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A Comparison of AVIRIS and Synthetic Landsat Data for Land Use Classification at the Urban Fringe

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Abstract

In this study I tested whether AVIRIS data allowed for improved classification over synthetic Landsat TM data for a location on the urban-rural fringe of Colorado. After processing the AVIRIS image and creating a synthetic Landsat image, I used standard classification and post-classification procedures to compare the data sources for land use mapping. I found that, for this location, AVIRIS holds modest but real advantages over Landsat for the classification of heterogeneous and vegetated land uses. Furthermore, this advantage comes almost entirely from the high spectral resolution of the sensor rather than the high radiometric resolution.

Keywords: *remote sensing, urban fringe, land use change, hyperspectral*

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A Comparison of AVIRIS and Synthetic Landsat Data for Land Use Classification at the Urban Fringe

Rutherford V. Platt

Introduction

In rapidly urbanizing areas, such as the Front Range of Colorado, maps fast loose their validity. Large areas of prairie or farmland land can be overrun by residential development in a matter of months. Remotely sensed data allows land use and land cover to be mapped quickly, relatively cheaply and frequently. With improved mapping of rapidly changing areas, planners will be able to better address issues associated with urban sprawl. However, the images used can significantly influence the accuracy of the classification. While it is commonly thought that greater spatial resolution is the key to better land use classification, finer spectral and radiometric resolution also have potential advantages that remain only partially explored.

Commonly, researchers use sensors such as those on Landsat or SPOT (Système Probatoire d'Observation de la Terre) satellites for mapping land use and land cover (Table 1). Of these, the Landsat sensors have greater spectral resolution and a longer time series, while SPOT provides better spatial resolution. Less traditional sensors may provide additional information that can improve mapping accuracy. The Airborne Visible Infrared Imaging Spectrometer (AVIRIS), for example, produces images with 224 spectral bands between .4 and 2.45 µm, compared to 6 bands for Landsat (not including the thermal band) and 4 for SPOT's multispectral scanner. Imagery with a large number of continuous spectral bands, such as AVIRIS, is called *hyperspectral* imagery. Though hyperspectral imagery has been used in studies of mineralogical mapping and ecology, it has rarely (if ever) been employed for land use mapping of the urban fringe since it is more expensive and only available in limited areas.

Table 1: Sensor Characteristics

	AVIRIS	Landsat TM	SPOT XS
Platform	Airborne	Spaceborne	Spaceborne
Spatial Resolution	20 m	30 m	20 m
Spectral Resolution	224 bands	6 bands	3 bands
Radiometric Resolution	High	Moderate	Moderate
Launch	1992	1982	1986

In this study, I tested whether AVIRIS data allowed for improved land use classification over synthetic Landsat data for a location on the urban-rural fringe of Colorado. I expected that the fine spectral and radiometric resolution provided by AVIRIS would help distinguish land cover types that are easily confused – irrigated urban areas and irrigated crops, for example. After processing the AVIRIS image and creating a synthetic Landsat image, I used standard classification and post-classification procedures to compare the data sources for land use mapping. I found that AVIRIS holds modest but real advantages over Landsat for the classification of heterogeneous and vegetated land uses. Furthermore, this advantage comes almost entirely from the high spectral resolution of the sensor rather than the high radiometric resolution.

Resolution and Mapping Accuracy: The Case of the Urban Fringe

Among the factors that may influence classification accuracy are a sensor's spatial, radiometric and spectral resolution. Spatial resolution describes the size each pixel represents in the real world. For example, a satellite with 30 m resolution produces pixels that measure a 30x30 m area on the ground. Radiometric resolution, in contrast, is the smallest difference in brightness that a sensor can detect. A sensor with high radiometric resolution has very low "noise". Finally spectral resolution is the number of different wavelengths that a sensor can detect. A sensor that produces a panchromatic image has very low spectral resolution, while one that can distinguish many shades of each color has high spectral resolution.

