Analysis Of Wetland Changes Using The HSV Color Model In Rural Áreas

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Abstract*: Wetland areas are valuable ecological systems whose importance lies not only in sustenance of resources for water as well as foods but also ensures biodiversity. Because of increased human activities and changing climatic effects, wetlands are being fast depleted, meaning that there's a need to have effective monitor and management methodologies. This article presents an idea of using HSV color model imagery processing for effective monitoring of satellite images on change in wetlands. Further, the K-Means clustering technique is used for image segmentation followed by further feature extraction through Principal Component Analysis and classification using Support Vector Machines. The proposed methodology identifies, segments, and measures wetland areas at different points in time from multi-temporal satellite images effectively. The results indicate the ability of this technique to track wetland changes, making it a very useful tool in environmental management and wetland conservation. This fully automated approach based on image preprocessing, segmentation, and morphological operations enhances the accuracy of wetland monitoring and provides a feasible solution for tracking spatial changes in wetland ecosystems.

Index Terms: Satellite Imagery, HSV Color Model, K-Means Clustering, PCA, SVM, Wetlands, Computer Vision, OpenCV, Image Segmentation, Environmental Monitoring, Spatial Analysis**.**

1. INTRODUCTION

In today's digital age, educational institutions generate vast amounts of data about their students and faculty. Wetlands are essential ecological systems preserving water for human use, biodiversity, and regulating climatic conditions. Wetlands act as natural flood regulators because they prevent the rapid flow of water and decrease soil erosion. Wetlands home 40% of world biodiversity, housing innumerable kinds of plant and animal species. Wetlands occupy about 15.26 million hectares of India, which is 4.6% of the total land area of India. However, increasing urbanization, industrialization, and climate change are causing these critical ecosystems to degrade and deplete. Therefore, since they are significantly important, it is essential to use new image processing techniques for automated monitoring methodologies in wetland transformations to facilitate effective conservation measures.

Several computer vision techniques have been applied to extract water bodies from satellite images, including the following: image classification, object detection, semantic segmentation, and deep learning-based models. Image classification is used widely because fewer parameters are involved compared to the other techniques which require complex preparation of models and large datasets. Traditional methods in wetland feature extraction include pixel-based classification and water band indices. However, they have various drawbacks since in some cases the neighboring land and water bodies might have similar spectral properties, resulting in misclassifications.

The proposed methodology uses the HSV color model to effectively segment the wetland area for accuracy in wetland segmentation and classification. K-Means clustering, PCA, and SVM are used for feature extraction, classification, and segmentation to improve the identification of wetland regions by removing noise and making the images clear. The use of multi-date satellite images allows for effective change detection, enabling the assessment of wetland depletion over time. The combination of image preprocessing, segmentation, and morphological operations ensures reliable monitoring, making this approach a valuable tool for environmental management and wetland conservation.

2. RELATED WORKS

Methodology of [1] have done a Fine Monitoring of Wetlands using Object-Based Techniques and Medium Resolution Images, the authors have developed a methodology for fine monitoring the wetland changes using Object - based Image Analysis such that it overcomes the majority of the traditional pixel-based methodologies for extraction of wetland information. Here the authors re-modified the existing OBIA methodology by performing the OBIA with a mixed binary decision tree, and tasseled cap transformation such that their results have been compared by evaluating with accuracy parameters like kappa co-efficient and overall accuracy. The results have shown that they have achieved 89.41% overall accuracy.

