# Comparative Analysis of Drone Orthophotos and Sentinel-2 Imagery for Accurate Mapping of Mediterranean Seagrass Distribution in Small Coastal Areas

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*Abstract*—The Mediterranean Sea harbors several seagrass species, such as Posidonia Oceanica. The Posidonia is a native species that has been deemed threatened despite being under protection. Hence, generating accurate and current distribution maps is crucial to conserve this species. This scientific study utilized various indices and remote sensing techniques, including drone imagery and Sentinel2 datasets to extract the location of the seagrasses from two small coastal regions in the islands of Malta. The precision of the findings was evaluated through comparison with ground truth information.

Index Terms—Posidonia Oceanica, Spatial Analysis, Remote Sensing.

## I. INTRODUCTION

Posidonia Oceanica (P.O) meadow, is an endemic plant that is found in the Mediterraneansea and is considered one of the most valuable ecosystems in the region [1]. Many biologists have studied the development of P.O. in various Mediterranean locations. Some of these studies observed a notable rise in density [2] however, other evidence from further research carried out in various habitats suggests a different trend, a particular one which highlights a global drop in P.O. at global level was done by Jorda [3].

Biologists search for specific biological features to investigate ecological changes in P.O. meadows. The most frequently observed P.O. characteristics as highlighted by Moreno [4] include:

(i) Density - this is calculated by counting the number of leaves present in each square meter of the meadow. (ii) Lower and upper depth limits - these define the geographic location and boundaries of the meadow. The upper depth limit, which is easily detectable through aerial or satellite imaging, is the closest part of the meadow to the coast, while the lower depth limit is the deepest boundary and can only be detected through remote sensing from vessels or underwater vehicles. These limits provide information on the meadow's dynamics, whether it is advancing or retreating and (iii) Bottom coverage - this is the percentage of the sea floor that is covered by live seagrass, in comparison to the proportion of the ground surface that is covered by sand, rocks, or dead P.O. matter. The conservation index, which indicates the dynamics of the meadow and its human impact, is expressed as Ci = P/(P + D), where P

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represents the percentage of live P.O. cover and D represents the percentage of ground covered by dead P.O. matter, sand, other algae or rocks.

Traditionally data gathering to obtain listed indicators was carried out by the use of surveys. There are several methods how such surveys are conducted. The classic point surveys were one which is used to collect data at discrete points within a study area, either at random or at predetermined locations. Another physical gathering survey is the Transect-based surveys, which involve collecting data along a linear path. The Grab and trawl survey method is used to collect samples and sediment. Surveys of this nature often come with numerous restrictions. They are time consuming and the information provided about the benthic habitat's ecologic function and geographic diversity is scarce [5].

Modern tools based on remote sensing and Satellite imagery and drone data has been introduced and utilized in research related to P.O. and C. Nodosa. Such modern tools are used to

complement the surveys, or in certain instances even replace. In small areas and small islands like Malta, satellite-based remote ensing techniques could have limitations in terms of time and spatial resolution make it challenging to ensure accuracy in data and results. Given the compact size, straightforward control, cost-effectiveness, and high spatial resolution of UAVs, the use of UAV remote sensing data for P. Meadows monitoring, could offer distinct advantages over remote sensing monitoring methods.

The aim of this study is to utilize remote sensing methodologies in conjunction with variations obtained from spectral indices, to identify seagrass coverage in 2 selected areas which contain a high distribution of P.O. The objective is to evaluate whether the variations in indices can be regarded as effective tools for identifying regions characterized by high or low densities of P.O. in the study area and assess whether data generated from the indices have characteristic frequency distribution signatures.

To attain the objectives of this study, four main tasks will be undertaken. Firstly, an image stitching approach will be devised. This algorithm will be based on the popular SURF algorithm, and will be used to create seamless orthophotographs of the sea and ocean from drone images. Secondly, mathematical algorithms for popular remote sensing indices will be incorporated to appraise the health, and position of Posidonia meadows. Indices used will be utilising the primary three true colour bands. Thirdly, in-situ data will be collected to validate the accuracy of the results obtained. Finally the remote sensing techniques based on drone images are to be compared to datasets obtained from Sentinel 2 to evaluate the precision of both methodologies, and to ensure the outcomes are consistent and mutually supported.

## II. METHODOLOGY

Two coastal areas have been selected: The first area under study is Balluta Bay Malta, situated in the town of St. Julian's in Malta a showed in Fig1. It is located at Latitude 35.917480 and Longitude 14.495081 and the surface area is 41699.25 m<sup>2</sup> The second Coastal area is St Thomas Bay, situated in the southern region of the Maltese islands at Latitude 35.852814, and Longitude 14.565762. The surface area for St Thomas bay is 151591.74 m<sup>2</sup>



Fig. 1. Position of Balluta Bay and St Thomas Bay

The following is an overview of the methodological workflow. A. The project was initiated by performing the task of data acquisition from aerial drones for the two sites.