Generally, it is thought that spatial resolution is the most important factor of the three for classification accuracy of built environments. For example, a study of Indonesia found that SPOT Multispectral (XS) images are superior to Landsat Multispectral Scanner (MSS) images for mapping of heterogeneous near-urban land cover because of SPOT's superior spatial resolution (Gastellu-Etchegorry 1990). The link between spatial resolution and classification accuracy, however, is sometimes tenuous. In heterogeneous areas, such as residential areas, it has been shown that classification accuracies may actually *improve* by up to 20% as spatial resolution is decreased (Cushnie, 1987). This occurs when the spectra in an urban environment blend to form an overall "urban signal" that can be easily distinguished from other land covers.

Radiometric resolution – a function of the "noisiness" of a sensor -- may also influence classification accuracy. Radiometric resolution varies significantly sensor-by-sensor and band-by-band depending on the dynamic range and signal to noise ratio (SNR) of the instrument. As a 10-bit sensor with a very high SNR, AVIRIS has superior radiometric resolution to the 8-bit Landsat sensors. Within the Landsat family, the Extended Thematic Mapper (ETM+) in Landsat 7 has a higher SNR than the Thematic Mapper (TM) in Landsat 4 and 5. While the advantages of high radiometric resolution are well documented in domains such as mineralogical mapping (e.g. Smailbegovic *et al.* 2000), for land use mapping these advantages depend on the classes of interest. For example, mapping urban versus rural land may not require as high radiometric resolution as distinguishing irrigated urban land versus irrigated cropland.

Finally, spectral resolution may influence accuracy of land use classification. One study showed the benefits of increased spectral resolution in classification of the urban fringe. The study used SPOT XS data to map farmland and urban land uses in New Zealand (Gao and Skillcorn 1998). In this case, using multispectral imagery improved the classification because vegetative land covers were easier to classify with an infrared band. In cases where different land uses have similar but separable spectra, high spectral resolution will likely improve mapping accuracy. When land uses are either spectrally inseparable or clearly distinct, however, additional spectral resolution may not improve classification accuracy. In these cases, the extra information could add heterogeneous "clutter" that complicates classification.

These studies show that increasing spatial/radiometric/spectral resolution may improve classification accuracy for land use mapping, but the net benefits often depend on the particular scene and classification system. In this study AVIRIS data was compared with synthetic Landsat TM and ETM+, all fixed at 20-meter spatial resolution, to determine the possible effects of increased spectral and radiometric resolution for land use mapping at the urban fringe in Colorado.

Image Processing

An AVIRIS flight line was acquired for September 30th, 1999 along the northern Front Range of Colorado. A single image cube was extracted that encompasses the northern edge of Fort Collins along with Horsetooth Reservoir and agricultural land (Figure 1).

Figure 1: A color-infrared composite of an AVIRIS image of Fort Collins and surroundings.

In order to convert at-sensor radiance into surface reflectance, an atmospheric correction was performed with High-Accuracy Atmosphere Correction for Hyperspectral Data (HATCH). Using spectral features within the data, HATCH creates pixel-by-pixel estimates of atmospheric composition. HATCH takes advantage of recent advancements in atmospheric radiative transfer, resulting in highly accurate atmospheric corrections (Qu *et al.* 2000).

In this study, an AVIRIS image was compared to synthetic Landsat images derived from AVIRIS. This method eliminated several sources of error that would be present if a real Landsat image were used. First, AVIRIS images from mid-1999 and earlier contain unsystematic distortions introduced by the pitch, yaw and roll of the aircraft (A device now sits on the sensor and records these movements so that the distortions may later be removed from the images). As a result, older AVIRIS images are difficult to register to other images with any precision. Secondly, the spatial resolution of AVIRIS (20 meters) is finer than that of TM and ETM+ (30 meters), necessitating a resampling procedure that would degrade and possibly introduce additional distortions to the image. Finally, the two images would be recorded at different times of the day, on different days, with different atmospheric conditions that would need to be corrected with different algorithms. Though it is likely that the cumulative effects of these differences would be small, they would no doubt introduce errors to the comparison.

