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Habitat Suitability Modeling of Seagrass on Santiago Island, Pangasinan Using Satellite Imagery-Derived Environmental Parameters

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Abstract

This study utilizes remote sensing and geospatial techniques to model the habitat suitability of seagrass ecosystems on Santiago Island, Pangasinan, Philippines. Sea surface temperature (SST), salinity, and bathymetry were derived from Landsat 8, Landsat 9, and Sentinel-2 images using various techniques and were used as input for seagrass habitat suitability modeling. Results showed that seagrasses thrive best at depths of 9–23 m, with suitability decreasing in shallower (0–1 m) and deeper waters (>30 m). Optimal salinity was between 17.5–22.5 PSU (Practical Salinity Unit), while SST of 25.3°C or lower supports seagrass growth. The habitat suitability model classified only 1.38% of the area as highly suitable and 20.57% as suitable, while 5.32% and 4.66% were less suitable and moderately suitable, respectively, with the majority (68.06%) falling under the least and not suitable categories. Validation using reference points and field data showed that the model shows moderate reliability. Accuracy reached 62.55% using 2013 seagrass occurrence data, and 63.45% using 2023 data. This improved to 76.71% and 67.75% when moderately suitable areas (suitability score of 50) were included. Overall, the findings highlight the ecological importance of seagrass meadows and demonstrate that remote sensing offers a scalable, cost-efficient approach for monitoring seagrass ecosystems, supporting conservation and policy development in the Philippines.

1. Introduction

1.1 Background of the Study

Seagrasses are aquatic flowering plants that form vital underwater meadows, supporting marine biodiversity, stabilizing sediments, and providing an ecosystem to coastal communities (FishCORAL Project - Region V, 2022). They are one of the most productive ecosystems in the world due to their contribution to marine life. However, the seagrass population is increasingly threatened by human activities, such as coastal development and pollution, which lead to habitat degradation.

According to Fortes (1991), seagrasses inhabit 70% of the ASEAN region's coastal zone, where recently there have been issues of resource exploitation, raising concerns of sustainability and recovery within this generation. The Philippines, being an archipelagic country and known for its growing population, has started urban developments near coastal areas, estuaries, and shallow waters, the specific places where seagrasses can thrive. This has led to seagrasses' habitat being intentionally removed or destroyed.

As the problem arises, there is a need to identify suitable areas where seagrasses can thrive. Santiago Island in Bolinao, Pangasinan is known for its rich seagrass habitats, making it a significant site for research and conservation. Bolinao was also the first in the Philippines to conduct an ecological assessment and transplant study regarding seagrasses, which paved the way for studying the degraded coastal areas in different parts of the Philippines, like in Palawan, Marinduque, Manila, and Bataan (Fortes, 1984). Identifying the distribution of seagrasses specifically in this area would help in identifying coastal zones by classifying possible seagrass beds, thereby boosting conservation efforts. These areas may serve as nurseries for seagrasses, and examining the potential spawning sites can enhance the accuracy and efficiency of ground-truthing activities.

This study aims to model the habitat suitability of seagrasses on Santiago Island, Bolinao, Pangasinan, by utilizing satellite imagery-derived environmental parameters, particularly sea surface temperature (SST), salinity, and bathymetry data. This supports sustainable planning and management of seagrass ecosystems and, by extension, of marine ecosystems in the country.

2. Methodology

2.1 Study Area

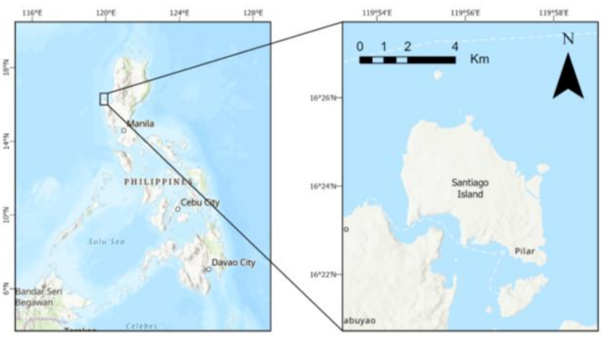

Figure 1. Area of Interest (Santiago Island, Pangasinan)

Figure 1 displays the study site which is in Santiago Island, Bolinao, located within the Lingayen Gulf, Philippines, and is known for its rich marine life, including significant seagrass beds. According to Fortes M.D. (1995), Bolinao contains the largest seagrass bed in northern Philippines, covering approximately 22,500 hectares. Furthermore, the site includes the Bolinao Seagrass Reserve (BSR), established in 2007 as the first reserve of its kind in Southeast Asia, encompassing around 20 hectares (Coastal Conservation and Education Foundation, 2011).

These seagrass beds serve as nurseries for fish, contribute to sediment stabilization, prevent coastal erosion, and support local fisheries and tourism, yet they are increasingly threatened by human activities like coastal development, pollution, and climate change.

