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Detection, Monitoring, and Mapping of Invasive Species

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Abstract
Invasive aquatic species pose serious ecological and economic threats by disrupting native biodiversity, degrading water quality, and altering ecosystem dynamics. Early detection is essential to prevent their spread; however, conventional field-based monitoring methods are time consuming, expensive, and spatially limited. This study proposes a satellite-based framework that integrates chlorophyll concentration analysis, geospatial mapping, and machine learning for the detection and monitoring of invasive species in aquatic environments. Chlorophyll data extracted from satellite imagery are preprocessed, georeferenced, and used as input features along with spatial coordinates to train a Support Vector Machine (SVM) classifier. The model achieved a classification accuracy of 99.982%, indicating high separability between invasive and non-invasive regions based on chlorophyll gradients. Spatial visualizations such as heat maps, scatter plots, and histograms revealed clear clustering patterns and invasion hotspots. The findings indicate that chlorophyll concentration serves as a dependable indicator for identifying the presence of invasive species. They further show that combining remote sensing techniques with artificial intelligence enables a monitoring framework that is both scalable and economically efficient. This integrated approach holds significant promise for real-time ecosystem monitoring and contributes to better-informed decision-making in environmental conservation and sustainable resource management.

Keywords: Invasive aquatic species, chlorophyll concentration, remote sensing, machine learning, Support Vector Machine (SVM), geospatial analysis, satellite imagery, environmental monitoring, ecosystem management.

1. Introduction

Invasive species, documented since the mid-nineteenth century, pose a significant threat to aquatic ecosystems worldwide. Once introduced, they often spread rapidly, forming dense surface growth that restricts light penetration and reduces dissolved oxygen, thereby disrupting native species and, in severe cases, causing localized ecological loss. These invasions also impose notable economic costs through their impact on fisheries, water quality, and recreational activities. While surface-dwelling invasive plants are suitable for remote observation, current monitoring approaches are generally labor-intensive, costly, and limited in spatial coverage. Remote sensing methods further face challenges in heterogeneous aquatic environments due to spectral similarities between invasive and native vegetation and limitations in image resolution. These factors highlight the need for automated and scalable monitoring solutions. Recent studies have integrated remote sensing data with artificial intelligence to improve invasive species detection by capturing subtle spatial and spectral variations. However, the use of chlorophyll concentration as an early indicator of aquatic invasions remains relatively underexplored. This study addresses this gap by analyzing chlorophyll data from the Bhuvan portal to support early detection and ongoing monitoring of invasive aquatic species, enabling timely assessment of water health through data-driven analysis. The rest of this paper is organized as follows. Section II reviews related work and discusses the limitations of existing approaches. Section III describes the methodology, including satellite data extraction and the training of the Support Vector Machine model. Section IV presents and analyzes the results, with emphasis on chlorophyll level visualization for invasive species identification. Finally, Section V concludes the study and outlines potential improvements and remaining challenges.

2. RELATED WORK

Studies focusing on hyperspectral imaging and AI-based approaches have shown that invasive species can be effectively tracked by capturing their distinct spectral signatures, improving species discrimination. Deep learning frameworks have been applied to automate identification and prediction, while hyperspectral remote sensing has enabled sub-pixel mapping of invasive vegetation. The reliability of invasive species classification was further strengthened through iterative accuracy assessment methods. Collectively, these studies demonstrate that combining spectral data with machine learning provides an effective strategy for invasive species detection [1–3].

Multispectral systems mounted on UAVs have been employed to detect invasive aquatic plants and generate detailed vegetation maps. To improve accuracy in complex environments, several studies addressed the challenge of distinguishing invasive species from morphologically similar native plants. Convolutional neural networks have also been successfully applied to identify invasive plants across diverse landscapes using satellite datasets such as WorldView-2 and PlanetScope. These findings highlight the potential of deep learning to scale invasive species monitoring through both UAV and satellite platforms [4–6].

