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A Survey on Satellite-Based Deep Learning Approach for Seagrass Mapping and Coastal Ecosystem Monitoring

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ABSTRACT :

Seagrass meadows are valuable coastal ecosystems since they offer habitat for marine organisms, contribute to coastal stability, and have the ability to store carbon. It is necessary to keep an eye on their condition and the way in which they are distributed over the area, but carrying out field surveys can involve a lot of time, cost, and repeated labour when covering large coastal regions. The present paper outlines a satellite-based deep learning system for the mapping of seagrass and for the monitoring of coastal ecosystems. The system makes use of multispectral satellite imagery, carries out image preprocessing, employs a structured image dataset, and applies a U-Net semantic segmentation model in order to tell the seagrass pixels apart from those which are not seagrass. Image enhancement is incorporated in order to improve the quality of the input, and a component for detecting temporal changes compares the maps from different dates in order to spot possible changes in the distribution of seagrass. A web-based dashboard is suggested for displaying the satellite images, the segmentation masks, the mapped areas and the change summaries. The model's performance is to be evaluated by comparing the predicted masks with the ground-truth masks using accuracy, precision, recall, Intersection over Union (IoU) and the Dice coefficient. The study sets out an end-to-end design for automated and repeatable seagrass mapping; however, the actual performance will depend on the quality of the imagery, the reference labels and the results of experimental validation.

Keywords: Coastal monitoring, deep learning, image segmentation, remote sensing, seagrass mapping, U-Net.

1. INTRODUCTION

Seagrass meadows are flowering plants which grow in shallow marine and coastal waters; they promote biodiversity by offering various marine organisms areas in which to feed, breed and find shelter. Moreover, seagrass can help to protect the coast and aid in the storage of carbon in marine sediments. It follows that changes in the size or state of these meadows have effects on the health of the ecosystem and on coastal management.

It is difficult to keep an eye on seagrass over large areas. Traditional field surveys might include the use of divers, boats, underwater observations and manual interpretation. Such activities can be costly, take a lot of time and are hard to carry out frequently along large or remote coastlines. Satellite remote sensing provides a method of observing coastal areas over a wide expanse and of returning to the same locations at different times. While multispectral satellite data can give information on surface and shallow-water features, the visibility of seagrass may be affected by water depth, turbidity, sun glint, the type of seabed and the image resolution.

Classification methods for images using conventional machine learning usually rely on spectrally selected bands, indices, and other features that have been manually designed. They can perform poorly when the input features fail to account for the complexity of coastal areas. Deep learning models are capable of learning useful representations from training images. Specifically, U-Net is a type of encoder–decoder convolutional neural network that is designed for pixel-level segmentation; its skip connections link together coarse contextual information and finer spatial details, which makes it appropriate for delineating habitat regions in images.

This project aims to develop a satellite-based seagrass mapping procedure using U-Net, including image preprocessing, semantic segmentation, temporal change detection, evaluation, and the creation of a web dashboard. While the project does not solely involve comparing machine learning and deep learning methods, its main emphasis is on the end-to-end mapping system and the visualization of its results.

2. PROBLEM STATEMENT AND OBJECTIVES

2.1 PROBLEM STATEMENT

Seagrass distribution maps may be unavailable, outdated, or difficult to update using field-based monitoring alone. Manually interpreting satellite images is also demanding, especially when seagrass must be separated from water, sand, algae, coral, or other benthic features. A practical system is needed to process suitable satellite imagery, generate consistent seagrass masks, compare results across dates, and present the outputs in an accessible format. The proposed solution must also account for the fact that model predictions are only as reliable as the imagery and reference masks used to train and evaluate the model.

2.2 OBJECTIVES

The project objectives are:

1. Collect suitable satellite images of coastal and shallow-water regions;
2. Preprocess imagery through resizing, normalization, noise handling, and relevant band selection or enhancement;
3. Organize images and ground-truth masks into training, validation, and testing sets;
4. Train a U-Net model for semantic segmentation of seagrass and non-seagrass regions;
5. Generate predicted masks and visual overlays;
6. Compare mapped outputs from different dates to identify potential changes;
7. Evaluate the segmentation results using standard metrics; and;
8. Present maps, statistics, and downloadable results through a web dashboard.

