Application of Unmanned Aerial Vehicles (UAVs) and Unsupervised Machine Learning in the Monitoring of Algal Ecosystems

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Abstract: The accurate monitoring of coastal algal ecosystems is imperative for the better understanding and conservation of their ecological condition. This study applies the technology of Unmanned Aerial Vehicles (UAVs) as a feasible alternative to more time-consuming traditional methods of ecological surveying. This is then paired with multispectral image processing and clustering techniques in order to create detailed maps of a coastal algal community in Batangas. The methodology entails the use of a multispectral camera recording in G/R/RE/NIR mounted on a DJI Mavic 3M drone flown over the region of interest. An orthomosaic was generated of the region from the images taken. After this, various remote sensing indices such as Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Leaf Chlorophyll Index (LCI), Normalized Difference Red Edge Index (NDRE), and Optimized Soil Adjusted Vegetation Index (OSAVI) were calculated to provide a more in-depth understanding of the vegetation in the region. K-means clustering was used to identify and segment within the image areas in which algal communities were present. The total algal coverage of the image was then calculated. Additionally, the health and condition of the algae was also observed. The above method demonstrates a less time and manpower-intensive process by which coastal ecosystems in the Philippines may be mapped and their health evaluated. Additionally vegetation indices that utilize red edge wavelength light such as NDRE and LCI were found to result in good clustering quality.

Key Words: Remote Sensing; Unmanned Aerial Vehicles; Environment; Unsupervised Machine Learning

1. INTRODUCTION

1.1 Background of the Study

For several decades, it has been known that anthropogenic climate change poses a serious and imminent threat to human societies and the natural world. There are a multitude of factors that contribute to this issue such as the prevalence of non-renewable energy sources, modern agricultural practices, and rapid urbanization of human societies to name a few. Resulting effects of climate change have already been observed such as the global increase in average temperatures, increased rates of respiratory diseases, and, of particular note to this study, the degradation of coastal ecosystems.

Coastal ecosystems play a vital and important role in the Earth's biosphere. Though only representing a small fraction of Earth's surface area, they are some of the most productive and biodiverse ecosystems. When measured in terms of net primary productivity, algal beds and coral reefs produce on average 2,500 tons of biologically relevant chemicals. This may be compared to other types of ecosystems such as temperate forests and grasslands which produce 1,200 and 600 tons respectively (Jackson & Jackson, 2000).

These ecosystems have historically been difficult to survey due to physical characteristics such as rocky coastlines, strong winds, and dangerous wildlife. Traditional methods of surveying utilize field teams to collect samples of relevant material in the region of interest which may later be analyzed by laboratories (Crane et al., 2007). On the other hand, remote sensing methods have utilized technologies such as satellite imagery in order to survey larger areas at faster speeds.

Unmanned Aerial Vehicles (UAVs) present themselves as a bridging alternative to the high resolution but low coverage in-situ surveying and the low resolution but high coverage satellite imagery. Their portability and rapid data collection allow them to be ideal candidates for remote sensing work (Anderson & Gaston, 2013).

Machine learning methods now present themselves as a quick, efficient, an accurate method by which remote sensing data may be analyzed. Clustering, segmentation, and labelling algorithms have been used to process satellite imagery and as such, they are suited for the processing of UAV imagery.

1.2 Review of Related Literature

UAVs have been used for the purposes of remote sensing applications for several decades. However, there has been a large increase in popularity in recent years due to the advent of affordable consumer UAVs together with advances in the field of artificial intelligence.

A study created a holistic framework for the application of UAVs in surveying plant ecology from pre-flight considerations to data processing (Cruzan et al., 2016). This study surveyed a 16-ha nature preserve located in the American state of Oregon. Variables out of the researchers control such as weather, wind speed, and topography were used to inform details about the flight such as the time, duration, and altitude. The result of the survey was a vegetation map of the region together with an elevation model. These were used to segment the region into trees, swales, hommocks, and bushes using a k-means classification algorithm. This current study also uses the k-means classification algorithm however multispectral light reflectance data is used rather than elevation and RGB imagery for the clustering.

