Reprinted from

Ninth International Symposium

Machine Processing of

Remotely Sensed Data

with special emphasis on

Natural Resources Evaluation

June 21-23, 1983

Proceedings

Purdue University
The Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907 USA

OPTIMAL LANDSAT TRANSFORMS FOR FOREST APPLICATIONS

T.L. LOGAN

Jet Propulsion Laboratory
Pasadena, California

A.H. STRAHLER

Hunter College
New York, New York

ABSTRACT

In agricultural applications of remote sensing, linear transforms of Landsat data, such as those of Kauth and Thomas, are known to be highly effective both for data compression and enhancement of crop identification accuracies. Typically, such transforms are based on the time-trajectory of crop pixels through measurement space as the crop increasingly obscures the soil, matures, scenesces, and is harvested. In natural vegetation applications, temporal variations are less important-- life-form differences among vegetation types lead to distinctive signatures for natural vegetation types that are more or less distinctive, independent of season. However, vegetation signatures are greatly influenced by their topographic position on the landscape, due to factors of differential illumination and complex bidirectional reflectance distribution functions. Thus, the question arises whether there are one or more transforms of Landsat data, beyond those already explored, that can accentuate the separability of natural vegetation classes in areas of diverse topographic relief. To answer this question, we investigated eleven transforms of four Landsat MSS channels.

Two contrasting methods were employed to rate the information content of the eleven transforms and four raw Landsat channels: divergence analysis and classification accuracy. Although the divergence analysis appeared to be quite sensitive to minor variations in computation induced by quantization of the raw Landsat data, divergence values were highest for the three transforms (9, 10, and 11) in which the second eigenvector, E2, appeared in the denominator. This result suggests that the second eigenvector performs a useful scaling function. For the Landsat image analyzed, the second eigenvector emphasizes the difference between MSS7 and the weighted sum of MSS4 and MSS5. Since this linear function is orthogonal to the first eigenvector, which weights all MSS bands positively and accounts for the overall "brightness" of the image, it reduces the effects of shadowing and differential illumination on vegetation signatures, producing the observed enhanced values for divergence.

In accuracy analysis, transform 11, the ratio of MSS4 and 5 and MSS6 and 7 averages (RAVE) divided by the second eigenvector (E2), archieved highest accuracies, followed by raw MSS4 and MSS5 bands. Band ratios such as RAVE are known to reduce the effects of differential illumination, but do so in a fashion clearly different from linear compounds such as E2. Since only one multichannel transform performed better than the two raw Landsat channels, the results suggest that transforms should be chosen with care for a particular application to natural vegetation.

This paper represents one phase of research carried out under NASA Contract NAS7-918 with the support of California Institute of Technology President's Fund Award PF-168.

1.0 BACKGROUND

Resource managers of state, federal, and private agencies constantly face the need to assess and inventory large areas of natural land cover in a timely and cost-effective manner. Thus far, Landsat classifications have been helpful in providing the data needed for such inventories. However, classification accuracies degrade when classification must distinguish between land cover classes which are similar in vegetation form and pattern, but differ in species composition. Spectral information alone is often insufficient to accurately distinguish stands of different coniferous tree species, or to differentiate various types of chaparral. This failure can make resource management difficult when the stands or vegetation types require widely different management practices.

Early research in the Doggett Creek vicinity of the Klamath National Forest (Strahler, et al., 1978) demonstrated that the incorporation of U.S. Geological Survey-Defense Mapping Agency elevation and derived compass-aspect information with multidate Landsat spectral data in conventional supervised classification of western North American forest species could produce average accuracies as high as 85 percent. The use of elevation data with spectral data in unsupervised classification, however, resulted in the swamping of spectral information by the topographic data.

Subsequent research (Strahler, 1981) showed that a standard deviation texture channel (derived from MSS5) combined with Landsat spectral data in an unsupervised procedure could produce classes that differentiated timber stands of uniform height and density reasonably well. When combined with an image predicting regional forest type (which denotes species composition) using elevation and aspect data, accurate timber stratum maps resulted that could be used to allocate timber volume samples as well as provide other forms of useful timber management information.

The combination of spectral tone, spatial texture and independent terrain information, therefore, appears to provide sufficient information for automatic characterization of natural vegetation resources. Tone is most important for recognizing the existence and presence of a feature. Texture combines with tone to measure local tonal variation. The topographic terrain information provides a powerful independent parameter well known for improving forest classification accuracies.

