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Mapping Seagrass Meadows and Assessing Blue Carbon Stocks Using Sentinel-2 Satellite Imagery: A Case Study in the Canary Islands, Spain †

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Abstract: This research evaluates the capability of Sentinel-2 satellite imagery for mapping *Cymodocea nodosa* meadows in El Médano (Tenerife, Canary Islands, Spain). A Level-1C image from 27 October 2022 was used. Atmospheric correction was addressed using the Sen2Cor tool, while Lyzenga's method was employed to account for the water column effect. Three supervised classifications were performed using Random Forest, K-Nearest Neighbors (KNN) and KDTree-KNN algorithms. These classifications were complemented by an unsupervised classification and in situ data. Additionally, the amount of blue carbon sequestered by the *C. nodosa* in the study area was also estimated. Among the classifiers, the Random Forest algorithm produced the highest F1 scores, ranging from 0.96 to 0.99. The results revealed an average area of 237 ± 5 ha occupied by *C. nodosa* in the study region, translating to an average sequestration of 111,000 ± 2000 Mg CO_2. Notably, the seagrass meadows in this study area have the potential to offset the CO_2 emissions produced by the industrial combustion plant sector throughout the Canary Islands. This research represents a significant step forward in the protection and understanding of these invaluable ecosystems. It effectively underlines the potential of Sentinel-2 satellite data to map seagrass meadows and highlights their crucial role in achieving net zero carbon emissions on our planet.

Keywords: *Cymodocea nodosa*; machine learning algorithms; classification; ecosystem services; InVEST

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1. Introduction

Seagrass ecosystems support rich marine biodiversity and are among the most productive ecosystems in the world, providing a wide range of ecological services such as nutrient cycling, erosion control, sediment stabilization, and habitats for numerous species [1]. Furthermore, they sequester and store substantial quantities of carbon, referred to as blue carbon. They are able to capture up to 35 times faster than tropical rainforests [2]. Nevertheless, various anthropogenic threats such as coastal development, water pollution, destructive fishing practices, and climate change are causing an accelerated loss of these valuable ecosystems. In fact, 29% of the known areal extent has disappeared since seagrass areas were initially recorded in 1879 [3].

Monitoring these ecosystems is, therefore, of paramount importance in order to define protected areas and carry out management and conservation tasks. While traditional in situ monitoring methods provide accurate results, they are frequently hindered by their expense, significant time consumption, and restricted coverage area. In response to those limitations, there has been a growing interest in leveraging satellite imagery as a cost-effective and large-scale alternative for monitoring these ecosystems [4,5].

Regarding the Canary Islands (Spain), an archipelago situated off the northwest coast of Africa, it is well known that the most common seagrass specie is the *Cymodocea nodosa*.

Therefore, the main objective of this research is to evaluate the ability of Sentinel-2 satellite data to map *C. nodosa* using machine learning algorithms and assess blue carbon stocks within the study area.

2. Materials and Methods

2.1. Study Area

This study focuses on El Médano, located in the municipality of Granadilla de Abona, on the island of Tenerife (Figure 1). Notably, El Médano is home to vast meadows of *C. nodosa*, making it a distinctive study site for mapping seagrass.