2.2 Datasets Used

The data used in this study were obtained from multiple satellite image collection platforms, specifically Google Earth Engine, USGS Earth Explorer, and the Copernicus Open Access Hub. Bathymetry and salinity data were processed from Sentinel-2 Level-2A imagery, which offers a spatial resolution of 10 meters. Sea surface temperature (SST) data were derived from Landsat 8 and Landsat 9 TIRS Level-2 Collection 1 imagery, which provides a spatial resolution of 30 meters. The acquisition date of February 2023 was chosen to minimize cloud cover and ensure relatively stable sea conditions typical of the dry season. According to the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the country experiences a dry season from December to May.

Validation of the processed datasets was conducted using seagrass distribution data from previous studies. These included the seagrass distribution data in Bolinao, Pangasinan, obtained from Tamondong (2013) and Camba et al. (2023). These datasets were used to assess the accuracy of the satellite-derived variables and enhance the reliability of the habitat suitability modeling.

2.3 Processing of Remote Sensing-Derived Parameters

2.3.1 Sea Surface Temperature (SST): One of the algorithms used to derive sea-surface temperature is the Split-Window Algorithm (SWA). Armono et al. (2017) stated that SWA is an algorithm capable of extracting sea surface temperature (SST) by calculating brightness temperature (BT) values using Bands 10 and 11 of Landsat 8. SWA makes use of Planck's Theorem. Chen et al. (2020) stated that Planck's law enables a direct relationship between radiance and temperature, facilitating the solution of the radiation transfer equation (RTE) set. Calculating the brightness temperature is dependent on the RTE and Planck's Law.

The Split Window Algorithm estimates land surface temperature by using two adjacent thermal infrared bands to minimize atmospheric effects, particularly water vapor, and improve temperature accuracy (Wang et al., 2019). The split-window algorithm was applied to calculate the SST from Landsat 8 and Landsat 9 TIRS C2 L1 imagery using thermal infrared bands (Band 10 and Band 11). The process involved converting the digital numbers of Bands 10 and 11 to brightness temperature.

The split-window method incorporated specific equations to derive surface temperature, ensuring more precise SST estimates for the study area. Equation (1) displays the formula used to obtain the spectral radiant value, which is used for Equation 2. Equations 2 and 3 show the formulas used in computing the sea surface temperature. Equation (2) applies a natural logarithm function to refine temperature estimation based on radiance data. Finally, the brightness temperatures calculated from Equation (2) using TIRS Band 10 (BT_{10}) and Band 11 (BT_{11}) are converted to sea surface temperature (Ts) in degrees Celsius using Equation (3).

$$L\lambda = M\lambda * Qcal + A\lambda \tag{1}$$

Where, $L\lambda$ = spectral radiant value
$M\lambda$ = adiance multiplicative scaling factor
$Qcal$ = level 1 pixel value
$A\lambda$ = radiance additive scaling factor

$$T = \frac{K2}{ln(\frac{K1}{L\lambda} + 1)} \tag{2}$$

Where, T = brightness temperature in kelvin
$K1$ = temperature constant in kelvin
$K2$ = temperature constant in kelvin
$L\lambda$= spectral radiant value

$$Ts = BT_{10} + (2.946 * (BT_{10} - BT_{11})) - 0.038 \tag{3}$$

Where, Ts = sea surface temperature in celsius
BT_{10} = brightness temperature value of band 10 in celsius
BT_{11} = brightness temperature value of band 11in celsius

2.3.2 Salinity: Salinity data were derived from Sentinel-2 L2A imagery, which provides atmospherically corrected reflectance values. The Cimandiri Salinity Algorithm (Mukhtar et. al, 2021) was applied using Band 2, Band 3, and Band 4 to calculate salinity values based on water surface reflectance using Equation (4). After deriving salinity values, a land masking was done to exclude non-water areas, resulting in a refined dataset that highlights salinity variations across the sea portion of the study area.

$$Y = 29.983 + 165.047 * B2 - 260.227 * B3 + 2.609 * B4 \tag{4}$$

Where, Y= sea surface salinity
$B2$ = Blue Band
$B3$ = Green Band
$B4$ = Red Band

The unit of measurement for salinity used in this study was Practical Salinity Unit (PSU). PSU is defined as one gram of salt per 1000 grams of water (PO.DAAC, 2022).

2.3.3 Bathymetry: The same Sentinel-2 L2A imagery was used to generate the bathymetry of the surrounding waters of Santiago Island. Pre-processing steps, such as cloud masking and median composite techniques, were used to remove cloud cover and enhance data quality. The Normalized Difference Water Index (NDWI) shown in Equation (5) was calculated for land masking. This index highlights the difference in reflectance between the green and near-infrared (NIR) bands, where water strongly reflects green light and absorbs NIR light. Pixels with NDWI values greater than 0.1 were classified as water, while those with values equal to or below 0.1 were classified as land. This land masking step was then followed by sunglint correction to remove bright reflections that could interfere with depth measurements.

$$NDWI = \frac{Green\ band - NIR\ band}{Green\ band + NIR\ band} \tag{5}$$

$$Bathymetry = m_0\left(\frac{log(1000 * Band_{Blue})}{log(1000 * Band_{Green})}\right) - m_1 \tag{6}$$

Where, m_0 and m_1 = calibration coefficients for local water conditions

Additionally, the Band Ratio Method using the Stumpf model (Stumpf et. al, 2003) shown in Equation (6) was applied to

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estimate water depth using m_0 and m_1 as calibration coefficients that adjust the model to local water conditions and the logarithmic ratio of blue and green bands.

