NOVA SOUTHEASTERN UNIVERSITY

HALMOS COLLEGE OF ARTS AND SCIENCES

ALGAL COVERAGE DETECTION AND CLASSIFICATION USING ENVI: CORRELATION WITH DISSOLVED OXYGEN LEVELS IN ELKHORN SLOUGH, CA.

By

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LIST OF ACRONYMS AND ABBREVIATIONS

ABW	Above the water
AC	Acres
CDMO	Central Data Management Office
Chl-a	Chlorophyll-a
DJI	Da Jing Innovations
DO	Dissolved Oxygen
ES	Elkhorn Slough
ESNERR	Elkhorn Slough National Estuarine Research Reserve
IAW	In accordance with
MP	Megapixels
RGB	Red Green Blue color spectrum
SAM	Spectral Angle Mapper
SAL	Salinity
SAV	Submerged Aquatic Vegetation
SQFT	Square feet
TEMP	Temperature
UAV	Unmanned Aerial Vehicle (drone)
UW	Underwater
WQ	Water Quality

I. ABSTRACT

Estuaries are exposed to varying stressors, whether they be physical, chemical, or environmental. The most notable of stressors is eutrophication of coastal and inland ecosystems. This is a result of increased supply of nutrients fueling production within the system. One outcome of this increased nutrient load to the system is that of algal blooms. These blooms can impact the aesthetic appearance and degrade the quality of health of the system. Many of these coastal zones and waterways are critical habitats for many biological (some endangered) species and serve as recreational areas for human populations. Elkhorn Slough, California is one of these critical habits. Over its history, land use and environmental changes have degraded the quality of the ecosystem. Elkhorn Slough National Estuarine Research Reserve (ESNERR) has been tasked with oversight and monitoring responsibilities to maintain the system at a suitable level for the native species to thrive. This study, in conjunction with ESNERR support, will use aerial imagery of designated restoration areas to investigate the ability to use spectral analysis techniques to identify, classify, and calculate the percent coverage of algae masses. The aim is to use the inherent spectral analysis toolboxes in Harris Geospatial's ENVI to ingest 3-band RGB imagery and differentiate and accurately classify algal coverage. The goal is to compare ENVI's performance and accuracy, using ground-truthed base-image against traditional, time-intensive hand analytics. There is an extensive imagery library that has not be analyzed. This study will assess the potential ability to automate the process and increase classification capabilities.

Keywords: Estuaries, Water Quality, Environmental Monitoring, Spectral Analysis, Elkhorn Slough, algae monitoring, dissolved oxygen, hypoxia, eutrophication

II. INTRODUCTION

A. BACKGROUND

Estuaries are remarkable systems common to global coastlines and are considered some of the most biologically productive environments in the world (Wise 2017). They provide ecologically and economically valuable wildlife refuge, biological nursery, and dynamic nutrient transformation zones (Chuwen et al 2009; Hoeksema et al 2018; Paerl et al 1998). Three-quarters of the world's population resides within coastal river basins; forty-four percent of that population lives within 150 km of the coast, and this percentage is even higher within the United States (Handler et al 2006; Le et al 2011; Paerl et al 1998). Increased awareness of, and attraction to these zones has created a dependence upon these systems for sustainment and recreation.

1. Estuary Definition

The term estuary is defined as a system characterized by and emphasis on riverine input and at least a periodic connection with the ocean; where some regions are described by their geometry of permanently open to the ocean, where others are closed from the ocean by a sand bar across their mouths, either intermittently, seasonally, or for a protracted period of time (Hoeksema et al 2018). These coastal zones are areas where terrestrial rivers meet ocean influences, impacting its ecological state or nature (Palmer et al 2011 and Plew et al 2015). Classification of estuaries varies according to different aspects, while the diversity of estuary types is well known from literature, the major contributors defining type are the relationships of tidal range, sediment status, and relative wave-tide-fluvial processes (Cooper 2001). Global coastlines vary in all the above-mentioned factors. Therefore, classification of an estuary may be difficult, each has a unique combination of tidal, climate, geomorphological, and river input (Palmer et al 2011). Traditionally, the classification has been attributed to the coastal geometry and the stratification owing to seawater intrusion (Hansen and Rattray1966). Independent of classification, estuaries have been and remain vital to commercial, and recreational industries; for the purposes of tourism, fisheries, and water supply (Le et al 2011).

2. Human Impact on Estuarine Systems

Estuaries have great capacity to support and maintain biodiversity (terrestrial & marine) and provide protection to coastal infrastructure by buffering energetic wave activity from the ocean. These low-profile systems provide a barrier to extreme flooding events associated with storms and hurricanes (Leonardi et al 2018). They are also the focal points for urban, industrial, and agricultural development and usage as recreational activities (Hoeksema et al 2018). Exchanges and interactions from increasing populations within coastal zones tend to have consequences, at times; significant. Large population densities and impacts of human activities on coastal ecosystems can result in various alterations such as deterioration of water quality (WQ) and significant changes in the hydrological and biogeochemical cycles and biodiversity (Guimaraes et al 2017), to name a few.

The physical layout of estuaries can be altered as well. The protective nature and energy-buffering capabilities provided creates a nutrient rich system within the sediments and encompassing water, adding to the economic worth and attraction (Kennish 2019). Flow patterns have been changed in many systems and estuaries have been diked to use land space and sediments for agricultural purposes (Figure 1) (Orescanin et al 2019). These expansions in estuarine land use alter critical hydrological and biogeochemical dynamics, impacting health and biological suitability further up or down stream, and historically dried out areas subside too low for marsh to survive (Clark and O'Conner 2019). A secondary affect from coastal wetland diking is the significant degradation of WQ throughout the system due to a lack of flushing (water residence time) behind tidal and flow control structures (Orescanin et al 2019).

Figure 1. Restoration of the Nisqually Delta (diked)

Population overcrowding and additional environmental stressing has the potential to negatively impact the system. The past few decades, research and studies have resulted in an increased focus in gaining a better understanding of the physical and biochemical balances that maintain “suitable” and “good” health of our global estuaries. It is of world-wide concern that estuaries are now considered the most degraded of all temperate marine ecosystems (Chuwen et al 2009). While increased regulatory efforts in the United States and elsewhere have yielded many improvements in environmental quality compared to a few decades ago, environmental degradation persists on a global scale and broad environmental goals have yet to be achieved (McCormick and Cairns 1994). Government agencies and the general public have become increasingly concerned about maintaining the quality of aquatic resources (Maznah and Omar 2010). The ability to protect biological resources depends on the ability to identify and predict the effects of human actions on biological systems; thus, the data provided by indicator organisms can be used to estimate the degree of environmental impact and its potential danger for others (Karr and Chu 1999).

