

Article

Satellite-Based Assessment of Intertidal Vegetation Dynamics in Continental Portugal with Sentinel-2 Data

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Highlights

What are the main findings?

- For intertidal the vegetation assessment, the Atmospherically Resilient Vegetation Index (ARVI) performed best among the 16 indices evaluated.
- Sentinel-2 imagery time series validated with ground truth allowed assessment of spatial variability of intertidal vegetation at a regional scale.

What is the implication of the main finding?

- Combination of Sentinel-2 data with high-resolution UAV information is a cost-effective and replicable approach for coastal monitoring.
- Detection of regional patterns and interannual fluctuations provides valuable information for adaptive management and conservation of vulnerable coastal ecosystems.

Abstract

Vegetated intertidal ecosystems, such as seagrass meadows, salt marshes, and macroalgal beds, are vital for biodiversity, coastal protection, and climate regulation; however, they remain highly vulnerable to anthropogenic and climate-induced stressors. This study aims to assess interannual changes in intertidal vegetation cover along the Portuguese mainland coast from 2015 to 2024 using Sentinel-2 satellite imagery calibrated with high-resolution multispectral unoccupied aerial vehicle (UAV) data, to determine the most accurate index for mapping intertidal vegetation. Among the 16 indices tested, the Atmospherically Resilient Vegetation Index (ARVI) showed the highest predictive performance. Based on a model relating intertidal vegetation cover to this index, an ARVI value greater than or equal to 0.214 was established to estimate the area covered with intertidal vegetation. Applying this threshold to time-series data revealed considerable spatial and temporal variability in vegetation cover, with estuarine systems such as the Ria de Aveiro and the Ria Formosa showing the greatest extents and marked fluctuations. At the national level, no consistent overall trend was identified for the study period. Despite limitations related to satellite image resolution and single-site validation, the results demonstrate the feasibility and utility of combining UAV data and satellite indices for long-term, large-scale monitoring of intertidal vegetation.

Keywords: Sentinel-2; continental Portugal; Vegetation Index; vegetation cover; UAV



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1. Introduction

Vegetated intertidal ecosystems, such as saltmarshes, seagrass meadows and macroalgae, are vital for biodiversity, coastal protection, and climate regulation [1]. Despite often occupying only a narrow strip of the global coastline, these ecosystems play an important role in carbon sequestration, sediment stabilisation, and nutrient cycling [2]. They include the most productive marine habitats and provide crucial ecosystem services, acting as carbon sinks and barriers to erosion and ocean-wave impacts. However, in recent decades, up to 50% of their global extent has been lost due to land-use change and climate stressors such as marine heatwaves and accelerated sea level rise [2–4]. Monitoring the spatial and temporal dynamics of intertidal ecosystems is therefore essential for both conservation and adaptive coastal management.

Recent advances in remote sensing (RS) technologies have significantly improved our understanding of intertidal and wetland ecosystems [5]. Several studies have focused on monitoring, mapping and assessing intertidal seagrass meadows using high-resolution satellite imagery, especially from Sentinel-2 satellites, and drone technologies [6]. These tools have provided valuable information on the phenology, distribution and ecological status of these vital coastal ecosystems. At the local scale, unoccupied aerial vehicles (UAVs) equipped with multispectral sensors provide very high-resolution (centimetre-scale) imagery, which is particularly effective for field verification of satellite data [7,8]. At the regional and national scales, open-access satellite data from the Sentinel-2 mission, operated within the framework of the European Space Agency's (ESA) Copernicus Program, enable systematic monitoring of coastal ecosystems. Sentinel-2 imagery offers a spatial resolution of 10 m and a revisit frequency of five days [9,10].

Open-access Earth observation data have enabled applications in long-term monitoring programs, including those implemented in data-scarce or resource-limited contexts [9,11]. This makes satellite remote sensing a viable and cost-effective option for continuous monitoring of intertidal habitats over large geographic areas. However, several limitations remain when applying remote sensing to intertidal environments. Image quality is often limited by cloud cover and tidal variability, factors that can reduce detection accuracy [9,10]. Furthermore, given the spatial resolution of open-access satellite imagery (10 m to 60 m for Sentinel-2 data) and the spatial variability of intertidal habitats, many intertidal pixels are prone to be of mixed nature, comprising a combination of vegetation, rocks, sediment, and water. This can distort the spectral signature for many small areas, leading to an underestimation of vegetation extents, especially in smaller or fragmented patches [8,12].

Despite these challenges, recent advances in satellite data processing and classification methods have improved the reliability of vegetation detection. This is the case of the work of Rowe Davies et al. [10], where a neural network model (ICE CREAMS v1.0) with Sentinel-2 time-series data was applied to track interannual changes in *Zostera noltei* meadows in Western Europe. Similarly, Mora-Soto et al. [11] developed a global map of intertidal giant kelp and green kelp forests based on Sentinel-2 data and threshold-based spectral indices. These applications highlight the growing potential of publicly available satellite imagery for long-term monitoring and conservation of vegetated coastal habitats, as well as adaptation to statistical models that enable monitoring or projections of these ecosystems.

Vegetation indices (VIs) derived from remote sensing surveys of coastal ecosystems have proven effective in mapping vegetation density at different scales, by detecting vegetation characteristics from multispectral images. The Normalised Difference Vegetation Index (NDVI), derived from red and near-infrared (NIR) reflectance, is one of the most widely used indices for assessing chlorophyll activity and estimating vegetation cover and biomass [8,9,11]. Although originally developed for terrestrial vegetation, NDVI and

its derivatives have been successfully applied to monitoring intertidal seagrass beds and macroalgae [13]; however, its performance can be limited in aquatic or mixed environments due to water column effects, substrate reflectance, and variable tidal conditions.

To address these limitations, a range of alternative VIs have been explored, such as the Atmospherically Resistant Vegetation Index (ARVI), the Soil-Adjusted Vegetation Index (SAVI), and the normalised Difference Water Index (NDWI), which have demonstrated improved performance in areas with high reflectance variability due to ground brightness or water interference [9]. Furthermore, spectral combinations, including red-edge bands and Short-Wave Infrared (SWIR), have shown great potential for capturing submerged or periodically flooded vegetation covers [11,12], while the Normalized Difference Moisture Index (NDMI), which strongly correlates with vegetation moisture content, is particularly valuable in coastal wetlands and estuarine environments, where hydrological variation drives vegetation dynamics [14].

Beyond spectral indices, advanced methods, such as Tassel Transformation (TCT) [15], which transforms spectral data into brightness, greenness, and wetness components, and Change Vector Analysis (CVA) [16], which assesses both the intensity and direction of spectral change, allows the detection of subtle land cover transitions or sudden disturbances, such as droughts or floods. These methods have proven useful for monitoring dynamic coastal habitats, and their responses to environmental stressors have expanded the capabilities of remote sensing [5,6].

A combination of hyperspectral and LiDAR derived vegetation metrics can be used to monitor temporal trends in coastal vegetation, including its response to extreme weather events, offering a more detailed and integrated understanding of ecosystem structure and function [17].

Complementary approaches include harmonic regression on Landsat derived VI time series to extract phenological characteristics of *Spartina alterniflora* along the Guangxi coast [18], and specialised indices like Mangrove Forest Index (MFI), designed to identify submerged mangrove forests using single tide Sentinel-2 imagery [19]. Combined with machine learning and ecological modelling, these integrated methods offer robust tools for long-term monitoring and management of dynamic intertidal and coastal vegetation.

Through analysis of satellite image time series, these indices and transformations support the assessment of interannual and seasonal trends in intertidal vegetation. This provides information on ecosystem health and its vulnerability to disturbances such as sea level rise, storms, and invasive species [4,10].

The aim of this study was to analyse interannual changes in intertidal vegetation cover along the coast of continental Portugal for the past decade (i.e., since Sentinel-2 data became available). The integration of Sentinel-2 imagery, drone based multispectral observations, and a wide range of vegetation indices is proposed to improve the monitoring of intertidal habitats. Therefore, 10 m resolution satellite remote sensing data are calibrated with high-resolution UAV data to assess (i) the distribution of coastal intertidal vegetation and (ii) its variation from 2015 to 2024. Several vegetation indices derived from satellite images are tested, assessing their ability to represent the true intertidal vegetation cover, obtained through very-high-resolution and in situ surveys for a test area. The applicability and limitations of the methodology and the use of these satellite data are discussed.

2. Materials and Methods

2.1. Procedure

Data processing involved several sequential steps designed to estimate and map intertidal vegetation cover using satellite data and the relationship between vegetation

indices and vegetation cover, validated for an area with high resolution and in situ information (Figure 1):

- Very-high-resolution multispectral UAV imagery from the Viana de Castelo area in northern Portugal was classified using supervised machine learning techniques to obtain reference maps of vegetation cover in intertidal zones.
- Statistical regression models were developed to quantify the relationship between UAV-derived vegetation cover and Sentinel-2 vegetation index values.
- The best-performing vegetation index was used for the estimation of vegetation cover. A model threshold value was established to determine which satellite pixels are vegetation.
- The selected VI and respective threshold were applied to the entire satellite time series of multispectral bands of the Sentinel-2 mosaics to assess the spatial extent and temporal variability of intertidal vegetation during the study period.

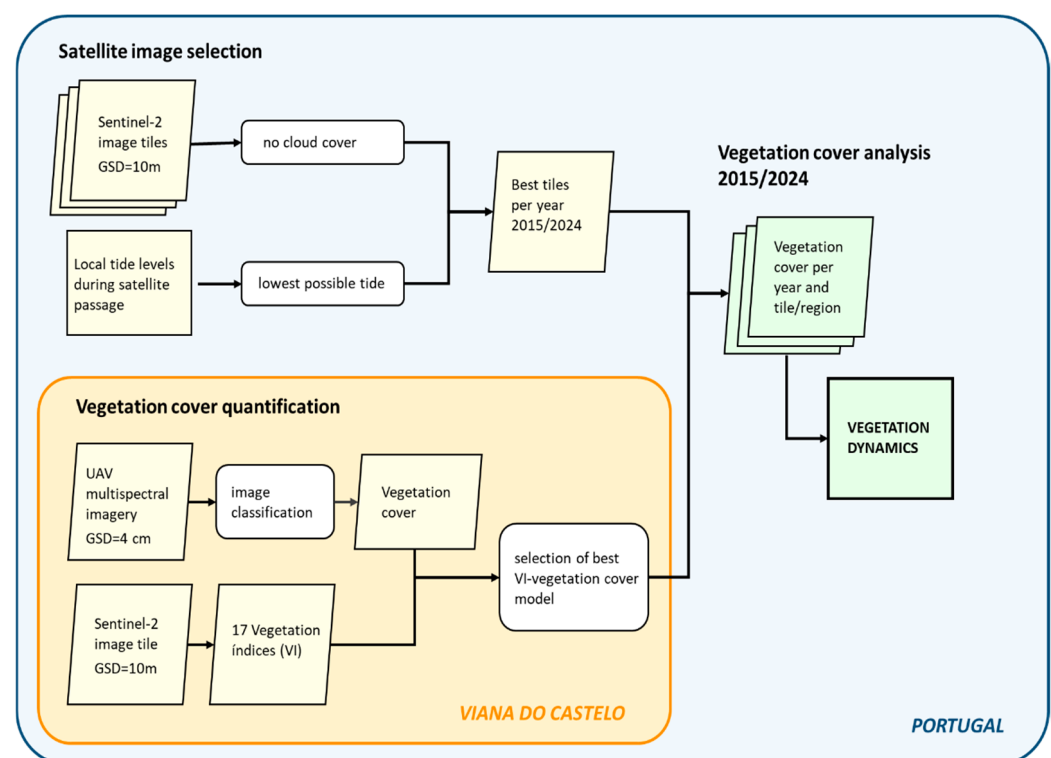


Figure 1. Outline of the adopted procedure, for the study area (the continental Portuguese coast; blue) and the validation area (near Viana do Castelo, orange) used to relate satellite image derived VI to intertidal vegetation cover.