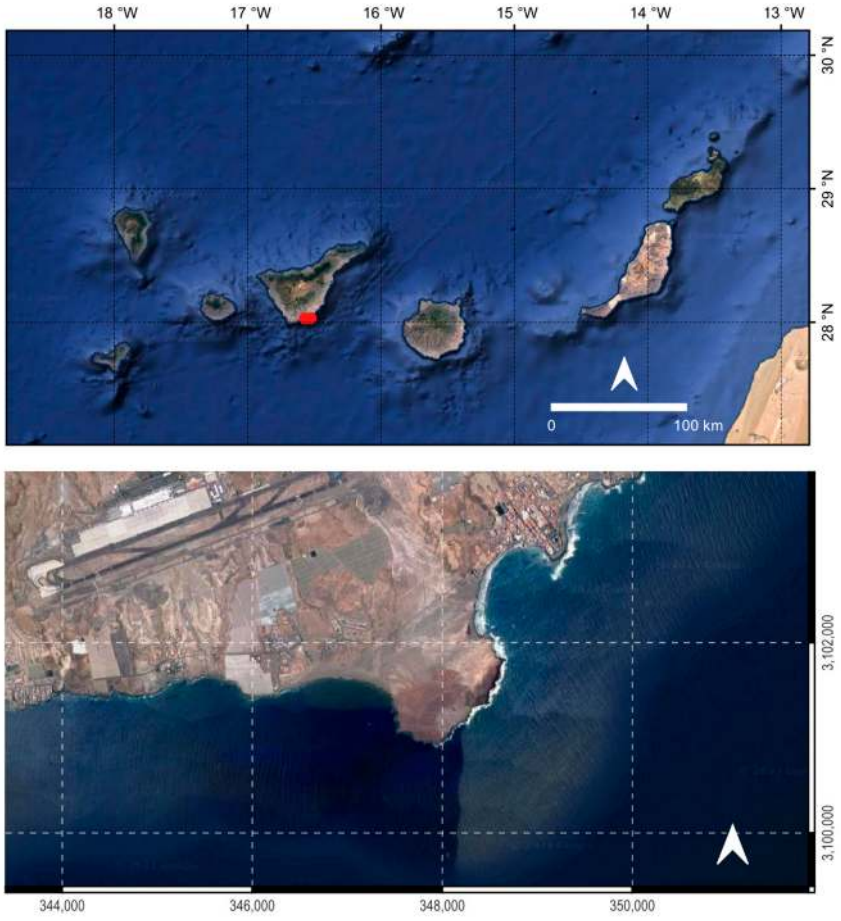


Figure 1. The Canary Islands archipelago, highlighting the study area (red rectangle) which encompasses La Tejita and El Médano beaches on Tenerife.

2.2. Field Data

Field data from 2016, provided by the Vice-Ministry of the Environment of the Canary Islands Government [6], stands as the only reference for mapping the *C. nodosa* meadows at El Médano. It is essential to acknowledge the potential significant changes that might have taken place since that time. Consequently, a mixed approach was followed to determine the training polygons for the classifiers, as detailed further.

2.3. Methodology

A level 1C (L1C) Sentinel-2 image, captured on 27 October 2022, containing top of the atmosphere (TOA) reflectance data was used. The main challenge faced was the attenuation of the reflected optical signal caused by both the atmosphere and the water column.

2.3.1. Image Pre-Processing

For this study, Sentinel-2′s 10-m resolution bands B2, B3, B4, and B8 were employed.

Sen2Cor (Version: v2.11) [7] was used to perform the atmospheric correction. The required aerosol optical thickness, water vapor column, and the ozone layer were sourced from the Sentinel-2 auxiliary files AUX_CAMSFO and AUX_ECMWF, both of which contain data from the European Centre for Medium-Range Weather Forecasts.

For masking out land pixels, a threshold value of 0.1 was imposed in the NIR band (B8) to perform a two-class classification. Afterwards, Sen2Coral (Version: v1.1) [8] was used to perform the sunglint correction in order to avoid pixel misclassification caused by the specular reflection of the light off the ocean's surface. Sen2Coral uses the Hedley's algorithm shown in Equation (1) [9],

$$R_i' = R_i - b_i \cdot (R_{NIR} - Min_{NIR}) \quad (1)$$

where R_i' is the corrected reflectance of the pixel in band i, R_i is the reflectance of the pixel in presence of sun glint in band i, b_i is the regression slope, R_{NIR} is the reflectance in the NIR band of the pixel in presence of sun glint, and Min_{NIR} is the minimum reflectance in the NIR band from all the pixels of the image.

To limit classification to areas of seagrass growth and comply with the 20–30 m depth constraint of the water column correction method, optically deep waters were masked out with bathymetry data provided by [6].

Finally, to perform the water column correction, Lyzenga's method [10] was employed. It consists of generating new synthetic bands, known as Depth Invariant Indexes, using attenuation coefficients (Equations (2)–(4)).

$$DII_{ij} = ln(L_i) - \left[\left(\frac{k_i}{k_j} \right) ln(L_j) \right] \quad (2)$$

$$\frac{k_i}{k_j} = a + \sqrt{(a^2 + 1)} \quad (3)$$

$$a = \frac{\sigma_{ii} - \sigma_{jj}}{2\sigma_{ij}} \quad (4)$$

DII_{ij} is the Depth Invariant Index of the i and j bands, L_i and L_j are the reflectances of the bands i and j respectively, k_i and k_j are the corresponding attenuation coefficients for each band, σ_{ii} is the variance of the band i, σ_{jj} is the variance of the band j and σ_{ij} is the covariance of the bands i and j.

