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Identification of Conifer Species Groupings from Landsat Digital Classifications

By using spectral curve characteristics and detailed photointerpretation, it was possible to place unlabeled spectral classes into accurately defined resource categories.

Abstract: *Approaches to assist in solving three major problems often encountered in Landsat computer classifications of forest land areas are discussed. Guided clustering in combination with unsupervised classification techniques are reviewed as effective methods for dealing with the problems of (1) spectrally heterogeneous training fields, and (2) unique spectral patterns often missed by a limited number of training fields. The third major problem discussed is that of assigning reliable resources labels to spectral classes developed from the classification process. Spectral curves were developed from the mean digital numbers (bands 4,5,6,7) of each spectral class. Comparisons of curve shapes were made between "known" (classes with reliable resource labels), and unknown (classes without labels) spectral classes. This comparison in conjunction with photointerpretation was an effective way of assigning reliable resource labels. The overall classification accuracy for identifying conifer species groupings, canopy density classes, and crown diameter categories was 0.83 considering omission errors.*

Introduction

Landsat has recently been used successfully as an intensive forest inventory tool (Strahler, 1979; Walsh, 1980). Innovative classification techniques, such as the incorporation of a *a priori* classification probabilities, terrain data, and recent improvements in computer soft-ware sophistication, have facilitated this application.

In the Fall of 1978, a cooperative research project was undertaken between Humboldt State University, NASA Ames Research Center, and the McCloud Ranger District of the Shasta-Trinity National Forest (U.S. Forest Service). The intent of the project was to complete a site-specific inventory of the timber resource of the McCloud Ranger District using Landsat digital data. This entailed the identification of conifer species groupings, forest canopy density classes, and crown diameter categories, as well as other general forest land-cover classes.

In the past, the identification of timber species groupings using Landsat digital data alone has been difficult (Strahler *et al.*, 1978). We have encountered at least three major problems in identifying tree species groupings. First, it is difficult to locate training fields that represent a spectrally pure resource type. Guided clustering has been used as a classification tool to overcome this problem (Gaydos and Newland, 1978; Fox and Mayer, 1979). Secondly, it is difficult to identify a sufficient number of training fields to account for slope, aspect, and other environmental variations present in each resource type. Unsupervised clustering allows the analyst to account for these spectral variations throughout large areas. The combination of the guided clustering spectral

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classes and unsupervised spectral classes has been suggested to be very helpful in reducing this problem (Mayer *et al.*, 1980). Third, we have experienced difficulty in assigning meaningful timber resource labels to the spectral classes generated from clustering.

In this article we will discuss the development of timber species groupings through guided clustering and unsupervised classification techniques. Furthermore, the problem of spectral class labeling will be addressed.

Study Area

Dominated by Mt. Shasta on its northwestern boundary, the McCloud Ranger District of the Shasta-Trinity National Forest (N.F.) lies 70 miles (113 km) northeast of Redding, California (Figure 1). The District encompasses approximately 521,000 acres (251,315 ha) of Federal as well as private land. Of this, 332,000 acres (134,359 ha) is N.F. land. Three-fourths of the District is contained within Siskiyou County and one-fourth within Shasta County.

Vegetative types in the District include mixed conifer (ponderosa pine, *Pinus ponderosa;* white fir, *Abies concolor;* Douglas-fir, *Pseudotsuga menziesii;* incense cedar, *Libocedrus decurrens;* lodgepole pine, *Pinus contorta;* and knobcone pine, *Pinus attenuata*), pure pine (ponderosa pine; sugar pine, *Pinus lambertiana,* western white pine, *Pinus monticola*), and true fir (white fir, and Shasta red fir, *Abies magnifica* var. *shastensis*). The true fir category can be found anywhere in the District. Typically, red fir occurs above 4,500 feet (1,368 m) and white fir can be found mixed throughout the District in elevations as low as 3,000 feet (937.5 m). Pure pine occurs primarily on the McCloud flats associating with mixed conifer, which covers the majority of the District.