A more recent study utilized a mixed UAV-Satellite approach in order to characterize algal coastal habitats in the wake of natural disasters in New Zealand (Tait, Orchard, & Schiel, 2021). Eight different reefs were chosen as the regions of interest for the study. The researchers utilized DJI Mavic Pro 2 drones equipped with high resolution and RGB and multispectral cameras. In situ measurements were used to validate and label images taken by the UAVs. These were used as training data for supervised machine learning algorithms. The trained model would then be applied to Sentinel-2 satellite images to increase the region of interest and to characterize a larger area. The researchers of the current study also seek to characterize coastal algal populations however using unsupervised machine learning methods.

Another study sought to review UAV imaging for the purposes of tracking harmful algal blooms (Wu et al., 2019). Harmful algal blooms in freshwater systems pose a serious threat to the proper function of the whole ecosystem. Multispectral and RGB sensors provide a number of vegetation indices that are used for the detection of algal blooms. These include NGRDI, NGBDI, GLI, AI, BNDVI, and NDVI. The researchers of this current study seek to further investigate other possible vegetation indices, particularly those which use red edge wavelengths of light not covered in the previous list of vegetation indices.

Finally, a local Filipino study sought to utilize UAVs for the purpose of tracking permaculture agriculture (Flores, Bagunu, & Buot, 2020). A 10-step methodology was developed by the researchers for use by small-scale farmers with an emphasis on affordability and ease of use. The image data was used to qualitatively inform decisions made by the farmers. In contrast to this, this current study seeks to extend the use of UAVs in the Philippines for the purposes of ecological tracking and management rather than just for agricultural use.

2. METHODOLOGY

2.1 Data Collection

The area of study was West of the municipality of Lian, Batangas (13° 59' 52.5834" N; 120° 37' 27.0948" E). This location is labelled as a protected area by the Philippines' Department of Environment and Natural Resources (DENR). Topographically, a shallow seabed stretches out from the beach for nearly 300 meters before dropping. Found within are populations of several species of algae such as *Sargassum cristaefolium,* a type of brown macroalgae (Cabrera et al., 2015).

This study utilized a DJI Mavic 3M (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with a 4K capable RGB camera and a multispectral camera. This multispectral camera possessed channels for Green (560 ± 16 nm), Red (650 ± 16 nm), Red Edge (730 ± 16 nm), and Near Infrared (860 ± 26 nm) wavelengths of light.

The drone flight was performed during noon time to minimize shadows produced in the image. All data processing and machine learning algorithms were implemented in a Python environment while geographic data was processed in QGIS.

2.2 Vegetation Indices

Several types of vegetation indices were calculated using the multispectral readings gathered by the UAV. These include Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), Green Normalized Difference Vegetation Index (GNDVI) (Gitelson et al., 1996), Normalized Difference Red Edge Index (NDRE) (Barnes et al., 2000), Optimized Soil Adjusted Vegetation Index (OSAVI) (Rondeaux et al., 1996), and Leaf Chlorophyll Index (LCI) (Datt, 1999).

All of these vegetation indices exploit the fact that chlorophyll reflects certain wavelengths of light (like green) while absorbing others (like red). As such, these are used to give accurate descriptions of the coverage and health of plant populations in the region of interest. These may be calculated with the following formulas:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad \text{(Eq. 1)}$$

$$GNDVI = \frac{NIR - Green}{NIR + Green} \quad \text{(Eq. 2)}$$

$$NDRE = \frac{NIR - RE}{NIR + RE} \quad \text{(Eq. 3)}$$

$$OSAVI = (1.16)\frac{NIR - Red}{NIR + Red + 0.16} \quad \text{(Eq. 4)}$$

$$LCI = \frac{NIR - RE}{NIR + Red} \quad \text{(Eq. 5)}$$

where:

$Green$ = green light reflectance (560 nm)
Red = red light reflectance (650 nm)
RE = red edge light reflectance (730 nm)
NIR = near infrared light reflectance (860 nm)

