Applying linear spectral unmixing to airborne hyperspectral imagery for mapping yield variability in grain sorghum and cotton fields

Chenghai Yang
James H. Everitt
Qian Du
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Chenghai Yang, a James H. Everitt, a and Qian Du b
a USDA-ARS Kika de la Garza Subtropical Agricultural Research Center, 2413 East Highway 83, Weslaco, Texas 78596
chenghai.yang@ars.usda.gov, james.everitt@ars.usda.gov
b Mississippi State University, Department of Electrical and Computer Engineering, Mississippi State, Mississippi 39762
du@ece.msstate.edu

Abstract. This study examined linear spectral unmixing techniques for mapping the variation in crop yield for precision agriculture. Both unconstrained and constrained linear spectral unmixing models were applied to airborne hyperspectral imagery collected from a grain sorghum field and a cotton field. A pair of crop plant and soil spectra derived from each image was used as endmember spectra to generate unconstrained and constrained plant and soil cover abundance fractions. For comparison, the simulated broad-band normalized difference vegetation index (NDVI) and narrow-band NDVI-type indices involving all possible two-band combinations of the 102 bands in the hyperspectral imagery were calculated and related to yield. Statistical results showed that plant abundance fractions provided better correlations with yield than the broad-band NDVI and the majority of the narrow-band NDVIs, indicating that plant abundance maps derived from hyperspectral imagery can be used as relative yield maps to characterize yield variability in grain sorghum field and cotton fields without the need to choose the best NDVI. Moreover, the unconstrained plant abundance provided essentially the same results for yield estimation as the constrained plant abundance either with the abundance sum-to-one constraint only or with both the sum-to-one and non-negativity constraints, indicating that the more computationally complex constrained linear unmixing does not offer any advantage over the simple unconstrained linear unmixing for this application.

Keywords: hyperspectral imagery, linear spectral unmixing, abundance fraction, narrow-band NDVI, precision agriculture, yield variability.

1 INTRODUCTION

Multispectral imagery and vegetation indices such as the normalized difference vegetation index (NDVI) have often been used to estimate crop yields and assess within-field yield variability [1-4]. More recently, airborne hyperspectral imagery has been evaluated for mapping crop yield for precision agriculture [5-7]. Hyperspectral imagery contains tens to hundreds of narrow bands and has the potential to differentiate and estimate biophysical attributes of interest better than multispectral imagery. However, since hyperspectral imagery has so many bands, it is not always practical to calculate all the possible vegetation indices from these narrow bands. For example, a 102-band hyperspectral image can produce 5151 (102!/100!/2!) NDVI-type vegetation indices if all possible two-band combinations are considered.

One method to reduce the spectral dimensionality in hyperspectral imagery is to apply stepwise regression analysis to yield data and hyperspectral imagery to identify optimum band combinations for mapping the variation in yield or to use principle components analysis
and stepwise regression to select the significant principle components that account for most of the variation in yield [6]. Another method is to calculate various vegetation indices from selected bands [7] or to calculate all possible narrow-band NDVIs [8]. After testing all the possible narrow-band NDVI indices and other methods on a variety of agricultural data, Thenkabail et al. [8] comes to the conclusion that a strong relationship with crop characteristics is located in specific narrow bands in the longer wavelength portion of the red, in the shorter wavelength portion of green, in one particular section of the near-infrared (NIR), and in the moisture sensitive NIR. This study recommended 12 narrow bands in the 350 nm to 1050 nm range of the spectrum for optimum estimation of agricultural crop biophysical information. Although stepwise regression can be used to identify the optimum bands for estimating yield, these bands are only the best for the image and yield data from which they are derived and might not be the best for different data sets. Similarly, the optimum narrow-band NDVI identified for one data set might not be the best for another. Therefore, it is necessary to use a technique that can take advantage of the spectral information in all the bands without the need to choose which bands to use.

Spectral unmixing techniques can be used to quantify crop canopy cover within each pixel of an image and have the potential for mapping the variation in crop yield. Each image pixel contains a spectrum of reflectance values for all the wavebands. These spectra can be regarded as the signatures of ground components such as crop plants or soil, provided that a component, referred to as an endmember, occupies the whole pixel. Spectra from mixed pixels can be analyzed with linear spectral unmixing, which models each spectrum in a pixel as a linear combination of a finite number of spectrally pure spectra of the endmembers in the image, weighted by their fractional abundances [9, 10].