Deep learning applied to UAV imagery has enhanced the identification of invasive species in aquatic ecosystems. In forest areas, hyperspectral UAV data effectively distinguished invasive plants from native vegetation across diverse terrains. Seasonal dynamics of grassland invasions were captured using machine learning in combination with multi-temporal Sentinel-2 imagery. Regional studies using medium-resolution satellite data also identified invasive pine populations, providing valuable insights for large-scale monitoring and management. Together, these studies underscore the benefits of integrating temporal, spectral, and UAV-based analyses for effective ecosystem management [7–10].

AI-enabled multispectral UAV imagery has improved invasive species detection in challenging environments. To monitor plants hidden beneath canopy layers, phenological indices were integrated with machine learning techniques. Comprehensive evaluations of recent advances in remote sensing and artificial intelligence highlight opportunities for further research. Additionally, remote sensing combined with deep learning has been applied in urban aquatic ecosystems to track the spatial and temporal growth of invasive plants. Additionally, in alpine grassland ecosystems, UAV hyperspectral imagery using sophisticated deep learning models produced accuracies of over 95%. These developments show that tracking systems for real time environmental control are highly accurate, scalable, and economical [11–15].

While Landsat, Sentinel, and hyperspectral sensors have been widely applied for invasive species detection, most studies rely on spectral classification and deep learning methods that are computationally intensive and often require costly high-resolution data. Medium-resolution sensors, though more accessible, are limited in species-level discrimination, particularly in aquatic environments where spectral overlap between invasive and native vegetation is common. Furthermore, many studies focus on image-based classification without explicitly incorporating biochemical indicators such as chlorophyll concentration. Consequently, there is a need for cost-effective, indicator-driven frameworks that use chlorophyll for scalable, real-time detection of invasive aquatic species. The proposed methodology addresses this gap by combining chlorophyll-based analysis with machine learning and geospatial mapping using freely available satellite products, enabling early detection with lower computational demands and broader operational feasibility.

Among satellite platforms, Landsat provides long-term data continuity and wide spatial coverage but is limited by moderate spatial resolution and revisit intervals. Sentinel-2 offers higher spectral resolution and more frequent revisits, making it suitable for aquatic vegetation monitoring. Hyperspectral sensors enable superior species differentiation through hundreds of narrow spectral bands, but their high cost, large data volumes, and processing complexity limit scalability. This study prioritizes accessible chlorophyll products from publicly available satellite platforms to ensure cost-effective deployment.

3. METHODOLOY

This research outlines a practical and structured method for tracking invasive species in water bodies by using chlorophyll concentration data Figure.1. This method uses satellite imagery, image processing, and mapping techniques to monitor the spread of invasive species over time. It aims to aid in the development of a dependable system for environmental monitoring. A collection of Satellite images showing chlorophyll concentration in water bodies is performed. These captured images are preprocessed, reduced to the dimensions (819×707 pixels),and also verified for uniformity initially. Each pixel is then mapped to corresponding coordinates by scaling the image based on known geographic boundaries.

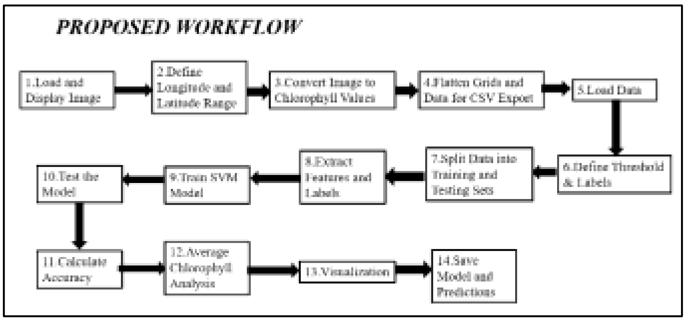

Figure. 1. Step-by-step process for tracking invasive species.