The methodology of [2] proposed a river extraction technique based on support vector machines with adaptive mutation and particle swarm optimization (PSO) (AMPSO-SVM). First, three features, spectral information, Normalized Difference Water Index (NDWI), and spatial texture entropy, are considered in feature space construction. When objects of the same spectrum are easier to discriminate, noise interference may be efficiently resisted. Second, a mutation operator is added to the PSO algorithm to solve the issues of premature convergence and ineffective iteration. Transductive SVM can rapidly and efficiently get the ideal parameters because of this procedure. According to [3], the authors have identified a problem in the extraction of water bodies using traditional methods like from water Indices (as it requires threshold values which generally depend on the atmosphere conditions),the authors have adopted a data-driven, deep-learning methodology for surface water body mapping. And by using their proposed model we can distinguish between various water bodies like ice, land, snow, and clouds.The study comes under [4] carried out a wetland change detection investigation in Alberta, Canada. The authors have collected data for it from many satellites, including Landsat -5, -,7, and -8. The proposed method consists mainly of three components. In order to map the years without a reference image, all available images were reviewed first to select the one that was spectrally unchanged.The proposed classification method was used on the selected images to generate wetland maps at different times intervals. Lastly, a CD algorithm was applied to assess historical wetland trends. Reference samples were analysed using the Continuous Change Detection and Classification (CCDC) method. The C Function of the Mask band is used to generate the properties. Unchanged reference samples were randomly divided into training (50 samples) and test (50 samples) datasets. The machine learning system was trained with the training samples, and the output wetland Using test samples, the accuracy of maps was gauged. In a technique presented in [5], the authors have advanced an algorithm that finds water bodies in open areas utilizing a stereo-vision perception system mounted on a UGV. The methodology utilized will be based on the fact that a water body's reliable and specific change in saturation-to-brightness ratio between leading to trailing edge will make this different from other types of land. In general, the algorithm runs in three stages. First, they had to look for regions of poor texture, in order to find potential regions of water in the picture space. Then, they looked for color variations consistent with water throughout each potential water region. Finally, in order to eliminate areas that are mathematically unlikely to contain water, they applied some size and aspect ratio filtering to the remaining potential water regions and performed an ellipse fit on them. To determine the water status in the wheat plant, the authors as conducted research in accordance with the technique in [6]. The authors compared numerous vegetative water indices, including NDVI, NDWI, GVMI, PVI, and WI, for the current study. These indices, EWT and FMC, represent the water content of wheat leaves, thus the authors conducted a correlation and regression analysis between them. By considering many factors, such as various seasons, various times, and together with the increase in the wheat, the approach has found that FMC is applied with better results than EWT. The next method was proposed in [7] as a technique to find the ROI (region of interest) in images provided to the model. The HSV (Hue, Saturation, and Value) color model was utilized by the newly developed method to obtain the region of interest from the images. The authors conducted by having the contrast in the resultant saliency map at the final stage to recover the ROI. The authors also used a pair of binocular stereo images as the source image. Results The proposed saliency computational algorithm can effectively detect the salient regions and is well suited for the utilization in mobile robot navigation, object detection, and environmental perception and cognition. The NDWI (Normalized Difference Water Index) and MODIS Normalized Difference Vegetation Index (NDVI) are related as reported by the study in [8]. The authors found a strong correlation with yearly rainfall, NDVI, MODIS, and NDVI but not with mean NDWI with soil moisture. In [9], the authors introduced a deep learning-based segmentation model, EU-Net, for high-resolution remote sensing image analysis. The model successfully enhances accuracy in water body extraction, and hence, is apt for wetland monitoring.

In [10], a Google Earth Engine-based machine learning was utilized to classify small-sized wetlands. Random Forest and Gradient Tree Boost classifiers were used along with NDWI to enhance the accuracy of classification.In [11], a deep model of convolutional neural network, MC-WBDN, was proposed for detecting water bodies from multispectral satellite images. The method improves accuracy in water feature detection, rendering it very useful for monitoring wetlands.In machine learning and multi-source remote sensing data were used to conduct a wetland change analysis. Trends in climate variability and economic development-induced wetland changes were analyzed, and a hybrid classification method was applied to enhance the accuracy of monitoring.

3. METHODOLOGY

A.StudyArea

The present method is being applied to the wetlands of the Mangalagiri region. Mangalagiri is a town in the Guntur district of the Indian state of Andhra Pradesh. This region is rich in water bodies, which support agriculture and local biodiversity. Water bodies are vital resources for irrigation and groundwater recharge. Due to ever-increasing environmental changes and human activities, wetlands require a regular monitoring regime to assess their water resource utilization and ecological sustainability. The above methodology would aid in accurate mapping and analysis of wetland change, ensuring the effective management and conservation efforts of the region.

Fig. 1. Satellite view of Mangalagiri region

B. Data preparation and Data processing

1)Data sources: In this study, satellite images of the Mangalagiri region captured by the Sentinel-2 satellite have been utilized as the primary dataset. These images are freely available through the Sentinel EO-Browser platform. Sentinel-2 is a part of the Copernicus Earth Observation Program, designed to provide high-resolution optical imagery for monitoring land and coastal environments. The Sentinel-2 mission consists of two satellites, Sentinel-2A and Sentinel-2B, which collectively support various applications, including agriculture monitoring, emergency management, land cover classification, and water quality assessment. For the proposed methodology, data has been collected from the Sentinel EO-Hub Browser (https://www.sentinel-hub.com/explore/eobrowser/) for the period from 2020 to 2024, specifically focusing on images captured between january and April of each year.