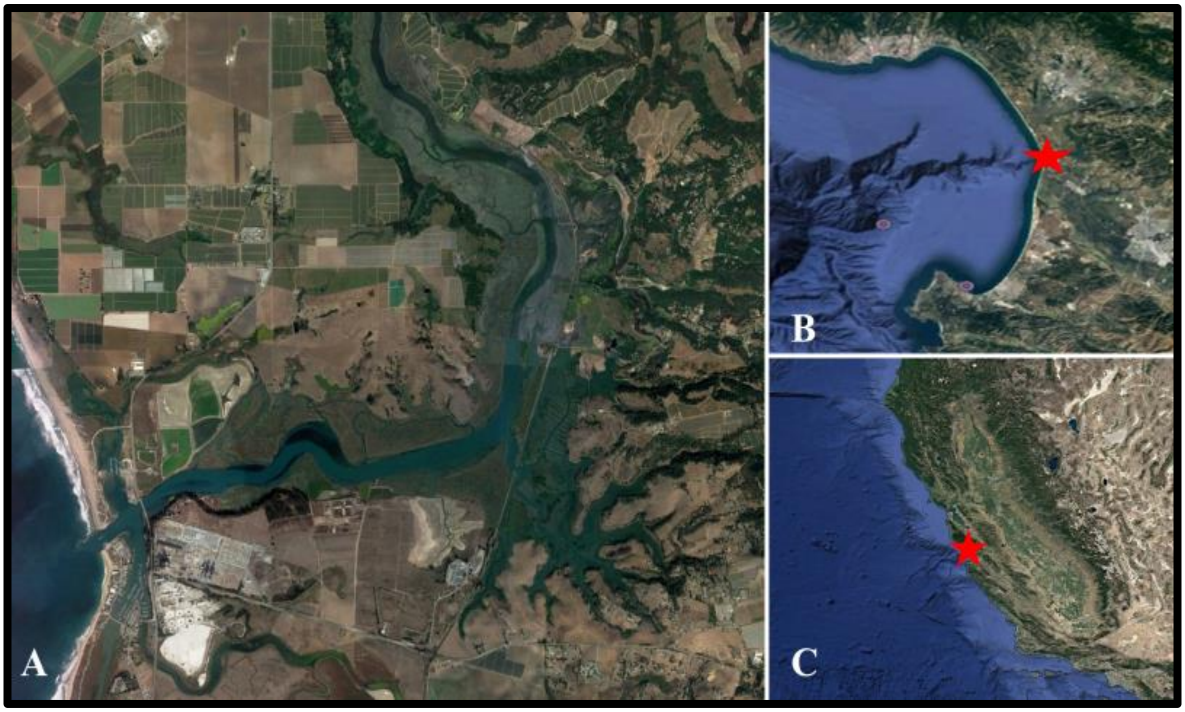
3. Eutrophication Impact

Eutrophication is one of the main WQ issues worldwide, affecting both freshwater and marine ecosystems (Guimaraes et al 2017). Eutrophication is defined as the supply of excess nutrients and supplements that result in excessive growth of primary producers. Plankton and microalgae can contribute up to 95% of the primary production distribution in response to readily available nutrients (Kotsedi et al 2012). All facets of a eutrophic system can and will be negatively impacted within the estuarine system, if not properly monitored and kept in check. Eutrophication of surrounding coastal waters is a problem of epidemic proportion and can have disastrous short- and long-term consequences for WQ and resource utilization (Millie et al 2004). Twomey and Thompson (2001) found that unmonitored eutrophic systems would progress to a level of biological and hydrologic degradation due to the emergence of harmful algal blooms (HAB's), which can result in the total loss of habitat biota, and commercial value.

Human activities compound the task of monitoring and assessing health status of estuaries. Resultant land alterations can increase nutrient loads, displaying nuisance algal blooms, degraded WQ, and habitat loss (Twomey and Thompson 2001). As Agencies and the general public have become more aware of the potential dangers associated with hydrologic flow alterations, significant time and effort has been put into understanding the primary production and algal concentrations (Geyer et al 2018; Guimaraes et al 2017; Handler et al 2006; Hoeksema et al 2018; Hubertz and Cahoon 1999; Kotsedi et al 2012; Maznah and Omar 2010; McCormick and Cairns 1994; Millie et al 2004; Sharp 2010; Paerl et al 1998; and Paerl et al 2007). Much of this work has focused on phytoplankton populations rapid response to physical, chemical, and biological changes in eutrophic estuarine systems (Hsieh et al 2007).

B. STUDY SITE

Elkhorn Slough (ES) is a 7-mile-long tidal estuary located in central California that is permanently open to Monterey Bay (Figure 2). It's a biologically rich environment that provides habitat diversity to resident and migratory birds, plants, marine mammals, and fish, and has been identified as a Globally Important Bird Area by the American Birding Conservancy, and recently received a RAMSAR classification for significant estuarine habitats (ESNERR 2019).



A: Aerial Image of the extent of ES., B: Location of ES in relation to Monterey Bay, CA., and C: Location of ES in relation to the California Coast.

Figure 2. Elkhorn Slough, Watsonville, CA

This ecological and economically valuable ecosystem, like many others across the globe, has been and is being threatened by local human impacts, such as agriculture and energy development. Local farming activities are responsible for introducing excess nutrients and other harmful pollutants that exacerbate biological and geochemical changes within the system. Eutrophication in estuaries surrounding these agriculturally and productive sites commonly suffer from the phenomena of hypoxic and anoxic conditions, due to the excessive algal growth and production from readily available nutrients (Bricker et al 2007). Alterations of the biogeochemical cycling can have long lasting impacts. ES has experienced episodic periods of hypoxic (DO < 2 milligrams per liter (mg/L)), and anoxic (DO = 0 mg/L) conditions within the various arms and branches of the estuary (Figure 3). Aside from the stresses of hypoxia and anoxia, DO levels greater than 5 mg/L are considered oxic and "suitable for supporting biological diversity. DO levels between 2 – 5 mg/L are a transitional zone, leading to a hypoxic environment.

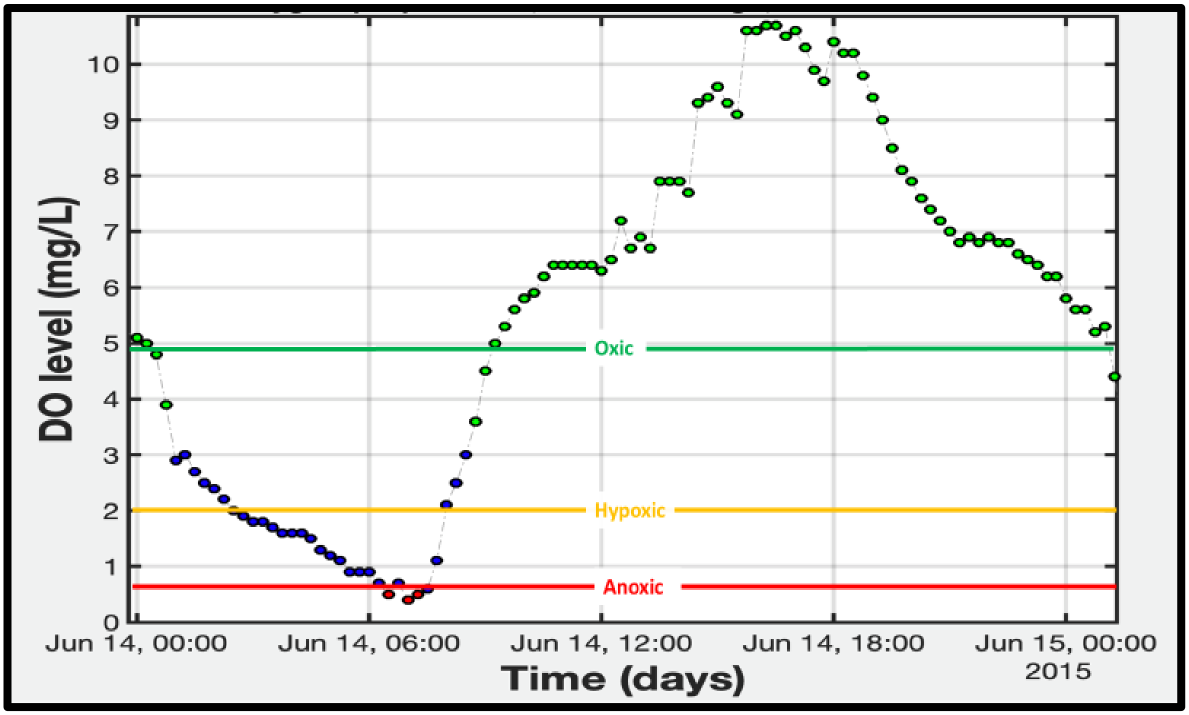


Figure 3. DO measurements collected from North Marsh (NM), ES.

ES supports hundreds of species of fish, invertebrates, and birds, and is considered one of the most extensive salt marshes in the state outside of San Francisco Bay (Jeppesen et al 2016). With this perspective, ES has been the focus of WQ monitoring and restoration efforts. Over the years of monitoring, ES has developed a report card based on WQ conditions. Monitoring sites within the Lower ES region have better WQ relative to the southern estuary sites and those located in the northern-most ES reaches, attributing the differences to existing water control structures (Mercado et al 2014). The range of daily average DO values was from 0.2 to 14 mg/L, with values dipping into the hypoxic zone in the summer months (Jun – Aug) (Schmit 2010). Biological and physical factors impact the variability of DO levels resulting from excess algal and plankton growth, and tidal exchange (residence times). In addition to those previously mentioned, restricted circulation in estuaries is now being considered a major factor. The majority of sites with poor WQ and increased hypoxia corresponded to those located behind these water control structures that restrict flow and increase the residence time; sites with better quality were close to the mouth and areas along the lower channel, which had unrestricted flow, full tidal exchange, and short residence time (Mercado et al 2014).

