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THE UTILITY OF THEMATIC MAPPER SENSOR CHARACTERISTICS FOR SURFACE MINE MONITORING

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I. ABSTRACT

An investigation was conducted to isolate the effects of three sensor characteristics (spatial resolution, data quantization, and spectral band configuration) on the thematic classification of remote sensing data acquired over an area containing surface coal mines. A fixed effects, no interaction analysis-of-variance (ANOVA) model and a balanced experimental design were used to evaluate the effect on classification accuracy of refining each characteristics from Landsat Multispectral Scanner (MSS) specifications to Thematic Mapper (TM) specifications. This approach required data for eight ANOVA treatments. The required data were obtained by a systematic degradation of TM data acquired over Clarion County, Pennsylvania, on August 28, 1982. Data for each treatment were independently classified into six land cover categories using supervised training and a per-pixel, maximum-likelihood decision rule. Classification accuracies were determined by comparisons to digitized ground reference data.

On the basis of ANOVA, data quantization and spectral band configuration did not significantly effect classification accuracy. The increase in spatial resolution from 80m to 30m, however, significantly improved classification accuracy. With the other two characteristics held constant, percent accuracies obtained with 30m data were greater than accuracies obtained with 80m data by an average of 17.8 percentage points. These results differed considerably from the results of a previous study. The discrepancy was attributed to differences between scene and category characteristics.

II. INTRODUCTION

The use of Landsat Multispectral Scanner (MSS) data for surface coal mine inventory and inspection has been extensively investigated (Anderson et al., 1977; Chase and Pettyjohn, 1973; Quattrochi, 1982). Despite encouraging research results, MSS data have not gained wide acceptance for operational surface mine monitoring. One reason for the lack of acceptance is the MSS spatial resolution. The 80m resolution is considered insufficient for detailed surface mine inspection (Russell, 1977).

The sensor payloads aboard the recently launched Landsat-4 (July 16, 1982) and Landsat-5 satellites (March 1, 1984) consist of an MSS and an advanced sensor, the Thematic Mapper (TM), with a refined spatial resolution (30m). Relative to the MSS, the TM also offers new and more optimally placed spectral bands and enhanced radiometric sensitivity quantized to eight-bits rather than six-bits (Table 1). These sensor refinements are expected to enhance the usefulness of TM data relative to MSS data.

An earlier study (Irons et al., 1977) with simulated TM data acquired by an airborne sensor indicated that TM data are potentially more useful than MSS data for surface mine monitoring. This earlier study, however, did not address the contribution of individual TM sensor characteristics to surface mine monitoring. The research reported here was conducted to assess the usefulness of actual TM data and to quantitatively evaluate the contribution of individual sensor characteristics to data utility for surface mine monitoring.

The research was further motivated by a thematic classification of actual and systematically degraded TM data acquired over an area of diverse land cover near Washington, D.C. (Williams et al., 1984). This investigation found that the additional TM spectral bands and the increased data quantization enhanced classification performance when a per-pixel, maximum-likelihood decision rule was used. The increase in spatial resolution (i.e., the decrease in instantaneous-field-of-view) from MSS to TM specifications, however, did not improve classification accuracy. In a follow-on study (Irons et al., 1984), this result was attributed to two counteracting effects of increasing spatial resolution: (1) the spectral variability of land cover categories often increases which can hinder classification; and (2) the proportion of mixed (boundary) pixels in a scene tends to decrease which can enhance classification performance. The study concluded that the ultimate effect of increasing spatial resolution depended on the spectral and field-dimension attributes of the land cover categories and suggested that TM scenes for a variety of geographic areas be analyzed to more fully assess TM data utility. The research reported here extended the general approach of Williams et al. (1984) to a new area which has been extensively disturbed by surface mining.

III. METHODS AND MATERIALS

A. EXPERIMENTAL DESIGN

The intent of the experimental design was to isolate the effect of each of three TM sensor characteristics (spatial resolution, data quantization, and spectral band configuration) on classification performance. An analysis-of-variance (ANOVA) approach was adopted to evaluate the effect of altering each characteristic from approximate MSS specifications to TM specifications. The application of ANOVA to the assessment of thematic classification is explained by Rosenfield (1981). This approach was applied to simulated TM data by Sigman and Craig (1981) and to actual TM data by Williams et al. (1984) and Irons et al. (1984).

