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# COMPUTER-BASED CLASSIFICATION ACCURACY DUE TO THE SPATIAL RESOLUTION USING PER-POINT VERSUS PER-FIELD CLASSIFICATION TECHNIQUES

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## I. ABSTRACT

The 42.5 microradian angular IFOV of the Thematic Mapper will provide a linear spatial resolution of approximately 30 meters from the nominal altitude of 710 km. This study determined the classification accuracies achieved with MSS data of four different spatial resolutions using two different types of classifiers.

The data were obtained on May 2, 1979 with the NASA NS-001 Thematic Mapper Simulator (TMS) over an area in north-eastern South Carolina from a height above ground of 5945 meters. Data sets simulating three different spatial resolutions were computed from the original 15 meter nominal spatial resolution data. The classification accuracies achieved with data of each of the four different spatial resolutions using a "per-point" Gaussian maximum likelihood (GML) classifier were compared. The classification accuracies obtained using simulated 30 meter spatial resolution data with a "per-point" GML classifier were compared to the accuracies achieved with a "per-field" classification approach (i.e., the \*SECHO, Supervised Extraction and Classification of Homogeneous Objects, classifier). The "pure field", or "field-center pixel", classification accuracies were determined using training fields and test fields. Accuracy comparisons were conducted with the Newman-Kuels' Range Test on the arcsin transformed proportions. The use of successively higher spatial resolution data resulted in lower overall ("field-center" pixel) classification accuracy. This trend was observed particularly in forest cover types, which are associated with relatively large levels of spectral variability across adjacent pixels. The use of the \*SECHO classifier resulted in a higher overall ("field-center" pixel)

classification accuracy than was obtained with the per-point GML classifier using the simulated 30 meter spatial resolution data.

## II. INTRODUCTION

The Thematic Mapper is scheduled to be placed into orbit during the third quarter of 1982. The 42.5 microradian angular IFOV of the TM scanner (from the nominal altitude of 710 km.) will provide data which represents an area on the ground of approximately one-sixth acre. The classification of the elements of a scene is dependent on the assumption that the area represented by a pixel is less than the field size associated with each of the cover classes to be identified [1,2]. Field size is used here in reference to the spatially contiguous area occupied by a single cover class. This implies that the relative frequency of pixels which represent more than one cover class (i.e., boundary pixels) is small. The satisfaction of this condition places a lower level constraint on the spatial resolution of an effective scanner system.

Conversely, the use of classification algorithms which employ the measured irradiance level of a single pixel in classifying the pixel (i.e., "per-point" classifiers) is dependent on the pixel representing an area sufficiently large such that the gross spectral characteristics of the cover class are represented by the pixel. That is, the pixel should represent an area sufficiently large such that the within cover class spectral variability is minimized. Variance in the spectral classes arising from the spatial distribution of regions of differing reflectances within the cover class is, to a large degree, dependent

on the spatial resolution of the scanner system with which the scene is sampled.<sup>1</sup> The relationship between the spectral class variance and the spatial resolution of the scanner system is highly dependent on the cover class represented by the data. This relationship between the variance of the spectral classes and the spatial resolution of the scanner system imposes an upper level constraint on the spatial resolution of an effective scanner system.

"Center-field pixel", or "pure-field", classification accuracies obtained with high spatial resolution data have generally been found to be lower than the accuracies achieved with lower spatial resolution data when using "per-point" classifiers [5,6,7,8,9,10,11,13]. The high within spectral class variance was often cited as the reason for the lower classification accuracies achieved when using high spatial resolution data with a "per-point" classifier [6,7,8,12]. Kan and Ball [5] presented the relationship between the spatial resolution of the data and the variance of the spectral classes. They employed transformed divergence (a measure of statistical separability between probability density functions) to infer expected classification accuracies due to spatial resolution. Their estimate of the spectral class variances, however, ignored the effects of clustering the data. Clustering the data representing each cover class substantially reduces the spectral class variance. The problem then becomes the high degree of spectral similarity between spectral classes representing different cover classes (e.g., shadow areas between pine compared to shadow areas between hardwood; or damp bare soil in agricultural fields compared to damp bare soil in clearcut areas, ...).