The average annual precipitation is 46 inches (117 cm), falling mostly as snow. Rainfall seldom occurs after June or before mid-September. Temperatures range from an average of 90° F (32° C) in the summer, to 15° F (−9.4° C) in the winter. Topography and elevations vary from the steep sided (80 percent slope) McCloud and Pit River Canyons in the southern part of the District, with a minimum elevation of 1,600 feet (448 m); to the McCloud Flats in the central part of the District, approximately 4,000 feet (1,219 m). Steep buttes and rolling terrain dominate the 5,000 (1,524 m) to 6,000 (1,829 m) foot Medicine Lake Highlands in the north and east part of the District. The slopes and glaciers of the 14,161 foot (4,316 m) Mt. Shasta characterize the northwest corner of the District.

Methods

Classification Approach

The Landsat classification was completed using guided and unsupervised clustering. The guided clustering method employed the selection of approximately 100 homogeneous timber resource training fields. Four conifer species groupings, two size classes, and two density categories were represented by these training fields. Clustering was performed on each training field, creating spectral statistics unique to the resource. This is referred to as guided clustering, or multi-clustered fields (Fleming *et al.,* 1975). Upon completion of guided clustering, spectral classes were compared to one another in a separability matrix. Similar classes were pooled together or deleted, on the basis of spectral similarity. The Swain-Fu distance statistic was used to determine spectral separability (Swain and Fu, 1972). The decision to pool or delete is based on the number of similar classes involved, the degree of spectral similarity be-

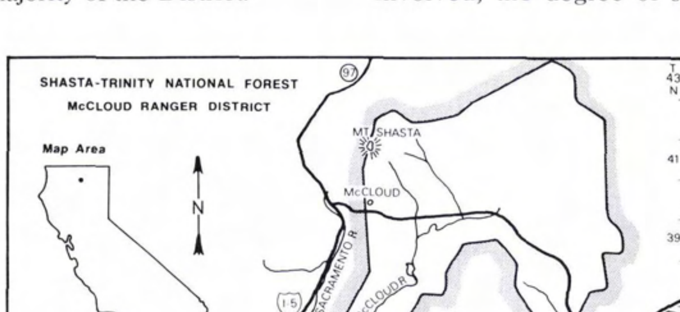

Fig. 1. A map of the McCloud Ranger District, Shasta-Trinity National Forest, California

tween classes, and the variance of the individual class. Individual spectral classses that exhibited spectral confusion (<0.45 Swain-Fu distance) with two or more classes were usually deleted. When only two spectral classes were similar they were pooled together. Furthermore, if a class was unique, it was retained unchanged in the statistics file (Fox and Mayer, 1979).

To identify spectral classes not developed from guided clustering, an unsupervised classification for the entire District was produced. The spectral classes developed from the unsupervised clustering (64 spectral classes) were merged with the guided clustering statistics (38 spectral classes) and edited to create the final statistics file (59 final statistics). The merging of the two statistics files was completed with the same procedure previously stated. These statistics were used to classify the Landsat data.

SPECTRAL CURVES

To complete the classification process, the spectral classes were assigned to resource categories. The introduction of unsupervised statistics compounded the spectral class labeling problem. Photointerpretation (PI) of the training fields was very helpful in determining the resource labels for each spectral class. Even though the PI was helpful, by no means was it the most ideal method. Spectral classes existed throughout the study area that were numerous, but scattered, never appearing in any recognizable forms or geographical locations. The difficultly in finding homogeneous areas (5 to 10 pixels) of alike spectral classes made it almost impossible to reliably assign resource labels. To help solve this problem, spectral curves for each class were constructed from the mean digital values in each of the four spectral bands; band 4, 0.5 to 6 μm; band 5, 0.6 to 0.7 μm; band 6, 0.7 to 0.8 μm; and band 7, 0.8 to 1.1 μm. The curves were used to assign resource labels to known and unknown spectral classes. Classes that were known to represent a particular resource category were plotted first. The unknown classes (classes without labels) were plotted and grouped according to curve shape when they closely resembled a known spectral class. PI was used to make final decisions as to the true resource identity when no similar curve shape could be found (Figure 2).