2.2. Satellite Image Selection and Processing

Sentinel-2 images (Level 2A) were obtained from the Copernicus Explore portal [20]. The data are provided in approximately 100×100 km tiles, 9 of which cover the continental Portuguese coastline (Figure 2); these tiles were generated by subdividing the satellite imagery according to the standardised grid system used in the Copernicus Sentinel-2 mission, ensuring complete spatial coverage of the study area. Image dates were selected applying the following criteria: negligible cloud cover, capture during spring/summer season, to avoid vegetation differences due to seasonality; and image capture date and time corresponding to the lowest tide possible. In this context, favourable tidal conditions correspond to the lowest predicted water levels (i.e., the most negative values), as these expose a larger area of intertidal substrate and vegetation to the satellite sensors. During higher tides, the satellite sensor might capture less reflectance from vegetated surfaces,

potentially leading to an underestimation of vegetation cover. To ensure good image quality, all satellite image tiles with up to 10% cloud cover were visually checked, selecting the image with the lowest tide that showed no significant cloud cover over the intertidal areas.

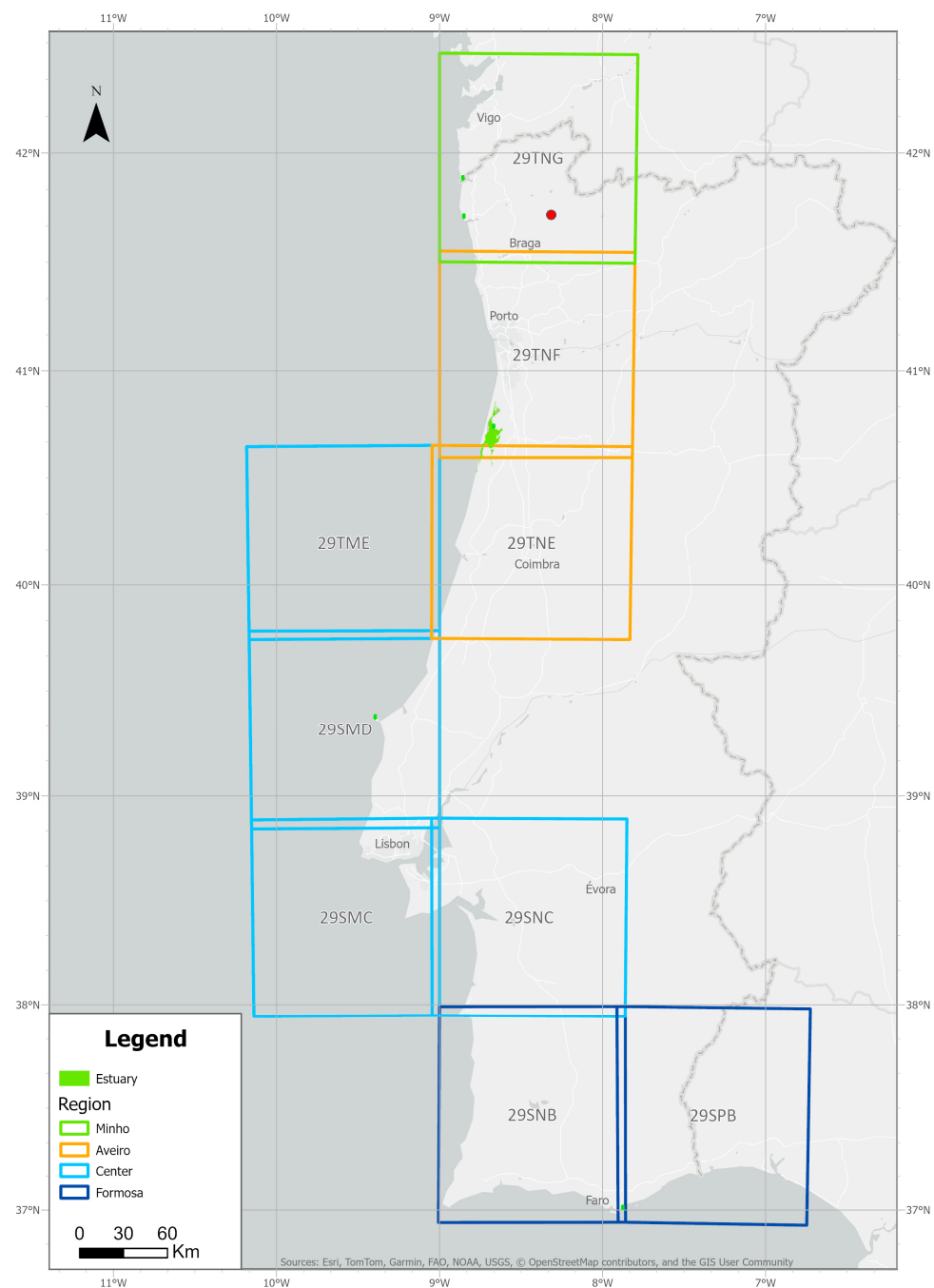


Figure 2. Location of the study area, the coast of continental Portugal, with the respective Sentinel-2 image tiles (the colours indicate which tiles were used for each region), and the validation area near Viana do Castelo (red dot); the four regions studied are shown: the Minho region with its estuary in the north, the Ria de Aveiro lagoon, the centre region and the Ria Formosa region in the South.

Tidal elevations were obtained from gridded sets of tidal harmonic constants (eight primary, two long period and three non-linear components) from the TPXO9-atlas with a 1/30 degrees' resolution, using the Tidal Model Driver (TMD) Matlab Toolbox (version 2.5) [21]. The selected model assimilates various altimetric products as well as other coastal datasets, providing accurate results for complex topographic areas and in shallow

waters. The astronomical tide was extracted for each satellite image tile (considering the coordinates in the centre of the respective coastal stretch), for all dates between May and August, for the years 2015 to 2024, for the time of satellite passage 11:21 h (UTC).

For each of the selected tiles, the Sentinel-2 Blue, Green, Red and NIR bands (central wavelengths 490 nm, 560 nm, 665 nm and 842 nm, respectively; 10 m resolution) were downloaded. The tiles, which are partially overlapping (Figure 2), were merged into a single mosaic per year, using the mean band values in the overlapping pixels (to avoid duplicate pixels for a single year).

The mosaic was then clipped to the intertidal zone. Given the tides in continental Portugal, which generally range between 2 m above and 2 m below Mean Sea Level (MSL), the study area was delimited to the coastal stretch with elevation up to 2 m above MSL, on the land side, and by 2 m below MSL on the ocean side. Elevations were obtained from the Digital Terrain Model (DTM) of a national LIDAR survey carried out in 2011 (data provided by the Portuguese Direção Geral do Território—DGT) [22], which has a spatial resolution of 2 m and covers the whole continental Portuguese coast. The resulting intertidal area was further visually checked and manually adapted to eliminate non-natural habitats (like forests, agricultural fields and parks) from the study area.

Analyses were conducted for the entire coastline and by region, considering geomorphological consistency and coastal configuration. Four regions were defined: Minho in the north, corresponding to tile 29TNG; followed by the Ria de Aveiro, a large lagoon, tiles 29TNF and 29TNE; the Centre with limited coastal vegetation, encompassing the areas surrounding Peniche, Lisbon, and Setúbal, tiles 29TME, 29SMD, 29SMC and 29SNC; and Ria Formosa, a second coastal lagoon system in the south, tiles 29SNB and 29SPB (analogously to the procedure adopted for the orthomosaic, the overlapping tile areas were divided between the respective tiles to avoid duplicated pixels).

The studied coastline includes three regions with large intertidal areas: the Minho estuary in the north, the Ria de Aveiro lagoon in the centre-north, and the Ria Formosa in the South. To analyse tidal influence on vegetation in each region, we created a tide index based on the average tide level across tiles, weighted by the intertidal area within each tile. This index may serve as an indicator that can help explain if and to what degree year-to-year changes in mapped vegetation area can be due to tide-level differences.

2.3. UAV Mapping of Vegetation Cover

Intertidal vegetation cover was assessed and quantified for an area of approximately 48,000 m² near Viana do Castelo (Figures 2 and 3), using very-high resolution multispectral UAV imagery.

In 17 June 2022, a DJI Matrice 200 drone (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with a MicaSense RedEdge-MX multispectral camera (EagleNXT, Wichita, KS, USA) was used to survey the study area, capturing imagery in five spectral bands: Blue (Central Wavelength (CW) 475 nm and Bandwidth (BW) 32 nm), Green (CW 560 nm, BW 27 nm), Red (CW 668 nm, BW 16 nm), Red Edge (CW 717 nm, BW 12 nm) and Near-Infrared (CW 842 nm, BW 57 nm). The flight was carried out during spring neap tide (water level about 1.5 m below MSL), at an altitude of 60 m, capturing images with 70% lateral and 80% longitudinal overlap, resulting in a Ground Sample Distance (GSD) of 4.0 cm.

Before the flight, ground control points (GCPs) were established and marked with crosses to ensure their visibility in the aerial imagery. The precise georeferencing of these points was conducted using a Sfaira One GNSS receiver (SingularXYZ, Shanghai, China) operating in RTK mode, with ground positional corrections provided by the Portuguese Network of Permanent Stations (RENAP).



Figure 3. Orthomosaic of the intertidal area near Viana do Castelo ($41^{\circ}41'45.6''\text{N}$, $8^{\circ}51'10.8''\text{W}$), used for the determination of vegetation cover and the selection of VI (the yellow polygon delimits the area surveyed with a multispectral camera).

The acquired images were processed using Agisoft Metashape Professional (Version 1.8.0) to create a multispectral orthomosaic. A sun sensor and a reflectance calibration panel were used to ensure reflectance agreement in the full image.

A supervised land cover classification was subsequently performed to assess the vegetation cover in the area. The classification was performed using QGIS 3.40.7 [23] and the Semi-Automatic Classification Plugin (Version 8.5.0), applying a Random Forest algorithm [24] with 700 trees and the minimum number to split equalling 2. Six land cover classes—emersed vegetation, dry sand, wet sand, submersed vegetation, rock, water—were selected based on three criteria: their relevance in the field, visual distinctiveness in the orthomosaic, and importance for the study aims.

Training areas were delineated through visual interpretation of the orthomosaic. Furthermore, an assessment of the spectral signature separability of training areas was conducted, leading to the adjustment or reselection of training areas for classes that exhibited a substantial spectral overlap, before proceeding with the classification.