The experimental design was based on a three factor fixed effects ANOVA model. The three factors corresponded to the three sensor characteristics, and two levels per factor were selected to approximate the TM and MSS specifications for each characteristic: 30m (TM) and 80m (MSS) spatial resolutions; eight-bit (TM) and six-bit (MSS) data quantization; and six spectral bands in the visible, near-infrared and middle-infrared portions of the spectrum (TM), compared to a subset of three spectral bands in the visible and near-infrared (MSS). The thermal infrared band of the TM was not considered due to the complication in experimental design presented by the 120m spatial resolution. All possible combinations of the three factors, given the two levels per factor, produced eight treatments for analysis (Table 2).

The data required by the eight treatments were obtained by systematically degrading actual TM data. Data for each treatment were classified into six land cover categories (water, agriculture, bare mine spoil, grass on mine soil, trees on mine spoil, and forest) using supervised training and a per-pixel, maximum likelihood classification algorithm. Classification accuracies were assessed by automated comparisons to digitized ground reference data. The ANOVA design enabled a quantitative evaluation of the effects of each factor on classification accuracy. Each of these data processing and analysis procedures is described below.

B. STUDY SITES

The general study area was Clarion County, Pennsylvania. The county is located within the Main Bituminous Coal Field of the Appalachian Plateau Physiographic Province. Dipping sedimentary strata of the Allegheny Group, formed during the Pennsylvanian geologic period, underlie Clarion County. The county is heavily forested and is characterized by rolling topography of moderate relief. Surface coal mining has disturbed extensive portions of the county and a range of bare to revegetated mine spoil conditions can be found there.

Color infrared aerial photography was acquired over the county on October 6, 1982, at a scale of 1:40,000. Four 241mm format (nine inch format) photographic frames were arbitrarily selected for photointerpretation. The four frames were enlarged to a scale of 1:10,000. Interpretations were limited to a 41cm square from the center of each frame to avoid the increased geometric distortion typically found at the edges of photographs. The surface areas depicted within each square served as a study site. Each of the four Clarion County sites covered an area of approximately 1680 hectares.

C. DIGITAL IMAGE DATA

Digital image data were acquired over Clarion County on August 28, 1982, by the Landsat-4 TM (Scene 40043-15244, Path 17, Row 31, Jamestown, New York).

The data were in the CCT-PT format generated by NASA's Scrounge System (Lyon et al., 1983). Data in this standard format have been radiometrically corrected and then resampled for geometric rectification. The resampling results in 28.5m square pixels.

The TM data corresponding to the four study sites were extracted from the scene. Each site was represented by a 160-by-160 pixel segment, and the data for the six reflective spectral bands were extracted. The four data segments were concatenated to form the data set corresponding to the first ANOVA treatment (Treatment A, Table 2).

D. TM DATA PROCESSING

The Treatment A TM data were systematically degraded (Table 2) to evaluate the effects of altering each sensor characteristic separately (Treatments B, C, and E), the effects of altering all possible combinations of two characteristics (Treatments D, F, and G), and the effects of simultaneously altering all three sensor characteristics under consideration (Treatment H). Each step of the degradation process was intended to approximate the impact of an MSS sensor characteristic on digital image data. The spatial degradation consisted of convolution with a three-by-three pixel unweighted average filter to approximate the 80m instantaneous-field-of-view (IFOV) of the MSS, sampled at two pixel (57m) increments. The two pixel increment was used because the 80m MSS data are resampled for geographic registration and provided to investigators in a digital format consisting of 57m square pixels. The spectral degradation consisted of a three-band subset of the TM data (bands TM2, TM3, and TM4) which resemble bands MSS1, MSS2, and MSS4. The reduction in quantization from eight-bits (TM) to six-bits (MSS) was accomplished by integer division by four. The degradation process is described in greater detail in Williams et al. (1984).

