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THE INFLUENCE OF MULTISPECTRAL SCANNER SPATIAL RESOLUTION ON FOREST FEATURE CLASSIFICATION*

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ABSTRACT

Inappropriate spatial resolution and corresponding data processing techniques may be major causes for non-optimal forest classification results frequently achieved from multispectral scanner (MSS) data. This paper presents the procedures and results of empirical investigations to determine the influence of MSS spatial resolution on the classification of forest features into levels of detail or hierarchies of information that might be appropriate for nationwide forest surveys and detailed in-place inventories. Two somewhat different, but related studies are presented. The first consisted of establishing classification accuracies for several hierarchies of features as spatial resolution was progressively coarsened from (2 meters)^2 to (64 meters)^2. The second investigated the capabilities for specialized processing techniques to improve upon the results of conventional processing procedures for both coarse and fine resolution data.

In general, classification performance for forest condition classes improved as spatial resolution was degraded. These results were aggregated to provide a measure of classification performance for more general hierarchies of features that included growth stage, cover type, and physiognomy. Classification performance for these more general hierarchies was substantially higher and also improved as spatial resolution was degraded.

Additional results reported illustrate: 1) the impact of boundary elements and non-homogeneities within forest features on classification accuracy; and 2) the effect of a constant classification rejection threshold for data of varying spatial resolution.

Specialized processing techniques which were investigated included multi-element classification rules for coarse resolution data and a new proportion-space classification technique for fine resolution data. The use of multi-element classification rules for the spatial resolution of (32 meters)^2 provided improved performance over the results of conventional single-element classification, especially for the most specific hierarchy of forest features. Such rules appear to offer a definite advantage for improving the classification of specifically-defined features with data having spatial resolutions

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comparable to the present Landsat and proposed Thematic Mapper MSS systems.

A proportion-space classification technique showed marked improvement for classifying forest features in data of fine resolution. The technique makes use of classified forest canopy spectral components which may in themselves provide information in support of intensive forest management efforts. Proportions of such components are subsequently used to classify forest features. Application of a proportion-space classification technique to fine resolution MSS data could be utilized in a multistage sampling approach for inventorying forest and rangeland resources.

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1. INTRODUCTION

The capability currently exists to acquire and analyze multispectral scanner (MSS) data of forested regions for a wide range of spatial resolutions. Landsat MSS data are among the coarsest in resolution while increasingly finer resolution can be provided by MSS systems mounted in high and low flying aircraft. The forest manager might justifiably ask the question: "which spatial resolution is optimal for classifying features of interest in forest resource surveys?" To help answer the question, one must determine the manner in which spatial resolution affects the classification of forest features. Additional considerations involve the level of information desired and the processing technique employed to provide the information.

Numerous experimental and semi-operational studies have analyzed the discriminability of forest features with MSS data. The vast majority of such studies have utilized data for a single, specific case of spatial resolution that may have been small enough to resolve individual components of forest stands or as large as Landsat resolution. However, the influence of spatial resolution on forest feature classification cannot be readily determined because of inconsistencies in other parameters associated with each study and its respective data set. These parameters might include the objectives of the study, the types of features within the scene, signal-to-noise properties of the data, number and placement of spectral bands, and processing techniques employed.

Two recent studies have shown evidence of improvements in classification accuracy as a result of degrading spatial resolution of MSS data [1,2]. Presented herein are the results of empirical investigations to determine more completely the influence of MSS spatial resolution on the classification of forest features [3,4,5]. Two somewhat different, but related studies are presented: (a) a study of the effect of spatial resolution on forest classification accuracy using a conventional multispectral processing technique and (b) the use of specialized processing techniques to improve upon the results of conventional processing procedures for both coarse and fine resolution data.

2. FOREST CLASSIFICATION ACCURACY AS A FUNCTION OF SPATIAL RESOLUTION

Approach

To provide for a thorough investigation into the effect of MSS spatial resolution on the classification of forest features, we desired data providing common ground area coverage for several cases of spatial resolution that varied from minimum areas small enough to resolve individual components of forest stands to areas large enough to approximate the coarse resolution of the present Landsat systems. To hold other variables constant (e.g., temporal variations, etc.) we degraded a single aircraft data set of inherent (2 meters)^2 resolution in successive steps to simulate 5 additional data sets having $(4)^2$, $(8)^2$, $(16)^2$, $(32)^2$, and (64 meters)^2 spatial resolutions.

