# Comparing the Successes of Image and Library Endmembers for Spectral Mixture Analysis with Hyperspectral Data

## I. Introduction

Many classification techniques used in remote sensing involve categorizing each pixel in a scene as one particular surface type based on which of a set number of training classes that pixel's spectral profile is most similar to. In reality, though, it is not necessarily accurate to assume that every pixel contains only one surface type, since as the spatial resolution of remotely sensed data gets courser, the likelihood that the area of one pixel will contain more than one distinct surface type increases. Other methods of spectral unmixing can be employed to extract further information from each pixel, like fractional abundances of a variety of surface types, rather than classifying each pixel as one distinct surface type. Spectral mixture analysis (SMA) is an important technique with a variety of applications in remote sensing that aims to unmix each pixel into its pure spectral components by assuming that the spectral profile of each pixel is a linear combination of the spectra of endmembers, which are the representative spectra of each of these pure components that comprise the image. There are multiple types of endmembers that can be used during spectral mixture analysis, including image endmembers, which represent extreme pixels extracted from a scene that are assumed to represent a pure component, or lab endmembers, which are measured spectra of materials known to be contained in the image. When spectra cannot be measured of the exact materials on site, measured spectra from similar materials to those known to be in the scene can be obtained from a library and used as endmembers.

SMA produces an abundance image for each of the components, or endmembers, that are present in the scene. These images and the calculated abundances can be used for the detection or classification of materials in a scene that cannot spatially resolved. For example, SMA was successful in accurately estimating the percent live cover of vegetation to ±4%LC and indicated the correct sense of change in vegetation (loss or gain) more accurately than NDVI in Owen's Valley, California (Elmore 2000). SMA was also used to estimate the distribution and percent cover of impervious surfaces in urban areas with an overall root mean squared error of 10.6% (Wu 2002), showing how this technique can be useful for tracking human development and other anthropogenic activities as well as natural changes in highly vegetated areas. However, while SMA gives accurate results in tracking change and indicating the distributions of certain surface types, the actual fractional abundances produced for each pixel during SMA using image endmembers are often inaccurate (Heinz 2001), so overall quantifications of material abundances cannot be accurately performed.

This project aims to produce images with lower error values during SMA by evaluating the results produced when different types of endmembers are used. Two questions will be answered:

1. What type of endmember, image or library, produces results with the lowest error values during SMA?
2. Can an optimal combination of the two types of endmembers be found that minimizes the error associated with SMA for the image being analyzed?

Evaluating the error values associated with the results of SMA can provide a good sense of which endmembers produce the most successful unmixing of the image, since they indicate how accurately each pixel can be decomposed into a linear combination of the endmembers being used, thus indicating which set of endmembers will give the best results during SMA.

## II. Principles

The process of performing SMA to analyze remotely sensed images intends to extract "subpixel information" (Chuvieco 2016) from those images by indicating the abundances of certain pure components that make up the scene that are contained within each pixel. The endmembers used in SMA are then meant to represent these pure components. There are various methods of obtaining different types of endmembers that can be used in SMA, and different types of endmembers will then produce different unmixing results.

One common way of obtaining endmembers for SMA is to extract their spectra directly from the image. These image endmembers can be found by locating pixels in the image that represent extreme values (i.e.: brightest pixel, darkest pixel, etc.) and using those spectra in the process of SMA. One benefit of image endmembers is that they are known to be representative of the materials in the scene, since they are taken directly from the image. However, when using extreme pixels as endmembers, there is no guarantee that those pixels are composed of just one pure component. There are some methods of endmember extraction from images that can produce purer endmembers than using the spectra of extreme pixels, like mathematically deriving spectra from the image with a set of mixing equations (Tompkins 1997). However, the only way to be certain that the endmembers being used represent pure components is to use spectra of known materials as endmembers.

