BIOMASS AND HEALTH BASED FOREST COVER DELINEATION USING SPECTRAL UN-MIXING

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ABSTRACT

Remote sensing is a well-suited source of information on various forest characteristics such as forest cover type, leaf area, biomass, and health. The use of appropriate layers helps to quantify the variables of interest. For example, normalized difference vegetation index (NDVI) and greenness help explain variability in biomass as well as health of forests. By delineating the forest into various predominant cover types, biomass and health pertaining to each forest cover type can be quantified. The relative size of the features as compared to sensor resolution can create mixtures of the component features within pixels and thereby decrease the accuracy of parameter estimations. Unmixing techniques unravel the mixed spectral components into fractional abundance estimates of selected end-members. The present study investigates the use of a spectral unmixing technique to portray forest cover types using minimum noise fraction (MNF) component 2, NDVI, and greenness derived from Landsat ETM+ imagery. The assumed purest pixels were identified for the four predominant forest covers of softwood, woody wetlands, hardwoods, and mixed forest using MNF transform followed by decorrelation stretch (DCS) and independent component analysis (ICA) algorithms. The pure pixels were used as region of interest (ROI) to derive fractional end-members using the mixture tuned match filtering (MTMF) subpixel approach of spectral unmixing. The unmixing technique was influential in deriving the component endmembers that need to be validated.

INTRODUCTION

Forest cover segmentation and area estimation involves a collaborative synthesis of remote sensing and Geographic Information Systems (GIS). One difficulty posed by remote sensing of diverse landscapes is that individual pixels may be composed of multiple cover classes. The degree of mixing is related to the resolution of the sensor. In such cases, in order to achieve accurate classification and area estimation, it is recommended that sub-pixel analysis be utilized. Spectral mixture/spectral un-mixing analysis is an easy technique to resolve sub-pixel abundance of vegetation, soils and other spectrally distinct materials that basically contribute to the spectral signal of mixed pixels. Spectral un-mixing finds partial least squares solutions to the mixture of spectral components to facilitate fractional estimates of selected endmembers.

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BACKGROUND – SPECTRAL UNMIXING

Mixed Pixel

The intricacy of land cover change over time and space is a key issue to understand the tangible and intangible forms that are associated with land cover. Spatial variability plays an important role with different landscape scales and different image resolutions. In order to characterize the fragmented nature of the landscape on a remotely sensed image, a better understanding of mixed spectral signatures is required. Much of remote sensing data hold mixed pixels as shown in Figure 1 due to sensor capabilities and resolution. Low resolution images with spatially large pixels have more spectrally mixed pixels when taken across fragmented landscapes (Crapper, 1984 and Campbell, 2002).

Figure 1. Conceptual depiction of mixed pixels. The red outlines represent pixel borders in low-resolution data. Clearly most of these areas represent different proportions of trees (green) and ground or herbaceous vegetation (lighter tones).

De Jong *et al*., (2004) suggested the following per-pixel methods for classification to account for variability in images:

- Extraction of homogeneous regions on the basis of spatial and spectral information;
  In this step, a kernel window moves through the image and compares four of its neighbor pixels with central pixel for similarity of signatures. If the signatures fall outside a user-defined epsilon (ε) band, which is otherwise known as support vector machine, then the pixel is labeled as a heterogeneous area otherwise it is labeled homogenous.
- Classification of the (homogeneous) image areas: Classification of the homogeneous regions is based on averaging the spectral signature of the nearest neighborhood of the 4 pixels of each homogenous region and assigning the value to the central output pixel.
- Classification of the remaining (non-homogeneous) image areas: The heterogeneous areas are classified using spatial and spectral information using the minimum distance to mean classifier.

Many researchers have tried to isolate pure signatures from spectral variations. Unfortunately, it is impractical to completely segregate mixed pixels from pure pixels even with the finest resolution data. However, mixed pixel recognition and characterization can be improved using spectral un-mixing techniques (De Jong *et al*., 2004).