The relative frequency of boundary pixels (as compared to non-boundary pixels) decreases with increasing spatial

<sup>1</sup>This source of variance is due to the spectral variability across adjacent pixels and has been referred to as "scene noise" [3,4], which conotes a data characteristic inherently detractive to information extraction. This relationship is considered to be highly dependent on the information extraction process or technique employed.

resolution of the data for any given field size. The rate of this trend decreases logarithmically with increasing field size [9]. Higher classification accuracies have been achieved with high spatial resolution data, when mensurational accuracy criteria were employed to evaluate the results, than were achieved with lower spatial resolution data [8,9].

Classifiers which employ the measured irradiance levels of a multiple of adjacent pixels, or a "cell" of pixels, in the class assignment decision logic are referred to as "per-field" classifiers [1,2,13,14]. Higher classification accuracies have been achieved with "per-field" classifiers when using data of relatively high spatial resolution than were achieved with the same data using a "per-point" classifier [3,8,10,12]. Approaches to classifying MSS data which can exploit the lower frequency of boundary pixels as well as the patterns in spectral variability among adjacent pixels associated with each cover class should provide a means of classifying areas with greater accuracy than is currently realized using Landsat MSS resolution data with "per-point" classifiers.

### III. METHODS AND ANALYSIS

#### A. DATA ACQUISITION

The data were obtained on May 2, 1979 with the NASA NS-001 Thematic Mapper Simulator (TMS) from an altitude of 5945 meters (MGD) over an area in northeastern South Carolina. Table 1 provides a summary of the waveband configuration, and respective sensitivity measures, for the NS-001 TMS and the design specifications for the Thematic Mapper. The flight lines were oriented north-south and were flown during mid-morning hours. Color and color infrared aerial photography of a scale of 1:40,000 were obtained at the time of over-flight.

#### B. DATA PREPROCESSING AND ADJUSTMENTS

The across-track change in scale of the imagery was adequately reduced by employing a geometric model which describes the ground resolution element dimensions as a function of the aircraft altitude, scanner IFOV, and the change in scan angle corresponding to the analog signal sampling interval. The data were

Table 1. Specification of the NS-001 Multispectral Scanner System as Compared to the Design Specifications of the Thematic Mapper System.

NS-001 Multispectral Scanner <sup>(1)</sup>				Proposed Thematic Mapper <sup>(2)</sup>			
Channel	Bandwidth (μm)	Low Level Input (W·CM <sup>-2</sup> ·SR <sup>-1</sup> )	NEΔp	Channel	Bandwidth (μm)	Low Level Input (W·CM <sup>-2</sup> ·SR <sup>-1</sup> )	NEΔp
1	0.45-0.52	8.7 x 10 <sup>-6</sup>	0.5%	1	0.45-0.52	2.8 x 10 <sup>-4</sup>	0.8%
2	0.52-0.60	6.8 x 10 <sup>-6</sup>	0.5%	2	0.52-0.60	2.4 x 10 <sup>-4</sup>	0.5%
3	0.63-0.69	5.0 x 10 <sup>-6</sup>	0.5%	3	0.63-0.69	1.3 x 10 <sup>-4</sup>	0.5%
4	0.76-0.90	4.4 x 10 <sup>-6</sup>	0.5%	4	0.76-0.90	1.6 x 10 <sup>-4</sup>	0.5%
5	1.00-1.30	6.0 x 10 <sup>-6</sup>	1.0%	5	1.55-1.75	8.0 x 10 <sup>-5</sup>	1.0%
6	1.55-1.75	6.2 x 10 <sup>-6</sup>	1.0%	6	2.08-2.35	5.0 x 10 <sup>-5</sup>	2.4%
7 <sup>(3)</sup>	2.08-2.35	4.7 x 10 <sup>-5</sup>	2.0%	7	10.4-12.5	300 <sup>o</sup> K	NEΔT=0.5 <sup>o</sup> K
8	10.4-12.5	NA	NEΔT=0.25 <sup>o</sup> K				

(1) Data was obtained from the "Operations Manual, NS-001 Multispectral Scanner," NASA; JSC-12715, April 1977.

(2) Data was obtained from Salomonson, 1978.

