LARS Information Note 110976

AN EMPIRICAL STUDY OF SCANNER SYSTEM PARAMETERS*

BY

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1976

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ABSTRACT

The selection of the current combination of parametric values (instantaneous field of view, number and location of spectral bands, signal-to-noise ratio, etc.) of a multispectral scanner is a complex problem due to the strong interrelationship these parameters have with one another. In this paper the results of an empirical study of this problem are presented. The study was done with the proposed scanner known as Thematic Mapper in mind. Since an adequate theoretical procedure for this problem has apparently not yet been devised, an empirical simulation approach was used with candidate parameter values selected by heuristic means.

The results obtained using a conventional maximum likelihood pixel classifier suggest that although the classification accuracy declines slightly as the IFOV is decreased this is more than made up by an improved mensuration accuracy. Further, the use of a classifier involving both spatial and spectral features shows a very substantial tendancy to resist degradation as the signal-to-noise ratio is decreased. And finally further evidence is provided of the importance of having at least one spectral band in each of the major available portions of the optical spectrum.

*This work was supported by NASA under Contract NAS9-14016

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INTRODUCTION

An important question in remote sensing is "what is the optimum set of specifications for a multispectral scanner system?" The correct answer depends upon the index of performance selected as well as the class of applications for which the sensor system is to be optimized.

There are several ways to attack this question; one is empirically, i.e. using experimental data to simulate various sensor parameter combinations. It is the results of such a study which are to be reported in this paper.

The ability to derive information from remotely sensed data gathered at a given time rests upon five classes of parametric values. These are:

1. The spatial resolution and spatial sampling characteristics
2. The spectral sampling and bands used
3. The signal-to-noise characteristics
4. The amount of ancillary data available
5. The classes to be used, i.e. the particular information desired

It is especially important to note that these factors are interrelated to one another. Thus, assuming an empirical approach, the problem resolves itself to searching a five dimensional parameter

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space relative to the index of performance. It is obvious that this search cannot be done in an exhaustive fashion due to the size of a five parameter space, i.e., the number of possible combinations of the parameters. In this study the search was localized around the proposed Thematic Mapper parameters[1], a region suggested by the state of the art of constructing spaceborne multispectral scanners and the expected cost factors involved. Even so, it was necessary to limit the number of combinations tested. The scope of this investigation was primarily limited to three parameters - spatial resolution, noise level, and spectral bands although some variation in others was introduced.

There were two indices of performance used in this study. One is the accuracy achieved on multispectral pixels drawn from the central portions of agricultural fields. In this case emphasis is placed upon the identification portion of the analysis task.

The second index of performance is the accuracy with which the correct areal proportions of each class in the flight line used could be estimated; this was done by determining the proportion of pixels assigned to each class by the classifier. In this case not only are "pure" pixels from the central portion of agricultural fields involved, but so are composite or multiclass pixels which overlap the field boundaries.

The general scheme of the study then was to simulate the desired parameter set by linearly combining the original pixels of the airborne data (IFOV $\approx$ 6 meters) to form simulated pixels of the desired IFOV, then to classify this flight line using a machine implemented Gausian maximum likelihood pattern classification algorithm, and measure the index of performance.

SIMULATION TECHNIQUES

Data Utilized - Both airborne multispectral scanner data and field spectrometer data were used in this study. The multispectral scanner data was collected by the 24 channel MSDS system[2] aboard an NC-130 over Finney County, Kansas, and Williams County, North Dakota, during the 1974-1975 growing season. Two flight lines of the MSDS data were selected for this study from a larger list of candidates. They were selected because the data quality was good, because they were collected at a suitable time in the crop calendar and because the location of the two sets was significantly different.

The spectrometer data used was collected by the NASA/JSC helicopterborne FSS S191-H system*, and the Purdue/LARS Exotech 20C system[3] over the Finney and Williams Counties intensive test sites and agricultural research farms. The spectrometer data also included data collected over the Purdue Agronomy Farm by the Exotech 20C system during the summers of 1972, 1973, and 1974. The spectrometer data were used to study wavelength band selections as well as to calibrate the airborne data for purposes of determining the signal-to-noise ratio.

Ground observations including field areas, crop types, and field maps collected by USDA-ASCS personnel and color IR photography collected by the NC130 aircraft were used to support the multispectral scanner and spectrometer overflights.

*This instrument is a modified version of the type of spectroradiometer carried aboard the Skylab spacecraft as a part of Earth Resources Experiment Package, experiment number S191.

Table 1. MSDS Data Selected for Simulation

Site	Date	Comments
Finney County, KS	7/6/75	Moderate banding
Williams County, ND	8/16/75	Good set

Preparation of Simulated Data - The simulation technique included spectral, spatial and radiometric considerations. A general discussion of the simulation technique is given in this section. A more detailed discussion of spatial simulation algorithms is given in reference 4.

a) Spectral Bands

MSDS system spectral bands which best matched proposed Thematic Mapper bands were selected. As seen in Table 2, the bands were relatively well matched. A combination of two MSDS bands was required to simulate one infrared band. The MSDS .53-.57 micrometer band was unavailable, and the .57-.63 micrometer band was substituted for simulation of the .52-.60 Thematic Mapper band. This substitution was recognized as suboptimal but the best alternative. The .74-.91 micrometer band was simulated as a result of speculation that Thematic Mapper bands 4 and 5 may be combined. A total of eight bands, therefore, were simulated.

Bands 4 and 5 were combined to form the .74-.91 micrometer band by equal weighted averaging after conversion to the reflectance domain. The combination of thermal bands was similarly achieved using the radiance domain.

b) Mean Angle Response Adjustment

A correction algorithm was applied to compensate for the non-uniform angular response characteristic due to the relatively wide view angle of the MSDS sensor. This effect is usually noted as one side of image nadir appearing brighter than the other side[5]. The primary cause of the effect is that the scanner sees illuminated portions of the target at certain view angles and the shaded side at other angles. The correction made was to normalize the average scene response for each look angle. The normalization was made on each flight line independently. The method used for angle correction was:

- compute the average response of each look angle
- smooth the average to the least square error third order polynomial fit
- compute the inverse polynomial multiplicative correction function required to transform the polynomial curve to a constant value
- apply the correction function to each scan line

c) Spatial Degradation

The spatial degradation procedure assumed a Gaussian total system modulation transfer function and compensated for aircraft scanner geometric distortions of unequal size and spacing of picture elements relative to scan look angle.