1. Hypothesis

Estuarine systems are the focal areas of WQ restoration efforts and monitoring programs. These complex environments have dynamic interactions that can alter, degrade and ultimately, result in habitat and species loss. Investigations into health maintenance and indicators of degradation are abundant with focuses on using algae as the primary variable (McCormick and Cairns 1994). Algae blooms can alter a system chemically and physically, and most notably deplete DO levels in the surface waters (Egerton et al 2014). Techniques use Chlorophyll-a (Chl-a) as a proxy for phytoplankton biomass, a primary response to eutrophication that leads to WQ degradation (Stanley 1993). A review of these studies, past and present, DO was not considered as a primary WQ parameter. Salinity (SAL), Temperature, Chl-a, and nutrients have primary emphasis placed on them as directly related to WQ conditions and health (Kotsedi et al 2012). without the need for hand-annotated estimates of algal coverage.

The objective of this research is to determine the reliability of using the ENVI to identify and classify algal (Ulva [sp]) coverage from 3-band RGB imagery collected remotely, within the NM site of ES. Furthermore, algae coverages estimated will be investigated to determine possible fluctuations in the DO seasonal trend. The hypotheses to be tested here are that 1) Harris Geospatial's ENVI spectral analysis program can be used to differentiate and accurately classify algal coverage (against verified base-imagery), automating algal coverage calculation within estuarine environments; and 2) Algae coverage can be used as an indicator of DO levels.

Image classification stats will be compared against the current hand-analysis technique, as a faster and accurate alternative process available for use.

III. FIELD AND ANALYSIS METHODS

This study was performed as a partnership with the Elkhorn Slough National Estuarine Research Reserve (ESNERR), to assess algal growth relationships with WQ at the four (4) sites within ES that are considered areas of concern for ecological impacts due to eutrophication (Figure 4). Identification of any correlations between the percent cover of algae and the area of an estuarine system is one that requires information from two main sources, 1 – WQ measurements (DO, SAL, temperature), and 2 – photographic images algae growth within the estuary over time. ESNERR collected aerial imagery over the NM site over the past four years and provided the images from their survey database. WQ data that was downloaded from the Central Data Management Office (CDMO) website. The images were initially classified by ESNERR using DroneDeploy and hand annotation. Here, images are classified using the spectral analysis program, ENVI to separate and calculate area coverage. That coverage was then compared to the corresponding time series of WQ data to identify trends or correlations between algae growth and changes in the DO and duration of hypoxia.

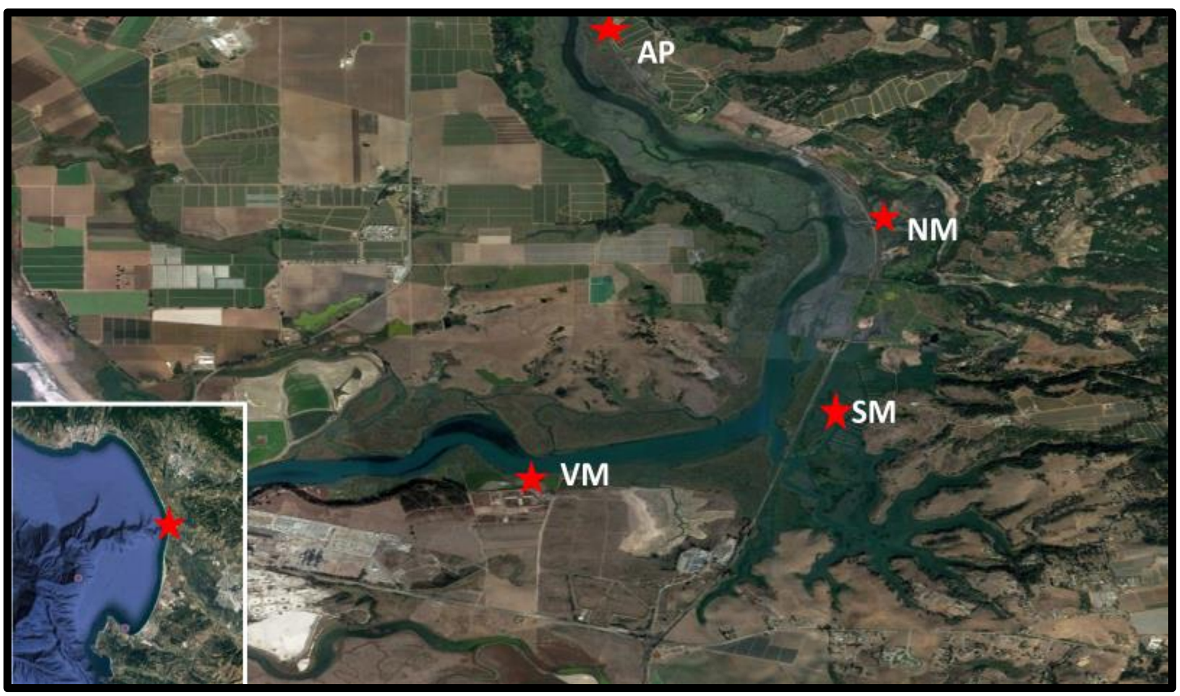


Figure 4. WQ sampling locations within ES.

Past studies have used various methods for algae coverage calculation, ranging from in-situ sampling to using Unmanned Aerial Vehicles (UAVs) as remote sensing surveys, to looking for the spectral signatures of chlorophyll-a (Chl-a) (Koparan et al 2018, Hansen et al 2017, Le et al 2013, Palmer et al 2013, Ali 2011, Egerton et al 2014, and Reif 2011). Matthew and Bernard (2013), like many of the previous studies found that Chl-a was a strong indicator and could be used as a proxy for algal and phytoplankton biomass. Their research found that Chl-a correlated to spectral reflectance in the 420 – 480 nm range. Other pigment characteristics found specifically to algae were found to have signatures in the 620 – 700 nm range, lending to the applicability of using remote sensing techniques and applications to quickly and accurately assess large areas of coastal waters (Matthew and Bernard 2013).

For this study, algal cover is estimated through spectral classification using ENVI with the imagery collected by UAV's during field studies. A recent study showed that ENVI offers multiple capabilities for classification, using various algorithms and regions of interest (ROI's) dictated by the user, and is accurate in identifying specific features or interest (Mielke 2019). ENVI, a spectral analysis program was selected to classify provided imagery for is ease and speed of automatic classification process

A. IMAGERY ACQUISITON

The ESNERR team started collecting and building a photographic library of ES in late 2015. These image surveys are conducted monthly or whenever feasible to access the site, using a UAV with a mounted camera. The Da-Jiang Innovations (DJI) Phantom 4 Pro quadcopter outfitted with a 20-megapixel (MP) camera (Figure 5) has been used to collect the 3-band (RGB color spectrum) images. Flight plans were preset and executed in an east-west direction with a nadir-looking orientation. Individual images are then stitched together using photogrammetry techniques, creating a full coverage ortho-mosaic image of the sample location. All was accomplished using the mapping software application DroneDeploy. Mission planning used a 75% front overlap with a 65% side overlap. Flights were flown at 60 meters (m) with a single pass and no perimeter oblique views. Historical weather and environmental conditions were collected, corresponding to each survey (Table 1) in order to account for variability in lighting.

Table 1. Flight Survey and Instrument Inventory

Image	**Jan 16**	**Feb 16**	**May 16**	**Apr 18**	**Jul 18**	**Sep 18**	**Oct 18**	**Jan 19**	**Mar 19**
Date taken:	12	10	02	09	25	17	25	23	04
Imaging Sensor:	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS	1/2.3" CMOS
Flight time:	1202	1351	1044	1325	1356	1322	1408	1258	1410
Wind speed (m/s):	2.2	4.0	3.1	5.4	1.3	4.9	1.3	2.2	3.6
Cloud cover:	Clear	Clear	Cloudy	Partly cloudy	Cloudy	Clear	Clear	Clear	Mostly cloudy
Pixel size (m):	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04

Meteorological data recorded at the time of flights. All times are local times (PST/PDT). GMT = +8/+7, respectively. Data was collected from the Elkhorn WX station (KCAWATSO38) (Weather Underground 2020). From here on, all images will be reference with the title listed here (month, year).

Figure 5. DJI Phantom 4 Pro Quadcopter.

Orthomosaic maps were processed and geo-rectified with DroneDeploy software using fixed ground control points which remained constant for each flight, then exported as geotiffs for use in ENVI. Nine (9) 3-band RGB geotiffs were provided for classification analysis in DroneDeploy (ESNERR) and ENVI (this study). These images are from the NM location

(Figure 5). Images analyzed here spanned from 2016 – 2019 and were taken across a variety of months.