A solution to all of these issues is not to use a Landsat image at all, but rather create a synthetic image that approximates its output. AVIRIS has 224 spectral bands between .4 and 2.45 μm at 10 nm intervals, and a spatial resolution of approximately 20 meters. In theory, then, an AVIRIS image contains all the information of a Landsat image for a given area. The atmospherically corrected AVIRIS image was used to create a synthetic TM and ETM+ image with a two-step process. First, the appropriate AVIRIS bands were combined to approximate the following Landsat bands:

Band 1: 0.45 - 0.52 μm (blue)
Band 2: 0.52 - 0.60 μm (green)

Band 3: 0.63 - 0.69 µm (red)
Band 4: 0.76 - 0.90 µm (near infrared)
Band 5: 1.55 - 1.75 µm (mid-infrared)
Band 7: 2.08 - 2.35 µm (mid-infrared)

Approximately 7 AVIRIS bands must be combined to form a single synthetic Landsat band, but these cannot be equally weighted. Each detector is most sensitive to the wavelength at the center of the sensor bandwidth, and progressively less sensitive to higher and lower wavelengths (Figure 2). Therefore the AVIRIS bands that fell in the middle of a Landsat band were weighed more than those that fell toward the edge of the band, according to a gaussian curve.

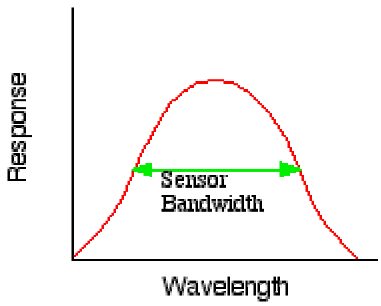


Figure 2: Sensitivity of a Sensor Band to a Range of Wavelengths

In the second step, the synthetic TM images were degraded to approximate the radiometric resolution present in actual TM and ETM+ (Table 2). AVIRIS has a far superior SNR than either Landsat sensor and therefore may outperform them even if spatial and spectral resolution has been equalized. The standard deviation of the spectrum over a fairly homogenous area, in this case a lake, provided an estimation of the noise present in each band of TM and ETM+. Gaussian noise images were created with a standard deviation equal to the noise of each band of each sensor over and above that of AVIRIS. These were added to each synthetic band to approximate the noise in the actual TM and ETM+ sensors.

Table 2: Standardized Noise Levels

Band #	AVIRIS*	ETM+	TM
1	1	2.64	11.4
2	1	7.07	16
3	1	7.79	8.43
4	1	6.48	8.06
5	1	10.41	25.4
7	1	16.38	38.3

* AVIRIS aggregated to Landsat bands.

Finally, the dynamic range of the images were degraded from 10 bits to 8 bits so that that values could theoretically range between 0-255 instead of 0-1023. The resulting synthetic images very closely approximated the spectral and radiometric resolution of actual Landsat images, only with a spatial resolution of 20 meters rather than 30 meters.

To reduce processing time and noise, a Minimum Noise Fraction (MNF) transform (Green *et al.* 1988) was performed on the AVIRIS cube and synthetic Landsat images. An MNF transform, similar to a principal components transform, derives a series of uncorrelated bands and segregates noise in the data. Unlike a principal components transform, a MNF transform equalizes the noise across bands so that image data with variance lower than noise is not hidden in higher bands. All MNF bands with an eigenvalue of less than 2 were eliminated since these bands contain mostly noise. The number of remaining bands equals the *dimensionality* of the image. In this case, the synthetic TM data had a dimensionality of 5, the synthetic ETM+ data had a dimensionality of 6, and the AVIRIS data had a dimensionality of 30. All subsequent analysis was conducted on these three reduced MNF images.

Classification Methodology

Myriad classification methods exist, and each with different benefits and restrictions. Unsupervised classification automatically separates land use into a number of computer-defined categories. Supervised classification assigns each pixel to a class by matching its spectra to that of a defined class. Linear spectral mixing derives pixel-by-pixel measures of "abundance" for pure materials. To confuse matters, each of these general classification methodologies has a number of different algorithms.