B. Upon successful completion of the acquired data, the next step, involved utilizing a stitching tool based on SURF to obtain generate orthophotos from the gathered drone photos for the two sites.

C. Divers gathered data from the 2 sites.

D. The orthophotos generated were manually classified to extract the position of P.O.

E. Multiple Remote sensing indexes were used to classify the orthophotos into P.O. and others.

F. Sentinel 2 dataset were downloaded from the SciHub.

G. The indexes used in step 4 were used again, but this time on the Sentinel 2 datasets.

H. Otsu method was employed on all generated images to obtain the optimal threshold.

I. Results are displayed and the data obtained from drone imagery is compared to data obtained from the Sentinel 2.

## A. Data gathering from Unmanned Aerial Vehicle UAV

The images from Balluta were collected on the 28-06-2022 and for St Thomas bay on the 14-06-2022. A total of 825 images were captured for Balluta bay and 1225 images for St Thomas Bay as showed in fig2. The drone used was a DJI Phantom 2 equipped with a L1D-20c\_10.3\_5472x3648 (RGB) camera. The camera is able to provide providing a full-frame equivalent focal length of 28mm , ISO for photos from 100 - 1600, for video from 100 to 3200, maximum image size 4000x3000; image format \* .JPEG. Automated flight paths were generated with the Pix4D Capture free drone flight planning application with an 80% overlap on both axes, and a flight altitude that ranged between 50–55 mmetres. Four photogrammetric flights were performed, one flight for each orthophoto. The camera was set to take vertical (nadir) images.

## B. Create Stitching algorithm based on surf

Step 2: The stitching algorithm to create the orthophotos was built utilizing the OpenCV library and the SURF image processing technique. The SURF (Speeded Up Robust Feature) algorithm is used in feature detection with OpenCV and programming languages to create mosaics from multiple photos [6]. For this study, Visual Studio with C++ framework was used since such setup allows to access parallel Graphics Processing Unit (GPU) processing and memory allocation.



Fig. 2(a). Drone Photo Position of Balluta Bay and (b) St Thomas Bay

To carry out the SURF process, it's necessary to divide it into the following steps:

- 1) Image Pre-processing: All drone images are pre-processed to slash noise and improve the features that need to be picked out. A loop to rotate through every image was created to achieve this.
- 2) Scale-Space Extrema Detection: All images are processed to find extreme points in scale-space, by the use of a Difference of Gaussian (DoG) filter. These extrema points are considered as potential keypoint candidates.
- 3) Keypoint Localization: By fitting a parabolic function to the surrounding data in the scale-space, the location and scale of each keypoint are fine-tuned.
- 4) Each keypoint/s in every image has an orientation assigned to it in order to make it rotation-invariant.
- 5) Keypoint Descriptor: By calculating the Haar wavelet responses in the area surrounding the keypoint, a descriptor is created for each keypoint.
- 6) Keypoint Matching: To match keypoints between several images, the keypoints and their descriptions are employed.
- 7) Image Stitching: Once the keypoints were computed and matched, a homography image alignment algorithm to align the images was used to form a seamless orthophoto

## C. Gathering of data from multiple sample Points

Random study points located on both sites were picked spread over the whole observation areas, and data was collected on

four distinct dates through direct observations with SCUBA diving and aquatic camera observation. The data collected was logged. Parameters included the study position geographical location, which was taken from the diver's computer and from the boat on-board geo-positioning sensors, the depth of the study point, generated from the diver held computer and from the boat sonar sensor and finally the class of the point under observation. The class was a selection to indicate whether the selected point contained seagrasses including P.O and C.Nodosa Furthermore the divers manually inspected the healthiness by counting its shoots count. Table 1 and Table 2 are showing the in-situ collected data for Balluta bay and St Thomas Bay respectively.