The work of several researchers in agriculture (Kauth and Thomas, 1976), geology (Soha and Schwartz, 1978) and forestry (Deering, et al, 1975) have suggested that certain transforms of Landsat data can enhance inherent information or at least permit a reduction in the number of data channels without substantial data loss (data compression). Use of such transforms offers a potential for improved classification accuracy with reduced computer costs. A single enhanced channel could prove particularly useful as a base for the standard deviation texture convolution. The purpose of this research is to investigate several of the better known Landsat transformations and assess their utility for accentuating the separability of general coniferous forest and related vegetation classes.

The computer processing for this research was carried out at JPL and UCSB using the Video Image Communication and Retrieval (VICAR) image processing system. Under continual development at JPL for the past ten years, the VICAR system was originally designed for enhancement of satellite pictures from the national's unmanned space exploration programs such as Mariner, Viking and Voyager. VICAR manipulates digital images expressed as eight-bit bytes, ranging in value from zero to 255. As part of the log-in procedure under which Landsat images in CCT format are converted to VICAR format, six and seven-bit sensor values are stretched to eight bits.

1.1 STUDY AREA

The study area used in this research is located in the Doggett Creek vicinity of the Klamath National Forest. The area comprises about 220 sq. km. of private and publicly-owned forest land in Northern California near the town of Klamath River. Located within the Siskiyou Mountains, elevations in the area range from 500m at the Klamath River, which crosses the southern portion, to 2065m near Dry Lake lookout on an unmanned summit.

A wide variety of distinctive vegetation types are present in the area. Life-form classes include alpine meadow, fir park, pasture, cropland, and burned, reforested areas. Forest vegetation includes, from high elevation to low elevation, such types as noble fir, mixed fir (noble, red and white), douglas fir, ponderosa pine-incense cedar, pine-oak, and oak-chaparral. Thus, the topographic and vegetational characteristics of the area are well differentiated.

2.0 LANDSAT TRANSFORMS

A textural transform of the type used by Strahler, et al. (1979) can provide transformed information only at a level relative to the amount present in the original data. A channel endowed with more pertainent information than another will provide more textural information after transformation. Landsat data, however, contain a range of vegetation reflectance information apportioned over four separate bands coverting the 0.5 to 1.1 micron wavelengths. While MSS4 band provides most coniferous vegetation information, there is still important data to be found within the MSS5 and infrared channels. Producing textural transforms of all four bands would provide too much non-vegetation information as well as over emphasize the redundant nature of Landsat data due to high channel intercorrelations. The redundant property of Landsat data, however, makes it a candidate for data compression. A single channel of compressed Landsat data could provide a powerful foundation for a textural transform.

Many techniques such as ratioing, principal components and discriminant analysis, have been used for the purpose of removing redundancy while retaining desired information. The success rate tends to vary with the purpose and procedure that are utilized. Considerable success has been reported in the literature when the emphasis has been on enhancing one particular feature such as gypsy moth defoliation (Williams, et al., 1979) or the urban/rural boundary (Friedman, 1980). Often, enhancement of one feature coincidentally enhances another. In this research, several of the more common compression techniques are investigated to determine if any have the potential for condensing Landsat data into a single channel which enhances the range of coniferous species-type classes. Fifteen channels of data are investigated.

Two families of data compression procedures have tended to be most popular largely because of the ease with which they can be formed: ratioing and principal components analysis (PCA). The most common ratio for vegetation purposes is:

$$(1) \quad \frac{MSS\ 5}{MSS\ 6}$$

(or visa versa or MSS7 in lieu of MSS6) as suggested by Kriegler, et al., (1969), Billingsley (1973), Vincent (1973) and Maxwell (1976). The ratio:

$$(2) \quad \frac{MSS\ 5}{MSS\ 4}$$

has also been used to emphasize just the key vegetation channels within Landsat data. A slight variation of this theme which retains the use of all four bands is the ratio of averages (RAVE):

$$(3) \quad \frac{\frac{MSS4 + MSS5}{2}}{\frac{MSS6 + MSS7}{2}}$$

and the ratio of sums divided by the differences (RASD):

$$(4) \quad \frac{(MSS4 + MSS5)\ /\ (MSS6 + MSS7)}{(MSS6 + MSS7) - (MSS4 + MSS5)}$$