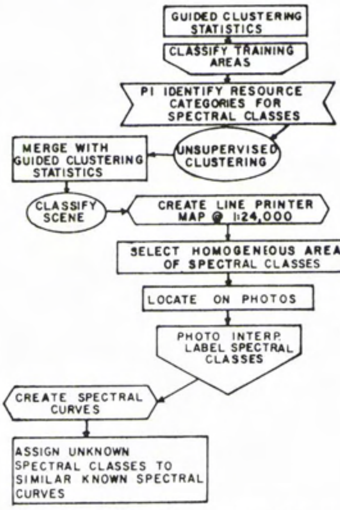

FIG. 2. Spectral class labeling procedure for McCloud Ranger District Landsat classification.

EVALUATION

The Landsat classified scene (1 August 1978) was evaluated using USFS color, 1:15,840 scale photography (July 1975). The photo coverage of the District was complete, which allowed for an unbiased random sample.

The Landsat image rows and columns were divided into 8 by 8 pixel primary sampling units (PSU). Thirty-nine PSU's were selected at random for evaluation. Once the PSU's had been outlined on the Landsat printout, they were located and mapped on the photographs through the use of a Kail Autofocus Projector. A black line grid was produced on clear mylar acetate to represent a pixel at the scale of the photograph. The grid was placed on the photo and locally fit (Mayer *et al.*, 1980). To further insure accurate grid location, the rows just above and below the actual evaluation site were interpreted and aligned on the photos with respect to the Landsat categories. This alignment was completed by an independent interpreter, which provided an effective photo to Landsat match, allowing for a systematic and unbiased approach to the local fit process. Once the grid had been satisfactorily placed onto the photo, photointerpretation was initiated. Each pixel was evaluated as to its photointerpretated land-cover identity and whether the Landsat classification was correct. The number of pixels sampled per class varied between 28 and 479. Estimations of the mean probability of correct classification were determined for each timber resource category and land-cover category defined.

RESULTS AND DISCUSSION

SPECTRAL RESULTS

The final Landsat mapping of the McCloud District contained 59 spectral classes. Each pair of classes was spectrally separable by at least a distance of 0.45 Swain-Fu separability (Swain and Fu, 1972). These spectral classes were aggregated into 16 timber and land resource categories of interest to the U.S. Forest Service (Table 1).

The spectral classes representing the mixed conifer category are shown in Figure 3. When ex-

TABLE 1. A LISTING OF THE 16 TIMBER AND LAND RESOURCE CATEGORIES DEVELOPED FROM LANDSAT DATA ON THE MCCLOUD RANGER DISTRICT

The resource labels for forested areas consisted of three alpha characters. For example:

MLG
- └─Density-% Crown Closure
- └─Size Class
- └─Species

SPECIES DEFINED AS:
- M = Mixed Conifer
- P = Ponderosa, Sugar, Western White Pine (>80 %)
- F = White, Red, and Douglas-Fir (>80%)
- L = Lodgepole Pine

SIZE CLASS:
- L = Commercial Trees (Crown Diameters 12′ +)
- S = Pre-Commercial Trees (Crown Diameters Generally <12′)

DENSITY CLASS:
- G = Good Stocking (40% + Crown Closure)
- P = Poor Stocking (<40% Crown Closure)

Combinations of the above constitute Landsat stratum labels. Below are equivalent CIA labels.

LANDSAT STRATUM	COMPARTMENT INVENTORY ANALYSIS STRATUM
MLG	M3N, M3G, M4N, M4G, M6G
MSG	M1N, M1G, M2N, M2G
MLP	M3S, M3P, M4S, M4P
PLG	P3N, P3G, P4N, P4G, P6G
PSG	P1N, P1G, P2N, P2G
PSP	P1S, P1P, P2S, P2P
FLG	R3N, R3G, R4N, R4G, R6G D3N, D3G, D6G, D4G, D4N
FLP	R3S, R3P, R4S, R4P, D3S D3P, D4S, D4P
LPG	L2N, L2G, L6G

(No size class for LP PINE)

In addition, the following non-forest categories were defined:*

BRUSH—This resource category may include several species of brush. Any pixel containing more than 75 percent brush would be placed into this category.

GRASS—Perennial grasslands were identified. Species, density and degree of maturity dictated the spectral response.

TRANSITION—This category describes areas of brush, grass and trees. Pixels classified as transition contained no more than 5 trees, which were scattered among the existing vegetation. Border pixels were placed into this category.

OAK/HARDWOOD—Any hardwood species found on the District were placed into this category.