To degrade resolution as realistically as possible, we implemented an algorithm that utilized typical MSS optics and electronics properties in the form of two spatial weighting functions [3]. Each weighting function was low pass filtered and truncated to span five successive resolution elements in directions along the scanline and along the flightline respectively. When quantized into five intervals and combined into an X-Y matrix, the two weighting functions created an array that, when successively centered on every other element in every other scanline and when multiplied and summed over the surrounding 5 by 5 group of pixels to generate a replacing pixel value, yielded a new data set having one-fourth the number of resolution elements per unit ground area (Figure 1). System noise inherent to the original data was preserved in the simulated data by inserting a quantity of randomly generated high-frequency noise sufficient to compensate for the calculated amount of noise reduction caused by the averaging effect of the spatial weighting array. Application of the spatial weighting array and noise insertion procedure to each successive data set in turn enabled the creation of additional data sets having twice the linear spatial resolution of the preceding set.

The MSS data set included 11 spectral channels collected by a Bendix Modular Multispectral Scanner (M^2S) from an altitude of 610 meters (2000 feet). The data were collected as part of NASA Mission No. 290 on 20 November 1974 over the Conroe Unit of the Sam Houston National Forest in east Texas. Data including approximately one million resolution elements, and providing ground area coverage illustrated in Figure 2, were successively degraded in resolution. Forest features were identified according to existing U.S. Forest Service timber stand maps. These features are listed as condition classes in Table 1.

All data sets of varying resolution were processed with a conventional supervised classification procedure that utilized signatures extracted from training sets inside each forest feature. Signatures for these features were extracted anew for each data set from training sets that covered equivalent ground areas in each case of spatial resolution. The ERIM linear decision rule was used to classify all resolution elements on an element by element basis into the respective signature distribution or an unclassified category. Results were tallied to provide the percent correct classification achieved within each feature. The percent of all resolution elements correctly classified in the data set was calculated to provide an overall classification accuracy for the hierarchy.

Classification performance for the hierarchy of condition classes represents the most detailed level of classification for this study. The classification results were aggregated to provide a measure of classification performance for features of more general hierarchies (Table 1). Condition classes were combined into cover types on the basis of species (pine regeneration was retained as a separate feature), and alternately, into features based on maturity that we called growth stages. For the most general hierarchy, all pine saw-timber features were combined into a single physiognomic class to be compared with pine regeneration.

The large range of view angles inherent to aircraft scanner data can result in signal variations caused by large changes in atmospheric path length and terrain bidirectional reflectance phenomena [6,7]. Analysis of scan angle variations in this data set indicated a reasonable degree of independence from such variations for the region of data located 30° either side of the flightline nadir. Thus, we confined the location of training sets and the determination of classification performance to this region.

Results

Figure 3 illustrates the overall classification accuracies that were achieved for the hierarchies of features classified. These accuracies represent the results achieved for training sets from which the signatures had been extracted. By showing classification performance for training sets, we represent an upper limit of performance that assumes each feature area is adequately described by its respective signature(s). Thus, the results are uncomplicated by the additional confusion to the classification performance that may be introduced by unaccounted for nonuniformities within nontraining portions of the features and by boundary elements. (Such confusion existed despite the relatively large proportions of feature areas designated as training sets.)

Classification performance for all hierarchies of features improved as spatial resolution was degraded. Additionally, classification accuracy was substantially higher for hierarchies of less specifically defined features. In other words, improvement in performance occurred as a result of aggregating the classification results of specific features into more general features. For each general feature, previous misclassifications of resolution elements among its specific features were properly counted as correct classification, reducing the total amount of misclassified elements for the respective hierarchy. Thus, the overall accuracy for classifying the physiognomic hierarchy of forest features is higher than for heirarchies of more specific classes — a not-surprising result.

The improvement in performance with degraded spatial resolution resulted from a reduction in scene variation that is inherent in the averaging of information over larger ground areas. This result is best illustrated in Figures 4 and 5 where, for two dimensions, the signature distributions for features are shown at resolutions of $(2)^2$ and $(32 \text{ meters})^2$, respectively. [In tests of spectral channel performance, the two spectral channels illustrated in these figures, namely the red (.65-.69 µm) and near-infrared (.95-1.03 µm) regions, had proven to be among the best for separating the features.]