Ideally, spectra could be measured from materials that are known to be present in the scene being analyzed and could then be used as endmembers. These lab endmembers remove the question of whether the endmembers are definitively pure because they are known to be representative of just one material that was measured. In addition, they will also definitely be representative of the materials in the scene, since they are spectra taken from those materials. However, acquiring these lab endmembers is not always a realistic possibility, since it would require visiting the location of the scene being analyzed. Instead, spectra can be taken from spectral libraries like those found in ENVI to be used as endmembers. Although these spectra may not exactly represent the materials found in the scene the way lab endmembers would, the most representative spectra can be selected by finding the endmember that minimized the error for a certain component known to be present in the scene (Dennison 2003). In addition, these library endmembers are still guaranteed to represent pure components since they are still spectra taken of just one material.

SMA can be viewed as an "inverse problem" that works backward from a known spectrum for each pixel to find the fractional abundances of each endmember present in that pixel. Two equations govern this process:

$$\sum_i F_i = 1 \qquad (1)$$

$$\sum_i F_i DN_i + e = DN \qquad (2)$$

The first equation states that the fractions of each endmember should sum to one for each pixel. The second equation shows how the remotely-sensed spectrum of the pixel is used to calculate the fraction of each of the endmembers based on the endmember spectra, and how an error term is incorporated to account for any aspects of the pixel spectrum that are not described by the endmember spectra. Since SMA involves finding the best solution to this system of equations where the wavelength bands of the sensor represent the variables and the abundance fractions of each endmember are the model parameters, it is necessary for the number of endmembers to be less than or equal to the number of bands in the image to uniquely solve for the fractions of each endmember with a meaningful error term. Especially for hyperspectral data, which has hundreds of individual bands, the number of endmembers is generally far fewer than the number of bands to give the best results.

The error term that is produced for each pixel during SMA is a root-mean-squared error (RMSE), which is calculated by taking the square root of the average of the squared error values for each band. It is important to find this RMSE term during SMA because it gives an indication of how well the endmembers selected can be used to unmix the scene. High RMSE values show that the endmembers being used are not able to give a complete description of the spectra being observed in the scene, while low error values indicate that the endmembers can be used in a linear combination to accurately produce the pixel spectra. Observing and comparing error values for multiple iterations of SMA on the same image can therefore give an indication of which endmembers can perform best in the unmixing of the scene.

In addition, two other criteria will be noted to ensure that the endmembers are performing well. First, based on Equation 1, the sum of all the endmember fractions for each pixel should be 1. In addition, all of the endmember fractions should be nonnegative, since these fractions are intended to represent the areal abundance of different surface types present in each pixel, and it is not possible to have a negative area for any surface type. Making certain that these two parameters are met during each trial of SMA with different endmembers will indicate that SMA can be performed to get mathematically feasible results with the endmembers being used, and then investigating the RMSE values will be the measure of success of the endmembers for each trial.

## III. Data and Methods


*Figure 1: True color image of Ninigret Pond to be used in SMA. Located at 41°21'14.8"N 71°40'22.4"W.*

Several iterations of SMA with different types of endmembers were performed on an image of Ninigret Pond in Charlestown, Rhode Island. This is a costal salt pond that experiences tidal exchanges with the ocean through breaks in a barrier beach. Surrounding vegetation includes marsh and dune grasses, coastal shrubs, and deciduous trees like the red maple. The image being analyzed was acquired in the autumn, so the scene contains both live and senescing vegetation. In addition to these naturally occurring surface types, there is also residential development nearby that can be seen in the image, giving a diverse range of materials that can be represented as endmembers during SMA. The image was acquired by AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) in hyperspectral resolution. This sensor has detectors to record values for 224 bands between 400 and 2500 nm, producing spectral profiles for each pixel that appear as a relatively continuous spectrum rather than values for discrete bands like Landsat or other multispectral sensors. The hyperspectral resolution of this data is important in allowing comparisons to be made between the spectra of the endmembers acquired from the image and the endmembers taken from a spectral library since both will be at a high spectral resolution.