Figure 1 shows a conceptual illustration of the simulated system spatial response. The simulated picture element in the scan line direction has a Gaussian point spread function with the IFOV specified as the distance between the half amplitude points; the Gaussian function is truncated beyond the 10 percent amplitude. In the along track direction, the point spread function is square. Using this definition of system point spread function, each degraded picture element was computed as the weighted average of higher resolution MSDS picture elements. Center-to-center spacing of degraded picture elements was equal to the width of the IFOV being simulated.

The aircraft scanner geometric distortion of unequal size and spacing of picture elements relative to scan look angle was accounted for. This "bow-tie" effect was factored into the computation of the weighting coefficients used to compute degraded pixel values. Since the coefficients used to counter the bow-tie effect were different for each simulated look angle, new weighting coefficients were calculated for each simulated pixel.

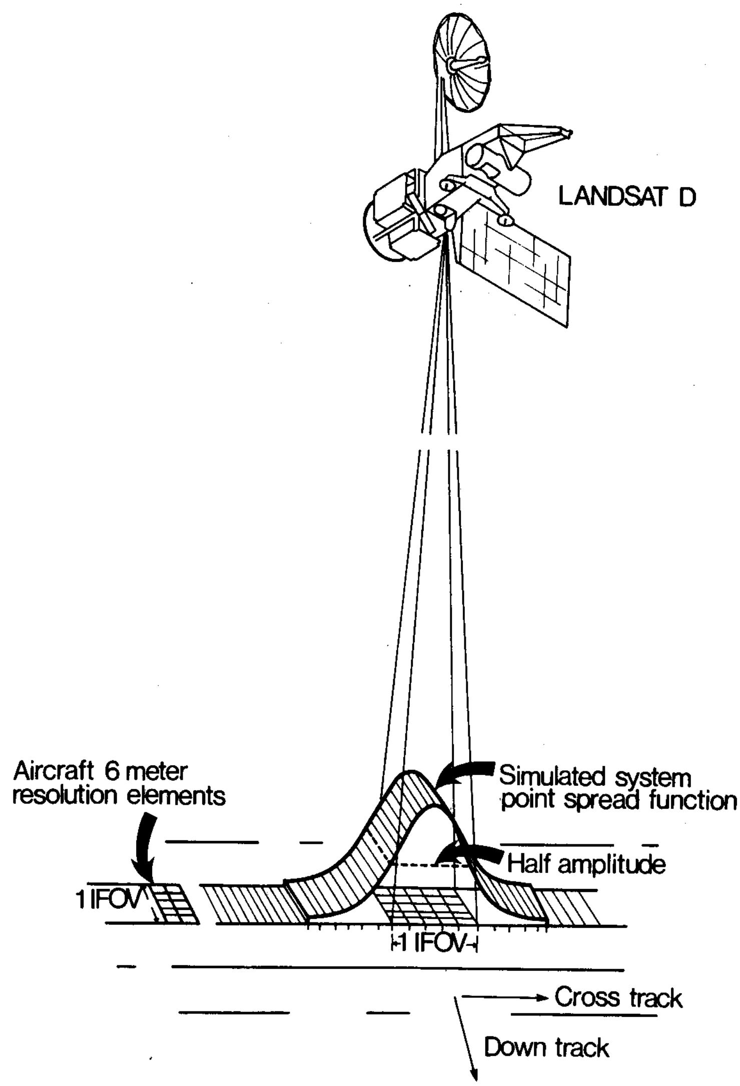

Figure 1. Conceptual Illustration of a Picture Element Viewed from the Satellite

Table 2. Correspondence of Thematic Mapper and MSDS Channels

Channel	Proposed Thematic Mapper Bands[1]	MSDS Bands
1	.45 - .52μm	.46 - .50μm
2	.52 - .60	.57 - .63
3	.63 - .69	.64 - .68
4	.74 - .80	.76 - .80
5	.80 - .91	.82 - .87
6	1.55 - 1.75	1.52 - 1.73
7	10.4 - 12.5	10.0 - 11.0+11.0 - 12.0
8	.74 - .91	.76 - .80+.82 - .87

d) Reflectance Scaling

Calibration of MSDS data was required to allow combinations of reflective bands as discussed above and to appropriately scale the data according to specified Landsat dynamic range parameters, see Table 3[1]. To satisfy these requirements, calibration was achieved by:

- assuming the scanner black-body calibration source response corresponds to zero scene reflectance,
- assuming the scanner calibration lamp corresponds to a scene reflectance equal to the lamp equivalent reflectance,
- and using linear interpolation from these two calibration points.

Lamp equivalent reflectance data was supplied by NASA/JSC. It was recognized that this method is not extremely accurate but it was believed to be adequate for purposes of band combination and dynamic range scaling. A more accurate calibration procedure is described below.

e) Signal-to-Noise Degradation

Ideally, the degraded data will have a negligible noise level such that the impact of various noise levels on classification accuracy could be studied. In this case, however, the input data noise level was extremely high and the noise level after spatial degradation was approximately equal to the level specified for the Landsat-D system. To study the effect of additional noise, however, specific quantities of noise were added. Noise was added in the form of white Gaussian random numbers with standard deviation scaled to the desired noise equivalent reflectance. Additional details on noise considerations and calibration requirements necessitated are given in the section on evaluation of simulated data.

f) Implementation

The simulation process was implemented in four computer processing phases. The phases were:

- selection of spectral bands from the MSDS 24 channel computer data tape and reformatting the data into the LARSYS Version 3.0 format[6].
- scan angle response normalization
- band combination, spatial degradation, and dynamic range adjustment
- addition of noise

Each phase produced separate outputs designed for analysis and processing in subsequent phases. Modularized processing had the advantage of providing data for analysis which had been processed in various stages of simulation. In addition, the method reduced processing redundancies. For example, a data set could be processed in phase four several times, each time adding a different level of noise, without the necessity of repeating previous processing steps.