Richardson and Weigand (1977) evaluated several vegetation models and found TV16 (Transform Vegetation Index with MSS6) as suggested by Rouse, et al.,(1973) and Deering, et al.,(1975) to be the most useful for estimating relative greeness:

$$(5) \quad \sqrt{\frac{MSS6 - MSS5}{MSS6 + MSS5} + 0.5}$$

They also developed the PV16 (Perpendicular Vegetation Index) to distinguish the spectral response of green vegetation from the response contributed by background soils:

$$(6) \quad \sqrt{(SOIL5 - MSS5)^2 + (SOIL6 - MSS6)^2}$$

where: $SOIL5 = -0.498+0.543*MSS5+0.498*MSS6$

$SOIL6=2.734+0.498*MSS5+0.498*MSS6$

Ratioing techniques are popular because they can often be easily performed digitally as well as photographically, and they also tend to reduce the effects of shadowing and atmospheric degradation.

Principal Components Analysis (PCA) techniques have also been found to be useful for data compression (Ready and Wintz, 1973, Fontanel, et al., 1975, and Jenson and Waltz, 1978). Principal components seeks to determine the best orthogonal linear combinations of data which can account for more variance in the data as a whole than any other linear combinations. The principal component was automatically scaled after transformation so that its histogram assumed a distribution centered at DN of 128, and the spread encompassed the full 256 DN range. With Landsat data, the first principal component:

(7) .2120*MSS4 +.2962*MSS5+.6051*MSS6 + .7079*MSS7 (E1)

weights all four channels positively according to the magnitude of their standard deviations. It thus generally reflects overall brightness, and is likely to be strongly influenced by differential illumination. The second principal component:

(8) .4648*MSS4+.7847*MSS5-.0753*MSS6- .4032*MSS7 (E2)

emphasizes the difference between visible and infrared bands; and contains the feature-specific information derived from the four Landsat channels that is the most useful PCA contribution to feature data compression. Haralick, et al. (1972) found that of the several transforms he tested, the principal components procedure best approximated the original picture.

A variation of the above ratioing and PCA techniques combines the two to produce the following channels:

(9) MSS5 / E2

(10) (MSS5 / MSS6) / E2

(11) RAVE / E2

Conceivably a synergism could occur as a result of transforming the four Landsat channels by the two very different mechanisms, and ratioing the two products (as in the case of RAVE/E2).

The last four channels of data to be tested consist of the Landsat bands, included so as to provide a scientific control to the experiment as well as provide a relative measure with which to rate and evaluate the merits of the other channels. Most remote sensing scientists are familiar with the relative information content of these channels, and can therefore use them to place the ratio and PCA channels in perspective.

3.0 TRANSFORM EVALUATION

Two constrasting methods were employed to rate the information content of the fifteen selected channels. The first is a divergence analysis test and the second is back-classification of the training sites. Both methods use training site data as the basis for their calculations.

3.1 DIVERGENCE ANALYSIS

Divergence analysis uses a covariance-weighted distance measure of class means to determine the total separability of class categories within a given channel. The total divergence value that is calculated can then be used to rate the individual channels, with the underlying assumption being that, for the purposes of this research, greater separation is an indication of more "information." Divergence analysis has been employed by Shlien, et al., (1973) and Goodenough and Narendra (1976), and is a common-place practice among users of LARSYS.

Results of the divergence analysis are reported in Table I, but are not considered reliable. The technique requires that the spectral data within the training sites have a Gaussian distribution. This is a common requirement among multivariate techniques including maximum likelihood classification that is often relaxed because it is virtually impossible to obtain. However, there are limits to which the Gaussian rule can be relaxed. The fundamental problem in this case lies with the nature of natural vegetation. Unlike agricultural training sites which tend to be homogeneous, well defined, and easily delineated, natural vegetattion nearly always has a high variation due to spacing of the vegetation (which lets in ground signature), modulating height, health, and other factors. Every effort was made in the selection of training sites to make them as homogeneous and demonstrative of the class to which they represent. However, many of the variations typical of natural vegetation do not appear in a single Landsat channel. Thus, training sites delineated based on MSS5 that look homogeneous is MSS5 may be rather heterogeneous when viewed in MSS7 or MSS4. This problem is particularly compounded in the ratio process when the second eigenvector image is involved. When a set of overlaying pixels from the four Landsat bands are very contrasting, the principal components process can produce an unusual grey value (DN). When such an odd DN is divided into its band 5 counterpart (as in the case of 5/E2), a very large or small output DN value may result that is uncharacteristic of the surrounding norm (Figure 1). If this high variance pixel falls in a training site, it will artificially raise or lower the mean of the training class. The divergence analysis technique, which relies on the class means for determining separability, will then be inflated producing unreliable results. Thus, divergence analysis is likely to be misleading in the analysis of classes of natural vegetation.

