. Preprocessing

Atmospheric corrections were applied during preprocessing to remove atmospheric disturbances. Atmospheric scattering and absorption correction improves image clarity and reliability. Moreover, we set a rigorous cloudiness criterion between 0 and 5 to select cloud-free images for analysis. This approach is crucial for limiting cloud cover's effect on the research results.

3.4. Water Feature Extraction

The presence of water in each image was quantified using two spectral indices: the Normalized Difference Water Index (NDWI) and the Modified Normalized Difference Water Index (MNDWI), calculated as follows:

$$NDWI = \frac{B_{green} - B_{NIR}}{B_{green} + B_{NIR}} \quad (1)$$

$$MNDWI = \frac{B_{green} - B_{SWIR}}{B_{green} + B_{SWIR}} \quad (2)$$

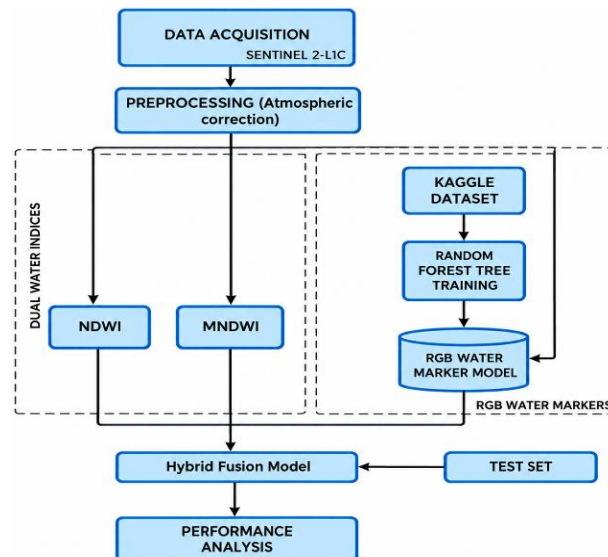


Figure 1: Hybrid spectral-visual fusion framework for enhanced water body detection in satellite imagery

The MNDWI index uses the green and short-wave infrared (SWIR) bands to reduce the influence of soil and vegetation, increasing the separability of water bodies. Based on empirical analysis, pixels with an MNDWI above 0.2 are classified as water bodies. This threshold-based extraction improves the efficiency of the proposed method. Using both NDWI and MNDWI

together helps identify discriminating spectral characteristics, improving accuracy and effectiveness in detecting water bodies using remote sensing images. The RF classifier uses these spectral characteristics as input to capture the complex relationships needed to differentiate water and non-water areas. The Random Forest method is ideal for water body classification because it can learn discriminant features from spectral signatures. In RGB images, water bodies tend to show reduced reflection in the red and green channels, while showing slightly elevated reflection in the blue channel. Using these spectral attributes, combined with water indices, enables more effective water-body classification without increasing misclassification by other land cover types. The random forest method utilizes ensemble learning by combining the outputs of several decision trees. Thus, the proposed method facilitates mapping and delineation of water bodies (Table 1).

Table 1: Comparative analysis of water body detection methods

Feature	NDWI and MNDWI (Conventional Indices)	Random Forest Classifier	Proposed Hybrid Fusion Model
Input Data	Multispectral bands from Sentinel-2 (Green, NIR, SWIR)	Extraction of RGB features from Sentinel-2	Fusion of NDWI, MNDWI, and RGB marker information
Feature Extraction	Generation of predefined spectral indices based on multispectral bands	Extraction of discriminative features from RGB images	Fusion of spectral index and RGB markers to obtain an overall set of features
Classification Approach	Thresholding-based extraction of water bodies	Supervised classification using a Random Forest model with RGB features	Supervised classification using a Random Forest model with spectral+RGB features
Detection Accuracy	Moderate; varies according to environment	High, based on training data quality and diversity	Better accuracy due to integration of spectral and spatial information
Computational Cost	Low	Moderate	High due to hybrid feature integration
Misclassification Issues	Problems Subject to influence from urban areas, murky water, and atmospheric conditions	Might be impacted by spectral similarity and needs proper feature selection	Minimizes mistakes from spectral confusion, shadows, and mixing of classes
Training Data Requirement	Not required (unsupervised method based on indices)	Necessitates the use of training samples	Necessitates the use of training data
Spectral Information	Uses water spectral indices alone	Based on RGB features	Combines spectral indices and RGB features for spatial aspects
Noise Robustness	Moderate	High when there is adequate training data	Increased noise resistance due to complementary feature extraction
Application Suitability	Suitable for large-scale water body mapping	Suitable for region-specific classification tasks	Suitable for robust water body detection in varied environments