B. IMAGE ANALYSIS PROCESSING

Image processing used ENVI for spectral signature identification and classification, similar to studies conducted using satellite imagery for coral reef habitat mapping and tracking of bleaching events in that remote imagery is processed (Riegl and Purkis 2005; Rowlands et al 2008). ENVI provides different methods of automatic classification through its use supervised and unsupervised internal algorithms (Mielke 2019).

ENVI's classification accuracy was dependent upon consistency throughout the process with all nine images. Image normalization was performed for assessment of the spectral classification capability and helped with comparison of classified outputs. Every ROI file consisted of the same five class types for feature identification. The included classes used a standard color scheme during classification (purple = dirt/mud, cyan = water, yellow = vegetation, bright green = algae (abw), and dark green = algae (uw)).

ENVI's classification process requires that the program have a set of "class types" composing ROI files for analysis and classification of remotely collected imagery. Ideally these ROI's are verified to what the environmental types are at a set time. For this study, 5 classes; algae (abw), algae (uw), dirt/mud, vegetation (other than algae), and water were identified as the prominent features across all images. Using the ROI function, each base image was used to ROI build files containing the spectral signatures of the 5 classes. Each of the class types is identified by drawing a polygon around features the correspond to the class. ROI files containing the desired class types was saved as an overlay to be used in classification.

This overlay serves as ground-truth for post-analysis error matrix and total coverage calculations. Class features selected in the ROI were verified during the field surveys by visual inspection from prominent features that remained constant across seasonal changes (increase in water level, etc.). Algae (abw and uw) coverage was the only variable feature but was evident and recognizable in all images. This in-situ verification of the base images will be the basis, assessing classification performance of ENVI. ROI files were required for each image because there was no anchor point, linking all images to a common projection.

Next step was to analyze each image with one of the various classification methods provided. The supervised Spectral Angle Mapper (SAM) was the choice algorithm during the classification process because of the nature of the algorithm to identify spectral signatures within the image. As previously mentioned, ENVI contains various classification algorithms. ENVI support documentation was reviewed to confirm the applicability to SAM to goals of this study (Harris1 2020). Supervision refers to the fact that training data or the generated ROI files is required for classification. Following the prompts within ENVI, each base image was used as the input file and compared against is corresponding ROI file. Completing the classification process, the output file will be the representation of the base image, colored in the scheme dictated by the ROI files and their class representation color.

Post- classification work included the creation of the error matrix comparing ENVI's producer accuracy to its user accuracy performance assessment. Producer accuracy measures ENVI's ability of correctly identify the algae classes, where user accuracy represents the probability measure of ENVI to place class type values (or pixels) into the correct class grouping. (Harris 2020). These matrices are generated internal to ENVI, in the confusion matrix toolbox. Tables 3 through 6 provide the accuracy assessment of ENVI's prediction capability for this study.

After the completion of the classification process and error matrix generation, quantification of the algal extent in the images was needed. Both ENVI and DroneDeploy had different procedures of calculating the overall percent coverage. The methods of both analysis tools for calculating total percentage are:

1. ENVI Calculations of Algae Coverage

Internal to ENVI's classification protocol, a text file (.txt) is generated with all the spectral information per classified image. The file contains class type name, area coverage (in pixel count and percent) of the image. Total algal coverage for each image was derived from the addition of both algae (abw and uw) class counts. Total percent coverage is annotated in Table 2.

2. ESNERR Calculations of Algae Coverage

Coverage calculations are performed in the web-based program DroneDeploy. This program requires using hand analysis of the imagery, marking and designating areas of interest, like using Google Earth (DroneDeploy 2020). Classification is conducted drawing polygons around visual areas of identifiable algal patches. Each polygon covers image pixels and internally converts those pixels to a corresponding area in acres (AC). All generated polygons areas were summed, then divided by the total marsh area (roughly 100.98 AC), yielding total coverage.

IV. RESULTS/DISCUSSIONS

A. IMAGERY ANALYSIS

The technique of using optical remote imagery for identification and habitat mapping has been documented as a suitable method within shallow water systems (Rigel and Purkis, 2005). Based on that premise, images collected from a UAV were collected and classified using ENVI and DroneDeploy. The classification performance of ENVI was evaluated and results were compared against the "hand-analysis" technique in DroneDeploy. Algal identification and coverage calculations were the primary focus of both methods and the basis of comparison. Table 2 shows resulting coverage comparisons between respective methods and measured DO levels at the time the nine (9) images were collected.

Table 2. Image Classification (ENVI/DroneDeploy) comparison with Avg DO.

IMAGE DATE	ENVI Spectral Calculation	Drone Deploy Calculation	Difference	DO Level (Avg)
JAN 16	16.3	14.5	+1.8	NA
FEB 16	18.5	14.7	+3.8	7.5
MAY 16	23.9	29.0	-5.1	3.5
APR 18	13.6	8.0	+5.6	4.5
JUL 18	14.0	2.8	+11.2	3.8
SEP 18	4.8	1.0	+3.8	2.8
OCT 18	13.0	4.9	+8.1	5.9
JAN 19	15.6	15.3	+0.3	8.1
MAR 19	17.1	11.5	+5.6	9.2

ENVI, DroneDeploy, and difference values are coverage percentages for algae. DO values are mg/L (average for the collection date of the image). Blue rows - wet season and orange rows - dry season.

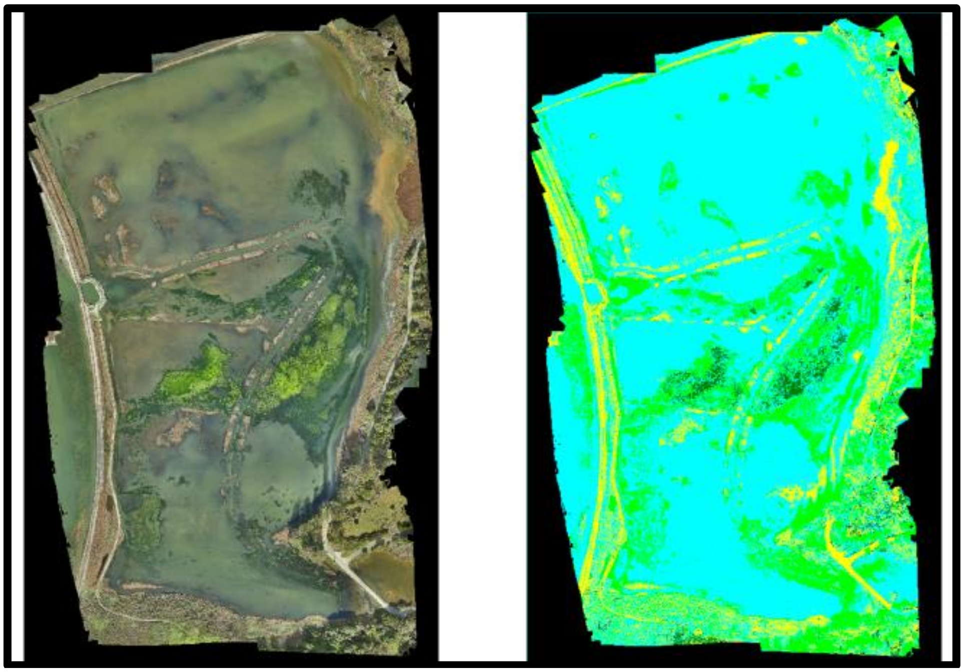
Total algal coverage (percent) varied between the two method capabilities. Overall, relative skill comparison between ENVI and DroneDeploy are very close with an RSME of 4.3%, indicating a good agreement in capability to identify and differentiate desired features. Comparisons shown in Table 2 represent estimates of the desired algae from a given images per each method, respectively. Four (4) images (two with smallest difference and two with the largest difference) are used to show the accuracy of ENVI and its automated analysis for brevity. These images will be referenced by the collection month and year (i.e., Jan 16, Jan

19, Jul 18, and Oct 18). Figures 6 through 9 are comparisons of ENVI classified outputs against the original 3-band RGB images.

Tables 3 through 6 represent the accuracy assessment of ENVI's prediction capabilities, compared to ground-truth data. ENVI was very precise with is classification protocol, effectively identifying greater than 90% of algae (both classes) coverage within the Jan16 images (Figure 6). The Jan 19 (Figure 7) similarly, posted similar results within the producer category which is ENVI's ability of correctly identify the algae classes (Harris 2020). There was a significant disparity in the user accuracy for Jan 19 (Figure 7). User accuracy represents the probability measure of ENVI to place class type values (or pixels) into the correct class grouping. (Harris 2020). ENVI performed at 51%, placing the features with similar pixel properties int to the algae (uw) class. Despite the confusion with submerged algae in the Jan 19 image (Figure 7), ENVI displayed excellent accuracy. Total coverages for Jan 16 (Figure 6) and Jan 19 (Figure 7) comparing ENVI's automation process against DroneDeploy hand-analysis were very close, at 1.8% and 0.3%, respectively (Table 2).