2.4 Suitability Analysis

The suitability analysis workflow for seagrass habitat, shown in Figure 2, integrated the Landsat-derived SST and Sentinel-2-derived salinity and bathymetry data, which were all resampled to 30 m for consistency. The input data were reclassified into suitability classes with corresponding scores based on ecological thresholds, with specific scores assigned to different ranges of SST (Table 1), salinity (Table 2), and bathymetry (Table 3) based on the work of Ozkiper et al. (2024).

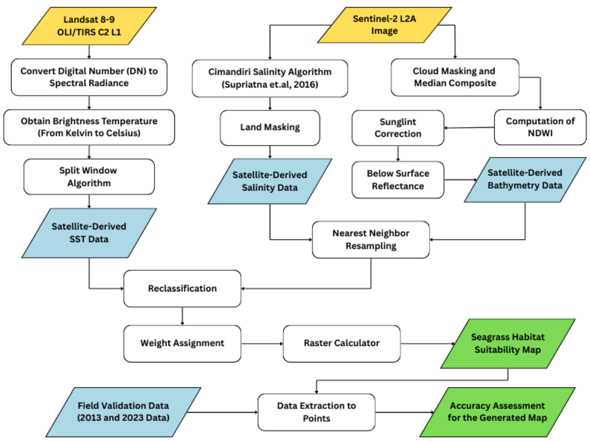

Figure 2. Suitability Analysis Workflow

Variable	Classes	Suitability Class	Scores
Sea Surface Temperature (SST) (in °C)	<25.3	Very suitable	100
	25.3-26.8	Suitable	80
	26.8-28	Moderately suitable	60
	28-28.4	Less suitable	30
	>28.4	Least suitable	10

Table 1. Suitability classes and scores for SST

Variable	Classes	Suitability Class	Scores
Salinity (in PSU)	<12.5	Least suitable	10
	12.5-17.5	Suitable	80
	17.5-22.5	Very Suitable	100
	22.5-27.5	Moderately Suitable	60
	27.5-32.5	Less Suitable	30
	>32.5	Least Suitable	10

Table 2. Suitability classes and Scores for the salinity

Variable	Classes	Suitability Class	Scores
Depth (in meters)	0-1	Less suitable	30
	1-9	Suitable	80
	9-23	Very suitable	100
	23-30	Suitable	80
	30-40	Moderately suitable	60
	40-50	Less suitable	30
	>50	Least suitable	10

Table 3. Suitability scores for bathymetry

Criteria weights used by Ozkiper et al. (2024) were also applied in this study. The weights were adapted since the environmental factors used in this study, namely SST, salinity, and bathymetry, are fundamental drivers of seagrass distribution worldwide, extending beyond any single region. Although local ecological variations occur, they are consistently recognized as key factors in seagrass habitat studies across diverse geographic contexts.

Ozkiper et al. (2024) grouped the parameters used in their study under three broader categories—climate, water quality, and geomorphology—each assigned an equal overall weight in the suitability analysis. Within each variable, however, the individual parameters were given different weights. Specifically, SST fell under the climate variable with a weight of 0.15, salinity was categorized under water quality with a weight of 0.24, and depth was classified under geomorphology with a weight of 0.54. As this study considered only three key factors, the individual parameter weights were determined using the following equations:

$$pw_i = 33 * (pw_c) \tag{7}$$

$$pw_f = \frac{pw_i}{\sum pw_i} \tag{8}$$

Where, pw_c = parameter cluster's weight (Ozkiper et al, 2024)
pw_i = weight of the parameter itself (Ozkiper et al, 2024)
pw_f = final weight of the parameter in this study

These reclassified datasets were combined using a weighted overlay to generate the seagrass habitat suitability map, which highlighted areas with varying levels of seagrass habitat suitability. The final weights used are shown in Table 4. These weights and classification thresholds served as the basis for generating the final habitat suitability map through a weighted overlay, highlighting areas with varying levels of potential seagrass presence.

Variable	Weight
Sea Surface Temperature (SST)	0.16
Salinity	0.26
Bathymetry	0.58

Table 4. Final Weights for the Parameters

Finally, the seagrass habitat suitability map was produced following six suitability classes, as shown in Table 5.

Suitability Range	Classification
0-10	Not Suitable
10-30	Least Suitable
30-50	Less Suitable
50-70	Moderately Suitable
70-90	Suitable
90-100	Highly Suitable

Table 5. Seagrass Habitat Suitability Classification (Adapted from Ozkiper et al., 2024).