When linear spectral unmixing is applied to an image, it produces a suite of abundance fraction images, one for each endmember in the model. Each fraction image shows the spatial distribution of the spectrally defined component as an NDVI image does. The fractional abundance of crop plants determined from linear spectral unmixing is a more direct measure of plant cover than an NDVI value. Yang et al. [11] applied this technique to hyperspectral imagery for mapping the variation in yield in two grain sorghum fields and their results indicate that plant abundance fraction images can be used as relative yield maps. They also examined how variations in endmember spectra affect the results and found that correlation coefficients between yield and unconstrained plant abundance fractions are not sensitive to the selection of plant and soil endmembers, though the correlation coefficients between yield and constrained plant abundance fractions are affected by the choice of endmember spectra. In this previous study, the constrained model was only subject to the abundance sum-to-one constraint, but the abundance non-negativity constraint was omitted. Also the unmixing technique has been applied only to grain sorghum. Therefore, it is necessary to examine the non-negativity constraint in the constrained model and to evaluate the technique for other crops. The specific objectives of this study were to: 1) apply unconstrained and constrained linear spectral unmixing to airborne hyperspectral imagery for estimating plant and soil abundance fractions in a grain sorghum field and a cotton field; and 2) relate grain yield to the abundance fractions and compare the correlations with those from all possible narrow-band NDVIs.

2 METHODS

2.1 Data collection

Airborne hyperspectral imagery and yield monitor data collected from a 13.6-ha grain sorghum field in 2000 and from a 22.0-ha cotton field in south Texas in 2001 were used for this study. The geographic coordinates near the centers of the sorghum and cotton fields were (98°02'28"W, 26°28'55"N) and (97°58'37"W, 26°29'14"N), respectively. The soil in the study
area is dominantly Delfina loamy fine sand. Grain sorghum and cotton are normally grown in rotation in these fields.

An airborne hyperspectral imaging system described by Yang et al. [12] was used to acquire the imagery. The system was configured to record imagery with 128 bands from 457.2 to 921.7 nm at 3.63 nm intervals. The imagery had a swath width of 640 pixels and a radiometric resolution of 12 bits. Images were acquired on 27 April 2000 from the sorghum field and on 12 June 2001 from the cotton field. At the imaging time, both the sorghum and cotton crops were approaching the maximum canopy cover, even though some areas of the fields had large soil exposure because of very sandy soil texture. The images were corrected for its geometric distortion using the reference line method [12], rectified to the Universal Transverse Mercator (UTM) coordinate system based on a set of ground control points, and radiometrically calibrated using three reflectance tarpaulins with reflectance values of 4, 32 and 48%. The images were resampled to 1-m pixel size by the nearest-neighbor algorithm during image rectification. The last 21 bands and the first 5 bands were removed due to low quantum efficiency near the NIR end of the observed spectrum and the noise in the first few bands of the blue region. The remaining 102 bands with wavelengths from 477.2 to 843.7 nm were used for analysis.

Yield data were collected with an Ag Leader PF3000 yield monitor (Ag Leader Technology, Ames, Iowa) integrated with a submeter AgGPS 132 receiver (Trimble Navigation Limited, Sunnyvale, California). Yield and GPS data were recorded simultaneously at one-second intervals. The yield monitor was calibrated before the harvest for each crop.

Considering the coarse yield data resolutions and positional errors, the 1-m pixel size for the hyperspectral and abundance fraction images were aggregated to 9 m for sorghum and to 8 m for cotton to be comparable with the effective cutting width of the harvesters. The yield values were similarly averaged from the data points within each larger pixel area.

2.2 Linear spectral unmixing

In a linear mixture model, the reflectance spectrum of any pixel can be considered as a linear combination of the spectra of all the ground materials (i.e., endmembers) resident in the pixel. Let $L$ be the number of spectral bands in an image and $r$ an $L \times 1$ pixel value vector for any pixel in the image. If there are $p$ endmembers present in the image, an $L \times p$ signature matrix $M = (m_1, m_2, \ldots, m_p)$ can be constructed, where $m_j$ represents the spectral signature (spectrum) for the $j$-th endmember. Assume that $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_p)^T$ is a $p \times 1$ abundance vector associated with $r$, where $\alpha_j$ denotes the unknown abundance fraction of the $m_j$ in $r$.

In the linear mixture model, $r$ is expressed as a linear combination of $m_1$, $m_2$, ..., $m_p$ as follows:

$$ r = Ma + n, \quad (1) $$

where $n$ is included to account for measurement and model errors.