The first trial of SMA tested used only image endmembers. These endmembers were selected through the iterative process used in Lab 6. First the brightest pixel was located by performing Principle Component Analysis to create an albedo image of the scene, then selecting the lowest value (highest albedo) pixel from this image. The spectrum for the brightest pixel was then used as an endmember along with an artificial dark pixel with reflectance values of 0 for all wavelength bands. SMA was performed with these two endmembers, then the pixel with the highest RMSE value was located to use as another endmember. This process was repeated to extract endmembers until the highest RMSE pixel no longer produced a unique endmember spectrum. Using this process, spectra for the following six endmembers were obtained: dry sand (bright), wet sand, live vegetation, senesced (non-photosynthetic) vegetation, residential, and water (dark).

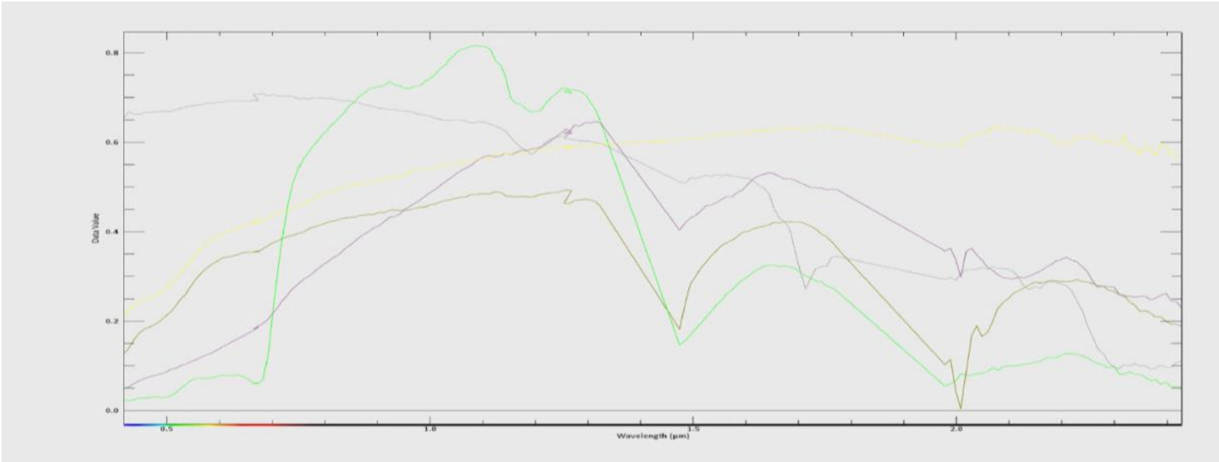

*Figure 2: Spectral profiles for endmembers used in SMA with image endmembers only: dry sand (yellow), wet sand (brown), live vegetation (green), senesced vegetation (purple), residential (gray), and water (black).*

Next, a second trial of SMA was completed using only image endmembers. Four endmembers were selected from the spectral libraries in ENVI from spectra of materials similar to those known to be present at Ninigret Pond. These endmembers were the only components of the scene that could be represented relatively well by the available spectra, although there were other components in the image that should have been represented with endmembers in SMA. The four endmembers chosen were dry sand, salt water, live vegetation, and senesced vegetation.