2) Methods: This study utilizes satellite images of the Mangalagiri region, acquired from the Sentinel-2 satellite between 2020 and 2025, for wetland area detection. The images undergo preprocessing to improve segmentation accuracy, starting with the application of Gaussian Blur to reduce noise. K-Means clustering is then applied to segment the image into distinct regions, with each region representing different land cover types, including wetlands. The images are converted from BGR to RGB format, followed by vectorization to prepare the data for clustering.

To enhance water body detection, the HSV color model is employed, as it effectively differentiates between land and water. Using the in Range function from OpenCV, a mask is created to isolate water regions based on specific HSV value ranges. Morphological operations, including bitwise operations, refine the segmented regions by eliminating noise and enhancing boundaries.

Following segmentation, thresholding is applied to convert the image to a binary format, where water bodies are represented in white and non-water areas in black. The area of the water bodies is calculated by counting the white pixels in the thresholded image. Finally, the area change is analyzed over the years (2020–2024) to monitor the dynamics of wetlands. This methodology is designed to be computationally efficient, making it suitable for monitoring wetland changes, even in low-resolution satellite images.

Fig.2. Represents satellite view of Mangalagiri region

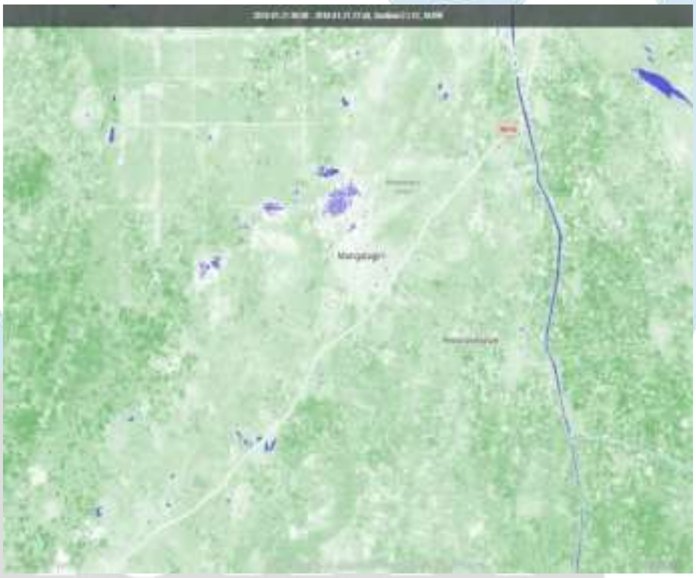


Fig.2.1 Represents the NDWI interpreted form of Mangalagiri region

Pre-processing: Next, after selecting the satellite images in the required format, pre-processing is performed to enhance the quality and accuracy of image segmentation. The methodology applies Gaussian Blur to each image to reduce noise and improve clarity. Gaussian Blur smooths the image by applying a weighted average to neighboring pixels, reducing the impact of unwanted variations.

