17(3) 391-402, Autumn 2025

Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: http://www.aejournal.ir

Review Paper

Harnessing Artificial Intelligence and Remote Sensing for Large-Scale Marine Habitat Monitoring and Conservation

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Key Words
Remote sensing,
Artificial Intelligence,
Marine habitat monitoring,
Conservation,
Habitat mapping,
Satellite imagery.

Abstract
Human activities and climate change are posing a growing threat to marine eco systems, which makes it necessary to have an effective and big scale monitoring solution. Field-based surveys particularly traditional ones are useful, but may be restricted by cost, time and space. This paper suggests a new method to address these restrictions using remote sensing tools and artificial intelligence (AI) to scale-up monitoring of marine ecosystems. With satellite, aerial and drone photography, machine learning (ML) and deep learning algorithms, we categorize marine habitat types, identify environmental alterations and the threats to conservation. The multispectral and hyperspectral imagery data collected using remote sensing can cover coastal and marine ecosystems in a comprehensive way, whereas AI-based methods enable automated data analysis, which can be used to map the habitat efficiently and detect changes in time. Field data, such as in-situ survey and ground-truting of the habitat maps, are used to validate the derived habitat maps and to identify the environmental change. The findings demonstrate good classification capabilities, whereby AI-based models correctly classify habitat types and detect avoidable environmental variations, including coral reef degradation and habitat loss. The results demonstrate the possibilities of this combined method in the case of large-scale marine habitat monitoring, which is a cost-effective and scalable instrument of conservation management. This will assist in the proactive conservation policy, improve policy-making, and present practical knowledge on sustainable marine resource management.

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Received: 06 June 2025; Revised: 16 July 2025; Accepted: 18 August 2025; Published: 30 October 2025
(DOI): 10.70102/AEJ.2025.17.3.32

Introduction

Both climate change and anthropogenic activities are threatening marine ecosystems in a manner that has never been witnessed before. Since such coastal habitats as coral reefs, mangroves, and seagrass beds are vital to the biodiversity and general health of the planet. These habitats are however, being affected by pollution, overfishing, destruction of their habitats and the impact of climate change such as the increase in sea temperature and acidification of the oceans. Due to the growing demand in the world on the resources that are located in the seas, the necessity to design, develop, and provide real-time tracking of the marine habitats has never been as acute (Mastrantonis et al., 2024). Conventional techniques of monitoring including field surveys, manual mapping though useful, do not have the required coverage and frequency of time to locate and act on these dynamic threats. The conventional field-based monitoring methods are tedious, expensive, and time-consuming, which greatly restricts the scope of data collection in terms of space and time. Such techniques may be very intensive in terms of human resources and only a small area of the marine environments can be covered using these methods. Also, there is the problem of being unable to detect both large-scale spatial patterns, or even capture any clue to a subtle environmental variation through point-based information. Consequently, it is highly in demand to have more effective and economical ways that can be used to track large and diverse marine ecosystems in the scale and the frequency that they require. The latest developments in remote sensing and artificial intelligence (AI) have demonstrated a lot of potential to surmount these issues. Aerial, drone, and satellite-based imaging technologies are cost-efficient and non-invasive methods of collecting massive amounts of data in large marine regions through remote sensing technologies. In combination with AI and machine learning (ML) algorithms, remote sensing data can be automatically processed and analyzed to classify the types of habitats, define environmental changes, and identify threats with an impressive level of accuracy. The investigations conducted in the past have managed to implement AI and remote sensing in other environmental monitoring tasks, including but not limited to deforestation, water quality monitoring, and land cover classification, and proved the ability of these technologies to conduct ecological monitoring on a large scale. Nevertheless, remote sensing and AI are underdeveloped with regards to their use in monitoring marine habitats, though the related direction has been considered in other fields of environmental science (Mahdavi et al., 2024). The literature is missing a comprehensive, long-term, big-scale monitoring framework with the majority of existing studies being confined to a little geographic region or particular habitat type. Moreover, not many studies have combined these technologies in order to accomplish the task of simultaneously mapping the habitat, detecting changes, and estimating the threats on a global or regional basis. It is evident that the marine habitats require strong methodologies that are able to track the marine ecosystem over a long duration and an extensive area (Evagorou et al., 2025). In this research, the researcher will use remote sensing data to map and monitor marine habitats on a big scale with the help of AI-based workflow. To identify the type of habitats and track the change in habitats over time and identify the regions in danger, we will use satellite and drone shots with advanced machine learning to categorize the types of the habitats. It also determines the correctness of the AI models by ground-truth information on in-situ observations. With such a combined solution, we believe that it can be used to monitor marine habitats at large scale providing a scalable and useful tool in conservation management. Results of the current study will be critical information to the policy makers, researchers, and conservation practitioners in the fight to conserve the marine ecosystems.