3. RELATED WORK

The project literature survey identifies several research directions relevant to remote sensing and coastal habitat analysis. Work listed by Mahmood et al. (2026) uses a U-Net-based benthic habitat mapping approach with WorldView-2/3 imagery. This direction is closely related to the proposed use of semantic segmentation, while also indicating that suitable training data and computational resources are important considerations. Kapoor et al. (2025) are listed as using a spatio-temporal transformer approach, illustrating the relevance of learning spatial patterns together with changes over time.

The survey also includes research that provides ecological and monitoring context. Lima et al. (2023) review seagrass ecosystem services, including their environmental value. Work by Vitousek et al. (2023) is associated with satellite remote sensing for broad-scale coastal monitoring. Jiang et al. (2023) are listed for bibliometric analysis of coastal research trends, while Lin et al. (2023) are associated with machine learning and time-series methods for water-quality prediction. These studies support the broader importance of coastal observation, but the supplied project notes do not establish that each one performs direct seagrass segmentation.

Earlier work in the survey includes ecological analysis by Tew et al. (2021), neural-network-based benthic recognition by Raphael et al. (2020), and the use of WorldView-2, RapidEye, and convolutional neural networks for seagrass mapping by Coffer et al. (2020). Traganos and Reinartz (2018) are listed in connection with Sentinel-2, semi-analytical inversion, and support vector machines for mapping Posidonia oceanica. Marcello et al. (2018) are associated with multispectral or hyperspectral imagery and support vector machines for seabed mapping.

The supplied survey further identifies Du et al. (2016) with Sentinel-2 and the Modified Normalized Difference Water Index (MNDWI) for water extraction, Hackeloeer et al. (2014) with georeferencing techniques, Lavery et al. (2013) with field-based seagrass carbon assessment, and Mason et al. (2011) with numerical ocean modelling. These approaches address different parts of the coastal monitoring problem: water identification, spatial alignment, ecological assessment, and ocean-condition modelling. They should not be treated as interchangeable seagrass segmentation methods.

Based on the survey, the proposed project combines image preprocessing, U-Net-based pixel classification, multi-date comparison, and a dashboard within one workflow. The supplied source provides author names, years, and brief approach summaries, but does not provide full publication titles, journals, volume numbers, page ranges, or DOIs. These bibliographic details must be checked against the original publications before submission.

4. EXISTING SYSTEM

The existing approach described in the project material uses conventional machine learning to classify seagrass from satellite imagery. Such a workflow commonly selects spectral bands, indices, or manually designed image features and then trains a classifier on those features. It can be useful when the features are informative and the training data represent the target environment.

However, the project notes identify several limitations. Manual feature selection requires domain knowledge and additional preparation. Spectrally similar underwater or coastal objects can be difficult to separate, and hand-engineered features may not fully describe complex spatial patterns. Results can also depend strongly on the quality of the training labels, the selected input features, and environmental conditions such as water clarity and depth. A classifier that performs well at one site may not generalize reliably to another site without suitable validation.

4.1 LIMITATIONS OF THE EXISTING APPROACH

The main limitations are the need for manual feature engineering, difficulty representing complex spatial context, possible confusion between seagrass and similar features, and sensitivity to training data. In addition, a classification output alone does not automatically provide a complete monitoring workflow. Multi-date comparison, quantitative evaluation, and clear visualization must be implemented as supporting components.

5. PROPOSED SYSTEM

The proposed system uses multispectral satellite imagery and a U-Net deep learning model to detect and map seagrass. It is designed as a sequence of connected modules: satellite data collection, image preprocessing, dataset management, model training and inference, segmentation output generation, visualization, evaluation, and a web dashboard. Temporal change detection compares mapped results from different image dates. This design aims to make the process more repeatable and easier to interpret than a workflow that relies only on manual image inspection.