A typical method to estimate the unknown mixing coefficients, $\alpha$, in Eq. (1), is the least squares error approach. The estimate from the least squares error is the one that minimizes the estimation residual

$$ \min_{\alpha} (r - Ma)^T (r - Ma). \quad (2) $$

Then the $\alpha_j$ values for all the pixels constitute the $j$-th fraction image, describing the spatial distribution of the $j$-th endmember. A large value in a fraction image means large abundance in the pixel location and a low value means small abundance.

Eq. (1) is referred to as the unconstrained linear spectral unmixing model. In order for the estimated abundance vector $\alpha$ to faithfully represent image pixel vector $r$, two constraints are
generally imposed on $\alpha$ in Eq. (1): (a) the abundance sum-to-one constraint, \( \sum_{j=1}^{p} \alpha_j = 1 \), and (b) the abundance non-negativity constraint, \( \alpha_j \geq 0, \ j = 1,2,\ldots,p \).

If no constraint is imposed, then the least squares solution to Eq. (2) is

$$ \hat{\alpha} = (M^T M)^{-1} M^T r, $$

where $\hat{\alpha}$ is the estimate of $\alpha$. If only the sum-to-one constraint is imposed, then Eq. (3) can be extended as

$$ \hat{\alpha} = \left( M^T M \right)^{-1} M^T \tilde{r}, $$

where $\tilde{r} = \begin{bmatrix} r \\ 1 \end{bmatrix}$, $\tilde{M} = \begin{bmatrix} M \\ 1^T \end{bmatrix}$, and $1$ being a $p \times 1$ column vector with all elements equal to 1.

If both constraints are imposed, there are no closed-form solutions to such a constrained linear unmixing problem. However, quadratic programming can be used to minimize the least squares estimation error in Eq. (2) and satisfy the two constraints simultaneously. Quadratic programming refers to a problem with a quadratic objective function and linear constraints (including inequalities). Eq. (2) with the sum-to-one and non-negativity constraints can be reformulated as

$$ \text{Minimize } f(\alpha) = r^T r - 2r^T \alpha M + \alpha^T M^T M \alpha $$

Subject to: $\alpha_1 + \alpha_2 + \cdots + \alpha_p = 1$

\[ 0 \leq \alpha_j \leq 1, \ j = 1,2,\ldots,p \]

This model is a typical quadratic programming problem. Linear optimization-based techniques presented in [13-14] were used to solve the problem.

Linear spectral unmixing analysis requires the spectra of the known endmembers. They can be obtained directly from the image, measured on the ground or derived from a spectral library. In this study, crop plants and bare soil were selected as the relevant endmembers. A pair of plant and soil spectra was extracted from each image to represent pure and healthy plants and bare soil and used as endmember spectra for spectral unmixing analysis for each field. To obtain pure spectra for crop plants, 100 pixels that had a bright red color on a color-infrared (CIR) image (corresponding to healthy plants and high yielding areas) were first identified from each image. Similarly, 100 pixels that contained pure bare soil were identified from each image. The endmember spectra for plants and soil for each image were obtained by averaging the spectra of the respective training pixels from that image. Alternatively, computerized methods such as the pixel purity index and the n-dimensional visualizer in ENVI (Research Systems, Inc., Boulder, Colorado) can be used to identify purest pixels for the endmembers. However, these automatic methods are not always reliable. For example, weed plants can be mixed with crop plants and atypical soil surface areas with too dark or too bright colors can be misidentified as typical soil. Since there were only two endmembers in this particular application, the simple manual approach was used.

2.3 Vegetation indices and correlation analysis

For comparison with linear spectral unmixing, both the broad-band NDVI and narrow-band NDVI-type indices were calculated. The 102 hyperspectral bands were averaged into the four wavebands in standard QuickBird multispectral imagery: blue (450-520 nm), green (520-600 nm), red (630-690 nm), and NIR (760-900 nm). The broad-band NDVI was calculated as follows:

$$ \text{NDVI} = (R_{NIR} - R_{Red}) / (R_{NIR} + R_{Red}), $$

where $R_{NIR}$ and $R_{Red}$ are the reflectance for the simulated NIR band and red band, respectively.
The narrow-band NDVI-type indices involving all possible two-band combinations of the original narrow bands are calculated as follows:

$$\text{NDVI}_j = \frac{(R_i - R_j)}{(R_i + R_j)}$$

where $R_i$ is the reflectance for band $i$, $i = 1, 2, \ldots, L-1$ and $R_j$ is the reflectance for band $j$, $j = i+1, \ldots, L$. There are 5151 NDVI-type indices for the 102-band hyperspectral images.