Classification accuracy was evaluated using individual pixels selected from the orthomosaic, where the ground truth class was determined through visual interpretation. Only pixels located within a homogeneous neighbourhood were considered for accurate assessment to minimise the influence of boundary effects. Specifically, a 5×5 pixels square neighbourhood (excluding the central pixel) was used, ensuring that each selected pixel was surrounded by 24 adjacent pixels of the same class. Pixels were randomly selected but only from areas that met this homogeneity criterion. Pixels were then compared to the corresponding supervised classification results, generating an error matrix for the classification. The number of pixels used for accuracy assessment was established based on the proportion of each class and the expected standard deviation, following the equation below [25].

$$N = \left(\sum_{i=1}^i (W_i \times S_i) / S_0 \right)^2 \quad (1)$$

where

N = number of pixels for accuracy assessment.

W_i = mapped area proportion of class i ;

S_i = standard deviation of stratum i ;

S_0 = expected standard deviation of overall accuracy.

The performance of the random forest classification was assessed using Overall Accuracy and the F1 score (Equation (2)) for the vegetation class, as this metric provides a balanced evaluation by incorporating both User Accuracy (UA) and Producer Accuracy (PA). The F1 score ranges from 0 to 1, where values closer to 1 indicate better classification performance.

$$\text{F1 score} = 2 \frac{\text{UA} \times \text{PA}}{\text{UA} + \text{PA}} \quad (2)$$

2.4. Vegetation Cover Assessment

The UAV-image classification of the validation area was used to quantify vegetation cover proportion in each of the satellite-image pixels, counting the pixels classified as (emersed or submersed) vegetation and determining the cover proportion (0 = no vegetation, 1 = the whole pixel is covered by intertidal vegetation) for each satellite pixel.

Several VIs were computed using Sentinel-2 image bands from 19 April 2022 (which showed the best tide conditions and no cloud cover over the Viana do Castelo area at a date close to the UAV survey) were tested to assess their relationship with intertidal vegetation cover proportion (Table 1). The relationship between satellite-image derived VIs and the vegetation cover determined through the high-resolution image classification was modelled using regression models. Five models were tested: linear model with vegetation cover proportion as response variable and the satellite-derived VI as predictor variable ($y \sim x$); with log-transformed response variable ($\log(y) \sim x$); with log-transformed predictor variable ($y \sim \log(x)$); with log-transformation of both response and predictor variables ($\log(y) \sim \log(x)$); and with the predictor as quadratic polynomial ($y \sim x + x^2$). Model outcomes were ranked according to their adjusted R^2 value, and the best performing model was used to assess intertidal vegetation cover and dynamics for the whole coast of continental Portugal.

The model was used to estimate cover density as well as total cover area per region and for the whole continental Portuguese coast.

Table 1. Description of the tested vegetation indices.

Name	Formula	Reference
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - Red}{NIR + Red}$	[26]
Renormalized Difference Vegetation Index	$RDVI = \frac{NIR - Red}{\sqrt{NIR + Red}}$	[27]
Coastal Redness Vegetation Index	$CRVI = \frac{Red - Green}{NIR}$	[28]
Difference Vegetation Index	$DVI = NIR - Red$	[29]
Ratio Vegetation Index	$RVI = \frac{Red}{NIR}$	[30]
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - Green}{NIR + Green}$	[31]
Enhanced Vegetation Index	$EVI = 2.5 \times \left[\frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times Blue + 1} \right]$	[32]
Soil Adjusted Vegetation Index	$SAVI = \frac{1.5 \times (NIR - Red)}{NIR + Red + 0.5}$	[33]
Normalized Difference Water Index	$NDWI = \frac{Green - NIR}{Green + NIR}$	[34]
Atmospherically Resistant Vegetation Index	$ARVI = \frac{NIR - Red - (Red - Blue)}{NIR + Red - (Red - Blue)}$	[35] ¹
Green Chlorophyll Index	$GCI = \frac{NIR}{Green} - 1$	[36]
Red-edge Chlorophyll Index	$RCI = \frac{NIR}{Red} - 1$	[36]
Chlorophyll Content Index	$CVI = \frac{NIR \times Red}{Green^2}$	[37]
Green Difference Vegetation Index	$GDVI = NIR - Green$	[7]
Enhanced Normalized Difference Vegetation Index	$ENVI = \frac{NIR + Green - 2 \times Blue}{NIR + Green + 2 \times Blue}$	[38]
Modified Green Red Vegetation Index	$MGRVI = \frac{Green^2 - Red^2}{Green^2 + Red^2}$	[39]

¹ Here: using the formula with an atmospheric self-correcting factor $y = 1.0$, as Kaufman and Tanre (1992) [35] have shown that when the vegetative cover is sparse and the atmospheric data are unknown (aerosol dimensions), the value of $y = 1.0$ permits a better adjustment for most remote sensing applications.

3. Results

3.1. Selected Satellite Images

The selected Sentinel-2 tiles with respective dates and tide conditions during image capture are presented in Appendix A, Table A1. Only for 2015 the same date was used for the whole country. For the other years, two to four different dates had to be selected to guarantee good-quality cloud-free images. The highest tide levels were found for the southern tiles (SNB, SPB), where tidal ranges are naturally a bit lower than at the western, Atlantic coast.

3.2. Classification Results

Six distinct land cover classes were defined based on visual interpretation of the high-resolution UAV imagery: emerged vegetation, dry sand, wet sand, submerged vegetation, rock, and water. To train the Random Forest classification model, 30 representative training areas per class were selected, each covering an area approximately 0.25 m² (50 cm × 50 cm). This resulted in 180 training areas, totalling approximately 27,000 pixels. These pixels served as input data for the random forest classification. The final land cover map derived from this classification is presented in Figure 4.

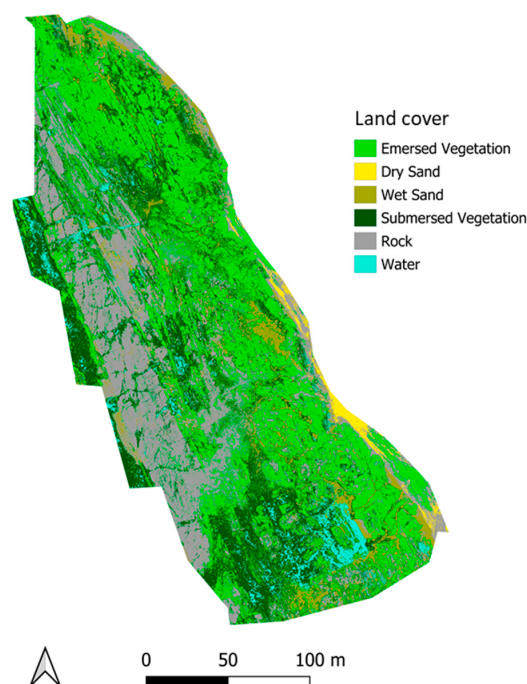


Figure 4. UAV-image classification with land cover types.

Land cover analysis revealed that emerged vegetation is the dominant category, with an area of approximately 18,003 m² and 37.7% of the total land area. Submersed vegetation and rock also occupy significant portions, with 10,995 m² (23.0%) and 12,177 m² (25.5%), respectively. Wet sand and water constitute smaller fractions of the landscape, occupying 3902 m² (8.2%) and 2208 m² (4.6%), respectively. Sand covers the smallest area, with only 497 m², or 1.0% of the total. These results highlight the prevalence of natural vegetation and rocky terrain.

Based on Equation (1), a total of 1678 pixels were randomly selected for accuracy assessment. The sample size was calculated assuming the class percentage area (W_i) shown in Table 2, a stratum-level standard deviation (S_i) of 0.8 for all classes, and a desired standard deviation of the overall accuracy estimate (S_0) of 0.01. Of the selected pixels, 1613 could be clearly interpreted and were used in the accuracy evaluation. The results of the classification accuracy assessment are presented in Table 2.

Table 2. Classification results (Veg.: Vegetation).

		Reference Map								
		Emersed Veg.	Dry Sand	Wet Sand	Submersed Veg.	Rock	Water	Total	Area (m ²)	Area %
Classified	Emersed Veg.	599	0	0	3	1	0	603	18,003	0.377
	Dry Sand	0	30	0	0	0	0	30	497	0.010
	Wet Sand	0	3	122	0	3	3	131	3902	0.082
	Submersed Veg.	16	0	3	334	2	12	367	10,995	0.230
	Rock	3	19	3	0	383	0	408	12,177	0.255
	Water	0	0	4	2	0	68	74	2208	0.046
	Total	618	52	132	339	389	83	1613		
Estimated Area		18,452	1154	3932	10,156	11,610	2478	47,781		
Area %		0.386	0.024	0.082	0.213	0.243	0.052			
SE Area		141	137	127	177	162	134			
95% CI Area		554	537	500	695	635	527			
Producer's Accuracy		0.969	0.431	0.924	0.985	0.985	0.819			
User's Accuracy		0.993	1.000	0.931	0.910	0.939	0.919			
F1 Score		0.981	0.602	0.928	0.946	0.961	0.866			
Overall Accuracy								0.952		

The accuracy assessment also provides estimated areas, based on Producer's and User's accuracy, which are accompanied by standard errors and 95% confidence intervals that provide clearer measures of uncertainty. For instance, the standard error for the emerged vegetation class was 141 m², corresponding to a 95% confidence interval of ± 554 m². Similar values were observed for smaller classes, such as dry sand (± 537 m²), indicating more precise area estimates for classes with larger areas.

The classification achieved an overall accuracy of 95.2. Most classes exhibited high producer's accuracies (>0.92 for emerged vegetation, submersed vegetation, and rock), though dry sand was a notable exception (0.431), indicating substantial omission error, likely due to spectral overlap with rock and wet sand. User's accuracies also presented satisfactory results (0.99 for emerged vegetation, 0.91 for submersed vegetation). Still, the zero omission error for dry sand might be related to its underrepresentation in the total area. According to the methodology used in this study, defined by Olofsson [25], the number of pixels used for classification accuracy assessment is proportional to the class area. This limited sample size likely contributed to the absence of observed commission error in the confusion matrix. F1 scores ranged from 0.602 (dry sand) to 0.981 (emerged vegetation), underscoring some imbalance in classification performance. The confusion matrix (Classified versus Reference Map cover in Table 2) revealed that most misclassifications occurred between spectrally similar classes—e.g., wet sand mislabelled as water or rock, and submersed vegetation mislabelled as water or emerged vegetation. Still, the overall results and F1 score, with the exception of the Dry Sand cover class, demonstrate robust overall performance and excellent performance for vegetation identification, indicating that classification results can be used as a reliable source for the vegetation cover assessment.

3.3. Vegetation Index-Vegetation Cover Model

The performance rankings of the vegetation cover proportion-VI regression models are presented in Table 3. Among all indices evaluated, ARVI (Atmospherically Resistant Vegetation Index) yielded the strongest predictive model, with the model equation:

$$\text{Vegetation cover proportion} = -0.1172 + 3.9656 \times \text{ARVI} - 3.6628 \times \text{ARVI}^2 \quad (3)$$

Table 3. Ranking of the best and second-best regression models per VI, showing model formula and adjusted R².