5.1 SYSTEM WORKFLOW

First, suitable satellite scenes are collected for coastal and shallow-water regions. Sentinel-2 is identified in the project material as a possible data source; other suitable imagery may be considered if its spatial, spectral, and temporal properties meet the project requirements. Relevant bands, acquisition dates, and geographic metadata are retained. Images are then prepared for consistent model input through resizing or resampling, normalization, noise or artifact handling, and band selection or enhancement.

The prepared imagery is organized into training, validation, and testing subsets. Each image used for supervised learning requires a corresponding ground-truth mask that labels seagrass pixels and non-seagrass pixels. The U-Net model learns from image–mask pairs. During inference, a new image is passed through the trained network to generate a predicted segmentation mask. The mask can be overlaid on the original image to make the predicted distribution easier to inspect.

For temporal monitoring, predictions from different dates are aligned to a common spatial reference and compared. A difference map can

indicate locations where the predicted seagrass class has appeared, disappeared, or remained stable. These differences should be interpreted as potential changes, not definitive ecological change, until differences in tide, water clarity, season, sensor properties, and image alignment have been considered. The dashboard presents maps, area summaries, and evaluation results to users.

5.2 U-NET SEMANTIC SEGMENTATION

U-Net consists of an encoder path and a decoder path. The encoder progressively extracts features and captures contextual information. The decoder upsamples feature maps to recover spatial detail and produce a pixel-level output. Skip connections transfer features from encoder stages to corresponding decoder stages, helping preserve boundaries and local information. In this project, the final output is intended to label each pixel as seagrass or non-seagrass.

Training requires correctly paired input imagery and reference masks. The training set is used to optimize model parameters, while the validation set helps monitor learning and tune choices such as the number of epochs, learning rate, or decision threshold. The test set should remain separate until final evaluation. Spatially neighboring image patches should be allocated carefully to reduce the risk of overly optimistic results caused by near-duplicate scenes appearing in both training and testing data.

5.3 TEMPORAL CHANGE DETECTION

Temporal change detection compares seagrass maps produced for two or more dates. After aligning the images and their predicted masks, each pixel can be categorized as persistent seagrass, possible gain, possible loss, or non-seagrass at both dates. Summaries of these categories can help users investigate where the mapped extent has changed. Reliable change analysis depends on comparable imagery, consistent preprocessing, accurate georeferencing, and stable model behavior across dates.

5.4 WEB DASHBOARD

The dashboard is planned as the user-facing component of the system. It will allow a user to select or upload an eligible satellite image, view the source image and predicted mask, inspect an overlay, and review mapped-area statistics. Where multiple dates are available, the interface will display the corresponding maps and change summaries. The interface may also support downloading maps and reports. The dashboard is intended to improve access to the results; it does not replace expert review of uncertain predictions.

6. SYSTEM ARCHITECTURE AND MODULES

The architecture follows a modular pipeline so that each stage can be developed and tested independently. The input to the workflow is satellite imagery with relevant metadata. The output is a set of seagrass segmentation maps, evaluation measures, and visual summaries.

Table 1. Proposed System Modules

Module	Main Function	Output
1. Satellite data collection	Collect coastal satellite scenes, bands, dates, and metadata.	Raw imagery
2. Image preprocessing	Resize/resample, normalize, handle artifacts, and enhance relevant bands.	Prepared images
3. Dataset management	Organize training, validation, and testing images with ground-truth masks.	Image–mask datasets
4. Deep learning model	Train and apply the U-Net segmentation network.	Model and predictions
5. Detection and segmentation	Classify pixels and generate seagrass masks.	Predicted masks
6. Visualization	Overlay masks and display mapped distribution.	Interpretable maps
7. Evaluation	Compare predictions with reference masks using metrics.	Evaluation scores
8. Web dashboard	Present images, statistics, date comparisons, and reports.	User-facing results

7. EVALUATION METHODOLOGY

The system will be evaluated by comparing the U-Net predicted mask against a ground-truth mask created or obtained for the same geographic area. Ground-truth labels should be checked for positional alignment and consistent class definitions. The test set should contain images that were not used during training or model tuning. Metrics will be reported on the held-out test set and, where possible, across more than one scene or coastal condition.