Correlation coefficients were calculated among yield, the six abundance fraction images (two unconstrained, two constrained with the sum-to-one constraint, and two fully constrained with both the sum-to-one and non-negativity constraints), the simulated broadband NDVI, and the 5151 narrow-band NDVIs for each of the two fields.

3 RESULTS AND DISCUSSION

Table 1 gives the univariate statistics of yield and unconstrained and constrained plant and soil abundance fractions derived from the hyperspectral images for the sorghum and cotton fields. Mean yield is 3436 kg/ha with a standard deviation of 1480 kg/ha for the sorghum field and 1404 kg/ha with a standard deviation of 640 kg/ha for the cotton field, indicating there existed large variability in yield within both fields.

Table 1. Univariate statistics of crop yield as well as unconstrained and constrained plant and soil abundance fractions derived from the 102-band airborne hyperspectral images for a sorghum field and a cotton field based on a pair of plant and soil endmember spectra extracted from the respective image for each field.

<table>
<thead>
<tr>
<th>Yield and endmember fraction</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sorghum field</strong>[^a^]:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield (kg/ha)</td>
<td>3436</td>
<td>1480</td>
<td>111</td>
<td>6022</td>
</tr>
<tr>
<td>UPF[^b^]</td>
<td>0.63</td>
<td>0.28</td>
<td>-0.15</td>
<td>1.01</td>
</tr>
<tr>
<td>USF</td>
<td>0.32</td>
<td>0.25</td>
<td>0.02</td>
<td>1.16</td>
</tr>
<tr>
<td>CPF1</td>
<td>0.64</td>
<td>0.28</td>
<td>-0.15</td>
<td>1.00</td>
</tr>
<tr>
<td>CSF1</td>
<td>0.36</td>
<td>0.28</td>
<td>0.00</td>
<td>1.15</td>
</tr>
<tr>
<td>CPF2</td>
<td>0.64</td>
<td>0.26</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>CPF2[^b^]</td>
<td>0.36</td>
<td>0.26</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Cotton field:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yield (kg/ha)</td>
<td>1404</td>
<td>640</td>
<td>24</td>
<td>3762</td>
</tr>
<tr>
<td>UPF</td>
<td>0.63</td>
<td>0.22</td>
<td>0.02</td>
<td>1.15</td>
</tr>
<tr>
<td>USF</td>
<td>0.27</td>
<td>0.17</td>
<td>-0.21</td>
<td>1.12</td>
</tr>
<tr>
<td>CPF1[^b^]</td>
<td>0.60</td>
<td>0.24</td>
<td>-0.05</td>
<td>1.18</td>
</tr>
<tr>
<td>CSF1[^b^]</td>
<td>0.40</td>
<td>0.24</td>
<td>-0.18</td>
<td>1.05</td>
</tr>
<tr>
<td>CPF2[^b^]</td>
<td>0.60</td>
<td>0.23</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>CPF2</td>
<td>0.40</td>
<td>0.23</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

[^a^] Number of samples was 1661 for the sorghum field and 2150 for the cotton field.

[^b^] UPF = unconstrained plant fraction, USF = unconstrained soil fraction, CPF1 = constrained plant fraction with the sum-to-one constraint, CSF1 = constrained soil fraction with the sum-to-one constraint, CPF2 = constrained plant fraction with the sum-to-one and positivity constraints, and CSF2 = constrained soil fraction with the sum-to-one and positivity constraints.
Ideally, fraction values should be within the 0-1 range, but in unconstrained fraction images they can be negative or exceed 1. For example, the unconstrained plant abundance varies from -0.15 to 1.01 for the sorghum field and from 0.02 to 1.15 for the cotton field. The unconstrained soil abundance varies from 0.02 to 1.16 for sorghum and from -0.21 to 1.12 for cotton. This is because spectral unmixing results can be affected by the purity of the endmembers and the number of endmembers. The linearity assumption of linear spectral unmixing is at best an approximation of the generally non-linear mixing of surface components. The constrained fractions with the sum-to-one constraint also have negative values and values greater than 1. The fully constrained fractions have values in the range of 0-1. Fig. 1 shows the fully constrained plant abundance fraction images derived from the hyperspectral images for the two fields. Red areas have small plant abundance values and represent pixels with a large exposure of soil and sparse plant cover. Conversely, green areas indicate large plant abundance values and represent pixels with dense plant cover.