This study used a variety of supervised classification algorithms but focused on a single one: the maximum likelihood (ML) classifier. ML is a widely accepted classification method because of its robustness and simplicity. The classifier operates by determining the probability that a pixel belongs to each class and then assigns the pixel to the class with the highest probability (for technical details see Richards 1996). It assumes that the spectrum of each class is normally distributed and requires that the class be defined by a minimum n+1 training pixels for n spectral bands. Other classifiers, such as the Mahalanobis Distance and Minimum Distance classifiers, produced similar results, but a lower overall accuracy than ML and so are not fully reported. Furthermore, a method of linear spectral mixing was tried, but with mixed results (see Appendix 1).

Using the ML classifier and training samples for 8 classes, the images were classified and a confusion matrix was generated for each classified image. The classification system was a modification of Anderson Level II (Anderson *et al.* 1976) and used the following land use categories: residential, commercial/industrial, water, irrigated cropland, fallow, shrub and brush rangeland, herbaceous rangeland and grassland, irrigated urban. Land uses that did not appear in the scene were eliminated (e.g. forest land), others were merged (commercial and industrial) and two new ones were created (fallow and irrigated urban). Training samples with a minimum of 300 pixels were defined using the interiors of relatively homogenous features in each land use class. Next, the supervised classification was compared to a ground truth image with the same categories. This ground truth image was created with a hand classification of a USGS 8-meter digital orthophoto quarter quad (DOQQ), taken on October 4th 1999, 5 days after the AVIRIS flight. Information from the national land cover data set (NLCD) and several bands of the AVIRIS data itself were used in the hand classification process when the land use was not clear from the DOQQ alone.

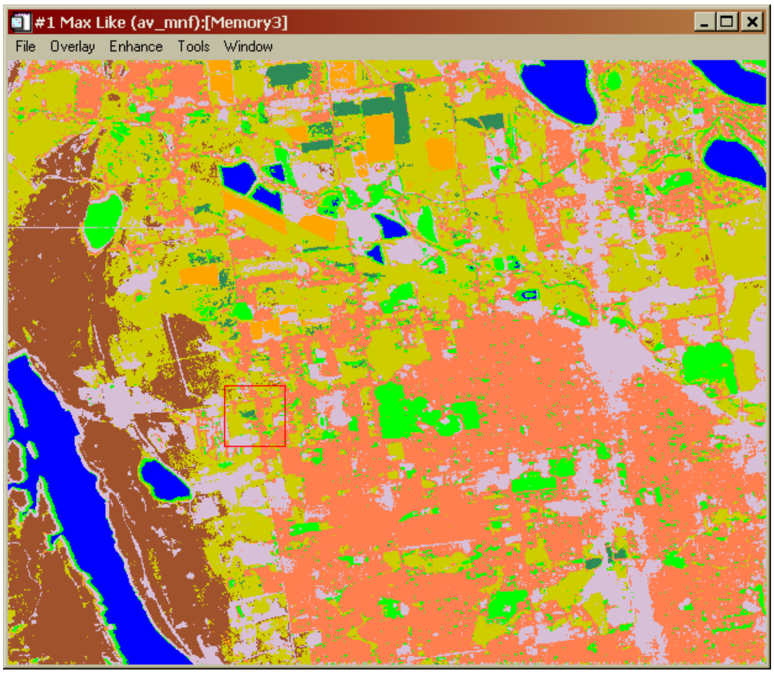
Results

Accuracy of a properly conducted supervised classification varies by category and typically ranges between 60%-90% depending on the classification scheme, the classifier, and the image itself. Using ancillary data, textural data, or post-classification rules may further increase the classification accuracy. These were not used in this study, however, since the goal was not to maximize classification accuracy, but to compare the performance of different image types with a commonly accepted classification procedure. Since the accuracy of the synthetic Landsat TM was virtually identical to that of the synthetic Landsat ETM+, only results for TM will be shown.