2.5 Validation

To validate the seagrass habitat suitability map, seagrass occurrence datasets from 2013 and 2023 (shown in Figure 3) were converted into points, and the suitability scores were extracted at these locations. The model's accuracy was then assessed by calculating the proportion of seagrass occurrence points that fell within areas classified as moderately suitable to suitable (suitability scores of 70–100). This can be mathematically expressed as:

$$Accuracy = \frac{\sum \quad (70 \leq Suitability\ Score\ Value \leq 100)}{Total\ Seagrass\ data\ points} \tag{9}$$

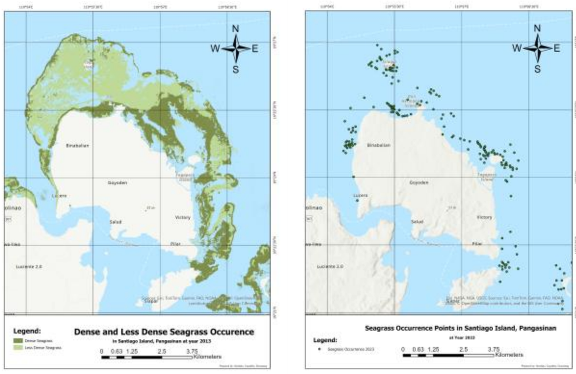

Figure 3. 2013 and 2023 Seagrass Occurrence in Santiago Island, Pangasinan.

2.6 Sensitivity Analysis

A one-at-a-time approach to sensitivity analysis was conducted to evaluate how variations in the input parameters influenced the extent of different levels of habitat suitability. This method assesses the model's stability and identifies which factors exert the greatest influence on the resulting map (Saltelli et. al, 2004).

In this study, the weights of sea surface temperature (SST), salinity, and bathymetry were systematically adjusted by 5% increments up to ±25% from their baseline values. For each adjustment, a new suitability map was generated, and pixel counts per suitability class were recorded. The percentage change in classification, relative to the baseline scenario (original weights), was then computed to quantify the sensitivity of each parameter.

3. Results and Discussion

3.1 Remote Sensing-derived Parameters

As shown in Figure 4, the SST map shows relatively uniform temperature conditions across the study area, with minimal variation between neighboring zones. A large portion of the area, about 86.88%, is classified as moderately suitable, covering most of the central sections around Santiago Island. Smaller portions are classified as less suitable (4.68%) and least suitable (2.12%), found mainly in scattered patches closer to nearshore areas where localized temperature fluctuations may occur.

3.1.1 Sea Surface Temperature (SST): Areas classified as suitable (6.32%), where sea surface temperatures are 25.3 °C or lower, are mainly concentrated along the northern and northeastern portions of Santiago Island, particularly near reef edges and deeper sections where slightly cooler waters are present. These zones provide the most favorable temperature conditions for seagrass growth, while the dominance of moderately suitable areas highlights the overall stability of SST across much of the study site.

Sea surface temperature is an important factor in promoting the growth of seagrass. In a study by Künne (2021), it was determined that plant physiological performance was reduced by an average of 39% by temperature change, and per 1°C experimental ocean warming, a reduction in seagrass performance of 11% was observed. This suggests that warmer oceans are detrimental to seagrasses.

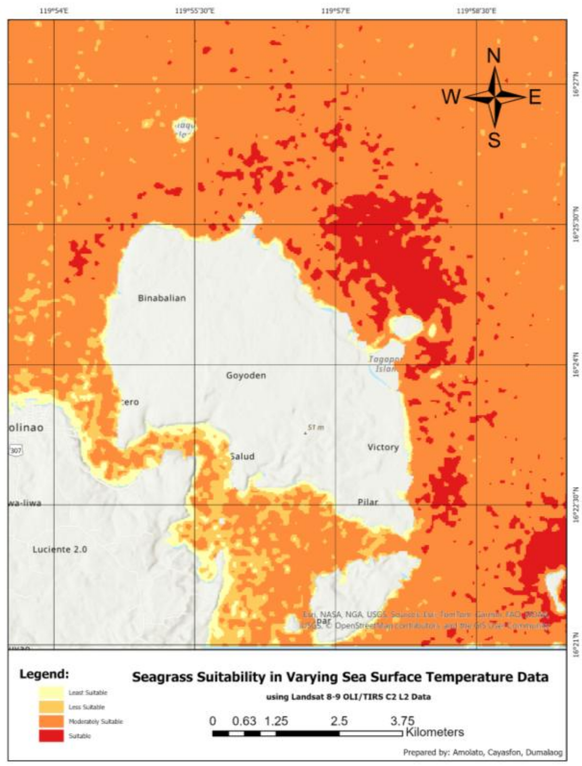

Figure 4. Seagrass Suitability in Varying Sea Surface Temperature (SST) Data

3.1.2 Salinity: According to Zhang et al. (2022), the suitability of seagrass growth, based on salinity data, is highest within the range of 17.5–22.5 PSU, where conditions are classified as very suitable. Suitability decreases as salinity values deviate from this range. Waters with salinity between 12.5–17.5 PSU are still suitable, while 22.5–27.5 PSU is considered moderately suitable. Beyond this, salinity values of 27.5–32.5 PSU are less suitable, and waters with salinity below 12.5 PSU or above 32.5 PSU are classified as least suitable. Figure 5 shows that highly suitable areas are located farther from the land, whereas areas near the shore are only within the suitable to moderately suitable range.