E. GROUND REFERENCE DATA

Ground reference data were essential to the assessment of classification accuracy. Such data were derived from the photointerpretation of the four enlarged frames of aerial photography. A photointerpreter first delineated the boundaries of the six land cover categories (water, agriculture, bare mine spoil, grass on mine spoil, trees on mine spoil, and forest) onto acetate overlays. The photointerpreter used a 15m (1.5 mm on the photograph) minimum mapping unit criterion. The delineated boundaries were then digitized using a hand-held cursor and digitization table. The digitized boundaries were registered to the TM data using image control points and digital rubber-sheet stretching. Finally, two files of digitized, registered reference data were generated in a raster format. One file consisted of 28.5m square raster cells and could be directly overlaid onto the digital image data with 28.5m square pixels (Treatments A, C, E, and G). The second file consisted of 57m square raster cells and could be directly overlaid onto the spatially degraded data (Treatments B, D, F, and H).

F. SELECTION OF TRAINING AND TEST PIXELS

The digitized ground reference data enabled the selection of a stratified random sample of image pixels for each ANOVA treatment. The strata were the six land cover categories depicted in the reference data. For each treatment, 330 pixels were selected from each category; 280 pixels served as training pixels while the remaining 50 pixels were used as test pixels. The six land cover categories were treated as equally important in subsequent analyses by virtue of the selection of an equal number of pixels from each category.

G. CLASSIFICATION

For a given ANOVA treatment, a particular land cover category was statistically represented by the means and covariance matrix of the multispectral data from the associated set of 280 training pixels. The statistics for all six categories were used by a per-pixel, Gaussian, maximum-likelihood decision rule to classify the 300 test pixels (six categories times 50 test pixels per category). Since the category associated with each test pixel was known from ground reference data, a contingency matrix was easily generated to display the portion of correctly classified pixels by category along with omission and commission errors. The sum of correctly classified pixels over the six categories divided by the total number of test pixels (300) formed the overall accuracy value used in subsequent analyses. These classification and accuracy assessment procedures were repeated for each ANOVA treatment.

H. EVALUATION OF RESULTS

The evaluation of the effect of each sensor characteristic on classification accuracy was based on a three-factor, fixed effects ANOVA model with no interactions. Fixed effects ANOVA models operate under three assumptions (Neter and Wasserman, 1974): (1) the observed responses for each treatment are normally distributed random variables; (2) each normal probability distribution has the same variance; and (3) the observations for each treatment are random observations and are independent of the observations for any other treatment. The additional assumption of no factor interactions (i.e., non-additivity) was included in these analyses because only one observation of overall classification accuracy was obtained per treatment. The limit of one observation rendered statistical tests of interactions impossible, but a statistically valid test of main factor effects could still be conducted under the no interaction model (Neter and Wasserman, 1974).

The use of the no-interaction model slightly deviated from the approach of Williams et al. (1984). In the earlier study, multiple observations of classification accuracy were obtained for each treatment by acquiring multiple random samples of training and test pixels. Repeated random sampling was not conducted for the research reported here because of concerns regarding independence. Multiple samples of the Clarion County TM data would extensively overlap due to the limited number of available pixels, and repeated training and testing with overlapping samples could not be regarded as independent experiments. Thus, the use of only one observation of classification accuracy per treatment was considered more suitable for the analyses reported here, and this approach more closely follows the analysis outlined by Rosenfield (1981).

The observed classification accuracies were transformed prior to ANOVA to create a new scale of measurement which more closely adhered to the model assumptions. The original accuracy values were binomially distributed proportions rather than normally distributed random variables. The variance of a sample proportion depends on the true proportion, and therefore, the variances of the observed accuracies could not be equal between treatments unless the accuracies were also equal. The arcsin (inverse-sine, square-root) transformation is commonly used to stabilize proportion variances for ANOVA (Neter and Wasserman, 1974; Rosenfield, 1981). This transformation was applied to the accuracy values in the following manner:

$$\theta = \text{Arcsin}\sqrt{p};$$

where:

p is a proportion (i.e., classification accuracy) and $0 \leq p \leq 1$; and θ is the transformed accuracy in degrees.