2.3.2. Classification and Blue Carbon Assessment

Due to uncertainties about changes in the seagrass patch relative to the 2016 in situ mapping, it was not possible to define training polygons using this data. Therefore, an initial unsupervised classification was performed using the K-Means algorithm and all the Depth Invariant Indexes. This approach provides a clearer understanding of potential changes in seagrass coverage. Training polygons were then defined in those pixels where the 2016 field data mapping intersected with the unsupervised classification.

The Random Forest (RF), K-Nearest Neighbors (KNN); and KDTree-KNN algorithms were used for supervised classifications. Furthermore, cross-validation method was applied to optimize algorithms' hyperparameters. The assessment of these classifications was done using the F1 score. This metric ensures a balanced evaluation, specially when there are varying quantities of training polygons for each class, providing a comprehensive understanding of the model's accuracy.

The InVEST Coastal Blue Carbon (Version: 3.8.0, USA, CA) model was used to quantify the Mg of CO_2 sequestered in the study area by the *C. nodosa*. Two primary look-up tables (LUT's) needed to be built considering biophysical factors of the *C. nodosa*. Research papers

employing this method in the Canary Islands [11,12] were analyzed for the completion of these LUT's. Within the scope of this study, each seagrass pixel is presumed to sequester the same amount of carbon. The total sequestered CO_2 can then be calculated for the whole study area by multiplying the total number of seagrass pixels identified in the mapping process, equivalent to seagrass hectares, by the sequestration rate per hectare

3. Results and Discussion

The outcome for the unsupervised classification conducted by the K-Means algorithm with a cluster count of $k = 4$ is illustrated in Figure 2a. Results reveal an area of 221 ha occupied by the *C. nodosa*. Figure 2b,c, show the highest and least extent of seagrass, respectively, after applying different supervised classification algorithms. The largest seagrass extent (245 ha) was achieved using the KNN algorithm with 5 neighbors, while the least seagrass extent (230 ha) was obtained using the RF algorithm with 11 trees.