Seagrasses are known to thrive in brackish waters, or in waters that are saltier than freshwater but not as salty as saltwater. Hence, seagrasses tend to grow in bays, estuaries, and coastal waters where brackish waters are prevalent (Australian Institute of Marine Sciences, n.d.). Also, regions with high evaporation rates exhibit elevated surface salinities, while areas with significant precipitation experience reduced surface salinities. Nearshore regions located close to large freshwater sources often have lower salinities due to dilution. This effect is particularly pronounced in areas where the geography of the land isolates the freshwater-receiving part of the ocean from the open sea (Byrne and Mackenzie, 2024).

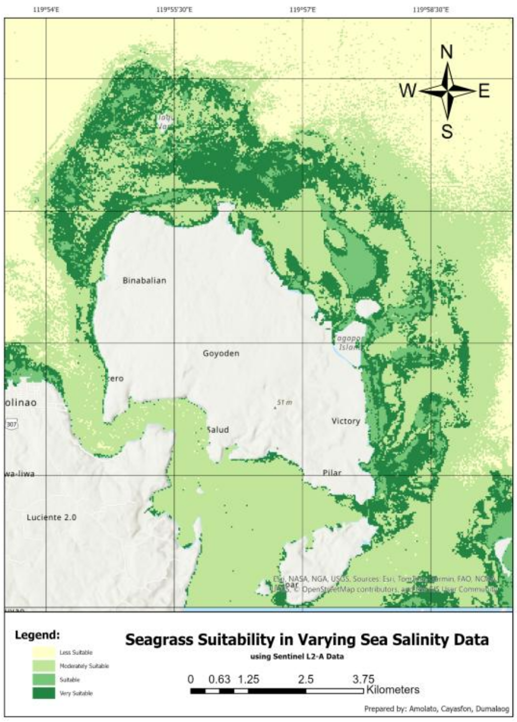

Figure 5. Seagrass Suitability in Varying Sea Salinity Data

3.1.3 Bathymetry: Figure 6 shows that seagrasses are not suitable in areas far from the land, while suitable to very suitable in areas near the land. In depths of no more than 1 meter, seagrass suitability decreases significantly due to potential disturbances from tides and temperature fluctuations. However, at slightly deeper zones of 1 to 9 meters, the conditions improve, making it a more suitable habitat. Beyond 23 meters, the suitability of seagrass progressively declines. At depths of 23 to 30 meters, the conditions remain moderately favorable, but further reductions in light availability start to affect growth. From 30 to 40 meters, suitability becomes moderate. Furthermore, at greater depths of 40 to 50 meters, suitability drops further as light penetration becomes insufficient for photosynthesis. In waters deeper than 50 meters, seagrass is the least suitable due to severely limited light and nutrient availability.

The bathymetric map obtained above demonstrates clear trends based on water depth and proximity to land. As per Ozkiper et al. (2024), seagrasses are most suitable to very suitable at depths ranging from 9 to 23 meters, where the conditions are ideal for their growth. This range likely offers optimal light penetration, stable temperatures, and nutrient availability. Seagrasses depend on photosynthesis for growth, requiring adequate sunlight, carbon dioxide, and nutrients to develop dense, healthy underwater meadows. However, since sunlight only penetrates from above, its availability decreases with increasing depth (SeaStore, 2024).