LAVA—Lava flows were prevalent on the District. All forms of lava were included.

SNOW—Snow was found only at high elevations in the form of glaciers on Mt. Shasta.

WATER—General category representing the lakes on the District.

* For the purpose of this article, all categories that were not timber related were combined into one category called "Other".

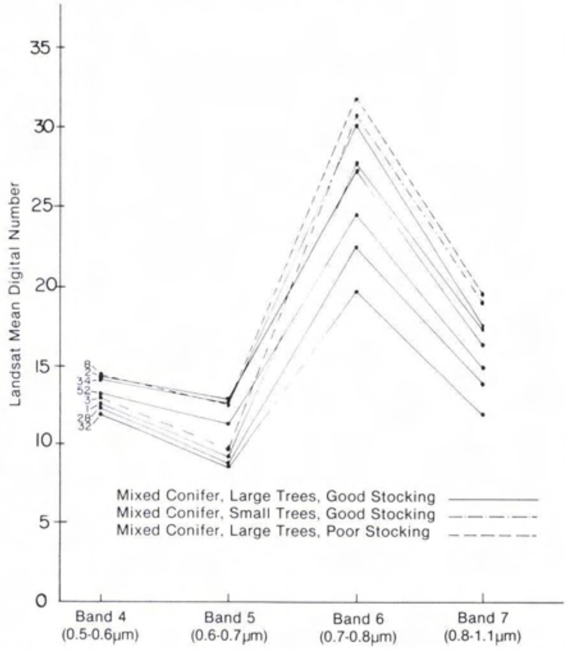

FIG. 3. The four band digital number patterns for the eight spectral classes assigned to the mixed conifer species grouping. Note: band 7 dn values are scaled from 0 to 63, band 4, 5, and 6 dn values are scaled from 0 to 127.

amining this graph it is important to notice the shape of the curve, especially the slope between the green (band 4) and the red (band 5) parts of the spectrum. It is our opinion that this slope is a significant factor in determining the resource identity. This was found to be true for the mixed conifer resource category. The digital number (dn) value for any band is not as significant as curve shape when trying to differentiate between species. We found that the digital number value is related to tree size and stocking level. Spectral class 8 is a typical example of mixed conifer, large trees, poor stocking (MLP). The moderately high dn value for band 5, compared with the other mixed conifer classes, is indicative of large, older trees having a poor stocking level. The high peak in band 6 is probably a result of low tree density and a highly IR reflective understory. By contrast, spectral class 3 is a good example of well stocked, small trees. The lower digital count in band 5 is a result of higher density. The high digital value in band 6 and 7 is due mainly to their young age. Small, younger trees tend to display more foliage in their upper canopies than large older trees. This might explain the high IR dn's and low red dn's found associated with the small trees.

In summary, it was found that the average downward slope between bands 4 and 5 (−2.53

dn/0.1 μm*) is the diagnostic feature which makes this resource category unique spectrally. Furthermore, the band 5, 6, and 7 digital numbers have strong correlation to the size and density of the trees.

Figure 4 displays the family of spectral curves for ponderosa pine. Spectral classes 4, 9, 17, 6, 18, and 45 exhibit a diagnostic average slope characteristic. The slight upward trend (+0.73 dn/0.1 μm*) from band 4 to band 5 differentiates this resource category from the others.

A cursory examination of this family of curves would indicate nonconforming slopes for spectral classes 55, 39, and 40, as well as the high digital values for classes 42 and 55. These anomalies can be explained. Spectral classes 55 and 40 appeared from the classified line printer maps to represent pixels occuring on the border between resource categories. These classes caused misclassification in the ponderosa resource category. During the spectral class labeling process, these classes were assigned to the ponderosa pine category. This was a direct result of their geographical location and a significant number of ponderosa pine trees per pixel. Spectral class 42 was frequently found in very young plantations. The trees were small (<12 ft crown diameter), but numerous. One would expect a lower overall band 4 and 5 digital value due to higher density. This was not the case. The small crown size, and the high percentage of exposed bare soil, probably caused the high digital counts. The very high value (50.27 dn) in band 6 is normal for young, vigorous trees.

Spectral classes 39 and 40 were identified as ponderosa pine with a brush understory. Brush exhibits a definite downward slope from band 4 to 5 (Figure 7). Class 39 had a higher percentage of brush than did class 40. This factor often caused misclassification with the mixed conifer category.

