Application of Linear Spectral unmixing to Enrique reef for classification

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ABSTRACT

Enrique Reef it is located in southwestern Puerto Rico at La Parguera. This reef presents various habitats such as sand, corals reefs and seagrasses. The classification of a complex marine habitat such as this is a difficult process. For this purpose a spectral unmixing approach was chosen. The unmixing decomposes a mixed pixel into a collection of endmembers and a set of fractional abundances that indicate the proportions of each endmember. A series of steps to reach a good classification were considered before applying the Liner Spectral Unmixing (LSU). A Minimum Noise Fraction (MNF) transformation was made to minimize noise. The Pixel Purity Index (PPI) is a means of finding the most "spectrally pure" pixels in the image. The most spectrally pure pixels typically correspond to mixing endmembers. After these processes, three endmembers were chosen seagrasses, mangroves and sand to apply the unmixing model to IKONOS imagery for estimating cover fractions and to complete and compare supervised and unsupervised classification after LSU. The fractions of seagrasses, sand and mangroves within the pixels did not worked as expected because the classifications generated misclassified the classes and the fraction cover data produce negative values.

Keywords: supervised classification, unsupervised classification, endmembers, spectral unmixing

INTRODUCTION

All Earth surface materials have specific spectral features, which are related to their composition. In an image, within a pixel various components are present, but regularly the algorithms for classification can not identify more than one class within the pixel; is for this reason that spectral unmixing is used. It is often the case in remote sensing that one wants to deal with identification, detection and quantification of fractions of the target materials for each pixel for diverse coverage in a region using unmixing approaches to discern the proportion of heterogeneity (Kanniah et al., 2001). Conventional satellite remote sensing classification procedures yield thematic coarse resolution data with only one class per pixel (Kanniah et al., 2001). Mixed pixels problem in remotely sensed satellite data often results in poor classification accuracy (Kanniah et al., 2001). Mixed pixels are problematic for statistical classification methods because most algorithms are based on the assumption of spectral homogeneity at pixel scale within a particular class of land cover (Small, 2003). The spectral unmixing method used for this project was Linear Spectral Unmixing (LSU). Linear mixture modeling assumes that the signal received at the satellite sensor depends on the proportion of individual surface components such as soil, water and vegetation present in a particular pixel and on the mixing process (Abdul Shakoor, 2003). The unmixing decomposes a mixed pixel into a collection of endmembers and a set of fractional abundances that indicate the proportions of each endmember. The contribution of each pixel is assigned in proportion to the percentage area each ground cover class occupies in that mixed pixel (Boardman, 1989). An endmember is a “pure” spectrum of a material or target and has a unique spectral signature. Image Endmembers are pure pixels from image itself. For this study, three endmembers were identified and then extracted from the image data for spectral unmixing purposes. The endmember selection included the following components: seagrasses, mangroves and sand. In order to do the spectral unmixing, good endmembers had to be chosen. The desire to extract from a spectrum the constituent materials in the mixture, as well as the proportions in which they appear, is important to numerous tactical scenarios where subpixel detail is valuable (Keshava, 2003). The importance of the spectral unmixing lies in its ability to improve the subpixel data and give realistic info. To execute the relevant work a series of objectives were resolute:

1. understand what is spectral unmixing,
2. apply the unmixing model to IKONOS imagery for estimating cover fractions of seagrass, sand and mangrove within the pixels
3. complete and compare supervised and unsupervised classification after LSU from Enrique Reef

METHODS

Study area: Enrique Reef is located in southwestern Puerto Rico at La Parguera. This reef presents various habitats such as sand, mangroves, corals reefs and seagrasses. Also, it is one of the most extensive keys in La Parguera and hence the ecosystems can be easily differentiated in an IKONOS image.

Sensor: The sensor to be used is a high resolution satellite, IKONOS. Launched in 1999, revisit time 3 days, with a radiometric resolution of 8bits. The imagery that was used is from February 19, 2006. This image contains 3 bands one in the red part of the spectrum, one in the green and one in the blue. The recent availability of images from high spatial resolution satellite sensors like IKONOS and Quickbird enable the mapping of land covers more accurately and they can also substitute the higher cost of airborne images (Kanniah et al., 2001). In a study conducted by Mumby and Edwards (2002) they compared an IKONOS image with other remote sensing images like Landsat TM, SPOT, CASI etc. and they found that the fine spatial resolution image of IKONOS could obtain a better thematic accuracy in mapping marine environments. The applications of this sensor includes: urban and rural mapping of natural resources and of natural disasters, etc.