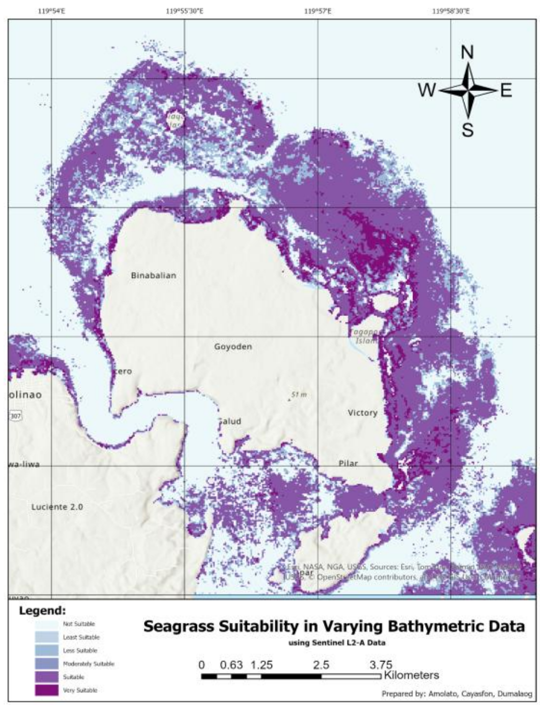

Figure 6. Seagrass Suitability in Varying Bathymetric Data

3.2 Seagrass Suitability Analysis

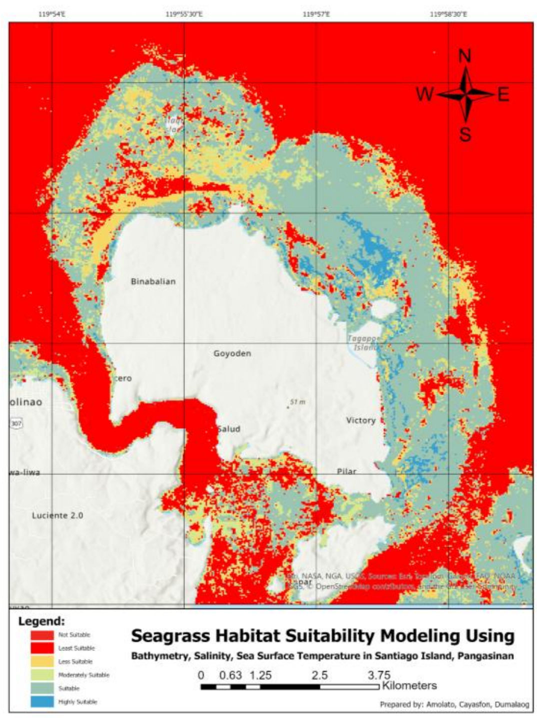

Figure 7. Final Seagrass Habitat Suitability Map

Figure 7 presents the seagrass habitat suitability map derived from the integration of the three satellite-derived parameters, SST, salinity, and bathymetry. The suitability scores range from 9.40 to 96.80. The final suitability map indicates that the majority of the area, at around 68.06% of the studied area, fell under the Not and Least Suitable categories. While 5.32% and 4.66% of the study area fell under Less Suitable and Moderately Suitable, respectively. 20.57% of the studied area was determined to be Suitable. Finally, only 1.38% was found to be Highly Suitable.

The final suitability map differed from the individually identified suitable areas based on SST, salinity, and bathymetry, as it captured the combined effects of all three environmental parameters rather than the influence of each factor in isolation. Given that bathymetry carried the greatest weight in the analysis, the majority of the highly suitable areas were concentrated at depths of 9–23 meters, highlighting this range as the most favorable for seagrass growth.

These findings are consistent with seagrass species previously documented in the Bolinao area. Fortes et al. (2012) reported *Enhalus acoroides*, *Thalassia hemprichii*, *Cymodocea serrulata*, *Cymodocea rotundata*, *Syringodium isoetifolium*, *Halophila ovalis*, and *Halodule uninervis*, which overlap with the suitable sites identified in this study. This indicates that the modeled habitat suitability aligns with actual species distributions, highlighting the influence of depth and other environmental factors.

3.3 Sensitivity Analysis

Sensitivity analysis was conducted to evaluate how variations in SST, salinity, and bathymetry (at ±5% increments up to ±25% from baseline values) affect habitat suitability classification. Tables 6-8 summarize the percent change in area per suitability class for each scenario.

Scenario	Not Suitable (%)	Least Suitable (%)	Less Suitable (%)	Moderate Suitable (%)	Suitable (%)	Highly Suitable (%)
-0.25	0.00	0.34	-3.88	0.00	-0.93	13.89
-0.20	0.00	0.34	-3.88	0.00	0.00	0.00
-0.15	0.00	0.34	-3.88	0.00	0.00	0.00
-0.10	0.00	0.03	0.00	0.00	0.00	0.00
-0.05	0.00	0.34	-3.88	0.00	0.00	0.00
+0.05	0.00	0.03	0.00	2.50	-0.07	-7.41
+0.10	0.00	0.03	0.00	2.50	-0.07	-7.41
+0.15	0.00	-0.83	11.04	2.50	-0.07	-7.41
+0.20	0.00	-0.83	11.04	2.50	-0.07	-7.41
+0.25	0.00	-0.83	11.04	2.50	-0.07	-7.41

Table 6. Sensitivity Analysis Results for SST

For SST, the suitability distribution showed moderate sensitivity. The most noticeable shifts were in the “Less Suitable” and “Very Suitable” classes, but changes generally remained within ±15% of baseline values. This suggests that SST variability influences habitat suitability but does not substantially alter overall patterns.

Scenario	Not Suitable (%)	Least Suitable (%)	Less Suitable (%)	Moderate Suitable (%)	Suitable (%)	Highly Suitable (%)
-0.25	0.00	0.44	-4.08	3.10	-0.49	-7.41
-0.20	0.00	0.40	-3.60	3.10	-0.49	-7.41
-0.15	0.00	0.40	-3.60	3.10	-0.49	-7.41
-0.10	0.00	0.40	-4.46	4.08	-0.49	-7.41
-0.05	0.00	0.34	-3.88	0.00	0.00	0.00
+0.05	0.00	-0.07	1.33	0.00	0.00	0.00
+0.10	0.00	-0.07	1.33	0.00	0.00	0.00
+0.15	0.00	-0.95	12.60	0.00	0.00	0.00
+0.20	0.00	-0.95	12.60	0.01	0.00	0.00
+0.25	0.00	-0.95	12.13	0.12	0.09	0.00

Table 7. Sensitivity Analysis Results for Salinity

For salinity, only minor changes were observed across all increments. The extent of suitable areas remained relatively stable, with shifts typically below ±5%. This indicates that habitat suitability is relatively insensitive to salinity fluctuations compared to the other parameters.