(3) Channel 7 (2.08-2.35 μm) was not operational at the time of the mission; all subsequent references to "channel 7" refer to the 10.4-12.5 μm waveband.

also truncated at +/-35 degrees to avoid large discrepancies in spatial resolution within each data set.

A study of the data quality revealed an apparent correlation between scan angle and response level. The relationships appeared to be sufficiently high to obscure sources of variation otherwise correlated with differences between cover classes. The data were adjusted using a model which described the variation in response level, for each channel, by column (to correlate to scan angle). The model was empirically derived from a subset of data, including areas external to the area subsequently classified, where no apparent stratification of cover class by column was present. The shape of each function was evaluated against both empirical [8,15,21] and theoretical work [15,16,22] prior to actual response level adjustment. The final data product was considered appropriate for analysis.

The original 15 meter spatial resolution data were used to compute the 30 x 30, 45 x 45, and 60 x 75 meter simulated spatial resolution data. This computation was conducted through the use of an unweighted arithmetic average of the measured irradiance levels of a "cell" containing the number of pixels corresponding to the desired simulated spatial resolution. The averaging was unweighted due to an insufficient number of pixels to provide a continuous function required to simulate the point spread function of each of the respective spatial resolutions.

### C. DEVELOPMENT OF TRAINING STATISTICS

A COMTAL Vision One/20 displaying a composite of channels 3, 4, and 5, in conjunction with the aerial photography, was employed to ascribe cover class labels to line-column coordinates in the imagery. The training fields were grouped on the basis of cover class. The groups of training fields were clustered individually to resolve the cover classes into a set of spectral classes. No pooling or deleting of spectral classes was conducted to avoid introducing another variable which would potentially affect the classification results achieved with data of each spatial resolution differently. Table 2 contains descriptions of the cover classes into one of which each element of the scene was classified.

### D. DEVELOPMENT OF TEST PIXELS

A systematic sampling approach was employed to generate a set of test pixels. A digital image grid with a 12 column by 30 row spacing (relative to the original 15 meter spatial resolution data) was generated for use in a graphics plane on the COMTAL. The systematic sampling approach provided a set of test pixels which would map precisely between the data of different spatial resolutions. The intention was to avoid introducing any sampling effects on the estimated classification accuracies which differed for data of different spatial resolution.

### E. DATA CLASSIFICATION

The training and test pixels of each of the four spatial resolutions were

classified with the LARSYS "per-point" Gaussian maximum likelihood (GML) classifier. The training and test pixels of the 30 meter spatial resolution data were classified using the LARSYS \*SECHO classifier.

Table 2. Description of Cover Classes Present in the South Carolina Study Area.

Cover Class	Number of Spectral Classes	Description of Cover Class
Tupe	3	Water tupelo; generally restricted to narrow ox-bow lakes and other areas of inundated soils.
Mveg	2	Misc. shrubs and small trees; located on saturated and inundated soils.
Crop	4	Row crops and small grain crops in varying stages of development and maturity.
Past	5	Pasture and old fields; plant cover varies from healthy, improved pasture grasses to senescent forbs and invader species.
Soil	3	Bare soil areas associated with agricultural activities; varies in sand, clay, and organic material content as well as moisture content.
Pthd	2	Pine-hardwood mix; generally varies between 35 to 65% hardwood intermixed with pine (determined by visual inspection).
Hwd	3	Old age bottom-land hardwood; sweet gum is the dominant species, crowns are large, inter-crown gaps are generally deep and result in dark shadowed areas.
Ccut	4	Areas subjected to clearcut forestry practices; ground cover comprised of dry to inundated soils without vegetation, to dense vegetative cover of slash, grasses, shrubs and residual trees. Windrowed slash is common on these areas.
Sghd	3	Second growth hardwood; species composition is highly diverse, crown height and diameter is variable, inter-crown gaps are generally shallow and do not result in dark shadowed areas.
Pine	2	Pine forest areas; the principle species is slash; long-leaf, and loblolly are common; age class varies from recently planted (5-10 years) to mature, closed canopy.