Spectral Unmixing

Spectral unmixing (Small, 2001; van der Meer and de Jong, 2000; Lu and Weng, 2004) is a way to derive fractions of spectrally pure features/components/endmembers by the phenomenon of deconvolution (van der Meer and de Jong, 2000). In low resolution imagery, the scene components are often smaller than the cell resolution and are non-detectable (Strahler, *et al.*, 1986). The relatively increasing smaller size of components with respect to the cell resolution leads to the concept of a mixed pixel that contains the sum of interacted reflectance's from various scene components as weighed by their relative proportions (Strahler, *et al.*, 1986 and Lu and Weng, 2004). As such, the underlying assumption of linearity of the mixed pixel can be decomposed into its constituent fractions (van der Meer and de Jong, 2000):

$$R_i = \sum_{j=1}^{n} f_j \operatorname{Re}_{ij} + \varepsilon_i \; \; and \; \; 0 \leq \sum_{j=1}^{n} f_j \leq 1 \text{ .... (1)}$$

where R_i is the reflectance of mixed pixel,
i= image band number,
f_j = fraction of end-member,
j = end-member, and

ε_i = Residual error

Within forest land cover, mixed pixels may pertain to various forest biophysical factors such as forest type, health, leaf area, biomass etc. Therefore, spectral unmixing can be used with appropriate reference data to derive proper fractions of the forest biophysical properties.

End-members

An end-member is the pure reflectance spectrum that is derived from a specific target material with no mixing with any other materials. Resolving end-members plays a crucial stage in the subpixel classification process because selection of end-members is similar to a training procedure in supervised image classification and is considered a difficult task (Hadjiisoannou, 1998). Two methods of end member determination (Small 2001) are:

- Determination from spectral library based on field or laboratory analysis, and
- Purest pixel based approach.

The purest pixel approach can overcome ground truth data limitations and also it possesses the added advantage of end member identification from similar atmospheric conditions (Van der Meer and de Jong, 2000). Image transformation techniques such as Principal Component Analyses (PCA) and minimum noise fraction (MNF) reduce data dimensionality into a few meaningful orthogonal axes as a way to find the purest pixel end members in the image.

CASE STUDY

This study employed satellite remote sensing in the test bed area shown in Figure 2 where the spectral unmixing approach was used to identify forest cover. The approach decomposed the spectral information into its constituent end member fractions. Four end-members were selected from the image that form four predominant forest covers of the image softwood forest, woody wetlands, mixed forest, and hardwood forests. The research was oriented to estimate forest cover type end members in a way that can be used as inputs to biomass and health estimations. The sequence of steps utilized for this research is outlined in Figure 3 and is explained below.

Figure 2. Location of Landsat data of the experimental area utilized for spectral unmixing process with reference to the state of Mississippi.

Minimum noise fraction (MNF)

MNF is an orthogonal transformation similar to PCA that has the advantage of enhancing image quality to facilitate end member identification (Green *et al.*, 1988). MNF reduces the spectral dimensionality into components of decreasing variances utilizing two transformation approaches of noise estimation and derivation of standard principal components respectively. The first transform uses the noise covariance matrix to decorrelate and rescale the noise in such a way that noise has unit variance with no correlation among the bands (Lu and Weng, 2004; ENVI, 2001). The second transform is a standard PCA approach of the noise whitened data (ENVI, 2001). Thus in MNF, noise components can be isolated thereby enhancing the image quality to improve estimations. As such, MNF in this research was used as a dimension reduction process to select a few meaningful components (MNF2, 3, and 4) based on scree plot approach.