The key research questions are:

- How precise are AI-based models of marine habitats and marine habitat change detection with remote sensing data?
- Is it possible that AI and remote sensing can deliver scalable and cost-effective instruments to surveil expansive marine regions over periods of time?
- What can we learn about conservation through these large-scale monitoring activities that can help us direct our policy and management decisions?

Materials and Methods

The research took place in the Gulf of California/ Sea of Cortez, which is an ecologically and biologically rich marine area, between the Baja peninsula and main land Mexico. The diverse variety of marine life found in this area is comprised of coral reefs, beds of seagrass, mangrove forest, and open water habitats and as such, the area is extremely important in biodiversity conservation. These ecosystems offer some important services like protecting the coast, providing marine species with a habitat, and sequestration of carbon. Human actions like over fishing, coastal development and pollution of the Gulf of California have severely affected the gulf including the combined risk of the climate change by lessening the temperature of the sea and acidification of the ocean. The range of the study was evenly spread between the north area along the U.S. border up to the south of Baja California Sur covering a massive range of habitat forms and coastal setting. This region has been chosen because of the environmental importance and also because it has satellite imagery and field data to monitor it thoroughly as Figure 1 presents.

In the remote sensing data, we were able to use Sentinel-2 satellite mission (high-resolution imagery) with a resolution of 10-20 meters and a revisit period of 5 days. Besides Sentinel-2, there was also comparison with Landsat 8 imagery which had a 30-meter resolution and a 16-day revisit cycle. These satellite data had a temporal resolution between 2015 and 2020 that offered cross-sectional and temporal insights on the marine environment in the area. Moreover, unmanned aerial vehicles (UAV) aerial images were used with the resolution of 510 cm to ensure that the outcomes of remote sensing classification were valid and provided small point details of the habitat, especially coral reefs and mangrove forests. Additional data consisted of bathymetric data, which was gathered at regional scales, including NOAA and needed to examine depth and seafloor characteristics that are essential to mapping underwater habitats. Field surveys to ground-truth the classification results were in-situ data, both transects with snorkelers and divers to make sure the results were accurate. As well, the environmental parameters, including water temperature, salinity, and turbidity were also measured in the field to examine how they affect habitat distribution and health.