For the Jul 18 (Figure 8) and Oct 18 (Figure 9) images, ENVI was efficient in its producer classification capability, classifying algal types, with accuracies ranging from 96% to 98% (Table 5 and Table 6). Significant errors occurred in the discrimination of algae (uw) pixels, with an accuracy at 8.2%. Oct 18 (Figure 9) did not see the same disparity that was exhibited in Jul 18 (Figure 8). Algae (uw) attribution was at 87%, with these variations possibly contributing to the total coverage differences of +11.2 and +8.1, respectively (Table 2).

1. January 16 – Field Survey



Cyan coloring indicates water. Yellow represents vegetations such as marsh grass (growing in the middle of the marsh). Light and dark shaded green indicates algae. Trees and shrubbery were classified in this grouping as well. Purple indicates exposed dirt and submerged mud regions. ENVI and DroneDepoly total algae was 16.3% and 14.5%, respectively (Table 2).

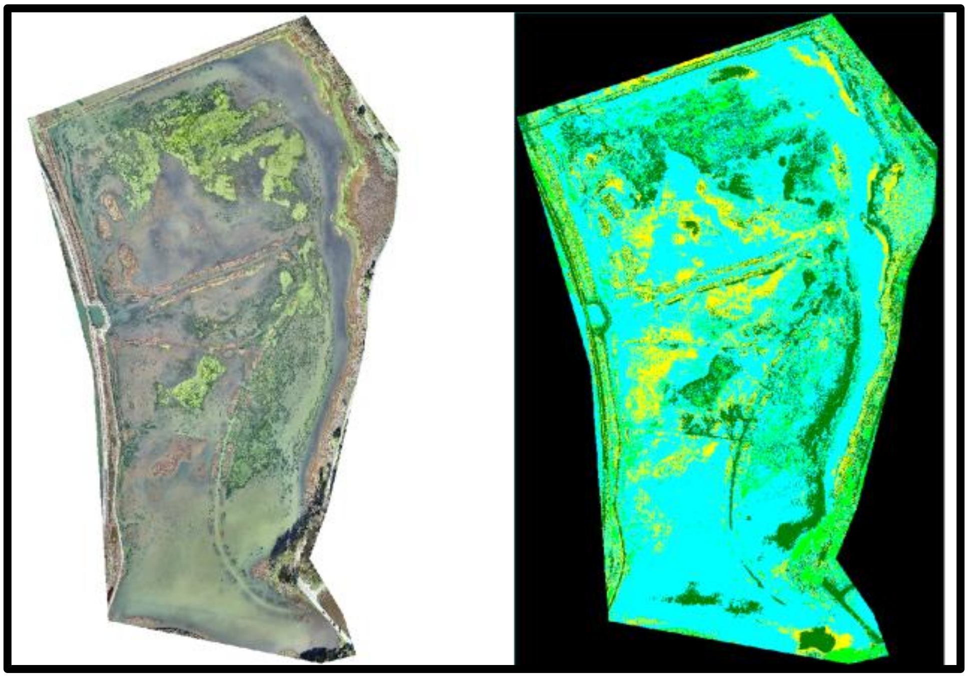
Figure 6. Jan 16 Original RGB vs ENVI classification

Table 3. Error Matrix for Jan 16

CLASSES - PREDICTED		CLASSES - GROUND TRUTH (PSEUDO)					
		Dirt and Mud	Water	Vegetation	Algae (UW)	Algae (ABW)	USER ACC.
	Dirt and Mud	**85.3**	0.0	5.2	0.0	0.0	87.3
	Water	8.0	**100.0**	3.9	0.4	9.1	96.2
	Vegetation	6.7	0.0	**88.1**	0.0	0.0	96.9
	Algae (UW)	0.0	0.0	0.0	**99.6**	0.0	**99.9**
	Algae (ABW)	0.0	0.0	2.8	0.0	**90.9**	**98.2**
	TOTALS	100.0	100.0	100.0	100.0	100.0	
	PROD. ACC	85.3	100	88.2	**99.6**	**90.9**	

Note - Values were generated using the ENVI Confusion Matrix toolbox. All values are percentages

2. January 19 – Field Survey



Cyan coloring indicates water. Yellow represents vegetations such as marsh grass (growing in the middle of the marsh). Light and dark shaded green indicates algae. Trees and shrubbery were classified in this grouping as well. Purple indicates exposed dirt and submerged mud regions. ENVI and DroneDepoly total algae was 15.6% and 15.3%, respectively (Table 2).

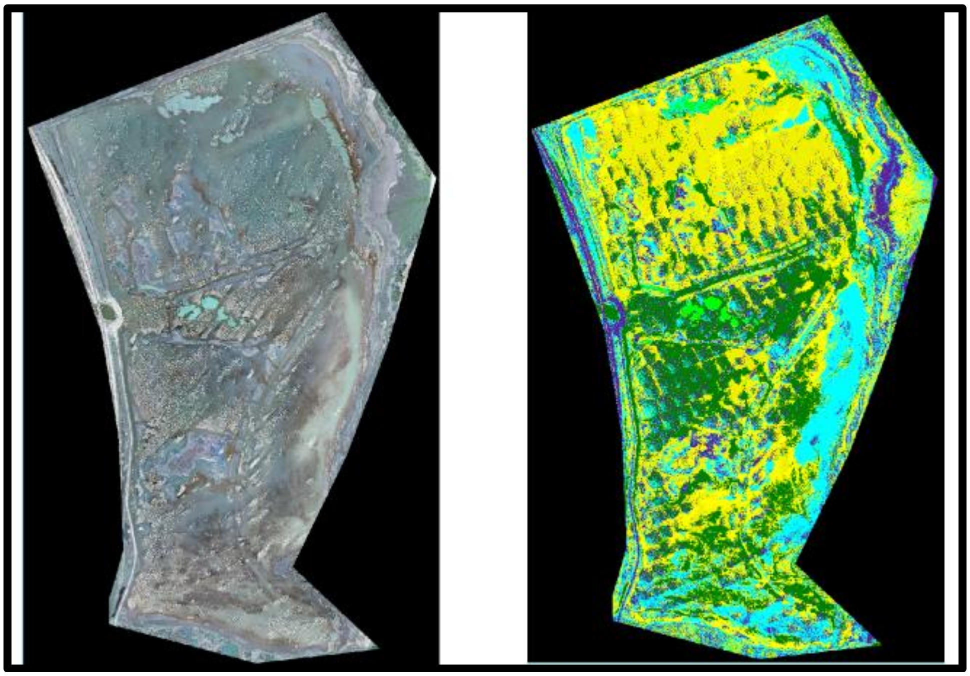
Figure 7. Jan 19 Original RGB vs. ENVI classification

Table 4. Error Matrix for Jan 19

	CLASSES - GROUND TRUTH (PSEUDO)					
CLASSESS - PREDICTED	Dirt and Mud	Water	Vegetation	Algae (UW)	Algae (ABW)	**USER ACC.**
Dirt and Mud	**91.0**	0.1	21.6	0.0	0.7	0.6
Water	0.0	**97.4**	2.9	0.7	0.4	92.2
Vegetation	9.0	1.6	**70.1**	0.1	0.2	98.3
Algae (UW)	0.0	0.5	5.4	**93.8**	2.1	51.4
Algae (ABW)	0.0	0.4	0.0	5.4	**96.6**	99.6
TOTALS	100.0	100.0	100.0	100.0	100.0	
PROD. ACC	91.0	97.4	70.1	93.8	96.6	

Note - Values were generated using the ENVI Confusion Matrix toolbox. All values are percentages

3. July 18 – Field Survey



Cyan coloring indicates water. Yellow represents vegetations such as marsh grass (growing in the middle of the marsh). Light and dark shaded green indicates algae. Trees and shrubbery were classified in this grouping as well. Purple indicates exposed dirt and submerged mud regions. ENVI and DroneDepoly total algae was 13.9% and 2.8%, respectively (Table 2).