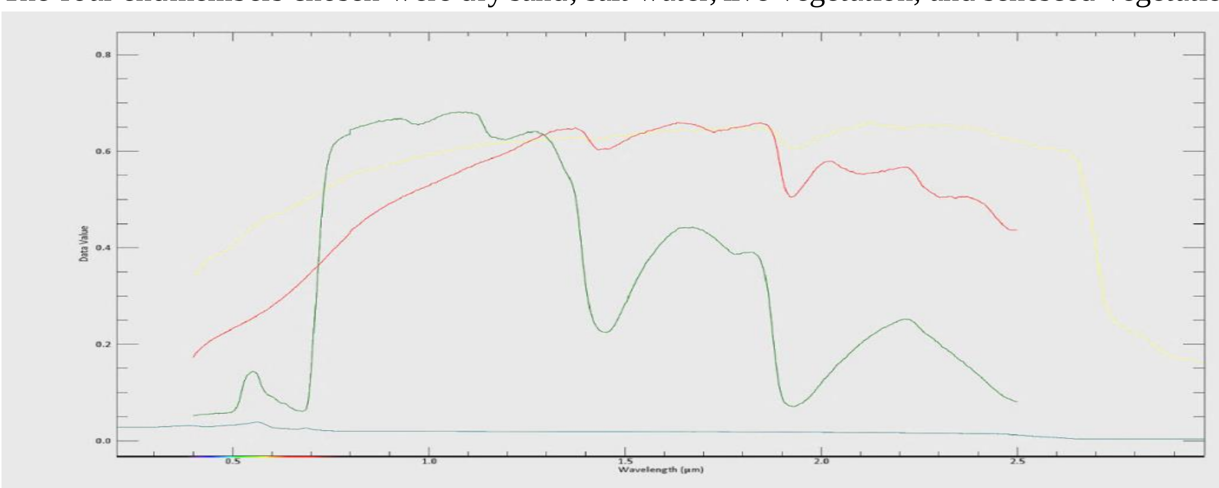

*Figure 3: Spectral profiles for endmembers used in SMA with library endmembers only: dry sand (yellow), live vegetation (green), senesced vegetation (red), and water (blue).*

Finally, the last trial of SMA incorporated a combination of both library and image endmembers. The result of the previous trial using only library endmembers was expanded upon by completing SMA using these four endmembers and then using the process of extracting image endmembers based on highest RMSE values from the first trial. Using this method, a total of seven endmembers were used in this trial of SMA: dry sand (library), salt water (library), live vegetation (library), senesced vegetation (library), wet sand (image), senesced vegetation (image), and residential (image).

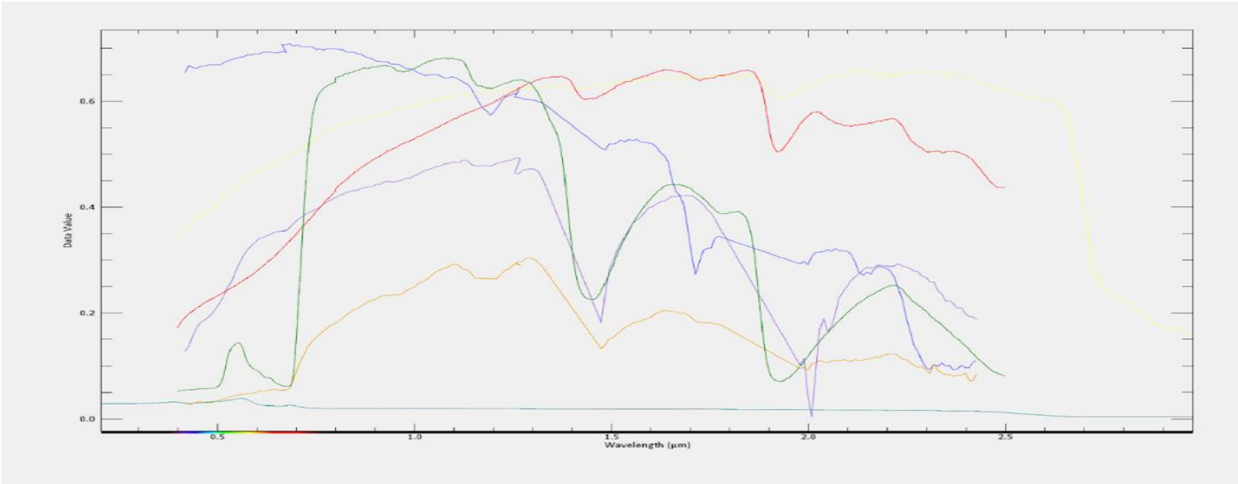


*Figure 4: Spectral profiles for endmembers used in SMA with library and image endmembers: dry sand (yellow), live vegetation (green), library senesced vegetation (red), water (light blue), wet sand (purple), residential (blue), and image senesced vegetation (orange).*

Throughout the process of extracting or choosing endmembers for each trial, the results of SMA were observed to confirm that the fractions for each pixel were summing to 1 and that there were no negative fractions to ensure that SMA was meeting a baseline of success in that it was providing meaningful values for each set of endmembers being tested. After the endmembers were chosen for each of the three trials, SMA was performed on the image to produce abundance images for each endmember and an RMSE image, and the highest RMSE value of each trial was observed as an indicator of the success of the endmembers used.