The transformed accuracies, θ, had an approximately constant variance of 821/300 (Bartlett; 1947; Rosenfield, 1981), where 300 is the number of classified pixels tested for each treatment to determine accuracy. The transformation had the added advantage of a tendency to improve the closeness of the distributions to normality (Bartlett, 1947; Neter and Wasserman, 1974).

The transformation was performed to permit a statistically valid assessment of factor effects by ANOVA. The transformation does not alter the status of classification accuracy as a meaningful value for further discussion.

The transformed accuracies were used in the ANOVA to compute F-statistics for the statistical evaluation of factor effects. Error mean square was the appropriate denominator of the F-statistic, but error mean square could not be calculated in the convential manner since only one observation per treatment was obtained. Although several investigators (Landgrebe, 1976; Rosenfield, 1981) have suggested the use of the transformed accuracy variance (821/300) as the denominator in this situation, a more conservative estimate of error mean square was selected for these analyses:

$$MSE = [SSTOT - (SSA+SSB+SSC)]/4$$

where:

SSTOT is total sum of squares; SSA is factor A (spatial resolution) sum of squares; SSB is factor B (data quantization) sum of squares; SSC is factor C (spectral band configuration) sum of squares; 4 is the degrees of freedom; and MSE is error mean square.

This estimate represented the variance remaining after main factor effects were taken into account. The use of this estimate in the F-statistic denominator made any conclusions of factor effect significance conservative under the nonadditivity assumption. In other words, rejection of a null hypothesis of no main factor effect could be statistically supported even if factor interactions actually existed. For this investigation, a null hypothesis was rejected if the appropriate F-statistic was greater than the 95% point of the F-distribution (i.e., factor effects were tested at an α-level of 0.05).

IV. RESULTS

A. CLASSIFICATION

Table 3 provides examples of the contingency matrices from which classification accuracies were derived. The diagonal elements of each matrix are the percentage (proportion times 100) of test pixels correctly classified for each class. The average of the diagonal elements equals the percentage of all test pixels correctly classified and is the overall accuracy value given in Table 2. The other elements are percent omission and commission errors. For example, the element in row 2, column 3 is the percentage of agricultural pixels incorrectly classified as bare mine spoil. This represents an omission error for the agriculture class and a commission error for the bare mine spoil class.

Table 2 lists the percent overall classification accuracies obtained for each treatment. The accuracy obtained with actual TM data (Treatment A) is greater than the accuracy obtained with the data which most closely approximated MSS data (Treatment H) by 16.3 percentage points.

B. ANOVA

Table 4 presents the F-statistics used to evaluate the effect of each factor on classification accuracy. The null hypothesis of no factor effect could not be rejected at an α-level of 0.05 for either the data quantization factor or the spectral band configuration factor. The effect of spatial resolution was considered strongly significant on the basis of the F-test.

The results of classification and ANOVA are graphically illustrated in Figure 1. The increase in spatial resolution from MSS specifications (80 m) to TM specifications (30 m) consistently and dramatically improved classification accuracy when the other two factors were held constant (Figure 1a). The average increase in accuracy was 17.8 percentage points. Although a no interaction ANOVA model was used for evaluations, the graphs indicate some interaction between spatial resolution and the other two factors. The increase in data quantization from six bits to eight bits slightly increased the classification accuracies for 30m data and slightly decreased the accuracies for 80m data (Figure 1b). Similarly, the change from the three-band configuration to the six-band configuration increased the accuracies obtained with 30m data and decreased the accuracies obtained with 80m data (Figure 1c). These interaction effects, however, appear small compared to the main effect of spatial resolution and were not considered sufficient cause to abandon the use of the no-interaction model.

V. DISCUSSION

To summarize this investigation, the effects of three sensor characteristics were quantitatively evaluated with respect to the thematic classification of remote sensing data acquired over a geographic area containing surface coal mines. ANOVA was used for the evaluation on the basis of a fixed-effects, no interaction model and a balanced experimental design. The three characteristics were spatial resolution, data quantization, and spectral band configuration. Two levels were considered for each characteristic; one level was the TM specification for the characteristic while the other level approximated the MSS specification. This experimental design required data for eight treatments which were obtained by the systematic degradation of TM data acquired over Clarion County, Pennsylvania, on August 28, 1982.