Figure. 1. Step-by-step process for tracking invasive species. A mesh grid function creates a coordinate grid function, which helps to map geographic coordinates—latitude and longitude—to every pixel. Chlorophyll concentration is determined by analyzing the RGB color values of the satellite images. These values are then matched to standard chlorophyll concentration levels, typically ranging from 0.2 to 4.8 mg/m³. The extracted data, including latitude, longitude, and chlorophyll values, is organized into one-dimensional lists for further processing, which involves data cleaning and formatting. The resulting dataset, containing latitude, longitude, and chlorophyll concentration, serves as input for training a machine learning model. For classification, a threshold is applied—for example, points with chlorophyll levels above 3 mg/m³ are labeled as invasive (1), while those below the threshold are labeled as non-invasive (0). This labeling enables the model to differentiate between areas likely affected by invasive species and unaffected regions.

$$label = \begin{cases} 1, C_i \geq Threshold \\ 0, otherwise \end{cases} \quad (1)$$

To compare the model performance, the data is divided into training (70%) and test (30%) sets via MATLAB's cv partition function. Feature extraction is done where chlorophyll concentration, latitude, and longitude are taken as input parameters to train the machine learning model. The Support Vector Machine (SVM) classifier with Radial Basis Function (RBF) kernel is employed due to its efficacy in high-dimensional classification problems. The SVM model is then trained on the extracted features and learns a decision boundary to predict invasive and non-invasive areas. The model is tested against the test set during training to quantify its predictive accuracy. Prediction model outputs are being compared against the labels and the calculated accuracy as follows:

$$Accuracy = \frac{\sum_{i=1}^{n} I(\hat{y_i} = y_i)}{n} \quad (2)$$

where y_i is the predicted label, and n is the number of test instances. The more detailed analysis is employed to analyze the distribution of chlorophyll concentration between non-invasive and invasive species. Then, the average concentration of chlorophyll for both of them is calculated using the following formula:

$$\overline{C} = \frac{1}{N} \sum_{i=1}^{N} C_i \quad (3)$$

where C_i is the concentration of chlorophyll for a particular data point, and N is the number of data points in a category. This approach enables comparison of chlorophyll levels between native and invasive plants. Model performance is evaluated using histograms that display the frequency of chlorophyll values for both plant types. Scatter plots overlaid on maps compare observed data with model predictions, providing insight into accuracy, while line graphs illustrate chlorophyll variation across different longitudes to identify spatial patterns.

The study area is divided into smaller blocks based on latitude and longitude to enhance spatial analysis. Invasive data points within each block are quantified and visualized on heat maps, highlighting regions with higher concentrations of invasive species. These maps facilitate tracking of affected areas and monitoring changes over time. The data was trained and tested using a Support Vector Machine (SVM) model. Overall, this method offers a straightforward and effective framework for monitoring invasive species using chlorophyll data. By integrating image processing, machine learning, and geospatial mapping, it supports more efficient and actionable environmental monitoring.

4. RESULTS AND DISCUSSION

phytoplankton and aquatic plant biomass, with elevated levels often linked to the presence of invasive aquatic species. Many invasive species grow rapidly and form dense surface mats, which accelerate nutrient uptake and alter water chemistry, frequently leading to abnormal algal blooms. This increased biological activity results in higher chlorophyll concentrations in affected areas compared to ecosystems dominated by native vegetation. Invasive plants can also trap sediments and nutrients, creating localized eutrophic conditions that further enhance chlorophyll production. As a result, persistently elevated chlorophyll levels serve as an indirect indicator of invasive species proliferation and can be detected via satellite imagery as zones of heightened biological productivity.