LSU: The images were analyzed using ENVI 4.1 software. First a dark pixel subtraction was completed in order to correct glint and complete an atmospheric correction; also a mask was built and applied to deep water pixels which are not considered any further. A Minimum Noise Fraction (MNF) transformation was made to minimize noise. This transformation identifies the locations of spectral signature anomalies. It assumes that an observed signal is being linearly mixed with a noise source which is uncorrelated with the true signal (ENVI Help 4.1). With IKONOS imagery, the MNF transformation usually produces principal components similar to those resulting from a traditional covariance-based PC rotation but offers the added benefit of normalizing the eigenvalues relative to the variance of the sensor noise estimate (Small, 2003). Then the MNF bands were used for the determination of Pixel Purity Index (PPI). The Pixel Purity Index (PPI) is a means of finding the most pure pixels in the image. The most spectrally pure pixels typically correspond to mixing endmembers. The Pixel Purity Index is computed by repeatedly projecting *n* -dimensional scatter plots onto a random unit vector (ENVI Help 4.1). The extreme pixels in each projection are recorded and the total number of times each pixel is marked as extreme is noted (Stein et al., 1999). A Pixel Purity Index (PPI) image is created in which the DN of each pixel corresponds to the number of times that pixel was recorded as extreme (ENVI Help 4.1). This type of tecnique has been developed to extract endmember spectra automatically from remotely sensed data (Stein et al., 1999). The algorithm finds appropriate spectra for endmembers. After these processes, three endmembers were chosen seagrasses, mangroves and sand. A bad endmember selection and identification can lead to meaningless fraction cover maps. These endmembers are then used for Linear Spectral Unmixing (LSU) and classification. LSU assumes that (i) spectral variation is caused by a limited number of surface materials (i.e. soil, water, shadow, vegetation), (ii) the pixel is a linear mixture of its constituents and (iii) all endmembers possibly contained in the pixel have been included in the analysis (Kanniah et al., 2001). During the unmixing process, a unit sum constraint was applied by adding a weighting factor of one because the sum of abundances is theoretically 1. This is the default unmixing algorithm. A summary of the methods is presented in fig 1.

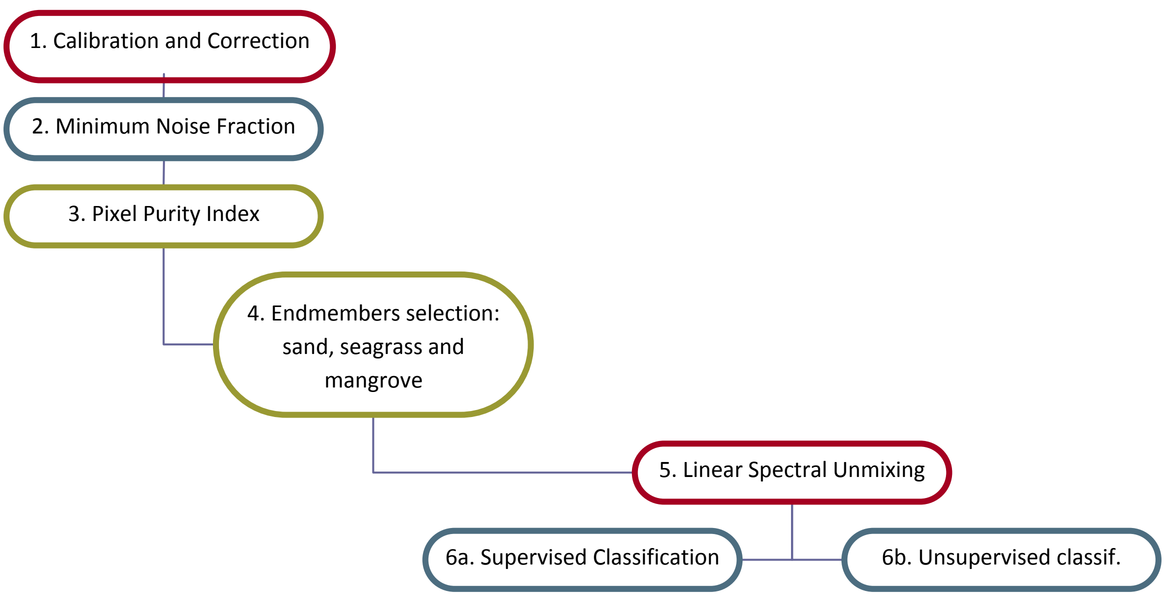


Figure 1. Methods diagram

RESULTS AND DISCUSSION

Figure 2 (a, b and c) shows the grayscale images of Enrique reef and the fraction cover product for each endmember. The fraction value ‘1’ is represented by white color and ‘0’ is represented by black color. The results obtained with this method is summarized in Table 1 where a number of ten pixels were chosen to see and compare fraction cover estimation for each pixel. The values ranges for those pixels are -7.82 to 3.77. The fraction cover values obtained were not expected because negatives values are found in the images. A unit sum constraint was applied by adding a weighting factor of one to achieve the sum of abundances equals to one, however the sums of the values are greater than one. Figure 3 (a, b, c and d) illustrates the four classification made after the spectral unmixing: two of the classifications are supervised minimum distance and maximum likelihood and two unsupervised kmeans and iso data. The classifications generated produced a misclassification in the minimum distance seagrass areas are confused with sand, in the max likelihood the sand areas are classified as mangroves. The unsupervised classification presented two classes (class 1 and 2) that dominate the data. Classification errors can occur when the signal of a pixel is ambiguous, perhaps as a result of spectral mixing, or due to overlap of spectral reflectance or when the signal is produced by a cover type that is not accounted for in the training process (Kumar et al., 2007). The principal reason for the misclassification is due to the poor spectral differentiation of the pure pixels between mangrove and seagrass fig 4. The results of classification and fraction covers did not worked as expected and new endmembers were applied to the data; step four in fig 1 was modified. The new endmembers include sand, seagrass and soft coral. In addition the mangroves were masked to eliminate them from the analysis**.** New fraction cover images were obtained; Figure 5 (a, b and c) shows the grayscale images of the fraction cover result for the new endmembers. The fraction value ‘1’ is represented by white color and ‘0’ is represented by black color. The results obtained with the new endmembers are summarized in Table 2 where the same ten pixels were chosen to see and compare fraction cover estimation for each pixel. The values ranges for those pixels are -3.26 to 5.60. Even though new endmembers were applied, the sums of the values were greater than one. Figure 6 (a, b, c and d) illustrates the new four classifications made after the spectral unmixing with the new endmembers. Both supervised classifications merge the data, as seagrass and deep water are classified as soft coral. Class 3 and class 2 dominates the data in the kmeans unsupervised classification and the isodata classification. The results improved but another modification to the methods was made. A Lyzenga's water column correction was applied to remove the water column. Step two in fig 1 was modified; the MNF transformation was not taken into account. New fraction cover images were obtained and Figure 8 (a, b and c) shows the grayscale images of the fraction cover result for the new correction. The results obtained with the new correction are summarized in Table 3 where the same ten pixels were chosen to see and compare fraction cover estimation for each pixel. The values ranges for those pixels are -1.52 to 2.09. After the correction, the sums of the values were equal or less than one. Figure 9 (a, b, c and d) illustrates the new four classifications made after the new correction and the spectral unmixing. The classifications improved and the best classification achieved for this project was the maximum likelihood (fig 9b) however, in a second trial this classification did not had success (fig 9c). The supervised classification enhanced the difference between soft coral and seagrass. Furthermore the unsupervised classification once again demonstrated the dominance of two classes; class 2 and 3. In figures 7 and 10 we can see the improvement of the differentiation of the spectral endmembers after Lyzenga's correction.