TABLE I: GATHERED DATA IN BALLUTA BAY

Seabed Type	Latitude	Longitude	Depth (m)	Shoot Count	
Posidonia	35,916358	14,494617	5,9	61	
Posidonia	35,916424	14,495657	4,4	44	
Posidonia	35,916453	14,496795	5,7	67	
Non-Posidonia	35,915595	14,497192	2,8	N/A	
Non-Posidonia	35,915427	14,494229	6,6	N/A	
Non-Posidonia	35,916016	14,495227	3,9	N/A	

TABLE II: GATHERED DATA IN ST THOMAS BAY

Seabed Type	Latitude	Longitude	Depth (m)	Shoot Count	
Posidonia with	25.052552	-	•	•	
coarse sand	35,853772	14,56732	3,5	41	
Posidonia with		1150050	-		
coarse sand	35,853094	14,568058	7,8	57	
Posidonia with					
coarse sand	35,852208	14,567178	4,4	67	
Posidonia with					
coarse sand	35,853312	14,565504	3,2	16	
Non Posidonia	35,852129	14,564282	1,9	36, 31	
Patches of					
Posidonia	35,851047	14,56576	2,2	72	

## D. Observation and identifying the obtained data

Observation and identifying the Accurately identifying and labelling classes is a crucial aspect of classification and analysis software. To achieve this, data was collected as described in step 3 to improve the know how of the area and gather first hand experience. Once data was collected, truth information obtained was linked to Google maps and UAV photography.

## E. Remote Sensing Indices

In this Section multiple indexes based on Red, Green and Blue true band colours are used to correlate values to the distribution and of P.O. The first index that was used is the Excess Green Index (ExGI). The ExGI index contrasts the green portion of the true colour spectrum against the red and blue to distinguish vegetation from other surfaces. This index is normally used on land and with other indices such as the NDVI. The ExGi has been shown to outperform other indices [7]. ExGI is calculated as follows:

$$ExGI = (2 * G) - (R + B)$$
 (1)

where G represents the green band reflectance, R represents the red band reflectance, and B represents the blue band reflectance.

The second index which was used is a self-tested variant extracted from the Green Leaf Index (GLI) and VARI. Both GLI and VARI are used to gauge how much greenery is there. Such indices are generally associated with land cover greenery. The greenery measure is based on the observation that healthy green leaves primarily reflect in the green portion of the spectrum while strongly absorbing light in the red and blue portions of the spectrum [8]. The variant which in this study is referred as the Seagrass Meadow index is calculated by

SgMI = 2 \* (Green-Red-Blue) / 2\* (Green + Red + Blue) (2)

where G, R, and B represent the spectral reflectance in the green, red, and blue bands, respectively. The numerator of the formula represents the difference in reflectance between the green band and the average reflectance of the red and blue bands, while the denominator represents the total reflectance in all three bands.

The last index that was used is the Green Normalized Difference Vegetation Index (GNDVI). This index is similar to NDVI except that it measures the green spectrum from 540 to 570 nm instead of the red spectrum. This index is more sensitive to chlorophyll concentration than NDVI. The GNDVI is calculated:

$$GNDVI = (Green - M) / (Green + M)$$
(3)

where G represents the spectral reflectance in the green band and M is a constant factor used to minimize the background noise and atmospheric effects.

It is worth noting that the choice of the constant value M can affect the sensitivity of the index and its ability to differentiate between different types of vegetation.

#### F. Data gathering from Unmanned Aerial Vehicle UAV

Satellite data were acquired from the Copernicus Scientific Hub, (The Copernicus Open Access Hub) maintained by the European Space Agency (ESA). The images from the

Sentinel-2 constellation were acquired at a 1c processing level, and an atmospheric correction was computed on all datasets with the Sentinel Toolboxes Application software. Sentinel-2 is a satellite system established by the European Commission as part of the Copernicus program. It consists of two satellites, Sentinel-2A launched in June 2015 and Sentinel-2B launched in March 2017. These satellites have a 10-day revisit frequency and are located at 786 km above the earth in a sun-synchronous orbit. This allows for any given region to be observed every 5 days at identical local solar times.

A Level 1C image taken on the 23<sup>rd</sup> of March 2022 at 09:50:31 with a nadir viewing angle of nearly 4 degrees, was used for this study. Since Sentinel-2 level 1C images are not corrected for atmospheric effects, the Sen2Cor toolbox was used to correct the reflectance values. This tool used a database of 24

look-up tables based on atmospheric conditions on Earth, with mid-latitude summer conditions and rural aerosol type selected for the correction due to the study area's proximity to land. The corrections carried out were following the procedure as detailed by Poursanidis [9].

## G-H. Find the best threshold for generated images

The indices were projected for the drone orthophotos and also the Sentinel 2 dataset. Once projected, the optimal thresholds for each index were determined using the Otsu's method, which minimizes intra-class variance. Otsu's method, named after Nobuyuki Otsu, is commonly utilized in computer vision and image processing to facilitate clustering-based image thresholding. This process involves converting a gray level image to a binary image. The algorithm operates under the assumption that the image is composed of two types of pixels, namely foreground pixels and background pixels, which are represented by a bimodal histogram. It then calculates the most favorable threshold value to separate the two classes in a way that minimizes their combined intra-class variance or maximizes their inter-class variance . The SNAP (Sentinel Application Platform) Toolbox was used to project the indexes on both the sentinel 2 dataset and the drone orthophotos.