3.2 CLASSIFICATION TEST

Back-classification of training sites is a technique that allows easy and rapid comparison of relative accuracies; however, its use for measuring absolute accuracies is suspect. The technique employs the same training sites areas utilized in the classification process to determine the number of correctly classified pixels. Thus, the same set of data used to train a classifier is also used to evaluate it. While this method has obvious short-comings for evaluating the exact accuracy of a classification, it is an acceptable technique when relative accuracies are to be compared.

The results of separately back-classifying the fifteen channels are shown in Table I. As would be expected for single channel classifications, the numerical accuracies are low. No "tuning" of the classifications was performed to enhance accuracies.

3.3 RAVE/E2 ANALYSIS

Of the fifteen channels investigated, the RAVE/E2 (Figure 2) contained the most vegetation information, with an average classification accuracy of 13.2% compared to 11.7% for the closest rival. This channel represents an enhancement in information over the raw Landsat classification. This is apparent from the number two position of MSS4, which theoretically should be the best single Landsat band for vegetation because of the strong reflectance peak of coniferous forests at 0.55 microns. Channels scoring lower than MSS4 would indicate a loss of information content, and channels scoring higher would represent a gain in information.

Other evidence suggesting utility for the RAVE/E2 channel can be found by looking at the percentages of unclassified pixels. In addition to having the highest classification accuracy, the RAVE/E2 channel also had the lowest percentage of unclassified pixels: 37.9%. This compares to 41.7% for MSS4 and 58.9% for MSS5. Thus, not only did the RAVE/E2 channel classify more pixels than the other channels, but it also classified a higher percentage of them correctly.

The mechanism which gives the RAVE/E2 channel an advantage over the others is likely related to an overall reduction in the effects of shadowing. Comparison of the transformed image with the original Landsat band 5 suggest that several of the steeper slopes that appear darker in the original imagery are being equalized in grey tone with related timber types on flater slopes in the transformed image. Indications of this effect appear in the left-middle bottom and upper middle-right edge of the imagery, where opposing slopes of similar types but differing DN due to shadowing in the original imagery receive similar DN in the transformed data. Classification accuracy would certainly be expected to improve if similar timber types on differing slopes were to receive similar DN ranges.

An overall reduction in the effects of shadowing could be expected from the RAVE/E2 channel. When shadowing affects all four Landsat bands equally, ratioing is known to remove most of the negative effects. At the same time, the second eigenvector from PCA displays most of the information left after overall brightness, as influenced by relative illumination, is accounted for in the first eigenvector image. Note that topographic shadowing is very evident in the first eigenvector image (Figure 3) when compared to the second eigenvector (Figure 4). It would, therefore, seem very plausible that the ratio of two transforms that are each known to compensate for differential illumination in a unique way could result in a synergistic output of superior quality to either taken separately. Further research is necessary to fully investigate and confirm this hypothesis.

The quality of the RAVE/E2 channel is heavily influenced by the PCA factor loadings. Variations in these values due to the presence or absence of clouds or snow, for example, could negatively or positively effect the discrimination capability of the RAVE/E2 channel. Table II shows the varying results that such effects can have. A minor change in the infrared loadings (.4648, .7847,-.0752, -.4031) improved classification performance to 14.0%, and had an effect in helping to discriminate open canopy Ponderosa Pine (POP_o). The number of unclassified pixels dropped to 33.2%*. Other changes had significantly negative effects. Rounding the factor loadings to (.5000, .8000, 0,-.4000) produced the worse average coniferous classification accuracy of 4.6%

Indiscriminant scaling during creation of RAVE/E2 can also have deleterious effects. Throughout all ratio channel processing, the attempt was made to produce an output standard deviation that was close to or within the Landsat range, since previous research had indicated that channels with extremely small local standard deviations, such as those typical of digital elevation, could easily swamp spectral data in an unsupervised classification operation. Thus, the RAVE portion of the RAVE/E2 transform was multiplied by 110, and after division by E2 (which was initially scaled), the quotient was multiplied by 60 (denoted as 110;60). This produced a standard deviation resonably close to the range of Landsat standard deviations.

The (110;60) scaling combination produced the best results for the RAVE/E2 channel. A neutral scaling of (100;100) produced poor results substantiating the need for a scaling of some design. Minor adjustments (Table II) to (100;60) and (100;50) produced some rather significant changes in individual category accuracies suggesting that like PCA, ratio scaling is a critical component of the channel transformation process.