Algorithm 2: Random forest tree for water body classification:

- **Require:** Feature vectors of water (W) and non-water (NW) samples, Number of decision trees (n_{trees})
- **Ensure:** Trained Random Forest Model (RF)

```

1: Initialize Random Forest Model RF
2: for  $i = 1$  to  $n_{trees}$  do
3:   Sample dataset with replacement to create subset  $S_i$ 
4:   Train decision tree  $T_i$  on subset  $S_i$  using:
5:     Features: NDWI, MNDWI, RGB values, texture measures
6:     Split criterion: entropy (information gain)
7:   Add trained decision tree  $T_i$  to RF
8: end for
9: return RF

```

The Random Forest Tree (RFT) algorithm classifies water bodies based on their spectral and colour characteristics derived from satellite images. During training, the algorithm calculates the NDWI and MNDWI spectral indices, along with the original

RGB bands, using Equations (1) and (2), respectively. All of these spectral bands are combined to form a hybrid feature vector that is fed into the Random Forest classifier. Random Forest uses ensemble learning and builds several decision trees from randomly generated subsets of the training data.

Algorithm 3: Predict using random forest model:

- **Require:** Trained random forest model (RF), Feature vector X
- **Ensure:** Classification label (Water/Non-Water)

1: for each decision tree T in RF do
2: Predict class label Y_T using T
3: end for
4: Aggregate predictions using majority voting
5: return final class label Y

The RFT training process, outlined in Algorithm 2, follows these steps:

- **Feature Extraction:** NDWI and MNDWI are calculated by Equation (1) and Equation (2), respectively, along with the RGB bands to construct the hybrid feature vector.
- **Random Sampling and Decision Tree Training:** Randomly select the training dataset using bootstrap sampling to create several data subsets. Each subset then independently constructs a decision tree using entropy-based information gain as the node-splitting criterion.
- **Majority Voting and Model Aggregation:** All decision trees classify each pixel as either water or non-water, and the final output is generated by majority voting across all decision trees, as given in Algorithm 3.

This ensemble learning framework improves the classifier's robustness and generalization by reducing overfitting while effectively capturing the spectral characteristics of water bodies. Combining image processing with the machine learning algorithm enables extraction of discriminative features from satellite images. In the proposed algorithm, we combine the spectral indices (NDWI and MNDWI) with RGB values to create a hybrid feature vector that captures both spectral and visual information about water bodies. This feature fusion improves classification accuracy, model robustness, and visual interpretation of the water region, as shown in Figure 2. Afterwards, the hybrid feature vector is applied to train the Random Forest Tree (RFT) classifier. As shown in Algorithm 2, the Random Forest algorithm effectively represents relationships among the features. It builds an ensemble of decision trees from random subsamples of the input data. Thus, ensemble learning not only improves the classifier's generalization but also helps distinguish water from other areas.

4. Results

This section evaluates the proposed water body detection method.

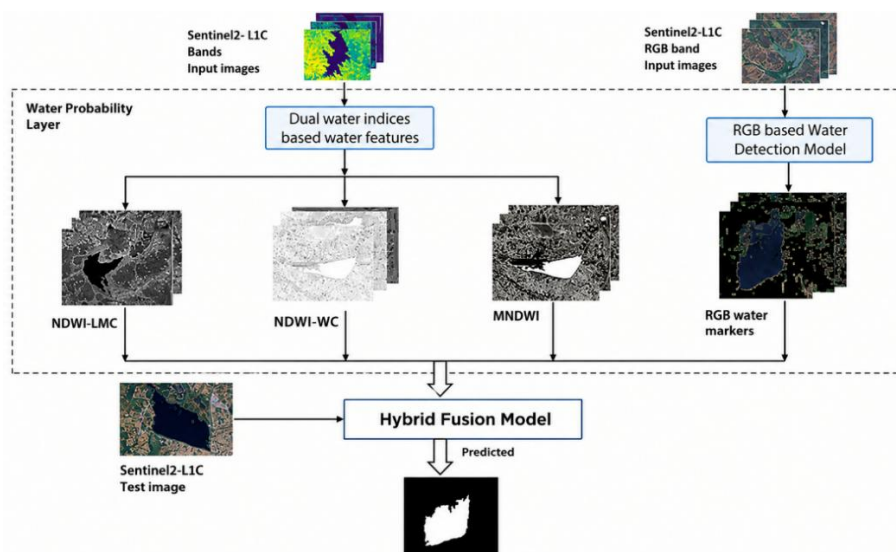


Figure 2: Integrated hybrid feature vector framework for enhanced water detection

The model's effectiveness will be evaluated through a comparative study of predicted and ground-truth labels for the test images. Quantitative performance metrics will include mean squared error (MSE), peak signal-to-noise ratio (PSNR), mean absolute error (MAE), intersection over union (IoU), and the F1 score.