The \*SECHO classifier is considered a "spectral/spatial" classifier [14,20]. A brief synopsis of how the algorithm operates is included here to provide a basis for understanding the results. A "homogeneity" statistic is computed for each "cell" (e.g., a 2-by-2 group) of pixels. The statistic is compared to an analyst specified threshold. If the value of the statistic relative to the threshold indicates that the cell is not "homogeneous", the pixels of the cell are classified with a "per-point" classifier. If the cell is deemed "homogeneous" it is stored and subsequently compared to neighboring "homogeneous" cells to determine whether the cells are sufficiently similar (based on a likelihood ratio of evaluated probability density functions, PDFs) to be merged, forming a "field" of similar pixels. The entire field is then classified by evaluating the sum of exponential components of the PDF associated with each spectral class.

#### IV. RESULTS AND DISCUSSION

##### A. COMPARISONS BASED ON TRAINING FIELDS

The overall percent correct classification accuracy among training pixels was found to decrease using data of increasingly higher spatial resolution when classified with a "per-point" GML classifier. This relationship is illustrated in Figure 1. The difference between classification accuracy of each spatial resolution was found to be significant at the 0.10  $\alpha$ -level.<sup>2</sup> The variation in percent correct classification (PCC) achieved for each cover class with data of each spatial resolution is illustrated in Figure 2. Figure 2 can be thought of as a response surface in terms of PCC which is a function of cover class and spatial resolution. The slope of the lines connecting the PCC levels across different spatial resolutions represents the rate of change of PCC with respect to spatial resolution for each cover class. The greatest changes in PCC with respect to the spatial resolution of the data were obtained for the pine-hardwood mix, old-age hardwood, clearcut, second growth hardwood, and pine cover classes. Very little change in PCC with respect to the data spatial resolution occurred for water tupelo,<sup>3</sup> marsh vegetation, crops, pasture, and bare soil. The relationships between PCC and the spatial resolution of the data for each cover class are statistically represented in Table 3.

The PCC achieved using the "per-point" classifier with data of each spatial resolution were significantly different ( $\alpha = 0.10$ ) only for the forest cover classes. This is believed to be due to the level of spectral variability across adjacent pixels associated with TMS data obtained over forest cover classes. This form of spectral variability is the digital homolog to the

<sup>2</sup>Differences in classification accuracy were evaluated using the Newman-Kuels' Range Test on the arcsin transformed proportions. The arcsin transformation is employed to transform the hypergeometrically distributed percentages into a normally distributed population [18,19].

<sup>3</sup>A detailed description of the stand geometry, the associated spectral reflectance characteristics, and the consequent pair-wise separabilities associated with the water tupelo cover class, as opposed to other forest cover classes, is provided by Latty [12].

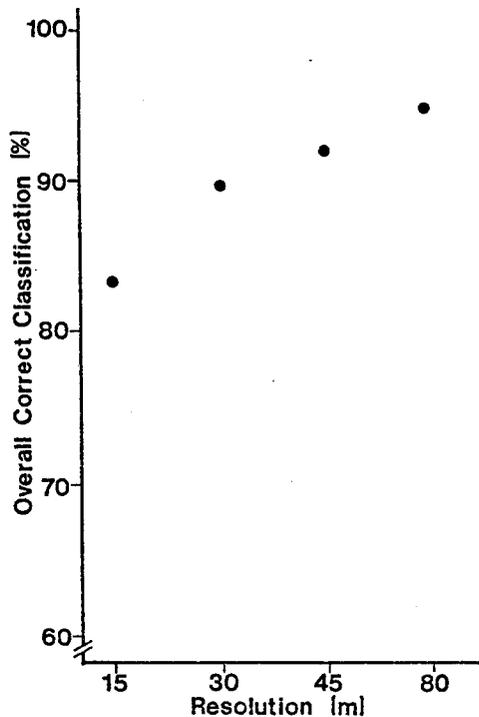


Figure 1. Overall Percent Correct Classification Achieved using Data of Four Different Spatial Resolutions Based on (field-center pixel) Training Field Pixels.