A total of 36 data runs were prepared for analysis. Four spatial resolutions were simulated for two flights of two dates. Seven levels of noise were added to the two flightlines. A list of data sets generated is shown in Table 4.

Evaluation of the Simulated Data - Examinations of the 24-channel multispectral scanner (MSDS) data revealed the presence of problems which resulted in limiting its usefulness. The true impact of the data problems were not known until simulation data were generated and classification results completed. Data quality problems present in the data are banding, bit errors, saturation, and inoperative bands.

Banding is evidenced in the imagery as alternating dark and light shading. The frequency of the banding varied from three to sixteen scan lines per band cycle for the flightlines considered. The banding

Table 3. Proposed Thematic Mapper Parameters[1]

Band (Micrometers)	Saturation Surface Reflectance	Noise NEΔρ NEΔρ	Spatial Resolution (Meters)
.45 - .52	20%	.005	30 - 40
.52 - .60	58%	.005	30 - 40
.63 - .69	53%	.005	30 - 40
.74 - .80	75%	.005	30 - 40
.80 - .91	75%	.005	30 - 40
1.55 - 1.75	50%	.005	30 - 40
10.4 - 12.5	270 - 330K	.5K	90 - 200
.74 - 91	75%	.005	30 - 40

can be seen in all MSDS reflective spectral channels (1-13) and channels 21 and 22 of the thermal data. Imagery illustrating the banding is shown in Figure 2. The banding signal amplitude has 1-15 data counts with larger amplitudes noted in spectral bands 1-8. It has been learned that the banding was probably caused by a loose mechanical joint within the detector housing and vibration of certain signal cables. The spatial degradation process significantly reduced the banding. Imagery illustrating the extent of banding noise reduction is shown in Figure 3.

System bit errors were noted in all spectral bands. This problem is illustrated in Figure 4. The histogram shows a much higher frequency of occurance of odd data counts than even. In addition, various higher order bit errors were indicated in various spectral bands. The bit errors tended to be masked by the spatial degradation process as illustrated in Figure 5; nevertheless, the impact on information content of the data must still be present.

Full scale saturation (data count 255) was noted in several spectral bands of several flightlines. Saturation occured not only for roof top and highway data, but also for agricultural areas which are of interest for analysis purposes. Saturated data points were omitted from all analysis since their values do not represent an accurate measure of relative scene radiance.

Sensor spectral bands for the .53-.57 and 4.5-4.75μm ranges were inoperative for all data collection missions.

<u>Procedure for Absolute Reflectance Calibration</u> - As discussed in another section, MSDS data were calibrated to reflectances using available saturation reflectance data with the assumptions of zero electronic offset and no atmospheric effects. This calibration was needed for band combination and range adjustments. After initial simulation data sets were generated and evaluated a refined calibration