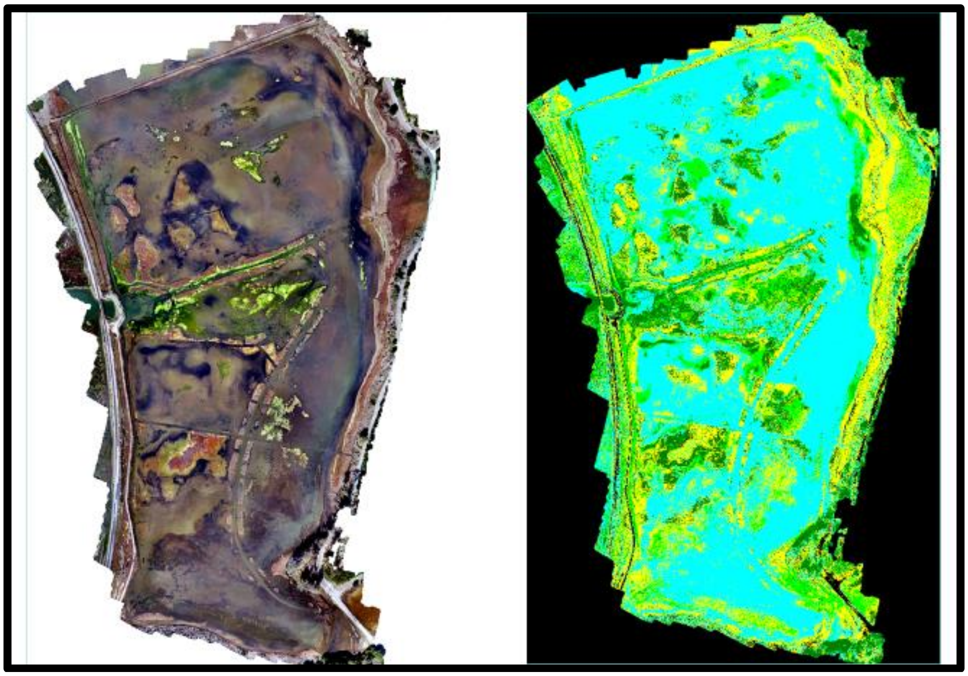
Figure 8. Jul 18 Original RGB vs ENVI classification

Table 5. Error Matrix for Jul 18

CLASSES - PREDICTED	CLASSES - GROUND TRUTH (PSEUDO): Dirt and Mud	Water	Vegetation	Algae (UW)	Algae (ABW)	USER ACC.
Dirt and Mud	**94.8**	46.9	0.2	0.6	1.0	56.0
Water	4.8	**0.1**	17.3	1.0	2.5	0.4
Vegetation	0.4	33.9	**80.6**	0.5	0.0	30.4
Algae (UW)	0.0	19.1	1.9	**97.9**	0.1	**8.2**
Algae (ABW)	0.0	0.0	0.0	0.0	**96.4**	**99.9**
TOTALS	100.0	100.0	100.0	100.0	100.0	
PROD. ACC	94.8	0.1	80.6	**97.9**	**96.4**	

Note - Values were generated using the ENVI Confusion Matrix toolbox. All values are percentages

4. October 18 – Field Survey



Cyan coloring indicates water. Yellow represents vegetations such as marsh grass (growing in the middle of the marsh). Light and dark shaded green indicates algae. Trees and shrubbery were classified in this grouping as well. Purple indicates exposed dirt and submerged mud regions. ENVI and DroneDepoly total algae was 13% and 4.9%, respectively (Table 2).

Figure 9. Oct 18 Original RGB vs ENVI classification

Table 6. Error Matrix for Oct 18

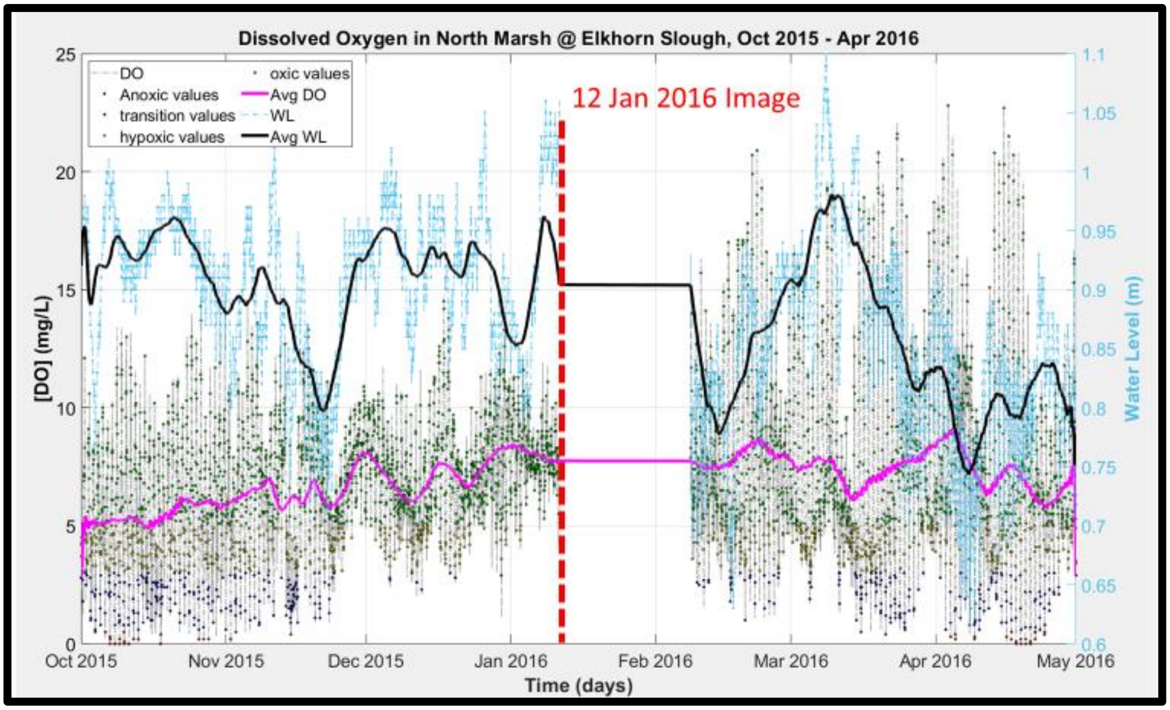
	CLASSES - GROUND TRUTH (PSEUDO)					
CLASSESS - PREDICTED	Dirt and Mud	Water	Vegetation	Algae (UW)	Algae (ABW)	**USER ACC.**
Dirt and Mud	**74.6**	0.0	18.6	0.0	0.0	72.9
Water	0.0	**98.3**	2.9	3.0	2.1	96.3
Vegetation	25.4	1.6	**76.9**	0.0	0.4	80.3
Algae (UW)	0.0	0.1	1.6	**96.5**	0.3	**87.1**
Algae (ABW)	0.0	0.0	0.0	0.5	**97.2**	**99.9**
TOTALS	100.0	100.0	100.0	100.0	100.0	
PROD. ACC	74.6	98.3	76.9	**96.5**	**97.2**	

Note - Values were generated using the ENVI Confusion Matrix toolbox. All values are percentages