In order to strengthen the results of spectral unmixing for biomass and health estimations, NDVI and greenness bands were derived using equation 1 and Table 1 respectively.

$$NDVI = \frac{Near\ Infrared - red}{Near\ Infrared + red} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ (2)$$

Table 1. Coefficients used to derive the greenness band (ERDAS 9.2)

Spectral band	Coefficient
TM1	-0.2848
TM2	- 0.2435
TM3	- 0.5436
TM4	0 .7243
TM5	0.0840
TM7	- 0.1800

A statistical correlation analysis was used to identify the selected MNF2, 3, and 4 components that were well correlated to NDVI and greenness. From the correlation analyses and scatter plots, greenness, NDVI, and MNF2 components were selected and layer stacked for further analysis.

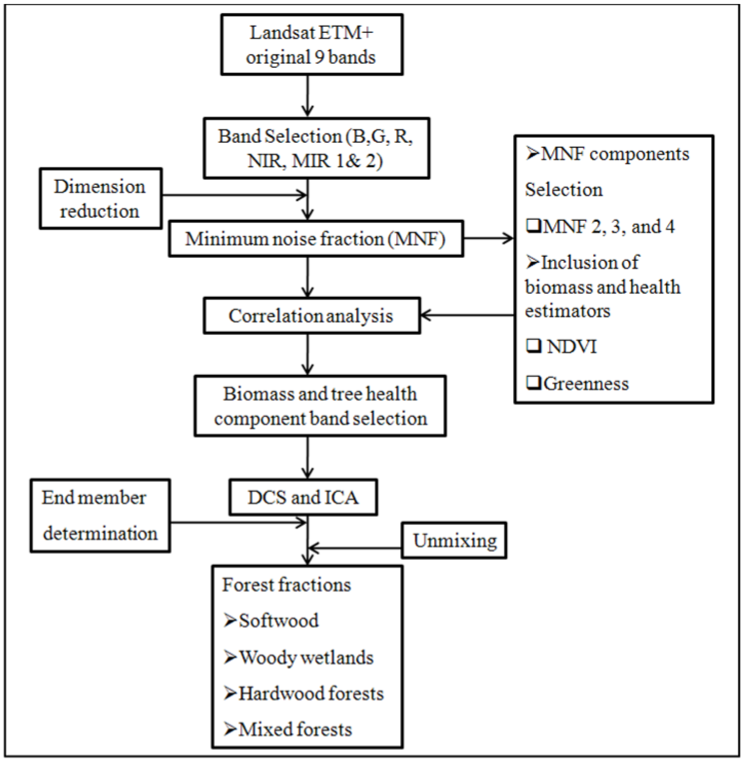

Figure 3. Flow chart depicting the un-mixing process utilized in this research

Decorrelation stretch (DCS)

The false color composite of NDVI, MNF 2, and greenness assigned to red, green, and blue colors respectively showed a low contrast to distinguish pure pixels of respective forest class end members. DCS enhances the color variations of the spatial information through decorrelation of the spectral information (Ruiz-Armenta and Pro-Ledesma, 1998). Also, DCS is very suitable for low resolution imagery with highly correlated homogenous spatial data sets to bring out contrasting color differences from one feature to the other (Gillespie *et al*., 1986). The stretch is basically applied along the principal axes ($P_{i,}$ i=1, 2, 3…n) across all the bands. Thus the algorithm results in highly correlated P1 followed by statistically independent zero covariance P2 (Ruiz-Armenta and Pro- Ledesma, 1998). DCS was implemented on the greenness, NDVI, and MNF2 composite to bring out the color contrast of the forest end members.

Independent component analysis (ICA)

ICA is a higher order statistical computational technique for feature extraction (ERDAS 9.2). The underlying principle involved in ICA estimation is the measure of non-gaussianity using higher-order statistics such as correlation, skewness, and kurtosis, entropy and negentropy measures in the data (ERDAS 9.2). In contrast (Figure 4) to the PCA, the ICA algorithm results in non-orthogonal uncorrelated and independent features that can be utilized in spectral unmixing, shadow removal, classification problems (ERDAS 9.2). As such from the resultant DCS image, ICA was used to obtain the independent components.

