**UNIVERSITY OF THE PHILIPPINES**
**OPEN UNIVERSITY**

**MASTER OF ENVIRONMENT AND NATURAL RESOURCES MANAGEMENT**

**DEXTER K. DAG-UMAN**

# MAPPING THE UNDERWATER FOREST: A DEEP LEARNING APPROACH TO SEAGRASS MAPPING DISTRIBUTION IN CALATAGAN, BATANGAS, PHILIPPINES, USING SENTINEL-2 SATELLITE IMAGERY

Special Problem Adviser:

**PEDCRIS M. ORENCIO, Ph.D.**
**Faculty of Management and Development Studies**

15 December 2025

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**PEDCRIS M. ORENCIO, PhD** ____________________
Faculty-in-charge, ENRM 290 (Special Problem) Date

**KARL ABELARD EDBERTO L. VILLEGAS, PhD** ____________________
Program Chair Date

**FINAFLOR F. TAYLAN, DProfSt**
Dean
Faculty of Management and Development Studies

____________________
(Date)

## DECLARATION

This is to certify that:

I. The special problem comprises only my original work towards MENRM except where indicated in the Preface

II. Due acknowledgement has been made in the text to all other material used

III. The special problem is fewer than 25,000 words in length, exclusive of tables, maps, bibliographies and appendices.

**DEXTER K. DAG-UMAN**
**Name**

## Acknowledgement

I want to sincerely thank Dr. Pedcris M. Orencio, my adviser, whose invaluable advice tolerance and knowledge have been essential to finishing this work. His support and academic guidance gave me direction, clarity and motivation from the very beginning of creating my research proposal to the last edits of this manuscript. In addition to providing me with academic guidance, he was a mentor whose professionalism and commitment to research have motivated me all along the way. Without his insightful comments and helpful criticism this study would not have developed to its current state.

Additionally, I would like to express my gratitude to the members of the Special Problem committee for generously sharing their time, expertise and viewpoints. Your insightful observations, tenacious questions and helpful suggestions improved the caliber of this study and forced me to act more creatively and approach it from a more comprehensive and in-depth perspective.

I also want to express my sincere gratitude to my wife, Lea Lynn H. Dag-uman and my entire family, whose love, understanding and sacrifices that made this paper possible. I am grateful for your understanding as I devote a great deal of time to my writing and research and for your constant support whenever I felt overwhelmed or lost. This academic journey has been made much more bearable by your prayers and support and your confidence in my abilities has given me the willpower to keep going.

Finally, I sincerely and profusely thank Almighty God for giving me the discernment tenacity and fortitude to finish this process. I felt His grace and direction in the most trying times which kept me going day after day. This accomplishment is not just mine rather it is evidence of His faithfulness.

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## Abstract

Around 71 percent of the earth's surface is covered by water primarily saltwater found in the oceans which are essential to the survival of a variety of marine ecosystems. Particularly considering the environmental issues facing the Philippines this study highlights the significance of seagrass beds essential but usually disregarded ecosystems that support the maintenance of water quality and carbon sequestration. To produce an accurate map of the distribution of seagrass in Calatagan, Batangas, high-resolution sentinel-2 imagery is analyzed using deep learning and advanced remote sensing techniques. The approach which includes spectral band selection, data collection and model training produces a deep learning model with an F1 score of 85 percent, precision of 86 percent and overall accuracy of 97.31 percent. The efficiency of remote sensing in monitoring vital coastal habitats in the face of increasing human threats is demonstrated by this study.

Through the combination of deep learning algorithms and remote sensing technology this work offers a novel approach to improve ecological analysis in coastal management. This study provides an important step in maintaining and preserving biodiversity by integrating scientific findings into practical conservation plans and strategies.

# I. INTRODUCTION

About 71 percent of the earth's surface is covered by water, of which about 96.5 percent is saltwater known as the ocean. Experts acknowledge that our oceans are crucial for life on earth. The ocean is a part of the global ecosystem and contains a variety of ecosystems which house a lot of tropical species of marine animals, and which contribute a lot to the biosphere. They represent a complex, interdependent system that ensures a fragile ecosystem including microscopic plankton that is essential to nutrient cycling to large blue whales considered the biggest creatures on the globe. Coastal environment is one of the most important marine ecosystems and is the place where land meets the sea. The habitat types found in this ecosystem include mangroves, coral reefs, seagrass beds, coastal lagoons and backwaters and similar ecosystems. These types of ecosystems have benefited humans directly and indirectly. To humans, this ecosystem provides food and medicine, and, most importantly, it protects coastal areas from natural disasters like typhoons and storm surges, as well as offering cultural services that often provide a tourism industry (NCCR, 2019).

Preserving the health and biodiversity of our oceans depends on coastal habitat. We often imagine coral reefs filled with endless corals, or beautiful mangrove forests. But to my surprise, there are many other species that rely on seagrass meadows for survival, and we tend to forget that. The seagrass and seagrass beds are one of the important coastal ecosystems offering a variety of services and benefits to marine life. Although seagrass beds may not get the same level of recognition as more prominent ecosystems such as mangrove forests and coral reefs, they provide several ecosystem services and are integral to the global carbon cycle; this unique environment is the focus of the research. Conservation and balance of the ocean environment involve seagrass. It stabilizes the sediments on the ocean bottom making water pure for marine life and preventing erosion. According to Fonseca and Cahalan (1992), these plants have extensive root systems which stabilize sediments extensively while the process also reduces wave energy and coats coasts protecting against cyclones as well as sea level rise. The importance of this function increases since extreme weather events and coastal areas are worsened by climate change. Seagrass also acts to improve water quality, by the epiphytic algae and detritus which it holds in position, thus preventing excessive growth of algae which is harmful to marine life. The filtration of pollutants by their epiphytes also increases water clarity and health, and thus the productivity of the surrounding marine habitats is also increased (Waycott et al., 2009). Several fish species use seagrass as a nursery, where they grow for a time before becoming ready to join the open ocean. This helps our marine ecosystem by filtering out contaminants which improve the quality of the water.

Seagrasses are abundant in shallow salty and brackish environments across the planet, from the tropics to the Arctic Circle. They are called for their tall, green, grass-like leaves. Seagrasses are sometimes mistaken for seaweed; however, they are more closely related to terrestrial flowering plants. They generate flowers and spores, as well as roots, stalks, and leaves. They evolved roughly 100 million years ago, and there are now about 72 distinct seagrass species divided into four major groupings. Seagrasses may produce broad underwater meadows that are visible from space (Reynolds, 2023). These shallow marine ecosystems, moreover, are also important in dealing with climate change. Recent research has found seagrass meadows can sequester carbon at 35 times the rate of tropical rainforests (UNEP, 2019). That’s impressive given seagrass meadows only cover 0.2 percent of the seafloor but score 10 percent of the ocean’s carbon. The World Wide Fund for Nature (WWF) adds seagrasses sequester 18 percent of the ocean’s carbon, 35 times faster than tropical rainforests (Tomassoni, 2024). So, seagrass ecosystems are a big player in climate change mitigation through carbon sequestration. Seagrass ecosystems are essential carbon sequestration participants in efforts to mitigate global climate change because they can take in carbon so well. Seagrass beds serve as a regulator and stabilizer of temperature in the environment next to them, trapping and storing enormous amounts of carbon and thus regulating or limiting the effects of global warming. The mechanism of sequestering atmospheric carbon by the ocean is termed "blue carbon." Seagrass meadows are very efficient in this context, capable of sequestering up to 83 million metric tons of carbon per year worldwide (Reynolds, 2023). The capacity to trap carbon not only mitigates climate change but also enhances the health of marine ecosystems, making the protection and restoration of seagrass environments essential. Seagrasses account for less than 0.2% of the ocean floor but they are responsible for approximately 10% of the carbon buried in the oceans annually (Duarte CM. 2002).

Long green, grass- like leaves type of species that can adapt to salty and brackish water like seagrass are commonly found in archipelagic country such as the Philippines. As dictates by its landform, hundred islands like the Philippines, simply means that long bay and shorelines are in large quantities, this type of environment is the very placed colonized by seagrasses (Fortes, 2017). With continuous loss of mangrove forest and bleaching of our coral reef, seagrass has become the last frontier of the country’s marine needs (Fortes, 2017). The condition of seagrass in the Philippines is continually declining due to threats from human activities such as coastal development, pollution, and overfishing, as well as climate change impacts like sea level rise and ocean acidification. In addition, land reclamation, boating and aquaculture are also significant threats to seagrasses around the world (Grech et al. 2012).

Whether we can conserve and preserve these precious marine ecosystems is entirely in our capability to comprehend seagrass distribution and health. By documenting locations of sea grasses, we allow observation of their dynamics through time and health checks indicate long term problems affecting the environment like pollution and global warming. It is this knowledge that will help us to take appropriate steps that can maintain the health of the coastal ecosystems as well as enhance the marine biodiversity and the preservation of the seagrass meadow across generations. The conventional method of seagrass mapping is field surveys and aerial photography, which is sometimes very costly, small scale and intensive. Field surveys are costly and do not cover large places yet offer detailed and precise records in terms of the sea grass distribution, biomass, and composition of the species. Aerial photography can be expedited to achieve extensive coverage but depends on the environmental factors like specialized work equipment's and skill, however, the clarity of water and weather they operate in. In response to these constraints, and to enhance the performance, precision and scope of seagrass habitat surveillance there is an emergent interest in adopting more sophisticated remote sensing methods that include deep learning mapping and satellite forms of monitoring images. In recent years remote sensing (particularly satellite imagery) has transformed the seagrass ecosystem monitoring game. Sentinel-2 mission, an initiative under the European Space Agency, has earned so much attention due to its ability to map seagrass. Sentinel-2 is also ideal in dynamic coastal ecosystems due to short revisit period of around 5 days and high rate of spatial resolution (10-20 meters) and is multispectral too. A study by Kuhwald et al., (2021) proved the effectiveness of sentinel-2 in seagrass habitats in the turbid waters of the

Western Baltic Sea. They demonstrated that they were able to distinguish various benthic habitats such as dense seagrass and mixed substrates of red/brown algae by correcting the satellite data with atmospheric and water column. Using this technique, they obtained very high classification accuracy to 5 meters of water depth. Similarly, Meister and Qu (2024) used machine learning algorithms and Sentinel-2 images to estimate the density of seagrass in Chesapeake Bay. They utilized field data in their approach to train models to categorize seagrass density under very sparse, dense classes. In fact, the overall accuracy of the Random Forest model was 87.4 percent; this indicates that satellite data and complex analytical procedures could be efficiently applied to the seagrass. The European Space Agency also announced that Sentinel-2 data allowed measuring the vast annual changes in the seagrass population in the intertidal areas of Western Europe and North Africa. The significance of these new findings to conservation and restoration of these precious ecosystems is that we are able to better realize time-ageing in seagrass fields. In a further research done by Humana et. al., (2023), the appropriateness of Sentinel-2 satellite imagery was mentioned when used in the identification of seagrass habitat in shallow Indonesian coastal waters. This kind of temporal variability in the tidal effects of water level variations was also important in the understanding of the satellite images because the spectral properties of the vegetation found underwater change significantly due to a variation in the water level. To curb this, they offered a strategy to differentiate between the seagrass when there is a low tide and the seagrass when it is submerged. From the analysis of the spectral response of seagrass in sentinel-2 images, the researchers stated that non-submerged seagrass had spectral responses similar to above-ground vegetation, hence extractable by the Normalized Difference Vegetation Index (NDVI). They found a distinct reflection peak at the 705 nm band for submerged seagrass, thus developing the Submerged Seagrass Identification Index (SSII) for aiding underwater identification. The technique allowed the complete mapping of seagrass areas, accounting for tidal effects and improving the accuracy of habitat evaluation. The study concluded that Sentinel-2 imagery, with high spatial resolution and distinct spectral bands, is very suitable for precise seagrass mapping in Indonesia, thus yielding useful information for conservation and management purposes.

## II. REVIEW OF LITERATURE

Deep learning is a method in the wider context of machine learning, which is based on artificial neural networks (ANNs), with stratified algorithms and computing units known as neurons (Coursera, 2023). Neural networks, or ANNs, are regarded as the main elements of deep learning algorithms that rely on the design and operations of the human brain. The idea of the “neural network” is the process of information exchange between brain cells. ANNs are supposed to simulate such communications and can recognize patterns and classify data. To perform recognizing, categorizing and interpreting visual input, e.g. in image and video analysis, a certain sort of neural network called convolutional neural networks (CNNs) has become popular (IBM, 2023). Convolutional neural networks (CNNs) are especially well-developed to process the images due to their distinctive scheme It is capable of identifying a huge variety of image patterns, both simple shapes and complex structures. This property has rendered CNNs essential in the systems of sorting and analyzing images, like the case of computer vision. Computer vision requires experts capable of extracting complicated data out of the huge and unorganized data sets. In 2018, researcher Li conducted a study that determined how effective CNNs were at recognizing features on images taken by satellites or planes. The paper has made comparisons between the performance of deep learning models such as CNNs and conventional machine learning algorithms. The results indicated that CNNs performed well in detecting fine details as deep learning was more precise and quicker than most traditional methods. On the same note, Singh et al., (2019) examined the effectiveness of machine learning in categorizing the land cover types based on satellite images. Their intention was to create extensive land maps. They have found that deep learning, and especially convolutional neural networks (CNNs), were more precise and reliable than their older counterparts. The use of CNNs made it possible to generate more detailed maps that were able to represent the various types of land such as forests, fields, and urban areas more precisely. This study has shown how advanced technologies like machine learning and convolutional neural networks can greatly increase our ability to scan and understand the surface of the earth in space. Deep learning is better than the conventional machine learning algorithms on image recognition tasks (Lecum et al., 2015). The application in natural language processing, computer vision and predictive modelling are perfect candidates for the use of deep learning, owing to its efficiency in learning high level features from large datasets. Application of deep learning models in environmental mapping and prediction (Kok et al., 2017) provides a potential for improving air quality prediction and monitoring system focusing on prediction of air quality in smart cities. In Lui et al. (2017) conduct study of deep neural network and their design and application, providing insights for the different applications of deep learning in several domains.

ESRI's ArcGIS Pro is a professional desktop GIS program that uses deep learning for object detection, object classification, and pixel classification of space-borne satellite images. In this study we will investigate the most recent deep learning capabilities of ArcGIS Pro for generating seagrass maps. Deep learning processes on the Sentinel-2 images will be performed using the ArcGIS Image Analyst Extension.

## III. STATEMENT OF THE STUDY

This study will improve the quality of mapping and monitoring of seagrass within the study area using deep learning algorithms and sentinel-2 optical satellite data. The combination of this two advanced technologies not only improves and enhances map-making precision but offers critical information for resource management and conservation. The primary advantages provide the following benefits:

### 1. Enhanced Mapping Accuracy

Traditional methods of seagrass mapping such as image classification and field surveys regularly face problems of precision and effectiveness. The deep learning algorithms have the ability to significantly improve the precision of seagrass distribution mapping by identifying complex patterns in the satellite data. This provides more accurate and reliable geographical data, which reduces errors that usually accompany conventional methodologies.

### 2. Cost-effective and Scalable Monitoring

The costly nature of fieldwork, including logistical costs and the need for qualified staff, often restrains seagrass monitoring because of the high costs associated with the fieldwork. Using the available Sentinel-2 satellite data in conjunction with automated deep learning classification is an ecological alternative to traditional survey methods. The technique enables large scale seagrass surveillance without the budgetary and time constraints incurred during field-based research. Therefore, resource managers can carry out long-term monitoring plans across extensive areas of coastlines without the high costs commonly associated with high ecological assessment. Seagrass meadows are dynamic ecology that is highly sensitive to changes in the environment such as coastal development, climate change and changes in water quality. Thanks to the Sentinel-2 satellites, it is possible to provide images twice every 5 days, which enables continuous time monitoring of such ecosystems. These consistent data gathering enable the researchers to observe seasonal changes and long-term changes in seagrass cover, early signs of degrading issues, and respond promptly to potential risks. This research improves management of the ecosystem by continuously monitoring the quality and area of seagrass meadows.

### 3. Implications for Conservation and Resource Management

Besides technological advancement, the study tries to ensure that its findings are exploited to promote conservation and sustainable management of resources. With this vision, not only the analytical tool on the deep-learning basis is the result of this study, but also the decision-support system to policymakers, marine conservationists, and local community. This mechanism allows officials to develop areas of priority to protect and evaluate the effects on humans and implement evidence-based conservation plans based on the proper spatial and temporal information. Moreover, the same strategy may be applied not only to the municipality of Calatagan, province of Batangas but in other coastal municipalities, thereby facilitating national endeavors to conserve seagrass in the whole of the Philippines.

The presented work improves the seagrass monitoring approach based on combining deep learning and remote sensing technology, which leads to a more efficient and cost-efficient and data-driven workflow. In addition, it highlights the critical role of research instruments in informing sustainable coastal management practices, therefore, by preserving the long-term environmental and health stability of seagrass habitats.