B. WQ SEASONAL ANALYSIS

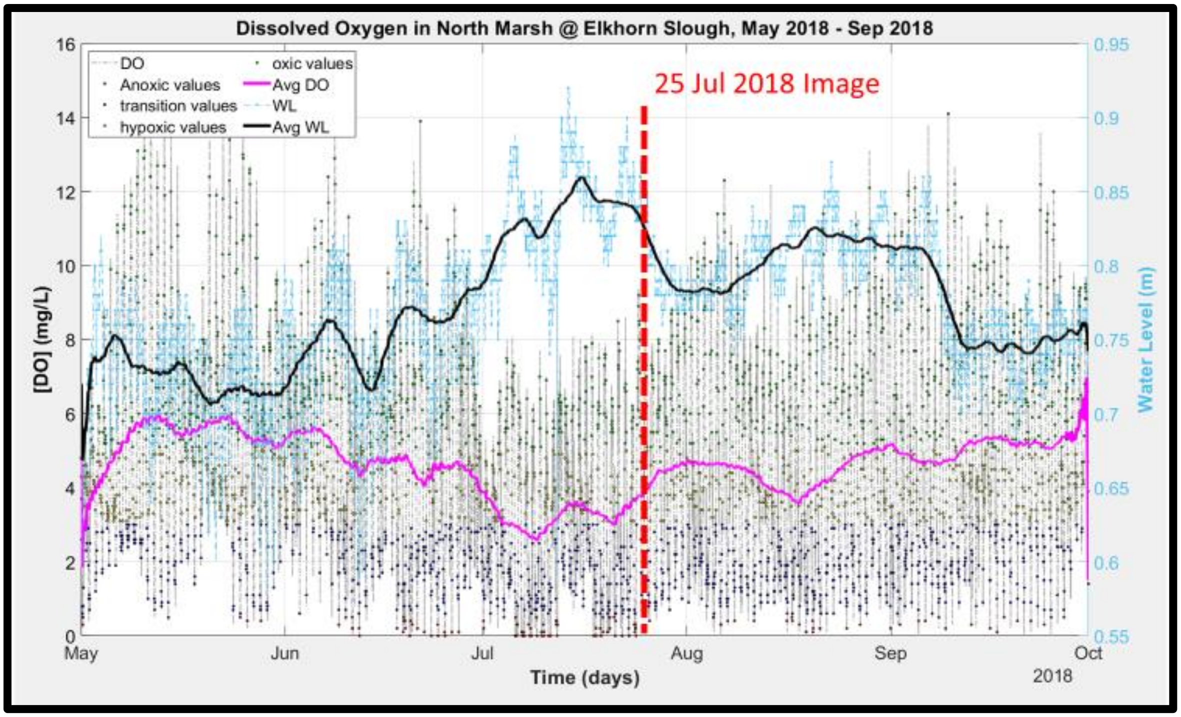
WQ analysis was conducted focusing on the variations within the DO levels, on data collected from the Central Data Management Office (CDMO), ranging from 2016 - 2020. The Central California Coast experiences two major seasons – wet, occurring from October to April and dry, from May to September. The data indicated seasonal trends present in DO measurements during we seasons where levels reach and maintain normal oxic conditions (DO > 5 mg/L), with low occurrences of hypoxia. Conversely, during dry seasons, the DO greatly varies, with more frequent hypoxic events and experiencing period of anoxia (DO < 0.5 mg/L). Figures 10 to 12 compare the wet and dry seasons for years 2016, 2018 and 2019, corresponding to images (Figures 6 -9 and Tables 3 - 6).

Trend lines (longer term averages) for both DO measurements and water level were analyzed for identification and comparison of seasonal trends. Trends were calculated by applying a seven (7) day moving filter (or moving average) over the data record, attempting to remove tidal influences and diurnal fluctuations. DO was divided up to identify the varying conditions. Green markers indicate oxic conditions; blue markers are the transition (2 -5 mg/L) state; yellow markers indicate hypoxic conditions, and red markers indicate the anoxic conditions.



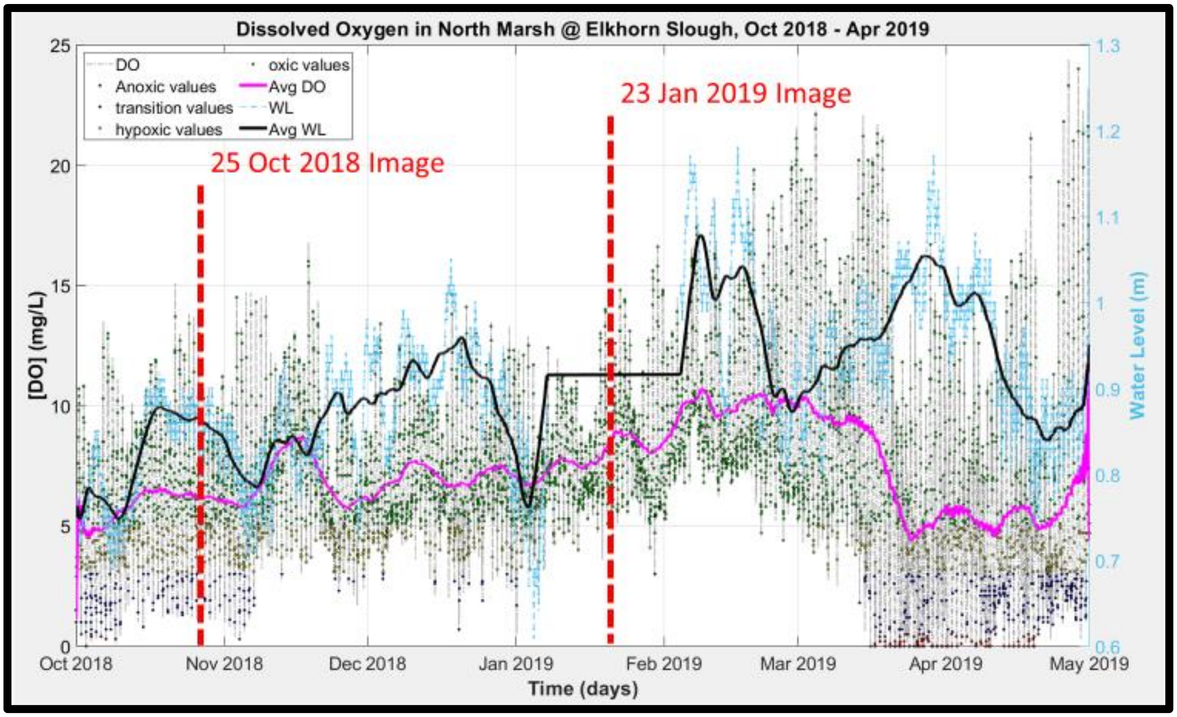
Time series of water level (cyan) and DO (colored) versus time for the wet season, 2019. Black line is the average water level, pin line is the average DO concentration. For DO, green markers indicate oxic conditions; blue markers are the transition (2 -5 mg/L) state; yellow markers indicate hypoxic conditions, and red markers indicate the anoxic conditions. Red dash lines indicated corresponding classification imagery.

Figure 10. 2016 Wet Season Trend



Time series of water level (cyan) and DO (colored) versus time for the dry season, 2018. Black line is the average water level, pin line is the average DO concentration. For DO, green markers indicate oxic conditions; blue markers are the transition (2 -5 mg/L) state; yellow markers indicate hypoxic conditions, and red markers indicate the anoxic conditions. Red dash lines indicated corresponding classification imagery.

Figure 11. 2018 Dry Season Trend



Time series of water level (cyan) and DO (colored) versus time for the wet season, 2019. Black line is the average water level, pin line is the average DO concentration. For DO, green markers indicate oxic conditions; blue markers are the transition (2 -5 mg/L) state; yellow markers indicate hypoxic conditions, and red markers indicate the anoxic conditions. Red dash lines indicated corresponding classification imagery.

Figure 12. 2019 Wet Season Trend

Average DO levels ranged between 5 – 10 mg/L, experiencing fewer hypoxic and anoxic periods throughout the season (Figs 10 and 12). Drier seasons experienced decreased average DO values, ranging from 2 – 8 mg/L, with significantly more hypoxic and anoxic occurrences (Figure11). DO variations show a strong agreement with drier months and lower water levels factoring into poorer WQ conditions, while the wet season and increased water levels indicated better WQ, respectively. The average DO values ranged from 2.8 – 9.2 mg/L, across the time range of the four images selected for classification accuracies (Figures 6 – 9 and Table 2).

C. IMAGERY AND WQ DISCUSSION

ENVI proved to be a suitable tool for quick and accurate algae classification from remotely sensed imagery. Classified Images and error matrices were generated in ENVI for each image provided. Table 6 shows the average classification accuracy (user and producer) for algae (abw and uw) classes across all images. Overall, ENVI's precision identifying specific class types and capability of placing correct features in correct classes is good. Larger variations in accuracy was seen in the programs ability to handle placement of algae, specifically submerged (uw) information into the correct class groupings, with an average accuracy of 58%. Algae on the surface (abw) was handled very well, posting user and producer accuracies ranging from 94% and 96%, respectively.

Table 7. ENVI Algal Classification Accuracies

		USER ACCURACY		PRODUCER ACCURACY	
		Algae (abw)	Algae (uw)	Algae (abw)	Algae (uw)
IMAGE	12 Jan 16	98.2	99.9	90.9	99.6
	10 Feb 16	99.9	63.5	97.4	99.0
	02 May 16	100.0	98.7	98.9	98.8
	09 Apr 18	71.0	0.3	99.1	91.8
	25 Jul 18	99.9	8.2	96.4	97.9
	17 Sep 18	91.6	27.6	98.5	77.8
	25 Oct 18	99.9	87.1	97.2	96.5
	23 Jan 19	99.6	51.4	96.6	93.8
	04 Mar 19	89.3	87.3	93.0	79.7
	Average	**94.4**	**58.2**	**96.4**	**92.8**

All values are percentage extracted from the Error Matrices generated at the conclusion of the classification process in ENVI.