4.1. Data Processing and Feature Extraction

To ensure quality analysis, systematic pre-processing and feature extraction of data are performed as follows:

- **Data Acquisition:** Sentinel-2 Images are obtained from the Copernicus Open Access Hub.
- **Preprocessing:** Sentinel-2 images are obtained through Sentinel Hub, where the Area of Interest (AOI) is identified through bounding box coordinates. Data acquisition occurs via the Sentinel Hub API, where spectral bands such as RGB, NIR and SWIR are selected. Images are calibrated and corrected for radiometric and atmospheric issues using Sen2Cor. Preprocessing activities also involve geospatial processing and transformation using GDAL and Rasterio, and image enhancement and feature extraction using OpenCV and NumPy.

4.1.1. Feature Extraction

- NDWI and MNDWI are computed based on predetermined spectral band ratios.
- RGB Features are extracted and converted to feature vectors.
- The extracted indices and features are fed into the RFC classifier, which consists of 10 estimators.

4.1.2. Labeling and Ground Truthing

We use manually labelled datasets and water reference maps to validate the models. Google Maps is used to validate the manually produced ground-truth data.

4.2. Dual Water Indices-Based Water Body Detection Model

The hybrid technique uses NDWI and MNDWI with RFC to extract water-body features. Table 2 shows the method's performance and demonstrates its effectiveness for water extraction, given strong precision and recall.

Table 2: Quantitative analysis of water model based on dual water indices

Test Water Bodies	MSE	PSNR	MAE	IoU	F1 Score
Thenkal Kanmai	2336.74	14.44	3.67	0.79	0.88
Kanigiri Reservoir	616.56	20.23	1.57	0.95	0.97
Keelakkuyilkudi	1727.61	15.75	2.41	0.0	0.0
Koothiyarkundu Kanmai	1173.43	17.43	4.19	0.82	0.90
Madakulam	683.37	19.78	1.20	0.82	0.90
Manur Pond	211.78	24.87	0.63	0.87	0.93
Sundrapadiyapurram	625.13	20.17	1.99	0.90	0.95
Vaigai Reservoir	51.32	31.02	0.12	0.98	0.99
Vandiyar Kanmai	76.96	29.26	0.23	0.98	0.99
Veerakerala	29.94	33.36	0.08	0.98	0.99

4.3. RGB-Based Water Body Detection Model

RGB spectral data is used for random forest classification for detecting water signatures. However, this model suffers from several problems, including atmospheric variability, shadows, and similar land-cover colours. Performance is illustrated in Table 3. However, the data show variance in prediction accuracy; for instance, “Thenkal kanmai” had the highest Mean Squared Error (MSE) of 16,648.05. This shows wide variation in the predictions. In contrast, “Manur pond” had the lowest PSNR (14.96), indicating poorer image quality and more noise interference.

In addition, “Veerakerala” exhibited a considerable Mean Absolute Error (MAE) of 89.29, which suggests a need for improvement in accuracy. The water body “Koothiyarkundu kanmai” had an Intersection over Union (IoU) of 0.53. This means the predicted regions closely matched the actual water bodies. This shows the need to improve water body detection techniques to ensure high prediction accuracy and reduce noise. Because researchers lack adequate access to high-quality, noise-free satellite images, our proposed system uses dual water indices together with RGB bands.

Table 3: Quantitative analysis of water model based on RGB water markers

Test Water Bodies in India	MSE	PSNR	MAE
Thenkal Kanmai	16648.05	4.55	81.91
Kanigiri Reservoir	14892.74	6.40	6.85
Keelakkuyilkudi	2139.19	14.82	7.65
Koothiyarkundu Kanmai	4553.32	11.54	13.04
Madakulam	11536.09	7.51	38.45
Manur Pond	2072.17	14.96	0.60
Sundrapadiyapurram	11182.37	7.64	4.86
Vaigai Reservoir	3683.61	12.46	1.70
Vandiyar Kanmai	17785.27	4.308	75.69
Veerakerala	12211.95	7.16	89.29

4.4. Hybrid Fusion Model

The new hybrid fusion uses NDWI and MNDWI spectral indices, along with RGB data, to create a composite spectral representation for detecting water bodies. This approach leverages the complementary nature of Sentinel-2 spectral bands and RGB imagery to make the information more distinctive, improving water body detection across different environmental conditions. The hybrid feature technique reduces the influence of shadowing, atmosphere and land-cover variation, making water body detection more robust. Table 4 summarizes the model's performance results. Table 3 shows the proposed hybrid fusion model's results for detecting ten Indian water bodies, based on metrics such as Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Mean Absolute Error (MAE).