Scenario	Not Suitable (%)	Least Suitable (%)	Less Suitable (%)	Moderate Suitable (%)	Suitable (%)	Highly Suitable (%)
-0.25	-100.00	-22.61	234.88	201.62	-28.91	-36.82
-0.20	-100.00	-22.61	239.72	194.79	-28.61	-36.82
-0.15	-100.00	-22.54	238.77	194.78	-28.61	-36.82
-0.10	0.00	-0.95	12.60	2.51	-0.07	-7.41
-0.05	0.00	-0.93	12.37	2.50	-0.07	-7.41
+0.05	0.00	0.34	-3.65	1.58	-0.42	0.00
+0.10	0.00	0.44	-4.95	-15.41	1.64	26.84
+0.15	3280.70	1.05	-27.36	-23.27	1.64	26.84
+0.20	3280.70	1.43	-23.16	-32.50	-0.52	55.46
+0.25	141191	-69.08	-23.16	-40.83	1.04	60.34

Table 8. Sensitivity Analysis Results for Bathymetry

Overall, bathymetry was the main factor influencing habitat suitability, causing the largest changes in the results. SST had a moderate effect, leading to noticeable but smaller shifts, while salinity showed only small changes, meaning the model was less affected by it.

3.4 Validation Using Seagrass Occurrence Data

To validate the seagrass habitat suitability map, the obtained suitable areas were compared with existing seagrass occurrence data. In the study by Ozkiper et al. (2024), only areas categorized as suitable or highly suitable were considered. When compared with the 2013 seagrass point data, 62.55% of the field-validated seagrasses coincided with the suitable locations identified in this study.

When compared with the 2023 seagrass point data, the validation match was 63.45%. Including moderately suitable areas increased the accuracy to 76.71%. Similarly, comparing it with the 2013 seagrass point data, it resulted in a 67.75% match, which also rose to 76.71% when moderately suitable areas were also considered.

The validation results were anticipated, given the number of environmental parameters considered. Camba and Ignacio (2023) generated a site suitability map for the same area using more environmental parameters, such as Chlorophyll a, among others. Additionally, changes over the 10-year period between the 2013 seagrass point data and the current map, such as the formation of sandbars and other environmental changes, may have affected the alignment between point data and suitable areas. Nevertheless, the results obtained reflect the moderate performance of the implemented approach in this study.

4. Conclusions and Recommendations

This study utilized habitat suitability modeling to assess seagrass distribution in Santiago Island, Bolinao, Pangasinan, by using satellite imagery-derived SST, salinity, and bathymetry. These environmental parameters were successfully derived from satellite images through well-established processes and algorithms in remote sensing, as well as GIS-based techniques, demonstrating the capability of geomatics approaches in supporting seagrass conservation efforts. Overall, 26.61% of the study area was classified as suitable for seagrass habitat (including Moderately Suitable, Suitable, and Highly Suitable classes), while 73.39% ranged from Less Suitable to Not Suitable. Validation of the suitability map with in situ seagrass occurrence data showed a moderately adequate accuracy of 62.55% to 76.71% despite having only three environmental parameters considered in this study.

In order to enhance the habitat suitability model, it is recommended to incorporate additional environmental parameters, such as light attenuation, turbidity, substrate type, water currents, and water dissolved oxygen. Additionally, incorporating higher-resolution in situ datasets for validating the environmental parameters derived from satellite imagery may further enhance model accuracy. Moreover, applying the model to longer temporal datasets can help identify trends that may be used to develop prediction models to describe seagrass habitat scenarios.

The results of this study can support conservation initiatives aimed at protecting seagrass species. The obtained suitable zones may serve as priority sites for establishing seagrass conservation zones. Local government units can focus on the identified suitable sites and designate them as protected areas to prevent further seagrass loss. Strengthened fishing regulations may also be enforced in areas identified as suitable for seagrass to help mitigate potential damage and ensure the protection of these benthic habitats.

Finally, the methodology employed in this study, while tailored to assessing seagrass habitat suitability in Bolinao, can be modified for application in other regions or marine environments. The core framework, which utilizes remote sensing-derived environmental parameters and GIS-based suitability analysis, remains transferable. It is recommended that environmental variables such as sea surface temperature, salinity, and bathymetry, as well as their respective weights, be adjusted in order to align with the optimal conditions of the target site. Likewise, the spatial and temporal resolution of the satellite imagery should be selected based on the geographic scale, environmental variability, and data availability in the new context. By implementing these adaptations, the methodological framework can be effectively extended to diverse marine ecosystems and other regions across the country, thereby supporting broader ecological monitoring and conservation planning.