## III. RESULTS

Fig3 and Fig4 displays the orthophoto results that were generated with the Open CV Surf algorithm within the OpenCV for both Balluta Bay and St Thomas Bay. The image stitching results and the method adopted produced a good results in terms of picture quality, resolution and smooth perspective of orthophoto. The pixel number for width and height size for the Balluta generated orthophoto were 14024 x 10059 and contained 141,067,416 pixels. The orthophoto pixel number for width and height size results for St Thomas bay were 13780 x 13490 and contained 186,082,200 pixels. The generated Ground Sample Distance (GSD) was 2.9cm<sup>2</sup> for Balluta Bay and 5.02cm<sup>2</sup> for St Tomas Bay



Fig. 3. Generated Orthophotos of Balluta Bay



Fig. 4. Generated Orthophotos of St. Thomas Bay

In order to better understand the classification makeup of Ballute Bay and St. Thomas Bay, a series of images to depict the indices results in Gray scale and coloured scheme were generated. (Fig 5) The resulting index maps were created using a consistent color scheme to facilitate comprehension of the data. The otsu method was employed on the grayscale images to obtain the best threshold values.



Fig. 5. Coloured index projection for Balluta Bay ExGI (a) SgMI (b) GNDVI (c) and St. Thomas Bay ExGI (d) SgMI (e) GNDVI (f)

The study results indicated that the pixel distribution on the three images, contained very little difference when projected onto the orthophotos generated by the drone(Fig 6). The pixel data was evaluated against ground truth information, and the outcomes derived from all three indices closely resembled the recorded data obtained from the ground. Table 2 records the pixel count generated from each index. Table 3 shows that the Balluta index had a maximum percentage variation of 1.97% and the St. Thomas Bay index had a maximum percentage variation of 2.3%, when compared to each other. When expressed in terms of total surface area, the percentage variations indicate that the seagrass surface area in Balluta ranged from 93,261m<sup>2</sup> to 101,349 m<sup>2</sup>, and from 343,917 m<sup>2</sup> to 322,589m<sup>2</sup> in St. Thomas Bay.

TABLE III: GENERATED NUMBER OF PIXE	S
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Location	Туре	Total Pixel count	ExGI px count	ExGI px %	SgMI px count	SgMI px %	GNDVI px count	GNDVI px %
Balluta Bay	Drone Ortho	141,067,416	34,966,528	24.78	33,529,551	23.75	32,148,403	22.81
St. Thomas	Drone Ortho	186,082,200	68,458,604	36.77	65,815,422	35.36	64,197,731	34.47
Balluta Bay	Sentinel 2	493	353	71.6	305	61.86	338	68.55
St. Thomas	Sentinel 2	1768	1273	72	1305	73.8	1491	84.33



Fig. 6. Balluta Bay ExGI (a) SgMI (b) GNDVI (c) ExGI and St. Thomas Bay (d) SgMI (e) GNDVI (f) indices projected on drone Orthophotos

Fig. 8. Balluta Bay ExGI (a) SgMI (b) GNDVI (c) ExGI and St. Thomas Bay (d) SgMI (e) GNDVI (f) indices projected on Sentinel 2 images

## IV. CONCLUSION

The objective of this study was to produce orthophotos through the utilization of drone imagery coupled with the OpenCV Surf algorithm, and to assess the precision of seagrass mapping employing three distinct indices and remote sensing methodologies. This was achieved by utilising the generated orthophotos in conjunction with Sentinel 2 datasets.

The results indicated that the image stitching method produced high-quality orthophotos with good resolution and perspective. The pixel distribution on the orthophotos closely resembled the ground truth information.

Upon utilization of three distinct remote sensing indices, namely the Excess Green Index (ExGI), the Green Normalized Difference Vegetation Index (GNDVI), and the Seagrass Mapping Index (SgMi) - a self-validated remote sensing variant, the resulting seagrass mapping on the generated orthophotos demonstrated substantial consistency. Additionally, minimal variation in pixel count and seagrass surface area was observed across the three indices.

Nonetheless, the application of identical methodologies and indices to the Sentinel 2 imagery yielded less precise outcomes due to the lower pixel resolution of the Sentinel 2 images. Furthermore, the outcomes demonstrated notable variability across the two distinct locations and differed significantly across the three indices employed.