At $(2 \text{ meters})^2$, the largely overlapping signature distributions obviously offered the least likelihood for successful discrimination of features. The large variance for each signature provides evidence of the spectral non-homogeniety within the training areas, and the small mean separation among the signatures indicates many similarities among the data values of resolution elements in all training areas. Thus, misclassifications of those elements by the resulting signature set will be high. As resolution was degraded, the variance of each signature became smaller while the means for the most part remained unchanged, causing the amount of statistical overlap (competition) among the signatures to decrease. Thus resolution elements in coarser resolution data should have higher probabilities of being correctly classified.[1]

Classification performance decreased somewhat when accuracies were computed over the entire area of each feature. Such decreased performance is attributable to greater percentages of misclassified and unclassified resolution elements and can be caused by the increased variance in data values, not completely represented by the feature training set, that results from nonuniformities over the entire feature and the effect of boundary elements around the perimeter of each feature. Figure 6 compares the overall classification performance for training sets to the lower performance achieved for total feature areas with and without boundary elements. In general, the decrease in classification performance for feature areas without associated boundary elements becomes greater in coarser resolution data, possibly suggesting the need for more careful training in coarse resolution data. The impact of included boundary elements serves to further reduce classification performance as spatial resolution degrades, owing to the increased ratio of boundary elements to total feature elements.

Classification performance as a function of spatial resolution was found to be subject to influence by the rejection threshold used in classifying the data. The rejection threshold represents a selected exponent value of the multivariate normal density function of each signature which determines the limits of decision space occupied by the respective signature. Resolution elements having classification exponent values greater than the rejection threshold of the signatures will be unclassified by the decision rule. Results of using a conventional classification approach showed that the use of a constant rejection threshold for all cases of spatial resolution caused a great increase in the percentage of unclassified resolution elements in very coarse resolution data (Figure 7). Presumably, an increased percentage of unclassified resolution elements occurs in coarser resolution data when the rejection threshold remains constant because a relatively smaller total decision space is represented by the decreasing sizes of the signature distributions. Large proportions of unclassified elements will obviously detract from the results of the classification effort and, if considered to be errors, can cause a significant decrease in classification performance for coarse resolution data. Judicious selection of thresholds can reduce the amount of such unclassified resolution elements. Thresholds used to generate the results in Figures 3 and 6 were varied as a function of spatial resolution to maintain a constant small proportion of unclassified elements.

3. USE OF SPECIALIZED PROCESSING TECHNIQUES

Conventional multispectral classification rules are based on information from one resolution element at a time. The previous application of one such rule showed improved classification performance for coarser cases of spatial resolution — apparently due to the reduced variation within the scene that occurs by averaging information over larger ground areas. Obviously,

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[1]When resolution was coarsened to $(64 \text{ meters})^2$, an insufficient number of resolution elements prevented computing a valid signature for the Immature Loblolly Pine feature. Thus, the abrupt increase in classification accuracies that occurs from $(32 \text{ meters})^2$ to $(64 \text{ meters})^2$ in Figure 3 is due in part to the absence of a competing signature during the classification of the data, again causing resolution elements to have high probabilities of correct classification.

there will be a limit to which data spatial resolution can be coarsened and still be useful for providing other aspects of scene information such as locational accuracy or accurate area measurement capabilities. Additionally, the presence of large signal variations in fine resolution data provides detailed information not available in coarse resolution data.

Technique for Coarse Resolution Data

Multi-element rules use information from groups of resolution elements when classifying a specific element. The so-called "nine-point" rules developed at ERIM [8] determine the classification of a resolution element on the basis of information from that element and its eight immediate neighbors. Such use of proximity information attempts to improve classification performance by incorporating the likelihood that a resolution element represents the same scene class as its neighbors. The influence of neighboring elements can be varied with the selection of a particular rule. Multi-element rules thus offer the potential for providing the improved classification performance of coarser spatial resolutions without the loss of other scene information that occurs with coarser resolutions.