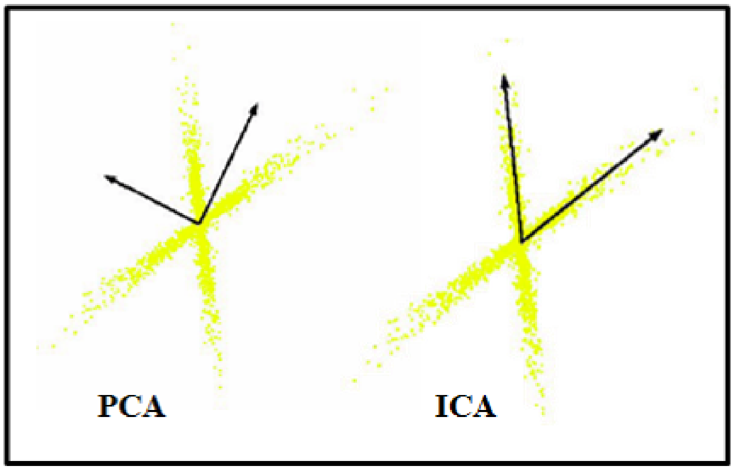

Figure 4. PCA and ICA transforms with orthogonal and non-orthogonal coordination respectively (Source: *http://www.pasteur.fr/~tekaia/BCGA/TALKS/Ahmed_Rebai_PCA-ICA.ppt*). The yellow represents pixel values of two uncorrelated image bands as depicted in feature space and the black arrows represent the transformation axes used to re-map the values to the transforms.

Selection of End-members from the Component Space

The four component end members of softwood forests, woody wetlands, hardwood forests, and mixed forests, were chosen for this study. A MNF-based DCS followed by the ICA approach was utilized to identify the purest pixels. The signature corresponding to the purest pixel of each component end member was used to unmix the components into their constituent fractions by applying mixture tuned matched filtering.

Mixture tuned matched filtering (MTMF)

Spectral unmixing can be done either at the pixel or subpixel level. Remotely sensed images are often associated with fuzzy end members that involve subpixel level approaches. MTMF is one such subpixel approach that involves a hybrid approach of matched filter method as well as theory of linear mixture. A constrained MTMF (Figure 5) produces a 0 to 1 match score and an infeasibility end member output (ENVI, 2001). The match score is based on the end member signature and the subpixel abundance where 1.0 indicates a perfect match with a low infeasibility value (ENVI, 2001).

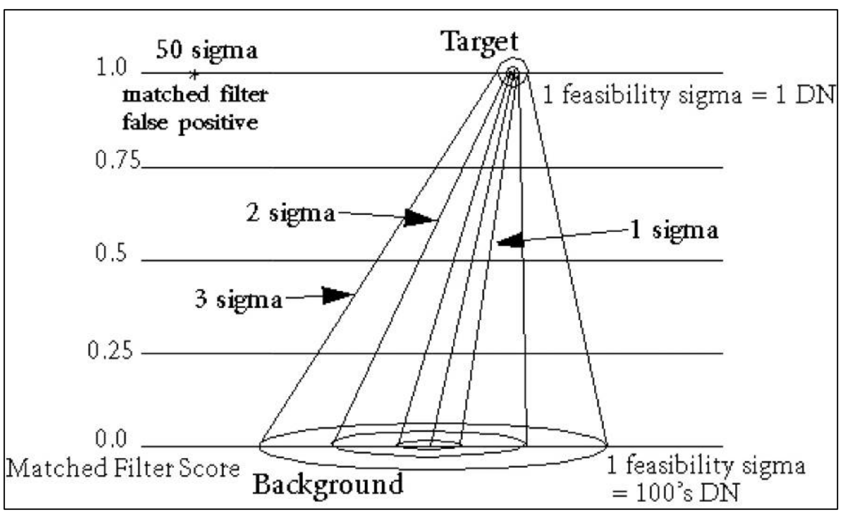

Figure 5. A constrained MTMF approach of spectral unmixing (ENVI, 2001), where sigma represent the standard deviation. The area represents the spread of the un-mixed fraction from 0 (no match) to a perfect match (1.0) on the y-axis.