Table 4: Quantitative analysis of hybrid water fusion model

Test Water Bodies in India	MSE	PSNR	MAE
Thenkal Kanmai	16648.05	4.55	81.91
Kanigiri Reservoir	15234.56	6.30	10.94
Keelakkuyilkudi	1848.16	15.46	3.84
Koothiyarkundu Kanmai	2831.34	13.61	6.68
Madakulam	3233.26	13.03	8.76
Manur Pond	1801.81	15.57	0.75
Sundrapadiyapurram	5928.00	10.40	2.72
Vaigai Reservoir	4396.23	11.70	7.68
Vandiyar Kanmai	12326.55	7.22	41.90
Veerakerala	7785.73	9.22	25.32

The results indicate that the proposed algorithm performs consistently well across water bodies that differ in size, neighbouring land-cover attributes, environmental conditions and so on. The low MSE and MAE scores for Manur Pond, Keelakkuyilkudi and Koothiyarkundu Kanmai indicate accurate mapping of these water bodies. In contrast, the high PSNR score indicates good image reconstruction. The performance variations in the larger dam lakes Thenkal Kanmai, Vandiyar Kanmai, and Veerakerala may be attributed to complex backgrounds, mixed pixels, and lighting variations in satellite images. Overall, the results indicate that the hybrid fusion approach adopted in this paper makes optimal use of spectral and spatial data.

4.5. Discussion

The experimental results show that a hybrid fusion methodology using NDWI, MNDWI, and RGB features performs well for water body identification. Unlike conventional methods that use either spectral indices or RGB data alone, the proposed approach combines complementary spectral and spatial features, improving the accuracy of water and non-water separation across different environments. The model performs consistently regardless of reservoir size and the presence of vegetation cover, atmosphere, and illumination conditions. Although performance varies within each test site because of differences in scene complexity and mixed pixels, hybrid features using Sentinel-2 spectral indices and RGB imagery are more robust. Table 4 further illustrates the advantages of the proposed framework. While NDWI and MNDWI clarify spectral features and RGB images clarify spatial features, this work's hybrid fusion technique combines both to provide a more informative feature set for water body pixel classification. This technique not only eliminates spectral confusion but also significantly improves water body classification accuracy. However, some limitations do exist. When analysed regions are highly heterogeneous and mostly consist of mixed pixels, the model is likely to perform less satisfactorily. However, the model's efficiency and effectiveness

rely heavily on the availability of cloud-free Sentinel-2 imagery. The next stage of this research involves shifting the paradigm to develop deep learning models for feature abstraction, including additional spectral bands and using cloud computing to improve the model's detection accuracy.

5. Conclusion

To summarise, the proposed technique is an effective fusion model that combines water body indices such as NDWI and MNDWI with the unique reflectance properties of RGB spectral data. This approach is novel because it dynamically integrates multiple data types and addresses the drawbacks of standard methods caused by mixed pixels and spectral confusion. This integrated approach uses advanced algorithms to extract detailed information from satellite image bands, enhancing feature extraction and providing a more complete depiction of water body features. The Sentinel bands can be combined with the RGB channels to create a multidimensional data representation. The RGB channels provide visible-colour information, while the Sentinel bands provide spectral information. This combination provides additional features that allow machine learning algorithms to identify complex patterns and changes in satellite data. Moreover, combining NDWI, MNDWI, RGB channels, and Sentinel bands enhances the identification and characterisation of water bodies by exploiting complementary spectral and visual information. The results from this technique could make a major contribution to remote sensing and water resource management. The proposed approach provides a viable foundation for improving water body detection, collecting precise spectral information and enabling effective water resource monitoring. This integrated approach shows that combining different remote sensing data sources can enable reliable and effective water body analysis.