Data for each treatment were independently classified into six land cover categories (water, agriculture, bare mine spoil, grass on mine spoil, trees on mine spoil, forest) using supervised training and a per-pixel, maximum-likelihood decision rule. Classification accuracy was determined for each treatment by automated pixel-by-pixel comparisons to digitized ground reference data. The eight accuracies were arcsin transformed to create a scale of measurement which more closely adhered to the assumptions of ANOVA. The effects of data quantization and spectral band configuration were not considered statistically significant on the basis of F-tests. The increase in spatial resolution from 80m to 30m significantly increased classification accuracy.

This investigation geographically extended the methodology applied by Williams et al. (1984) to a Washington, D.C., TM scene. The results obtained with the Clarion County TM data, however, differed considerably from the results obtained by Williams et al. (1984). To briefly review, both increasing data quantization and adding the three spectral bands to the configuration improved classification accuracies obtained with the Washington, DC data, but spatial resolution did not significantly effect accuracy. The insignificance of the spatial resolution effect was attributed to two counteracting consequences of increasing resolution: (1) category spectral variability tends to increase which can hinder classification; and (2) mixed pixel proportions tend to decrease which can enhance classification.

The analyses of the Clarion County data indicate that the reduced proportion of mixed pixels had a greater influence on classification accuracy than did any increase in spectral variability at the higher spatial resolution. The six Clarion County land cover categories often occurred in fields with narrow dimensions as shown by the large proportions of mixed pixels associated with most categories (Table 5). The higher resolution data (28.5m square pixels), however, contained much fewer mixed pixels than the spatially degraded data (57m square pixels), and the total mixed pixel proportion for the high resolution data was 24.1 percentage points less than the total proportion for the degraded data (Table 5). For comparison, the total mixed pixel proportion for the Washington, D.C., TM data was only 19.5 percentage points less than the proportions for degraded (again, 57m square pixels) data when five land cover categories were considered (Irons et al., 1984; Table 3). The surface mined landscape of Clarion County represented a distinct geographic situation of narrow features for which the TM spatial resolution was of immediate benefit in thematic classification.

The results of the investigation reported here indicate that six-bit data from three visible and near-infrared spectral bands were as useful as eight-bit data from all six reflective TM bands for the recognition of the six land cover categories depicted in the Clarion County data. The increased quantization did not appear to enhance any between-category boundaries in spectral data space. The additional spectral bands did not seem to increase contrasts between categories over the contrasts provided by the visible and near-infrared observations.

Digital image data from the Landsat satellites are frequently used to generate thematic maps through the application of per pixel, maximum-likelihood decision rules. Classification accuracy was selected as a quantitative indicator of data utility for both this investigation and by Williams et al. (1984). Taken together, the two studies show that the contributions of advanced TM sensor characteristics to data utility depend heavily on the scene and the categories-of-interest. For some scenes, the eight bit quantization can enhance between-category boundaries and the new spectral bands can provide data from portions of the spectrum when category reflectivities become disparate. The categories-of-interest in other scenes may already be separable with data from visible and near infrared spectral bands, but the categories may occur in small fields. In this case, the TM 30m resolution can enhance classification by reducing the proportion of mixed pixels relative to MSS data. In particular, the results reported here demonstrate that the TM spatial resolution can be of immediate benefit for certain applications such as surface mine monitoring.

TM data utilization is not limited to thematic mapping by per pixel classification. Relative to MSS data, TM data provide information with greater radiometric precision and from additional spectral regions. This information can be applied to the determination of surface feature attributes and to the observation of physical surface processes as well as to classification. Also, increasing the spatial resolution from 80m to 30m has consequences which are not exploited by a per-pixel, maximum-likelihood decision rule. The increased resolution clarifies shapes, sharpens boundaries, and accentuates the textural appearance of categories. These consequences can facilitate the visual photointerpretation of imagery, and the development of new classification algorithms which exploit these consequences can potentially improve automated classification performance. This investigation focused on the use of TM data for thematic mapping. TM data utility will become even more apparent as more data applications and alternate classification approaches are explored.