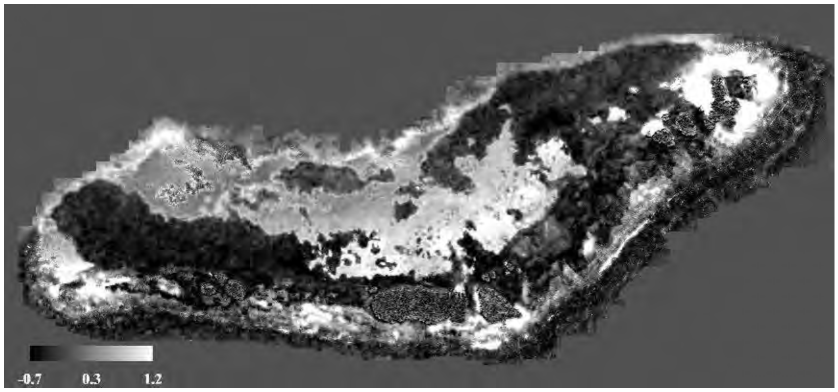
CONCLUSION

The Linear Spectral Unmixing is a tool to decompose the pixels into the abundance of its components. The application of the unmixing model to IKONOS imagery for estimating cover fractions of seagrass, sand and mangrove within the pixels did not worked as expected due to the poor spectral resolution of the image. After completing the supervised and unsupervised classification after LSU from Enrique Reef the best classification was minimum distance due to the errors in the maximum likelihood classification. The misclassification could occur when endmembers were mimicked by other spectra; this type of error could be avoided by knowing in advance what endmembers were spectrally similar (Adams et al., 1995). The fraction cover products for marine environments are not correct unless a water column correction is applied because of the additional mixing of the water signal with the components of interest that is detected by the sensor.

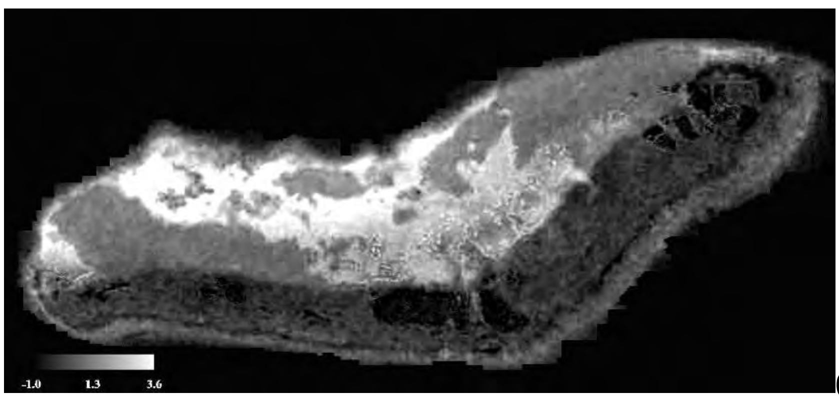
RECOMMENDATIONS

To improve this work it is important to compare the fraction covers to field data in order to verify the data obtained through the images. In addition field spectral data is necessary to choose better endmembers and facilitate the selection of it also because a good choice of endmembers is the most important step for a good spectral unmixing. Mixed pixels may cover a region containing different classes of ground cover of varying proportions, and therefore alter the traditional image classification approach which assigns a particular class of ground cover to each pixel (Kanniah et al., 2001). The application of the MNF transformation to Lyzenga corrected images is recommended to test if the fraction cover data improved. Moreover the use of a hyperspectral images should fit better for spectral unmixing due to the spectral resolution of the images.