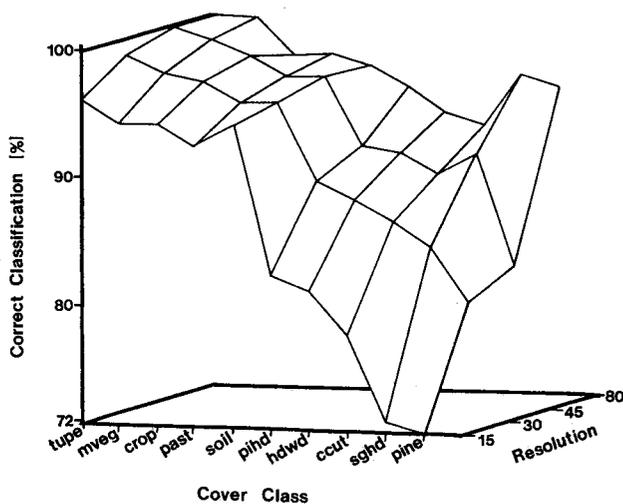


Figure 2. Percent Correct Classification Achieved for each Cover Class using Data of Four Different Spatial Resolutions, Based on Omission Frequencies in Training Field Pixels.

Table 3. Statistical Evaluation of Percent Correct Classification by Cover Class for each Spatial Resolution Based on the Frequency of Omission in Training Field Pixels.

Cover Class	Spatial Resolution				Harmonic Mean
	15 Meter	30 Meter	45 Meter	80 Meter	
Tupe	96.3 <sup>a</sup>	98.9 <sup>a</sup>	100.0 <sup>a</sup>	100.0 <sup>a</sup>	182.49
Mveg	94.7 <sup>a</sup>	97.6 <sup>a</sup>	99.2 <sup>a</sup>	100.0 <sup>a</sup>	150.64
Crop	94.8 <sup>a</sup>	97.1 <sup>a</sup>	98.1 <sup>a</sup>	97.3 <sup>a</sup>	771.28
Past	93.2 <sup>a</sup>	95.6 <sup>a</sup>	96.6 <sup>a</sup>	97.4 <sup>a</sup>	503.43
Soil	94.9 <sup>a</sup>	95.7 <sup>a</sup>	96.7 <sup>a</sup>	96.6 <sup>a</sup>	1019.80
Phhd	83.7 <sup>a</sup>	89.8 <sup>b</sup>	91.6 <sup>b</sup>	95.1 <sup>b</sup>	146.22
Hwd	82.5 <sup>a</sup>	88.5 <sup>b</sup>	91.2 <sup>c</sup>	93.3 <sup>d</sup>	2092.56
Ccut	79.3 <sup>a</sup>	87.0 <sup>b</sup>	89.7 <sup>c</sup>	92.4 <sup>d</sup>	2297.24
Sghd	72.9 <sup>a</sup>	85.1 <sup>b</sup>	91.3 <sup>c</sup>	96.3 <sup>d</sup>	1183.66
Pine	72.1 <sup>a</sup>	81.1 <sup>b</sup>	82.9 <sup>b</sup>	95.5 <sup>c</sup>	420.12

Dissimilar superscripts within each particular cover class, between spatial resolutions, denotes a significant difference at the  $\alpha = 0.10$  level of confidence, based on the Newman-Keuls' Range test conducted on the arcsin transformed proportions. The harmonic mean is defined as  $HM = \frac{n}{\sum_{i=1}^n 1/N_i}$ , where N=number of pixels for the *i*th data set, n = the number of data sets. Use of harmonic mean, in lieu of the arithmetic mean, provides an "unbiased" estimate of the sample variance by effectively weighting the lower sample sizes higher than the large sample sizes.

"texture" characteristic of aerial photography obtained over forest areas. The spectral variability across adjacent pixels is one component of the within spectral class variance. This component of the within class variance increases with increasing spatial resolution [1].

The overall percent correct classification achieved for training pixels using 30 meter spatial resolution data with the \*SECHO classifier (94.1 percent) was significantly greater, at the 0.10  $\alpha$  level, than was achieved with the "per-point" classifier (89.3 percent). Figure 3 illustrated the training field classification accuracies achieved with the two classifiers using the 30 meter spatial resolution data, for each cover class. The statistical evaluation of the differences for each cover class are summarized in Table 4. The PCC levels achieved with the \*SECHO classifier were higher than the PCC levels achieved with the per-point GML classifier for all cover classes for which the difference in PCC levels were found to be significant ( $\alpha = 0.10$ ).