Spectral class 55 was found to be associated with plantations. Exposed bare soil and dead grass, resulting from low tree density, probably caused the high dn values. Since our density categories considered 40 percent crown closure (cc) and greater as good stocking, the lower cc (40 to 45 percent) and the fact that the trees were small, gave this spectral class a band 4 to 5 slope similar to the transition resource category (Figure 7).

Figure 5 contains the spectral curves for fir. This family of curves resembles ponderosa pine. The differentiating factors are the steep upward average slope (+3.18 dn/0.1μm) between bands 4 and 5 and the low dn in band 7. At first glance, it may seem abnormal for the red dn value to be higher than the green. Many studies show that red re-

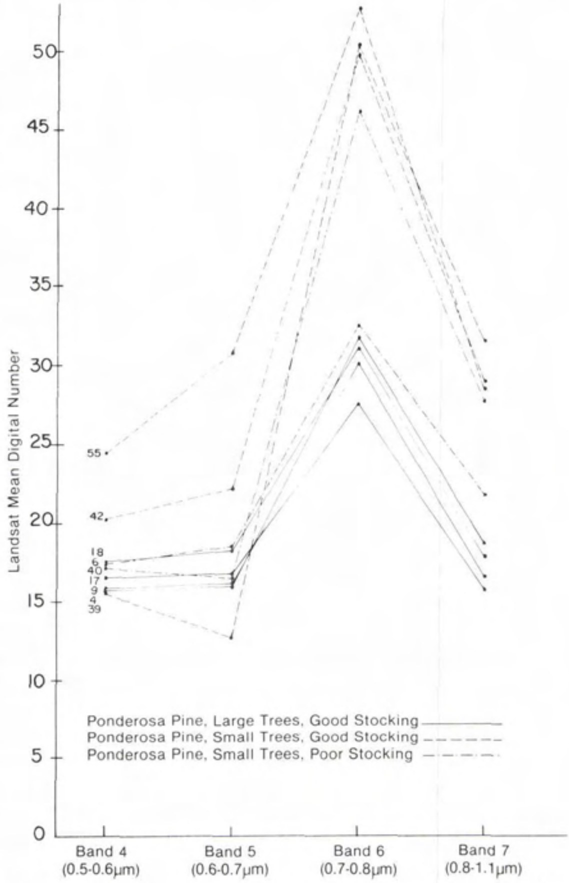

FIG. 4. The four band digital number patterns for the nine spectral classes assigned to the ponderosa pine species grouping. Note: band 7 dn values are scaled from 0 to 63, band 4, 5, and 6 dn values are scaled from 0 to 127.

flectance is traditionally lower than the green, when examining vegetation (Kalensky and Wilson, 1975). Research summaries by Steiner and Guterman (1966) concerning Russian data on spectral reflectance of vegetation, soil, and rock types show that this may not always be the case. The Russian work on the influence of crown and stand structure on reflectance indicates that, when examining whole crowns, the red reflectance is often equal to or slightly higher than the green reflectance. It is our belief that the soil type (white pumice soil), the wide node/internode relationship of fir, and the minimum amount of needle surface area exposed may have contributed to the upward slope between band 4 and 5.

When examining these curves for uniqueness, it is interesting to note the low digital value of band 7 relative to band 5. The other species categories have digital values for band 7 differing from band 5 by not more than −2.05 to +9.22. The fir exhibits

* Slope values calculated as $\Delta y/\Delta x$ assuming that Δx is represented by the difference in μm of the band center point (0.1 μm), Δy is the measured change in dn.