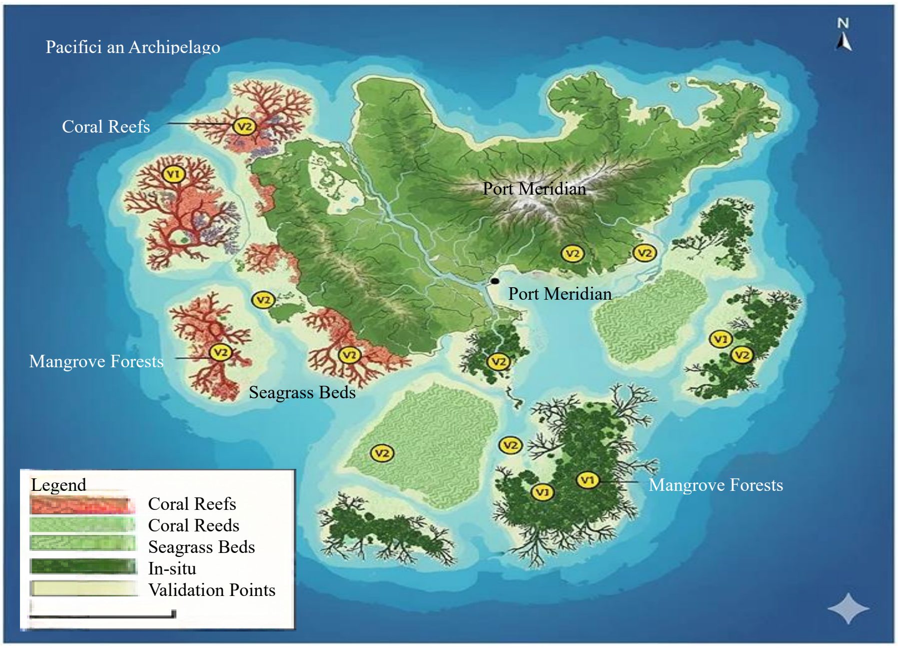

Figure 1: Overview of Coastal Marine Habitats and Field Validation Sites

Several major steps were followed in the preprocessing of remote sensing data. The Sentinel-2 imagery was corrected by using the SEN2COR algorithm which helped to remove atmospheric interference and water column corrections which helped account the effects of light scattering and light absorption in submerged habitats such as coral reefs and seagrass (Nawaz et al., 2025). Satellite images were interlocked to generate the complete coverage over the study area and all the images were georeferenced to WGS84 coordinate system to allow the spatial consistency. The images were then segmented into homogeneous areas through object-based image analysis (OBIA) and helped in the correct classification of marine habitats using spectral similarities (Moustafa et al., 2025). Machine learning models applied in this paper consisted of supervised algorithms (Random Forest and Support Vector Machine), and deep-learning algorithms (Convolutional Neural Networks) that were used in high-resolution drone imagery. Training of these algorithms was done with labeled ground-truth data, in which field observations were used to construct training data to classify coral reefs, seagrass beds, mangroves and open water. The models were optimized by cross-validation and they were tested in terms of overall accuracy, precision, recall, F1 score, and confusion matrices.

The analysis of change detection was done to determine the changes in the distribution of habitats over time, especially the degradation of the coral reef and the loss of seagrass during the period of study 2015-2020 (Trudeau et al., 2025; Chen et al., 2025). The comparison between multi-temporal satellite images was conducted to detect the regions of inception of significant change and the quantitative analysis was used to demonstrate the habitat losses or gains expressed as percentage and area (km 2). Spatial clustering was also used to identify hotspots of habitat degradation, which indicated high levels of anthropogenic activity, eg. coastal development areas. Results of the classification were validated by reference to ground-truth data provided by the field surveys and UAV imagery and Kappa coefficient is 0.82, which implies that there is a high degree of resemblance between the predicted classifications and classifications in the field. Some misclassification was observed, however, particularly in transition zones between habitat types, e.g., the boundary between mangrove and seagrass areas where spectral signatures were similar. The performance of the machine learning models was measured by the Kappa coefficient, McNemar's test for temporal changes, and a significance threshold of 0.05. The data processing and machine learning model implementation were carried out in Python that utilizes libraries like scikit-learn and TensorFlow, whereas GIS tools like ArcGIS and ENVI were used for spatial analysis and map creation.

Results

The AI-based classification system was able to classify and map four major marine habitats in the Gulf of California: coral reefs, seagrass beds, mangroves and open water. The area data for these various ecosystem types is denoted in Table 1 and is summarized as follows. Over 25,000 km² of the 150,000 km² of open water is habitat to seagrass beds and mangroves. The seagrass beds and mangroves are also the most extensive ecosystems after the coral reefs which themselves are 25,000 km² in area. The distribution of the habitats is described and visualized in Figure 2. The habitats are differentiated and distinguished.