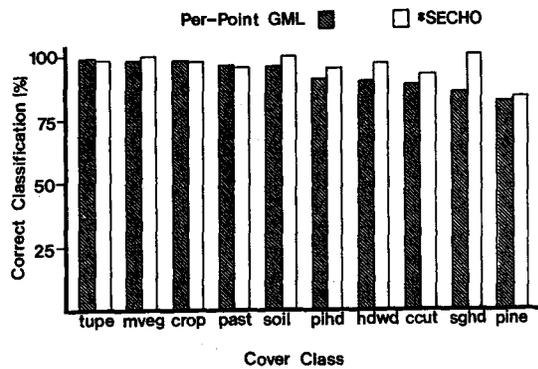


Figure 3. Percent Correct Classification Achieved for each Cover Class using the Per-point GML Classifier Compared to the \*SECHO Classifier, using 30 meter Spatial Resolution Data, Based on Omission Frequencies in Training Field Pixels.

Table 4. Statistical Evaluation of Percent Correct Classification by Cover Class Achieved with the Per-point GML Classifier Compared to the \*SECHO Classifier, Based on Frequencies of Omission in Training Field Pixels.

Cover Class	Per-Point GML	*SECHO	Harmonic Mean
Tupe	98.9 <sup>a</sup>	97.4 <sup>a</sup>	350
Mveg	97.6 <sup>a</sup>	100.0 <sup>b</sup>	294
Crop	97.1 <sup>a</sup>	96.6 <sup>a</sup>	1445
Past	95.6 <sup>a</sup>	94.1 <sup>a</sup>	987
Soil	95.7 <sup>a</sup>	99.3 <sup>b</sup>	1946
Plhd	89.8 <sup>a</sup>	93.6 <sup>a</sup>	314
Hdwd	88.5 <sup>a</sup>	95.5 <sup>b</sup>	3997
Ccut	87.0 <sup>a</sup>	90.4 <sup>b</sup>	4277
Sghd	85.1 <sup>a</sup>	99.8 <sup>b</sup>	2242
Pine	81.1 <sup>a</sup>	82.2 <sup>a</sup>	805

Dissimilar superscripts within each particular cover class, between spatial resolutions, denotes a significant difference at the  $\alpha = 0.10$  level of confidence, based on the Newman-Keuls' Range Test conducted on the arcsin transformed proportions.

The difference in PCC achieved with the \*SECHO classifier as compared to the per-point GML classifier were generally larger for those cover classes which were associated with relatively high levels of spectral variability across adjacent pixels (e.g., old age hardwood, clearcut areas, and second growth hardwood).

## B. COMPARISONS BASED ON TEST PIXELS

The overall PCC based on test pixels achieved using the "per-point" GML classifier with data of each spatial resolution are illustrated in Figure 4.

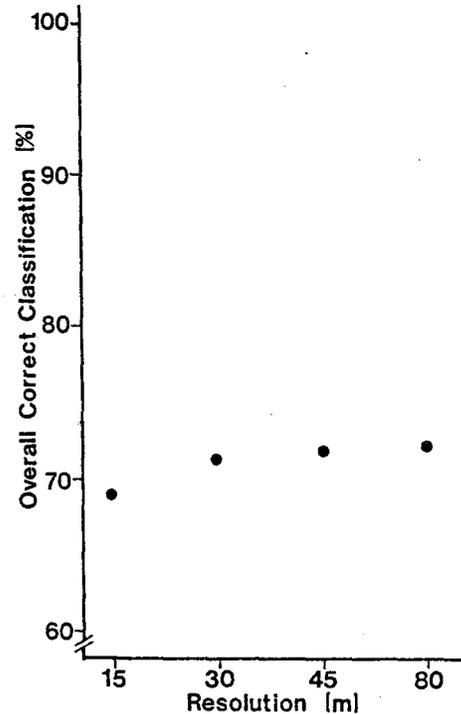


Figure 4. Overall Percent Correct Classification Achieved using Data of Four Different Spatial Resolutions, Based on Test Pixels.