Four multi-element decision rules (known as BAYES9, PRIOR9, PREF9, and VOTE9) were used to classify the (32 meters)^2 resolution case. All four multi-element rules showed improved performance over the classification results achieved with the single-element rule for (32 meters)^2 data. For the most detailed hierarchy of features (condition classes), classification accuracies ranged from 13 to 25 percent better (Figure 8). Three of the rules consistently showed performances that were higher than the single-element classification results achieved for (64 meters)^2 data. Thus, it appears that judicious selection of a nine-point rule can offer improved classification performance that is greater than an improvement that might be realized with standard classification procedures used on coarser resolution data.

Of the four multi-element rules, classification results were always highest for PREF9. This rule uses as its decision criterion the average, over nine elements, of the posterior probability of a feature at each resolution element. Comparison of these results with the results of the single element rules indicates that the increase in accuracy is largest for the hierarchy of condition classes with lesser increases in performance noted for hierarchies of more general features. This trend suggests that when classification accuracy is low using standard techniques, then specialized processing techniques give more improved accuracy that when accuracy is high with standard techniques. Thus, multi-element rules appear to be advantageous for improving the classification of detailed features that may be required in some forest surveys.

Technique for Fine Resolution Data

Poor classification performance achieved with the application of a conventional processing technique to fine resolution data was attributed to the large, overlapping variances of the signatures (Figure 4). These large variances were caused by the wide range of spectral variation within each feature area that resulted from individual resolution elements falling entirely within various spectral classes of forest canopy components such as illuminated pine tree crowns, hardwood tree crowns, illuminated and shadowed understory, etc. The great overlap of signature distributions was caused by the fact that each spectral class of canopy component occurred within several feature areas.

The proportion-space classification technique which we developed and implemented on the fine resolution (2 meters)^2 data entailed a two-stage procedure that ultimately discriminates features on the basis of average proportions of classified component spectral classes that occur within feature areas. The first stage of the procedure utilized the large variance in the data to classify resolution elements into their respective component spectral class, regardless of feature area. Signatures for the conspicuous component spectral classes in each feature area were defined with the aid of large-scale color-infrared photographs and a zoom transfer scope. Subsequent analysis indicated little capability for reliably discriminating between similar types of component spectral classes from feature to feature. Therefore, we combined such signatures and assessed discriminability for the resultant eight signatures representing different spectral classes of canopy components. Table 2 indicates relatively high classification performances for this set of signatures when used to classify a selected set of resolution elements in all feature areas.

Use of the eight component signatures for classifying representative regions of data within each feature revealed expected differences in the proportions of resolution elements that were classified into the various component spectral classes. Figure 9 illustrates the proportions for the regions of data classified within each feature. (Note that two separate data regions were classified within pine regeneration in order to observe the extremes of tree density that existed within the feature.) We had anticipated that differences in component proportions from feature to feature would exist, such as manifested in Figure 9, and that the classified proportions of component spectral classes within each feature could possibly provide a means for discriminating among features.

The second stage of the procedure was implemented by partitioning each representative data region into cells of 1000 $(2m)^2$ resolution elements (each cell measuring 50M by 80M ground coverage). For each cell, we established a new data vector giving the proportions of previously classified component spectral classes. Thus, a new "proportion space" was defined for describing the cells. These data vectors were averaged together to compute signatures defining component proportions in each feature. Finally, the proportion signatures were used to classify each 1000-element cell in proportion space. Figure 10 illustrates the greatly improved performance achieved for the proportion-space technique as compared to the conventional classification performance previously achieved with fine resolution data.

The procedure described here demonstrates the potential utility of fine resolution MSS data for forest resource surveys. The capability to classify such data into various spectral classes of forest canopy components can in itself provide information to support intensive forest management efforts. For example, proportions of classified canopy components enable the determination of crown closure for various tree crown spectral classes that may influence management decisions affecting silvicultural or pest control operations. Additionally, the application of the proportion-space classification technique can provide accurate forest feature discrimination at a more general level. Such capabilities could be advantageous in multistage sampling surveys of forestry and rangeland resources.

4. CONCLUSIONS

Use of a supervised multispectral data classification approach which incorporated a standard single-element linear decision rule resulted in improved overall classification performance for several hierarchies of forest features in six MSS data sets that ranged in spatial resolution from (2 meters)^2 to (64 meters)^2. Improvement was attributed to a reduction in the number of misclassified resolution elements that occurred as a result of reduced competition among signature distributions. Reduced competition presumably resulted from a reduction in scene variance that is inherent in the averaging of information over larger ground areas.