## IV. OBJECTIVES OF THE STUDY

The present research is an attempt to map seagrass meadows and seagrass area in Calatagan, Batangas, Philippines with deep learning algorithm and using Sentinel-2 satellite image data. This method deals with the acute necessity of efficient and inexpensive observation of ocean-related ecosystems that are becoming more and more vulnerable to environmental destruction. The objective of the research will be to develop a tool which will not only enhance seagrass mapping but also help in conserving the resources and the maintenance of the resources. The necessity of accurate and effective monitoring of these important coastal ecosystems explains the purpose behind this aim.

1. **Develop Deep Learning Model:**

The primary goal of the study is to develop a deep learning model to detect and categorize seagrass meadow based on a satellite-derived picture generated by Sentinel-2. The model will be trained using quality labelled datasets to recognize seagrass prominent spectral and spatial features. Consequently, it will be in a position to distinguish between real seagrasses and other coast and marine characteristics. This model is a very efficient and automated solution to image analysis based on the power of deep learning and significantly improved the accuracy and reliability of seagrass detection. Compared to the traditional methods of classification, which are usually labor-intensive and open to inconsistencies, the CNN-based approach provides improved accuracy and scalability of mapping seagrass ecosystems, and reliability. This development assists in better environmental surveillance and intensifies conservation.

### 2. Map Seagrass Distribution:

Once the deep learning model is fully trained and optimized, the next critical step is to apply it to Sentinel-2 satellite image. The objective of this process is to generate high-resolution georeferenced maps of seagrass meadows of Calatagan, Batangas, Philippines. The result maps will provide a comprehensive and spatially accurate representation of the distribution of seagrass, which will essentially describe the areas covered by seagrass and the specific geographic location of seagrass habitats within the studied area. High-resolution seagrass distribution maps become important tools in the decision-making process of coastal resource managers. This valuable information is utilized by conservationists in creating and utilizing preservation strategies that match certain ecological needs. In addition, policy makers can easily integrate the findings of such researches into long term sustainable approaches to coastal development that promote the equal balance between environmental conservation and economic growth. The gathered information could be used to precisely define the areas requiring urgent intervention such as active seagrass restoration programs and marine protected area development to ensure future ecosystem stability to enhance habitat restoration programs.

### 3. Assess Model Accuracy:

With the accuracy assessment, a strict check of reliability and efficiency of the designed deep learning model will be conducted wherein the predictions of the model upon reference data obtained via the conventional validation methods will be compared and contrasted with the analysis of high-resolution satellite imagery (including Google earth). Together these different validation methods give a systematic way of assessing the model's ability to accurately detect and classify seagrasses and seagrass meadows. Accuracy assessment helps to validate the deep learning model and its accurate classification, thereby ensuring that the maps generated are representative of realistic seagrass distribution. By quantifying the classification accuracy (e.g. commission and omission error, precision, recall, and overall performance metrics), we can refine and optimize the overall classification efficiency of the model. If classification accuracy is high, we can therefore feel more confident in the classification accuracy of our model and use it more reliably for ecological research, conservation planning and coastal resource management.

In addition, validation of the predictions of the model for field data and high-resolution remote sensing will increase the credibility of the seagrass distribution maps generated by the model. As important as these outputs are for ensuring decision-making in the most appropriate way, providing the required habitat protection and guiding sustainable management practices, it is necessary to ensure they are both trustworthy and valid. The validation process will further increase the effectiveness of the model as an efficient and reliable way of monitoring seagrass ecosystems and evaluating changes over time.

**4. Explore Temporal Monitoring:**

The research examined the possibility of tracking the trend of seagrass meadows by using Sentinel-2 satellite images as Sentinel-2 is a repeated and long-term spot to monitor changes in seagrass distribution by seasons and even by years. The analysis is conducted using time-series images of seagrass as one of the ways of comprehension of changing seagrass ecosystems and factors that might lead to their productivity or degradation. The time-lapse seagrass record is extremely essential to its proper management as it can prove the status and preservation of such communities. That can be the early indications of degradation and assisting in identifying the necessity to take conservation measures and whether the restoration projects succeed. However, at the end of this study, evidence of the necessity to employ satellite technology to carry out long-term monitoring of the environment is supplied in order to support the process of decision making in conservation and management of the seagrass and coastal areas.

Besides building a deep learning model, the study will be oriented to the model applied to coastal resources management and conservation, where seagrass maps and monitoring tools will play a critical role in availing data required to make decisions by coastal managers, environmental planners and policy makers. Using these tools stakeholder groups will be able to identify areas at risk from degradation, prioritize conservation and restorement projects and will also be able to monitor progress over time to identify successes and weaknesses of conservation strategies and improve them. Ultimately, the study will help build into better coastal management and long-term protection for seagrass, since it will provide accurate and up-to-date data to ensure conservation plans are effective and sustainable for generations to come.

**Significance of the Objectives**

**Improve Seagrass Monitoring:**

The research aim is to overcome the limitations of conventional seagrass mapping approaches and develop an efficient, accurate and economically feasible way to monitor the seagrass habitat. Conventional methods, such as field surveys and manual mapping, are slow, labor intensive and costly and limit the frequency and extent at which seagrass can be monitored. Technology-driven remote sensing, deep learning and geographic information systems (GIS) will enable improved mapping accuracy, faster data processing and large-scale monitoring. The results will allow researchers and conservationists to more frequently and accurately monitor seagrass changes to achieve better conservation and management outcomes.

**Data-Driven Conservation:**

Each component of this study provides valuable information for conservation and management by providing accurate, timely and up-to-date maps of seagrass distribution. This tool will be an important enabling tool for making informed decisions on habitat protection, restoration and sustainable coastal management. Formerly allowing us to make objective and up-to-date maps of seagrass coverage and health, this study will provide conservationists and policymakers with objective data on where they are most at risk, as well as useful recommendations on how to protect and restore seagrass habitat as well as how restoration projects enhance long-term fisheries and biodiversity.

**Understanding Seagrass Dynamics:**

Sentinel-2 imagery can be used to monitor variability of seagrass ecosystems, allowing researchers to investigate how seagrasses respond to environmental conditions and human activities over periods of time. The frequent revisit period, spatial resolution and multispectral imaging capabilities of Sentinel-2 make it possible for this monitoring to be achieved to detect changes in meadow growth, decline and recovery patterns that are key to studying how seagrasses adapt to natural variability, climate change and anthropogenic environmental factor, providing insights that will help with conservation planning, ecosystem management and policy development.

## V. RATIONALE

In this study, we combine advanced deep learning methods towards high-resolution Sentinel-2 satellite imagery for the accurate mapping and delineation of seagrass meadows in Calatagan, Batangas, Philippines. We incorporate aspects of artificial intelligence (AI) and remote sensing to efficiently, and automatically identify, classify, and study these essential coastal ecosystems with greater precision than was previously possible. The method also enables improvement of traditional mapping procedures by enhancing with machine learning algorithms that have been trained on spectral and spatial characteristics of seagrass, reducing the conventional dependence on the field survey procedure and enhancing accuracy as well as scalability. Deep learning can be used to automate the seagrass assessment process, which is quick, repeatable, and cost-efficient to monitor the extent and time-varying health in terms of changes to the seagrass.

This approach to data collection and using that data to manage seagrass meadows enables timely decisions and concrete actions for local managers, researchers, and agencies, as they work to protect and restore seagrass meadows. As seagrass meadows help to protect marine biodiversity, protect coastlines, and sequester carbon, sustainable management is an important step in meeting threats of development, pollution, and climate change. We are working to develop a reliable and scalable data collection framework for continually monitoring seagrass meadows to aid the larger initiatives of marine ecosystem conservation and climate resilience.

**Importance of Seagrass:**

Seagrass meadows are known as the “lungs of the sea” and for good reason. The flowers maintain biodiversity and ecosystem equilibrium, and act as a habitat for many species including fish, crustaceans, and endangered sea turtles. Along with those reasons, seagrass meadows work as natural buffers to the coast which protects it from shoreline erosion. These meadows also work as strong tools to fight against climate change by capturing a massive amount of carbon dioxide, which helps-along with the meadows-aid in polishing the water by fulling out toxins and excess nutrients.

**Monitoring Challenges:**

Conventional techniques of seagrass mapping including underwater direct surveys are labor-intensive and time-consuming and therefore pose significant challenges. Traditional methods typically involve large amounts of fieldwork using divers, remote operating vehicles (ROVs), or sonar to take measurements, which always require specialized equipment, trained staff, and significant funds. Hence, they are priced costly as well as logistically cumbersome hence impractical to large scale and due to high frequency of monitoring that needs frequent monitoring. In addition, the performance of underwater surveys is restricted by environmental factors because of the state of the water, the variations in tide and weather conditions, which may affect visibility and accuracy of data. Also, the methods tend to produce localized data so the process of achieving a wide spatial coverage is challenging, especially in a large and remote coastal area. Also due to the reliance on manual interpretation there is an issue of discrepancy in data collection and categorization, and this may undermine the reliability of the long-term monitoring initiatives.

**Deep Learning Potential:**

Deep learning methods have been highly effective in tagging seagrass habitat precisely and efficiently in relation to spaceborne satellite observations. This innovative technology has achieved significant contributions in the area of remote sensing, especially in the detection of objects and processing images with the assistance of the opportunities of convolutional neural networks. Convolutional neural networks (CNN's) are advanced machine learning algorithms, which are effective in cases of large-resolution satellite photographs, especially in the environmental monitoring field. They are conditioned to identify complex patterns in space and spectrum and afterwards apply such data to true measurements and analysis identification of seagrass meadows across a broader aspect of the coast. The advantage of CNNs is that they have the ability to recognize and self-taught hierarchical features in data. Such features are not just the basic features like color and texture, but also complex structural features that play a very significant role in the identification of the sea grasses as well as where they thrive. Therefore, CNNs significantly enhance the accuracy and reliability of mapping.

**Sentinel-2 Data:**

The satellites Sentinel-2 is equipped with MSI sensors which have enhanced optical sensors. These are sensors that record high-resolution multispectral views of the earth surface. The satellite sensors on the MSI are color-coordinated with multiple wavelengths, which provide it with a very high level of the ability to take pictures of the surface of the earth. Such a device as MSI sensor (Multispectral Instrument) is an ideal seagrass necessity in that it is able to monitor minimal variations within the water color, turbidity, and submerged vegetation. This behavior makes seagrass meadows critical in the process of detecting and mapping due to its location and abundance (Foley et al., 2015). The MSI has 13 spectral bands that cover the visible, near infrared (NIR) and shortwave infrared (SWIR) spectral bands. Such wavelength diversity enhances the ability to distinguish seagrass ecosystem among other aquatic plants, benthic and floating components as well as particles. The spatial resolution of the sensors is 10 m, 20 m and 60 m respectively. Small finely detailed satellite sensors that are used will permit continuous observation. There are also the Sentinel-2 satellites that visit the same area, but with a throughput of five days (Foley et al., 2015). This enables satellites to examine seagrass ecosystems over a period of time. This system presents seasonality, disrupting changes, and preface of different stages of land cover change by seagrass.

**Conventional mapping of Seagrass and Seagrass beds**

The seagrass meadows are valuable coastal ecosystems which provide a variety of ecosystem services like the provision of habitats, carbon storage and coastal protection. To grasp the seagrass conservation and efficient management, we should understand the position and extent of seagrass. As much as the traditional mapping methods have been utilized, they possess limitations. It has been a significant endeavor upon the marine ecologists and conservationists to determine the locations of the seagrass beds. This has had an extensive involvement with traditional methods that have offered primitive data to the management practice. Nevertheless, despite the fact that these approaches have been invaluable, they have various shortcomings that can affect the seagrass monitoring activities with regard to efficiency and effectiveness.

Field surveys also referred to as the ground truthing method is one of the most conservative and critical methods. Field surveys entail traveling to seagrass meadows physically and taking information on species cover, density, and composition utilizing either snorkeling, SCUBA diving or wading. The advantage of the ground truthing is that it is extremely accurate and species specific, but it is time-consuming and tedious. Obstructing this process would be when the regions are not as readily available and the extreme weather conditions or turbidity of the waters have made data retrieval functions hard (McKenzie et al., 2001).

Although traditional mapping methods have provided sufficient data, they are limited in the following ways:

1. Temporal Constraints: These methods normally give a static representation, which makes it hard to follow the dynamic alterations that take a place in seagrass meadows with time.
2. Spatial Limitations: The coverage will often be limited to the easily reachable areas, meaning that remote, deep, or otherwise problematic locations will have a data gap.
3. Costly and Resource-Intensive: Major challenge can be the costs of employing specialists and expenditure on equipment of conducting field surveys.
4. Environmental Factors: There is a possibility that some of the traditional techniques will not prove to be as useful in case the tides, water conditions, and the weather change.
5. Data Inconsistency: The differences in data quality might be caused by the variations in the expertise and methodologies of the observers and as such there are chances of discrepancies in the long-term monitoring programs.

**Advanced mapping techniques for seagrass and seagrass bed**

The seagrass ecosystems have important ecological functions in the coastal ecosystems such as settlement of seafloor sediments, habitation, and a substantial carbon sink. Precise mapping and tracking of the seagrasses are a crucial requirement in conservation as well as management. These sea grass mapping businesses normally take advantage of on-site surveys and aerial images. Nevertheless, not all techniques are primitive thus making a call to the state of the art when employing them in mapping and monitoring of these sensitive ecosystems. The next innovative technique of seagrass mapping and monitoring in the effect of deep learning is the introduction of medium-resolution satellite imagery, especially the Sentinel-2 mission provided by the European Space Agency (ESA) which replaces the traditional methods in various ways.

The approaches to the mapping and monitoring of seagrass spatial distribution have evolved radically with the evolution and access of medium-resolution satellite images, such as sentinel-2, and the ever more robust deep learning algorithms. In the past, the mapping of seagrass has been heavily dependent on traditional methods such as field-based surveys, aerial photography as well as acoustic methods. Sentinel-2 was however a breakthrough in mapping seagrass.

This mission has Sentinel-2A and Sentinel-2B satellites that have a Multispectral Instrument (MSI) that measures images with spatial resolutions of between 10 and 60 meters in 13 spectral bands with visible, NIR and SWIR wavelengths. The variability of the signatures permits to discriminate the species of seagrass in details, identify stressful circumstances and evaluate the water quality parameters, which influence the health of seagrass. The deep learning methods have been included in the satellite images to improve the analysis capability, e.g., Sentinel-2 data. Actually, machine learning artifacts and especially deep learning (and, specifically, convolutional neural networks, CNNs) perfectly is suitable to this requirement of operating on large amounts of data and identifying complicated forms in satellite data. These models too are capable of being trained on known seagrass habitats and this is a valuable approach to improving the accuracy of the classification result and to reducing the cost associated with manual interpretation of the information. Deep learning models continuously evolve with the addition of new data in comparison to the traditional image classification properties and therefore deal with the dynamic environment. The game changer of seagrass monitoring sensors is sentinel-2 and a deep learning because of their spatial coverage and therefore capability to provide more frequent observations than traditional approaches. Sentinel-2 has a global coverage and can revisit every five days, thus giving researchers more chances to monitor seagrass meadow variations in a more consistent and frequent manner than ever before. It is much better than the previous field surveys, which can be seasonal or a one-time event, and it constrains our inclination to record the short-term or gradual change (Duffy et al., 2019; Hedley et al., 2022). The other significant advantage is the deep spectral resolution of Sentinel-2, which, in combination with the deep learning strategy, makes it possible to improve the identification of even minor changes in seagrass health and distribution. Such hi-tech procedures are capable of detecting transformations that would not be otherwise visible using the traditional mapping techniques (Caballero et al., 2021). Using this technology, scientists can learn and preserve these vital ecosystems more through any alterations of the environment.

The application of conventional mapping tools has played a significant role in the study of the biology, conservation, and protection of seagrass ecosystems. The thing is they have enabled us to know seagrass ecosystems better and more efficiently, but in the process a lack of innovation in this area has rendered them more inapplicable than ever. To illustrate, the high-resolution remote sensing, drone data acquisition and GIS analytics are recent ones that assist in improving detection and monitoring of seagrass habitats. By mapping with both traditional as well as emerging technologies, we will be able to optimize the precision, efficiency and depth of our seagrass ecosystem assessment. This integration allows us to take advantage of a more in-depth, data-driven approach to ocean protection and sustainability.

## VI. SCOPE AND LIMITATIONS

One of the notable limitations that have been understood in this research is the significant computational requirements that are associated with deep learning for image classification. Deep learning systems or algorithms are intricate in nature and are noted for the handling of enormous amounts of high-resolution spatial data, therefore having high computational requirements. While ArcGIS Pro does have in-built capabilities for deep learning processes, the successful execution of the processes depends heavily on advanced hardware configurations. Specifically, proper utilization of deep learning in ArcGIS Pro requires a strong central processing unit (CPU), high-end graphics processing unit (GPU) with sufficient VRAM (video memory), and sufficient system memory (RAM) to handle intensive datasets and model training processes. In cases where these hardware requirements are not fulfilled, users can encounter a variety of issues, such as inability to execute deep learning tools, learning rates significantly impaired, and decreased efficiency or accuracy in classification results.

With growing technology in the discipline, subsequent studies can benefit from the implementation of cloud-based computing environments and GPU-enabled virtual machines, which offer scalable computing resources on demand. The technology solutions will tend to reduce local hardware limitations and ensure more efficient processing of big geospatial data. In addition, the implementation and utilization of optimized algorithms along with lean deep learning models can ease computational loads, thus allowing increased access to deep learning methods among geospatial practitioners with limited computing capabilities. Although deep learning offers a convenient solution to image classification and seagrass mapping, its application in the real world is limited by technology. Technological advances and integration in the cloud will be necessary to bridge these limitations and improve model performance and deep learning real-world application to GIS and remote sensing.