## IV. Results

The first trial of SMA completed with the Ninigret Pond image using only image endmembers produced a relatively successful unmixing of the scene. After determining the 6 endmembers to be used, the SMA resulted in 6 new scenes showing the abundances of those six endmembers as well as one image showing the areas of high and low RMSE values. The maximum value of RMSE observed after SMA using only image endmembers was 3.4%. To provide a comparison, the highest RMSE value after completing SMA on the Owen's Valley image used in Lab 6 was 4.2%, meaning that the image endmembers used in this trial of SMA on the Ninigret Pond scene were able to describe the components of the scene with relatively high accuracy and provide useful results in mapping the different surface types shown in the scene.

The method of endmember extraction used was also successful in finding the best number of endmembers to be used in the unmixing of the scene. To select each successive endmember, the RMSE image produced in that iteration of SMA was examined to give insight on which pixel should be used for that endmember. This method was also helpful in clearly showing that all useful endmember pixels had been found once the six endmembers used had been located. The final endmember extracted was wet sand, and the RMSE image resulting from this final iteration of SMA with these six endmembers showed a similar pattern for high values as the wet sand endmember. In addition, the spectral profile of the highest RMSE image appeared to be very similar as the spectral profile of the wet sand endmember, meaning that using the spectrum of the highest RMSE pixel as an endmember would no longer be useful in representing a unique component in the image.

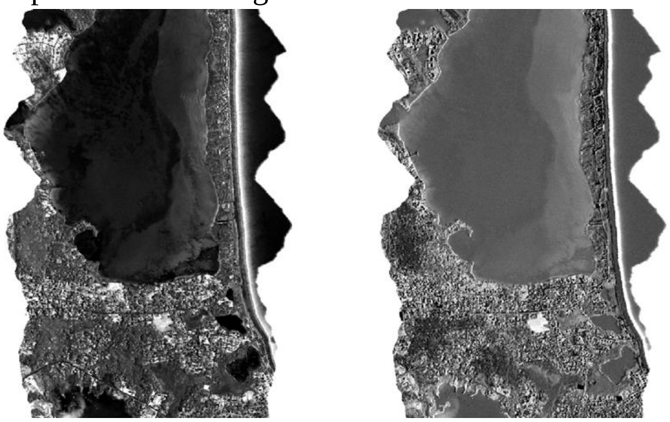

*Figure 5: RMSE image after final iteration of SMA with image endmembers only (left) and wet sand endmember abundance image (right) showing similar distributions of high and low values.*

The second trial of SMA using only library endmembers had the worst performance out of the three trials since it had the highest RMSE values. In this trial, only one iteration of SMA was completed with four endmembers pre-selected from the spectral libraries available in ENVI. Only four endmembers were used since only four of the components observed in the image could be well represented by the available spectra in the ENVI library. Performing SMA with these four endmembers produced a maximum RMSE value of 9.0% in the results, which was the highest value out of the three trials. This high RMSE indicates that the library endmembers were unable to fully represent the components in the scene. Comparing the spectra of the image and lab endmembers used for dry sand, live vegetation, senescing vegetation, and water shown in Figures 2 and 3, the profiles of the endmembers of the same components appear relatively similar. This indicates that the library endmembers chosen are accurate in describing each of the components they are meant to represent. Thus, the high RMSE values seen during this trial likely come from the fact that not all the components are represented with