As expected, improvements in classification performance were noted for hierarchies of more general (aggregated) forest features. Such consistently better classification of more general levels of detail illustrates why higher levels of accuracy can be expected for large-area reconnaissance surveys dealing with generally-defined features than for detailed inventories of specifically-defined features.

Specialized processing techniques applied to both coarse and fine resolution data were shown to offer great potential for improved forest feature classification. Multi-element rules demonstrated the apparent capability for providing the improved classification performance of coarser spatial resolutions without the loss of other scene information that occurs in coarser resolutions. Such rules appear to offer a definite advantage for improving the classification of specifically-defined features with data having spatial resolutions comparable to the present Landsat and proposed Thematic Mapper MSS systems.

A proportion-space classification technique showed marked improvement for classifying forest features in data of fine resolution. The technique makes use of proportions of classified forest canopy components which may in themselves provide information in support of intensive forest management efforts. Application of a proportion-space classification technique to fine resolution MSS data could be utilized in a multistage sampling approach for inventorying forest and rangeland resources.

Results presented here have shown that the accuracy for classifying forest features with MSS data is greatly dependent on the spatial resolution of the data, the level of detail desired, and the processing technique employed. Consideration of these parameters for specific situations can begin to serve as guidelines that will enable forest managers to select the proper data acquisition and processing procedure to get the desired results.

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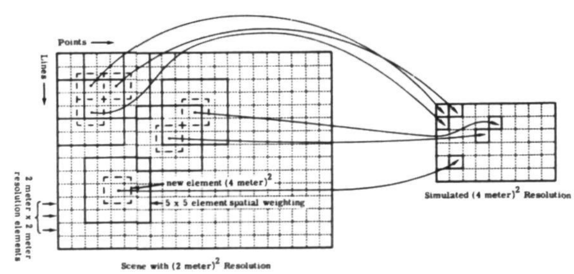

FIGURE 1. ILLUSTRATION OF TECHNIQUE FOR SIMULATED DOUBLING OF LINEAR SPATIAL RESOLUTION

TABLE 1. HIERARCHIES OF FORESTRY FEATURES FOR WHICH CLASSIFICATION PERFORMANCE WAS DETERMINED IN THE SAM HOUSTON NATIONAL FOREST (TEXAS)

Physiognomy	Cover Type	Condition Class	Growth Stage
Pine Sawtimber	Shortleaf Pine	1 Shortleaf Pine Sawtimber - Immature	Immature Pine Sawtimber
		2 Shortleaf Pine Sawtimber - Mature	Mature Pine Sawtimber
	Loblolly Pine	3 Loblolly Pine Sawtimber - Immature	Immature Pine Sawtimber
		4 Loblolly Pine Sawtimber - Mature	Mature Pine Sawtimber
Pine Regeneration	Pine Regeneration	5 Loblolly Pine Seedling and Sapling	Pine Seedling and Sapling

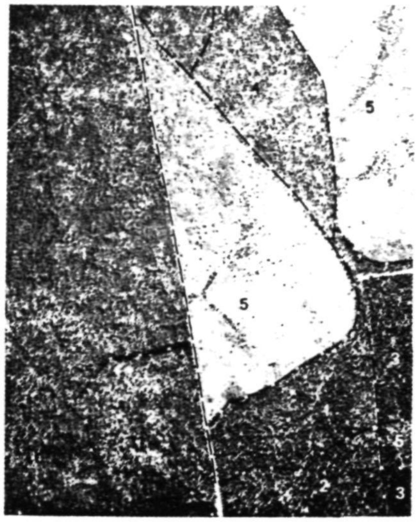

FIGURE 2. FOREST FEATURES IN MSS DATA, CONROE UNIT, SAM HOUSTON NATIONAL FOREST

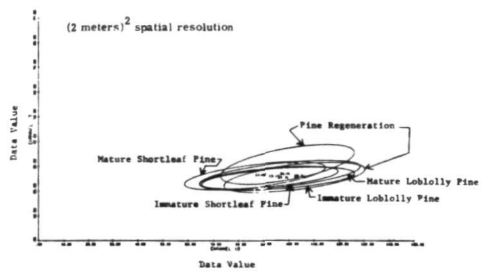

FIGURE 4. SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES IN (2 METERS)^2 RESOLUTION DATA