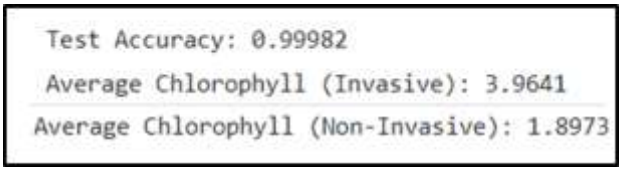

Figure 2: Model Performance Results

Figure 2 shows how well the machine learning model performed in identifying and tracking invasive species. The model achieved a high test accuracy of 0.99982, demonstrating its strong predictive performance. On average, invasive species exhibited higher chlorophyll concentrations (3.9641 mg/m³) compared to non-invasive species (1.8973 mg/m³), indicating that chlorophyll content is a valuable feature for distinguishing between invasive and native plants.

Compared to Random Forests and Convolutional Neural Networks (CNNs), the Support Vector Machine (SVM) used in this study is computationally efficient and well-suited for small, feature-based datasets such as chlorophyll levels and spatial coordinates. While Random Forests handle non linear relationships effectively, they are less capable of capturing spatial patterns. CNNs can learn complex spatial features directly from images but require large labeled datasets and higher computational resources. In this context, SVM offers a practical balance of accuracy, simplicity, and interpretability, making it suitable for scalable implementation.

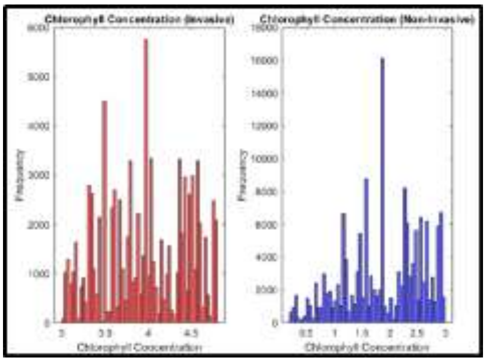

Figure. 3: Chlorophyll Concentration Distribution in Invasive and Non-Invasive Areas

Figure. 3 compares chlorophyll concentration in invasive (left) and non-invasive (right) regions using histograms. Invasive areas depict the chlorophyll levels between 3.0 and 4.5 mg/m³, with a clear peak from 3.5 to 4.0 mg/m³. Figure 3 indicates that higher chlorophyll content is common in areas affected by invasive species. In contrast, non-invasive regions range between 0.5 and 3.0 mg/m³, with a peak around 2.0 mg/m³, which is considered typical conditions for healthy, native vegetation. The more frequent occurrence of lower chlorophyll values in non-invasive areas highlights the variations. These opposite trends support the idea that high chlorophyll levels are linked to the spread of invasive species. Chlorophyll concentration is a useful feature for setting classification thresholds before the application of machine learning algorithms.