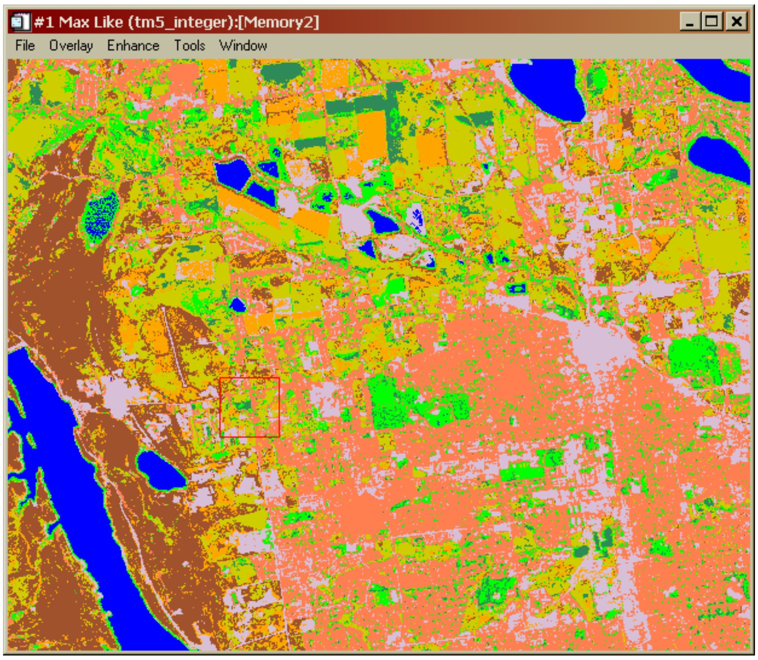
Visually, the ML classifications produced similar results, though the AVIRIS classification appears to have smoother edges and fewer isolated pixels (Figure 3). The accuracy assessment verified that the AVIRIS classification was superior to that of the synthetic TM image (Table 3). This remained true with all four classifiers tested, though not all classifiers performed the same.

Table 3: Classification Accuracy

	AVIRIS		Synthetic Landsat		Difference	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
Parallelpiped	35	0.25	30	0.19	5	0.06
Minimum Distance	72	0.64	64	0.54	8	0.10
Mahalanobis Distance	69	0.61	53	0.43	17	0.18
Maximum Likelihood	73	0.65	68	0.59	5	0.06



(a) AVIRIS



(b) Synthetic TM

Figure 3: Supervised Classification Using (a) AVIRIS and (b) Synthetic TM.

Water is blue, residential is pink, urban irrigation is light green, irrigated agricultural is dark green, fallow is orange, commercial/industrial is white, rangeland is brown, grassland is yellow.

Since ML was the most accurate and conservative, all subsequent results are reported from this classification. Using ML, classification of AVIRIS improved 5% over synthetic Landsat, while the Kappa coefficient (which compensates for correct classification by chance) increased from .59 to .65. With other classifiers the difference was even greater – the Mahalanobis Distance classifier provided a 17% increase in performance for AVIRIS. Overall, the ML classifier produced the highest classification accuracies for both AVIRIS and synthetic Landsat, and the difference between the two was the smallest.

At the class level, changes in classification accuracy varied widely (Table 4). Producer's accuracy measures the chance that a pixel is classified as '*x*' given that the ground truth indicates that it is '*x*'. It is sensitive to errors of omission. User's accuracy describes the chance that the ground truth images indicates that it is '*x*' given that it has been classified as '*x*'. It is sensitive to errors of commission.

Table 4: Percent Accuracy by Class (ML Classification)

	Producer Accuracy			User Accuracy		
	AVIRIS	TM	Change	AVIRIS	TM	Change
Residential	82	71	11	74	75	-1
Shrub/Brush	71	75	-5	92	75	18
Urban Irr	63	56	7	49	33	17
Fallow	66	77	-11	87	29	58
Herbaceous	59	55	4	70	65	5
Com/Indust	71	60	11	49	59	-9
Water	87	91	-4	100	99	0
Irrigated	72	68	4	73	36	37

Using the AVIRIS image, the producer accuracy improved in 5 of 8 classes but decreased for the other three. Built areas – residential and commercial/industrial – both improved by 11 percentage points, while urban irrigated areas improved by 7. At the same time, the classification accuracy of fallow decreased by 11 and shrub/brush decreased by 5. For these land covers, the classification using AVIRIS failed more often to identify the classes. Because a large portion of the image is composed of the classes that improved, however, the AVIRIS led to an improvement in overall classification accuracy.