MTMF is appropriate in the case of user-defined end members when compared to other subpixel methods of unmixing such as Linear and matched filter unmixing techniques (ENVI, 2001) as was employed in the present unmixing approach.

RESULTS

The original ETM+ image contains a lot of statistical noise and important spectral feature information. The MNF transform (Figure 6) is helpful to isolate noise from the image and select a few meaningful MNF components based on the scree plot approach. The scree plot (Figure 7) was useful to distinguish between useful MNF components and noise components. MNF1 possessed the maximum eigen value and variance (94%, Table 2) that can be considered to be very similar to the original image. Similarly the lower eigen values and variance (< 1%) components (MNF 5, and 6) represent noise in the image (Figure 6). As such MNF1, 5, and 6 were excluded for this analysis.

Table 2. The Eigen values and the associated variance of the MNF components

Component	Eigen value	Variance
MNF1	106.05	93.95
MNF2	2.23	1.97
MNF3	2.06	1.83
MNF4	1.07	0.95
MNF5	0.82	0.72
MNF6	0.65	0.558

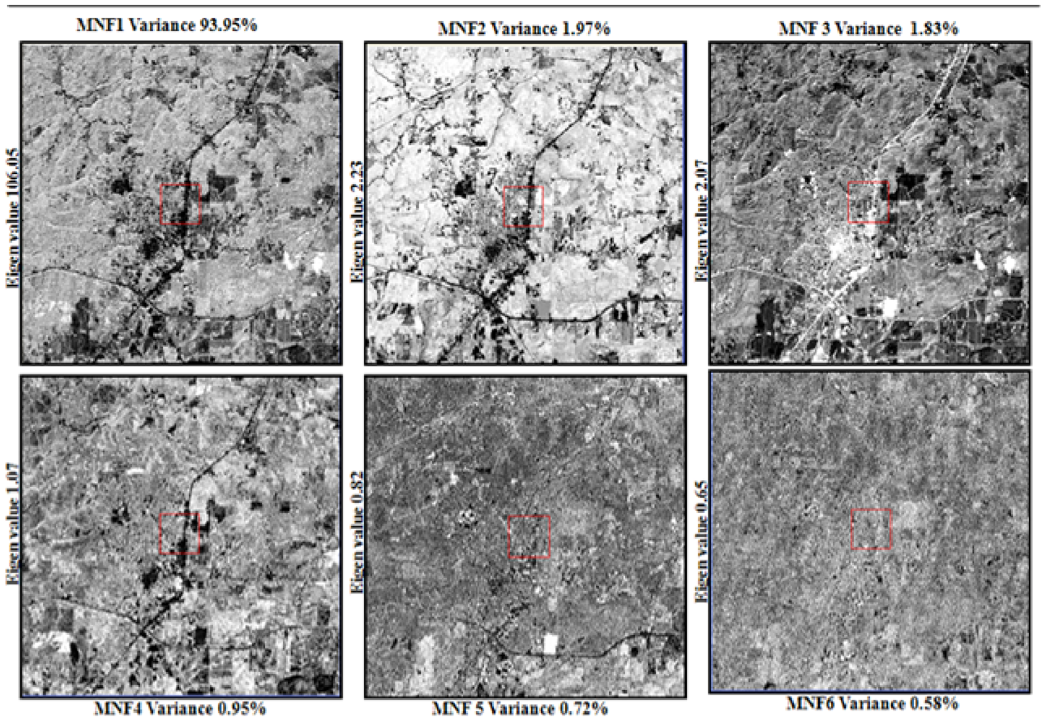

Figure 6. Resultant spectral (MNF 1, 2, 3, and 4) and noise (MNF5, and 6) components of the MNF transform.