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BIOGRAPHICAL SKETCHES

James R. Irons received his B.S. degree in Environmental Resources Management in 1976 and his M.S. degree in Agronomy in 1979 from the Pennsylvania State University. Since 1979, he has worked as a physical scientist in the Earth Resources Branch at NASA's Goddard Space Flight Center. He has worked primarily on analyses of simulated and actual Thematic Mapper data for general land cover mapping and for surface mine monitoring. His current effort involve the development and utilization of multispectral linear array technology for the remote sensing of earth resources.

Ruth L. Kennard received her B.S. degree in Biology from Trinity College, Burlington, Vermont in 1974. She is a member of the technical staff of Science Applications Research. She is currently involved in automated processing of Multispectral Scanner, Thematic Mapper, Spot Simulator and SE-590 digital data.

Table 1. Comparison of Landsat TM and MSS sensor characteristics

Band Designation	Thematic Mapper (TM) Bandpass (Micrometers)	Thematic Mapper (TM) Radiometirc Sensitivity (NEΔρ)	Multispectral Scanner Subsystem (MSS) Bandpass (Micrometers)	Multispectral Scanner Subsystem (MSS) Radiometric Sensitivity (NEΔρ)
Spectral Band 1	0.45 - 0.52	0.8%	0.5 - 0.6	0.57%
Spectral Band 2	0.52 - 0.60	0.5%	0.6 - 0.7	0.57%
Spectral Band 3	0.63 - 0.69	0.5%	0.7 - 0.8	0.65%
Spectral Band 4	0.76 - 0.90	0.5%	0.8 - 1.1	0.70%
Spectral Band 5	1.55 - 1.75	1.0%		
Spectral Band 6	10.40 -12.50	0.5' Kelvin (NEΔT)		
Spectral Band 7	2.08 - 2.35	2.4%		
Ground IFOV		30 meters (Bands 1-5, 7)	82 meters (Bands 1-4)	
		120 meters (Band 6)		
Data Rate		85 megabits/sec	15 megabits/sec	
Quantization Levels		256	64	

Table 2. Classification accuracies and transformed accuracies for each ANOVA treatment.

Treatment Designation	Factor Level: Spatial Resolution	Factor Level: Data Quantization	Factor Level: Spectral Band Configurations	Percent Overall Classification Accuracy (P X 100)	Transformed Accuracy (Arcsin $\sqrt{P}$)
A	30m	8 bits	6 bands	62.3	52.14
B	80m	8 bits	6 bands	41.3	40.01
C	30m	6 bits	6 bands	61.7	51.75
D	80m	6 bits	6 bands	43.7	41.36
E	30m	8 bits	3 bands	60.7	51.16
F	80m	8 bits	3 bands	42.7	40.78
G	30m	6 bits	3 bands	60.3	50.96
H	80m	6 bits	3 bands	46.0	42.71

(NOTE: Items underlined are those factor levels different from Treatment A levels, i.e., actual TM data.)

Table 3. Contingency matrices for Treatments A and B. Diagonal elements are percent correctly classified pixels for each class. The other elements are percent omission and commission errors.

a) Treatment A

Ground Reference	Classification: Water	Agriculture	Bare Mine Spoil	Grass on Mine Spoil	Trees on Mine Spoil	Forest
Water	76	10	4	0	6	4
Agriculture	2	66	4	8	4	16
Bare Mine Spoil	0	0	72	16	12	0
Grass on Mine Spoil	0	10	14	56	16	4
Trees on Mine Spoil	6	12	12	12	32	26
Forest	2	16	0	2	8	72

b) Treatment B

Ground Reference	Classification: Water	Agriculture	Bare Mine Spoil	Grass on Mine Spoil	Trees on Mine Spoil	Forest
Water	54	16	0	0	14	16
Agriculture	4	72	0	6	0	18
Bare Mine Spoil	4	10	54	22	10	0
Grass on Mine Spoil	2	46	12	22	8	10
Trees on Mine Spoil	8	22	18	6	18	28
Forest	2	56	2	8	4	28