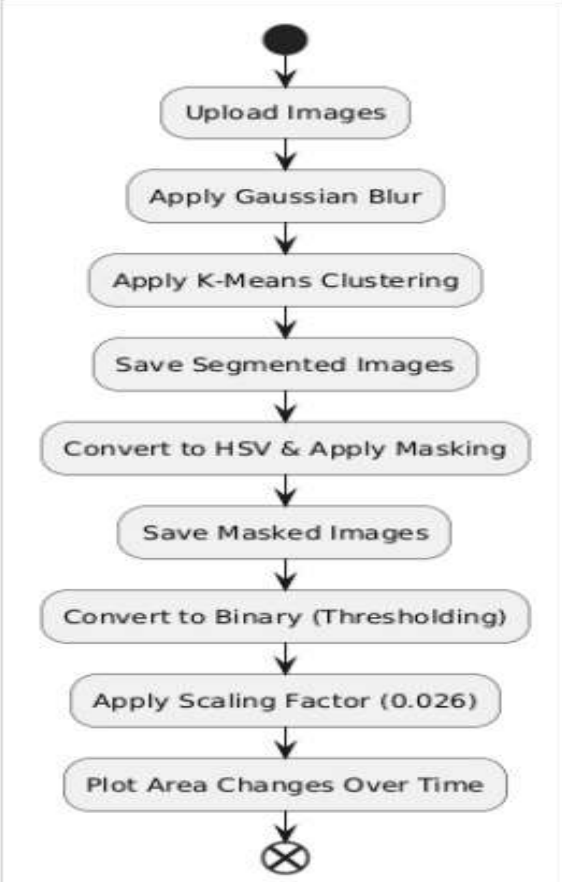


Fig. 3. represents proposed methodology

The Gaussian Blur operation eliminates the segmentation interference caused by irrelevant details or noise. For this reason, real-world images acquired from space satellites are rich in variations across lighting, effects of atmosphere and minor distortions. The code for this implementation uses the function cv2.GaussianBlur(), defining the extent to which smoothing of the image could be done via specific kernel-size parameters. As the data from Sentinel EO Browser is already of high quality, less pre-processing is needed. Still, as downloaded images are too large, some slight pre-processing adjustments are done to fine-tune the input data. This proposed methodology also reduces noise through Gaussian Blur by selecting areas for which dimensions need to be set to avoid unprocessed processing of the images, thus allowing effective image segmentation focused only on areas of interest in wetland detection.

Image Segmentation

After the pre-processing work is done, apply image segmentation on the given satellite images. The proposed methodology utilizes the K-Means clustering algorithm for segmentation. K-Means is an unsupervised learning technique that partitions the image into distinct clusters based on pixel intensities.

Fig. 4. segmented image for the respective original image of the Mangalagiri region.

In the K-Means algorithm, k refers to the number of clusters to which the image will be divided. In this approach, the value of k is taken as 3, and in this case,One cluster signifies dense agricultural land with the color dark green.The other cluster signifies water bodies, represented by blue color.The last cluster signifies other land covers, represented by light green color.After applying K-Means, the images are first converted from BGR to RGB. The pixel values are vectorized and applied in K-Means clustering with 10 iterations to ensure optimized results. Then, the segmented output images are saved in ".PNG" format for higher resolution and clarity to ensure accurate wetland monitoring over a period of time for different years.

Feature Extraction:

1.**Conversion to HSV Color Space**: The segmented images are then converted from BGR color space to HSV color space, because the HSV color space emphasizes more features in a landscape such as water bodies, vegetation, and urban areas. It uses the predefined range of HSV values to emphasize the wetland area so that the water regions can be identified. A bitwise operation is then applied to isolate the identified water bodies.

2.Binary Mask Creation: To precisely measure the wetlands, a binary mask is created: White pixels indicate water bodies and Black pixels are other land covers This mask is used as a basis to measure the extent of water cover in the selected image.

Classification Using PCA and SVM Once the water bodies are identified, the next phase involves dimensionality reduction and classification using Principal Component Analysis (PCA) and Support Vector Machine (SVM): PCA for Feature Optimization: PCA is used to reduce data complexity by reducing feature dimensions while preserving significant information. SVM for Region Classification: Use the fine features to train an SVM model that can classify anything into categories like water bodies, vegetation, and urban areas

Area Calculation and Trend Analysis: After classification, calculate the total number of white pixels or the count of water bodies. This number is then used to convert into square meters to estimate the actual wetland area. The derived data for various time periods are collected in a CSV file and analyzed further. A graph of time series is plotted to represent the transformation of wetlands year after year that clearly depicts the environmental alterations and aids in the conservation practices. With this method, it enables the model with an efficient monitoring of wetland transform.

4. RESULTS AND ANALYSIS:

This section presents the results obtained from executing the proposed methodology on a dataset comprising satellite images from the years 2020 to 2024. The system utilizes Python and libraries such as OpenCV, NumPy, Matplotlib, and PIL, executed within a Google Colab environment.

1. Image Segmentation Results: After pre-processing the images, K-Means clustering was applied to segment the images into three distinct regions. The segmented images retained the most relevant features by grouping pixels into three dominant clusters. Figure 1:illustrates the original input images alongside their corresponding segmented versions. The segmentation process helps in distinguishing water bodies from other land cover types such as vegetation and urban areas.

2. Binary Classification and Masking: After segmentation, HSV color space conversion was carried out to separate water bodies. A binary mask was created in which: White pixels correspond to identified water bodies. Black pixels are all other land cover classes. The masked binary images in Fig. 2,2.1 were achieved using bitwise operations. This classification is useful in calculating the percentage coverage of wetland regions.