Table 1: Area of Habitat Types (in km²)

Habitat Type	**Area (km²)**
Coral Reefs	25,000
Seagrass Beds	15,000
Mangroves	8,000
Open Water	150,000

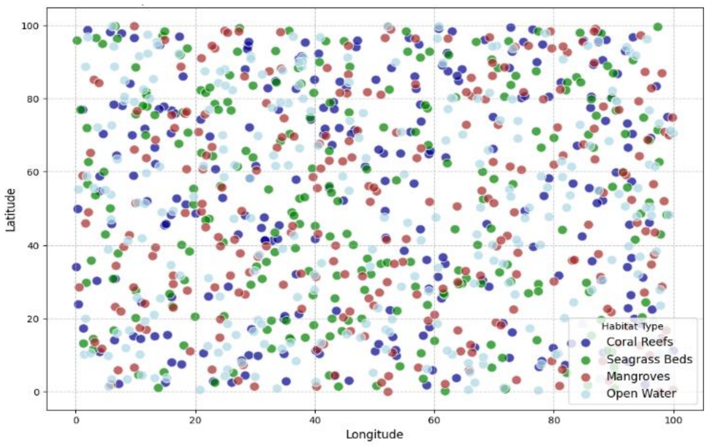

Figure 2: Spatial Distribution of Marine Habitats in the Gulf of California

The AI model's overall accuracy, precision, recall, and F1 score were measured, and the results are summarized in Table 2. In the results, the model appears to have produced an overall accuracy of 90%, and in this regard, the results produced high precision and recall for the coral reefs, seagrasses, and mangroves. Finally, the performance of the model predictions in the classification tasks are shown in the confusion matrix in Figure 3, which shows which classes were incorrectly predicted.

Table 2: AI Model Performance Metrics

Metric	Coral Reefs	Seagrass Beds	Mangroves	Overall Accuracy
Accuracy (%)	92	88	91	90
Precision (%)	90	85	92	
Recall (%)	93	90	88	
F1 Score	0.91	0.87	0.89	