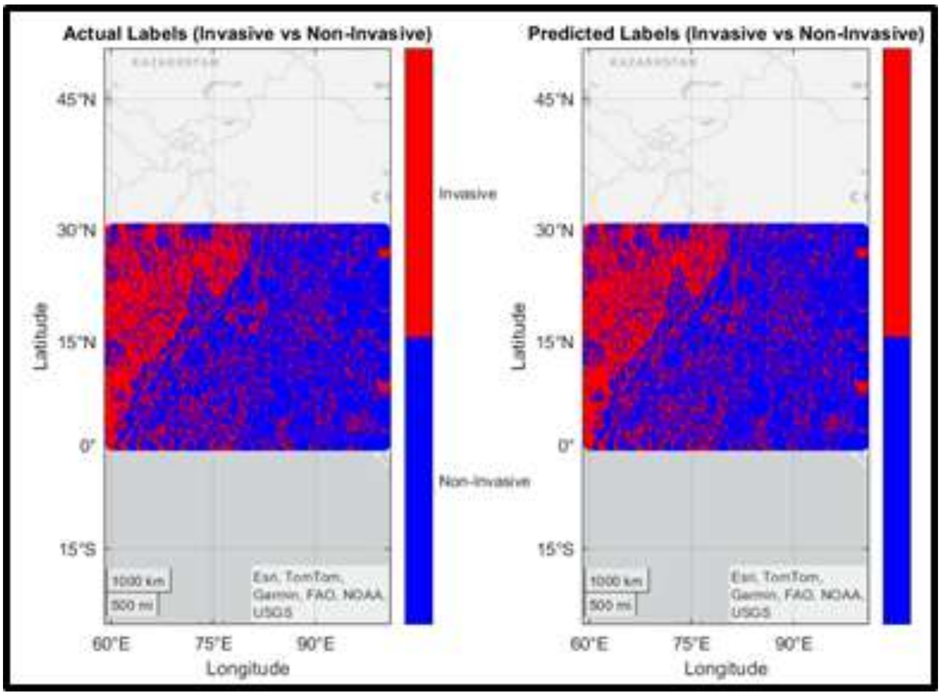

Figure 4: Actual vs Predicted Labels for Invasive Species Distribution

Figure 4 compares the actual and predicted labels for invasive species distribution. In the images, invasive regions are marked in red and non-invasive ones in blue. While minor differences exist between actual and predicted results, the overall spatial patterns are consistent. These mismatches are likely due to overlapping chlorophyll values near boundary regions, causing occasional misclassifications. Accuracy may be improved by refining model parameters or including additional variables such as seasonal or environmental factors.

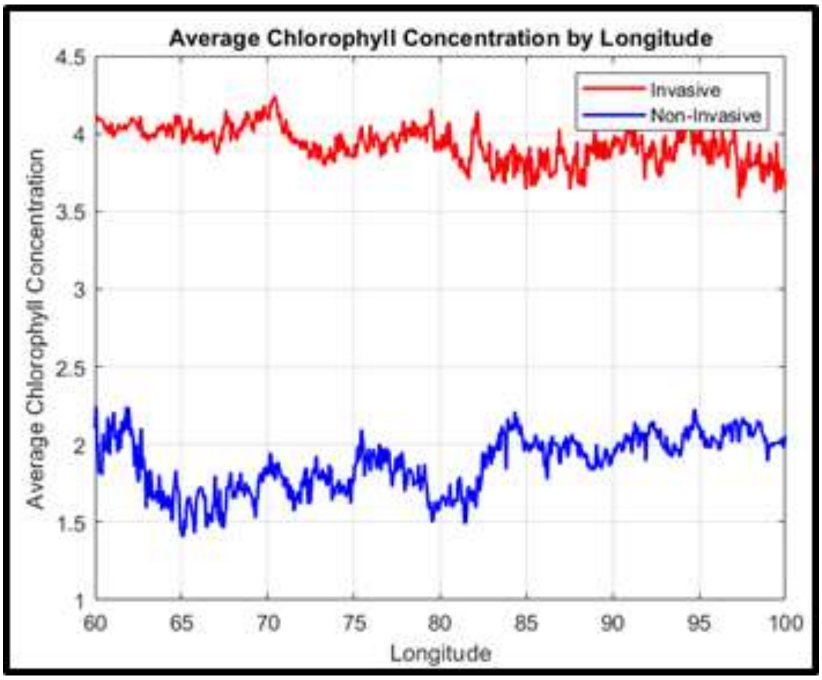

Figure. 5: Mean chlorophyll levels in invasive and non-invasive zones plotted by longitude.

Figure 5 shows that the red line representing invasive regions consistently has higher average chlorophyll concentrations compared to the blue line for non-invasive areas. This suggests a link between invasive species presence and increased chlorophyll levels, which could be due to factors like more frequent algal blooms or changes in water quality. Both invasive and non-invasive regions show variations in chlorophyll along the longitude, influenced by factors such as seasonal shifts, water currents, nutrient levels, and local environmental conditions.