2.3 k-means Clustering

k-means clustering is an unsupervised machine learning method that seeks to generate a k number of clusters within a given data set. This is achieved by minimizing the Euclidean distance between every data point and its associated "mean" (Hall, 2012). Mathematically, the objective function to be minimized is given by:

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - \mu_j\right\|^2 \quad \text{(Eq. 6)}$$

where:

k = total no. of clusters
j = cluster
n = total no. of data points
i = data point
$x_i^{(j)}$ = data point belonging to cluster j

μ_j = centroid of cluster j

In the context of this paper, the Euclidean distance that is being minimized is between a data point's vegetation index value and the centroid vegetation index value, not the actual distance. Various values of k are tested and the most accurate iterations are chosen for further analysis.

2.4 Silhouette Analysis

Silhouette analysis is a technique that identifies the quality of clustering within a clustered data set. A Silhouette coefficient may range from -1 to 1 with negative coefficients representing a failure of the algorithm to cluster (Shahapure & Nicholas, 2020). For an individual data point, the Silhouette coefficient is calculated by the following formula:

$$s = \frac{b(n) - a(n)}{max\{a(n), b(n)\}} \quad \text{(Eq. 7)}$$

where:

$a(n)$ = the distance between a data point and its associated centroid
$b(n)$ = the distance between a datapoint and the centroid of the next nearest cluster

The Silhouette score of a particular cluster is simply the average of all Silhouette coefficients assigned to data points within that cluster. These may be plotted in a histogram-like plot called a Silhouette plot in order to better understand the quality of clustering resulting from the algorithm.

2.5 Algal Characterization

Once segmented, clusters are labelled to their corresponding habitat based on the value of their vegetation index. Afterwards, these clusters are characterized by their total area coverage, mean, and standard deviation.

3. RESULTS AND DISCUSSION

The data used in this study was gathered in March 2023. Within this region, a 4.5-ha rectangular area centered around the submerged portion of the image was chosen for analysis.

3.1 Optimization of Vegetation indices

The gathered RGB and multispectral images were used to generate several orthomosaics. From the multispectral data, vegetation index maps were also generated.

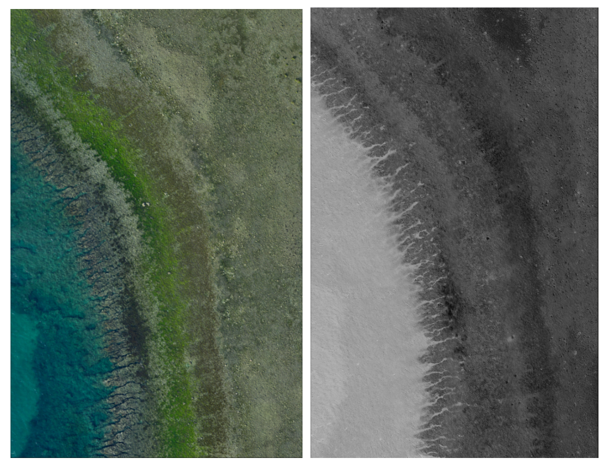

Fig. 1-2. RGB Orthomosaic (left) and NDRE Orthomosaic (right)

The optimal vegetation indices were chosen by running the clustering algorithm for each vegetation index from two until ten. The average Silhouette score of each vegetation index was plotted against the number of clusters in the iteration.

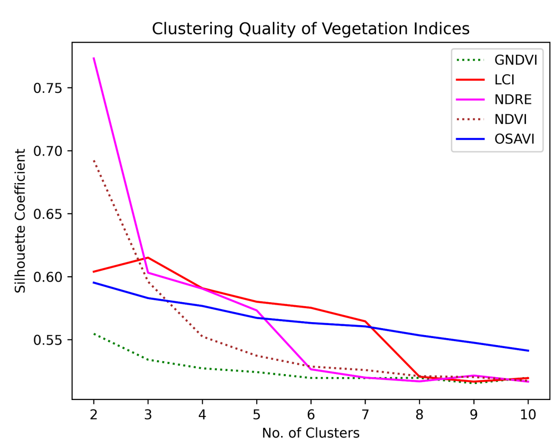

Fig. 3. Line plot of Silhouette scores vs. number of clusters

As expected, there is a general trend towards a lower Silhouette score as the number of clusters increases. This is due to over clustering of the data.