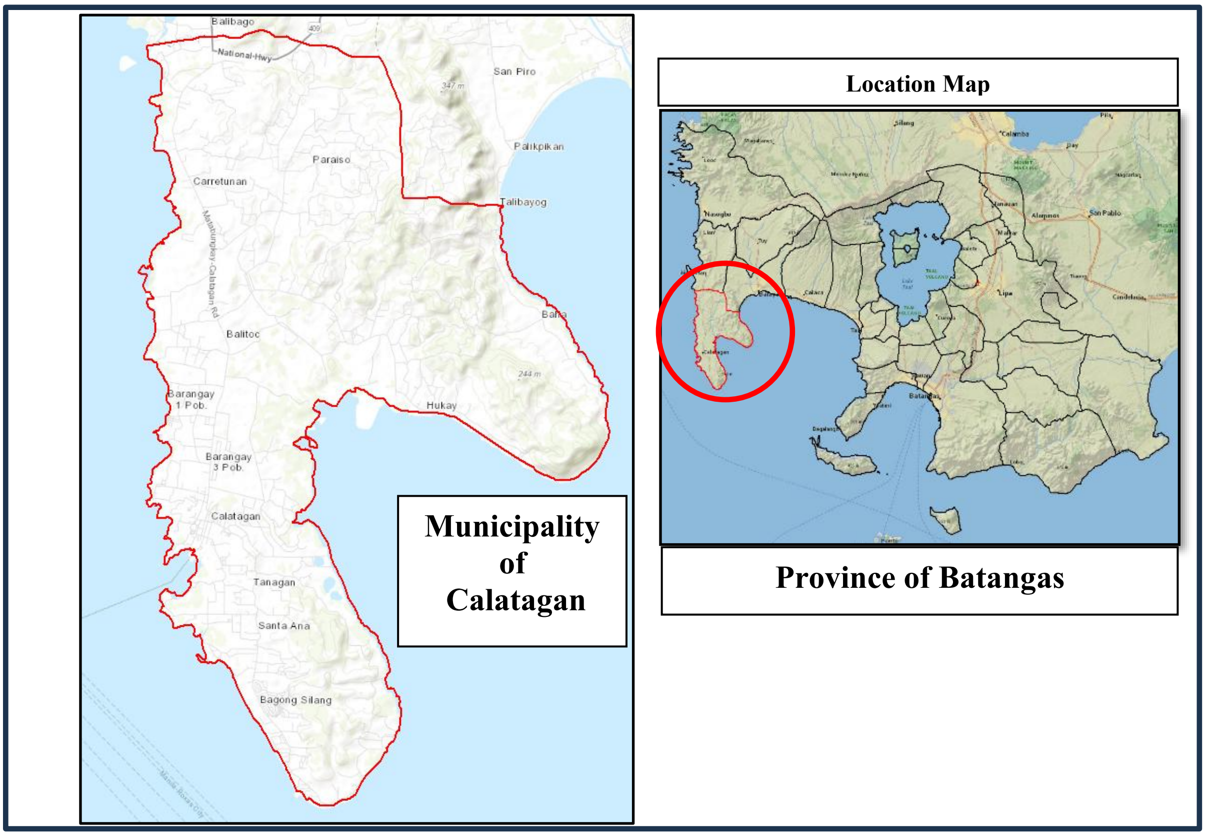
Figure 6.1. Minimum hardware requirements to process deep learning model.

| Specifications | Minimum requirement | Recommended |
|---|---|---|
| Operating system | Windows 10 or 11 (64-bit) | Windows 10 or 11 (64-bit) |
| Processor (CPU) | Quad-core Intel i7 or AMD Ryzen 5 | Multi-core processor with a high clock speed (e.g., Intel Xeon, AMD Ryzen 9, or better) |
| Memory (RAM) | 16 GB | 32 GB or more |
| Graphics Processing Unit | NVIDIA GPU with at least 4 GB of VRAM and CUDA support (e.g., NVIDIA GTX 1050 or better) | NVIDIA GPU with 8 GB or more VRAM (e.g., NVIDIA RTX 3080/3090, NVIDIA Quadro |

| | | |
|---|---|---|
| | | RTX 5000 or better)<br><br>CUDA support: Ensure the GPU is CUDA-enabled (CUDA 10.1 or higher) |
| Storage | 500 GB SDD | 1 TB SSD or more |

## VII. DESCRIPTION OF THE STUDY AREA

Figure 7.1. Location map of the study area.




Calatagan, officially known as the Municipality of Calatagan is a second-class municipality in the province of Batangas, Philippines. The population was 58,719 at the time of the 2020 census. The known Calatagan Peninsula is within the area between the West Philippine Sea and Balayan Bay. Known for their pristine sand, their beaches on the peninsula are also popular vacation and leisure destinations. Calatagan municipal encompasses an extending whole promontory into the Verde Island Passage at the heart of the Coral Triangle, the so-called center of the center of the world's marine biodiversity in its 2007 Smithsonian Institute study. It is noteworthy that many marine species are prevalent in the passage and in the nearby island. You don't need to travel a great distance to see it in Calatagan. Calatagan, a coastal municipality located in the southwestern part of Batangas province in the Philippines, experiences type I climate under the Modified Coronas Classification system. This climate type is characterized by two distinct seasons: a pronounced dry season from November to April and wet season from May to October. The heaviest rain usually falls between June and September, brought in by the southwest monsoon, locally known as Habagat. On the other hand, the sunniest and driest months, especially from March to May, make it ideal for farming and tourism, as the warm weather attracts visitors and supports outdoor activities. The water places that surround Calatagan are true treasures. There is an underwater environment with abundant life found off the beach which has sea stars, crabs, colorful fish and corals swimming in shallow waters and seagrass areas. Going deeper into the water gives chances to observe sea turtles, sharks, and bigger fish that swim close to coral walls and artificial reefs such as the famous underwater pyramids of the town which were constructed there to protect the area.

Calatagan beaches, consisting of Stilts Calatagan Beach Resort and Burot Beach with beautiful white sand also attract residents as well as the international people visiting the beach. Calatagan balances environmental awareness with beach activities to retain its relaxed natural environment with many visitors. Calatagan remains a marine research and conservation center also besides its natural beauty with coral nurseries and community-based preserved areas being some of the conservation efforts to ensure that the living treasures of the sea can be preserved to the generation to come as well. But Calatagan is not a vacation place only, but it is a serious ecological line, a school with no walls where marine science is put into action, and where those are clean who wish to reestablish some communication with nature in her purest aspects. And the community ensures that there is the balance and thus they learn the rhythms of the ocean and they impart those rhythms to the young generation so that this special place may endure throughout eternity.

The marine environment in Calatagan harbors at least eight different species of seagrass that also thrives through an unbelievable amount of life. This plentiful biodiversity includes prominent species such as *Enhalus acoroides* as well as *Thalassia hemprichii* (CARSU Journal, 2020*)*. These underwater meadows are not just pretty things but key to the local environmental balance since they grow into a strong marine home. These seagrass beds are important because they support local fisheries. Subsequently, regional fisheries can strengthen the livelihoods for and nurture the inhabitants within Calatagan. The vigor that these fishing communities show is affected with respect to the seagrass' health.

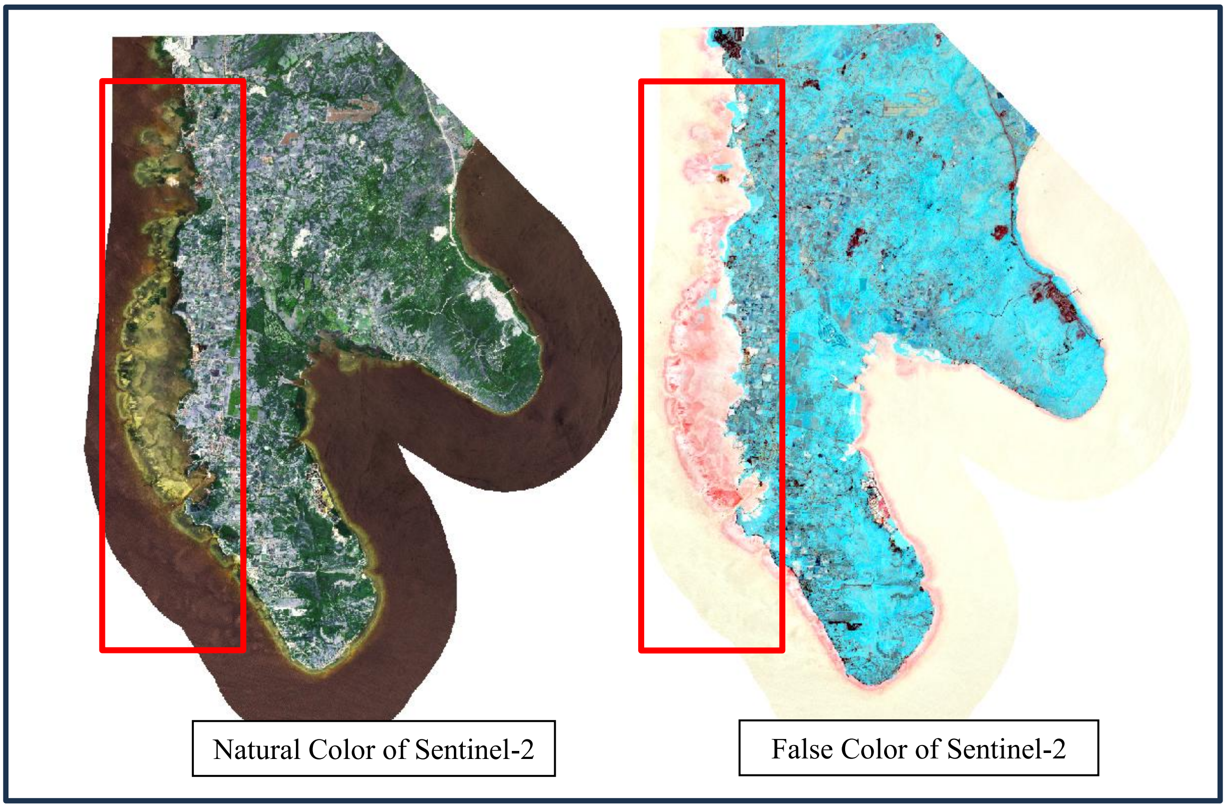
However, these seagrass ecosystems are at risk from a wide range of human activities. Coastal development, which includes the growth of resorts and related infrastructure has put forth habitat degradation via practices like dredging and land reclamation. Also, we see that vessels and recreational watercraft in large parts due to lack of anchor regulations play a great role in direct harm to the seagrass via their propellers and anchors which in turn uproots the vegetation and creates scar tissue on the bottom of the sea (Journal News, 2024). Land use strategies and sedimentation challenges on the coast increasing sedimentation, primarily attributed to inadequate inland land-use practices, poses a significant challenge to the coast. The first ones are runoff and aquaculture effluent that contains an excessive amount of nutrients. These nutrients provide large blooms of algae to the coastal systems. The algae blooms block water areas, which greatly limit the penetration of light, which is required in the photosynthesis of the seagrass.

In addition to that, the pollution associated with untreated sewage, oil and synthetic materials enhances the worsening of water quality hence decreasing the resilience of the vulnerable ecosystem. Ideally, the problem of sediment caused by poor land utilization at the upper register has far-reaching effects that need to be handled through specialities and remedial activities (Coast.ph). Paradoxically, some of the best intended green programs have posed a threat to the seagrass. In certain areas, the mishandling of reforestation, relying on misplaced reforestation of mangroves has led to the planting of trees in the sea grass areas. The above solution has an impact on the regular flow and leads to light-dependent grass shading. The specified transformations end up having more adverse than beneficial results (Haribon Foundation, 2017).

Depletion of seagrass in Calatagan would not just be threatening to the marine biodiversity- it would also help to present a grave danger to the local-coastal communities on which fisheries and eco-tourism depend. This has necessitated the fact that immediate protection and management intervention is done in these ecosystems. Calatagan seagrass resource requires an effective and feasible plan on how to manage the resources sustainably and protect them. It will require a multidisciplinary approach where integration and active involvement of the local community is to be taken. It must be centered on few extensive measures- baseline information collections on the ecosystems through scientific study, intelligent oceanic planning and strict implementation of the regulations on pollution. The local communities should also feel a sense of participation because their participation will be a great factor when it comes to the completion and the sustainability of the conservation programs. To solve the problem of the developing disappearance of these ecosystems and provide seagrass to withstand the current environmental stress. As climate change and fast shore side development continue to increase, the seagrasses at Calatagan act as the first line of defense long before people noticed them because they were underwater silently, sustaining life, as well as storing carbon and preserving shoreline. They are not only an ecological issue but also social and economic and even climatic needs, which are demanding urgent response.

**FOCUS OF THE STUDY**: (Seagrass distribution)

Figure 7.2. Sentinel-2b satellite imagery of municipality of Calatagan showing the potential area of Seagrass and Seagrass beds.




With its distinct spectral signature, seagrass can be effectively detected using Sentinel-2 satellite imagery- in other words, it reflects and absorbs sunlight in a way that's different from other things found in the ocean/sea, like coral, algae, or sand. This is how seagrass stands out in satellite images. The nature of seagrass unique luminosity relates to how light interacts with the leaves themselves. Seagrass contains chlorophyll, like all plants do- it absorbs most blue and red light for photosynthesis but reflects the green portion of visible sunlight. That's why seagrass looks green to human eyes. On top of this, near-infrared light-which is mostly absorbed by water-can also be reflected by the leaves of plants. Different types of plants (with different leaf structures and pigment content) reflect this light in different amounts, even in clear shallow water.

By capturing 13 bands of data, including visible, near-infrared, and shortwave infrared light, the Sentinel-2 satellite is particularly good at tracking these changes, whether it be the difference between seagrass and non-vegetation changes or general shifts in whole populations. Some of these bands (like those in red, green, blue, and near-infrared part of the spectrum) are just what we need for identifying vegetation such as seagrass. More importantly, the Sentinel-2 imagery is periodic (after every five days) hence we can see how large or small seagrass populations are growing or reducing over time because of any form of disturbance. Thus, seagrass is light reflector, but in such a manner that differs significantly with the environment, and Sentinel-2 is able to detect those minor variations. This means that it is a valuable, affordable, instrument of mapping and tracking of seagrass in oceanic surroundings-without actually being physically in the water.

This research paper considers the mapping of seagrass and seagrass beds located in the municipality of Calatagan, Batangas which are densely populated with marine life and have ecological significance. The purpose is to come up with a better way of mapping the areas of seagrass growth which is very essential in ensuring such important ecosystems are preserved against the growing threats of coastal growth, contamination, and climatic transformation. By so doing, the research will involve the use of deep learning software, which is a form of artificial intelligence that is particularly efficient in the analysis of complex and large data sets such as satellite images. Specifically, with the data on Sentinel-2 satellite images, where measurements are made of several ranges of light concurrently, this will allow surface seagrass to be detected in space as a result of how it bounces light, rather than water, sand or coral. Deep learning models, such as those known as convolutional neural networks (CNNs), can learn to detect patterns in this imagery which then allows for automatic detection and classification of seagrass areas. It will be much more accurate and quicker than manual or rule-based mapping methods.

The study aims to generate detailed and reliable seagrass maps for municipality of Calatagan by integrating deep learning and satellite data. The maps can help inform local conservation efforts, marine plans and MPAs, providing a baseline from which the health of the coastal environment can be monitored over time.

# VIII. METHODOLOGY

Recently, there have been substantial developments in remote sensing technologies and machine learning techniques which have shown their ability for remote and large-scale mapping of aquatic ecosystems, such as mangrove forests (Heumann, 2011) and wetlands (McCarthy et al., 2018). Based on these developments, this study uses a deep learning algorithm to classify Sentinel-2 imagery and produce a detailed map of seagrass distribution in the municipality of Calatagan, Batangas. The first will be to acquire and pre-process the Sentinel-2 satellite imagery covering the municipality of Calatagan to make the data high quality for further analysis.

The methodology for acquiring, processing, analyzing and interpreting data for mapping the distribution of seagrass will be carried out systematically in this research. Here is a comprehensive analysis of each step:

## 1. Data Acquisition:

### 1.1 Sentinel-2 Satellite Imagery:

#### 1.1.1 Data Source:

Use the Copernicus Open Access Hub (https://browser.dataspace.copernicus.eu/) or other trusted data portals to access Sentinel-2 data seamlessly. Use these platforms to access high-quality, multispectral imagery for applications such as land use and land cover mapping, vegetation analysis, and environmental monitoring. Your dataset search will leverage high powered search and filtering capabilities to source datasets that meet spatial and temporal criteria, enabling them to tailor data for remote sensing and GIS product analyses.

### 1.1.2 Satellite image selection:

Download Sentinel-2 satellite imagery of study area in Calatagan, Batangas, Philippines. Multispectral imagery at high spatial resolution is provided (10 meters' resolution in visible and near infrared bands and 20 meters' resolution) by Sentinel-2 and is therefore suitable for seagrass mapping.