The differences between the PCC levels achieved with data of each spatial resolution were not found to be significant at the  $\alpha = 0.10$  level of confidence. The magnitude of the differences between classification accuracies achieved for training pixels and test pixels is much larger than the magnitude of the differences between PCC levels achieved for data of each spatial resolution. This indicates that the degree to which the training classes represent the entire area to be classified is a more important determinant of classification accuracy than is the resolution of the data with which the classifications are conducted. However, the training field pixels are considered to provide a more sensitive estimate of the comparative PCC levels

achieved due to either spatial resolution of the data or the classifier employed, since the factors affecting the outcome are more nearly restricted to the "resolution" factor, or the "classifier" factor, than when test pixels are used to conduct the comparison.

Figure 5 demonstrates the relative classification accuracies, for each cover class based on test pixels, achieved with data of each spatial resolution using the "per-point" GML classifier. Table 5 provides a summary of the statistical evaluation of the differences between data of each spatial resolution for each cover class.

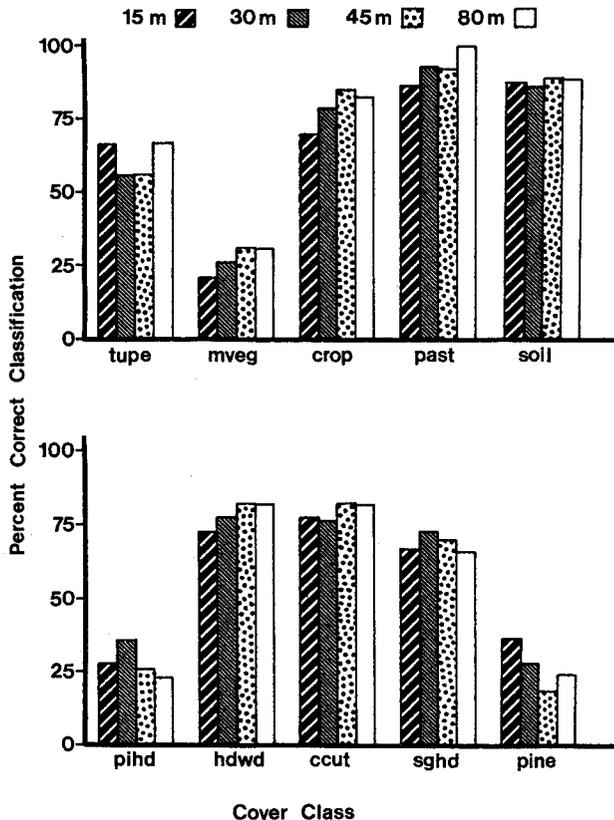


Figure 5. Percent Correct Classification Achieved for each Cover Class using Data of Four Different Spatial Resolutions, Based on Omission Frequencies in Test Pixels.

Table 5. Statistical Evaluation of Percent Correct Classification by Cover Class for each Spatial Resolution, Based on the Frequency of Omission in Test Pixels.

Cover Class	Spatial Resolution				Harmonic Mean
	15 Meter	30 Meter	45 Meter	80 Meter	
Tupe	66.7 <sup>a</sup>	55.6 <sup>a</sup>	55.6 <sup>a</sup>	66.7 <sup>a</sup>	9.0
Mveg	21.1 <sup>a</sup>	26.3 <sup>a</sup>	31.6 <sup>a</sup>	31.6 <sup>a</sup>	19.0
Crop	69.7 <sup>a</sup>	78.8 <sup>a</sup>	84.8 <sup>a</sup>	82.1 <sup>a</sup>	31.86
Past	86.7 <sup>a</sup>	92.9 <sup>a</sup>	92.3 <sup>a</sup>	100.0 <sup>a</sup>	13.52
Soil	87.5 <sup>a</sup>	85.9 <sup>a</sup>	81.7 <sup>a</sup>	86.9 <sup>a</sup>	62.97
Pihd	29.0 <sup>a</sup>	35.5 <sup>a</sup>	25.8 <sup>a</sup>	22.6 <sup>a</sup>	31.00
Hdwd	72.4 <sup>a</sup>	77.6 <sup>ab</sup>	81.4 <sup>b</sup>	81.4 <sup>b</sup>	156.00
Ccut	77.5 <sup>a</sup>	76.1 <sup>a</sup>	81.7 <sup>ab</sup>	88.4 <sup>b</sup>	70.59
Sghd	66.7 <sup>a</sup>	72.4 <sup>a</sup>	69.4 <sup>a</sup>	65.5 <sup>a</sup>	121.49
Pine	36.4 <sup>a</sup>	27.3 <sup>a</sup>	18.2 <sup>a</sup>	36.4 <sup>a</sup>	11.00

Only the PCC obtained for a subset of the cover classes characterized by large levels of spectral variability across adjacent pixels (i.e., old-age hardwood and clearcut areas) were significantly different at a 0.10  $\alpha$ -level, when evaluation was based on test pixels.