NDVI and GNDVI are both shown to reach a low average Silhouette score rapidly trending towards a value around 0.53. These findings indicate the two are poor choices for the use of image segmentation.

OSAVI demonstrates a unique behavior as its Silhouette score decreases in an approximately linear manner as opposed to the “elbow shape” observed in other vegetation indices. Despite this, the Silhouette Coefficients are seen to be only middling in comparison to the other vegetation indices at numbers of clusters.

For the smaller cluster values, it is seen that LCI and NDRE have the highest Silhouette scores. This reflects a greater quality of clustering in these two vegetation indices when compared to the others. The prevalence of both of these vegetation indices suggests that red edge wavelength light is a relevant variable to consider when clustering algal imagery as both indices factor in red edge light. As such, these two vegetation indices were selected for further analysis.

3.2 Clustering Quality

To determine the quality of the clustering, Silhouette plots of the clustered data were generated. Generally, average Silhouette scores were found to be just under 0.6 and there is only a minor level of misclustering.

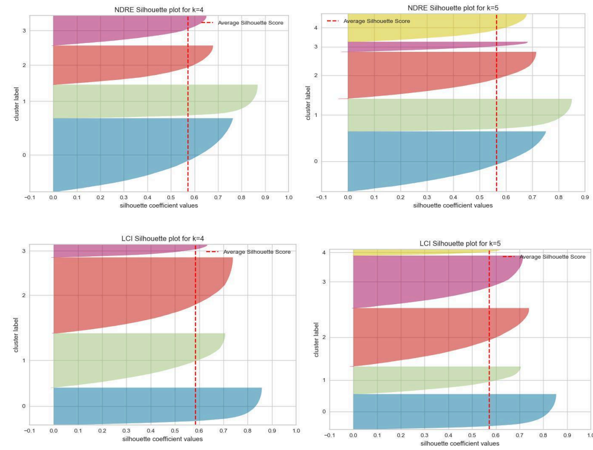

Fig. 4. Silhouette plots for NDRE k=4 (top-left), NDRE k=5 (top-right), LCI k=4 (bottom-left), and LCI k=5 (bottom-right)

For a clustering of k=4, both NDRE and LCI are comparable to one another. LCI possesses a slightly higher silhouette score and thus, a slightly more accurate level of clustering.

For a clustering of k=5, NDRE is seen to be superior to LCI in terms of average Silhouette Score. Despite this, the plots for NDRE also possess tails towards negative values showing a small level of misclustering. This suggests that though using NDRE on average clusters data points better, it is more prone to outliers that can be misclustered.

3.3 Analysis of Algal Coverage and Health

The resulting clusters for k=4 and k=5 were then analyzed to determine what each cluster represents. This included referencing both the original image data taken in RGB with the segmented image.

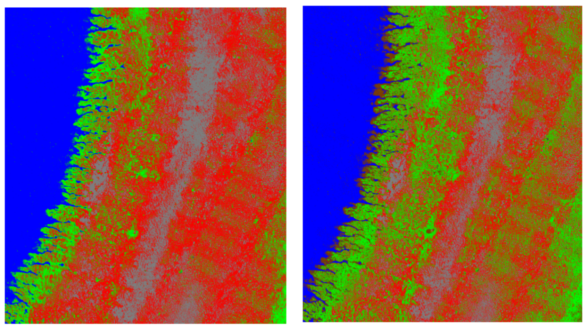

Fig. 5-6. Segmented NDRE maps for k=4 (left) and k=5 (right). Mapped clusters are sublittoral zone (blue), green algae (green), sea floor (red), bare rocks (grey), and miscellaneous (brown).

The four clusters common to both vegetation indices and values of k were noted to be the sublittoral zone, green algae, sea floor, and bare rocks. In order of decreasing vegetation index value, the *sublittoral zone* represents the part of the image of deep water in which light cannot penetrate all the way down to the surface. It appears as a dark blue in the RGB image and covers roughly a quarter of the image.