FIGURES AND TABLES



(a)



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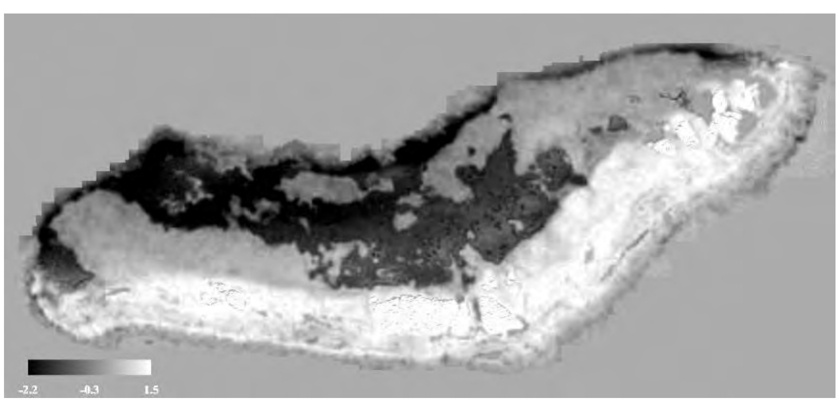
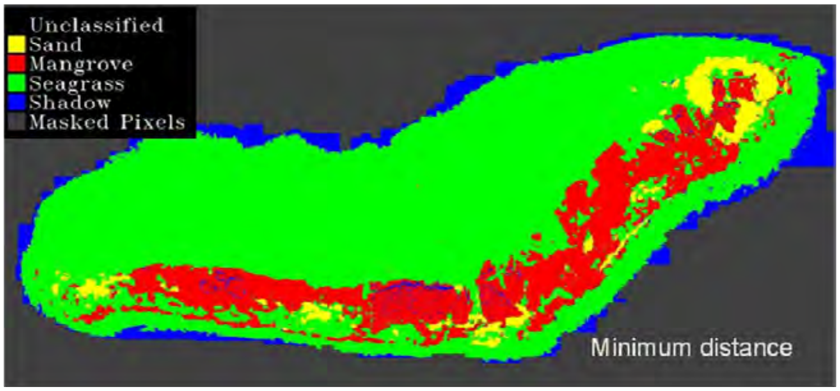


(c)

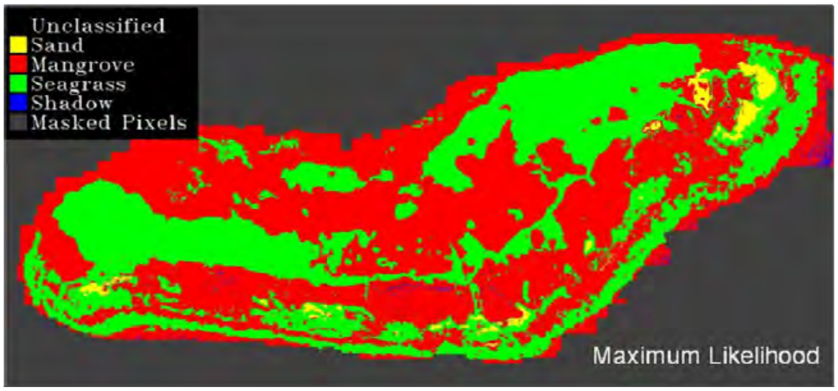
Figure 2. Fraction image from IKONOS: (a) sand; (b) seagrass; (c) mangrove

Pixel (X)	Pixel (Y)	Sand	Seagrass	Mangrove	SUM
5495	982	0.76	0.74	-1.89	1.5
5553	1177	0.98	0.65	-0.07	1.63
4894	1111	0.97	0.83	-0.07	1.80
4959	998	-0.41	-0.50	0.31	-0.91
5300	927	0.15	-0.01	-0.82	0.14
5429	1130	-1.04	-6.78	3.11	-7.82
5147	1109	-0.27	3.77	1.12	3.50
5048	957	0.60	-1.15	-1.06	-0.55
5416	894	0.89	1.89	-2.30	2.78
5593	817	0.42	-0.34	-1.03	0.08

Table 1. Enrique reef fractions cover estimation with endmembers of sand, seagrass and mangrove



(a)



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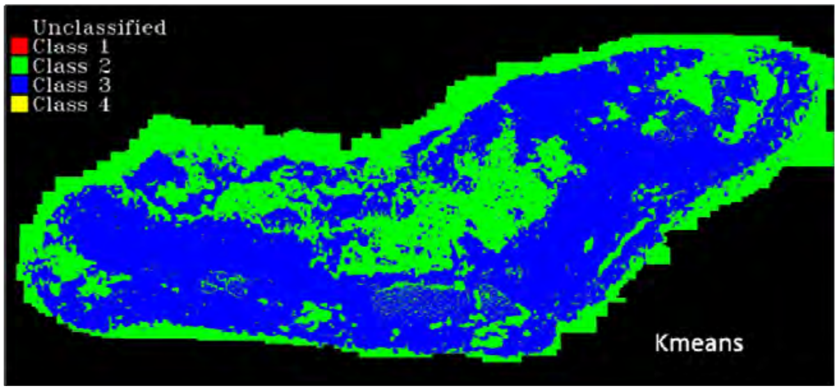
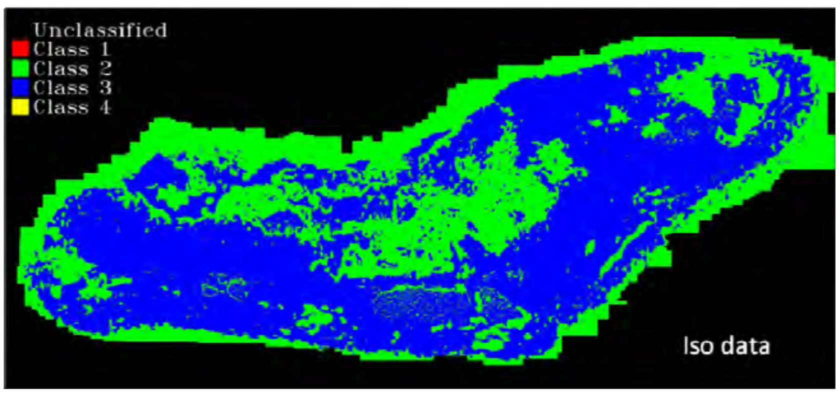