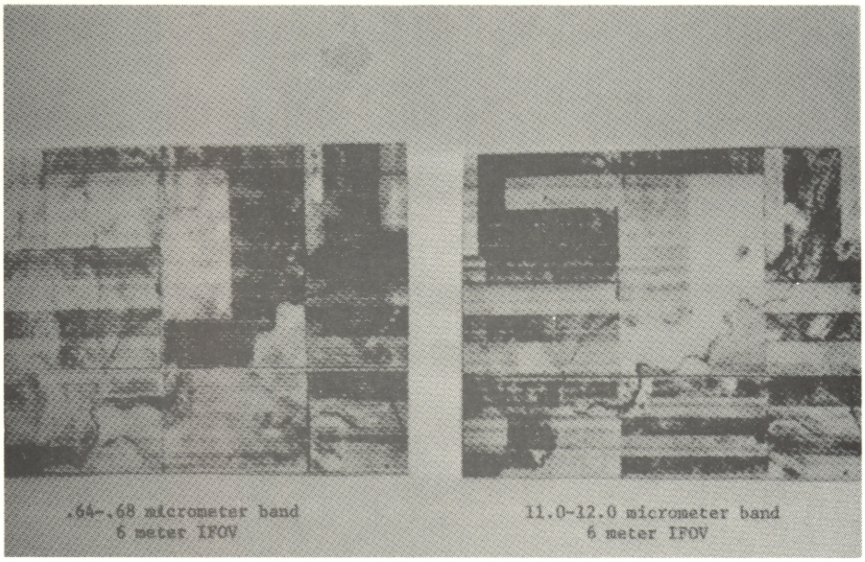

Figure 2. Unprocessed MSDS Data Showing Banding Noise

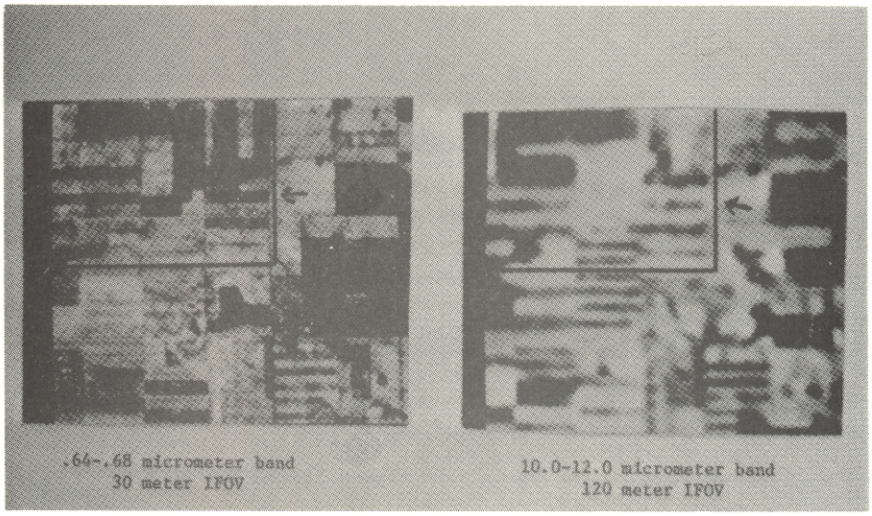

Figure 3. Simulated Data Showing Reduced Banding Noise

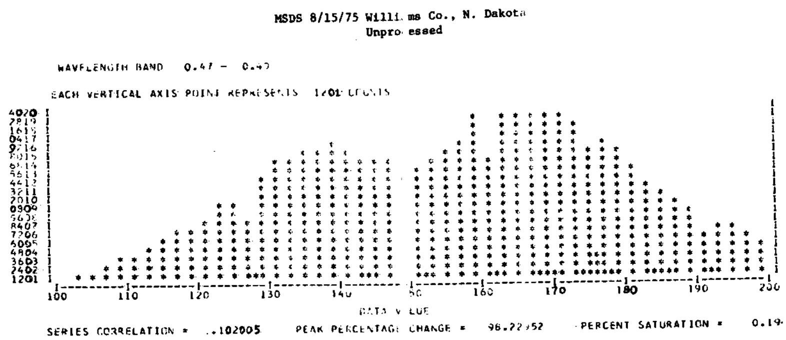

Figure 4. Histogram Illustrating Digitization Bit Errors

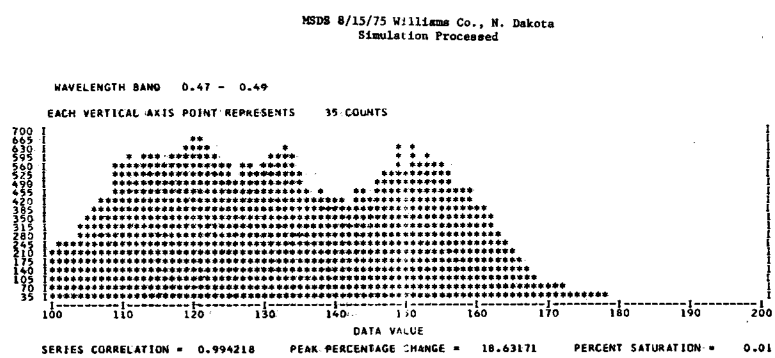

Figure 5. Hitogram Illustrating Digitization Bit Error Masked by the Spatial Degradation Processing

Table 4. Simulation Data Sets Analyzed

LARS Run	Test Site	Date Collected	Simulated Resolution*	Noise Added** NE$\Delta\rho$
75001730	Williams	8/15/76	30	0
75001740	Williams	8/15/76	40	0
75001750	Williams	8/15/76	50	0
75001760	Williams	8/15/76	60	0
75003730	Finney	7/6/76	30	0
75003740	Finney	7/6/76	40	0
75003750	Finney	7/6/76	50	0
75003760	Finney	7/6/76	60	0
75001731 thru 75001737	Williams	8/15/76	30	.0025, .005, .0075 .01, .015, .02, .03
75001741 thru 75001747	Williams	8/15/76	40	.0025, .005, .0075 .01, .015, .02, .03
75003731 thru 75003737	Finney	7/6/76	30	.0025, .005, .0075 .01, .015, .02, .03
75003741 thru 75003747	Finney	7/6/76	40	.0025, .005, .0075 .01, .015, .02, .03

*Reflective data only, all thermal data at 120 meters
**For thermal channel NEΔT is 100 times value listed

procedure was implemented. (The project time frame did not permit use of the refined procedure during the simulation processing.) The primary purpose in implementing the refined procedure was to enable an accurate determination of signal-to-noise levels and to enable accurate addition of noise for simulation of data with higher noise levels. The steps followed in this refined procedure was as follows.

Near the time of a low altitude MSDS overflight, reflectivity spectra of five canvas calibration gray panels were determined by a truck mounted spectroradiometer system referenced to pressed barium sulfate powder. Gray panel reflectivities and MSDS response data were related through linear regression. The regression equation, transforming low altitude MSDS data to absolute scene reflectivity, was then used to compute mean reflectivities of agricultural fields within the low altitude flightline. Being clearly distinguishable in the high altitude MSDS data (actual panels were not), these large fields were then used as calibration panels for the higher altitude case. Field reflectivities were related to MSDS high altitude relative response data through linear regression yielding a linear function which could then be used to transform high altitude relative data to (absolute) reflectance.

A least square error regression analysis was used which yielded the coefficients to the equation

$$y = A + Bx$$

For purposes of noise level computation, only the B term is needed. The noise level N is then

$$N = B\sigma$$

where B is the reflectance transform term from the regression analysis and σ is the standard deviation of data values when scanning a constant target. Sigma was derived from the sixteen samples per scan line collected as the scanner low black body calibration source was viewed. The sixteen samples per scan line of calibration data were treated as an image and spectrally degraded in the same way as the ground scene data producing one calibration sample per simulated scan line. The standard deviation of the simulated calibration samples multiplied by B is the measure of noise used. Table 5 shows noise levels derived in this fashion. In addition, the B term was used to determine the magnitude of random numbers required in order to add a specified level of noise to the data. The standard deviation, σ, of the random numbers required to add a NE$\Delta\rho$ of N is

$$\sigma = \frac{N}{B}$$

And finally, to test the functioning of the scan angle response normalization algorithm, the 30 meter data from the North Dakota flight line was analyzed with a procedure intended to find if any effects of sun or scanner angle could be seen in the classification. The flight line was divided lengthwise into thirds and training fields were taken from each third. The three training sets were compared in the SEPARABILITY processor of LARSYS Version 3.1[6] and no apparent differences due to location across the flightline could be seen. The flightline was also classified with the combined training sets and again no differences associated with training set locations were found in the classification.

Analysis Procedures Used

Each analyst was allowed some freedom in the training set selection but the procedures used did not differ greatly. Each analyst

Table 5. Noise Levels of Simulation Data Before Adding Noise

Wavelength Band	Williams County, ND August 15, 1975 NEΔρ 30 Meter Resolution	Williams County, ND August 15, 1975 NEΔρ 40 Meter Resolution	Finney County, KA July 6, 1975 NEΔρ 30 Meter Resolution	Finney County, KA July 6, 1975 NEΔρ 40 Meter Resolution
.46 - .50	.001	.001	.003	.002
.57 - .63	.002	.002	.009	.005
.64 - .68	.006	.005	.017	.010
.76 - .80	.008	.008	.022	.012
.82 - .87	.006	.005	.004	.003
1.52 - 1.73	.003	.003	.023	.013
.76 - .87	.004	.004	.009	.005

selected areas from which training fields were taken. One flightline was divided into one mile wide strips across the full width and alternating strips were used for training. The other flightline was divided into three two-thirds mile strips down the full length of the flightline and alternating one by two-third mile sections were used for training. In each case, then, training sets were taken from one half of the area and were distributed systematically over the entire flightline. These candidate training areas were clustered primarily for image enhancement of the field boundaries so that the training fields could be more easily selected. There was, however, an additional effect from clustering. This was the definition of spectral subclasses within fields and when subclasses were found the analyst could adjust the training sets to sample them.