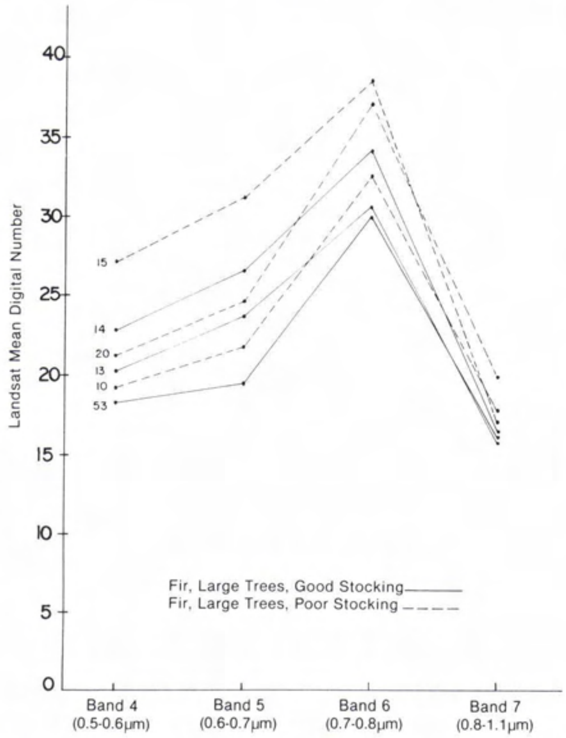

FIG. 5. The four band digital number patterns for the six spectral classes assigned to the fir species grouping. Note: band 7 dn values are scaled from 0 to 63, band 4, 5, and 6 dn values are scaled from 0 to 127.

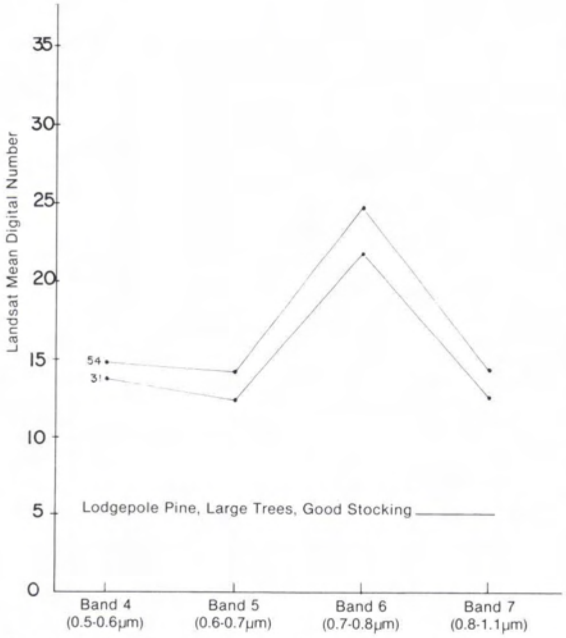

FIG. 6. The four band digital number patterns for the two spectral classes assigned to the lodgepole species grouping. Note: band 7 dn values are scaled from 0 to 63, band 4, 5, and 6 dn values are scaled from 0 to 127.

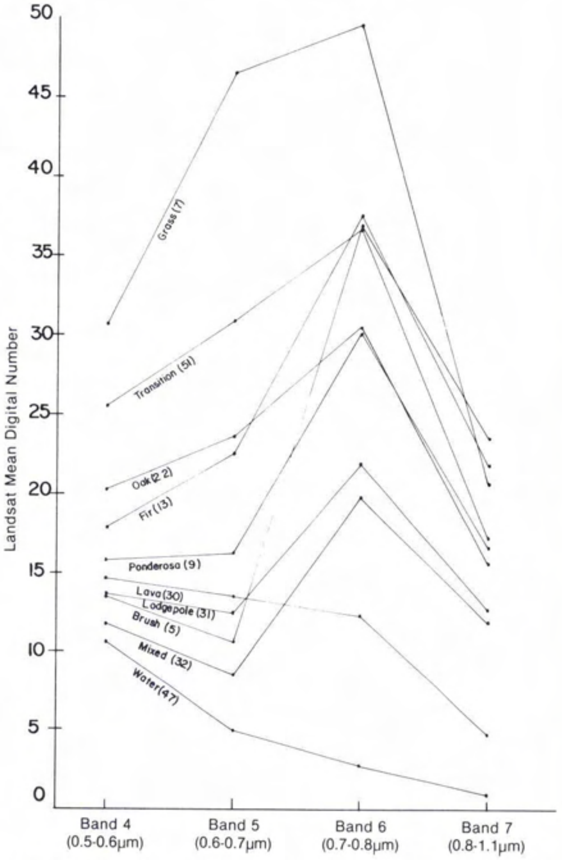

FIG. 7. The four band digital number patterns for the representative spectral classes of the major resource categories defined. Note: band 7 dn values are scaled from 0 to 63, band 4, 5, and 6 dn values are scaled from 0 to 127.

a larger negative difference, with a range of −3.28 to −13.9 digital numbers.