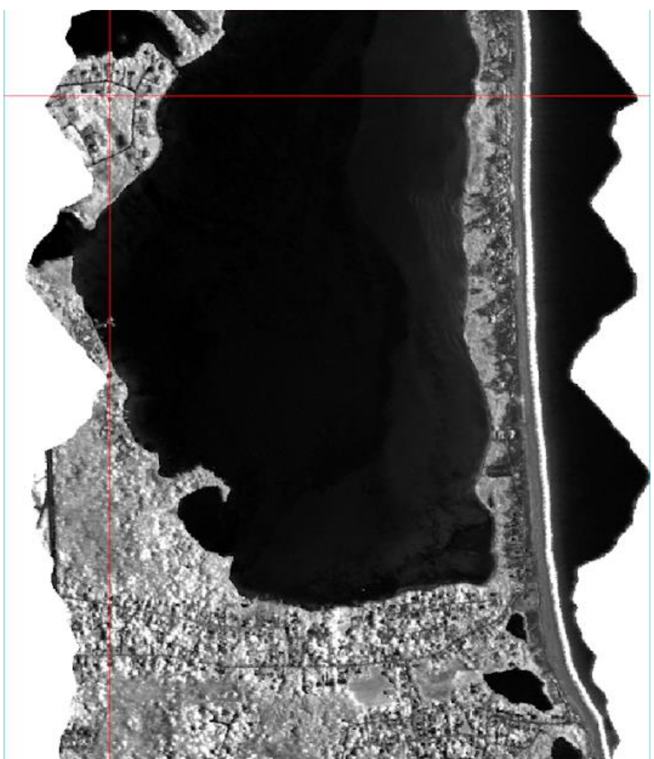

*Figure 6: RMSE image from library endmember only SMA trial.*

endmembers, rather than the library endmembers doing a poor job of representing the components in the scene that do have an associated endmember. The RMSE image produced during this trial of SMA showed a distinct pattern in the distribution of high RMSE areas in the scene. The brightest RMSE pixels were clustered in residential areas. These pixels were not being well represented since there was no endmember associated with a residential area surface type. Hence, the library endmember only trial of SMA was unsuccessful because it was unable to provide an endmember to describe each of the components in the scene.

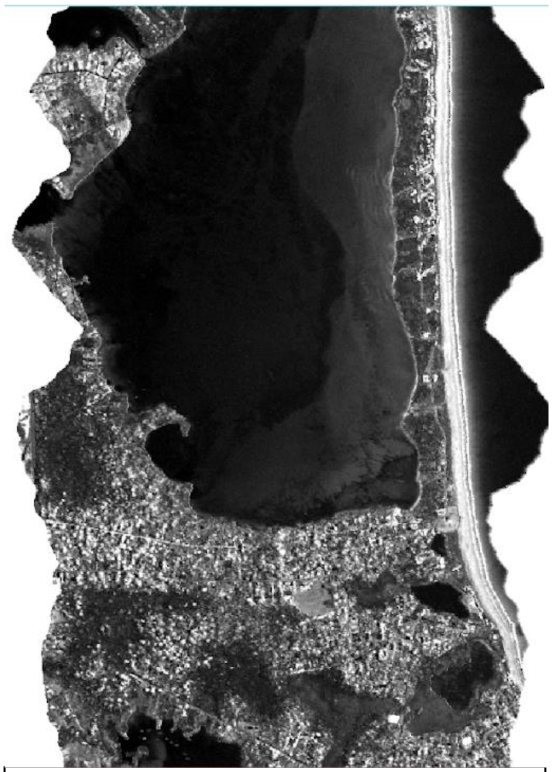

*Figure 7: RMSE image from library and image endmember combination SMA trial.*

The final trial of SMA using both library and image endmembers provided the most successful combination of endmembers that were able to best represent the components in the scene and minimize the RMSE values. During this trial, the four pre-selected library endmembers were used along with three additional image endmembers. This combination of endmembers produced an unmixing with a maximum RMSE value of 3.2%, which is the lowest out of the three trials, indicating that this set of endmembers gives the best representation of the components in the scene. The RMSE image that resulted from this unmixing also showed scattering of high values across the scene that did not seem to correspond to one distinct surface type, meaning that there were not additional components in the scene that were not represented by an endmember.