References

Armono, H. D., Cahyono, A. B., Pribadi, C. B., Saptarini, D., 2017. Estimation of Sea Surface Temperature (SST) using split window methods for monitoring industrial activity in coastal area. *Applied Mechanics and Materials*, 90–95. doi.org/10.4028/www.scientific.net/AMM.862.90

Australian Institute of Marine Science (AIMS), n.d. Seagrasses. aims.gov.au (15 December 2024)

Byrne, R. H., Mackenzie, F. T., 2024. Salinity distribution. Encyclopedia Britannica. (15 December 2024)

Camba, M. M., Ignacio, J. R., Tamondong, A., Blanco, A., 2023. Seagrass habitat sustainability modeling for Bolinao-Anda, Pangasinan using maximum entropy and random forest.

Chen, C., Chu, Y., Fu, J., Guo, B., Zheng, H., 2020. A split-window method to retrieve sea surface temperature from Landsat 8 thermal infrared remote sensing data in offshore waters. *Estuarine, Coastal and Shelf Science*, 236. doi.org/10.1016/j.ecss.2020.106626

Coastal Conservation Education Foundation, 2011. Coastal databases: Information for coastal management. coast.ph. (22 August 2025)

FishCORAL Project – Region V, 2022. Field guide on seagrass. Bureau of Fisheries and Aquatic Resources (BFAR). (15 December 2024)

Fortes, M. D., 1991. State of seagrass ecosystems and resources in the Philippines. semanticscholar.org (13 August 2025)

Fortes, M. D., 1995. Bolinao Seagrass Demonstration Site (BSDS): Food security through capacity building in seagrass ecosystem management.

Fortes, M. D., Ooi, J. L. S., Tan, Y. M., Prathep, A., Bujang, J. S., Yaakub, S. M., 2018. Seagrass in Southeast Asia: A review of status and knowledge gaps, and a road map for conservation. *Botanica Marina*, 61(3), 269–288. doi.org/10.1515/bot-2018-0008

Fortes, M., Go, G. A., Bolisay, K., Nakaoka, M., Uy, W., Lopez, M., Leopardas, V., Leriorato, J., Hinoguin, A. D., Watai, M., Honda, K., Edralin, M., 2012. Seagrass response to mariculture-induced physico-chemical gradients in Bolinao, northwestern Philippines. Proceedings of the 12th International Coral Reef Symposium, 9–13.

Künne, J., 2021. A meta-analysis of temperature treatment effects on global seagrass performance. (Bachelor's thesis, GEOMAR Ocean Research Institute).

Mukhtar, M. K., Supriatna, S., Dwi Mandini Manessa, M., 2021. The validation of water quality parameter algorithm using Landsat 8 and Sentinel-2 image in Palabuhanratu Bay. IOP *Conference Series: Earth and Environmental Science*. doi.org/10.1088/1755-1315/846/1/012022

Ozkiper, O., Allegri, E., Bianconi, A., Vuong Pham, H., Furlan, E., Simide, R., van der Geest, M., Critto, A., 2024. A GIS-MCDA approach to map environmental suitability of Posidonia oceanica meadows as blue nature-based solutions in the Mediterranean eco-region. *Science of The Total Environment*, 955. doi.org/10.1016/j.scitotenv.2024.176803

PO.DAAC, 2022. Physical Oceanography Distributed Active Archive Center (PO.DAAC). podaac.jpl.nasa.gov

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity analysis in practice: A guide to assessing scientific models. doi.org/10.1002/0470870958

SeaStore, 2024. Seagrass: Basic facts. seegraswiesen.de (16 December 2024)

Stumpf, R. P., Holderied, K., Sinclair, M., 2003. Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnology and Oceanography*, 48(1), 547–556. doi.org/10.4319/lo.2003.48.1_part_2.0547

Tamondong, A. M., Blanco, A. C., Fortes, M. D., Nadaoka, K., 2013. Mapping of seagrass and other benthic habitats in Bolinao, Pangasinan using Worldview-2 satellite image. *2013 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, Melbourne, VIC, Australia, 1579–1582. doi.org/10.1109/IGARSS.2013.6723091

Wang, M., He, G., Zhang, Z., Wang, G., Wang, Z., Yin, R., Cui, S., Wu, Z., Cao, X., 2019. A radiance-based split-window algorithm for land surface temperature retrieval: Theory and application to MODIS data. *International Journal of Applied Earth Observation and Geoinformation*, 76, 204–217. doi.org/10.1016/j.jag.2018.11.015

Zhang, Y.-H., Yu, B., Liu, Y.-C., Ma, W., Li, W.-T., Zhang, P.-D., 2022. The influence of decreased salinity levels on the survival, growth and physiology of eelgrass Zostera marina. *Marine Environmental Research*, 182. doi.org/10.1016/j.marenvres.2022.105787