### 1.1.3 Spectral Band selection:

Choose from Sentinel-2 images spectral bands responsive to the presence of seagrass. Such bands extend into the visible, near infrared, and shortwave infrared spectrum.

### 1.1.4 Spectral Band upscale:

To realize the optimum utilization of Sentinel-2 satellite data for seagrass mapping and analysis, we resample/rescale the 20-meter spatial resolution of short-wave infrared (SWIR) bands to 10 meters' image resolution. Upscaling brings the spatial information of all the spectral bands to a consistent level, and hence the low-resolution bands become comparable to the high-resolution visible and near-infrared (NIR) bands. By improving image clarity and spectral integrity, upscaling enables more accurate habitat delineation, biomass estimation, and environmental monitoring. This methodological enhancement supports better detection of changes in seagrass cover, improves classification accuracy, and aids in more effective coastal ecosystem management and conservation efforts.

1.1.5 Temporal Coverage:

Select images from several dates to document seasonal fluctuations in seagrass coverage and to evaluate potential temporal change. Besides the choice of the images, it is also important to pay attention to the tide information when obtaining satellite images. Tides may have considerable influence on the visibility and area of seagrass area particularly in shallow water.

**2. Data Pre-processing:**

2.1 Image Pre-process*:*

Apply superior image processing and image enhancement mechanisms to enhance the power of Sentinel-2 datasets. These contain creation of composite images to emphasize certain spectral characteristics, use of clipping of images so as to put emphasis on certain areas of interests, and further improvement of image quality. They can be used in land use and land cover mapping, vegetation monitoring and in environmental assessment through better visualization, interpretation and analysis.

2.1.1 Spectral Indices:

Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) are some of the important vegetation indices used when identifying the seagrass meadows among other aquatic and terrestrial vegetation. These indices make use of the spectral reflectance of Multispectral Instrument (MSI) on Sentinel-2 to highlight the properties of vegetation that help in differentiating it over adjacent water bodies, barren land, and sediments beds.

**3. Apply deep learning model to map Seagrasses:**

A systematic workflow is critical for mapping seagrass meadows using deep learning methods. This encompasses creating a classification schema, preparing annotated training data, training a deep learning model, and applying the model for pixel-based classification. This methodology is delineated in detail below.

3.1 Create a Classification Schema

3.1.1 The first step is to create a classification schema that will serve as the framework for the areas to be mapped. In this, Seagrass will be the dominant focus but additional classes like water, sand, and other submerged vegetation will aid in improving accuracy of classification.

3.1.2 Obtain satellite images of high resolution and manually delineate training samples by drawing polygons around the verified seagrass areas. These labeled polygons will later be used as ground truth data for the deep learning model's training.

3.2 Prepare and export the training dataset

3.2.1 Convert the labeled data into a format that is suitable for deep learning applications. This process typically involves isolating image tiles that contain labeled characteristics and standardizing the spectral values.

3.2.2 Use the "Export Training Data for Deep Learning" tool in ArcGIS Pro to generate image chips, annotation files, and the metadata necessary for model training. The exported dataset must meet the specifications of the deep learning model architecture being used, such as TensorFlow, Pytorch, or Keras.

3.3 Train the Deep Learning Model

3.3.1 First use the “Train Deep Learning Model” function of ArcGIS Pro to create a model such as a Convolutional Neural Network (CNN) or a U-Net segmentation model.

3.3.2 Fine-tune hyper-parameters like learning rate, batch size, and number of epochs for the model to enhance performance.

3.3.3 While training the model, critical metrics such as accuracy, precision, recall, and loss functions must be kept in check, for that would determine how to evaluate the learning process of the model and how to change it to achieve better results.

3.4 Evaluate and Refine Model Performance

3.4.1 Monitor the training process by evaluating accuracy and loss curves over time. An effectively trained model typically exhibits a steady decrease in loss values along with a corresponding increase or stability in accuracy across training epochs. Consistent trends in these metrics indicate that the model is learning effectively and generalizing well to the data. Sudden spikes or plateaus may suggest issues such as overfitting, underfitting, or learning rate imbalance that may require further tuning.

3.4.2 Use independent test datasets to check how well the model works on new data. This helps assess if the model is generalizing properly. If needed, adjust the model's settings or structure to improve its accuracy and performance.

3.5 Classify pixels Using Deep Learning

3.5.1 After completing the training process, deploy the trained model on Sentinel-2 imagery to classify pixels and generate a comprehensive seagrass distribution map.

3.5.2 The Classify Pixels Using Deep Learning tools in ArcGIS Pro execute the model to create a high-resolution thematic raster map which accurately shows seagrass coverage.

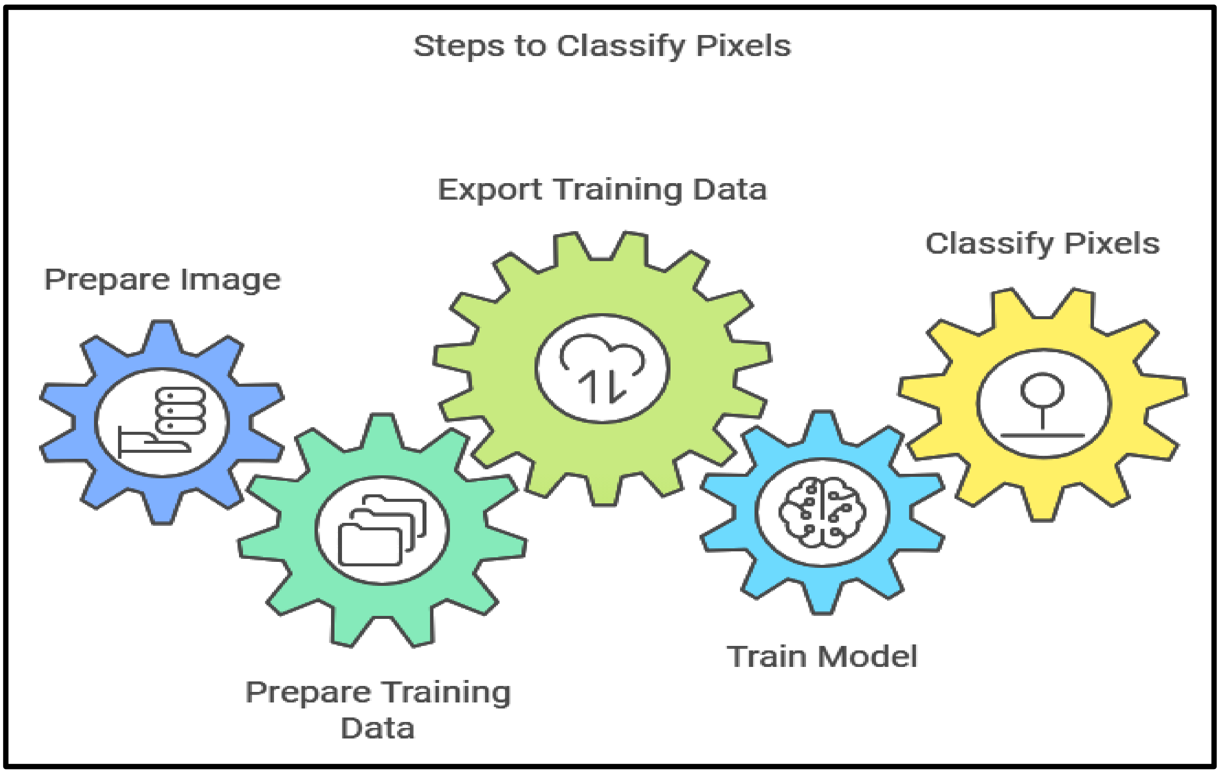
3.5.3 The final seagrass distribution map requires enhancement through post-processing techniques which include noise reduction and spatial filtering and smoothing to achieve better accuracy.

Through visual digitization, the research will delineate seagrass and seagrass beds to create the training samples. The trained 'seagrass' polygons are then exported as training data with the help of deep learning tools in the ArcGIS Pro Image Analyst extension. The training data will be used by these tools to identify similar seagrass and seagrass bed features within the entire satellite image of the study area. In an iterative experiment, the outcome will be optimized using deep learning models through various set of hyper parameters. We will then run the model and validate the output. The study will perform comparative analysis and image validation.

## Sampling Design

The complete deep learning workflow is being used in this research, and the ArcGIS Image Analyst extension within ArcGIS Pro will be utilized to run this complete deep learning workflow, as seen in figure iv. This extension with its set of advanced tools supports performing all the stages of the analysis within one such platform in a convenient way.

Figure 8.1. Deep Learning workflow in using ArcGIS Pro.




## Training Data Collection

The training data used in this study were primarily derived from two key sources: very high-resolution satellite imagery available through Google Earth, and the officially published Coastal Resource Map produced by the National Mapping and Resource

Information Authority (NAMRIA). Google Earth imagery delivered visually intricate, high-resolution optical data which enabled the manual detection and digitization of seagrass beds through spectral and textural analysis. The method proved exceptionally effective for mapping seagrass patches in swallow coastal regions where canopy structure and coloration remain detectable. The NAMRIA Coastal Resource Map functioned as a dependable reference dataset by providing authoritative and validated spatial information about seagrass distribution along with other coastal habitats. The maps came up as a result of intense field survey alongside geospatial analysis that increased credibility as well as the contextual accuracy of the training samples.

With the aggregate of these sources the training dataset was obtained that represented the seagrass extents and conditions in different geographic settings. The first stage of the study was also based on the high-resolution visual interpretation and government-validated habitat data, which helped to create a solid base on which the deep learning model training was performed without the physical field data collection.

**Improving the Methodology for Sustainable Resource Management**

The data should be collected of good quality; however, it is equally more important that the methodology should be adequate so that the data that will be collected remains sound and useable in a guaranteed resource management programme in the long run. The following are some of the ways that can be used to enhance the data collection, management and application, such that the results of this study enhance wise decision making and add to the preservation of the coastal ecosystems.

1. Standardizing Data Collection and Validation

The following data collection methods and validation have to be standardized to give the data collected is accurate and consistent:

1.1 Field Survey Uniformity: The methodologies of data collection based on GPS-tagged surveys, drone mapping, boat-based surveys, and similar data collection, should have uniform data collection methods, whereby the collected data will be compatible regardless of the location. Such uniformity also contributes to more accurate predictions of the model.

1.2 Regular Field Validations: It is referred to as regular field validation since it is more likely to carry out accurate checks later. This is so that the forecasts made by the model are in line with what is taking place on the surface land/actual ground. In many cases this may be enough to view satellite data since it is rather off particularly with cloud cover or atmospheric conditions.

1.3 Stratified Sampling: We are collecting data based on the various species of seagrasses not only by the depth of water but also by the turbidity and density of the canopy. It would allow the data to capture what the reality is when it is related to the diversity of seagrass habitat; hence it would assist in enhancing model performance in relation to changing conditions.

2. Enhancing our Model and Embracing uncertainty:

In developing trust in our models, an elemental channel among building trust is open communication about our confidence levels. The following are effective approaches that can be taken to this objective:

2.1 Sensor Errors: There are camera and equipment malfunctions, but the identification of them paves the way to identify possible improvements.

2.2 Environmental Factors: The manner in which images are taken is based on weather conditions that require us to follow our ways in order to capture aspects as they are.

2.3 Human Error: The occurrence of data entry errors and corrections does occur but detecting them is encouraged to facilitate better training and procedural development.

By having the awareness of possible flaws and the way they impact our model, we know which specific areas need to be improved when it comes to either quality of data or methodological practices. Studying the recurring issues in specific satellite captures, we can pursue alternative data repositories, dedicating financial resources to high-quality instruments, and obtain a reliable output.

3. Improving Model Transparency and Understanding Uncertainty:

In the case of uncertainty, it is vital to point out any possible errors in our predictions. The following tools might be useful in this attempt:

3.1 Confidence Intervals: These intervals are the state of uncertainty of our forecast. They act as a reminder that despite our levels of confidence we are still capable of error.

3.2 Error Maps: These are represented as graphic images of locations where our model lacks confidence. An illustration here is when considering plant development in various locations, through an error map, we are able to identify areas where our estimates are less reliable. Such information enables the stakeholders to concentrate on such unclear areas, which could result in field studies in order to enhance data collection.

4. Engaging stakeholders for continuous feedback:

The stakeholders should be kept involved in the process in order to make the model useful and relevant:

4.1 Interactive Dashboards Allow the easy visualization of the distribution maps and the trends of seagrasses by the stakeholders in real-time. These tools are able to display predictions as well as confidence and context. An example that these tools present is that when these tools come into the hands of local communities, government agencies and conservation group, there would be much easier time to read and make informed decisions under the guidance of the data. Among the attractions of such tools is the fact that the interpretation as well as the execution of actions that involve data is made effortlessly easier to all individuals.

4.2 Feedback Loops: Empower the stakeholders to integrate the local knowledge and identify the mis-alignments in the system. Feedback is given to us by the stakeholders who indicate our areas of data shortcoming. Such connections enable ongoing model enhancements because they help the model mirror daily operational realities.

4.3 Regular Stakeholder Involvement: Stakeholders must remain active participants during both the development stage and during revision processes.

Ongoing consultations and workshops ensure the model stays functional and applicable to real-world working situations.

5. Integrating Model Outputs into policy and management:

The model's results can only be effective if they become integrated elements of current policy framework and management strategies.

5.1 Partnering with Agencies: The partners involved in the seagrass mapping activities – intergovernmental and governmental consortium-will find that the results are crucial in guiding significant choices in marine spatial planning, coastal zoning, and managing protected areas for local and national Philippine authorities such as the Department of Environment and Natural Resources (DENR) and the Bureau of Fisheries and Aquatic Resources (BFAR). The findings of the model also deliver information applicable in the real-world management.

5.2 Adaptive Management: An adaptive management strategy will also make sure that there is a regular update of the model with new information and accordingly the way the management strategies are revised accordingly. This makes management dynamic and flexible to different environmental changes along the coastlines.

5.3 Long-term Monitoring Programs: With the model being a baseline, by establishing long-term monitoring, it will be possible to track the changes in seagrass distribution and health with time. This is useful information that can be used in future decision making and makes the model reliable in the future in terms of resource management.

This study provides guidance on mapping and managing seagrass, specifically improving data collection and management practices, improving stakeholder involvement, and integrating the model into policy frameworks. These options would keep data and models relevant and adaptable so that informed and sustainable decision-making can be made for the future to benefit the protection and conservation of coastal ecosystems.

## DATA SOURCE SPECIFICATION

Sentinel-2 mission consists of two satellites – Sentinel-2A and Sentinel 2B, launched in June 2015 and July 2016 respectively. These satellites are devoted to Earth observation equipped with a Multi-Spectral Instrument (MSI) having 13 spectral bands, spectral resolution of 10, 20, and 60 meters. In certain frequencies, the sensor can detect objects as small as 10 meters on the ground, producing high-resolution images (see Table 8.1.).

**A summary of a few important specifications is below:**

1. Orbit: The Sentinel-2 satellites conduct operations from an altitude of 786 kilometers in a sun-synchronous orbit. With the satellites passing over the same location at approximately the same local time each day, this orbit guarantees consistent illumination conditions. At 10:30 Mean Local Solar Time, the satellite passes through the descending node, which is the point at which it transitions from north to south. This provides the most favorable illumination conditions for the acquisition of images.

2. Revisit Time: Sentinel-2 has two operational satellites, with a five-day revisit time. This frequent coverage makes it possible to monitor, in effect, dynamic changes in Earth's surface, such as vegetation growth, water fluctuations, and urban development.

3. Swath Width: With its wide swath width of 292 kilometers, the sensor is well suited to map large areas in a single pass. This characteristic improves operational effectiveness and data acquisition over large landscapes.

4. Design Life: Sentinel-2 is designed for a 7-year mission life. Yet they carry enough fuel (123 kg) to orbit for up to 12 years, including Fuel for end of life deorbit maneuver fuel. Indeed, this extended operational lifespan guarantees a long period of continuous flow of Earth observation data.

Table 8.1.

*Specification of Sentinel-2 satellite sensor*

| Launch | June 2015 (2A) & July 2016 (2B) |
|---|---|
| Orbit | Sun-synchronous at altitude 786 km, Mean Local Solar Time at descending node: 10:30 (optimum Sun illumination for image acquisition) |
| Revisit Time | 5-days from 2-satellite constellation |
| Swath Width | 292 km |
| Design Life | 7 years (carries consumable for 12 years: 123 kg of fuel including end of life deorbiting) |
| Radiometric Resolution | 12-bit |
| Spatial Resolution | 10/20/60 meters |
| Temporal Resolution | 5 days |
| Spectral Resolution | 13 bands |

There are 13 spectral bands available on the Sentinel-2 satellite, but this research will concentrate on just 7 of them. More specifically, the analysis will make use of 10 meters' spatial resolution visible bands, and Near-Infrared band (NIR) with Narrow NIR bands and two SWIR (shortwave infrared) at a 20 meters' spatial resolution. This approach accounts for the heightened resolution of visible bands while including beneficial information provided by Narrow NIR and SWIR band which would help in performing a relatively better integrated analysis over the study areas. Among the listed spectral bands, only those indicated by red text have been identified in this study as relevant for image analysis. Band 8A, 11, and 12 have their resolution upscale to 10 meters to match Sentinel-2's higher band resolution (see Table 8.2.).