VI	Best		Second-Best	
	Model	Adjusted R ²	Model	Adjusted R ²
ARVI	$y \sim x + x^2$	0.549	$y \sim x$	0.517
NDVI	$y \sim x + x^2$	0.479	$y \sim \log(x)$	0.470
RVI	$y \sim x + x^2$	0.475	$y \sim x$	0.468
GCI	$y \sim x + x^2$	0.474	$y \sim \log(x)$	0.466
GNDVI	$y \sim x + x^2$	0.444	$y \sim \log(x)$	0.441
NDWI	$y \sim x + x^2$	0.444	$y \sim x$	0.424
RCI	$y \sim x + x^2$	0.440	$y \sim \log(x)$	0.436
CVI	$y \sim x + x^2$	0.371	$y \sim \log(x)$	0.364
RDVI	$y \sim x + x^2$	0.317	$y \sim x$	0.316
SAVI	$y \sim x$	0.307	$y \sim x + x^2$	0.306
EVI	$y \sim x$	0.289	$y \sim x + x^2$	0.288
ENDVI	$y \sim x + x^2$	0.222	$y \sim x$	0.216
DVI	$y \sim x + x^2$	0.214	$y \sim x$	0.207
GDVI	$y \sim x + x^2$	0.197	$y \sim x$	0.181
MGRVI	$y \sim x$	0.145	$y \sim x + x^2$	0.144
CRVI	$y \sim x + x^2$	0.102	$y \sim x$	0.101

This model achieved an adjusted R^2 of 0.549, indicating that it explained about 55% of the observed variation in vegetation cover proportion (with values between 0 and 1) for the Viana do Castelo site. The next-best VIs were NDVI, RVI, and GCI, which exhibited comparable performance, with adjusted R^2 values ranging between 0.474 and 0.479.

The best-performing (ARVI) model showed significant variability (scatter) and a curved relationship that was best fitted by a polynomial (Figure 5).

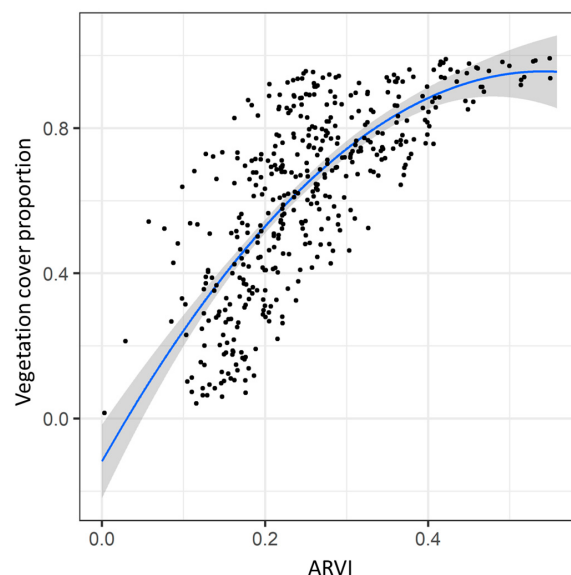


Figure 5. Best performing model with fitted curve (blue line) and 95% confidence intervals (grey area).

The regression model provides estimates of vegetation cover proportion for different satellite-image-derived ARVI values. For instance, an $ARVI = 0.102$ corresponds to 25% vegetation cover in the satellite pixel, $ARVI = 0.189$ to 50% cover, and $ARVI = 0.304$ to 75% cover. The area of the pixels with an $ARVI \geq 0.215$ corresponds to the area effectively covered by intertidal vegetation. Using this threshold value to consider a satellite pixel as vegetated in our validation site, the total intertidal vegetation cover estimated using the satellite image was 26.800 ha. The area of vegetation cover obtained from the high-resolution image classification was 26.758 ha. Therefore, the sum of satellite image pixels with $ARVI \geq 0.214$ was computed, for each satellite image tile, region and year, to estimate the area of intertidal vegetation cover and its dynamics for continental Portugal.

3.4. Intertidal Vegetation Dynamics

Using the best performing ARVI-based model, the vegetation cover proportion was analysed along the continental Portuguese coast, computing the intertidal areas with at least 25%, 50% and 75% vegetation cover (i.e., $ARVI \geq 0.102$, $ARVI \geq 0.189$, and $ARVI \geq 0.304$, respectively) for the 100-m² satellite pixels. Vegetation cover varies over time, particularly in areas with low vegetation density in the Ria de Aveiro and Ria Formosa regions (Figure 6). The Minho region shows comparatively more satellite pixels with high coverage, suggesting that the Minho estuary has higher intertidal vegetation density than the larger Ria de Aveiro and Ria Formosa systems.

Using ARVI threshold ($ARVI \geq 0.214$) that reproduces the total area covered with vegetation for the validation site, we estimated intertidal vegetation cover area for the continental Portuguese coast and for the four regions (Table 4).

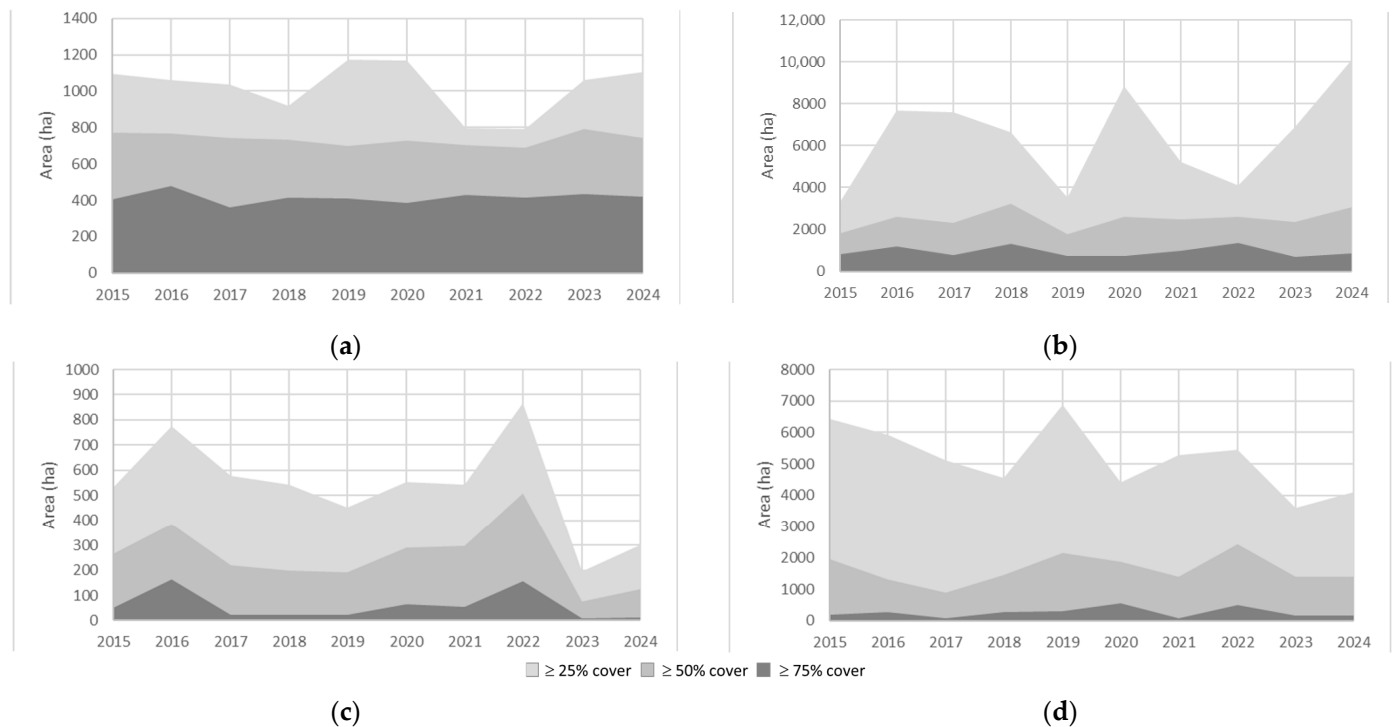


Figure 6. Dynamics of vegetation cover: estimated areas, calculated from satellite-image pixels, with at least 25%, 50% and 75% vegetation cover, per year, for the Minho (a), Ria de Aveiro (b), Centre (c) and Ria Formosa (d) regions.

Table 4. Area covered by intertidal vegetation (in ha) from 2015 to 2024, for the Portuguese coast (All) and per region, with respective satellite tile code (see Figure 2).

Year	All	Minho	Ria de Aveiro			Centre			Ria Formosa	
		29TNG	29TNE	29TNF	29SMC	29SMD	29SNC	29TME	29SNB	29SPB
2015	3524.1	625.2	182.9	1280.4	36.4	125.7	18.5	0.6	1000.1	254.3
2016	4537.3	671.1	390.8	1889.5	58.0	123.0	165.4	0.5	922.0	317.1
2017	2964.2	592.4	222.2	1492.7	23.4	101.0	10.0	0.2	413.1	109.3
2018	4278.5	606.0	327.8	2208.8	3.5	97.1	24.3	0.5	781.6	228.9
2019	3516.8	558.0	173.1	1212.9	52.3	48.1	19.0	0.1	1167.3	286.1
2020	4160.9	582.3	283.4	1647.5	31.1	134.8	39.5	0.0	1139.6	302.7
2021	3622.1	582.6	273.2	1675.8	59.0	116.4	27.8	1.0	767.6	118.6
2022	4823.2	574.6	397.4	1755.5	70.9	187.0	85.9	7.4	1529.0	215.5
2023	3428.1	649.9	182.5	1536.8	2.1	13.8	27.8	0.2	809.9	205.2
2024	3821.3	594.6	270.0	1942.2	17.2	28.8	25.0	0.0	719.7	223.8

The results revealed marked spatial and temporal variability in vegetation cover area along the Portuguese coast, particularly in extensive estuarine systems such as the Ria de Aveiro and the Ria Formosa (Figures 7 and 8).

The combined total vegetation cover area across all coastal regions reached its lowest level in 2017, with 2964 ha and its highest level in 2022, with 4823 ha, representing 4.1% and 6.8% of the total intertidal area, respectively. The 2022 maximum was followed by a marked decline in 2023 and a partial recovery the following year. Over the ten-year study period, the national average vegetation cover was approximately 3868 ha, corresponding to 5.4% of the total intertidal area. Nationally, interannual differences ranged from −29% (losses from 2022 to 2023) to +44% (gains from 2017 to 2018).

The results per region are presented in Tables 4 and A2. The Minho region (tile 29TNG) presented relatively stable vegetation cover throughout the decade, covering on average 604 ha, i.e., 8.5% of the intertidal area. The lowest vegetation area recorded was 558 ha in 2019, the highest value observed during the study period was 671 ha in 2016 (Figure 8a). There is no apparent consistent relationship between tidal conditions in

the satellite scenes selected for this area and vegetation cover area estimates. The least favourable tidal level of the decade (-1.11 m) coincided with the second-lowest vegetation cover detected, and the best tidal level with the third-highest vegetation cover area.