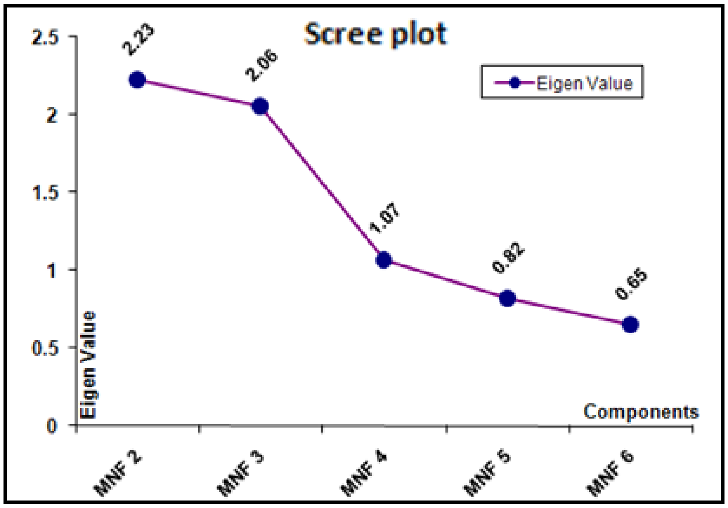

Figure 7. Scree plot approach used to distinguish the useful and noise components in the MNF transform. MNF 5 and 6 (Eigen value <1) refer to noise that fall at the base of the curve.

The results of the correlation analysis (Table 3) of MNF 2, 3, 4, NDVI, and greenness components suggests that only MNF component 2 is closely related to the greenness and NDVI components. The cross checks with the scatter plots (Figure 8) also strengthens interpretation of the positive association of MNF component 2 to the greenness and NDVI components. The positive correlation suggests that the greenness, NDVI, and MNF component 2 composite would be more promising in estimating biomass as well as health of the forest end-members. The other MNF3 and MNF4 components seem to have a weak negative correlation to greenness and NDVI.

Table 3. Results of univariate and correlation analysis

Component	Min.	Max.	Correlation coefficient to greenness	Correlation coefficient to NDVI
Greenness	0	80	1	0.587545
NDVI	-0.972973	0.978022	0.587545	1
MNF2	-37.875374	14.009801	0.406879	0.582916
MNF3	-19.611166	49.166443	-0.485582	-0.384895
MNF4	-56.970963	39.749516	-0.234093	0.057906

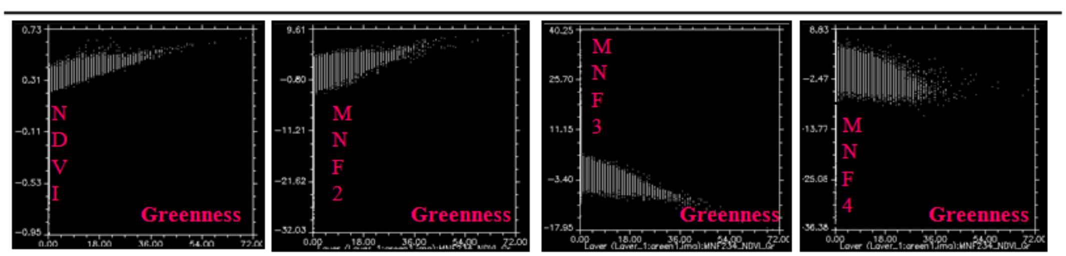

Figure 8. Scatter plots of the selected bands (NDVI, MNF 2, 3, 4) against greenness band

The application of DCS to this moderate resolution imagery with isolated homogenous areas enhanced the color contrast from one feature to the other. It enhanced the color contrast of boundaries within a homogenous forest cover (Figure 9). DCS was successful in achieving no band to band correlation of greenness, NDVI, and MNF component 2. ICA utilized the skewness, kurtosis, and entropy measures of these non-correlated components to derive independent components. ICA implementation on the resultant DCS image enhanced the image quality and contrast (Figure 10) of one independent component to the other such as to distinguish softwood from hardwoods, woody wetlands from water and various fallow lands.