That ratio transforms can provide a valuable tool for selective enhancement of specific features is very evident in this research. While the RAVE/E2 channel would appear to offer the best all around general enhancement of coniferous forest vegetation, the (5/6) / E2 channel might be better for examination of open canopy douglas fir, or the green band for high and low density white fir. The best channels for specific conifer and general vegetation types are highlighted in Tables I and II.

4. CONCLUSIONS

Coniferous Landsat data can be compressed into a single channel containing more information than any of the original individual inputs using the following transform (RAVE/E2):

$$\left(\frac{(((MSS4+MSS5)/2)/((MSS6+MSS7)/2)*110)}{\text{Second Eigenvector}}\right)*60$$

where the second eigenvector has linear factor loadings of (.4648,.7847, -.0752,-.4031) and was scaled to spread the distribution over 256 DN levels with the center at 128. This information gain appears to be unique among similar transforms discussed in the literature, which all suffer an informational loss during the compression process. However, RAVE/E2 is a technologically complex channel to generate, and considering the radiometric variation common between Landsat scenes, it it unlikely that the PCA loading disclosed here would be of wide applicability. It is probable that Landsat MSS4 which ranked second best in coniferous information content is the best all-around dependable single channel of data. The extra effort to utilize transformed Landsat channels will probably provide only a subtle, if any, improvement in average classification accuracy. For enhancement of specific classes, the use of certain transforms may be quite beneficial (Table I). But for the general classification of coniferous forest Landsat data, the raw channels will probably provide a result comparable to the best of any classification based on transformations of the raw channels tested herein.

5.0 REFERENCES

1. Billingsley, F.C., 1973. "Some Digital Techniques for Enhancing ERTS Imagery," Management and Utilization of Remote Sensing Data. Symposium of the American Society of Photogrammetry, Sioux Falls, South Dakota.

2. Deering, D.W., J. Rouse, Jr., R. Haas and J. Schell, 1975. "Measuring 'Forage Production' of Grazing Units from Landsat MSS Data," in: Proceedings 10th International Symposium on Remote Sensing of Environment, Environmental Research Institute of Michigan, Ann Arbor, pp. 1169-1178.

3. Fontanel, A., C. Blanchet and C. Lallemand, 1975. "Enhancement of Landsat Imagery by Combination of Multispectral Classification and Principal Component Analysis," in Proceedings NASA Earth Resources Symposium, Vol. 1-B, NASA TMX-58168, pp. 991-1012.

4. Friedman, Steven Z., 1980. Mapping Urbanized Area Expansion Through Digital Image Processing of Landsat and Conventional Data, JPL Publication 79-113, NASA Jet Propulsion Laboratory, Pasadena, California.

5. Goodenough, David and P.M. Narendra, 1976. "Feature Subset Selection in Remote Sensing," Pre-

*Part of the seemingly large percentage change occurring here may be due to the statistically small number of pixels in some of the training classes.

sented at the Milwaukee Symposium on Automatic Computation and Control.

6. Haralick, R.M., J.D. Young, D.K. Goel, and K. S. Shanmugam, 1972. "A Comparative Study of Data Compression Techniques for Digital Image Transmission," in Fourth Annual Earth Resources Program Review, Vol. II, Chapter 38, NASA-TM-X-68397 p. 27-33.

7. Jenson, S.K., and F.A. Waltz, 1978. "Canonical Analysis and Principal Components Analysis in Remote Sensing," Prepared under U.S. Geological Survey Contract No. 14-08-0001-16439, by Technicolor Graphic Services, Inc., Sioux Falls, South Dakota.

8. Kauth, R.J., and G.S.Thomas, 1976. "The Tasselled Cap -- A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as seen by Landsat, " in: Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafeyette, Indiana, (June-July).

9. Kriegler, F.J., W.A. Malila, R.F. Nalepka and W. Richardson, 1969. "Preprocessing Transformations and their Effects on Multispectral Recognition," in Proceedings of the Sixth International Symposium on Remote Sensing of Environment, Environmental Research Institute of Michigan, Ann Arbor, pp. 97-122.

10. Maxwell, E.L., 1976, "Multivariate System Analysis of Multispectral Imagery," Photogrammetric Engineering and Remote Sensing, Vol. 42, No. 9, September, pp. 1173-1186.