In the future, the authors intend to perform a time-series analysis utilising more drone orthophotos, with a particular emphasis on the SgMI index and to create algorithms to distinguish the Posidonia Oceanica from other species.

### IV. CORRELATING THE RESULTS OBTAINED FROM DRONE IMAGES TO THE SENTINEL 2 DATASET.

The procedure used on the drone datasets was repeated on the satellite dataset in order to compare the outcomes from the two remote sensing methods. The 2 areas were reprojected by the use of the snap toolbox.(Fig 7)



Fig. 7. Sentinel 2 image for (a) Balluta Bay and (b) St. Thomas Bay

When applying the same methodology and the same identical indices to the Sentinel 2 image as did with drone orthophotos, results showed less responsive outcomes as recorded in Table

3. This is attributed to the 10m x 10m pixel resolution provided by Sentinel 2 images. In Balluta Bay, the findings reveal that the quantity of pixels depicting seagrasses ranged from 305 when utilizing the SgMI index and 353 with the ExGI index in Balluta Bay and 1273 SgMi pixel count vs the 1491 GNDVI pixel count in St. Thomas Bay. These variations in pixel count translates to a surface area range of 4800m<sup>2</sup> and 218000m<sup>2</sup>. Upon visual inspection of the Sentinel 2 datasets, it was observed that the projection and distribution of seagrasses varied significantly between the various indexes and that the majority of the area under as showed in Fig 8. It is noteworthy to emphasize that the drone-derived orthophotos reported an average seagrass coverage of 23.78%, while the utilization of Sentinel 2 imagery using the same methodologies yielded a surface area projection of 76.71%.

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#### REFERENCES

 Badalamenti, F., Alagna, A., Fici, S. (2015). Evidences of adaptive traits to rocky substrates undermine paradigm of habitat preference of the Mediterranean seagrass Posidonia oceanica. Scientific Reports, 5, 8804.

#### https://doi.org/10.1038/srep08804

- [2] J. Terrados and F. J. Medina-Pons, "Inter-annual variation of shoot density and biomass, nitrogen and phosphorus content of the leaves, and epiphyte load of the seagrass Posidonia oceanica (L.) Delile off Mallorca, western mediterranean," Sci. Marina, vol. 75, no. 1, pp. 61–70, 2011. https://doi.org/10.3989/scimar.2011.75n1061
- [3] G. Jordà, N. Marbà, and C. M. Duarte, "Mediterranean seagrass vulnerable to regional climate warming," Nature Climate Change, vol. 2, no. 11, pp. 821–824, 2012.C. Y. Lin, M. Wu, J. A. Bloom, I. J. Cox, and M. Miller, "Rotation, scale, and translation resilient public watermarking for images," *IEEE Trans. Image Process.*, vol. 10, no. 5, pp. 767-782, May 2001.

https://doi.org/10.1038/nclimate1533

- [4] D. Moreno, P. A. Aguilera, and H. Castro, "Assessment of the conservation status of seagrass (Posidonia oceanica) meadows: Implications for monitoring strategy and the decision-making process," Biol. Conservation, vol. 102, no. 3, pp. 325–332, 2001. https://doi.org/10.1016/S0006-3207(01)00080-5
- [5] Wright, D. and W. Heyman, 2008. Introduction to the special issue: marine and coastal GIS for geomorphology, habitat mapping, and marine reserves. Marine Geodesy 31, 223-230. https://doi.org/10.1080/01490410802466306
- [6] J. Wang and J. Watada, "Panoramic image mosaic based on SURF algorithm using OpenCV," 2015 IEEE 9th International Symposium on Intelligent Signal Processing (WISP) Proceedings, Siena, Italy, 2015, pp. 1-6, doi: 10.1109/WISP.2015.7139183. https://doi.org/10.1109/WISP.2015.713 9183
- [7] Larrinaga, A., & Brotons, L. (2019). Greenness Indices from a Low-Cost UAV Imagery as Tools for Monitoring Post-Fire Forest Recovery. Drones, 3(1), 6.

https://doi.org/10.3390/drones3010006

- [8] Louhaichi, M., M. Borman, and D. Johnson. "Spatially Located Platform and Aerial Photography for Documentation of Grazing Impacts on Wheat." *Geocarto International* 16, No. 1 (2001): 65-70. https://doi.org/10.1080/10106040108542184
- [9] Poursanidis, D., Traganos, D., Reinartz, P., Chrysoulakis, N. (2019). On the use of Sentinel-2 for coastal habitat mapping and satellite-derived bathymetry estimation using downscaled coastal aerosol band. International Journal of Applied Earth Observation and Geoinformation, 80, 58-70.

https://doi.org/10.1016/j.jag.2019.03.012



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