The *green algae* cluster was identified to have higher values for either vegetation index. This is as expected considering that the vegetation indices are a method of quantifying photosynthetic activity. It also covers approximately a quarter of the region of interest.

The *sea floor* cluster is the largest cluster representing over a third of the region of interest. Despite this, it covers a narrow range of vegetation index values in both NDRE and in LCI. This has lower vegetation index values than the green algae cluster though this does not mean that it is devoid of algal activity. It is likely that other forms of algae such as brown algae exist within this region.

Finally, representing the smallest area coverage is the *bare rocks* cluster. This cluster was found to have low vegetation index values and visually appears like bare rocks. It is highly likely that there is little to no photosynthetic activity occurring in this area due to these observations.

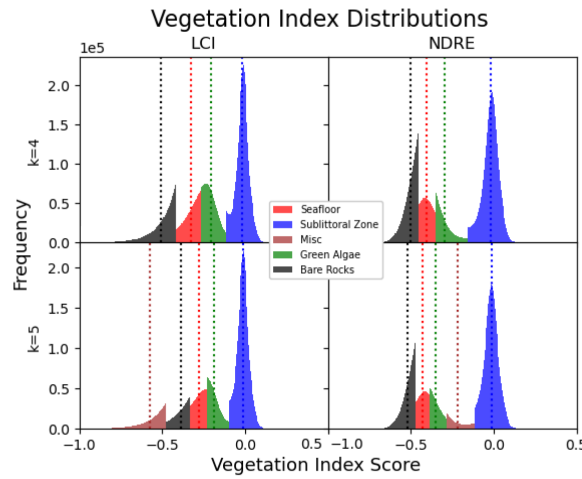

Fig. 7. Distributions of vegetation indices by cluster for LCI k=4 (top-left), NDRE k=4 (top-right), LCI k=5 (bottom-left), and NDRE k=5 (bottom-right)

Upon considering the fifth additional cluster labelled as a “miscellaneous” cluster, an interesting difference was noted between LCI and NDRE. In LCI, this additional cluster possesses lower values than the bare rocks cluster. Most likely, the clustering algorithm isolated the barest rocks as part of this cluster.

When using NDRE however, the new miscellaneous cluster possesses values in between the sublittoral zone and green algae clusters. It is likely then that the region represents the most photosynthetically productive portion of algae in the image.

A general observation is that apart from the sublittoral zone, all other regions are centered around negatively valued centroids. This would suggest lower levels of near infrared light across these clusters which conflicts with the fact that chlorophyll concentration is associated with higher values of near infrared light. It is possible that this is due to the water skewing the amount of near infrared light reaching the UAV’s multispectral camera. Further research is required to investigate this claim.

Table 1. Summary of area coverage (%) of each cluster

Vegetation Index	Sea Floor	Sublittoral Zone	Green Algae	Bare Rocks	Misc.
NDRE (k=4)	37.6	24.8	22.3	15.3	N/A
LCI (k=4)	37.8	25.5	29.2	7.5	N/A
NDRE (k=5)	31.4	23.6	23.5	15.5	6.0
LCI (k=5)	36.8	25.4	24.8	9.3	3.7

4. CONCLUSIONS

This study used UAV imaging and k-means clustering to characterize and analyze the status of algae in a coastal ecosystem. These methods may be applied further in other environmental studies.

It was found that k-means clustering is a suitable method for initial analysis of a coastal region. It is quickly and effectively able to segment the region of interest into clusters with low levels of misclustering. The use of Silhouette analysis is effective in verifying the quality of clustered data. Additionally, findings suggest that red edge light is relevant to the good clustering of multispectral imagery of coastal regions. The best performing vegetation indices both included red edge light. This claim may be further supported in future studies.

Future research may be directed towards the use of other unsupervised machine learning algorithms or vegetation indices for the purpose of algal monitoring. In-situ studies performed in the region of interest may be used to verify findings of this study as well.

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