Table 8.2.

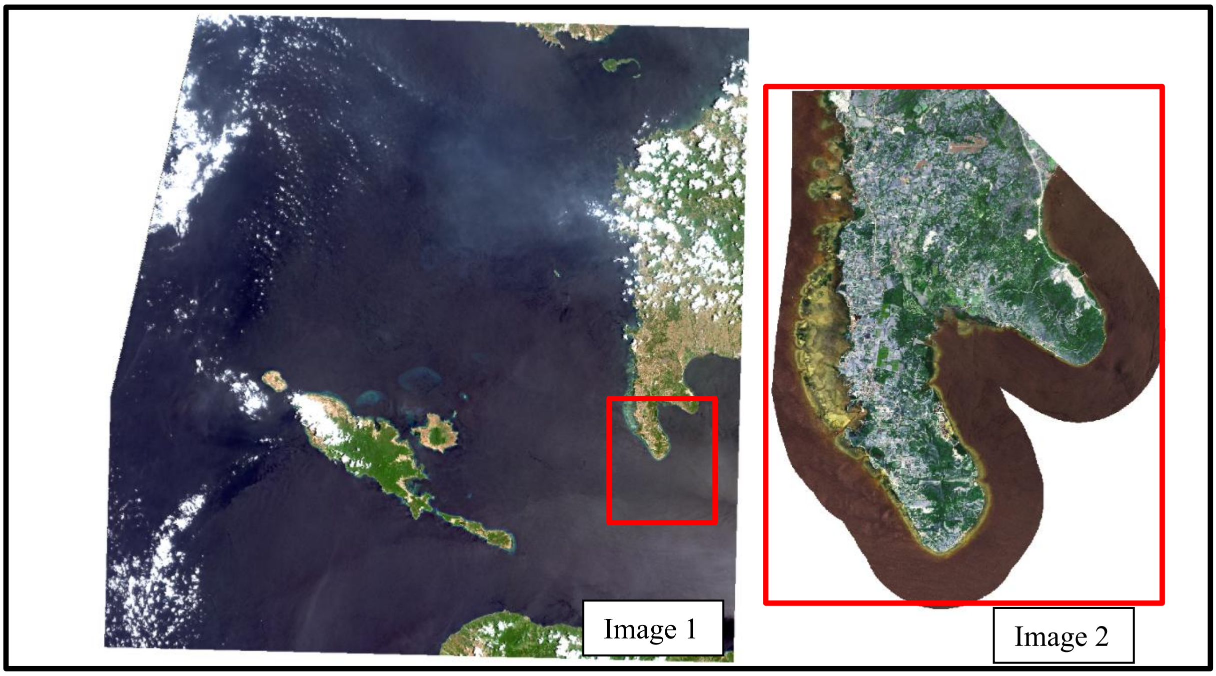
*Sentinel-2 satellite image spectral bands*

| Sentinel - 2 Bands | Description | Central Wavelength (µm) | Spatial Resolution (m) |
|---|---|---|---|
| 1 | Aerosol | 0.443 | 60 |
| 2 | Blue | 0.490 | 10 |
| 3 | Green | 0.560 | 10 |
| 4 | Red | 0.665 | 10 |
| 5 | Vegetation Red Edge | 0.705 | 20 |
| 6 | Vegetation Red Edge | 0.740 | 20 |
| 7 | Vegetation Red Edge | 0.783 | 20 |
| 8 | Near-Infrared (NIR) | 0.842 | 10 |
| 8A | Narrow NIR | 0.865 | 20 (10) |
| 9 | Water vapour | 0.945 | 60 |
| 10 | SWIR - Cirrus | 1.375 | 60 |
| 11 | Shortwave Infrared | 1.610 | 20 (10) |
| 12 | Shortwave Infrared | 2.190 | 20 (10) |

# IX. RESULTS

The Sentinel-2 satellite image dated April 16, 2025, is downloaded in the Copernicus portal hub (https://browser.dataspace.copernicus.eu/) with no cost covering the study area of the research. The satellite passes through the same location at around 2:15 PM every 5 days comprising of twin satellites orbiting the earth (Sentinel-2A and Sentinel-2B). The trend in the tide and timetable of Batangas province shows that around 4:00 in the afternoon is the second lowest tide of the province and this indicates that seagrass is more exposed to surface during this time (Tide-Forecast.com, 2025). The sentinel-2 space-borne satellite images require data preprocessing, such as image sub-setting and upscaling. The upscaling method implies that each of the spectral bands used in the study has its spatial resolution increased from 20 meters to 10 meters. Sub-setting or image clipping was used to extract the study's specified area, which in this case was the municipality of Calatagan, Batangas. The visual distinction of seagrass was increased within the satellite imagery through advanced image enhancement techniques. It is essential in the accurate separation of seagrass areas as well as in the identification and selection of these same precise training samples for subsequent analysis (see Figure 9.1.).

Figure 9.1. Sentinel-2 image acquired in April 16, 2025 (1) full scene (2) subset.




Training samples were generated in polygon format or shapefile extension, following a classification schema for the seagrass category. Using ArcGIS tools, these samples were manually digitized, resulting in a total of 13 training polygons, as illustrated in Figure 9.2. and 9.3. Using Export Training Data for Deep Learning tool, the training samples are saved in a chosen folder in tiff format, together with labelled or classified images. Then these samples are then split to 20% for testing the trained deep learning model and 80% for training the model, so that the deep learning model learns well and can be checked accurately.

Figure 9.2. Training samples of seagrass overlaid in Sentinel-2.

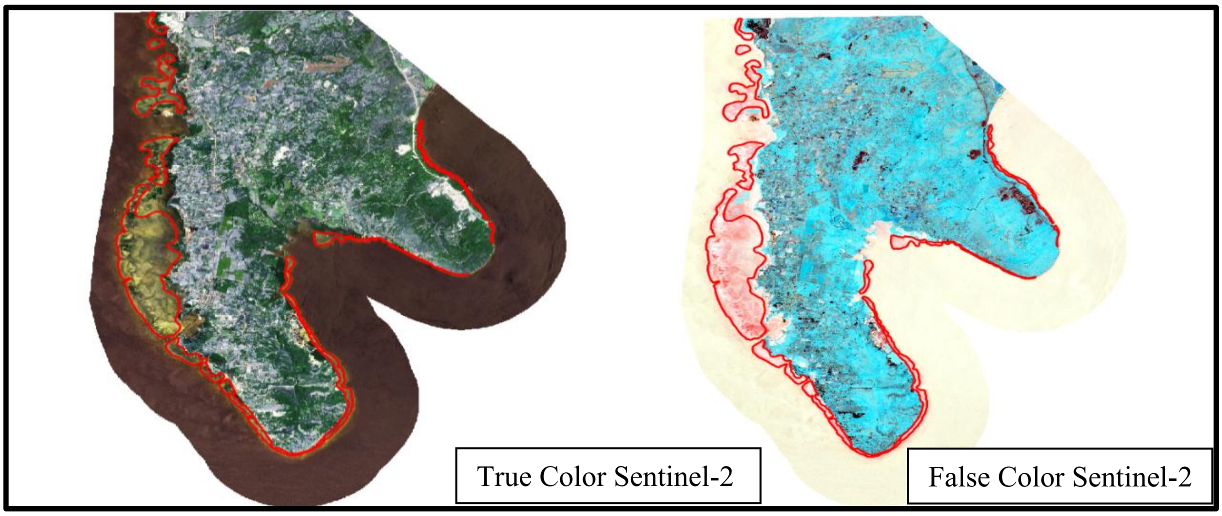



Figure 9.3. Generation of training sample Classification schema.

TrainingSample_new_schema

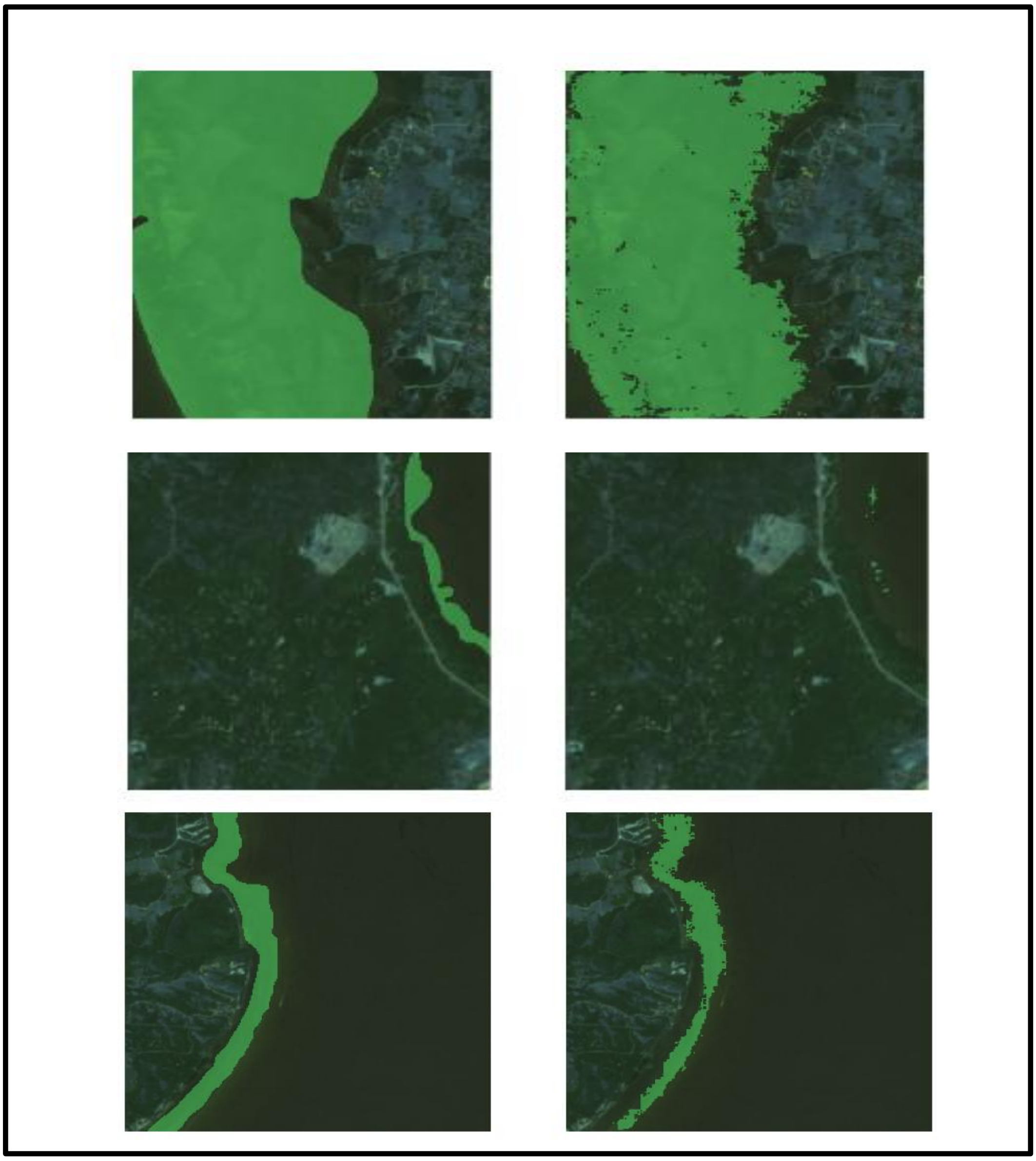
Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear De

| | FID | Shape | Classcode | Classname | Classvalue | RED | GREEN | BLUE | Count |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | Polygon ZM | Code_0 | Seagrass | 1 | 82 | 231 | 106 | 6220 |
| 2 | 1 | Polygon ZM | Code_1 | Seagrass | 1 | 153 | 48 | 96 | 3431 |
| 3 | 2 | Polygon ZM | Code_2 | Seagrass | 1 | 153 | 236 | 23 | 1991 |
| 4 | 3 | Polygon ZM | Code_3 | Seagrass | 1 | 7 | 158 | 207 | 80275 |
| 5 | 4 | Polygon ZM | Code_4 | Seagrass | 1 | 124 | 247 | 240 | 14973 |
| 6 | 5 | Polygon ZM | Code_5 | Seagrass | 1 | 187 | 153 | 97 | 9809 |
| 7 | 6 | Polygon ZM | Code_6 | Seagrass | 1 | 68 | 20 | 133 | 7948 |
| 8 | 7 | Polygon ZM | Code_7 | Seagrass | 1 | 121 | 63 | 87 | 1435 |
| 9 | 8 | Polygon ZM | Code_8 | Seagrass | 1 | 177 | 229 | 200 | 10673 |
| 10 | 9 | Polygon ZM | Code_9 | Seagrass | 1 | 132 | 72 | 228 | 8006 |
| 11 | 10 | Polygon ZM | Code_10 | Seagrass | 1 | 33 | 23 | 83 | 2447 |
| 12 | 11 | Polygon ZM | Code_11 | Seagrass | 1 | 52 | 201 | 180 | 337 |
| 13 | 12 | Polygon ZM | Code_12 | Seagrass | 1 | 50 | 245 | 209 | 664 |

Click to add new row.

The Exported training data was fed to the Train Deep Learning Model tool, which generated a set of image chips. In the case of image chips, smaller, zoomed-in sections of the whole set of images are created for the model to focus on, specifically picking the feature or object of interest. Those chips are important because their size — how big or small they are — can have a large impact on how well the model learns and recognizes patterns as it trains. For instance, if the image chips are too large, the model may pick up unneeded details; or if it is too small, the model may overlook important stuff. Figure 9.4. shows how this well-considered size of the image chips helps refine the training and improve the model’s accuracy. In total, 207 small image sections (so-called 'image chips') of size 256 pixels by 256 pixels were created. These are image chips, serving as focused snapshots of larger images that have been specially sized to only capture what is important at 256 pixels across.

Figure 9.4. Sample of Image chips created to train deep learning model.



For this study, we configured a deep learning model with appropriate parameters to achieve optimal training given the limited processing power of the computer. To train the model we gave it 30 epochs, meaning it passed over the whole training dataset 30 times so that the learning also became better over time. We set the batch size to 16, which means the model will update its parameters, after it processes 16 images at a time. We chose this smaller batch size because it would fit in with the available computing capability as well as be a manageable number to initially train with. For image classification task, we used a well-known ResNet34(Residual Network with 34 layers) as backbone. The effectiveness of ResNet34 stems from the use of ‘residual learning,' which helps more information to flow in each layer to the next. The model will better identify objects or features in images as it goes deeper, as our approach helps keep important details as the model goes deeper.

The analysis of the model shows a 0.86 precision, or 86 percent — it correctly predicts 86 percent of the times it marks the prediction as positive. This precision allows us to define a parameter that would tell us how often the model's positive predictions are correct, this is like how often it says something is positive. The recall is another important metric that gives us how well the model caught all actual positive cases from the dataset. The recall of the model in this study is 0.83, that is to recall comes out to be 83 percent of which 83 percent of true positive cases in the data were correctly identified by the model. In other words, precision is checking if the model found the right positives and recall is knowing if there are any positives are missing. For this model, we have an F1 score of 0.85 or 85 percent, combining precision and recall. F1 score is the harmonic mean of precision and recall — it is a well-balanced view of whether a model can accurately and comprehensively identify positives. To summarize, precision ensures that those positives are correct, recall that the model shouldn't ignore any of them and the F1 score shows us the model's overall performance.

Figure 9.5. Analysis of the model per class metrics.

**Analysis of the model**

**Per class metrics:**

| | NoData | Seagrass |
|---|---|---|
| **precision** | 0.983575 | 0.864667 |
| **recall** | 0.986881 | 0.835688 |
| **f1** | 0.985225 | 0.849930 |


```
    "per_class_metrics":
"{\"NoData\":{\"precision\":0.9835746884,\"recall\":0.9868810773,\"f1\":0
.9852250814},\"Seagrass\":{\"precision\":0.8646672368,\"recall\":0.835687
6373,\"f1\":0.8499304652}}"
}
```


This metric of accuracy shows how frequently a deep learning model predicts things right. The value is calculated by dividing the number of correct predictions by total number of predictions that the model makes and comes out as 0 to 1, where 1 means the perfect accuracy. More precisely, accuracy is the percentage of times the model got it right. The accuracy for this model was 0.931 or 97.31 percent, indicating that this model did acknowledge the intended patterns in the data and thus performed well. The reliability of the model in making accurate predictions is really evidenced by 97 % accuracy, which means that for all predictions made at times, the model was correct 97 percent of the time. This is a powerful predictor of model effectiveness, particularly in tasks that involve remote sensing data.