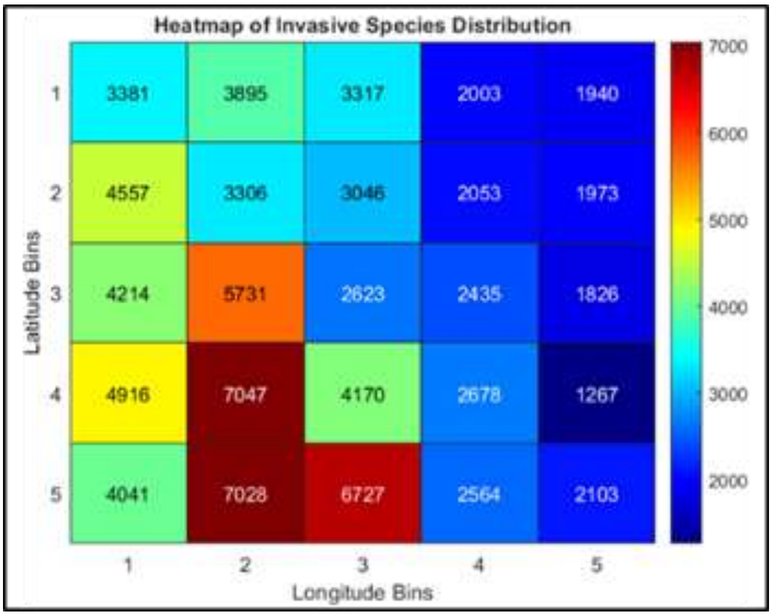

Figure 6: Heatmap Distribution of Invasive Species

Figure 6 shows a heat map displaying invasive species distribution across latitude and longitude bins. Each cell on the map represents a specific geographic area, with color intensity reflecting the number of invasive species present. Darker, more saturated colors indicate hotspots where invasive species are heavily concentrated, suggesting regions where targeted control and management efforts are needed. Lighter areas correspond to fewer or no invasive species. These heat maps reveal spatial patterns, providing a valuable tool for planning effective monitoring and management strategies. The software used in this study includes:

- MATLAB (R2022a) with Image Processing and Statistics & Machine Learning Toolboxes
- QGIS 3.22 for GIS analysis
- Bhuvan Portal for satellite chlorophyll data retrieval

The findings demonstrate a clear relationship between elevated chlorophyll levels and the presence of invasive aquatic species. Rapidly growing invasive plants form dense surface layers and alter water conditions by trapping nutrients and sediments, often resulting in increased algal activity and higher chlorophyll concentrations. These changes make affected areas distinguishable in satellite imagery. The model achieved a high classification accuracy of 99.982%, indicating excellent reliability in differentiating invasive and non-invasive regions using chlorophyll concentration and spatial data. However, such high accuracy warrants caution, as it may indicate potential data imbalance or over fitting. Further testing with independent datasets and cross-validation would strengthen confidence in the model’s performance. Overall, the results confirm that chlorophyll concentration is a reliable indicator of invasion and that the proposed approach is effective for large-scale monitoring of aquatic ecosystems.

5. Conclusion

The findings of this study indicate that chlorophyll concentration obtained from satellite imagery can be effectively used to detect invasive aquatic species when combined with geospatial analysis and an SVM-based classification approach. The results consistently showed that invasive regions exhibit higher chlorophyll levels and clear spatial clustering compared to areas dominated by native vegetation, supporting the use of chlorophyll as a distinguishing indicator. Visual outputs such as heat maps, scatter plots, and basic statistical summaries helped in clearly identifying invasion hotspots and made the results more intuitive for practical ecosystem management. Although the framework offers a scalable and cost-efficient alternative to extensive field surveys, its accuracy may be influenced by atmospheric effects, seasonal variability, and the limited inclusion of environmental factors. Future studies could strengthen this approach by incorporating additional parameters such as water temperature, turbidity, nutrient concentration, and dissolved oxygen, applying multi-temporal analysis to capture seasonal dynamics, integrating higher-resolution hyperspectral or UAV data, and exploring deep learning methods like CNNs along with automated alert systems to enable more reliable and continuous monitoring of invasive aquatic species.

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