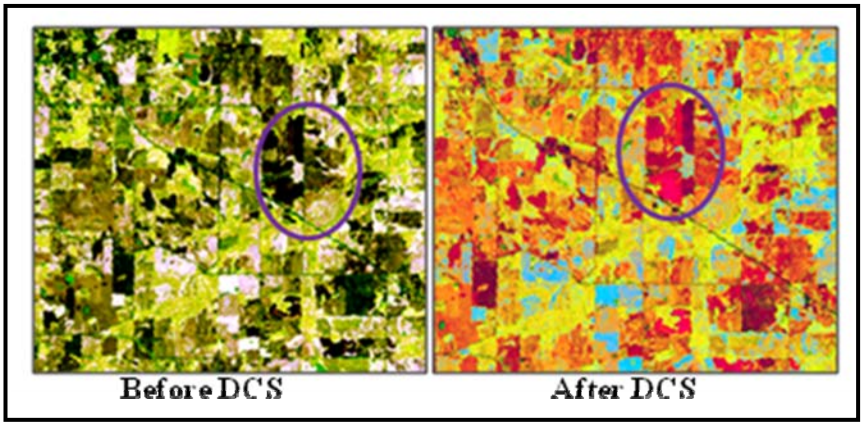

Figure 9. Result of RGB composite of NDVI, MNF2, and greenness bands before and after DC stretch. The circled portion indicates the color contrast among the component features in an area of forest land.

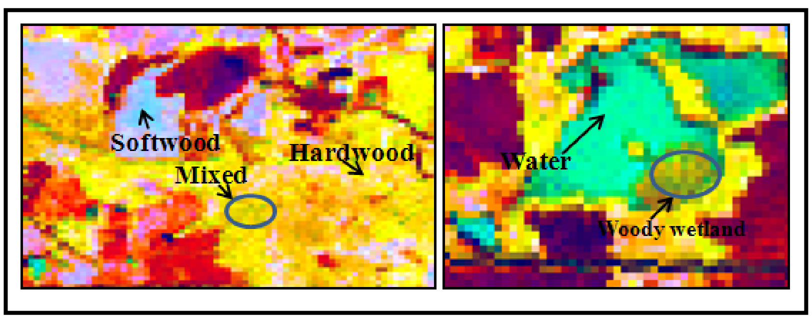

Figure 10. Enhancement of representative forest end-members as a result of ICA approach.

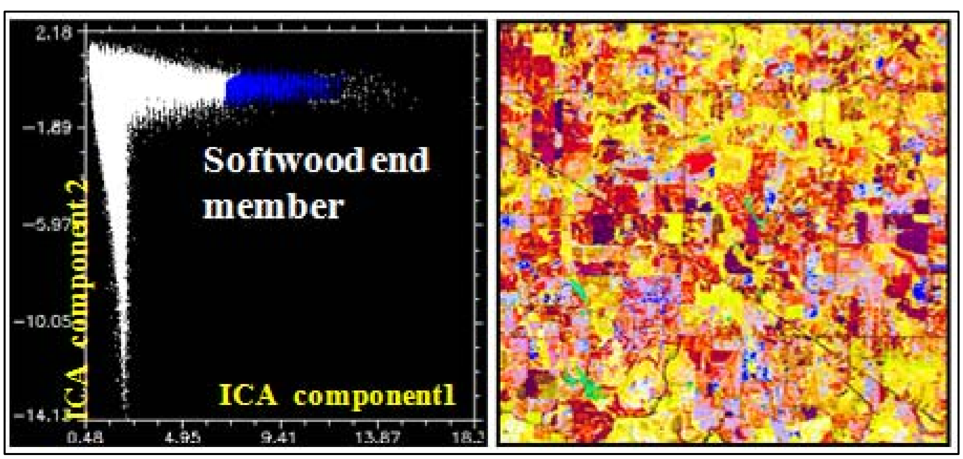

Figure 10. Left: Softwood end-member purest pixels from the non-orthogonal ICA approach. The white represents pixels of two component end members and blue represents the selected pure pixels of the soft wood end- member. Right: the corresponding softwood pixels in the ICA image