User's accuracy benefited much more from AVIRIS than did producer's accuracy. Of the 8 classes, 4 strongly benefited from AVIRIS – fallow improved by 58 percentage points, while irrigated improved by 37, shrub/brush by 18 and urban irrigation by 17. Only commercial/industrial substantially decreased (-9%) in user's accuracy using AVIRIS. This indicated that there were fewer "false positives" of these vegetation and soil-based classes but more "false positives" for commercial areas.

The change in the confusion matrix between the two classifications reveals the details of the improvement in classification (Table 5). Along the diagonal, numbers indicate the change in classification accuracy by class for AVIRIS over synthetic Landsat. On the off-diagonal numbers show the change in misclassification; a negative number indicates that the classification does not confuse these classes as often using AVIRIS. Reading from top to bottom, one can assess where classification accuracy increased and where it decreased using AVIRIS. Overall, AVIRIS improved the ability to distinguish several easily confused classes including residential versus vegetated land uses; commercial/industrial versus fallow, shrub/brush, and residential; and urban irrigation versus irrigated crops and herbaceous rangeland.

Table 5: Change in Classification Matrix (ML Classification)

Synthetic TM → AVIRIS ↓	Residen-tial	Shrub/ Brush	Urban Irrigation	Fallow	Herbac-eous	Com/ Indust	Water	Irrigated Crops
Residential	11	0	6	2	10	-3	-3	7
Shrub/Brush	-3	-5	-1	-3	-8	-4	-1	-1
Urban Irrigation	-2	0	7	0	-2	0	1	-6
Fallow	-2	-7	-1	-11	-7	-4	0	0
Herbaceous	-4	3	-5	1	4	0	0	-4
Com/ Indust	0	9	2	11	5	11	8	1
Water	0	0	0	0	0	0	-4	0
Irrigated Crops	-1	0	-8	0	-1	0	0	4

The net improvement did not take place in all categories, however. Using AVIRIS, the classification accuracy of fallow decreased due to increased confusion with commercial/industrial. Shrub/brush was also more likely to be confused with commercial/industrial, though less likely to be confused with fallow.

Discussion

The classifications of the two images contained similar types of misclassifications. Residential areas were sometimes confused with vegetated land uses because both have mixtures of soil and vegetation. Similarly, commercial/industrial areas were sometimes confused with fallow and shrub/brush because all of these land uses may contain highly reflective exposed ground. Water was misclassified in places because differences in chlorophyll content, depth and turbidity sometimes gave it similar spectral characteristics to other classes. Urban irrigation was confused with irrigated crops and herbaceous rangeland because all have leafy plants high in chlorophyll that reflect strongly in the infrared. Since there are often many-to-one or one-to-many relationships between a spectrum and land use, these errors are common under almost any classification system or sensor. However, beneath the similarities, there were important differences between the classifications.

Overall, the results support the hypothesis that AVIRIS data contained information over and above synthetic Landsat that helped to improve classification accuracy for land use in this image. In terms of producer's accuracy, this improvement appeared to be most pronounced in land use classes with a large amount of vegetation such as residential land, urban irrigation, herbaceous grassland, and irrigated agriculture. The improvement in these classes most likely occurred because the signal of vegetation – part of the mix for all these classes – contained some distinction that only AVIRIS could pick up. This could be a distinct vegetation type, moisture content, stress level or other spectral characteristic that set a given land use apart from another land use. In addition, improvements in producer's accuracy tended to be in spectrally heterogeneous classes such as residential and commercial/industrial. Perhaps the

AVIRIS image was able to detect the full range of features that appeared in these classes. In addition to changes in producer's accuracy, the user's accuracy improved across most classes. The "false positives" decreased, in some cases dramatically, again perhaps because subtle signatures in the spectrum distinguished easily confused classes.