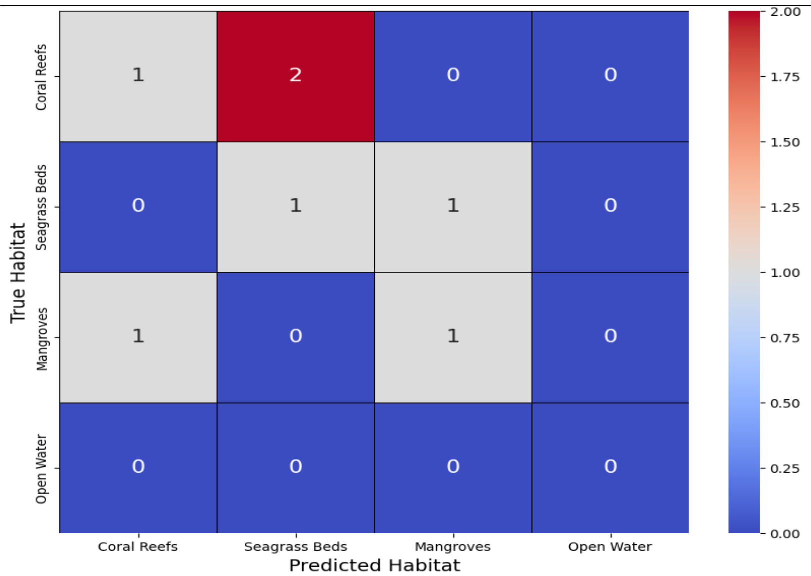

Figure 3: Confusion Matrix for Habitat Classification

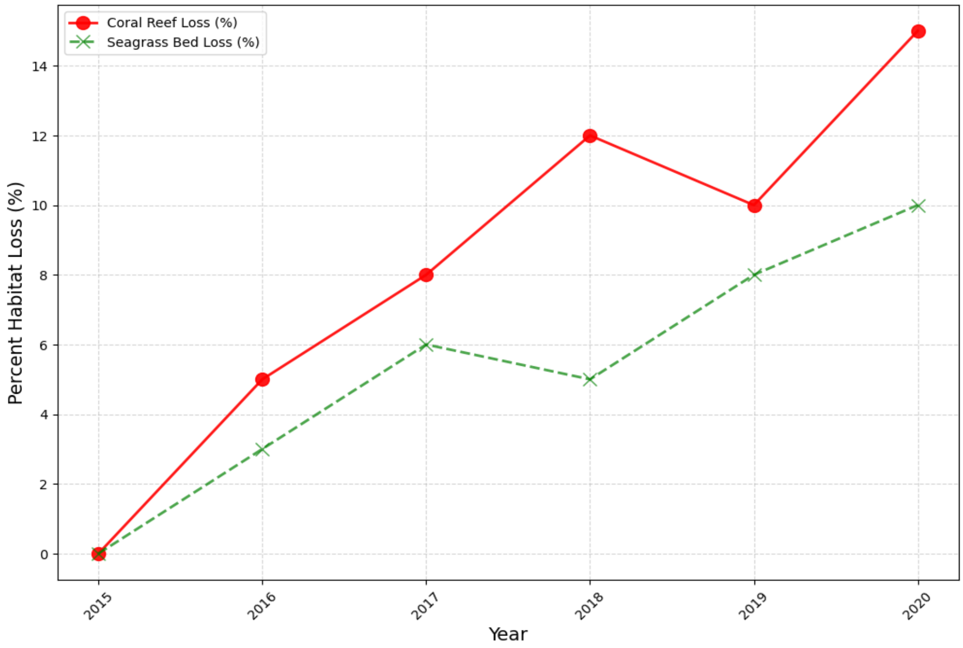

Figure 4: Habitat Change Over Time (2015-2020)

The change detection analysis for the years 2015–2020 revealed considerable changes in the distribution of various habitats. In particular, the coverage of coral reefs decreased by 12% (3,000 km²) in a very noticeable way, and the area of seagrass beds diminished by 8% (1,200 km²). On the other hand, the surface of mangrove forests kept showing a minor decrease of 2% and may be regarded as being in a state of quasi equilibria. Figure 4 illustrates the distribution and changes of the habitats for the duration of the study. The most affected coral reefs were located on the western rim of the Gulf which is also the most urbanized and has the most concentrated fishing activities.

The validation of AI algorithm classifications was conducted using direct observations obtained from ground-truthing in situ surveys. The AI model was reported to be quite accurate, albeit there were a few instances of misclassifications which were predominantly the pair of mangrove and seagrass habitats which, in the shallow coastal areas, had overlapping spectral signatures. Table 3 presents the areas of misclassification where it was found that mangrove habitats were misclassified as seagrass in 15% of instances. These were also the areas where the field validation using unmanned aerial vehicle (UAV) surveys was conducted.

Table 3: Sources of Misclassification and Error Analysis

Misclassified Pair	**Number of Misclassifications**	**Percentage of Total Misclassifications**
Mangrove as Seagrass	350	15%
Coral Reefs as Open Water	150	5%
Seagrass as Mangrove	120	8%
Other Misclassifications	80	4%