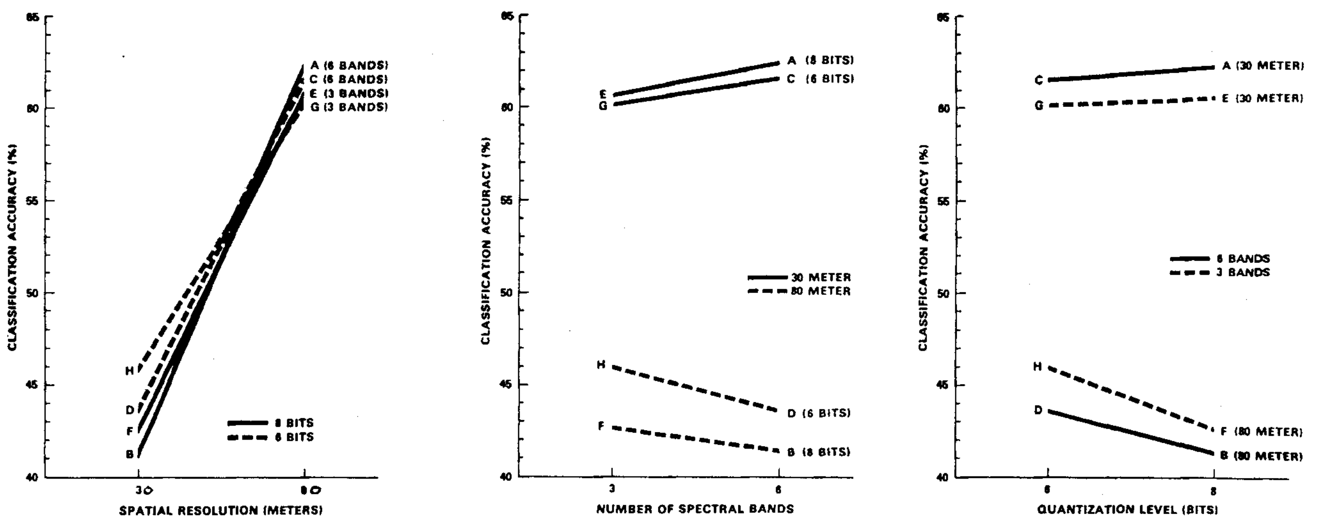
Table 4. Analysis-of-Variance results.

Factor	Degrees of Freedom	Sum of Squares	F-Statistic	F(0.95;α,4)*
Spatial Resolution	1	211.66	219.34	7.71
Data Quantization	1	0.90	0.93	7.71
Spectral Band Configuration	1	0.02	0.02	7.71
Total	7	216.44	224.29	6.09
Error	4	3.86		

* F(0.95;α,4) is the 95% point of the F-distribution with parameters α and 4. α is the degrees-of-freedom associated with the factor and 4 is the degrees-of-freedom associated with error. The factor effect was considered significant (i.e., the null hypothesis was rejected) if the F-statistic was greater than F(0.95;α,4).

Table 5. Proportion of mixed pixels associated with each land cover category. A pixel was considered to be a mixed pixel if any of its eight nearest-neighbor pixels were associated with a different land cover category. Mixed pixel identification was achieved by use of the digitized ground reference data.

Category	28.5m-by-28.5m pixels	57m-by-57m pixels
Water	70.5%	96.8%
Agriculture	49.3%	75.0%
Bare Mine Spoil	55.8%	79.5%
Grass on Mine Spoil	53.6%	80.8%
Trees on Mine Spoil	67.4%	89.5%
Forest	36.3%	58.6%
Total Over All Categories	46.5%	70.6%



(a)Effects of spatial resolution.

(b)Effects of spectral band configuration.

(c)Effects of data quantization.

Figure 1. The effects of each sensor characteristic, with the other two characteristics held constant, on percent classification accuracy. The letters on the graphs refer to the ANOVA treatments in Table 2.