(c)



(d)

Figure 3. Supervised and unsupervised classification images: (a) supervised minimum distance; (b) Supervised maximum likelihood (c) unsupervised kmeans; (d) unsupervised Isodata

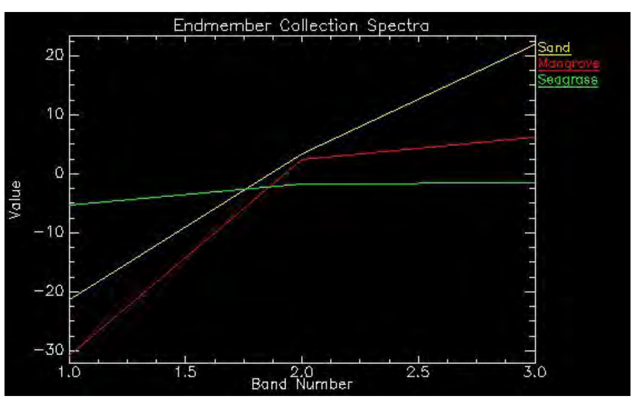
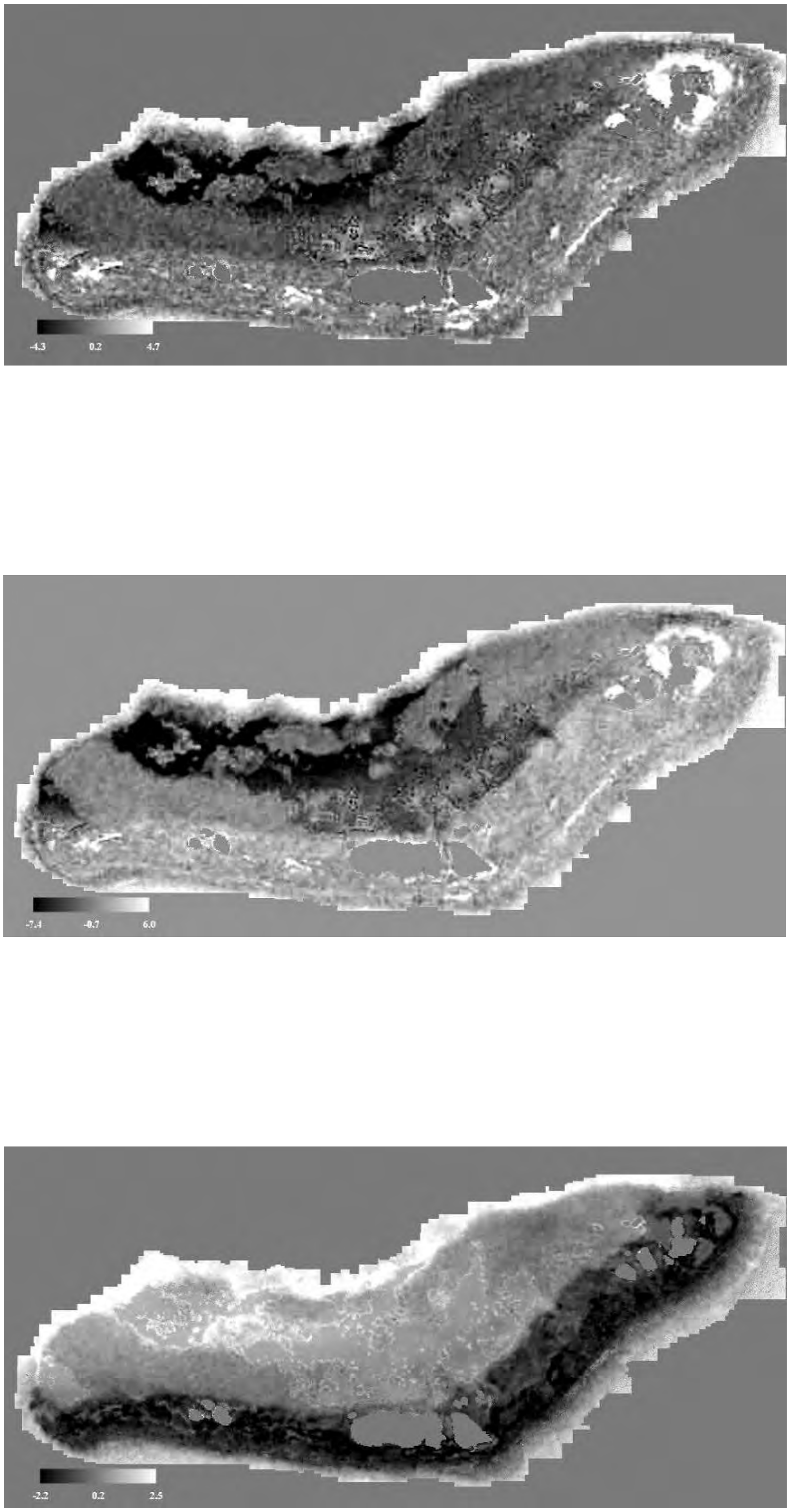