Fig. 1. Fully constrained plant abundance fraction images derived from the 102-band airborne hyperspectral images for a sorghum field and a cotton field based on a pair of plant and soil endmember spectra extracted from the image for each field.
The mean unconstrained plant abundance is 0.63 for both the sorghum and cotton fields, indicating mean plant canopy cover was approximately 63% at the time of the image acquisition. The sum of the plant and soil abundance fraction is 0.95 for sorghum and 0.90 for cotton. Although the unconstrained model does not force the endmember abundance fractions to sum to 1, the sum is still close to 1, indicating the unconstrained two-endmember linear unmixing model is appropriate for characterizing plant and soil cover in the images. Mean constrained plant abundance with the sum-to-one constraint is 0.64 for sorghum and 0.60 for cotton and these values are similar to the mean unconstrained abundance fractions. Mean constrained plant abundance fractions with both the sum-to-one and positivity constraints are essentially the same as those with the sum-to-one constraint except that the abundance values are within the 0-1 range.

Table 2 summarizes the correlation coefficients ($r$) of crop yield with plant and soil abundance fractions for both fields. Yield is positively related to unconstrained and constrained plant abundance fractions, and negatively related to the unconstrained and constrained soil abundance fractions. Unconstrained plant abundance fractions have slightly stronger correlations with yield than the unconstrained soil abundance fractions, whereas constrained plant and soil abundance fractions have identical absolute correlations because they sum to unity. The correlation coefficients for the unconstrained plant abundance fraction are 0.85 for the sorghum field and 0.67 for the cotton field, whereas the $r$-values for the unconstrained soil abundance fraction are -0.82 for sorghum and -0.61 for cotton. The $r$-values for the partially and fully constrained plant abundance fraction are 0.85 for sorghum and 0.66 for cotton. The lower $r$-values for the cotton field are partially due to the fact that some of the variability in yield cannot be explained by the variability in cotton canopy.

Table 2. Correlation coefficients ($r$) between yield and endmember fractions derived from 102-band airborne hyperspectral images for a sorghum field and a cotton field based on a pair of plant and soil endmember spectra extracted from the respective image for each field

<table>
<thead>
<tr>
<th>Endmember fraction</th>
<th>Sorghum</th>
<th>Cotton</th>
</tr>
</thead>
<tbody>
<tr>
<td>UPF$^{[a]}$</td>
<td>0.85$^{[b]}$</td>
<td>0.67</td>
</tr>
<tr>
<td>USF</td>
<td>-0.82</td>
<td>-0.61</td>
</tr>
<tr>
<td>CPF1</td>
<td>0.85</td>
<td>0.66</td>
</tr>
<tr>
<td>CSF1</td>
<td>-0.85</td>
<td>-0.66</td>
</tr>
<tr>
<td>CPF2</td>
<td>0.85</td>
<td>0.66</td>
</tr>
<tr>
<td>CSF2</td>
<td>-0.85</td>
<td>-0.66</td>
</tr>
</tbody>
</table>

[a] UPF = unconstrained plant fraction, USF = unconstrained soil fraction, CPF1 = constrained plant fraction with the sum-to-one constraint, CSF1 = constrained soil fraction with the sum-to-one constraint, CPF2 = constrained plant fraction with the sum-to-one and positivity constraints, and CSF2 = constrained soil fraction with the sum-to-one and positivity constraints.

[b] All r-values are significant at the 0.0001 level. Number of samples was 1661 for sorghum and 2150 for cotton.

In comparison, the correlation coefficient between yield and the simulated broad-band NDVI is 0.83 for the sorghum field and 0.61 for the cotton field. These $r$-values are lower than those for the unconstrained or constrained plant abundance, indicating that a plant abundance fraction can be a better index than the broad-band NDVI.

Fig. 2 shows the contour maps of absolute $r$-values between yield and each of the 5151 possible NDVIs for both the sorghum and cotton fields. The absolute $r$-values vary from 0 to 0.88 for sorghum and from 0 to 0.72 for cotton. The $r$-values are generally larger when one band has wavelengths smaller than 730 nm and the other band has wavelengths larger than 730 nm for both fields. However, the best $r$-values (>0.85) occur when one band is around...
730 nm and the other was over 760 nm for the sorghum field. Also large $r$-values (>0.825) for the sorghum field occur when one band in a pair has wavelengths between 550 nm and 575 nm and the other has wavelengths between 575 nm and 690 nm. Based on the contour maps of $r$-values, better NDVI images are more likely to be obtained by selecting one band in the visible region and the other in the NIR region.