Color infrared photographic mosaic prints were made from photographic data collected concurrently with the scanner data. Informational class information provided by ground observations was transfered to clear plastic overlays on the mosiac print. The analyst could then easily locate the corresponding fields in his cluster maps and assign the field coordinates to the informational classes.

Statistics were calculated for each training area and compared using the LARSYS SEPARABILITY processor. Similar classes were combined, where indicated, and the data set was used to classify the flightline. Training areas were included in the test fields but actual field boundaries did not necessarily correspond between the training and test fields since the test fields had been pre-selected for the entire flightline.

The entire training set selection procedure was repeated for each resolution size so that any effects on training set selection which might be caused by data point resolution size would be included in the analysis results. An example is the increasing difficulty and eventual impossibility of selecting samples from small, or narrow, fields as the resolution size increases.

The two indices of performance previously mentioned were each applied. Classification (identification) accuracy was evaluated using test sample performance while proportion estimation (identification and mensuration) was carried out over the flightline as a whole. Further details on each of these is as follows.

The test performance is the overall classification accuracy (number of test pixels correctly classified divided by the total number of test pixels) of the test field pixels. The test fields were selected in the original six meter data by choosing the largest rectangular block of pixels that would fit within the agricultural field so that no boundary pixels were included. The test field boundaries were then found in the degraded spatial resolution such that no "super" pixels (degraded spatial resolution pixels) containing boundaries were included. Some of the original test fields were discarded in this process because they became too small, i.e. there were no pure field center "super" pixels.

The RMS error of information class proportion estimates for the flightline was found by calculating the percent of the flightline classified as a particular class and comparing it with the ASCS ground collected estimate using equation (1).

$$\text{RSM Error} = \frac{\sum_{i=1}^{N} (C_i - C'_i)^2}{N} \qquad (1)$$

where N = number of information classes

C_i = percent classified as information class i

C'_i = percent of class i estimated from ASCS ground collected data

The informational classes used for the two flightlines are given in Table 6.

Landsat 2 data for the two flightlines were also analyzed, but test fields were not selected for the Landsat data.

RESULTS

<u>Spatial Resolution Parameter</u> - The test performance results indicate a general upward trend as the IFOV increases from 30 meters to 60 meters for the two flightlines (see Figure 6). The upward trend in the test performance of the two flightlines is presumed to be caused by the better signal-to-noise ratio in the larger instantaneous field of view (IFOV) data. A 60 meter pixel is simulated by averaging approximately 100 six meter pixels as compared to approximately 25 for a 30 meter pixel.

The number of test fields varied in inverse relation to the IFOV, since as the IFOV increased, the probability that some test fields would not contain any pure pixels increased. To determine if this situation rather than improved signal-to-noise ratio might have caused the upward trend in the classification performance for larger IFOV's a common set of test fields were selected to test the performance of the classifications. The test performance increased slightly, 0 to .7%, however, the trend was the same.

Table 6. Informational Classes Used in the Analysis

Williams County, ND	Finney County, KA
8/15/75	7/6/75
Harvested Wheat	Harvested Wheat
Unharvested Wheat	Corn
Grasses/Pasture	Grain Sorghum
Fallow	Grasses/Pasture
Other (corn-oats)	Fallow

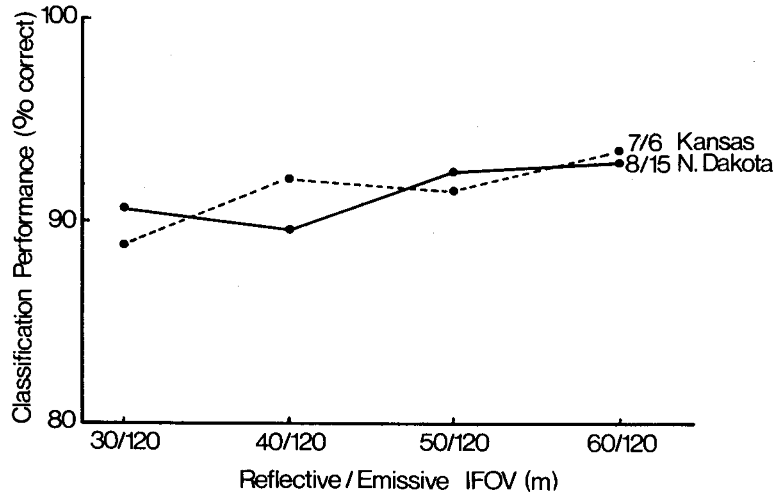

Figure 6. Classification Performance vs. Spatial Resolution

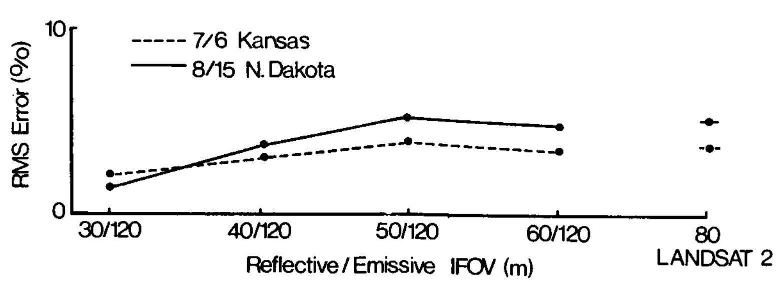

Figure 7. RMS Error of Proportion Estimates vs. Spatial Resolution Using Channels 2, 3, 4, 5, 6 and 7

The decreased percentage of field center pixels as the IFOV increases can be noted from the percent of the flightlines used for test (see Table 7). The percentage of field center pixels used for testing dropped approximately 10 percent from 30 to 60 meters.