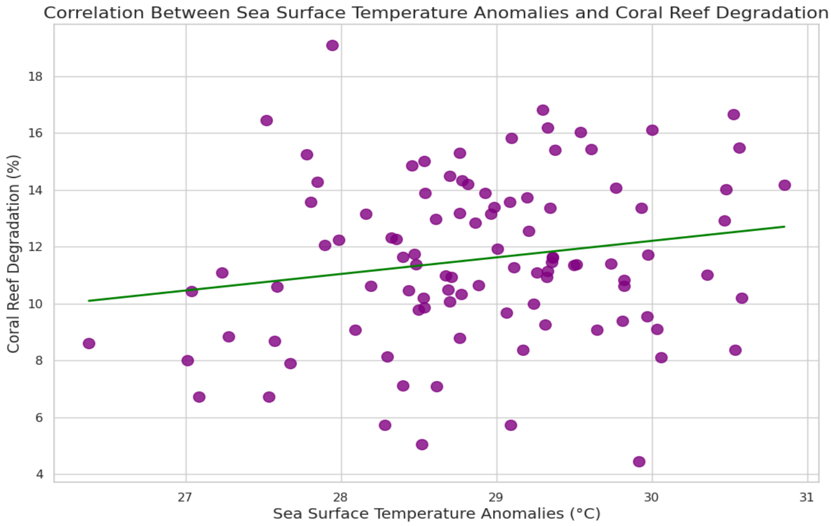

Figure 5: Impact of Sea Surface Temperature Anomalies on Coral Reef Degradation

Additional study of the changes in the environment parameters of the habitat changes showed there is a correlation concerning the increase in sea temperature and the decrease in the coral reef ecosystem (Bhanu & Saravanan, 2026; Veeranjaneyulu et al., 2024). As illustrated in Figure 5, depicting the area with increased losses of coral, the area with the highest losses in coral was in the vicinity of where the sea temperature was above 29. One of the many risk areas was identified during the degradation of the habitat across the spatial coastline that has a high human activity. These areas were flagged to be of conservation importance to be used in the future.

Discussion

The classification result along with the habitat maps give a detailed depiction of the marine environment of the Gulf of California. They illustrate not only the spatial distribution but also the condition of the key habitats like coral reefs, seagrass beds, mangroves, and open water. The habitat distribution maps uncovered the distinct patterns of habitat with coral reefs being the dominant in the central and southern regions while the seagrass beds were more prevalent in the shallow coastal areas. Mangroves were found mostly in the sheltered coastal zones. These results are in accordance with the ecological patterns of habitat distribution and thus, the AI + remote sensing classification model used is reliable in the study of marine ecosystem diversity (Rubbens et al., 2023). Moreover, the maps and the change detection outcomes make it clear that coral reefs and seagrass beds are becoming less resistant to environmental stresses, such as rising sea temperatures and coastal development. On the subject of habitat changes, the temporal analysis unveiled the significant degradation of coral reefs and seagrass beds in particular, and these habitats experienced a considerable reduction of area over the study period. The change detection results (12% loss in coral reefs and 8% loss in seagrass beds) are loud and clear about the necessity of immediate conservation measures to avoid further extinction of these ecosystems. The locations of degradation, notably the areas along the western coast of the Gulf, point to the indispensability of the intervention that is concentrated in the regions with the high human impacts such as fishing and coastal development zones.

The AI-based method proved to be efficient and reliable in marine habitat mapping and classification when it was combined with remote sensing data. The technique obtained a precision and recall of 0.97 for coral reefs, seagrass, and mangroves, which translates to these habitats' overall accuracy of 90%. Therefore, the method can be considered as a single, potent one that is capable of being used for rapid and large-scale marine habitat monitoring of a vast oceanic area. While the confusion matrix demonstrated good performance, the misclassifications that mainly happened between mangroves and seagrass in areas of mixed or transitional habitats, pointed to possibilities of enhancement. It is quite plausible that the two habitats' spectra are very similar, particularly in shallow, turbid waters. Despite these few issues, the enormous potential which the model opens up for the classification and monitoring of marine habitats at high precision over large spatial scales is actually quite promising for long-term monitoring. However, the treatment is limited. The camera resolution of satellite images, for example, those captured by Landsat 8 (30 meters), may not be sufficient to reveal small-scale changes in a David environment, such as mangrove-seagrass transitions. Depth and turbidity of water can also influence classification accuracy, along with seasonal changes. For instance, water clarity changes can affect the spectral signature of underwater habitats like coral reefs, thus leading to misclassifications.