The lodgepole resource category is characterized in Figure 6. The average slope is slightly downward (−1.05 dn/0.1 μm) between bands 4 and 5. This subtle downward slope separates this category from mixed conifer (average −2.5 dn/0.1 μm) and ponderosa pine (average +0.73 dn/0.1 μm).

It was difficult to identify low density categories of lodgepole or knobcone pine. Dense (>40 percent crown closure) stands of these species provided good identifiable spectral responses. When the stand density dropped below the 40 percent threshold, it was difficult to identify unique spectral responses that could be accurately called lodgepole pine. The low density lodgepole areas were usually included in the transition category.

Figure 7 is a graph of spectral curves displaying representative spectral classes for each resource category. The graph shows the typical slope characteristics for each conifer resource type. From

TABLE 2. MATRIX OF CLASSIFICATION ACURACIES FOR TREE SPECIES/SIZE/DENSITY

		Landsat											
	Category	MLG	MSG	MLP	PLG	PSG	PSP	FLG	FLP	LPG	Other	Total	Proportion Correct
Photointerpretation	MLG	407	29	8	32	0	1	3	2	5	6	493	.83
	MSG	19	108	5	4	0	2	0	1	0	1	140	.77
	MLP	24	5	69	3	0	1	0	9	2	11	124	.56
	PLG	18	2	2	225	0	2	0	8	2	5	264	.85
	PSG	0	2	1	7	24	2	0	1	0	3	40	.60
	PSP	0	0	0	6	3	44	0	1	1	3	58	.76
	FLG	1	0	1	4	0	0	63	10	1	6	86	.73
	FLP	0	0	1	9	0	1	10	136	0	8	165	.82
	LPG	7	0	0	3	0	0	2	0	48	3	63	.76
	Other	3	3	3	15	1	0	8	8	12	1010	1063	.95
	Total	479	149	90	308	28	53	86	176	71	1056	2496	.85
	Proportion Correct	.85	.72	.77	.73	.86	.83	.73	.77	.68	.96	.85	

this, one can observe the subtle but distinct slope characteristic. The remainder of the resource categories (water, lava, grass, etc.) have typical predictable curve shapes and relative positions (Lillesand and Kiefer, 1979).

EVALUATION OF CLASSIFICATION ACCURACY

Accuracy data for a pixel-by-pixel comparison of the Landsat classification with air photointerpretation is presented in Table 2. A one percent, random start, cluster sample of the McCloud Landsat classification was completed to provide this data (Yamane, 1967). The table indicates the number of pixels classified by Landsat as well as pixels identified by photointerpretation.

The rows in the table indicate the number of pixels truly found in a particular resource category from photointerpretation. We assumed that photointerpretation provided the true vegetative cover. This assumption of correct photointerpretation was considered accurate as the photointerpreter had extensive knowledge of the District as well as the photos. The number of pixels classified into a particular resource category by Landsat is indicated in the columns of the table.

Classification accuracies were generally above 80 percent for the timber resource categories. Before one judges these accuracy levels to be too low for timber inventory work, it is important to analyze where and how errors were made. Of the 493 pixels that were truly MLG, 86 were misclassified into other categories (Table 2). However, 37 were placed into other size and density categories of mixed conifer and 43 were placed in the other conifer categories. Notice that this pattern of error distribution is consistent for the other timber resource categories. In general, classification errors were insignificant (3.2 percent) in terms of placing forest pixels in non-forest categories.

An aggregation of the timber type variables was completed to demonstrate the mapping of tree species alone (Table 3). Most categories were above 80 percent (omission and commission) with the exception of lodgepole pine. The high accuracy (0.94 relative to omission errors) for mixed conifer can be attributed to the large amount of training data available, as mixed conifer is the most abundant resource type on the District. The low (0.68 relative to omission errors) accuracy for lodgepole was a result of insufficient training data

TABLE 3. MATRIX OF CLASSIFICATION ACCURACIES FOR TREE SPECIES

		Landsat						
	Category	Mixed	Ponderosa	Fir	Lodgepole	Other	Total	Proportion Correct
Photointerpretation	Mixed	674	43	15	7	18	757	.89
	Ponderosa	25	313	10	3	11	362	.86
	Fir	3	14	219	1	14	251	.87
	Lodgepole	7	3	2	48	3	63	.76
	Other	9	16	16	12	1010	1063	.95
	Total	718	389	262	71	1056	2496	.91
	Proportion Correct	.94	.80	.84	.68	.96	.91	

and its extensive association with the other conifer species.