Figure 4. Spectra of endmember chose for LSU

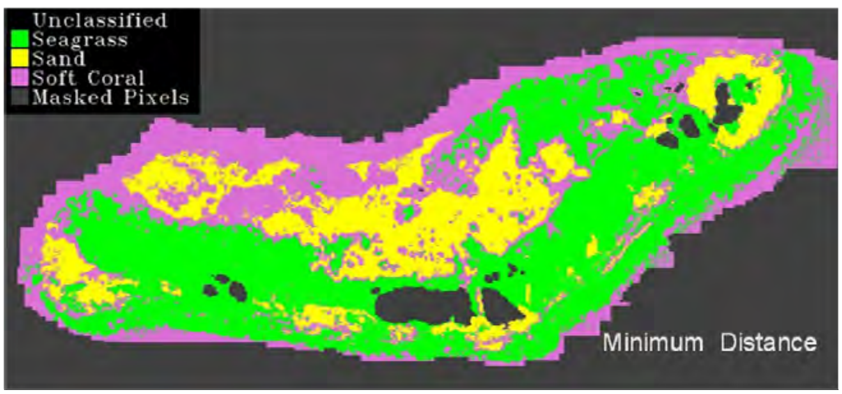


(a)
(b)
(c)

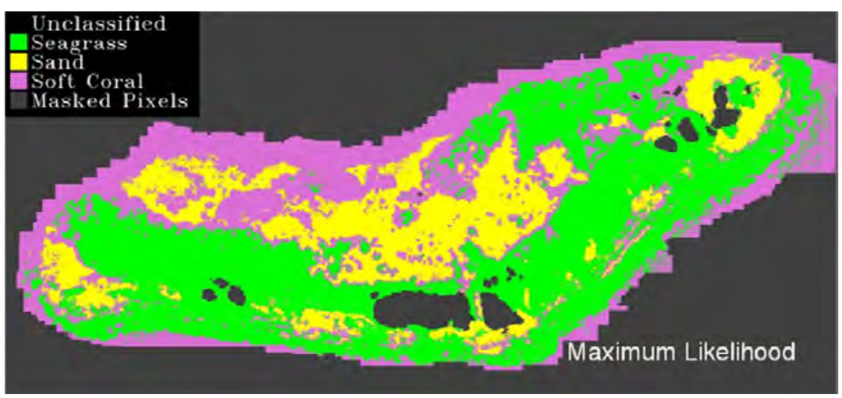
Figure 5. Fraction image with new endmembers: (a) sand; (b) seagrass; (c) soft coral

Pixel (X)	Pixel (Y)	Sand	Seagrass	Soft coral	SUM
5495	982	-0.70	-2.43	0.54	-2.59
5553	1177	3.05	3.16	-0.61	5.60
4894	1111	2.97	3.09	-0.65	5.41
4959	998	-0.59	-0.30	0.28	-0.61
5300	927	-0.71	-1.48	0.48	-1.71
5429	1130	0	0	0	0
5147	1109	0	0	0	0
5048	957	0.62	-0.49	0.71	0.84
5416	894	-1.24	-3.26	0.37	-4.13
5593	817	-0.12	-1.12	0.55	-0.69

Table 2. Enrique reef fractions cover estimation with endmembers of sand, seagrass and soft coral



(a)



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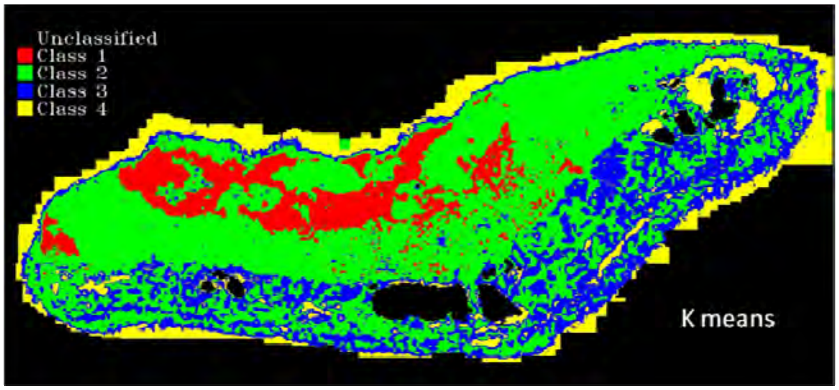
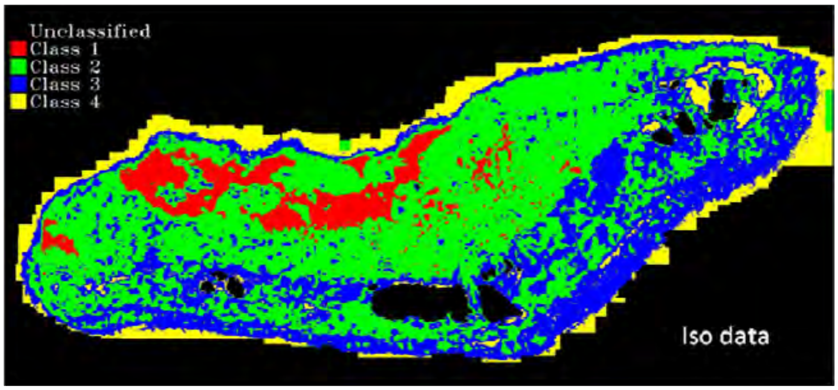


(c)



(d)

Figure 6. Supervised and unsupervised classification images: (a) supervised minimum distance; (b) Supervised maximum likelihood (c) unsupervised kmeans; (d) unsupervised Isodata