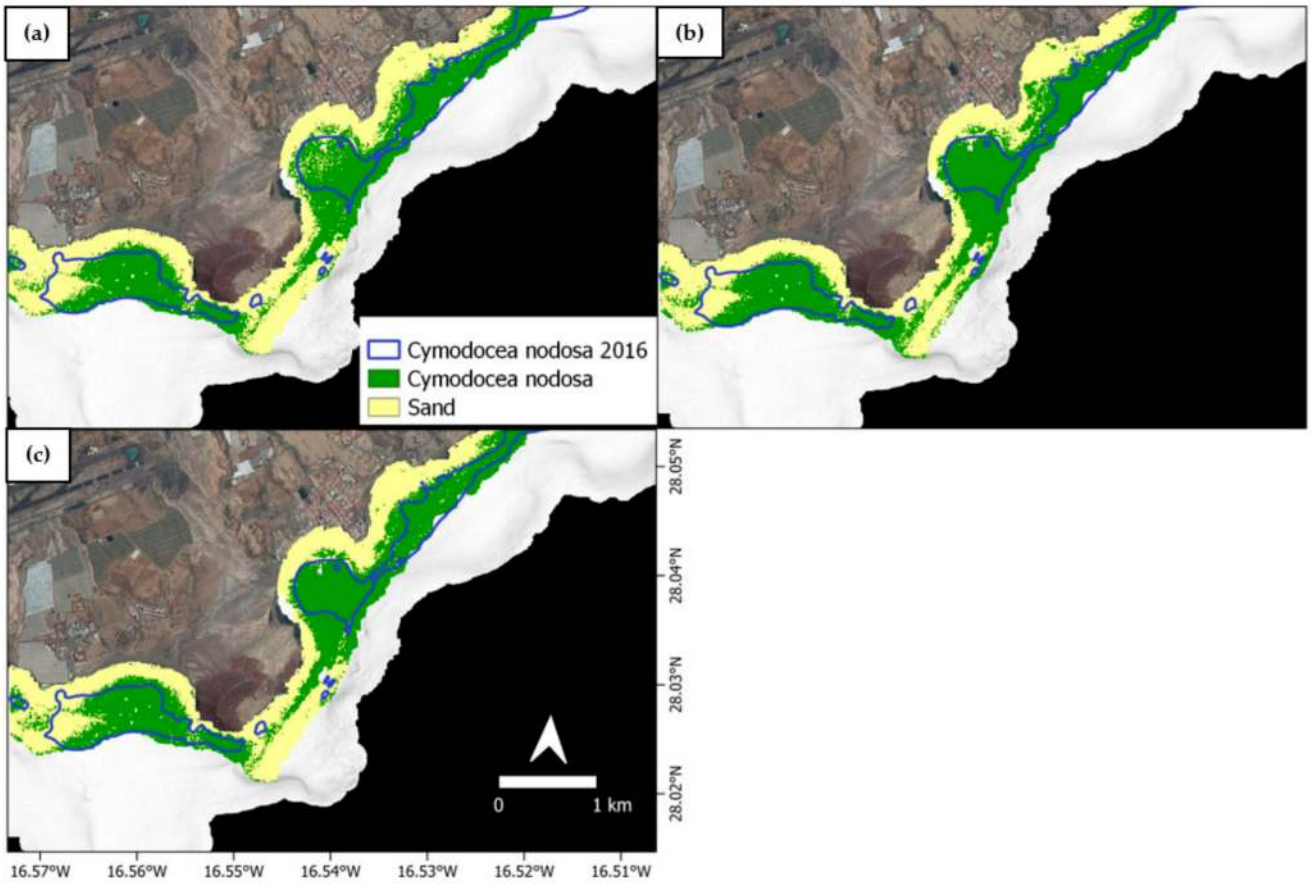


Figure 2. Classification results for unsupervised and supervised methods. In situ seagrass data is outlined in blue. Classified seagrass areas are shown in green. All other coverings are labeled as "sand" and colored in yellow: (**a**) Unsupervised classification, (**b**) KNN supervised classification, (**c**) RF supervised classification.

Upon completion of the classification process, the RF algorithms demonstrated the top F1-scores, falling within a range of 0.96 to 0.99. In contrast, both KNN and KDTree-KNN showed lower F1-scores, with values ranging between 0.84 and 0.96.

In a previous study [4] using WorldView-2 imagery and Lyzenga's water column correction method, the authors obtained an accuracy of 71.84% when mapping *C. nodosa* in this study area. The results were noisier, resulting in worse metrics. This may be due to the difference in spatial resolution between the WorldView-2 (1.8 m) and Sentinel-2 (10 m). Higher spatial resolution can detect more nuanced turbidity variations, while Sentinel-2 inherently averages turbidity (reflectance values) due to its larger pixel size, resulting in a

smoother image. Consequently, when applying Lyzenga's water column correction method to Sentinel-2 image, the turbidity variations are not as pronounced as those observed in the WorldView-2 image, and therefore, the performance increases. In contrast, our results are in agreement with those of other research which compares the performance of WV-3 and Sentinel-2 in mapping benthic habitats using Lyzenga's method [5]. They found that WV-3 pixels appeared to be noisier than Sentinel-2 ones.

From the hectares of seagrass determined by each of the algorithms, an average of 237 ± 5 ha was calculated. Using this average value, the blue carbon sequestered in the study area was estimated to be 111,000 ± 2000 Mg of CO_2. When comparing these figures with the annual CO_2 emissions from various sectors in the Canary Islands, it was found that the seagrass in the study area could offset the CO_2 emissions from the entire industrial combustion plant sector of the Canary Islands, which totaled 76,430 Mg of CO_2 in 2019 and 61,690 Mg of CO_2 in 2020 [13].

4. Conclusions

This study has successfully demonstrated the capability of Sentinel-2 satellite imagery to map and monitor seagrass meadows in the Canary Islands. The pre-processing workflow implemented presents a promising approach for handling Sentinel-2 image data in similar studies across different locations. Furthermore, this study, has clearly demonstrated the instrumental role seagrass ecosystems can play in regional strategies to achieve net zero carbon emissions.

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Conflicts of Interest: The authors declare no conflict of interest.

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