Figure 9.6. Showing deep learning model overall accuracy and multispectral imagery with a 256 X 256-pixel size format.


```
"accuracy": "9.7310e-01",
"resize_to": 256,
"IsMultispectral": true,
```


There is a learning curve in deep learning, that is, a graph showing how models' performance increases as trained on more data or throughout more training cycles called epochs. Normally, a learning curve draws performance metrics like accuracy or loss over time and graphs how well the model performs on the training data (data it's learning from) and validation data (not previously used in training). Learning curves are excellent for determining how well or poorly a model is trained. These measurements are employed to assist in detecting problems like overfitting — where a model is strong on training data but weak on validation data. This implies that perhaps the model learned some of the details in the training set rather than generalize it, and hence it suggests the memorization, which seems not a good behavior for generalization. And if the model doesn't perform well with training and validation data, that could mean the model under fitting — that is, the model has not learned enough from the data available. To sum it up, learning curves are easy to look at to see whether a model is well balanced, learning effectively, and ready to make good predictions on unseen data. In this study, we see that the learning curve for the model is learning quite effectively, even though there are a few ups and downs throughout the beginning of the training. As the model gets familiar with the data and starts to make sense of the patterns, you will see these minor bumps, or "noise" in the beginning as the model learns. In practice, it is nice to see the curve flatten as training continues, which it definitively is, as it is a strong indicator of when the model fits well to the task. A progression of training and validation loss metrics illustrates the model's learning trajectory across 120 batch iterations. The validation loss maintains a stable, low value without upward movement, while both losses exhibit a consistent downward trend. The model's performance indicates effective generalization without overfitting, as it learns meaningful data patterns rather than memorizing training examples (see Figure 9.7.).

Figure 9.7. Learning curves (training and validation loss curve) of deep learning models.

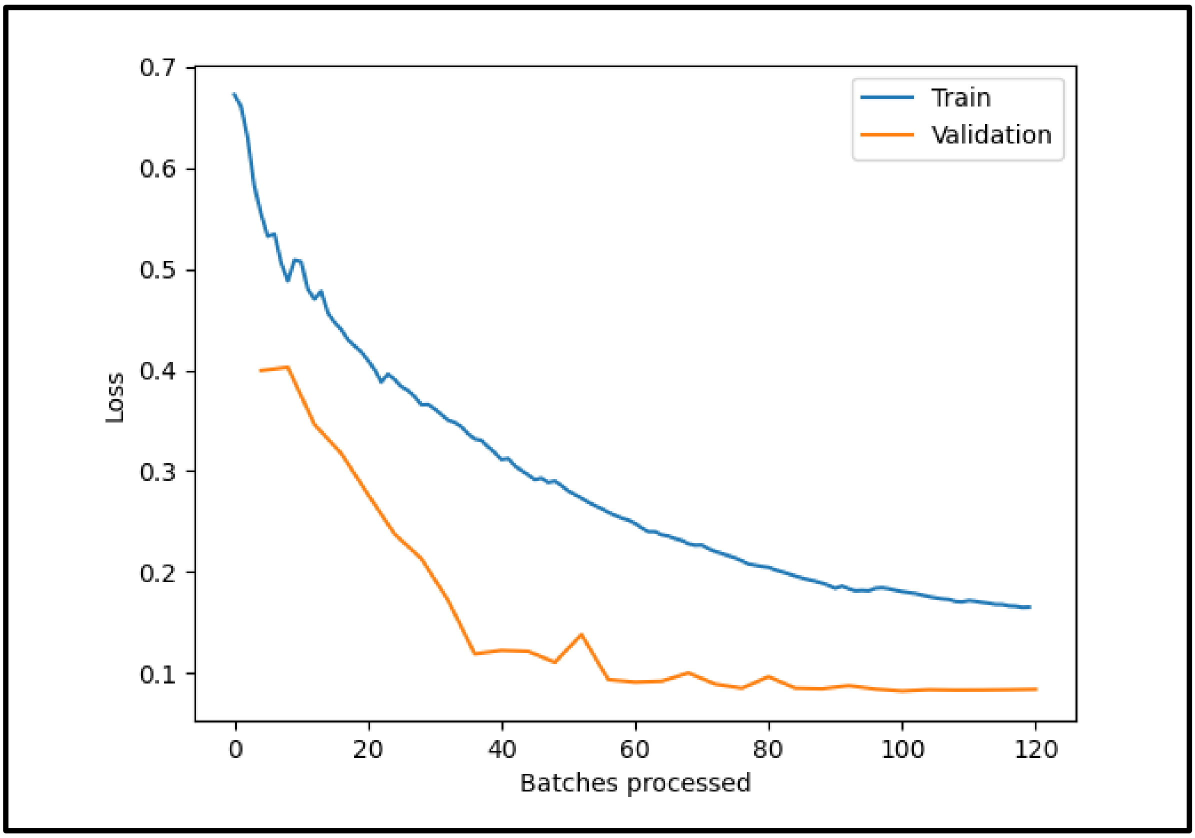
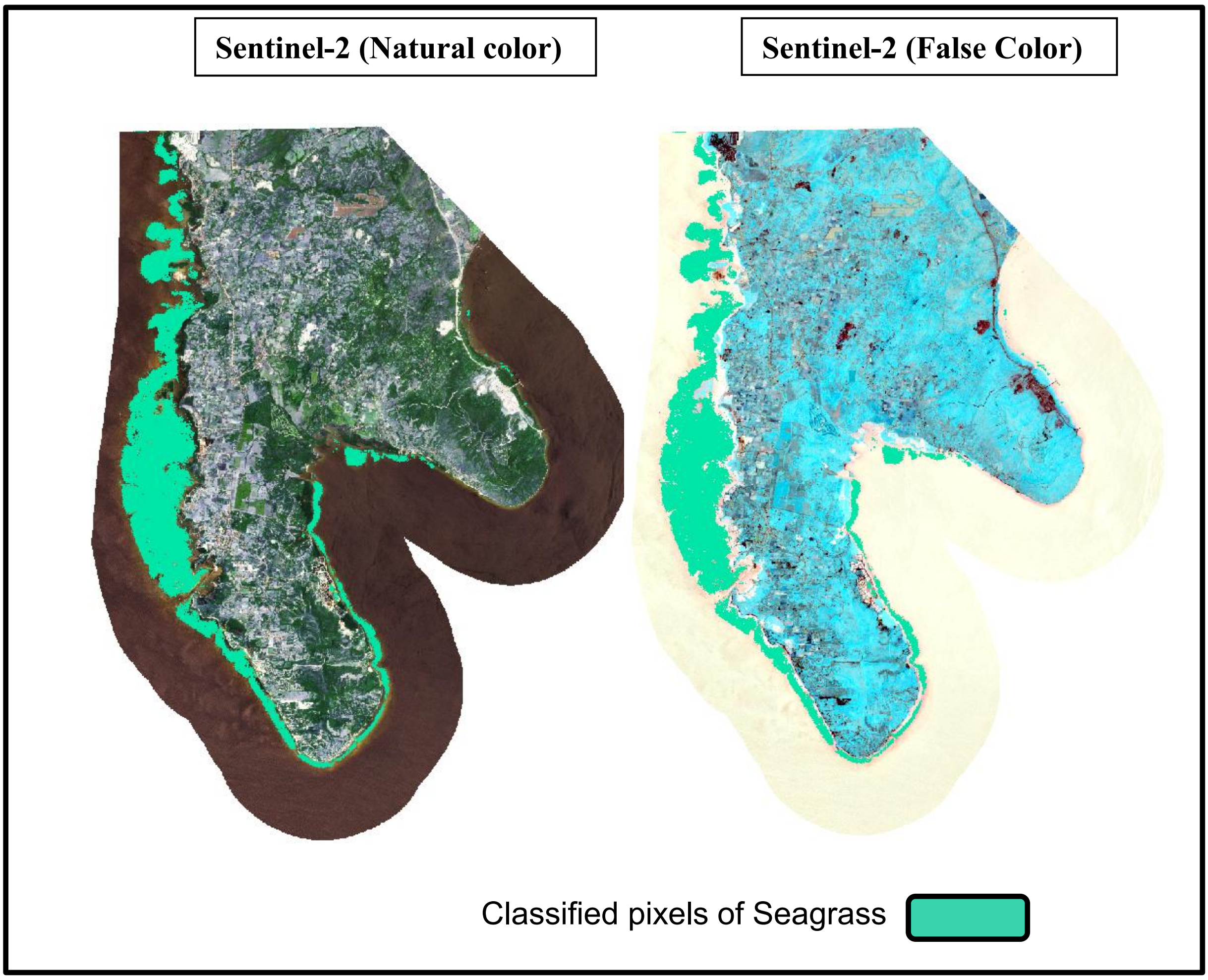


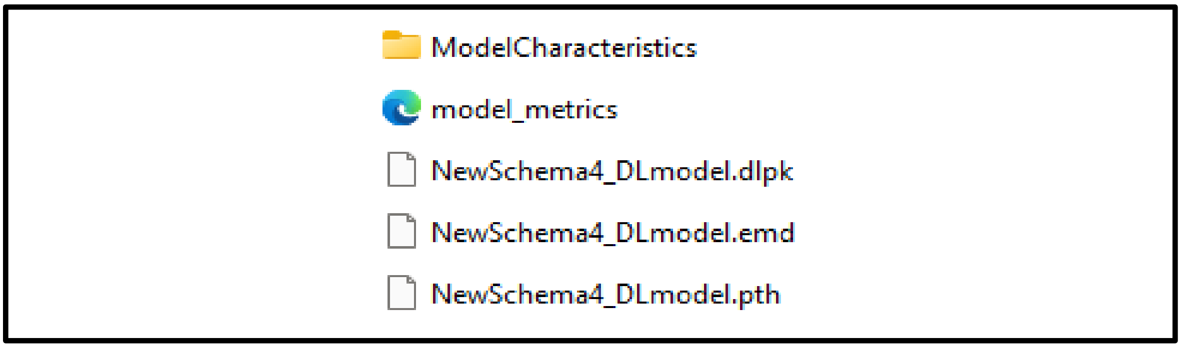
Figure 9.8. Results of Seagrass classification using the trained deep learning model.



# X. RESULTS AND DISCUSSION

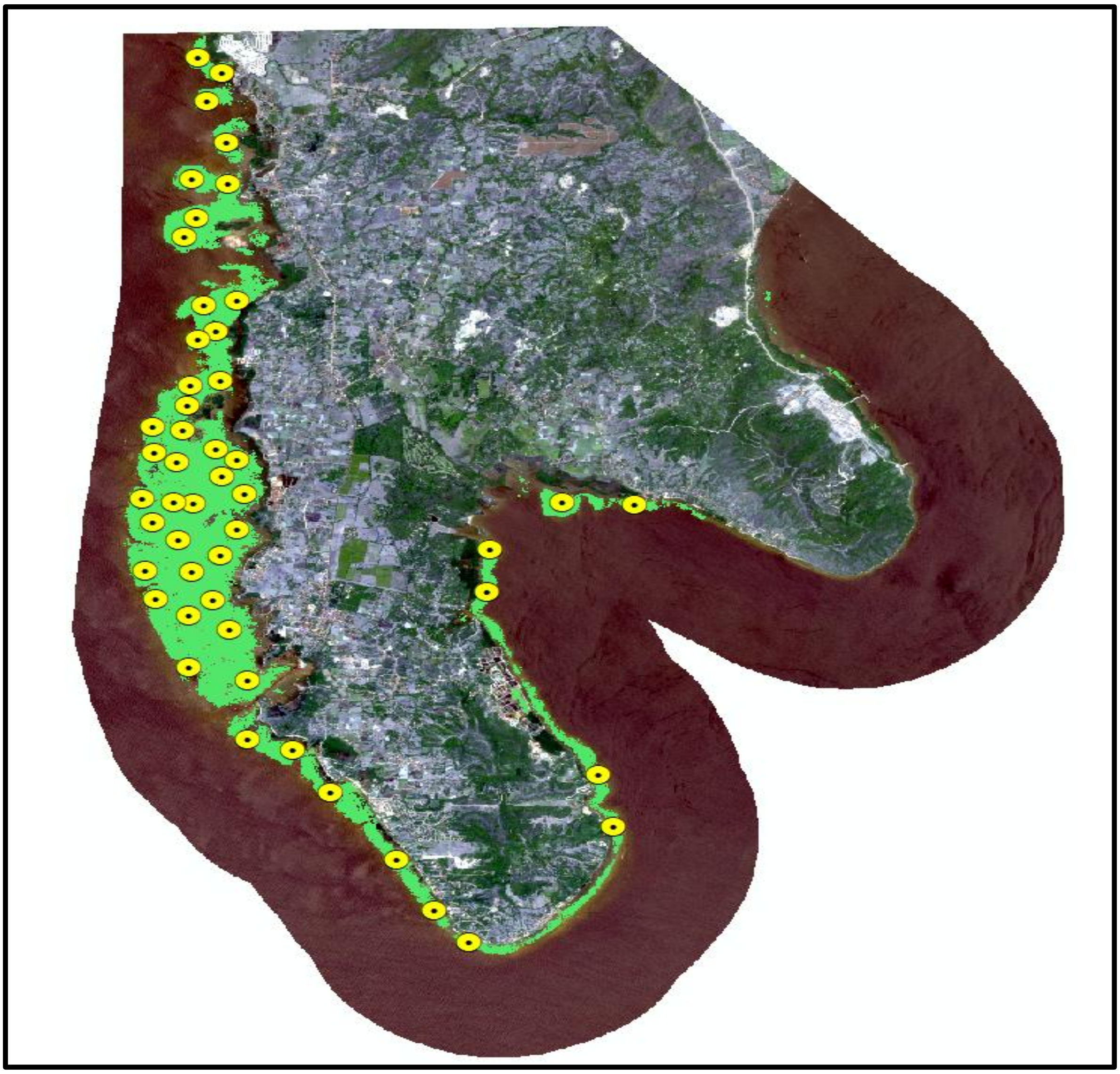
Comprehensive evaluation of the ArcGIS Pro deep learning model's training outcome regarding seagrass will be done. In this assessment, the model will be thoroughly examined in relation to specific model metrics: Often shown in a tabular format, these are: 1) precision, 2) recall, 3) F1 score and 4) accuracy. Additional information included in the model_metrics.html file is the model type and backbone used, the learning rate, training and validation loss, model analysis, and sample results.

Figure 10.1. Figure displays the essential folder content for deep learning project.




A systematic generation process produced set of accuracy assessment points to evaluate the deep learning model's performance in seagrass cover classification. These reference locations function as validation points where seagrass classification results are cross-checked against ground-truth information or high-resolution reference data by comparing predicted class labels. This process aims to evaluate the model's classification performance while detecting misclassification origins to guarantee the seagrass distribution map's reliability. The evaluation process has been a key aspect in the remote sensing activities where advanced deep learning tools are applied since they provide confidence measure of spatial outputs as well as enhancing reliability of the mapping project. Using stratified random sampling, or proportional random sampling, up to 50 sampling points were generated. This technique provides sampling based on the proportionate representation of the distinct subgroups or strata into which the classification/population is divided. This is designed to improve the work's accuracy and representativeness.

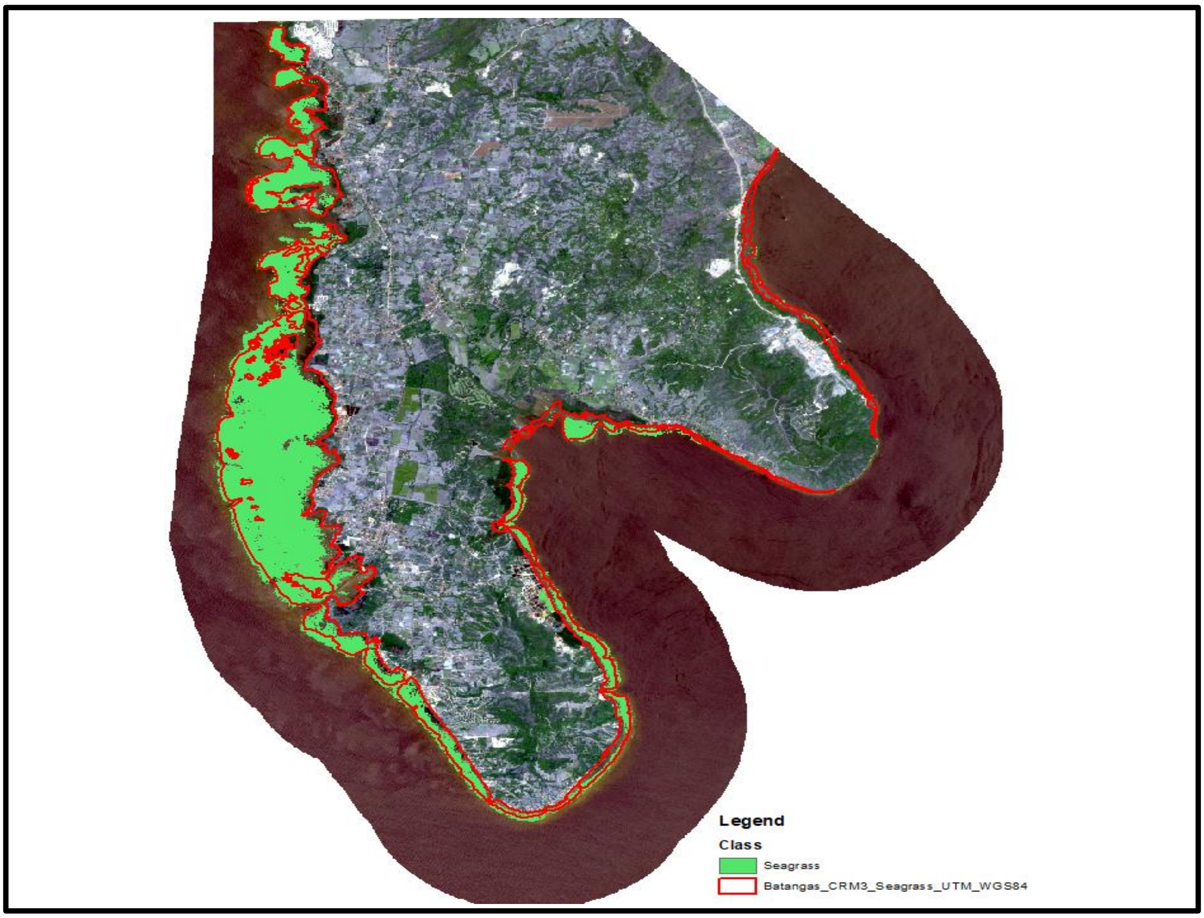
Figure 10.2. Creation of accuracy assessment points of the classified pixels (Seagrass).