One problem that was encountered in this trial was the repetition of the senescing vegetation endmember. One of the initial library endmembers used was intended to represent the senescing vegetation component; however, during the process of extracting image endmembers, another senescing vegetation endmember was chosen. Using multiple endmembers to represent one component is a technique that has been used to decrease endmember variability during SMA (Somers 2011), but comparing the spectra for the image and library senescing vegetation endmembers shows that they have very different reflectance values, and therefore are likely not both successful in representing the same component. To combat this problem, another trial of SMA using image and lab endmembers was then completed without using the library senescing vegetation endmember, which resulted in an unmixing with a maximum RMSE value of 3.0%, showing that the set of endmembers containing only the image senescing vegetation endmember gave the best representation of the components in the image.

One application of surface type classification using the results of the three trials of SMA was tested to serve as another metric of the success of each of the three sets of endmembers. The long strip of barrier beach seen in the right-hand side of the image serves as a relatively uniform surface that is made almost entirely out of the dry sand component. Using Google Earth, this surface composition was able to be verified to give a high certainty that this portion was almost entirely covered by dry sand and should therefore have a very high fraction of the dry sand endmember shown in the results of SMA. Using a false color RGB image of the scene with red in the senesced vegetation band, green in the live vegetation band, and blue in the dry sand band, the barrier beach portion of the image was investigated to determine the relative abundances of these three endmembers in that area.

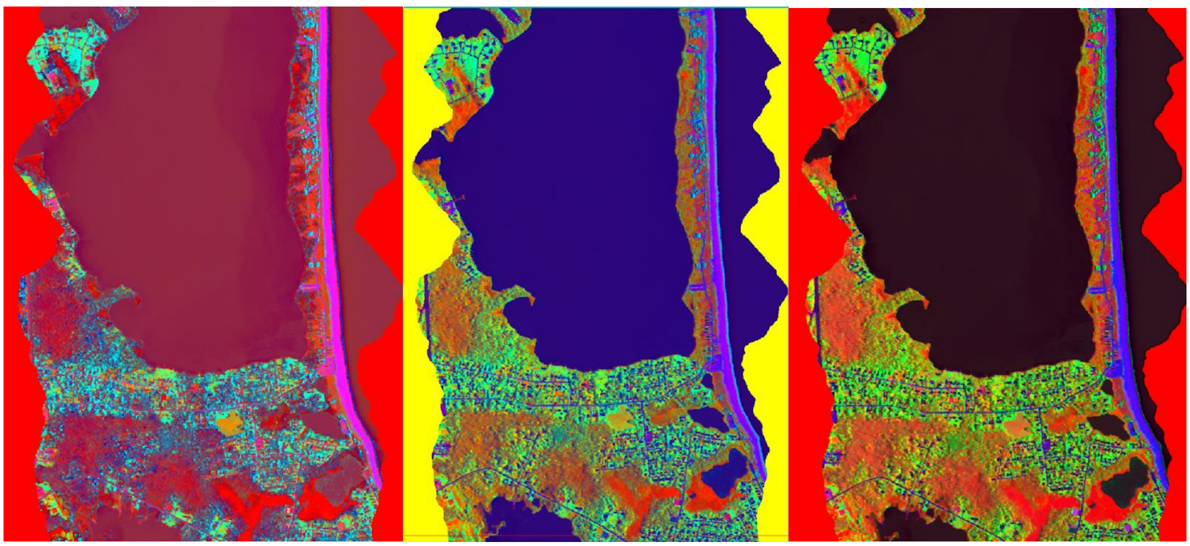

*Figure 7: False color RGB images of Ninigret Pond using SMA results from image endmember only trial (left), library endmember only trial (center), and endmember combination trial (right). Red is in the senesced vegetation band, green is in the live vegetation band, and blue is in the dry sand band.*

In both the image endmember only and library endmember only false color images, the barrier beach appears as a mixture of multiple endmembers since it appears as pink or purple, rather than pure blue, which would indicate an almost 100% fraction of dry sand in the area. In the image created using the combination of image and library endmembers, the beach appears as a completely blue section of the image, meaning that those pixels are being recognized as having very high fractions of dry sand, and very low fractions of all other endmembers. Since the portion of the image being observed is known to be almost entirely sand, this result shows that the combination of library and image endmembers gives the best result in classifying surface types in the image, since it gives a high fraction of the dry sand endmember in the beach area.