11. Ready, P.J., and P.A. Wintz, 1972. "Information Extraction, SNR Improvement, and Data Compression in Multispectral Imagery," IEEE Transaction on Communications, Vol. COM-21, No. 10, October, pp. 1123-1130.

13. Richardson, A.J., and Cl.L.Wiegand, 1977. "Distinguishing Vegetation from Soil Background Information, "Photogrammetric Engineering and Remote Sensing, Vol. 43, No. 12, December, pp. 1541 -1552.

13. Rouse, J.W., R.H. Haas, J.A. Schell and D.W. Deering, 1973. "Monitoring Vegetation Systems in the Great Plains with ERTS," in The Third Earth Resources Technology Satellite-1 Sympsoium, Vol. 1, NASA Goddard Space Flight Center, Maryland, pp. 309-317.

14. Shlien, Seymour, and David Goodenough, 1973. "Automatic Interpretation of ERTS-A Imagery Using the Maximum Likelihood Decision Rule", Canada Centre for Remote Sensing Research, Report 73.2.

15. Soha, J.M., and A. Schwartz, 1978. "Multispectral Histogram Normalization Contrast," in: Proceedings of the Fifth Canadian Symposium on Remote Sensing, Victoria, British Columbia, (August).

16. Strahler, A.H., 1981. "Stratification of Natural Vegetation for Forest and Range land Inventory Using Landsat Digital Imagery and Collateral Data; International Journal of Remote Sensing, Vol. pp. 1515-41.

17. Strahler, A.H. T.L. Logan and N.A. Bryant, "Improving Forest Classification Accuracy from Landsat by Incorporating Topographic Information," in Proceedings Twelfth International Symposium on Remote Sensing of Environment, Environmental Research Institute of Michigan, Ann Arbor, Michigan, pp. 927-942.

18. Strahler, A.H., T. L. Logan and C.E. Woodcock 1979. "Forest Classification and Inventory System using Landsat, Digital Terrain, and Ground Sample Data," in Proceedings Thirteenth International Symposium on Remote Sensing of the Environment, Environmental Research Institute of Michigan, Ann Arbor, Mich., pp. 1541-1557.

19. Vincent, R.K., 1973. "Ratio Maps of Iron Ore Deposits Atlantic City District, Wyoming," in Symposium on Significant Results Obtained from the Earth Resources Technology Satellite-1, Vol. 1, SP-327, NASA Goddard Space Flight Center, Greenbelt, Maryland, pp. 379-386.

20. Williams, D.L., M.L. Stauffer, and K.C. Leung 1979. "A Forester's Look at the Application of Image Manipulation Techniques to Multitemporal Landsat Data," in Fifth Machine Processing of Remotely Sensed Data Symposium, LARS, Purdue University, West Lafayette, Indiana, pp. 368-376.

BIOGRAPHICAL DATA

Thomas L. Logan is a geographer with eight years of experience working in the Earth Resources Applications Group of the Image Processing Applications and Development Section at the Jet Propulsion Laboratory. His emphasis has centered on the remote sensing and image processing of forestry and range applications, as well as general Geographical Information Systems technology, texture analysis, classification techniques, and cartographic applications. Mr. Logan received his B.A. degree in Geography from the California State University, Northridge, in 1976. He received his M.A. degree in 1978 from the University of California at Santa Barbara, where he is currently progressing toward a Ph.D.

Alan H. Strahler is the chairman of the Department of Geology and Geography at Hunter College, City University of New York. His emphasis has centered on the remote sensing of biogeographical topics including forest and range applications, canopy modelings, physical geography, image classification and segmentation, and general Geographical Information Systems technology. Dr. Strahler received his BA and PhD in Geography from Johns Hopkins University, and taught for six years at the University of California, Santa Barbara. He is the joint author of several physical geography textbooks.

TABLE I - CLASSIFICATION AND DIVERGENCE RESULTS

Overall and individual classification accuracies for each of the fifteen tested data channels are provided below. Outlined boxes highlight the best channel for a given class category. Total divergence scores are not considered reliable.