A comparative analysis will also be conducted between seagrass estimated from the trained deep learning model and the Coastal Resource Management (CRM) data of National Mapping and Resource Information Authority (NAMRIA). The investigation performed image validation procedure to determine both the precision and dependability of remotely sensed data classifications for seagrass features. The validation was done in a thorough visual comparison of the classified seagrass pixels to the features in the updated Coastal Resource Map (CRM) supplied by the National Mapping and Resource Information Authority (NAMRIA). This comparison aimed to assess how well the remotely sensed classification output matched the spatial patterns found in authoritative reference data. The generated shapefile of seagrass features was examined for extend and distribution against those recorded in the CRM. The assessment concentrated exclusively on the spatial extend of classified seagrass polygons to determine the correspondence between remote sensing classification and current coastal resource inventories. The seagrass extent within the municipality of Calatagan based on the Coastal Resource Management (CRM) project of the National Mapping and Resource Information Authority (NAMRIA) is approximately 2,195 hectares with a comparison of around 1,869 hectares as estimated by the deep learning classification model which represents a difference of 326 hectares, showing that the deep learning model underestimated the seagrass coverage to the CRM data of NAMRIA. Despite the underestimation of the seagrass using the deep learning model algorithm, it shows high potential for automated mapping of the said habitat.

Moreover, the result of the deep learning will also be compared with satellite imagery, such as the Google earth imagery, and will be validated. Results of the training model will be discussed as well as comparison of the conventional and deep learning procedures. This study shows that the deep learning model developed performs well and makes promising predictions about seagrass habitats. But its performance needs some fine tuning. That is, getting the model to see and predict better seagrass habitats, using Sentinel-2 satellite imagery, by adjusting some parts of the model, such as parameters or training data. By making all these details even more refined, the model becomes even more accurate and dependable at locating seagrass areas, making it a better tool for monitoring habitat and conservation efforts.

Figure 10.3. Deep learning model classified pixels and Updated seagrass of NAMRIA overlaid in Sentinel-2 natural color band combination.




To validate the accuracy of the classified pixels using the deep learning model, the “Create Accuracy Assessment points” tools in ArcGIS Pro was employed. This process generated 50 stratified random sampling points distributed across the classified pixels of seagrass datasets (see Figure 10.2).

Each stratified Random Sampling Points is associated with two data fields:

1. Classified: This attribute reflects the classification outcome assigned through the image classification process. In this context, each sampling point is labeled with a specific class-namely, Seagrass. The classified values used in this study are based on the outputs generated by the deep learning model algorithm.
2. Ground Truth**:** This field serves as the reference data for validation purposes. It contains the actual class labels derived from field-verified information, representing the true class labels at each sampling location. In this study, the ground truth data are based on the updated Coastal Resource Map (CRM) of NAMRIA.

During the accuracy assessment, the class labels assigned in the classified image were systematically compared against the true class labels obtained from the ground truth dataset. In this study, the classified dataset comprises the pixels classified by the deep learning model, whereas the updated Coastal Resource Map (CRM) provided by NAMRIA serves as the reference ground truth data.

Table 10.1

*The table illustrates the stratified random sampling points of the classified pixels as presented within a confusion matrix*

<table>
<tr><th rowspan="6">Classified pixels using deep learning model</th><th colspan="4">Updated Seagrass of NAMRIA</th></tr>
<tr><td>CLASS NAME</td><td>Seagrass</td><td>Non-Seagrass</td><td>Total</td></tr>
<tr><td>Seagrass</td><td>43</td><td>7</td><td>50</td></tr>
<tr><td>Non-Seagrass</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>Total</td><td>43</td><td>7</td><td>100</td></tr>
<tr><td>Classification Accuracy (%)</td><td>86%</td><td>14%</td><td>100%</td></tr>
</table>

The confusion matrix looks at how well the deep learning model's classifications match up with NAMRIA's updated seagrass data. In the analysis we see that the deep learning model identified 43 seagrass pixels which correspond with the reference data. These correct predictions represent 86% of the model's output which in turn means that 86% of what the model reported as seagrass in fact was seagrass in the ground truth. Also, the model identified all 43 reference seagrass pixels which gave it a 100% producer's accuracy for the seagrass class. Also, we see that the model mislabeled 7 non-seagrass pixels as seagrass which means it reported some areas to have more seagrass coverage than what is present thus contributing to the classification error. Also, the model did not put any pixel in the non-seagrass class at all which meant that there were no true negative or false negative predictions. Overall, we see that the model does a great job at detecting seagrass which is fine, but it falls short in terms of non-seagrass which has an accuracy of only 14%. While the model does very well at identifying seagrass what it needs is more work put into improving performance for non-seagrass which in turn will see better balance and generalization of the model.

# XI. RECOMMENDATION AND CONCLUSION

**In summary:**

The research looks at how to use artificial intelligence - specifically deep learning algorithms - and high-resolution satellite imagery to improve the monitoring of seagrass ecosystems. Seagrass meadows are an important part of coastal ecosystems. They help with carbon storage, stabilizing shorelines, filtering water, and providing important nursery habitats for marine life. Using traditional field-based mapping is helpful, but it has some problems, such as being too expensive, having limited spatial coverage, and proven to be logistically challenging. The study addresses such challenges with the utilization of sentinel-2 imagery and convolutional neural network (CNN) in ArcGIS Pro in automatically classifying and mapping seagrass habitats in Calatagan, Batangas. The research process involved pre-processing of satellite data, development of a classification schema, generating training samples, training a deep learning model (backbone ResNet34), pixel classification, and accuracy assessment with both ground-truth reference data (NAMRIA updated CRM dataset) and google earth imagery.

- Overall accuracy: 97.31 %
- Precision: 86%
- Recall: 83%
- F1 Score: 85%
- Classified seagrass extent: 1,869 hectares
- NAMRIA reference seagrass extent: 2,195 hectares

The results indicate that the deep learning model has underestimated the area by 326 hectares compared to NAMRIA dataset. Yet, the spatial correlation and pattern recognition within seagrass regions remained valid to a high degree, thereby confirming the model's reliability. Though categorization power of the model remained weak in detecting non-seagrass features, stratified random sampling methodology 50 points value tested that it was outstanding in detecting whether seagrass existed or not. This implies that the multi-class detection capacity should be enhanced.

It is important to note that the study demonstrated the possibility to use artificial intelligence along with remote sensing to offer continuous and scalable seagrass surveillance, which is an essential component in effective resource management and policy formulations.

**Recommendation:**

On the basis of the findings and the conclusions of this work, some of the most significant recommendations are outlined in order to improve the usage of the deep learning and remote sensing to seagrass ecosystems monitoring, particularly in the Philippine coast. Firstly, the deep learning-based approach of seagrass classification in this study must be deployed across different coastal areas across the country. Given the vast amount of seagrass meadows throughout the nation's coastline, a broader use of this technique might be essential to creating a baseline dataset for seagrass distribution at the national level. Such information would be essential for guiding the country's marine spatial planning, as well as helping it fulfill its commitments under the Sustainable Development Goals (SDGs) and the Convention on Biological Diversity (CBD).

To offer a boost to the classification accuracy, it is important that the model be enhanced to identify and distinguish various forms of habitats other than seagrass. This expansion involves other benthic groups of coral reefs, algae, sandy bottoms, and sub-aquatic vegetation. Through training the model to identify these features, it will be more effective in eliminating false positives while offering a better ecologically broad picture of coastal habitats. Furthermore, this would improve the use of the model in supporting marine zoning and impact assessments.

With the huge computing needs that accompany deep learning techniques, it is recommended that future implementations take advantage of cloud computing platforms and GPU – accelerated virtual machines. This will enable researchers and agencies to conduct larger – scale or more often monitoring operations without the constraints of local hardware. Other than this, the products of this study in the form of seagrass distribution maps and change detection results should be integrated into coastal planning and management plans. These data products can be used by local government units (LGU), the Department of Environment and Natural Resources (DENR), and the Bureau of Fisheries and Aquatic Resources (BFAR) to inform the establishment of marine protected areas (MPAs), identify habitat degradation, and identify conservation priorities.

Finally, the five-day revisit interval of Sentinel-2 imagery offers a unique opportunity for the implementation of a long-term satellite monitoring program of seagrass. This will enable the capacity of resource managers to detect seasonal trends, track restoration, and act quickly in response to impending problems like sedimentation or coastal development and thus provide timely and data-driven responses.

After mapping seagrasses, the method proposed here can be applied very successfully to other coastal habitats (mangroves, coral reefs, and tidal flats). Through retraining the deep learning model on the dataset from a particular habitat, such as a reference habitat, we find that the method is applicable to the identification and monitoring of a broad range of ecological categories. For example, mangrove forests could be distinguished from other vegetation by applying multispectral imagery, which can be used to evaluate canopy density and the distribution of the canopy. Similarly, coral reefs could be studied by bathymetric and hyperspectral data for studying the cover of coral reefs, quantifying reef health and early monitoring of coral bleaching. Tidal flats and salt marshes can also be monitored by using seasonal satellite imagery and the tidal cycle data. This technique provides a more scalable alternative for local changes in extent and condition of a tidal habitat.

Also crucial to the success of this approach is the delivery of technical capacity to local government mappers who are responsible for conserving and managing coastal resources. Developing this capacity will ensure that the technology is not restricted to the domain of labs or academies but is embedded in local control. Transferable skills include its ability to have training workshops for the LGU technical staff and having easily understandable manuals to guide their data preparation and model accuracy validation, among other factors, and be able to deploy tools that do not need expensive software licenses. There could also be mentorship programs and continued collaboration on national agencies, universities and local government units. Integrating the methodology into local government ensuring that the output of coastal management programs - such as updated habitat maps – are directly related to planning, monitoring and reporting requirements.

**Conclusion:**

This study was able to establish the integration of deep learning models with Sentinel-2 satellite data as a viable and effective method for seagrass meadow mapping in Calatagan, Batangas, Philippines. The deep learning model, using the ResNet34 architecture in ArcGIS Pro, was successful in having a high accuracy classification of 97.31 percent, precision of 86 percent, recall of 83 percent, and perfect producer's accuracy of 100 percent for the seagrass class. These results confirm the high ability of the model to correctly identify and delineate seagrass areas.

The model's capacity to extrapolate seagrass coverages over large areas is to its advantage as a useful tool for coastal resource estimation. While a 326 – hectare difference was observed relative to NAMRIA's baseline, variability of this character is acceptable for satellite-based classifications and is partly accounted for by spectral confusion and the model's bias towards the dominant class (seagrass).

From the perspective of resource management, the findings of this study are of significant important:

- **Spatial accuracy** allows for crucial habitats to be conserved.
- **Temporal replicability** mirrors seasonal and long-term monitoring.
- **Cost-effectiveness and automation** enable wider use in other LGUs and protection sites.

The incorporation of modern remote sensing and deep learning algorithm to complement ecological analysis is also a major focus of this study, as opposed to labor-intensive and piecewise, it is recognizable that ecological analysis should focus on holism rather than the use of data as the foundation of a coastal management plan. The resultant maps and methods do not only give visualizations, but they also give actionable information which may be incorporated into the marine spatial planning (MSP), coastal zoning, and marine protected area and zoning (MPA) planning.

Along with direct utilization of the technique in the mapping of seagrass, the technique has larger consequences to the management of coastal resources due to its interrogative properties (i.e. it can be utilized with other significant coastal habitats like mangroves, coral reefs and tidal flats), which demonstrates the value of deep learning as a versatile technology habitat observing with various ecosystems.

Equally important is that technology alone will not ensure long-term results, training technical know-how to local government units (LGUs) and to community stakeholders would be critical in promoting the incorporation of this methodology into long-term management practices – such as training, provision of readily accessible tools and developing partnerships with national agencies and academic institutions. It also serves the interests of local governments by contributing not only to scientific research but also to operational research and management.

Finally, this work constitutes a scientific breakthrough in the field of conservation and a management tool, offering a first evidence for how innovative techniques such as deep learning can bridge the gap between science and practice and empower decision-making towards coastal conservation; by exploiting different habitats using the methodology and by making the approach available for local use, the work achieves two objectives: protecting biodiversity and strengthening community resilience to environmental change.

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# APPENDIX A

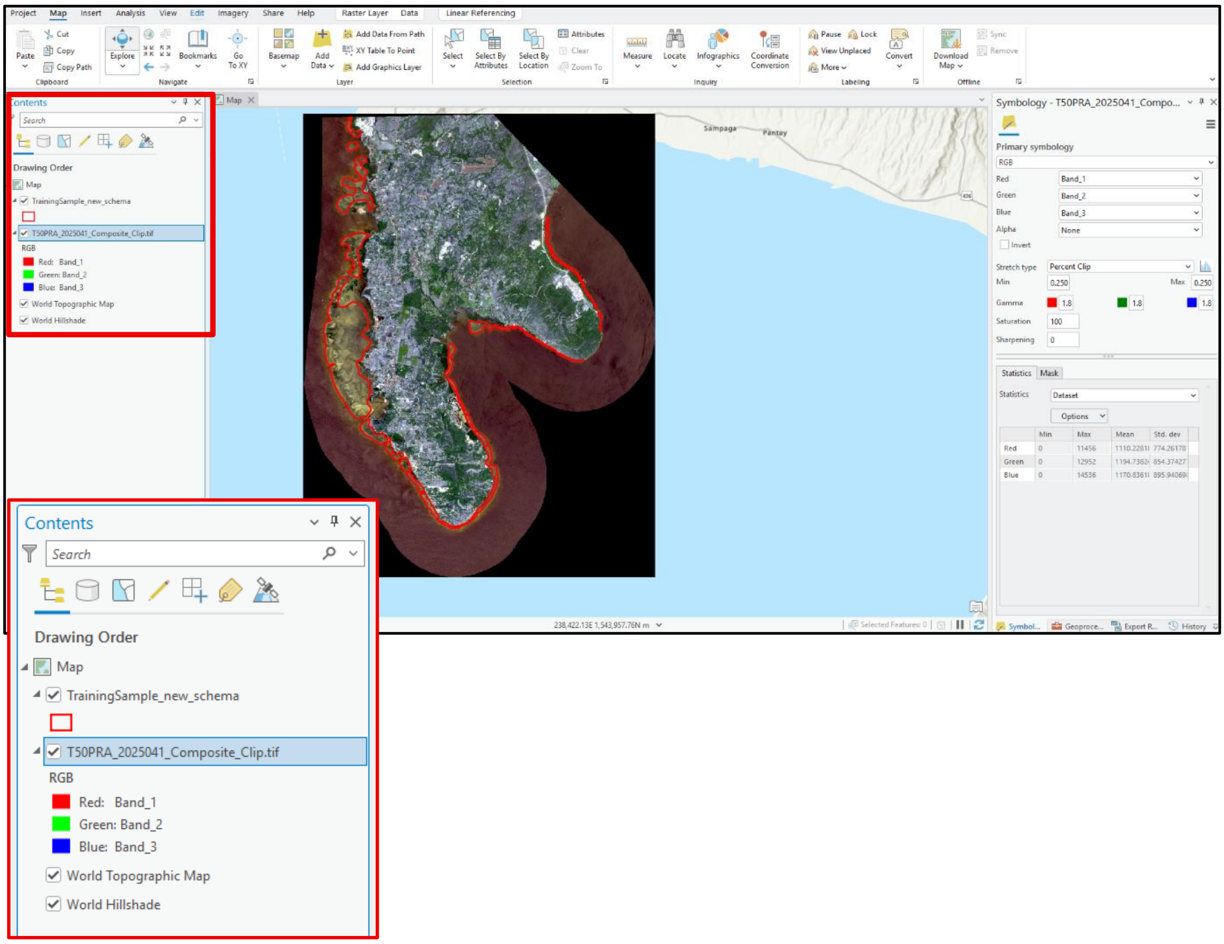
## PROCEDURE IN CLASSIFYING SEAGRASS DISTRIBUTION USING DEEP LEARNING ALGORITHM

Research parameters adopted in this work:

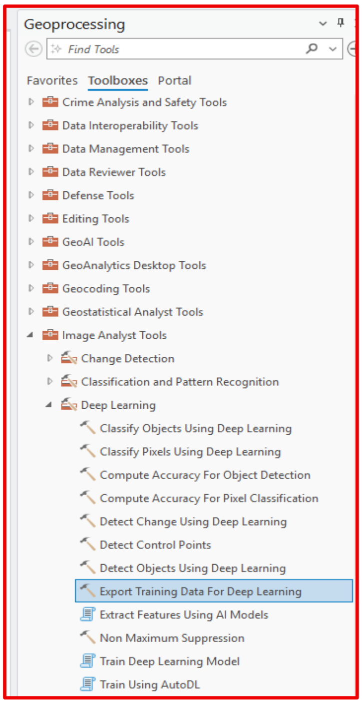
| | |
|---|---|
| Epoch | 30 |
| Validation (%) | 20 % |
| Batch Size | 16 |
| Backbone Model | ResNet-34 |
| Training Sample | 13 Polygons |
| Chip Size | 256 |
| Stride | 128 |

**STEPS AND PROCEDURES**

| | |
|---|---|
| a. Pre-processing of Satellite Imagery (Sentinel-2) | a.1 Image composite (layer stacking)<br>a.2 Image Clipping<br>a.3 Image enhancement |
| b. Generation of training datasets (labelled polygon in shapefile format) | b.1 From ArcGIS Pro Load the satellite image (Sentinel-2)<br>b.2 Create and digitize training samples labelled as seagrass<br>b.3 From the image menu bar, Select Classification Tools and open *"Training Samples Manager"*.<br>b.4 Then create *Schema*.<br>b.5 Load the Training Sample polygons and save. |



Export the training data (Schema)




c.1 In the toolboxes, Select *Geoprocessing tools.*
c.2 Then select *Image Analyst tools*.
c.3 Select *Deep Learning*.
c.4 Select *"Export Training Data for Deep Learning"*.