Fig. 2. Contour maps showing absolute correlation coefficients between crop yield and all possible narrow-band NDVIs derived from 102-band airborne hyperspectral images for a sorghum field and a cotton field. When band $i = $ band $j$, NDVI$_{ij} = 0$ and correlations don’t exist (shown by the diagonal line). The number of samples used to calculate each $r$ value was 1661 for sorghum and 2150 for cotton.
The best NDVIs have larger correlations with yield than the best abundance fraction images for both fields. Nevertheless, the best abundance fraction-based $r$-values (0.85 for sorghum and 0.67 for cotton) are better than 97.1% and 96.0% of the 5151 NDVI-based $r$-values for the sorghum field and the cotton field, respectively. If the objective of a study is to determine the best correlation based on actual yield data, all possible narrow-band NDVIs could be derived to identify the best NDVI. However, if the objective is to generate a spectral map from a hyperspectral image to characterize the spatial variation in yield without knowing the actual yield, an unconstrained or constrained plant fraction image based on a pair of plant and soil spectra will be a better choice. A plant abundance fraction image appears to provide a better relative yield map than an NDVI image derived from two randomly selected bands. An NDVI image uses only two narrow bands, whereas a plant fraction image is based on all bands in the image. Although an NDVI image could provide better $r$-values than a plant fraction image as shown in this study, the best NDVI identified from one image is unlikely to be the best NDVI for another. Moreover, the best NDVI can only be identified if the yield is known and all possible narrow-band NDVIs or at least the NDVIs with red and NIR band pairs are calculated. On the other hand, the plant fraction image can be generated using all the bands and a pair of plant and soil endmember spectra without the need to know the actual yield. It also has the potential to be as good as or even better than the best NDVI. Therefore, linear spectral unmixing techniques can be used alone or in conjunction with other traditional VIs in mapping yield variability and other applications.

4 CONCLUSIONS

This study demonstrates the use of linear spectral unmixing techniques to derive plant and soil abundance fractions from hyperspectral imagery for mapping the variation in yield for both grain sorghum and cotton. Both unconstrained and constrained plant abundance fractions provide better $r$-values with yield than the broad-band NDVI and the majority of the narrow-band NDVIs derived from the hyperspectral images for both crops. In practice, a plant abundance fraction image can be a better representation of relative yield than an NDVI image derived from two bands if no yield sampling data are available.

Compared with the constrained results, the unconstrained abundance fractions provide essentially the same correlations with yield. Therefore, it is recommended to use unconstrained linear unmixing for generating plant abundance and relative yield. Unconstrained linear unmixing has less computational complexity and, more importantly, unconstrained results can be used to evaluate the accuracy of the endmember spectra and unmixing results. If the endmember spectra are accurate, the sum of the plant and soil abundance fractions should be close to 1 and the number of pixels with negative values or values greater than 1 should be small. Imposing constraints to abundance fractions may not help improve the unmixing results. This supports the conclusion by Rogge et al. [15] that abundance fractions can automatically satisfy the two constraints if the number of endmembers and their spectral signatures are accurate. The unmixing technique can be used for other crops to generate plant abundance or relative yield maps, but more experiments are necessary to evaluate this technique for other crops under diverse growing environments.

Acknowledgments

We thank Rene Davis and Fred Gomez of USDA-ARS at Weslaco, TX for acquiring the imagery for this study and Jim Forward of USDA-ARS at Weslaco, TX for assistance in image rectification and calibration. Thanks are also extended to Rio Farms, Inc. at Monte Alto, TX for use of their fields and harvest equipment.
References


Chenghai Yang is an agricultural engineer with the USDA Agricultural Research Service’s Kika de la Garza Subtropical Agricultural Research Center at Weslaco, Texas. He received his B.S. and M.S. degrees in agricultural engineering from Northwest Agricultural University in China, and his Ph.D. degree in agricultural engineering from the University of Idaho. He
has authored or coauthored numerous journal articles and other technical publications on remote sensing applications. His current research is focused on the use of remote sensing and other spatial information technologies for mapping invasive weeds in rangeland and wetland ecosystems and for mapping crop yield and growth conditions for precision agriculture. He is a member of the American Society of Agricultural and Biological Engineers (ASABE) and the American Society for Photogrammetry and Remote Sensing (ASPRS).