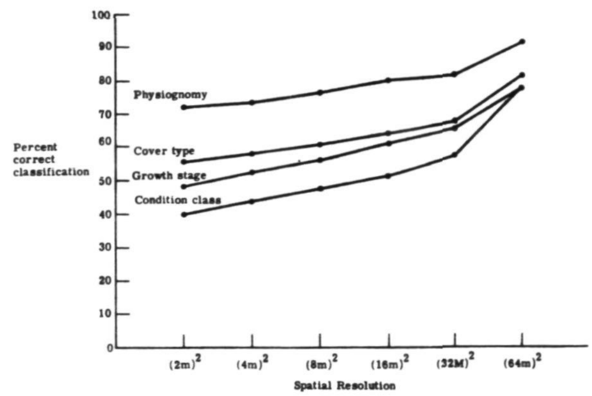

FIGURE 3. CLASSIFICATION ACCURACIES FOR HIERARCHIES OF FORESTRY FEATURES GENERALLY IMPROVE WITH COARSER SPATIAL RESOLUTION WHEN CONVENTIONAL TECHNIQUES ARE UTILIZED

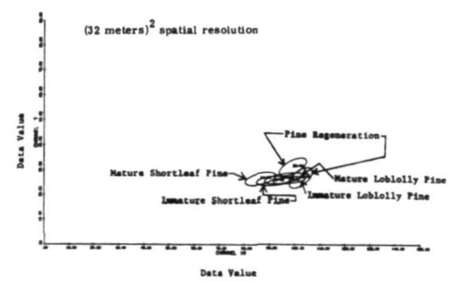

FIGURE 5. SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES IN (32 METERS)^2 RESOLUTION DATA