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References

1. D. Sun, G. Gao, L. Huang, Y. Liu, and D. Liu, "Extraction of water bodies from high-resolution remote sensing imagery based on a deep semantic segmentation network," *Sci. Rep.*, vol. 14, no. 6, pp. 1–13, 2024.
2. Q. Zhao, X. Dong, G. Li, Y. Jin, X. Yang, and Y. Qu, "Classification and regression tree models for remote recognition of black and odorous water bodies based on sensor networks," *Sci. Program.*, vol. 2022, no. 1, pp. 1–12, 2022.
3. S. Jin, Y. Liu, S. Fagherazzi, H. Mi, G. Qiao, W. Xu, C. Sun, Y. Liu, B. Zhao, and C. G. Fichot, "River body extraction from Sentinel-2A/B MSI images based on an adaptive multiscale region growth method," *Remote Sens. Environ.*, vol. 255, no. 3, pp. 1–48, 2021.
4. M. Li, P. Wu, B. Wang, H. Park, H. Yang, and Y. Wu, "A deep learning method of water body extraction from high-resolution remote sensing images with multisensors," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, no. 2, pp. 3120–3132, 2021.
5. M. W. Ahmed, A. Alshahrani, A. Almjally, N. Al Mudawi, A. Algarni, and K. Al Nowaiser, "Remote sensing image interpretation: Deep belief networks for multi-object analysis," *IEEE Access*, vol. 12, no. 9, pp. 142360–142379, 2024.
6. C. Qiao, J. Luo, Y. Sheng, Z. Shen, Z. Zhu, and D. Ming, "An adaptive water extraction method from remote sensing image based on NDWI," *Journal of the Indian Society of Remote Sensing*, vol. 40, no. 3, pp. 421–433, 2012.
7. Z. Gao, Q. Wang, T. Mei, X. Cheng, Y. Zi, and H. Yang, "An enhanced encoder-decoder network architecture for reducing information loss in image semantic segmentation," *arXiv preprint*, arXiv:2406.01605, 2024. [Accessed by 16/03/2025].
8. W. G. Buma, S. Lee, and J. Y. Seo, "Recent surface water extent of Lake Chad from multispectral sensors and GRACE," *Sensors*, vol. 18, no. 7, pp. 1–24, 2018.

9. T. V. Bijeesh and K. N. Narasimhamurthy, "Surface water detection and delineation using remote sensing images: A review of methods and algorithms," *Sustain. Water Resour. Manag.*, vol. 6, no. 4, p. 68, 2020.
10. R. Miao, T. Ren, K. Zhou, Y. Zhang, J. Song, G. Zhang, and J. Wang, "A Method of Water Body Extraction Based on Multiscale Feature and Global Context Information," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, no. 6, pp. 12138–12152, 2024.
11. M. Feng, J. O. Sexton, S. Channan, and J. R. Townshend, "A global, high-resolution (30-m) inland water body dataset for 2000: First results of a topographic–spectral classification algorithm," *Int. J. Digit. Earth*, vol. 9, no. 2, pp. 113–133, 2016.
12. L. Meng, Z. Zhang, W. Zhang, J. Ye, C. Wu, D. Chen, and C. Song, "An automatic extraction method for lakes and reservoirs using satellite images," *IEEE Access*, vol. 7, no. 5, pp. 62443–62456, 2019.
13. K. N. Markert, F. Chishtie, E. R. Anderson, D. Saah, and R. E. Griffin, "On the merging of optical and SAR satellite imagery for surface water mapping applications," *Results Phys.*, vol. 9, no. 6, pp. 275–277, 2018.
14. J. F. Pekel, A. Cottam, N. Gorelick, and A. S. Belward, "High-resolution mapping of global surface water and its long-term changes," *Nature*, vol. 540, no. 7633, pp. 418–422, 2016.
15. G. Wang, M. Wu, X. Wei, and H. Song, "Water identification from high-resolution remote sensing images based on multidimensional densely connected convolutional neural networks," *Remote Sens.*, vol. 12, no. 5, pp. 1–20, 2020.
16. M. Wieland and S. Martinis, "A modular processing chain for automated flood monitoring from multispectral satellite data," *Remote Sens.*, vol. 11, no. 19, pp. 1–23, 2019.
17. T. D. Acharya, D. H. Lee, I. T. Yang, and J. K. Lee, "Identification of water bodies in a Landsat 8 OLI image using a J48 decision tree," *Sensors*, vol. 16, no. 7, pp. 1–16, 2016.
18. T. Halder, D. Chakraborty, R. Pal, S. Sarkar, S. Mukhopadhyay, N. Roy, and S. Karforma, "A hybrid approach for water body identification from satellite images using NDWI mapping and histogram of gradients," *Innov. Syst. Softw. Eng.*, vol. 20, no. 2, pp. 111–120, 2024.
19. K. Jagruth, V. M. Manikandan, and R. K. Kumar, "Water body identification from the satellite images using color component analysis with morphological operations," in *Proc. 12th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, 2021.
20. A. Hollstein, K. Segl, L. Guanter, M. Brell, and M. Enesco, "Ready-to-use methods for the detection of clouds, cirrus, snow, shadow, water, and clear sky pixels in Sentinel-2 MSI images," *Remote Sens.*, vol. 8, no. 8, pp. 1–18, 2016.

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