Variations seen in ENVI's ability to place class type information into the correct class grouping can be associated to the process routines that look at placing similar image pixels into similar classifications. Hestir et al (2008) conducted a similar study looking at submerged aquatic vegetation (SAV) and found that pixel composition of the target species presented a common problem due to spectral signature blending with surrounding vegetation and like-features.

Variations in the algae (uw) percentages across images (Table 6) appear to be impacted by pixel confusion, particularly where the visible algae resembled that of the surrounding water. Use of spectral analysis identifying vegetation submerged below the water surface tend to have similar characteristics of the surrounding water (Everitt et al 1999). Similarly, high amounts of organic material (other than algae) could have common appearance and spectral signatures as true algae. This was evident across all images, where surrounding trees were identified as algae (abw). Everitt et al (1999) noted that water alters spectral information and interpretation within remotely sensed imagery.

Since the images are 3-band RGB, pixel blending occurred from common spectral information across different features, as noted between algae (abw) and tress. Picture resolution contributed to varying classification results and accuracies. Resolution and distortions from both the equipment and natural events (i.e., sun glints, wind, cloud cover, etc.) impacted the programs ability classification against ground-truth features. Prevailing weather conditions not only impact image quality but can impede the spectral measurements that can be collected by the sensor (Hestir et al 2008).

The general understanding is that when more algal biomass is present, WQ conditions will tend to decrease owing to respiration dominating the oxygen budget within the system. However, images from the July to Oct indicated some of the lowest algal coverages, comparatively (Table 1). The corresponding WQ data (Figure 11) showed increased hypoxic and anoxic events during 2018, not following the assumption of more mass equating to more oxygen use. This data suggests that more is occurring, likely at shorter periods than the currently used (monthly) imagery can measure, altering the oxygen budget at the NM location, deteriorating WQ conditions and ecologic impacts due to eutrophication within the system. More research is needed to understand if algal coverage is accounting for the larger portion of DO fluctuations or if other processes are contributing to the varying oxygen levels throughout the wet/dry seasons on the Central California Coast.

V. CONCLUSIONS

ENVI performed well compared to hand-analysis techniques in Drone Deploy, using polygons to identify regions or interest. Both methods can be used for estimating the coverage or extent of potential impacts to estuarine health. ENVI provides the capability to quickly classify remotely sensed images with 90% accuracy. Some distortion and confusion within pixel identification, contrast, and confusion occurred reducing accuracy. The key to good classification performance is well-developed ROIs. Images with better resolution and definitive desired features will tend to distinguish and classify with less error.

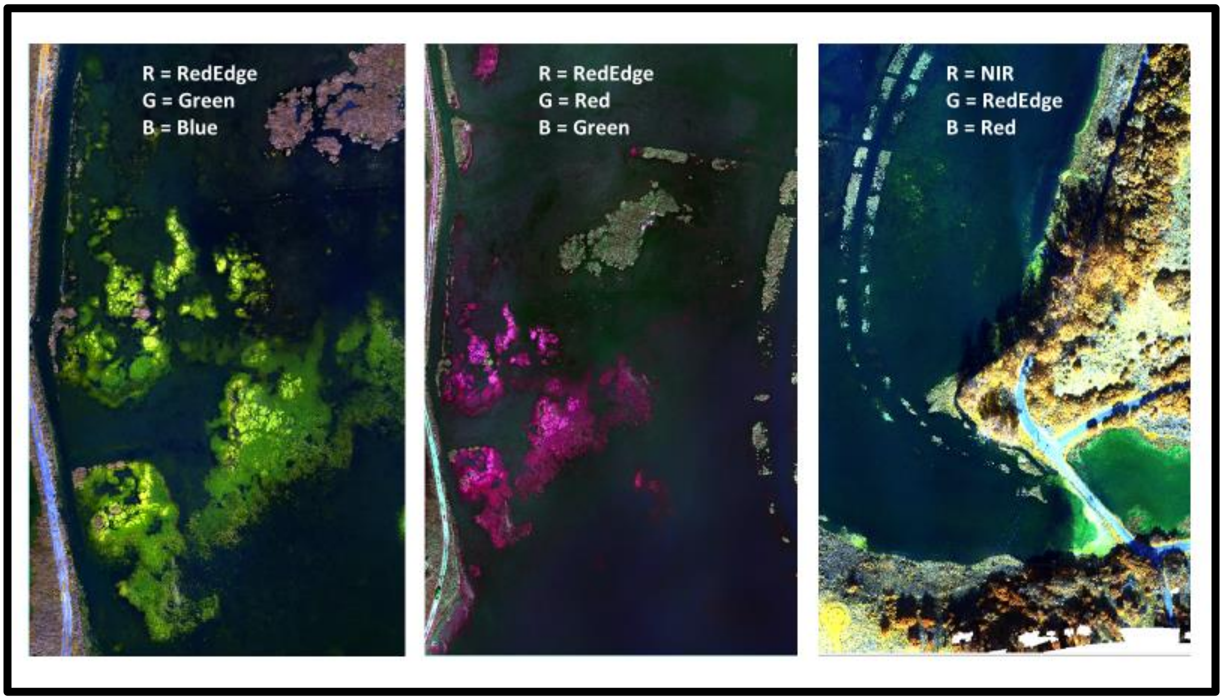
ENVI's ability to accurately classify imagery provides a useful tool for environmental monitoring field, particularly looking at proxies of prevailing WQ conditions such as algae. The capabilities to identify algal coverage from spectral information with high accuracy (Table 6) is truly a significant accomplishment considering that most algal coverage analysis is estimates. The one true accurate method for identifying algal coverage is with in-situ water sample collections and calculation (Katz et al 2018).

This spectral analysis tool enables large environments to be monitored and assessed in relatively short time periods. Imagery analysis, through ENVI can be performed on the scale of hours vice days. Use of ENVI enhances the frequency of monitoring and assessment opportunities as well. Remotely sensed data can be acquired from field site visits or satellites over remote, hard to access locations. ENVI could be considered more accurate due to the spectral nature of the analysis, benefiting coastal assessments and monitoring programs. The benefit from the use of a spectral analysis tool is to reduce the amount of time dedicated to hand (user intensive) analysis of the images.

The value of remote sensing for assessing and managing wetlands is well established (Everitt et al 1999). Previous works have shown that algae and phytoplankton are good indicators for use due the visible signature of Chl-a, around 440 nm and a plankton-specific pigment, phycocyanin; which absorbs at 620 nm (Matthews and Bernard 2013). ENVI performed very well identifying algae with minimal misclassification due to its ability to spot the peaks the above-mentioned ranges.

Future work may include more frequent flights over impacted estuaries and coastal waters. Algae impacts and response times to environmental stressors is relatively short, on the scale of hours to days (Sanford et al 1990). Daily to weekly flights coupled with the faster image processing time could highlight the short response times that lead to algal blooms and water quality degradation.

ENVI has a high potential for performing multi and hyperspectral classification studies. Multi and hyper-spectral imaging provides the potential for collecting enhanced spatial and spectral resolution, better understand optically complex aquatic ecosystems (Ryan et 2014, and Xi et al 2015). Figure 13 shows the potential channel manipulations capability within ENVI.



Images were collected over NM from a Micasense Altum-M camera on a DJI Inspire UAV. Band 1 = Red channel, Band 2 = Green, Band 3 = Blue, Band 4 = RedEdge (707 nm – 727 nm), and Band 5 NIR (800 nm -880 nm) (Mielke, 2019). Left image is near true color looking nadir on algae. Center image is the same area, changing channels to RedEdge, red and green. Right image is looking over trees, water and algae (in the lower right image corner) with NIR, RedEdge, and blue channels.

Figure 13. Band Manipulation Features with ENVI

This increased spectral analysis capability may potentially increase accuracy and feature definition of desired regions. ENVI is equipped to handle this task. Mielke (2019) performed a study into the ability to train the ENVI's neural networking to classify varying bottom types and beach features, increasing ENVI's standard classification percentage. ENVI's accuracy, capability and use in conjunction with WQ data and models may be useful for identifying and tracking degrading conditions or coastal areas and inland aquatic environments.

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