The clear contrast of the four forest cover end members obtained from the ICA (example given in Figure 10) was used to identify the purest pixels of pertinent end members (Figure 11). The purest pixel signature of each forest cover was apparently successful in to unmixing the ICA image into end member fractions using the MTMF subpixel unmixing approach. MTMF resulted in a fractional (Figure 12) and infeasibility fractions for each end member. The scatter plots of the fractional and infeasibility fractions are valuable in eliminating the unmatched pixels thereby improving the accuracy of estimations in future work. Further interactive stretching of the MTMF scored fractions is useful for identifying only the pixels of the target end-member (ENVI, 2001).

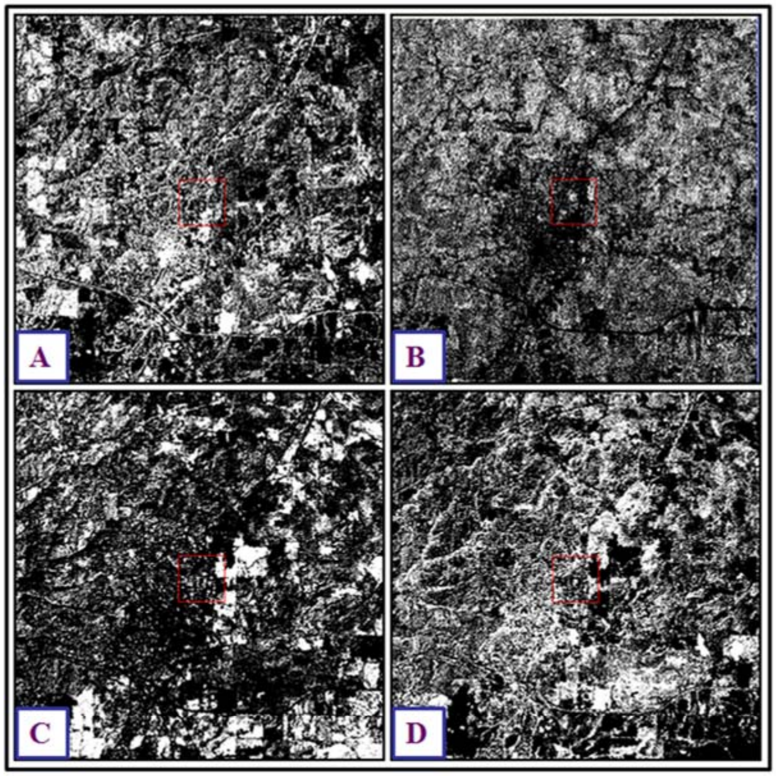

Figure 12. Fractional forest cover end-members derived from spectral unmixing A-Soft wood, B-Woody wetlands, C-Hardwood forest, and D- Mixed forest. Dark tones indicate low proportion and light tones indicate high proportion composition of each pixel for each end-member

CONCLUSIONS

This research utilized the MTMF sub pixel unmixing approach to delineate assumed biomass and health-based forest covers. MNF transform was implemented to separate the noise and spectral components. Decorrelation stretch brought out the needed color contrast of the highly correlated vegetation cover which was separated into independent components using the ICA approach. The results need to be validated with appropriate ground truth data. With accuracy evidence, MTMF unmixing may be very valuable to delineate forest end member fractions. A detailed accuracy assessment would also strengthen the MTMF added advantage of improving the end-member estimation that eliminates the sensitivity to end member selection. Thus this approach of spectral unmixing the forest cover would be helpful to distinguish various forest covers, variation in forest health, estimation of biomass, leaf area index, or any related forest biophysical parameters depending on the availability of the relevant ground truth data.

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