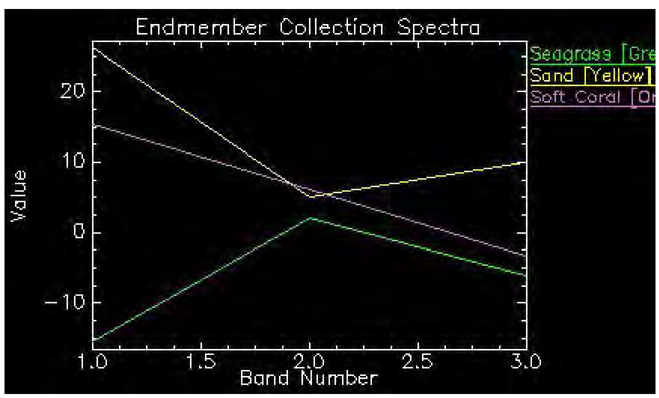
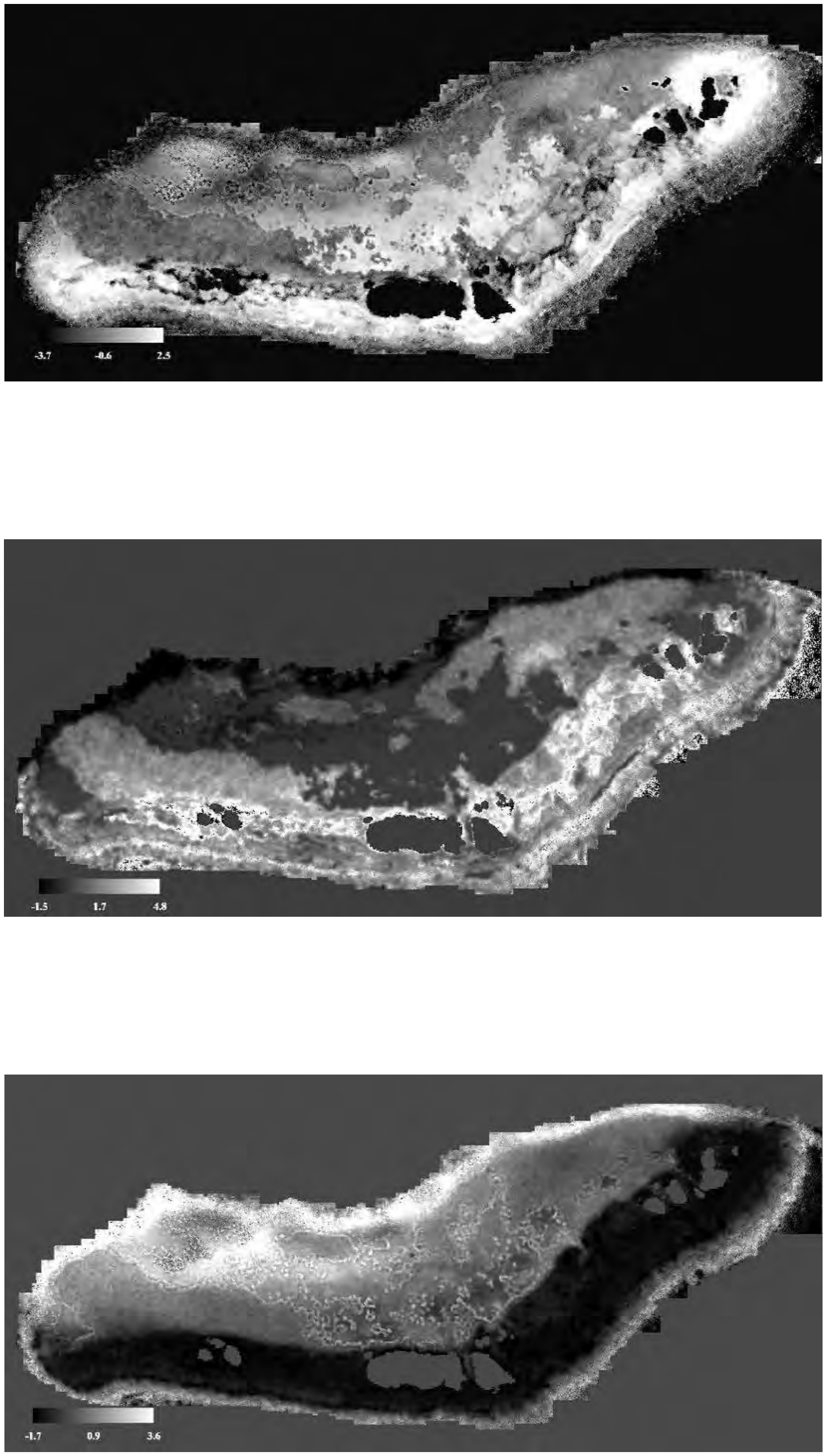


Figure 7. Spectra of new endmember chose for LSU



(a)

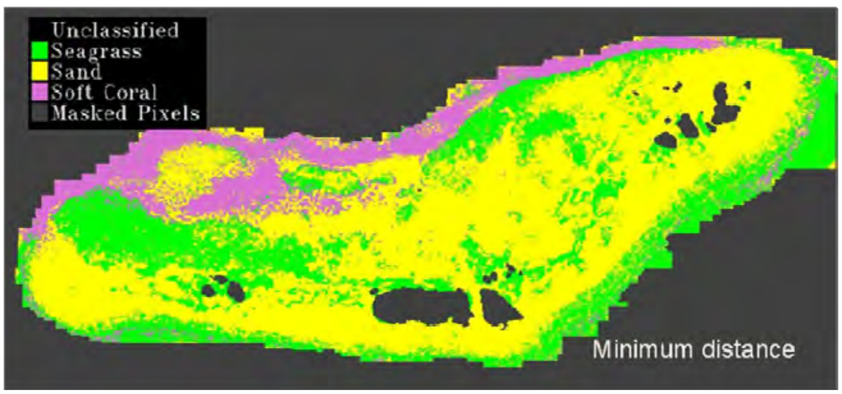
(b)