## V. Conclusion

This project aimed to compare two different types of endmembers that can be used in SMA on a hyperspectral image of Ninigret Pond to determine which could give the best results with the lowest error values. The image endmembers being used had the benefit of being extracted directly from extreme pixels found in the scene, meaning that they would definitely provide spectra that were characteristic of the materials being observed in the scene. However, it could not be guaranteed that the image endmembers represented pure components, since the pixels they were taken from could still represent mixed surface types. On the other hand, the library endmembers were known to represent pure components, but some of the components that were unique to the scene could not be accurately represented by an available library endmember.

The results of the three trials showed that a combination of image and library endmembers produced SMA results with the lowest RMSE values, meaning that this set of endmembers gave the best representation of the components in the scene. This is likely because the combination of these endmember types was able to guarantee that some of the endmembers were pure components while also being able to provide endmembers to represent all components present, even those that were unique to this image.

In addition to having the lowest RMSE values, the trial of SMA using this combination of endmembers also performed the best in classifying large areas of relatively uniform and pure surface types. This confirmed that this set of endmembers not only provided the best representation of the components of the scene, but also was the most useful in making surface type classifications of the scene using the results of SMA, which is an important application of this type of analysis.

One known shortcoming of SMA is that, even though it can be useful in the detection and classification of certain materials, the results of this analysis do not necessarily provide accurate fractions of the components found in each pixel. In the scope of this project, it would not be possible to test the accuracy of the component fractions just by analyzing the results of SMA using the different sets of endmembers, since the actual fractional abundances of each component in each pixel are unknown. With further time and resources, one possible extension of this project could be to perform the same analyses on a more recent image of the scene, and then conduct ground truthing to find the true component abundances in areas of the image to compare them to the abundance values produced through SMA. This would be able to give further information of the relative successes of the different types of endmembers being tested. Another extension of the project would be to acquire spectra of the components in the scene from the actual location itself and test these spectra as endmembers against the image and library endmembers currently being used, since these endmembers might be expected to give the best results, as they would be both definitively pure and representative of the components in the scene.

## VI. References

Chuvieco, E. (2016), Fundamentals of Satellite Remote Sensing. *CRC Press.*

Dennison, P. E., Roberts, D. A. (2003), Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. *Remote Sens. Environ.* 87:123-135.

Elmore, A. J., Mustard, J. F., Manning, S. J., Lobell, D. B. (2000), Quantifying Vegetation Change in Semiarid Environments: Precision and Accuracy of Spectral Mixture Analysis and the Normalized Difference Vegetation Index. *Remote Sens. Environ.* 73:87-102.

Heinz, D. C., Chang, C. I. (2001), Fully Constrained Least Squares Linear Spectral Mixture Analysis Method for Material Quantification in Hyperspectral Imagery. *IEEE Transactions on Geoscience and Remote Sensing.* 39:529-545.

"Ninigret Pond and Conservation Areas" from www.audubon.org.

Somers, B., Asner, G. P., Tits, L., Coppin, P. (2011), Endmember variablility in Spectral Mixture Analysis: A review. *Remote Sens. Environ.* 115:1603-1616.

Sun, H., Qie, G., Wang, G., Tan, Y., Li, J., Peng, Y., Ma, Z., Luo, C. (2015), Increasing the Accuracy of Mapping Urband Forest Carbon Density by Combining Spatial Modeling and Spectral Unmixing Analysis. *Remote Sens.* 7:15114-15139.

Tompkins, S., Mustard, J. F., Pieters, C. M., Foryth, D. W. (1997), Optimization of Endmembers for Spectral Mixture Analysis. *Remote Sens. Environ.* 59:472-489.

Wu, C., Murray, A. T. (2002), Estimating impervious surface distribution by specral mixture analysis. *Remote Sens. Environ.* 84:493-505.