The decrease in accuracy for certain classes is more difficult to explain. For example, the producer's accuracy for fallow, water, and shrub/brush decreased with AVIRIS. In these fairly homogenous land uses, perhaps AVIRIS provided spurious spectral "clutter" that simply complicated classification, and provided no additional useful information over synthetic Landsat. Since the ML classifier was forced to choose a class for every pixel (e.g. no unclassified pixels), the additional information could potentially have decreased classification accuracy. The decrease in user's accuracy for commercial and industrial land is also difficult to explain. It is possible that certain spectral similarities between fallow and commercial/industrial are not evident in the wavelengths included in synthetic Landsat. In these cases, spurious similarities between the land uses would only be detected by AVIRIS.

Conclusion

In this study, a supervised classification with AVIRIS was more accurate than one with synthetic Landsat TM for land use classification at the urban fringe. Which image a researcher should choose, provided both are available, largely depends on the purpose of the study. If the goal is to accurately identify existing built and highly vegetated land covers – important for mapping sprawl, for example -- AVIRIS holds an apparent advantage. If the objective is to minimize "false positives" for land uses with a mix of soil and vegetation, AVIRIS again holds an advantage. On the other hand, AVIRIS produced a greater number of "false positives" for commercial/industrial land and performed poorly in classifications of relatively homogenous, less-vegetated land uses such as fallow and shrub/brush. If these are the classes of greatest interest, perhaps Landsat should be used.

Since classification accuracy is dependent on a number of factors besides resolution, caution should be used in extending the conclusions of this study to other research. For example, other classification systems such as the Food and Agriculture Organization's Land Cover Classification system (LCCS) or the V-I-S system will clearly yield different classification accuracies for the two sensors (see Di Gregorio 2000 and Ridd 1995 for a description of these classification systems). Furthermore, a different mix of land covers could be easier or more difficult to distinguish than those in this Colorado scene.

A final finding of this study is that the overall advantage of AVIRIS came not from its high radiometric resolution, but from its high spectral resolution. This further weakens the argument that land use mapping often does not benefit by high spatial resolution imagery. Furthermore, it indicates that future satellites used for land use mapping, such as upcoming Landsat missions, should include detectors with high spectral resolution.

Appendix 1: Linear Mixing With Mixture Tuned Matched Filtering

In addition to the supervised classification described in this study, I compared the performance of the two images using Mixture Tuned Matched Filtering (MTMF), a specialized procedure for linear spectral mixing. Unlike ML, which classifies pixels in hard categories, MTMF derives the abundance of specified endmembers. The results were mixed, and the techniques are new so these procedures were not used in the main study. They could, however, be used in later research.

To conduct the MTMF, the “hourglass” procedure was used (see Boardman 1995). This procedure consists of three steps: an MNF transform, a pixel purity index, and the actual MTMF mapping process. The MNF transform is similar to a principal components transform only it ensures that each band has an identical noise level. The pixel purity index (PPI) is an iterative procedure that helps find pixels that are the spectrally pure, rather than mixtures. These pixels were then displayed in an *n*-dimensional visualization (*n* is equal to the number of bands in the MNF transformed data), which projects a rotating plot the pure pixels onto the screen. Using the *n*-d visualization and the image, I selected pixels representing endmembers or “pure” materials.

The final step of the “hourglass” procedure is to map endmembers. The maximum number of endmembers that may be identified in an image is equal to $n+1$, where n is the number of bands. In this case, the AVIRIS image had 16 endmembers, 10 of which were associated with urban features, 3 of which were associated with water and shore and 3 of which were associated with irrigated agriculture. The TM image, in contrast, consisted of 4 endmembers: water, irrigated agriculture, grassland, and built. Images of the abundance of these materials were generated using the MTMF algorithm. Finally, land use was mapped by creating a R-G-B composite, using red for “built” abundance, green for “irrigated agriculture” abundance and blue for “water” abundance. When a single category contained multiple endmembers, these abundance images were added together. For example, in the case of AVIRIS the abundance images of all 10 endmembers associated with the built environment were summed to create a single image of abundance of built materials.

It was clear that this method was probably not appropriate for heterogeneous land covers. The AVIRIS image showed gross misclassification throughout (Figure 4). A handful of irrigated agricultural plots were correctly identified (in green), but others were mistaken for built areas. Water was poorly mapped because lakes have different spectral signals depending on depth, algae content and other factors. Built areas were poorly mapped, perhaps because of the lack of representitiveness of the built endmembers. These were derived from large urban structures (parking lots, strip malls, etc.), rather than from residential structures, which are generally mixed with trees and vegetation and thus not the "purest" pixels. These residential structures may be composed of different materials.