Table 7 also indicates that a significantly higher proportion of the Kansas flightline was used for testing than the North Dakota flightline. This is due to the larger field size in Kansas (see Table 8).

The RMS error of the proportion estimates for the flightline (Figure 7) indicate that the least error is obtained using a 30 meter spatial resolution. The RMS error increased as the IFOV increased from 30 meters to 40 meters to 50 meters and then leveled off or dropped slightly as the spatial resolution increased from 50 meters to 60 meters. The RMS error increased again for the Landsat 2 data. The Landsat 2 data have an IFOV of approximately 90 meters if the definition of spatial resolution being applied for the Thematic Mapper is used; the spatial resolution of Landsat 2 is more commonly known as 80 meters.

The reduced error in the proportion estimates as the IFOV is reduced is due to the increased ratio of pure field center pixels to boundary pixels. The test performance criterion was based only on the pure field center pixels. Many errors occur in classifying boundary pixels because very often they are not similar to either of the classes that they represent. For example, a pixel including both bare soil and wheat may appear similar to grass.

The criteria using RMS proportion estimation error includes the boundary errors; however, it should be noted that they are not a direct measure of boundary errors.

It is possible for the boundary errors to cancel each other over a given area so that the proportions estimates obtained from the classifications are more nearly correct. The proportion estimation error, however, would seem to be the preferred index of performance for an overall comparison of the differences of spatial resolutions, because this criterion is based on all pixels in the flightline, and both identification and mensuration are involved. Better area estimates are clearly possible with the small of the five IFOV's.

An analysis of variance was run on the RMS errors for the four resolutions using the RMS errors for the twelve sections in each of the two flightlines to determine if the differences were significant. A partially nested design with equal cell sizes from the BMD Biomedical Computer Programs was used (BMD08U)[7]. The differences in the RMS errors for the four resolutions were significant at the .05 significance level (see Table 9).

Noise Level Parameter - The analysis technique for the noise level parameter included using the training fields selected in the no noise added case and re-estimating the multivariate Gaussian statistics in each of the seven noise-added data sets for a particular IFOV and flightline. Each of the noise added data sets were then classified using simulated Thematic Mapper channels 2, 3, 4, 5, 6, and 7. See Figures 8 and 9.

To actually simulate different noise levels in data from satellites, the variable of analyst's determination of field boundaries might have been included. This would have necessitated the time consuming routine of the selection of training areas from each noise added data set independently from the other sets. Tests were run which illustrated

Table 7. Percentage of Test Sites Used for Training and Test

Performance Criteria	Percentage of Test Site for Given Resolution (m) 30	40	50	60
	Kansas 7/6			
Train	25	35	36	37
Test	55	50	46	42
	North Dakota 8/15			
Train	19	21	20	21
Test	27	24	23	19

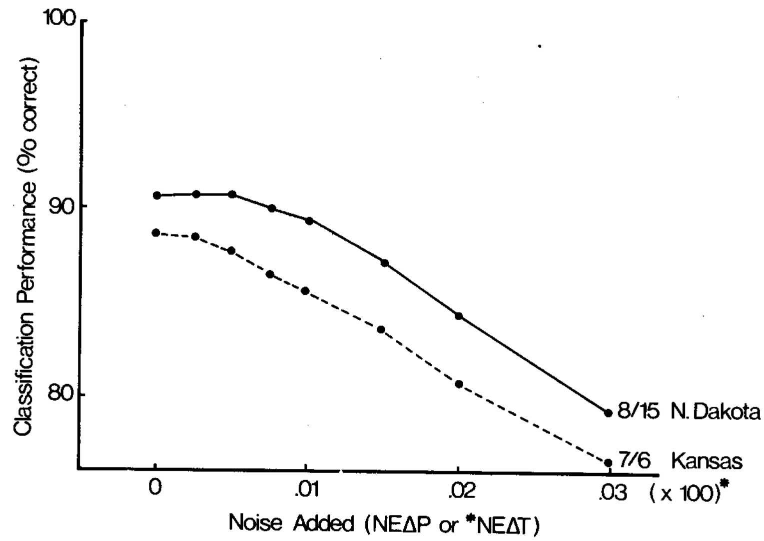

Figure 8. Classification Performance vs. Noise Added for 30/120 Meter Resolution. Channels used for Classifications were 2, 3, 4, 5, 6, and 7.

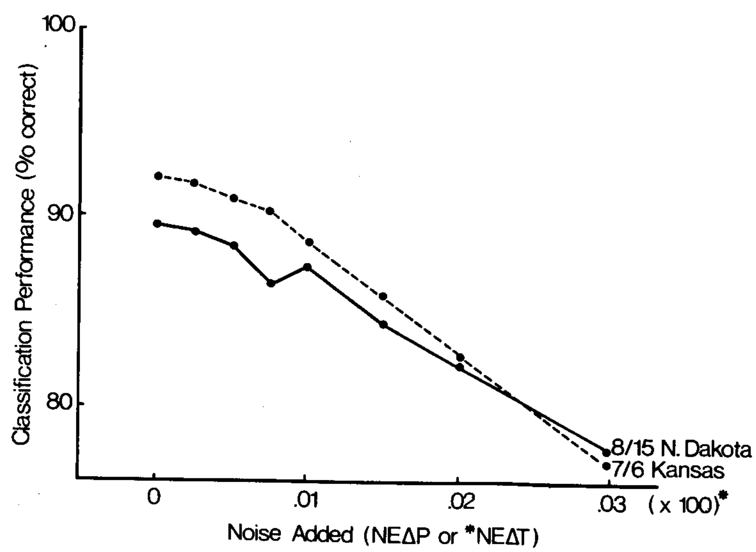

Figure 9. Classification Performance vs. Noise Added for 40/120 Meter Resolution. Channels used for Classifications were 2, 3, 4, 5, 6, and 7.