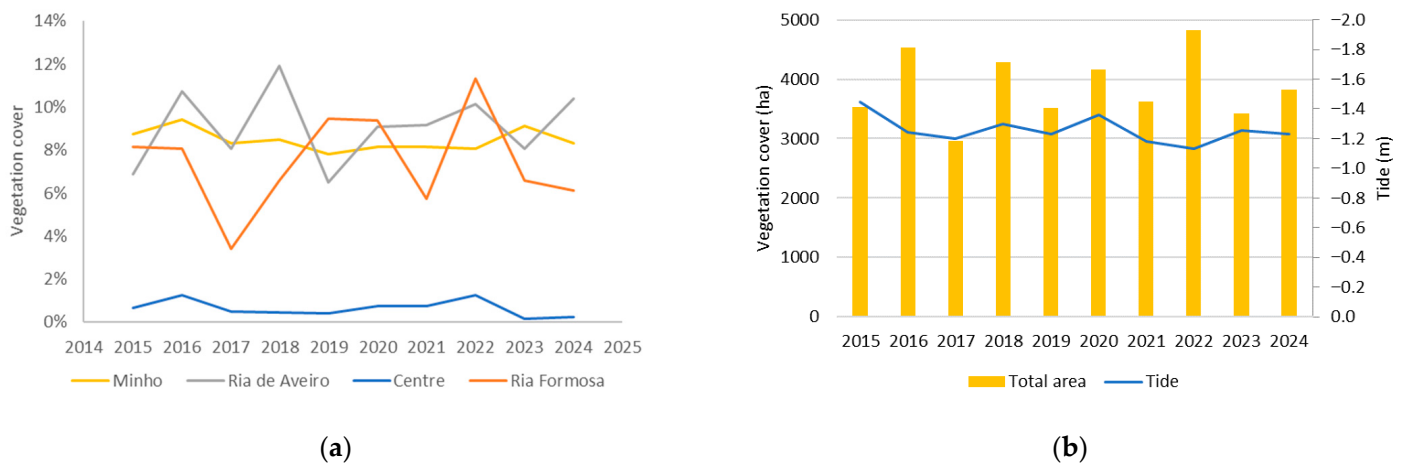


Figure 7. Estimated vegetation cover area over time (per year), in percentage of total intertidal area, per region (a) and estimated vegetation cover area (in ha) for the whole coast, with the blue line representing the tide index, i.e., the weighted average of the water level (astronomical tide) during satellite image capture, weighted by the tiles' intertidal areas (b).

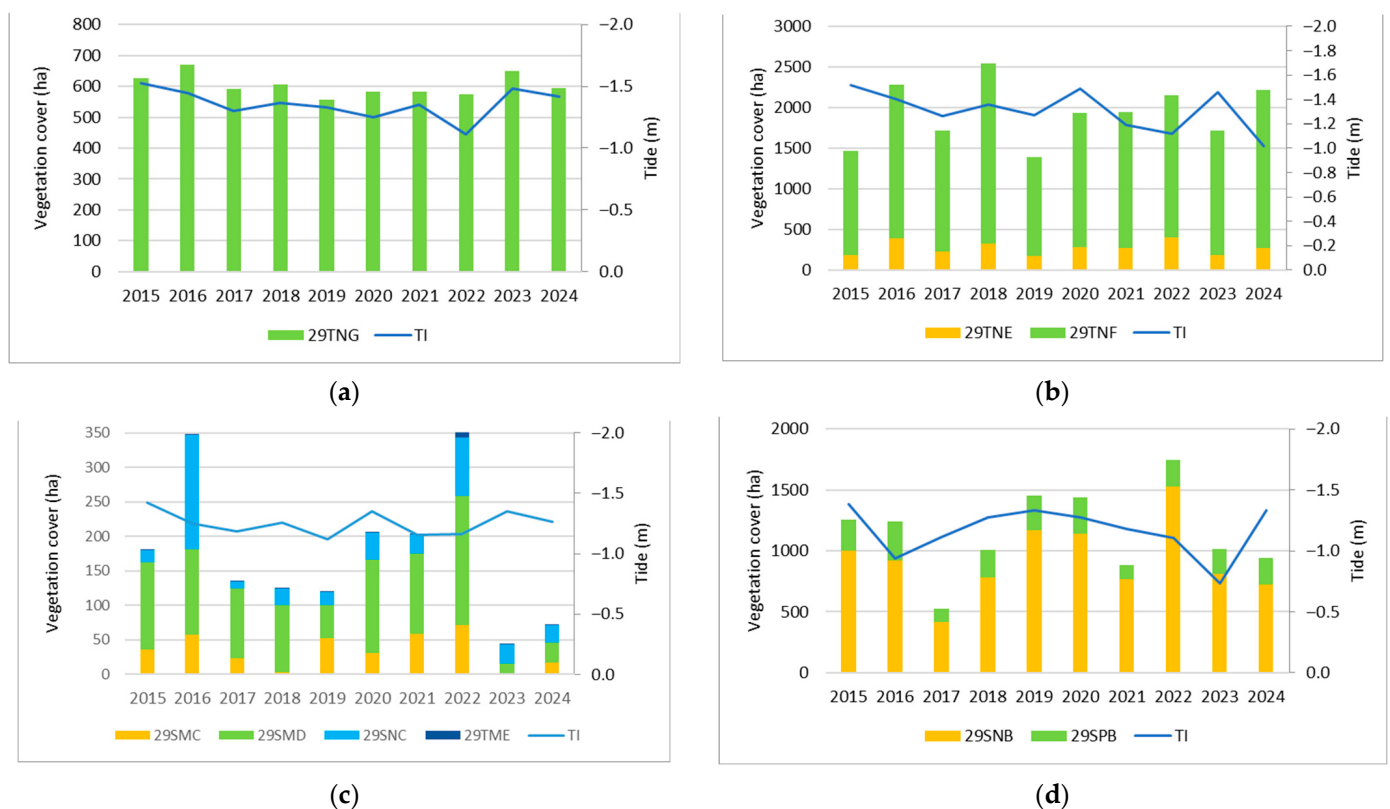


Figure 8. Intertidal vegetation cover areas, per year, for the Minho (a), Ria de Aveiro (b), Centre (c) and Ria Formosa (d) regions; the blue line represents the weighted average of the water level (astronomical tide) during satellite image capture, weighted by the tiles' intertidal areas.

The Ria de Aveiro lagoon and estuarine system (tiles 29TNE and 29TNF) was overall the region with the highest vegetation cover area, on average 1935 ha, i.e., 9.1% of the intertidal area. Vegetation area ranged from a maximum of 2537 ha in 2018 to a minimum of

1386 ha in 2019, representing a marked decrease of 45%. No clear relationship was observed between tidal variation and vegetation cover area variation. Notably, the most favourable tidal conditions, recorded in 2015 (−1.53 m), and the least favourable, recorded in 2024 (−1.01 m), did not correspond to years with the highest or lowest vegetation cover area (Figure 8b).

The Central region, which encompasses four satellite mosaic tiles (29SMC, 29SMD, 29SNC, and 29TME), is the region with the lowest vegetation cover, which is on average 178 ha, i.e., 0.65% of the intertidal area. The maximum vegetation cover percentage recorded was only 1.27%, equivalent to 351 ha in 2022, while the minimum was 44 ha in 2023. Tidal values in this region are like those observed in the Aveiro region, with the most favourable tide occurring in 2015 (−1.5 m) and the least favourable in 2024 (−1.01 m). Again, no consistent tide-area relationship was observed (Figure 8c).

The Ria Formosa coastal lagoon system (tiles 29SNB and 29SPB) presented a dynamic vegetation pattern with notable interannual variability. On average, vegetation covers 1151 ha, i.e., 7.49%, of the intertidal area. The lowest vegetation cover was recorded in 2017 (522 ha), while the highest was in 2022 (1744 ha). This region also registered the most unfavourable tidal value of the entire continental Portuguese coast, reaching −0.73 m in 2023. Like other regions, the most favourable tidal value was observed in 2015 (−1.39 m). Although there is no clear direct relationship between tidal levels and vegetation cover area estimates in Ria Formosa, data from 2018 to 2021 suggest a pattern (curve) that could indicate some influence of tide levels on the results. However, the variation is low and not consistent for all years (Figure 8d).

Overall, all vegetated areas along the continental Portuguese coast experienced fluctuations in vegetation cover throughout the study period. However, a closer analysis of regional trends reveals different temporal patterns, meaning that the national extremes do not consistently reflect local maxima and minima. For example, the Minho region recorded its highest vegetation cover area in 2016 and its lowest in 2019. The Aveiro region, on the other hand, reached its maximum in 2018 and its minimum in 2019. The Central region, recorded its maximum in 2022 and its minimum in 2023. The Ria Formosa recorded its maximum in 2022 and its minimum in 2017.

Interestingly, despite these regional differences, 2022 was a good year for intertidal vegetation for all regions but Aveiro. Minimum values were much more variable across regions. These regional differences highlight the spatial heterogeneity of vegetation dynamics and the influence of regional environmental conditions on shaping intertidal vegetation cover percentages.

The methodology also allows detailed analysis of intertidal vegetation cover. For instance, in the Ria de Aveiro, the vegetation cover area decreased markedly from 2018 to 2019. According to the ARVI maps, vegetation is particularly dense in the central-most eastern part of the lagoon (Figure 9, where red tones represent higher ARVI values); the ARVI ranges between 1 and −1, with values closer to 1 indicating greater vegetation cover. Between 2018 (Figure 9a) and 2019 (Figure 9b), the overall ARVI decreased, but in this particular area, it increased, as can be seen in the difference map (Figure 9c) that highlights areas with notable changes.

Using the threshold established in this study, $ARVI \geq 0.214$, the change in vegetation cover area (i.e., pixels considered as covered in vegetation) is also clearly visible (Figure 10). Although for much of the intertidal zone along the continental Portuguese coast changes are difficult to assess visually, due to the spatial resolution and level of detail in the satellite images, in larger areas, such as the Aveiro estuary and the Ria Formosa lagoon, local changes are easily detectable.