Conclusions

Guided clustering has allowed the development of a maximum number of low variance spectral classes. These classes precisely represent the timber type groupings identified in this inventory project. Classification accuracy ranged from 0.83 overall for species, size, and density to 0.88 overall for species alone (all accuracy proportions relative to errors of omission). The comparative curve shape of these spectral classes is diagnostic for the species groupings defined. The slope of the curve between bands 4 and 5 was most characteristic. Stands dominated by ponderosa pine were represented by spectral curves having a slight upward trend from band 4 to band 5 (average slope of +0.73 dn/0.1 μm). Stands dominated by true fir species showed an average upward slope of +3.18 dn/0.1 μm, while mixed conifer stands exhibited an average downward slope of −2.53 dn/0.1 μm. Stands dominated by lodgepole pine showed a reduced downward average slope (−1.05 dn/0.1 μm).

By using representative slope characteristics and detailed photointerpretation, it was possible to place unlabeled spectral classes into accurately defined resource categories.

References

Fleming, M. D., S. S. Berkebile, and R. M. Hoffer, 1975. *Computer-aided analysis of Landsat-1 MSS data: A comparison of three approaches, including a "modified clustering" approach.* Purdue University, Laboratory for Applications of Remote Sensing, LARS Information Note 072475.

Fox, L. III, and K. E. Mayer, 1979. Using guided clustering techniques to analyze Landsat digital data for mapping forest land cover in Northern California. *Proceedings of the Fifth Int. Symp. on Machine Processing of Remotely Sensed Data.* Purdue University, LARS, Lafayette, Indiana, pp. 364–367.

Gaydos, L., and W. L. Newland, 1978. Inventory of land use and land cover of the Puget Sound region using Landsat digital data. *General Research*, U.S.G.S. Vol. 6(6): 807–814.

Kalensky, Z., and D. A. Wilson, 1975. Spectral signatures of forest trees. Presented at the *Third Canadian Symposium on Remote Sensing*, Edmonton, Alberta.

Lillesand, T. M., and R. W. Kiefer, 1979. *Remote Sensing and Image Interpretation.* John Wiley and Sons, Inc., New York. 612 p.

Mayer, K. E., L. Fox III, and J. L. Webster, 1980. Forest condition mapping of the Hoopa Valley Indian Reservation using Landsat data. *Proceedings of the First International Symposium of Remote Sensing for Natural Resources.* University of Idaho, Moscow, pp. 217–242.

Rohde, W. G., 1978. Digital image analysis techniques required for natural resource inventories. *AFIPS Conference Proceedings.* Vol. 47. U.S.D.I. Geological Survey, EROS Data Center, Sioux Falls, South Dakota, pp. 93–106.

Steiner, D., and T. Guterman, 1966. *Russian data on spectral reflectance of vegetation, soil and rock types.* Final Technical Report. University of Zurich, European Research Office, pp. 77, 87, 89.

Strahler, A. H., T. L. Logan, and N. A. Bryant, 1978. *Improving forest cover classification accuracy from Landsat by incorporating topographic information.* Calif. Inst. Tech., Jet Propulsion Lab, Pasadena, Calif., pp. 1–16.

Strahler, A. H., T. L. Logan, and C. E. Woodcock, 1979. Forest classification and inventory system using Landsat, digital terrain, and ground sample data. *Proceedings of the Thirteenth International Symposium on Remote Sensing of Environment*, Ann Arbor, Michigan, pp. 1541–1557.

Walsh, S. J., 1980. Coniferous tree species mapping using Landsat data. *Remote Sensing of Environment* 9(1) 11–26.

Yamane, T., 1967. *Elementary Sampling Theory.* Prentice-Hall, Inc., New Jersey, pp. 186–232.

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