	CHANNEL	Hd	DF_O	POP_O	WF_O	RF_O	RF_C	WF_C	DF_C	POP_C	MEAD	SPARSE	SMALL TREES	GRASS	SCALING	AVERAGE CONIFEROUS ACCURACY	AVERAGE OVERALL ACCURACY	TOTAL DIVERGENCE
1	RAVE/E2	$\boxed{19.0}$	$\boxed{18.1}$	0	11.1	$\boxed{29.7}$	$\boxed{19.2}$	12.8	5.2	9.4	$\boxed{16.6}$	$\boxed{37.4}$	0.5	0	110;60	13.2	13.8	1153
2	GN	15.6	11.1	0	$\boxed{17.0}$	2.1	$\boxed{19.2}$	$\boxed{21.0}$	12.7	$\boxed{10.3}$	7.6	13.7	0	$\boxed{19.3}$	-	11.7	11.5	690
3	RD	10.6	10.0	8.0	10.0	4.2	13.2	10.6	11.9	6.6	4.8	5.9	6.0	7.1	-	9.3	8.4	836
4	E/E2	15.3	7.4	0	16.4	17.0	15.6	3.0	0	1.8	0	3.6	1.1	11.5	100	7.65	7.1	952
5	5/6	6.9	5.9	4.5	5.8	12.7	10.8	6.7	11.5	0	9.0	9.2	8.8	6.2	90	7.2	7.5	760
6	RAVE	10.6	5.9	3.8	4.7	10.6	10.8	12.1	2.7	2.8	8.3	1.5	6.0	5.6	110	6.7	6.6	724
7	TVI6	8.3	5.1	6.2	8.2	8.5	9.6	6.7	8.3	0	5.5	1.7	9.9	3.4	200	6.6	6.3	755
8	IR2	9.2	5.1	4.5	6.4	14.8	9.6	0	6.7	4.7	0	5.8	1.1	2.1	-	6.5	5.4	645
9	5/6/E2	18.2	2.9	$\boxed{13.6}$	0	10.6	14.4	3.0	2.0	2.8	11.1	14.1	1.1	19.0	90;100	6.2	8.7	1025
10	5/4	10.1	7.4	0	11.1	0	0	8.2	$\boxed{14.3}$	2.8	7.6	11.8	0	3.4	100	5.5	5.9	711
11	RATSD	15.3	10.0	6.2	0	8.5	7.2	0	7.5	0	5.5	5.3	$\boxed{32.5}$	4.6	20	4.9	7.9	800
12	E2	5.7	4.8	3.1	5.8	6.3	0	8.8	4.3	2.8	4.8	5.3	3.3	5.0	-	4.5	4.6	794
13	PVI6	7.8	5.5	4.8	7.6	4.2	6.0	0	3.5	0.9	0	5.1	5.5	5.3	1.9	4.1	4.3	625
14	IR1	7.8	6.6	0	4.7	6.3	2.4	8.5	4.3	0	3.4	5.3	3.8	6.8	-	4.1	4.6	610
15	E1	1.7	3.3	1.3	2.9	2.1	1.2	0.9	0.7	0	2.0	6.1	2.2	3.4	-	1.6	2.1	662
Number of Training class Pixels		383	268	286	169	47	83	327	250	105	144	633	179	320				

TABLE II - PCA AND SCALING EFFECTS

Overall and individual classification accuracies for each of the fifteen tested data channels are provided below. PCA Test assumes (110;60) Scaling. Scaling test uses PCA factor loading of (.4648, .7847, -0.753, -.4032). Outlined boxes highlight the best channel for a given class category.

PCA TEST

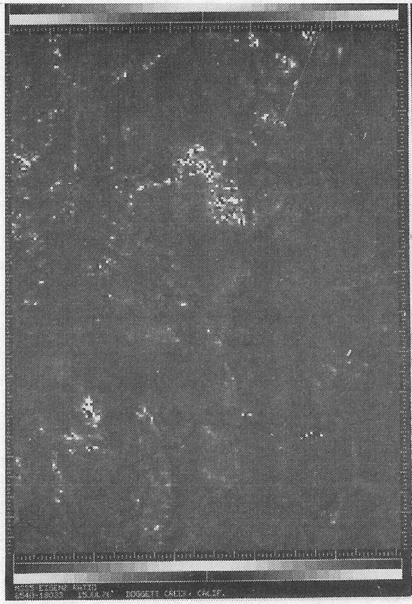
Hd	DF_O	POP_O	WF_O	RF_O	RF_C	WF_C	DF_C	POP_C	MEAD	SPARSE	TREES	GRASS	PERCENTAGE UNCLASSIFIED	AVERAGE CONIFEROUS ACCURACY	AVERAGE OVERALL ACCURACY	PCA FACTOR LOADINGS
19.0	18.8	$\boxed{9.4}$	12.3	29.7	18.0	10.6	4.0	$\boxed{9.4}$	15.9	37.6	0	0	33.2	14.0	14.2	.4648, .7847, -.0752, -.4031
19.9	16.6	0	8.8	0	18.0	10.0	$\boxed{5.2}$	$\boxed{9.4}$	15.9	36.8	0	0	47.5	8.5	10.8	.4648, .7847, -.0742, -.4021
18.4	19.6	0	9.4	0	16.8	13.4	3.2	5.6	17.3	36.8	0	0	45.9	8.5	10.8	.4648, .7847, -.0762, -.4041
19.3	18.8	0	10.5	0	18.0	12.1	3.2	5.6	16.6	36.8	0.5	0	45.5	8.5	10.9	.4638, .7837, -.0752, -.4031
21.0	15.9	0	9.4	0	18.0	12.5	4.7	5.6	15.9	23.9	0	0	51.5	8.3	9.8	.4658, .7857, -.0752, -.4031
15.0	12.2	0	9.4	0	0	7.9	4.7	2.8	16.6	29.2	0.5	15.0	56.9	4.6	8.7	.5000, .8000, 0, -.4000
14.1	16.6	0	0	0	10.8	10.9	2.7	3.7	15.2	29.7	0	$\boxed{27.8}$	52.1	5.6	10.1	10000, 20000, 0, -10000