(c)

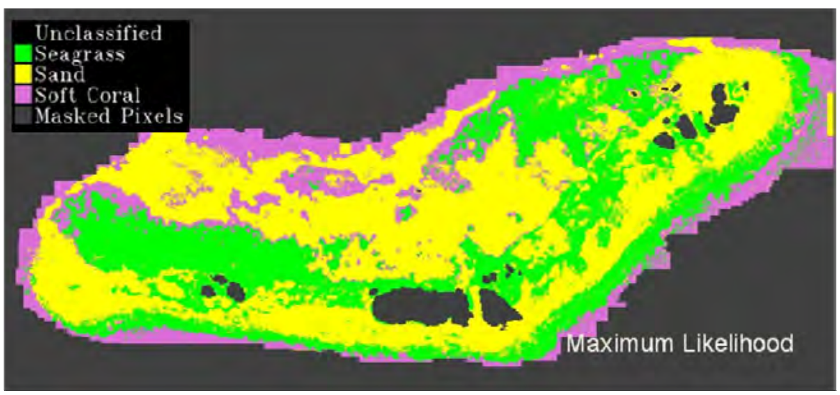
Figure 8. Fraction image Lyzenga's water column correction: (a) sand; (b) seagrass; (c) soft coral

Pixel (X)	Pixel (Y)	Sand	Seagrass	Soft coral	SUM
5495	982	1.37	0.14	-0.54	0.97
5553	1177	2.09	0.33	-1.52	0.90
4894	1111	2.08	0.34	-1.52	0.90
4959	998	0.58	0.38	-0.03	0.93
5300	927	1.04	0.19	-0.27	0.96
5429	1130	0	0	0	0
5147	1109	0	0	0	0
5048	957	1.51	0.15	-0.72	0.94
5416	894	1.38	0.16	-0.55	0.99
5593	817	0.21	-0.29	1.01	0.93
5046	956	-0.11	0.09	1.11	1.09

Table 3. Enrique reef fractions cover estimation with endmembers of sand, seagrass and mangrove after Lyzenga's water column correction

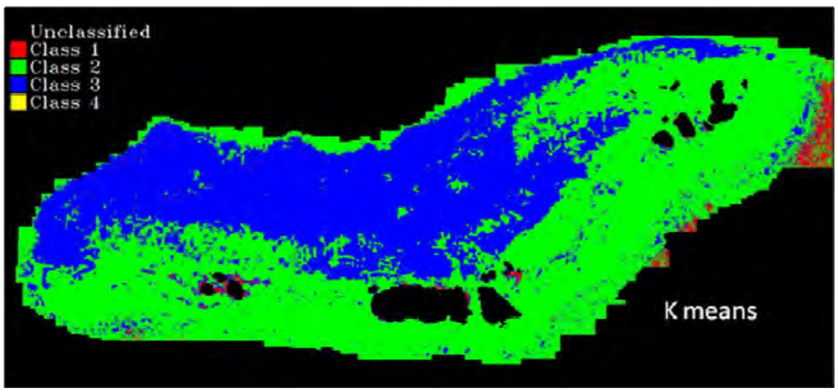


(a)



(b)

(c)



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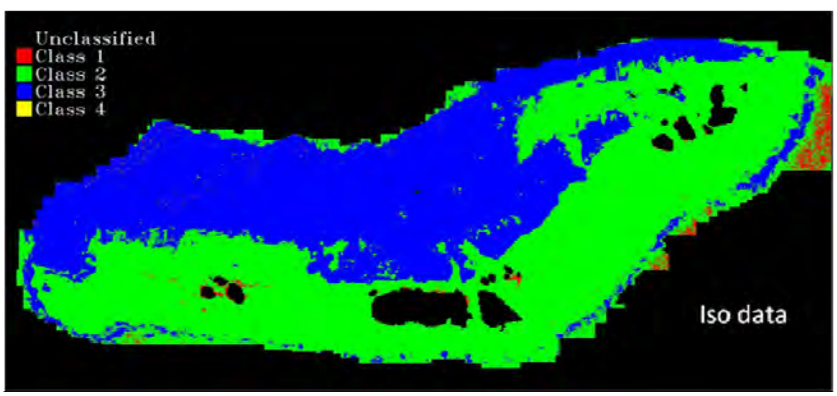

(e)

Figure 9. Supervised and unsupervised classification images: (a) supervised minimum distance; (b) Supervised maximum likelihood second trial (c) Supervised maximum likelihood (d) unsupervised kmeans; (e) unsupervised Isodata

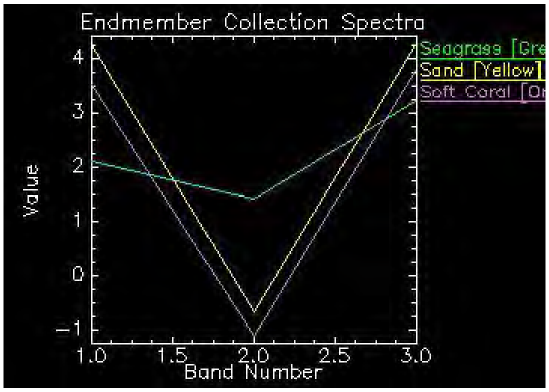

Figure 10 . Spectra of sand, seagrass and soft coral endmembers after Lyzenga's correction

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