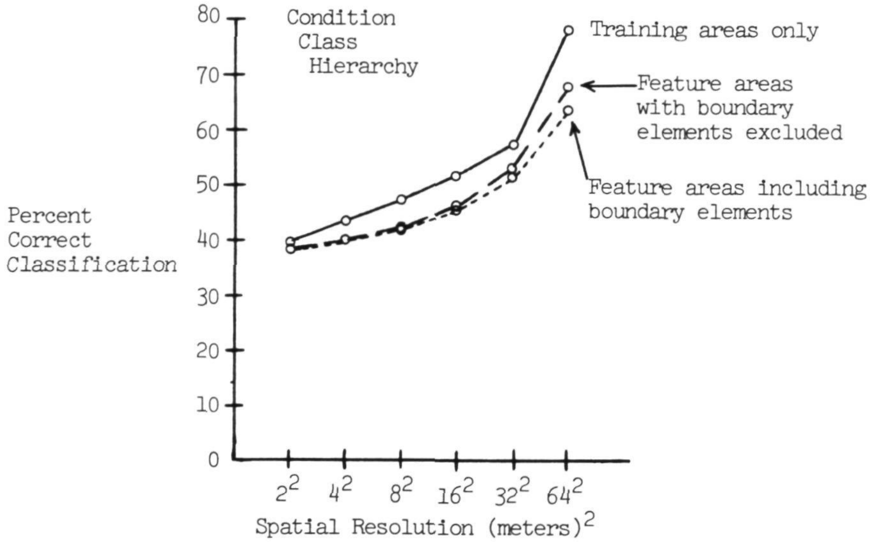

FIGURE 6. COMPARISON OF CLASSIFICATION PERFORMANCE FOR TRAINING SETS WITH THAT OBTAINED FOR TOTAL FEATURE AREAS

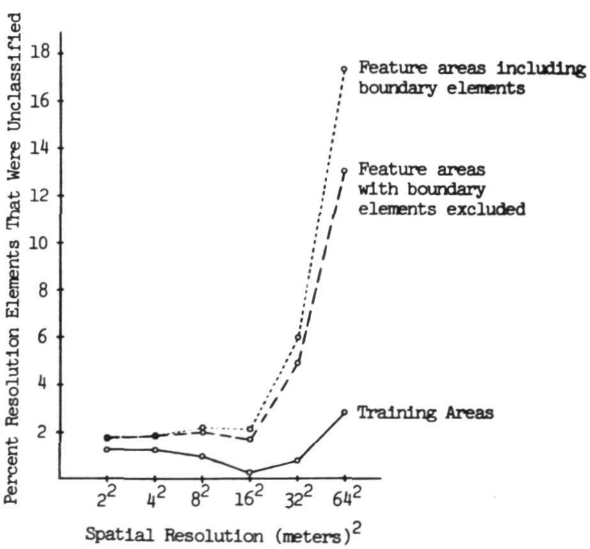

FIGURE 7. EFFECT OF SPATIAL RESOLUTION ON PERCENT OF RESOLUTION ELEMENTS WHICH WERE UNCLASSIFIED WITH A CLASSIFICATION REJECTION THRESHOLD HELD CONSTANT AT THE .001 LEVEL OF SIGNIFICANCE

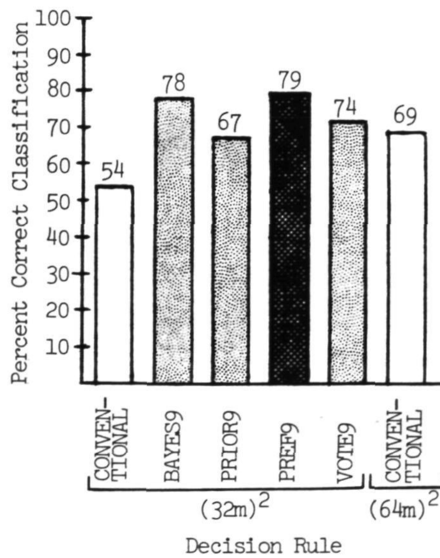

FIGURE 8. COMPARISON OF OVERALL CLASSIFICATION PERFORMANCES ACHIEVED FOR THE CONDITION CLASS HIERARCHY OF FEATURES. Results are for total feature areas with boundary elements excluded.

TABLE 2. RESULTS OF CLASSIFYING SELECTED RESOLUTION ELEMENTS IN ALL FEATURE AREAS

Component Spectral Class		Percent Correct
Illuminated Pine Crowns	Class I	72.9
	Class II	84.5
Illuminated Hardwood Crowns	Class I	86.9
	Class II	70.0
Illuminated Leafless Trees		95.3
Shadowed Pine Crowns		87.1
Shadowed Understory		96.2
Illuminated Understory		90.4

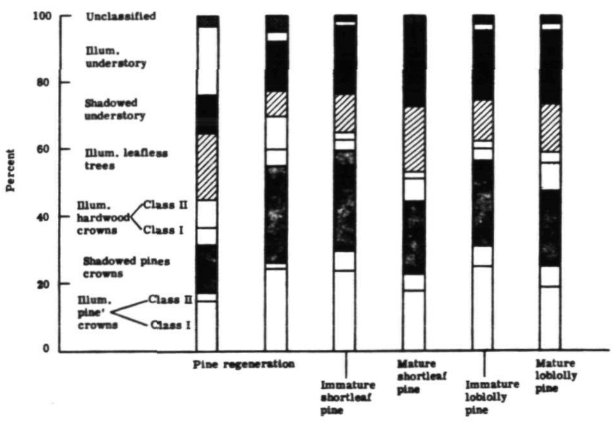

FIGURE 9. PROPORTIONS OF CANOPY COMPONENT SPECTRAL CLASSES THAT OCCURRED WITHIN AREAS REPRESENTATIVE OF EACH FEATURE

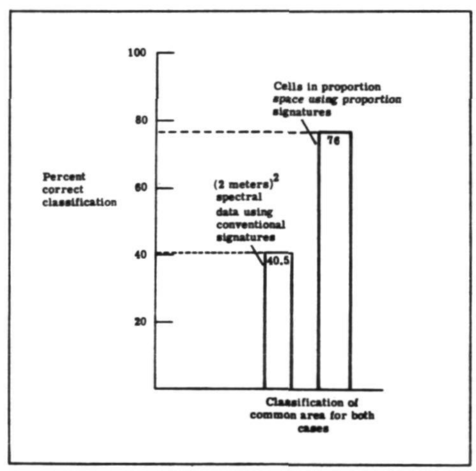

FIGURE 10. COMPARISON OF PROPORTION-SPACE AND CONVENTIONAL CLASSIFICATION PERFORMANCE AVERAGED OVER ALL FOREST FEATURES