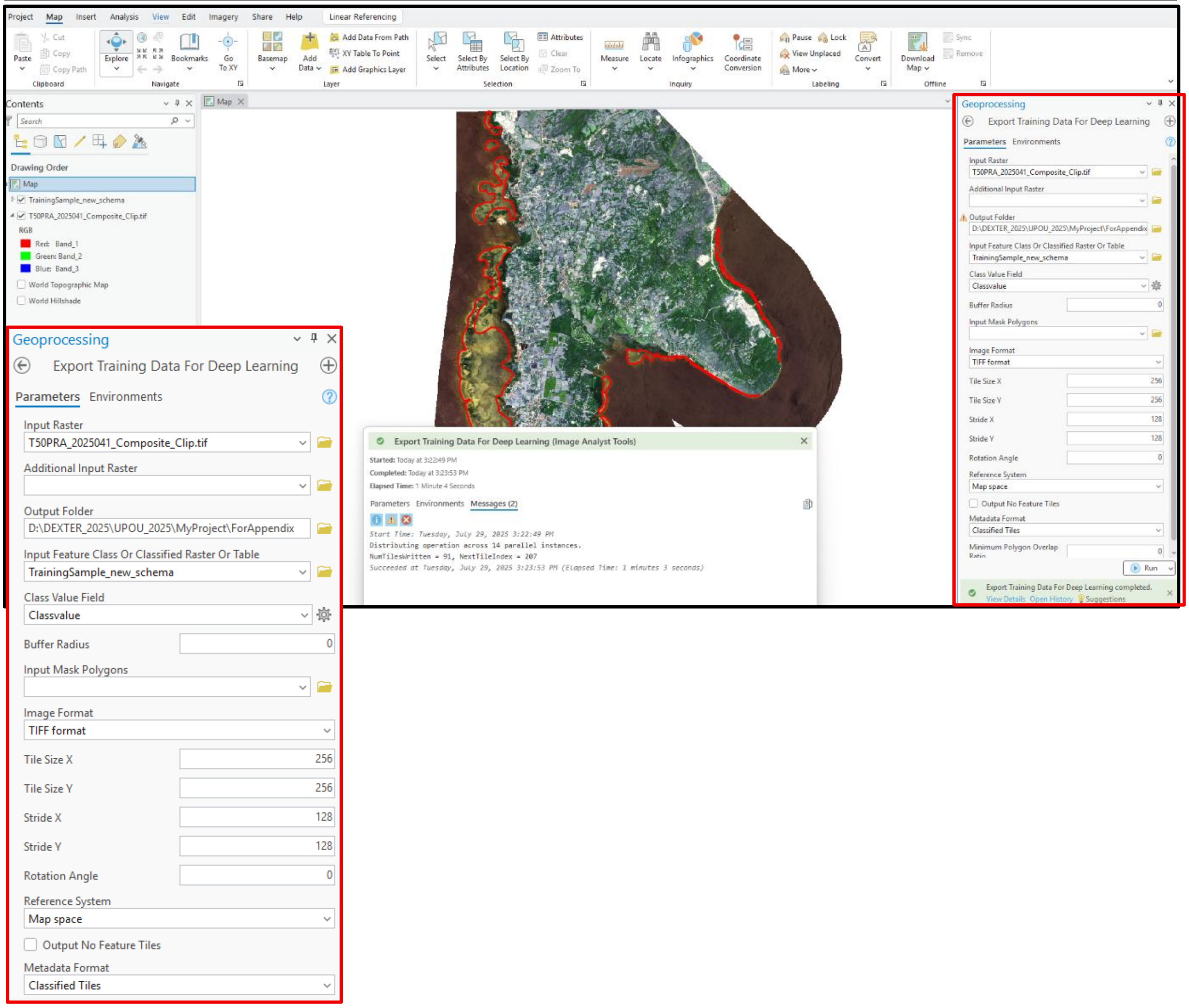
c.5 Set the Following parameters:

- ➢ In the Class Value field: Class Value
- ➢ Image Format: .tiff
- ➢ Tile Size X, Y: 256
- ➢ Stride X, Y: 128
- ➢ Rotation Angle: Default
- ➢ Reference System: Map Space
- ➢ Metadata Format: Classified Tiles

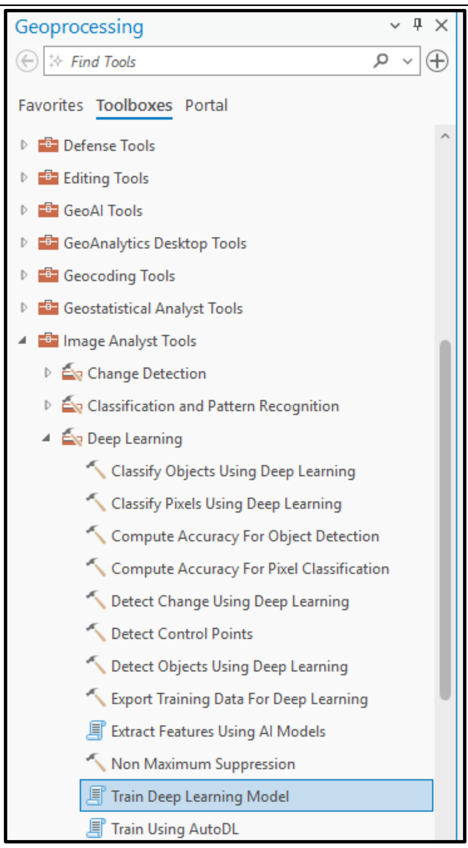
c.6 Set the Following Environment

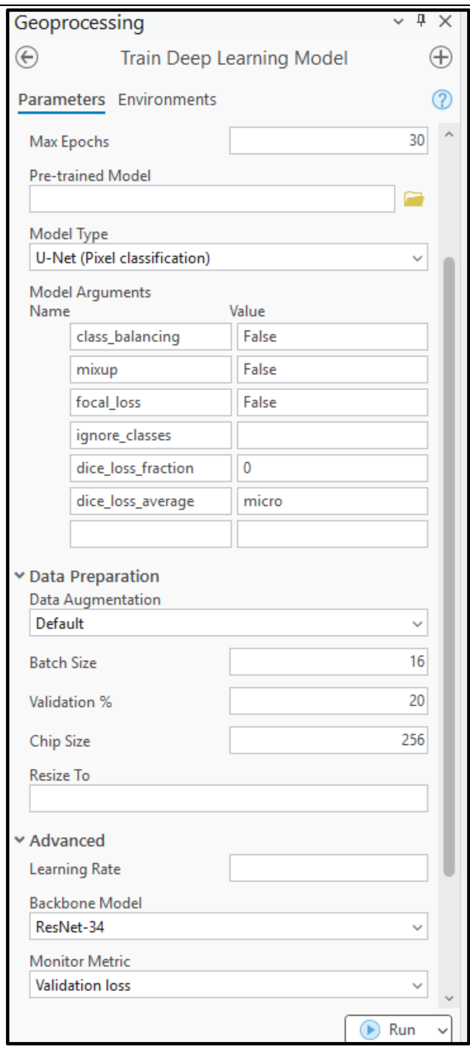
- ➢ Processing Extent: Default
- ➢ Raster Analysis: Maximum Inputs

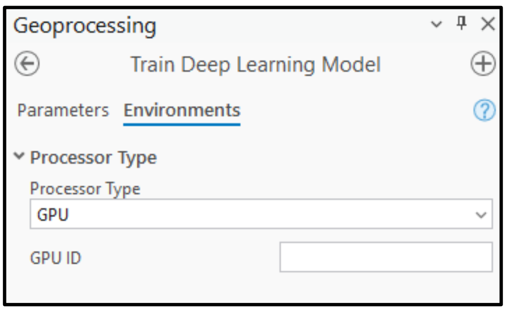
c.7 Click "*Run*"



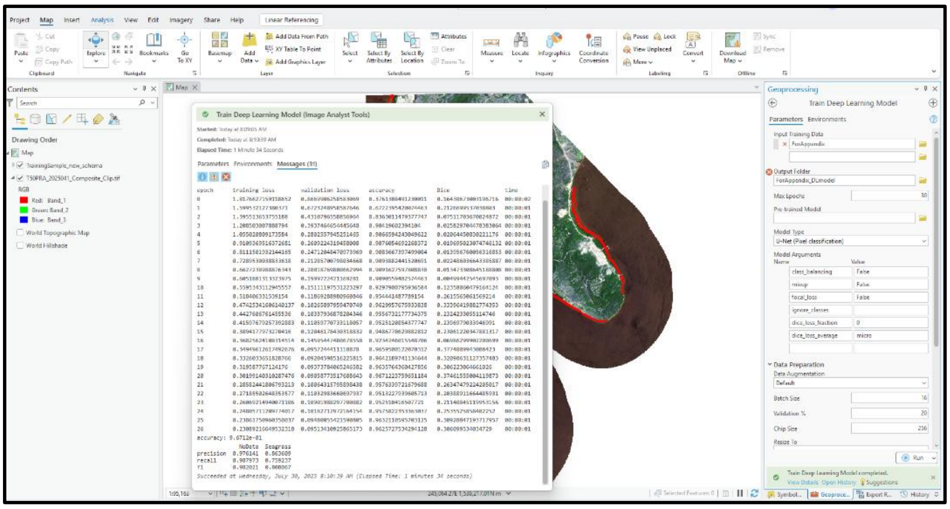
| | |
|---|---|
| c. Train the Deep Learning Model | d.1 Set the following Parameters<br>➢ Load the generated exported training model<br>➢ Create output folder<br>➢ Max Epoch: 30<br>➢ Model Type: U-Net (Pixel Classification)<br>➢ Batch Size: 16<br>➢ Validation: 20 %<br>➢ Chip Size: 256<br>➢ Backbone: ResNet-34<br>➢ Monitoring Matrix: Validation loss<br>➢ Weight initialization scheme: Random<br>d.2 Set the following Environments<br>➢ Processing Extent: Default<br>➢ Parallel Processing: Default<br>➢ Processor Type: GPU<br>➢ GPU ID: Default<br>d.3 Click "*Run*" |



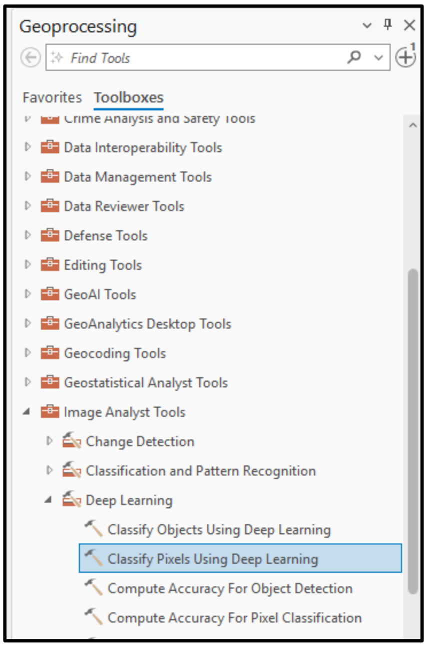



## Training Deep Learning Model Result

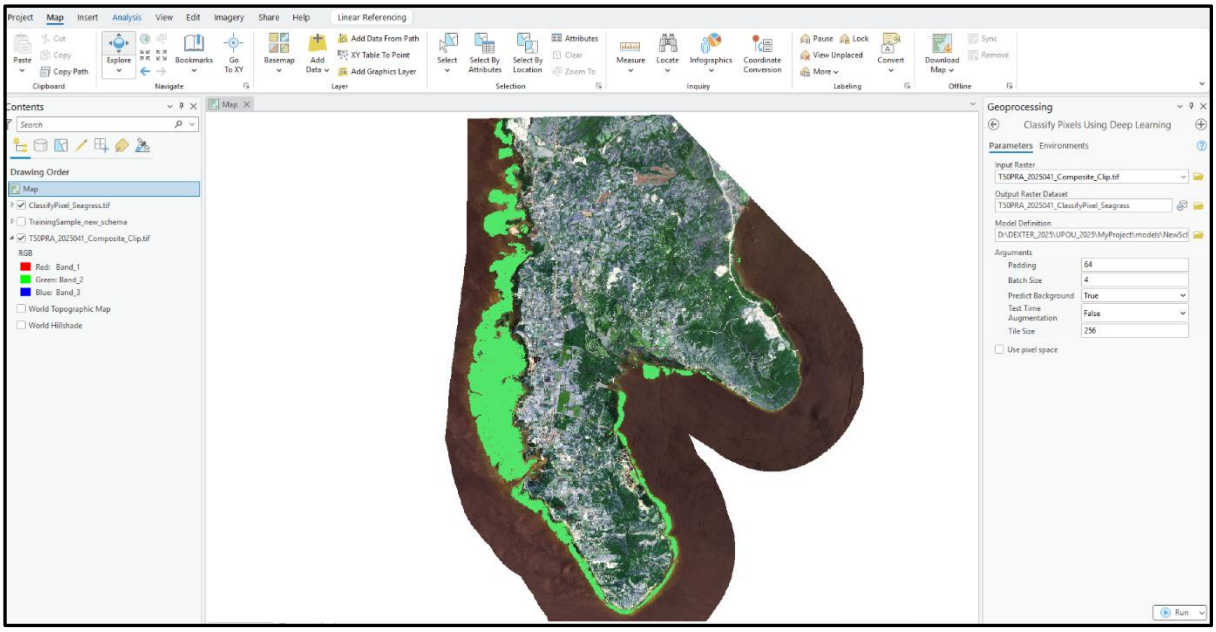


| | |
|---|---|
| d. Classify the pixel using Deep Learning | e.1 In the Geoprocessing Tool, Select Image Analyst tool then Click Deep Learning.<br>e.2 Select Classify Pixels using Deep Learning<br>e.3 Set the parameters<br>➢ Input the raster image<br>➢ Create output raster datasets<br>➢ Load the model definition, .dplk extension<br>➢ Arguments name and values, use default settings.<br>e.4 Set the following Environments<br>➢ Output coordinate system:<br>➢ Processing Extent: Default<br>➢ Parallel Processing: Default<br>➢ Raster Analysis: Cell Size (Maximum Inputs)<br>➢ Processor Type: GPU<br>➢ GPU ID: Default<br>e.5 Click "*Run*" |




## Deep Learning Model Definition

## Result of Classify Pixels using deep learning



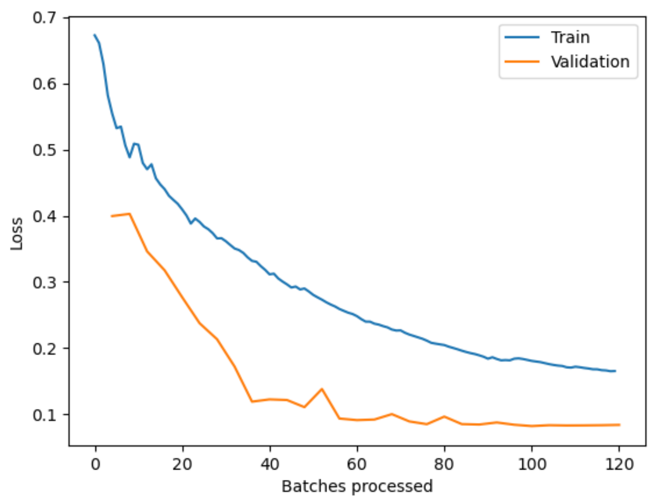

## Learning Curve (Analysis of the Model)

**UnetClassifier**

**Backbone:** resnet34

**Learning Rate:** slice('1.3183e-05', '1.3183e-04', None)

**Training and Validation loss**




**Analysis of the model**

**Per class metrics:**

| | NoData | Seagrass |
|---|---|---|
| **precision** | 0.983575 | 0.864667 |
| **recall** | 0.986881 | 0.835688 |
| **f1** | 0.985225 | 0.849930 |