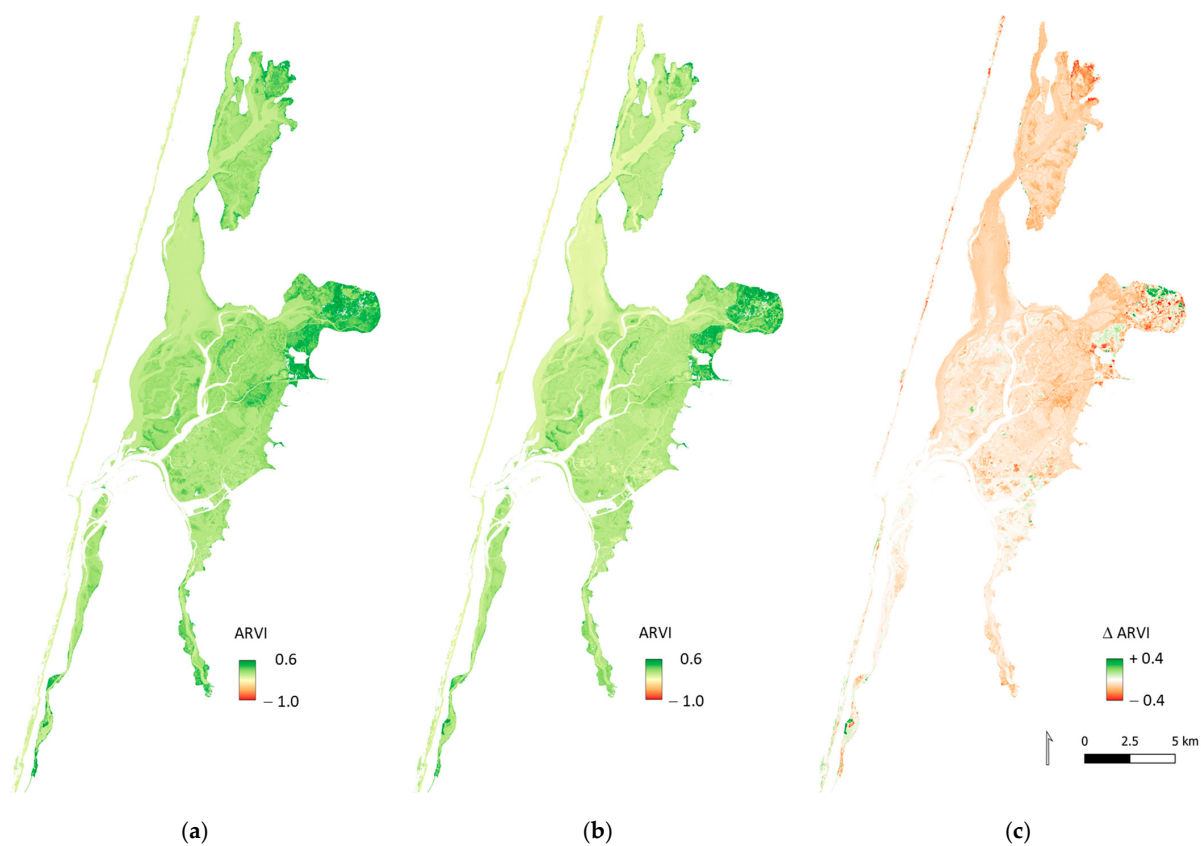


Figure 9. ARVI values for the Ria de Aveiro lagoon for 2019 (a) and 2020 (b), and the differences between these years (c), with red indicating lower and green higher ARVI.

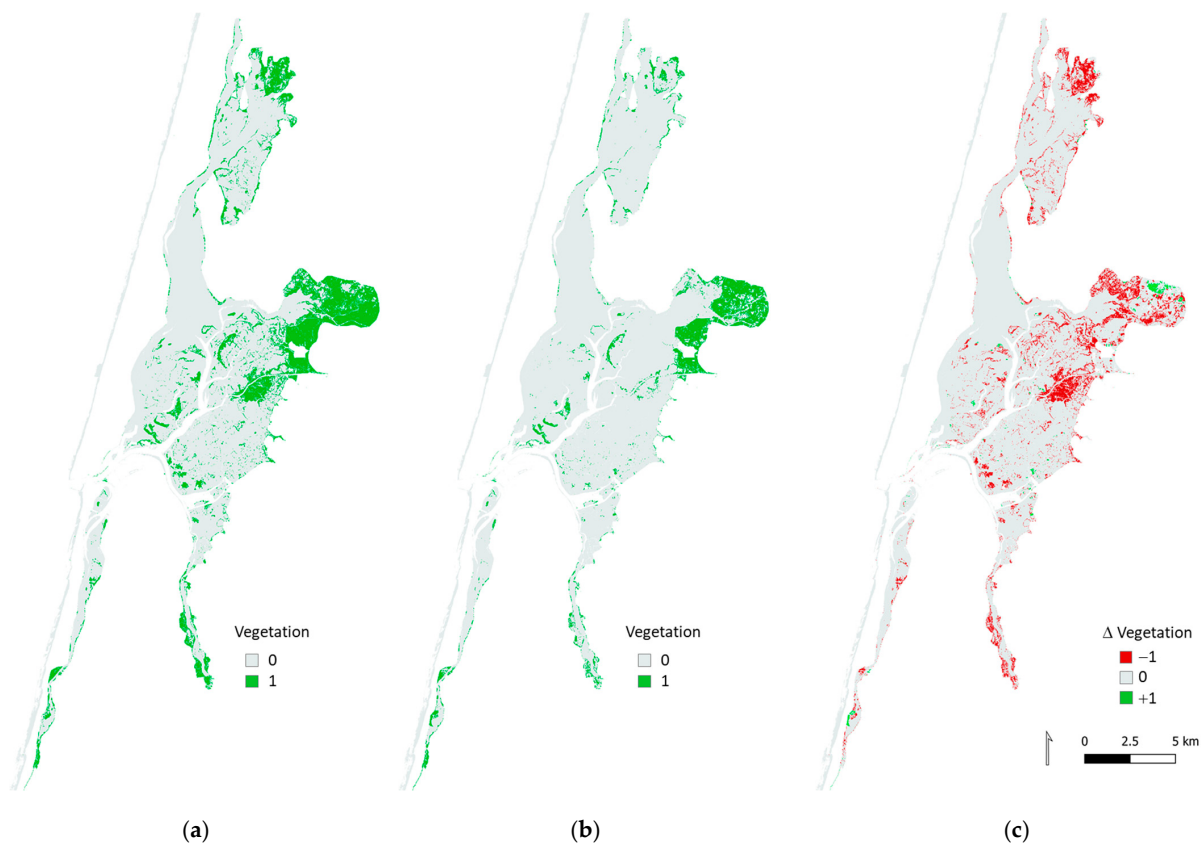


Figure 10. Intertidal vegetation cover in the Ria de Aveiro Lagoon for 2018 (a) and 2019 (b), and the differences between these years (c), with red indicating loss and green gain.

4. Discussion

4.1. Satellite Images

Survey conditions, namely tide levels and season, can affect vegetation cover estimates and, therefore, comparisons between surveys/years. This limitation has been widely noted in coastal and wetland remote sensing studies, where water level and timing of image acquisition strongly influence vegetation detectability [5,6]. To analyse the quality of the satellite images and account for tidal conditions, cloud-free Sentinel-2 images were carefully selected to coincide with low tide events. This selection criterion was crucial, as intertidal vegetation is most visible and most accurately detected when located above the waterline. However, achieving a consistent correspondence between low cloud cover and low tide across all images covering the entire Portuguese coast proved challenging. All selected images had less than 10% overall cloudiness, but nonetheless, clouds often obscured the coastal zone specifically, making it necessary to select images with less optimal tides in some cases. Consequently, some satellite scenes inevitably corresponded to intermediate low-tide levels. In these cases, parts of the intertidal zone remained submerged during acquisition, potentially obscuring vegetation and attenuating spectral signals, especially in the NIR band. Similar effects of partial submersion on spectral indices have been reported in estuarine and seagrass systems [9,10]. This introduces uncertainty into vegetation indices and can affect vegetation detection and quantification. Nonetheless, the threshold used for the chosen VI, to quantify vegetation cover area, was calculated considering both immersed and submersed vegetation and should represent both. Furthermore, the results were analysed considering the tide conditions (Figures 7 and 8). A tidal index was calculated for each region, defined as the average of tide level weighted by the intertidal area of tiles at the time of image acquisition. This index was based on the constant passage time of the Sentinel-2 satellites (approximately 11:21 a.m. local time), ensuring temporal consistency across all images.

To limit seasonal effects, i.e., reduce vegetation variability and improve comparability between years, image acquisition was limited to the spring and summer months (May through August). Most of the images were acquired during the summer months, mainly in August, July or June, when intertidal vegetation typically reaches its seasonal peak [40]. However, two tiles correspond to images from May 2022 (Centre region) and 2023 (Ria Formosa). These exceptions were due to persistent cloud cover in the region during the summer months. While this variation in acquisition dates could introduce some seasonal effects, especially in more dynamic ecosystems, the use of a standardised acquisition time and the regional best-possible tides can help reduce the potential influence of immersion and ensure comparability across years and regions.

Overall, while the combination of seasonal filtering and cloud filtering provided a solid basis for image selection, the dynamic nature of the coastal zone and Sentinel-2's fixed time of passage limited the ability to capture images with consistent data and cloud cover characteristics for all locations and years. This highlights the importance of integrating the data with the best features for the raster analyses and tidal models, whenever possible and available, as has also been emphasised in broader coastal ecosystem monitoring frameworks [1,10].

4.2. Vegetation Cover

Vegetation cover was validated by classifying multispectral drone acquired images with a spatial resolution of 4 cm. This very-high-resolution dataset enabled precise delineation of vegetated and unvegetated areas (except for dry sand), capturing the local scale spatial variability typical of intertidal zones. Drone based classification proved highly

accurate, serving as a reliable ground truth dataset and validating the potential of drone mapping for detailed vegetation monitoring in coastal environments.

However, comparing this high-resolution reference data with Sentinel-2 imagery with a spatial resolution of 10 m revealed a clear limitation, given that (i) intertidal habitats present a high-resolution spatial variability and fragmentation, and (ii) 10 m pixels are consequently often of mixed nature. In many intertidal zones, particularly those characterised by patchy vegetation, a single satellite imagery pixel is likely to encompass a mixture of multiple land cover types, such as emerged vegetation, sediments (dry sand, wet sand), rocks, and shallow waters. This intra-pixel heterogeneity produces an average spectral signal, which can obscure or distort the vegetation specific reflectance patterns on which vegetation indices identifies.

As a result, the correspondence between drone derived vegetation cover and satellite derived vegetation indices can be weakened, especially in areas with sparse vegetation. Despite these limitations, the use of Sentinel-2 still offers considerable value, enabling consistent, large-scale monitoring across broad spatial and temporal domains. While local accuracy is lower compared to drone data, satellite mapping provides a generalizable and scalable dataset for the entire Portuguese coastline. This makes it useful for identifying broader vegetation trends, regional dynamics, and long-term changes, even if local scale heterogeneity is partially lost.

4.3. Vegetation Indices (VIs)

Among the 16 VIs tested, ARVI exhibited the strongest correlation with vegetation cover (adjusted $R^2 = 0.55$), followed closely by NDVI, RVI, and GCI (with adjusted R^2 of 0.48, 0.48 and 0.47, respectively). The superior performance of ARVI may be attributed to its atmospheric correction factor [41], which incorporates the blue band to adjust the red reflectance and reduce the impact of atmospheric aerosols—a common issue in coastal environments.

The good performance of NDVI and RVI also suggests that simpler spectral indices might be sufficient in areas with minimal atmospheric distortion. In contrast, indices more sensitive to water and sediment, such as the Modified Red-Green Vegetation Index (MGRVI) and the Reddening Coastal Vegetation Index (CRVI), showed weaker correlations with vegetation cover. This lower performance can be attributed to both their spectral design and the specific environmental conditions of intertidal zones. The CRVI, a recently proposed index [28], indicated specifically for coastal vegetation, showed surprisingly poor results. This VI incorporates the green band, which is particularly sensitive to background reflectance of moist soils and sediments, and, in coastal environments, where moist substrates, sparse vegetation, and tidal exposure are common, green reflectance can dominate the spectral signal. This can lead to misclassification of unvegetated areas as vegetated, reducing the accuracy of the index in estimating vegetation cover.