The overall classification accuracies, based on test pixels, achieved with the 30 meter spatial resolution data using the \*SECHO classifier (75.0 percent correct) was not significantly higher ( $\alpha = 0.10$ , based on 545 observations) than the accuracy achieved with the per-point GML classifier (71.0 percent correct). The differences in PCC achieved for each cover class using a per-point GML classifier as compared to the \*SECHO classifier, based on test pixels, are illustrated in Figure 6. Only the differences in PCC associated with the clearcut cover class were found to be significant ( $\alpha = 0.10$ ). The sensitivity of the tests for "real" differences is limited, for many cover classes, by the number of test pixels available. Since the estimate of the variance of the transformed proportions is a constant, inversely proportional to the number of test pixels, the sensitivity to "real" differences between PCC is directly proportional to the square root of the number of test pixels. The estimation of PCC for the area classified is caught

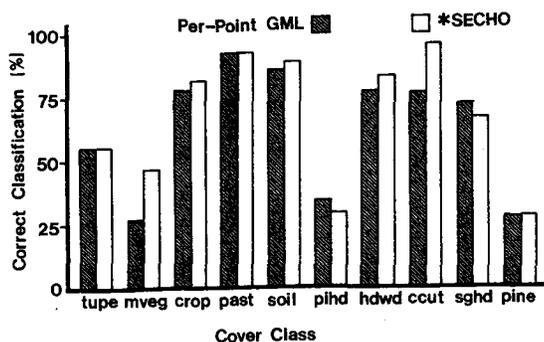


Figure 6. Percent Correct Classification Achieved for each Cover Class using the Per-point GML Classifier Compared to the \*SECHO Classifier, using 30 meter Spatial Resolution Data, Based on Omission Frequencies in Text Pixels.

in the quandary of including a sufficiently large number of pixels to provide a sensitive test for "real" differences, and providing a sampling technique which assures that each test pixel satisfies the "sample" criteria. The domain of the inference afforded by the results evaluation technique employed should also be explicitly understood.

#### V. SUMMARY AND CONCLUSIONS

The results obtained in this study demonstrate: 1) the use of successively higher spatial resolution data resulted in lower overall, field-center pixel, classification accuracies when classifications were conducted with a "per-point" GML classifier; 2) higher classification accuracies were achieved with the "per-point" classifier using 60 x 75 meter (as opposed to higher) spatial resolution data in cover classes associated with relatively high levels of spectral variability across adjacent pixels (i.e., old-age hardwood, second growth hardwood, pine forest, and clear-cut areas); 3) differences in classification accuracies achieved with data of different spatial resolution were not significant ( $\alpha = 0.10$ ) for cover classes associated with relatively low levels of spectral variability across adjacent pixels (i.e., pasture, crops, bare soil, or marsh vegetation); 4) higher classification accuracies were achieved using the \*SECHO classifier with 30 meter spatial resolution data, than were

achieved with the per-point GML classifier; 5) the largest increases in classification accuracies were achieved with the \*SECHO classifier in cover classes associated with relatively high levels of spectral variability across adjacent pixels; and 6) the difference in accuracies observed for training pixels as compared to test pixels was greater than the differences due to the spatial resolution of the data, or the classifier employed.

#### VI. RECOMMENDATIONS

A numerical measure of the spectral variability across adjacent pixels needs to be developed, or adopted from the literature. The degree of ordination of the various ground cover classes needs to be determined in an attempt to reveal the characteristics of the data of different spatial resolutions, obtained over cover classes of variable structure and geometries. This work should be designed to support work conducted in evolving classifiers which exploit this source of information about the scene in the classification decision logic.

A meaningful combination of the error of commission and omission needs to be developed for conducting classification performance evaluations by cover class. Perhaps the arithmetic mean of the two error estimates would provide the needed combination.

#### VII. ACKNOWLEDGEMENTS

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