7.1 PERFORMANCE METRICS

Accuracy measures the proportion of correctly classified pixels among all evaluated pixels. Precision measures how many pixels predicted as seagrass are actually seagrass, while recall measures how many reference seagrass pixels are detected. Intersection over Union (IoU) measures the overlap between the predicted and reference seagrass regions relative to their union. The Dice coefficient measures overlap using twice the intersection divided by the total number of predicted and reference positive pixels. Precision, recall, IoU, and Dice are particularly useful because a large non-seagrass background can make accuracy appear high even when seagrass detection is weak.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$
$$Precision = TP / (TP + FP);$$
$$Recall = TP / (TP + FN)$$
$$IoU = TP / (TP + FP + FN);$$
$$Dice = 2TP / (2TP + FP + FN)$$

Here, TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively, with seagrass treated as the positive class. Metric values should be reported only after running experiments; this paper does not claim achieved accuracy or other numerical performance.

7.2 VALIDATION CONSIDERATIONS

The quality of the final map depends on the quality of reference masks, the resolution of the satellite imagery, water conditions, and the distribution of training examples. Evaluation should inspect both numerical metrics and visual examples, including difficult scenes. The model should be tested on representative conditions and its limitations documented. If the training labels are incomplete or inconsistent, measured performance may not reflect true environmental accuracy.

8. EXPECTED OUTCOMES AND APPLICATIONS

The expected outcome is a working prototype that accepts suitable satellite imagery and produces a map of predicted seagrass distribution. The system is also expected to provide overlays that make model outputs easier to review, metric-based evaluation against reference masks, and date-to-date comparison maps where suitable imagery is available. The dashboard will bring these outputs together in a single interface.

Potential applications include supporting coastal habitat inventories, helping researchers identify areas for further field inspection, and providing a repeatable starting point for monitoring seagrass extent. Mapped changes may help prioritize locations for conservation assessment. The system is intended as a decision-support tool rather than a replacement for field surveys or ecological expertise. Any reported change should be interpreted in the context of image quality and local environmental conditions.

9. LIMITATIONS AND FUTURE ENHANCEMENT

Satellite-based detection is challenging in turbid water, at greater water depths, under strong sun glint, or when seagrass has a similar spectral appearance to other benthic features. The available spatial resolution may be insufficient for small or fragmented meadows. Training and evaluation also require trustworthy reference masks, which may be costly or difficult to obtain. A model trained in one region may not transfer directly to another region because water properties, species, substrate, and sensor conditions can differ.

Future work can expand the training dataset across seasons and locations, improve reference-label quality, and compare alternative loss functions or model configurations. Additional sensor sources and environmental covariates may be investigated if they are available and appropriate. Change detection can be strengthened by standardizing acquisition conditions and quantifying uncertainty. Dashboard enhancements may include map filters, area trends, export options, and a record of image dates and preprocessing settings to support reproducibility.

10. CONCLUSION

This paper proposes a satellite-based deep learning system for seagrass mapping and coastal ecosystem monitoring. The design combines satellite data collection, image preprocessing, dataset management, U-Net semantic segmentation, temporal change detection, evaluation, and a web dashboard. In contrast to workflows that depend mainly on manually selected features, the proposed model learns image representations from labeled examples and generates pixel-level seagrass masks. The planned evaluation uses accuracy, precision, recall, IoU, and Dice coefficient, while the dashboard supports visual interpretation of mapped outputs. The system offers a structured and potentially scalable approach to coastal habitat monitoring, but its effectiveness must be demonstrated through experiments using suitable imagery and reliable ground-truth labels. Future implementation and validation will determine its practical accuracy and usefulness.

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