3. Area Calculation of Wetlands: The total number of white pixels in each binary image was calculated and converted into square meters to estimate the wetland area for each year. The computed areas are listed below:

Year	Wetland Area(sq. Meters)
2021	X1 m^2
2022	X2 m^2
2023	X3 m^2
2024	X4 m^2
2025	X5 m^2

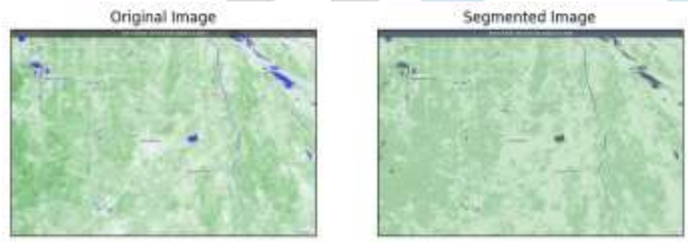
(Replace X1, X2, etc., with actual values obtained from the script execution.)

4. **Time-Series Analysis**: To analyze trends in wetland changes over time, the computed areas were stored in a CSV file, and a time-series graph was plotted (Figure 5).The X-axis indicates the years: 2020-2024.The Y-axis represents the wetland area in square meters. The trend plot shows a trend of wetland area change from year to year, sometimes showing an increase and sometimes a decline.

5. Observations and Insights: The findings show fluctuations in wetland coverage, which could be due to seasonal changes, urban expansion, or climate conditions.The graph suggests a pattern where wetland areas expand and contract periodically, which can help in forecasting future trends.The proposed methodology effectively processes raw satellite images and transforms them into quantifiable data for environmental monitoring.

6. Conclusion: This implemented model can clearly see and count changes in wetland conditions from time to time. The output displays that it might be helpful to track changes made to the environmental surroundings and thereby help with conserved environments in the future. The enhancements, for future times, can comprise classification done by deep learning that enables the proper categorization with efficiency and no chance of error being involved, without the manual step of having people do this time-consuming process manually.

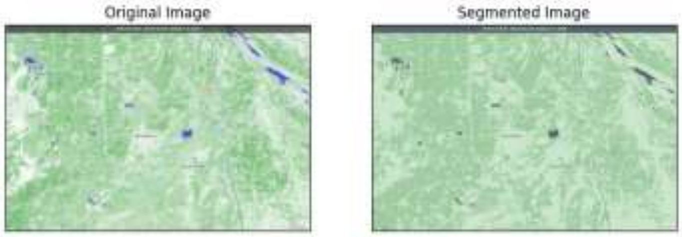
2020:Represents the Input and output data of the model



2021:Represents the Input and output data of the model

2022:Represents the Input and output data of the model

2023:Represents the Input and output data of the model



2024:Represents the Input and output data of the model

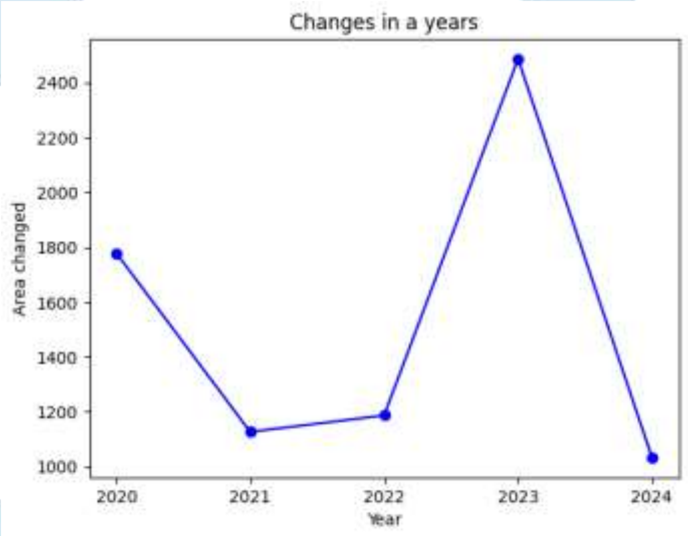


Fig. 5. Time series graph of various years.