4.4. Vegetation Dynamics

The application of the ARVI-vegetation cover model to Sentinel-2 time-series data from 2015 to 2024 revealed clear spatial and temporal patterns in the distribution of intertidal vegetation along the Portuguese coast. The results underscore substantial regional variability, influenced by differences in coastal geomorphology, hydrodynamic exposure, and anthropogenic pressures.

Considering different vegetation cover levels (satellite pixels with at least 25%, 50% or 75% vegetation cover), interannual variability was particularly visible in pixels with less cover. For these pixels, which have a larger area occupied by other land cover types, discrimination and quantification of intertidal vegetation is likely more difficult and prone to errors.

In terms of intertidal vegetation area, defined by pixels with $ARVI \geq 0.214$, the Minho River estuary (tile 29TNG), located in northern Portugal, presented relatively stable vegetation cover area during the study period, suggesting a possible influence of tidal variation on vegetation extent. Specifically, the lower vegetation coverage in 2022 coincided with less favourable tidal conditions, while the higher coverage in 2023 aligned with better tidal conditions. However, this apparent relationship was unique to the Minho estuary, as the other studied regions did not exhibit similar results. The observed stability in intertidal vegetation reflects the buffering function of fluvial and tidal channels and the efficient sediment retention in this large estuarine system. Furthermore, for this region, the selected tiles have quite similar tides for the study period, which may have contributed to stable values.

The Aveiro lagoon and estuarine system (tiles 29TNE and 29TNF) exhibited the most extensive vegetation cover area of all regions, standing out as a key site for intertidal vegetation on the continental Portuguese coast. Annual totals peaked at 11.9% of vegetation cover in 2018, with a notable decline in the following year, 2019, when cover fell to 6.5%. Subsequent years showed a recovery trend. The long-term consistency can be attributed to the region's protected geomorphology, its high sediment retention capacity and reduced wave exposure, factors that together favour robust and persistent plant growth [42]. This area is covered by two different tiles, with different tides and, for 2021, different dates, which may have influenced the vegetation index calculated and their variation. But detailed analysis revealed no visible difference between tiles (Figures 9 and 10), suggesting that results are reliable.

The Central region (tiles 29SMC, 29SMD, 29SNC, and 29TME) showed the lowest vegetation cover area during the study period. While the estimated vegetation cover occasionally was relevant in these areas, reaching values as high as 253 ha in grid 29SMD in 2022, the overall pattern was characterised by marked interannual variability. This was most evident in 2023, when vegetation cover declined dramatically, from 351 ha in 2022 to just 44 ha in 2023. These drastic losses possibly reflect the region's high exposure to hydrodynamic forces, such as wave action, strong currents, and sediment removal, which limit the long-term persistence of vegetation. These fluctuations suggest that when conditions are briefly favourable, vegetation can colonise or expand, but these gains can be quickly reversed by coastal disturbances.

The Ria Formosa coastal lagoon (tiles 29SNB and 29SPB) displayed marked variability in vegetation cover area, with annual values reaching a regional maximum of 1744 ha in 2022 and a minimum of 522 ha in 2017. Nevertheless, a generally resilient vegetation state was maintained in this area. The observed fluctuations are likely due to local sedimentary dynamics, tidal cycles, and seasonal variability, rather than abrupt disturbances. The data suggests that Ria Formosa hosts a relatively stable and productive intertidal plant community over the long term.

Despite selecting satellite image dates corresponding to optimal tidal conditions, the analysis revealed that the most favourable tides did not necessarily result in the highest vegetation cover estimates. For instance, 2015 had the most advantageous tidal levels, yet this did not translate to greater vegetation extent in all regions. This suggests that the estimated vegetation cover differences are reliable, and not merely due to tide differences affecting the estimates.

5. Limitations

The main limitations of the methodology used are related to the available data. The freely available Sentinel-2 satellite images have a spatial resolution of 10 m, which is low compared to the fine-scale heterogeneity of intertidal vegetation. Therefore, satellite data likely include mixed pixels that reduce the accuracy of vegetation quantification, especially

in fragmented or patchy habitats. The temporal resolution (with a revisiting time of 5 days) limits the availability of images captured during low tidal conditions. Satellite image quality is further often hampered by clouds.

Another limitation is that vegetation-cover-VI modelling was based on a single test site (Viana do Castelo), which, while representative of intertidal conditions in northern Portugal, may not represent all the variability present in the national coastal systems. The intertidal habitats analysed in this study include diverse vegetation types and geomorphological settings. Applying a single modelling approach to all habitats can introduce errors, especially in cases where the dominant species or substrate type differ significantly.

Despite efforts to select satellite images in low tide conditions during the spring/summer season, differences in water levels at the time of image capture may have affected vegetation discrimination and, therefore, the estimated cover area. The classification, which includes both emerged and submerged vegetation, can be sensitive to small tidal shifts that influence spectral reflectance.

6. Conclusions

This study highlights the value of integrating high-resolution drone imagery with medium-resolution satellite data to monitor intertidal vegetation dynamics at regional and national scales. The use of vegetation indices derived from Sentinel-2 imagery, particularly the Atmospherically Resilient Vegetation Index (ARVI), proved effective in estimating intertidal vegetation cover in continental Portugal, despite limitations associated with pixel mixed-cover and tidal variability. Long-term analysis (2015–2024) revealed spatial and temporal dynamics, including maximum vegetation extent in 2022 and pronounced declines in 2017 and 2023, with regional patterns determined by geomorphological and hydrodynamic factors. While validation was limited to a single test site, successful modelling across a heterogeneous area suggests that the approach is robust and scalable. However, site-specific factors such as tidal timing, image quality, and habitat heterogeneity are likely to influence the accuracy of remotely sensed vegetation estimates. Future efforts should consider expanding UAV validation to additional, different sites and incorporating tidal correction algorithms, including the possible existence of storm surges, to further refine vegetation cover estimates. Overall, despite limitations, the presented methodology offers a replicable and cost-effective framework for large-scale, long-term monitoring of vegetated coastal ecosystems, supporting conservation and adaptive management in the face of climate and anthropogenic change.

The application of a vegetation index threshold derived from regression models allowed for the estimation of the extent of intertidal vegetation along the continental Portuguese coast over a 10-year period (2015–2024). This long-term analysis revealed both temporal and spatial variability, highlighting regional differences in the structure and resilience of intertidal habitats.

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

Abbreviations

RTK	Real-Time Kinematic
GNSS	Global Navigation Satellite System
GCP	Ground Control Points
BW	Bandwidth
CW	Central wavelength
DGT	General Directorate of the Territory
DMT	Digital Terrain Model
MSL	Mean Sea Level
TMD	Tidal Model Driver
MFI	Mangrove Forest Index
LiDAR	Light Detection and Ranging
CVA	Change Vector Analysis
TCT	Tassel Transformation
SWIR	Short Wave Infrared
NDMI	Normalized Difference Moisture Index
NDWI	Normalized Difference Water Index
NDVI	Normalized Difference Vegetation Index
SAVI	Soil Adjusted Vegetation Index
ARVI	Atmospherically Resistant Vegetation Index

Appendix A

Detailed description of dates and tidal values on that exact date for each tile covering the continental Portuguese coast (Table A1) and vegetation cover areas in for the continental Portuguese coast, resulting from the best-performing vegetation-cover-VI model (Table A2).

Table A1. Dates (day/month/year) and tide conditions for the selected Sentinel-2 image tiles.

Year	Best	Minho	Ria de Aveiro		Centre				Ria Formosa	
		29TNG	29TNE	29TNF	29TME	29SMD	29SMC	29SNC	29SNB	29SBP
2015	Date Tide	04/08/2015 −1.53	04/08/2015 −1.50	04/08/2015 −1.53	04/08/2015 −1.50	04/08/2015 −1.47	04/08/2015 −1.38	04/08/2015 −1.38	04/08/2015 −1.39	04/08/2015 −1.36
2016	Date Tide	21/08/2016 −1.45	21/08/2016 −1.37	21/08/2016 −1.44	21/08/2016 −1.37	21/08/2016 −1.32	21/08/2016 −1.19	21/08/2016 −1.19	09/07/2016 −0.94	09/07/2016 −0.94
2017	Date Tide	11/08/2017 −1.30	11/08/2017 −1.24	11/08/2017 −1.29	11/08/2017 −1.24	11/08/2017 −1.20	27/06/2017 −1.17	27/07/2017 −1.16	26/07/2017 −1.12	13/08/2017 −1.09
2018	Date Tide	17/06/2018 −1.37	17/06/2018 −1.34	17/06/2018 −1.37	17/06/2018 −1.34	17/06/2018 −1.31	17/07/2018 −1.22	17/06/2018 −1.22	15/08/2018 −1.28	15/08/2018 −1.25
2019	Date Tide	03/08/2019 −1.33	03/08/2019 −1.23	03/08/2019 −1.31	03/08/2019 −1.23	07/06/2019 −1.20	07/06/2019 −1.12	03/08/2019 −1.03	05/08/2019 −1.34	05/08/2019 −1.32
2020	Date Tide	23/07/2020 −1.25	22/08/2020 −1.46	22/08/2020 −1.51	22/08/2020 −1.46	22/08/2020 −1.42	22/08/2020 −1.30	22/08/2020 −1.30	22/08/2020 −1.29	22/08/2020 −1.23
2021	Date Tide	12/08/2021 −1.35	25/08/2021 −1.15	29/05/2021 −1.24	28/07/2021 −1.11	28/06/2021 −1.11	12/08/2021 −1.19	12/08/2021 −1.19	12/08/2021 −1.19	12/08/2021 −1.15
2022	Date Tide	02/08/2022 −1.11	18/07/2022 −1.11	18/07/2022 −1.12	19/05/2022 −1.23	18/06/2022 −1.17	15/08/2022 −1.20	18/06/2022 −1.10	18/06/2022 −1.11	18/06/2022 −1.09
2023	Date Tide	05/08/2023 −1.48	05/08/2023 −1.44	05/08/2023 −1.48	05/08/2023 −1.44	05/08/2023 −1.40	05/08/2023 −1.31	05/08/2023 −1.31	23/06/2023 −0.74	11/05/2023 −0.73
2024	Date Tide	25/07/2024 −1.42	09/08/2024 −1.01	09/08/2024 −1.03	09/08/2024 −1.01	24/08/2024 −1.36	24/08/2024 −1.31	24/08/2024 −1.31	23/08/2024 −1.35	23/08/2024 −1.30

Table A2. Vegetation cover areas (in ha) per region and year.