Table 8. Characteristics of the Agricultural Fields by Flightlines

Location	Date	No. Fields	Ave. Field Size		Field Size Range	
			Hectares	(acres)	Hectares	(acres)
Kansas	7/6/75	187	15.9	(39.3)	.4-65	(1-161)
N. Dakota	8/15/75	250	11.9	(29.3)	.4-194	(1-480)

Table 9. Analysis of Variance Results for Spatial Resolution

Source	Sum of Squares	Deg. of Freedom	Mean Square
I - resolution	1.83	3	.61
J-- flightline	1.94	1	1.94
K(J) - sections	19.87	22	.90
IJ	.57	3	.19
IK(J)	4.99	66	.08

F value {I/IK(J)} = 8.10 $F_{.95}(3.99) \approx 2.76$

that the data clustered nearly the same for the noise levels of .0025 to .015 NEΔρ added. The field boundaries, however, were difficult to distinguish in the cluster maps for the noise levels of .02 and .03 NEΔρ added levels. In light of these results the performances found for the .02 and .03 NEΔρ noise added levels may be optimistic, since the field boundary delineation difficulty is not included.

The original plans were to simulate the .005 NEΔρ noise level planned for the Thematic Mapper for all channels (also .01 NEΔρ for channel 6) together with .5, 1.3, 1.6, 2 and 3 times that noise level. The noise level present in the original MSDS data, however, was too high for the original plans. After the averaging to simulate 30 to 60 meters, the noise level for the channels were of the same magnitude as planned for the Thematic Mapper - the 0 added noise case. To simulate higher levels .0025, .005, .0075, .01, .015, .02, and .03 NEΔρ (x100 for NEΔT) noise levels were added to the 0 added set. The calibration for the noise addition was obtained using the grey panels at the calibration location in the intensive test site and the truck mounted spectrometric data as previously described.

In each of the four data sets analyzed across all eight noise levels, once the level of noise added became greater than the noise already in the data, the train and test performances fell off significantly. It is difficult, however, to draw any conclusions relative to the Thematic Mapper since the noise levels were not constant across all bands.

<u>Spectral Band Parameter</u> - The first analysis technique for the wavelength band set as the parameter consisted of selecting training areas to represent spectral classes from cluster maps obtained using simulated Thematic Mapper channels - 2, 3, 4, 5, 6 and 7 - the same technique as used for the spatial resolution parameter.

The simulated 30 meter North Dakota - 8/10 and Kansas - 7/6 flightlines were then classified using four different feature sets. The results are in Figures 10 and 11.

The four feature sets selected resulted from considerations of possible ways to reduce the number of proposed channels to six plus attempts to grossly simulate the present Landsat 1 and 2 scanners. Channels 1, 2, 3, 4, 5, 6 and 7 represent the originally proposed Thematic Mapper channels[1]. Channels subsets 2, 3, 4, 5, 6 and 7 and 1, 2, 3, 6, 7 and 8 represent frequently discussed combinations of six channels. Channel 8 is the combination of channels 4 and 5. Feature set 2, 3, 4, and 5 grossly approximates the same spectral range as covered by the present Landsat 1 and 2 scanners.

The results indicate that slightly higher performances are possible for these data sets when Thematic Mapper channel 1 is included. The results also indicate little or no change in performance if Thematic Mapper channels 4 and 5 are combined into one channel. An analysis of variance was run for three feature sets (feature set 2, 3, 4, and 5 was not included) using the RMS errors for the twelve sections in each of the two flightlines to determine if the differences were significant. The same analysis of variance design as described above for the spatial resolution was used. The differences in the RMS errors for the three feature sets were significant (only slightly) at the .05 significance level (see Table 10). It is possible that the previously described unusual noise in the MSDS data is acting to minimize any significant differences due to spectral band changes.

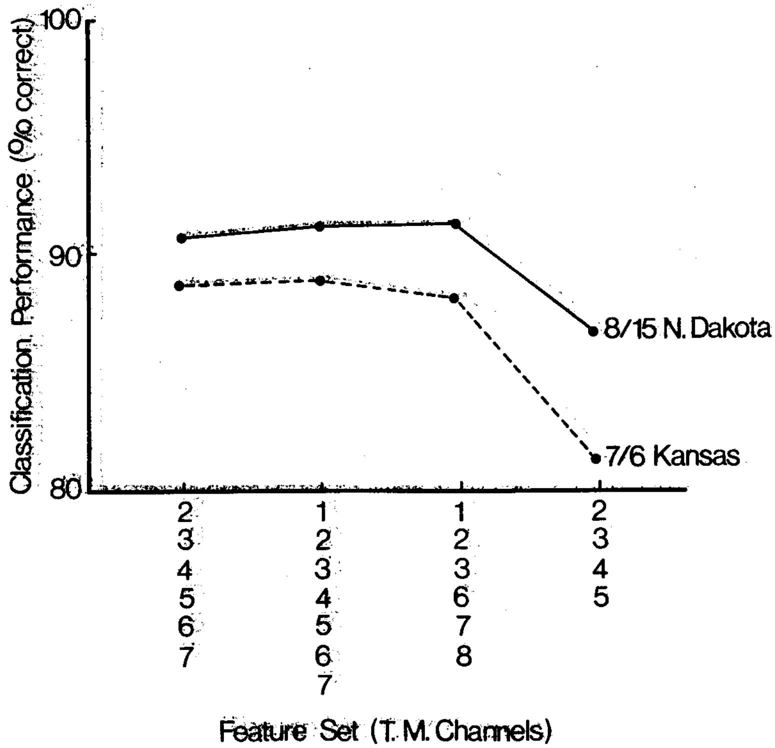

Figure 10. Classification Performance vs. Spectral Bands. The Spatial Resolution was 30/120 Meters.

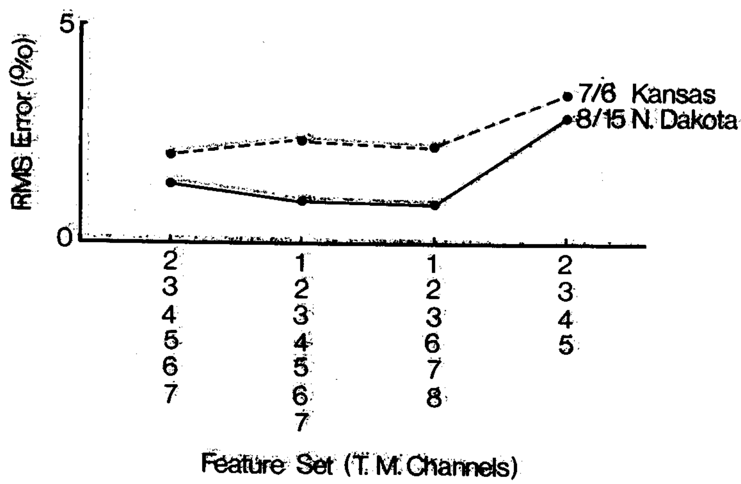

Figure 11. RMS Error vs. Spectral Bands. Spatial Resolution was 30/120 Meters.