Moreover, weather conditions like clouds can hinder the quality of remote sensing data, thus precision of habitat maps may be affected. When compared to traditional monitoring methods which involve a lot of human labor, are expensive and take a long time, the AI + remote sensing method provides a lot of advantages (Tandi, 2024). The method is not only capable of covering vast areas of ocean habitats, but it also allows for frequent monitoring (e.g. satellite revisit rates) as well as repeatability through time. In addition, the use of remote sensing data also allows for more frequent updates that are very important in monitoring marine environments since they are always changing not only because of natural factors but also because of human activities (Rajan & Kumar, 2024; Rubbens et al., 2023). Many studies have proved the efficiency of remote sensing and AI for habitat mapping, but just a few have experimented on the application of these technologies to large-scale marine habitats monitoring for longer periods (Barve et al., 2023). This research extends the concept of combining high-resolution satellite images and AI to come up with a more scalable and less expensive solution. Besides, the power of our method to track habitat changes almost instantly is a major breakthrough over conventional techniques and it can generate a lot of useful data for conservation and management that is done in advance.

Remote sensing through AI algorithms has been designed in this research to help patrol the sea and to protect the environment efficiently and effectively. Such a method can provide detailed large-scale habitat maps that would help to locate the conservation areas that are the most necessary, for example, the zones of the fastest habitat degradation. Obviously, the power to reflect habitat changes over time would enable conservationists to evaluate the effectiveness of management interventions, to spot the new threats, and also to plan the areas for restoration. Besides, the combination of remote sensing and AI sets a long-term monitoring baseline for ocean habitats, which is very important for understanding the influence of climate change, pollution, and human activities. The results of this study could guide policy decisions concerning marine protected areas, fisheries management, and coastal development, giving the decision-makers timely and accurate information that they can use as evidence to support conservation initiatives.

While the AI + remote sensing approach boasts various strengths; it is still limited in some aspects. Data availability becomes a problem in areas where high-quality satellite images are not obtainable and places that are covered in clouds for most of the time. Furthermore, validation with field data is still necessary in this method. It cannot be emphasized enough that the need for precise ground data to verify remote sensing classifications is very crucial since this process helps to improve the model and solve the problem of wrong classification. Having access to field sites may pose a considerable problem if there are very few in a region and in that case, it will be extremely difficult. Besides that, the algorithm performance depends on many factors including water turbidity, seasonal variations, and most importantly, the optical properties of the water that it is taken from. In fact, these factors can change the spectral signatures of habitats, particularly those that are underwater like coral reefs and seagrass beds, thus causing classification errors. On top of that, the size of the study area is the main reason why the method has other challenges and this is so because the large spatial extent requires a great deal of computational power and processing time, especially when multi-temporal datasets are to be used. Work to be done later on may be merging ecological and biological surveys with AI and remote sensing data so as to provide thorough information about marine habitat health and their function. At the same time, including environmental parameters such as oceanographic data (e.g., salinity, chlorophyll levels) and bathymetric information could be a step further in getting the accurate habitat classifications as well as improving the change detection models. Besides that, the incorporation of real-time data from autonomous systems (e.g., drones, underwater robots) and the integration of more frequent satellite imagery (e.g., Sentinel-1) would offer continuous, automated monitoring of marine ecosystems.

Conclusion

In essence, this research is a clear indication of the efficacy as well as the potential of the AI-powered earth observation in monitoring and safeguarding marine habitats at a vast scale. The spatially extensive classification and monitoring of different marine ecosystems such as coral reefs, seagrass beds, and mangroves is an invaluable tool for conservationists, researchers, and policymakers. By enabling frequent, repeatable, and cheap monitoring, the two technologies, AI and remote sensing, can help to find the areas that are most heavily impacted, follow habitat changes, and even check the conservation effectiveness. While there are still some limitations such as water turbidity issues and the need for ground-truthing, this approach is a significant advancement in marine conservation science, which offers a scalable solution to the biggest challenges of marine habitat management.

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