Year	Vegetation Cover (ha)			
	Minho	Ria de Aveiro	Centre	Ria Formosa
2015	769.84	1810.92	263.83	1957.45
2016	769.15	2618.35	384.40	1311.92
2017	743.5	2315.46	218.88	897.04
2018	734.88	3221.44	199.37	1455.46
2019	699.42	1753.08	189.99	2152.51
2020	728.99	2599.91	289.70	1873.40
2021	701.53	2476.61	297.93	1404.67
2022	690.66	2600.78	509.08	2420.17
2023	790.32	2336.16	76.17	1403.42
2024	742.11	3064.51	124.58	1389.79

References

- Howard, J.; Hoyt, S.; Isensee, K.; Pidgeon, E.; Telszewski, M. Coastal Blue Carbon: Methods for Assessing Carbon Stocks and Emissions Factors in Mangroves, Tidal Salt Marshes, and Seagrass Meadows-UNESCO Biblioteca Digital. Available online: <https://unesdoc.unesco.org/ark:/48223/pf0000372868> (accessed on 17 July 2025).
- Duarte, C.M.; Losada, I.J.; Hendriks, I.E.; Mazarrasa, I.; Marbà, N. The role of coastal plant communities for climate change mitigation and adaptation. *Nat. Clim. Change* **2013**, *3*, 961–968. [\[CrossRef\]](#)
- Manca, F.; Benedetti-Cecchi, L.; Bradshaw, C.J.A.; Cabeza, M.; Gustafsson, C.; Norkko, A.M.; Roslin, T.V.; Thomas, D.N.; White, L.; Strona, G. Projected loss of brown macroalgae and seagrasses with global environmental change. *Nat. Commun.* **2024**, *15*, 5344. [\[CrossRef\]](#)
- Capistrant-Fossa, K.A.; Dunton, K.H. Rapid sea level rise causes loss of seagrass meadows. *Commun. Earth Environ.* **2024**, *5*, 87. [\[CrossRef\]](#)
- Rundquist, D.C.; Narumalani, S.; Narayanan, R.M. A review of wetlands remote sensing and defining new considerations. *Remote Sens. Rev.* **2001**, *20*, 207–226. [\[CrossRef\]](#)
- Malthus, T.J.; Mumby, P.J. Remote sensing of the coastal zone: An overview and priorities for future research. *Int. J. Remote Sens.* **2003**, *24*, 2805–2815. [\[CrossRef\]](#)
- Meyer, M.d.F.; Gonçalves, J.A.; Cunha, J.F.R.; Ramos, S.C.d.C.e.S.; Bio, A.M. F Application of a Multispectral UAS to Assess the Cover and Biomass of the Invasive Dune Species *Carpobrotus edulis*. *Remote Sens.* **2023**, *15*, 2411. [\[CrossRef\]](#)
- Meyer, M.d.F.; Gonçalves, J.A.; Bio, A.M.F. Using Remote Sensing Multispectral Imagery for Invasive Species Quantification: The Effect of Image Resolution on Area and Biomass Estimation. *Remote Sens.* **2024**, *16*, 652. [\[CrossRef\]](#)
- Zoffoli, M.L.; Gernez, P.; Rosa, P.; Le Bris, A.; Brando, V.E.; Barillé, A.-L.; Harin, N.; Peters, S.; Poser, K.; Spaias, L.; et al. Sentinel-2 remote sensing of *Zostera noltei*-dominated intertidal seagrass meadows. *Remote Sens. Environ.* **2020**, *251*, 112020. [\[CrossRef\]](#)
- Davies, B.F.R.; Oiry, S.; Rosa, P.; Zoffoli, M.L.; Sousa, A.I.; Thomas, O.R.; Smale, D.A.; Austen, M.C.; Biermann, L.; Attrill, M.J.; et al. Intertidal seagrass extent from Sentinel-2 time-series show distinct trajectories in Western Europe. *Remote Sens. Environ.* **2024**, *312*, 114340. [\[CrossRef\]](#)
- Mora-Soto, A.; Palacios, M.; Macaya, E.C.; Gómez, I.; Huovinen, P.; Pérez-Matus, A.; Young, M.; Golding, N.; Toro, M.; Yaqub, M.; et al. A High-Resolution Global Map of Giant Kelp (*Macrocystis pyrifera*) Forests and Intertidal Green Algae (*Ulvothryceae*) with Sentinel-2 Imagery. *Remote Sens.* **2020**, *12*, 694. [\[CrossRef\]](#)
- Gendall, L.; Schroeder, S.B.; Wills, P.; Hessing-Lewis, M.; Costa, M. A Multi-Satellite Mapping Framework for Floating Kelp Forests. *Remote Sens.* **2023**, *15*, 1276. [\[CrossRef\]](#)
- Légaré, B.; Bélanger, S.; Singh, R.K.; Bernatchez, P.; Cusson, M. Remote Sensing of Coastal Vegetation Phenology in a Cold Temperate Intertidal System: Implications for Classification of Coastal Habitats. *Remote Sens.* **2022**, *14*, 3000. [\[CrossRef\]](#)
- Rahman, S.; Mesev, V. Change Vector Analysis, Tasseled Cap, and NDVI-NDMI for Measuring Land Use/Cover Changes Caused by a Sudden Short-Term Severe Drought: 2011 Texas Event. *Remote Sens.* **2019**, *11*, 2217. [\[CrossRef\]](#)
- Chen, C.; Fu, J.; Zhang, S.; Zhao, X. Coastline information extraction based on the tasseled cap transformation of Landsat-8 OLI images. *Estuar. Coast. Shelf Sci.* **2019**, *217*, 281–291. [\[CrossRef\]](#)
- Bovolo, F.; Bruzzone, L. A Theoretical Framework for Unsupervised Change Detection Based on Change Vector Analysis in the Polar Domain. *IEEE Trans. Geosci. Remote Sens.* **2007**, *45*, 218–236. [\[CrossRef\]](#)
- Suir, G.M.; Jackson, S.; Saltus, C.; Reif, M. Multi-Temporal Trend Analysis of Coastal Vegetation Using Metrics Derived from Hyperspectral and LiDAR Data. *Remote Sens.* **2023**, *15*, 2098. [\[CrossRef\]](#)
- Yao, H.; Chen, M.; Huang, Z.; Huang, Y.; Wang, M.; Liu, Y. Remote sensing monitoring and potential distribution analysis of *Spartina alterniflora* in coastal zone of Guangxi. *Ecol. Evol.* **2024**, *14*, e11469. [\[CrossRef\]](#)

19. Jia, M.; Wang, Z.; Wang, C.; Mao, D.; Zhang, Y. A New Vegetation Index to Detect Periodically Submerged Mangrove Forest Using Single-Tide Sentinel-2 Imagery. *Remote Sens.* **2019**, *11*, 2043. [CrossRef]
20. European, U. Copernicus Data Space Explore Portal. 2025. Available online: <https://dataspace.copernicus.eu/explore-data> (accessed on 15 May 2025).
21. Egbert, G.D.; Erofeeva, S.Y. Efficient Inverse Modeling of Barotropic Ocean Tides. *J. Atmos. Ocean. Technol.* **2002**, *19*, 183–204. [CrossRef]
22. Direção-Geral do Território. National LIDAR Survey–Portugal. 2011. Available online: <https://www.dgterritorio.gov.pt/> (accessed on 15 May 2025).
23. QGIS.org. 2024. QGIS Geographic Information System. QGIS Association. Available online: <http://www.qgis.org> (accessed on 5 March 2024).
24. Belgiu, M.; Drăguț, L. Random forest in remote sensing: A review of applications and future directions. *ISPRS J. Photogramm. Remote Sens.* **2016**, *114*, 24–31. [CrossRef]
25. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Wulder, M.A. Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **2014**, *148*, 42–57. [CrossRef]
26. Rouse, J.W.; Haas, R.H.; Deering, D.W.; Schell, J.A.; Harlan, J.C. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation; November 1974. Report No.: E75-10354. Available online: <https://ntrs.nasa.gov/citations/19750020419> (accessed on 2 July 2025).
27. Roujean, J.-L.; Breon, F.-M. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. *Remote Sens. Environ.* **1995**, *51*, 375–384. [CrossRef]
28. Zeng, J.; Sun, Y.; Cao, P.; Wang, H. A phenology-based vegetation index classification (PVC) algorithm for coastal salt marshes using Landsat 8 images. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *110*, 102776. [CrossRef]
29. Richardson, A.D.; Duigan, S.P.; Berlyn, G.P. An evaluation of noninvasive methods to estimate foliar chlorophyll content. *New Phytol.* **2002**, *153*, 185–194. [CrossRef]
30. Pearson, R.; Miller, L. Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie, Pawnee National Grasslands, Colorado. In Proceedings of the Eighth International Symposium on Remote Sensing of Environment, Ann Arbor, MI, USA, 2–6 October 1972.
31. Gitelson, A.A.; Kaufman, Y.J.; Merzlyak, M.N. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sens. Environ.* **1996**, *58*, 289–298. [CrossRef]
32. Huete, A.R.; Liu, H.; van Leeuwen, W.J.D. The use of Vegetation Indices in Forested Regions: Issues of Linearity and Saturation. In Proceedings of the IGARSS'97—1997 IEEE International Geoscience and Remote Sensing Symposium Proceedings, Remote Sensing—A Scientific Vision for Sustainable Development, Singapore, 3–8 August 1997; Volume 4, pp. 1966–1968.
33. Huete, A.R. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [CrossRef]
34. Gao, B. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [CrossRef]
35. Kaufman, Y.; Tanré, D.; Holben, B.; Markham, B.; Gitelson, A. Atmospheric Effects on the NDVI—Strategies for Its Removal. *Sch. Nat. Resour. Fac. Publ.* **1992**, 1238–1241.
36. Gitelson, A.A.; Viña, A.; Ciganda, V.; Rundquist, D.C.; Arkebauer, T.J. Remote estimation of canopy chlorophyll content in crops. *Geophys. Res. Lett.* **2005**, *32*, L08403. [CrossRef]
37. Vincini, M.; Frazzi, E.; D'Alessio, P. A broad-band leaf chlorophyll vegetation index at the canopy scale. *Precis. Agric.* **2008**, *9*, 303–319. [CrossRef]
38. Rasmussen, J.; Ntakos, G.; Nielsen, J.; Svendsgaard, J.; Poulsen, R.N.; Christensen, S. Are vegetation indices derived from consumer-grade cameras mounted on UAVs sufficiently reliable for assessing experimental plots? *Eur. J. Agron.* **2016**, *74*, 75–92. [CrossRef]
39. Bendig, J.; Yu, K.; Aasen, H.; Bolten, A.; Bennertz, S.; Broscheit, J.; Gnyp, M.L.; Bareth, G. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 79–87. [CrossRef]
40. Chapman, V.J. *Coastal Vegetation: Pergamon International Library of Science, Technology, Engineering and Social Studies*; Elsevier: Amsterdam, The Netherlands, 2016; ISBN 978-1-4832-7958-9.
41. Miura, T.; Huete, A.R.; Yoshioka, H.; Holben, B.N. An error and sensitivity analysis of atmospheric resistant vegetation indices derived from dark target-based atmospheric correction. *Remote Sens. Environ.* **2001**, *78*, 284–298. [CrossRef]
42. Santos, R.; Ito, P.; de los Santos, C.B. Relatório Científico II: Os 10 Principais Ecossistemas de Carbono azul em Portugal Continental. Available online: <https://gulbenkian.pt/publications/relatorio-cientifico-ii-os-10-principais-ecossistemas-de-carbono-azul-em-portugal-continental/> (accessed on 18 July 2025).

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