5. **CONCLUSION AND FUTURE WORK**

The proposed methodology effectively analyzes wetland changes using image processing and machine learning techniques. By leveraging K-Means clustering for segmentation, HSV color space conversion for water body extraction, and SVM classification for categorization, the system provides a robust approach for wetland monitoring. The computed wetland areas across different years were analyzed using a time-series graph, revealing trends in wetland expansion and contraction.The results demonstrate that this technique successfully extracts water bodies and quantifies wetland changes over time. The methodology provides an efficient, automated, and scalable solution for environmental monitoring, particularly in assessing the impact of urbanization and climate change on wetlands.

Future Work: Although the proposed model achieves promising results, several enhancements can be incorporated for improved accuracy and efficiency: Integration of Deep Learning: Advanced models like CNNs or U-Nets can be employed to enhance segmentation accuracy and automate classification.

Higher Resolution Satellite Imagery: Using high-resolution Sentinel-2 or Landsat-8 imagery can improve the precision of wetland area estimation.

Temporal Analysis with Climate Data: Incorporating rainfall, temperature, and land-use data can help in understanding the external factors influencing wetland changes.

Real-Time Monitoring System: Developing a real-time GIS-based monitoring dashboard can provide stakeholders with up-to-date insights on wetland conditions.

Hybrid Classification Models: Combining traditional ML techniques (SVM, PCA) with deep learning models can enhance classification accuracy and adaptability to diverse environments.

By implementing these advancements, the proposed methodology can evolve into a more comprehensive and automated tool for wetland conservation and environmental sustainability.

6. REFERENCES

[1] K. Luo and P. M. P. Mornya, "Fine Monitoring of Wetlands at Provincial Large-Scale Using Object-Based Technique and Medium-Resolution Image," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 12, no. 8, pp. 2878-2888, Aug. 2019, doi: 10.1109/JSTARS.2019.2918321.

[2] X. Li, X. Lyu, Y. Tong, S. Li, and D. Liu, "An Object-Based River Extraction Method via Optimized Transductive Support Vector Machine for Multi-Spectral Remote-Sensing Images," in IEEE Access, vol. 7, pp. 46165-46175, 2019, doi: 10.1109/ACCESS.2019.2908232.

[3] F. Isikdogan, A. C. Bovik, and P. Passalacqua, "Surface Water Mapping by Deep Learning," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 11, pp. 4909-4918, Nov. 2017, doi: 10.1109/JSTARS.2017.2735443.

[4] M. Amani et al., "Wetland Change Analysis in Alberta, Canada Using Four Decades of Landsat Imagery," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 10314-10335, 2021, doi: 10.1109/JSTARS.2021.3110460.

[5] A. Rankin and L. Matthies, "Daytime Water Detection Based on Color Variation," 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2010, pp. 215-221, doi: 10.1109/IROS.2010.5650402.

[6] A. Ajmal, C. Hollitt, M. Frean, and H. Al-Sahaf, "A Comparison of RGB and HSV Colour Spaces for Visual Attention Models," 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ), 2018, pp. 1-6, doi: 10.1109/IVCNZ.2018.8634752.

[7] Wang Pu, Kong Fanming, Ding Huiyan, Zhao Liuhui, and Nie Jianliang, "A Comparison Between Different Vegetation Water Indices in the Ability of Monitoring Water Status of Wheat in April," 2008 International

Workshop on Earth Observation and Remote Sensing Applications, 2008, pp. 1-6, doi: 10.1109/EORSA.2008.4620332.

[8] Y. Zhang, X. Li, and J. Wang, "Water Body Extraction from High Spatial Resolution Remote Sensing Images Using EU-Net," Scientific Reports, 2024. https://www.nature.com/articles/s41598-024-67113-7

[9] S. Kumar and A. Mishra, "Machine Learning-Based Classification of Small-Sized Wetlands Using Google Earth Engine," AIMS Geosciences, vol. 10, no. 2, 2024. https://www.aimspress.com/article/doi/10.3934/geosci.2024005

[10] X. Chen, L. Yang, and H. Xu, "Deep-Learning-Based Multispectral Satellite Image Segmentation for Water Body Detection," IEEE Transactions on Geoscience and Remote Sensing, vol. 62, no. 5, 2024. Available at: https://ieeexplore.ieee.org/document/9492784

[11] M. Patel, R. Singh, and P. Verma, "Wetland Change Mapping Using Machine Learning Algorithms and Multi-Source Remote Sensing Data," Sustainability, vol. 14, no. 1, 2024. Available at: https://www.mdpi.com/2071-1050/14/1/439