SCALING TEST

4.0	5.5	0	7.0	10.6	8.4	3.3	1.2	0.9	4.8	21.7	$\boxed{1.1}$	13.7	71.1	4.6	6.3	200;100
10.6	10.0	0	8.2	0	12.0	7.0	1.2	2.8	9.0	24.7	0	10.6	62.3	5.2	7.4	200;60
11.5	10.3	0	5.8	0	10.8	9.4	2.3	5.6	10.4	24.8	0	13.4	59.8	5.5	8.0	100;100
15.8	18.8	0	0	$\boxed{34.0}$	$\boxed{24.0}$	13.1	4.7	8.4	21.5	22.6	0	17.1	38.0	12.9	13.8	100;60
$\boxed{22.2}$	$\boxed{23.7}$	0	$\boxed{15.8}$	0	$\boxed{24.0}$	$\boxed{17.6}$	4.3	7.5	$\boxed{22.2}$	$\boxed{38.7}$	0	0	29.9	11.6	13.5	100;50

LEGEND

Hd = Hardwood	RF_O = Red Fir Open Canopy
DF_O = Douglas Fir Open Canopy	RF_C = Red Fir Closed Canopy
POP_O = Ponderosa Pine Open Canopy	WF_C = White Fir Closed Canopy
WF_O = White Fir Open Canopy	DF_C = Douglas Fir Closed Canopy
Mead = Meadow	POP_C = Ponderosa Pine Closed Canopy



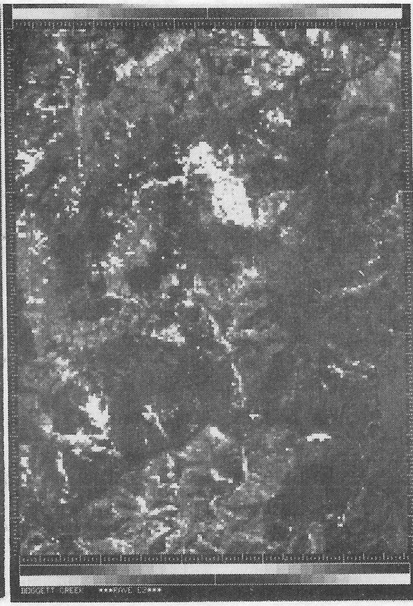


Figure 1. SATURATED PIXELS. MSS5/E2 unenhanced transform channel showing the saturated white and black pixels that occasionally occur when Landsat data is divided by the second principal component. Saturated pixels represent areas of unusual contrast between Landsat bands. Any saturated pixel falling into a training site used for divergence analysis would significantly alter statistical means rendering the technique unreliable.

Figure 2. - RAVE/E2. This transform represents the ratio of the four Landsat band averages divided by the second principal component of the four bands. It was the only transform to gain information content relative to Landsat MSS4.

Figure 3. - EIGEN 1. The principal component (Eigenvector 1) of Landsat PCA highlights the reflectance differences between spectral channels due to wavelength, and therefore contains only marginal vegetation information.

Figure 4. - EIGEN 2. Comparison with the first eigenvector (Fig. 3) shows how the second eigenvector from Landsat PCA displays the subtle variations within image features, with most interband wavelength contrasts removed. The combination of PCA data compression with conventional ratioing of Landsat bands produces a potentially useful synergism.