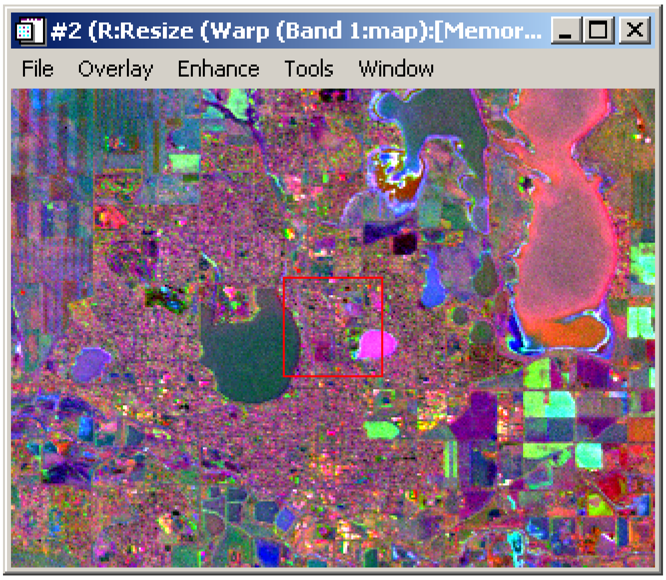


Figure 4: Abundance of endmembers from AVIRIS image.
Red is urban, green is irrigated agriculture and blue is water.

Surprisingly, the MTMF procedure produced better results with TM than with AVIRIS (Figure 5). Water was well classified. Built areas appeared as red and mixtures of red, though were sometimes difficult to see. Irrigated agricultural land appeared as dark green, while fallow fields with little living vegetation appeared as light green.

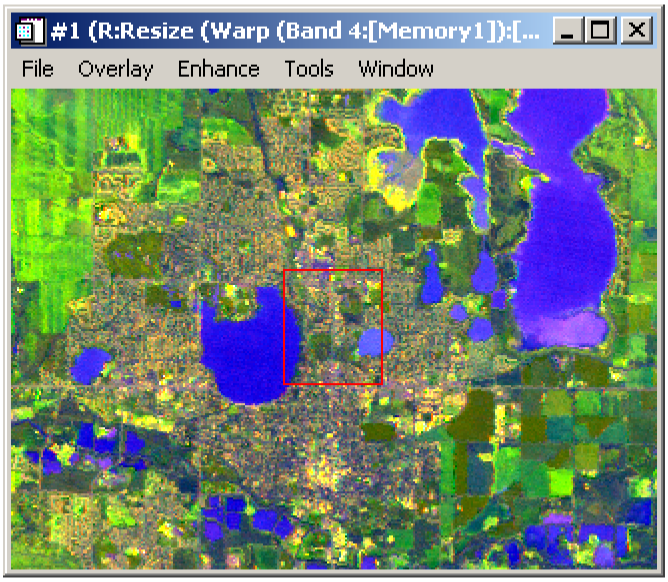


Figure 5: Abundance of endmembers from TM image.
Red is urban, green is irrigated agriculture and blue is water.

Methods of linear mixing show great promise for mapping of land use, but several problems remain. First, the maps created by this procedure are visual representations that are difficult to interpret quantitatively or to validate. To address this, statistical links could be drawn between the abundance of endmembers and land uses. However, this would move the procedure back into the realm of supervised classification and eliminate the additional information that MTMF derives. A second problem is that, surprisingly, the procedure did not work well with AVIRIS data. One possible explanation for this is that there is a substantial amount of non-linear mixing of the endmembers detected by AVIRIS. For example, a highly reflective surface could “draw up” a pixel’s spectrum even though it may cover only a small portion of the pixel. This would cause a pixel to show high abundance for small or spurious land covers. Because of these current limitations, the MTMF procedure was not appropriate for this study.

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