A second analysis technique relative to spectral band selection is to study the correlation of the proposed Thematic Mapper (T.M.) channels. While correlation (or the lack of it) is not, in general, a direct indicator of the useful information content of a feature, it tends to correctly show trends. The correlation studies were conducted for the agricultural crops in the intensive test sites and at the Purdue Agronomy Farm, sampling the growing season using spectrometer data. The correlation of the proposed Thematic Mapper band .52 - .60μm and the MSDS substituted band .57 - .63μm was also studied. Concern existed that the .57 - .63μm channel of the MSDS data did not represent the .52 - .60μm Thematic Mapper channel well. Also included in the correlation study were the Skylab S192 scanner bands which cover the range between 1.0 and 1.3μm which the proposed Thematic Mapper does not at present include. The cross correlation tables thus derived are shown in Tables 11 - 13*. Specifications for the data sets used are given in the Table captions.

The correlation of T.M. band .52 - .60μm and MSDS band .57 - .63μm for the agricultural crops given in the tables ranged between .93 and .99. This tends to indicate that the use of the MSDS band .57 - .63μm can represent the T.M. band reasonably well, even though the MSDS band includes part of the slope between the green peak reflectance and the chlorophyll absorption band in the red.

Concern also exists that T.M. bands .74 - .80μm and .80 - .91μm are highly correlated or more strongly stated - entirely redundant. The results of the correlation study support other studies showing that the channels are highly correlated. The correlation of the two channels ranged between .98 and 1.0. The plot shown in Figure 12 illustrates the high degree of correlation in the simulated channels using the MSDS data for the entire 8/15 North Dakota flightline.

*Additional such results are given in reference 4

Table 10. Analysis of Variance Results for Classification Feature Sets

Source	Sum of Squares	Deg. of Freedom	Mean Square
I - feature set	.16	2	.06
J - flightline	.01	1	.01
K(J) - sections	27.4	22	1.24
IJ	.02	2	.01
IK(J)	.04	44	.01

F value {I/IK (J)} = 5.96 $F_{.95}\,(2,44) \approx 5.14$

Table 11

Correlation of Selected Wavelength Bands Using Spectrometer Data

Location: Purdue University Agronomy Farm, West Lafayette, Indiana
Instrument: Exotech 20C
Dates: July 6 - August 29, 1972; July 6 - October 5, 1973;
July 16 - August 15, 1974

Crop	No. Observations
Corn	353
Soybeans	105
Bare Soil	66

CORRELATION MATRIX

SPECTRAL BAND	0.52 0.60	0.57 0.63	0.63 0.69	0.74 0.80	0.80 0.91	0.98 1.08	1.09 1.19	1.20 1.30	1.55 1.75
0.52 0.60	1.000								
0.57 0.63	0.993	1.000							
0.63 0.69	0.963	0.987	1.000						
0.74 0.80	-0.020	-0.064	-0.120	1.000					
0.80 0.91	-0.038	-0.080	-0.136	0.981	1.000				
0.98 1.08	0.015	-0.022	-0.069	0.958	0.941	1.000			
1.09 1.19	0.040	0.010	-0.026	0.923	0.904	0.976	1.000		
1.20 1.30	0.092	0.084	0.063	0.848	0.841	0.904	0.936	1.000	
1.55 1.75	0.252	0.301	0.348	0.292	0.281	0.423	0.511	0.719	1.000

Table 12

Correlation of Selected Wavelength Bands Using Spectrometer Data

Location: Intensive Test Site, Finney County, Kansas
Instrument: FSS/S191H
Date: November 5, 1974

Crop	No. Observations	Crop	No. Observations
Wheat	1073	Pasture	10
Alfalfa	76	Grain Sorghum	102
Corn	248	Fallow	152

CORRELATION MATRIX

SPECTRAL BAND	0.45 0.52	0.52 0.60	0.57 0.63	0.63 0.69	0.74 0.80	0.80 0.91	0.98 1.08	1.09 1.19	1.20 1.30	1.55 1.75
0.45 0.52	1.000									
0.52 0.60	0.965	1.000								
0.57 0.63	0.956	0.984	1.000							
0.63 0.69	0.909	0.946	0.985	1.000						
0.74 0.80	-0.028	0.155	0.051	0.041	1.000					
0.80 0.91	-0.078	0.106	0.011	0.014	0.994	1.000				
0.98 1.08	-0.019	0.166	0.091	0.113	0.962	0.977	1.000			
1.09 1.19	-0.014	0.142	0.065	0.093	0.920	0.934	0.958	1.000		
1.20 1.30	0.074	0.209	0.147	0.184	0.840	0.854	0.905	0.949	1.000	
1.55 1.75	0.782	0.816	0.851	0.878	0.075	0.065	0.171	0.136	0.255	1.000

Table 13

Correlation of Selected Wavelength Bands Using Spectrometer Data

Location: Agricultural Research Farm, Garden City, Kansas
Instrument: Exotech 20C
Dates: October 18 - November 5, 1974

Crop	No. Observations	Crop	No. Observations
Wheat	33	Corn	6
Grain Sorghum	17	Soybeans	3
Sugar Beets	11	Alfalfa	1
Bare Soil	3		

CORRELATION MATRIX

SPECTRAL BAND	0.52 0.60	0.57 0.63	0.63 0.69	0.74 0.80	0.80 0.91	0.98 1.08	1.09 1.19	1.20 1.30	1.55 1.75	10.40 12.50
0.52 0.60	1.000									
0.57 0.63	0.928	1.000								
0.63 0.69	0.753	0.940	1.000							
0.74 0.80	-0.137	-0.371	-0.533	1.000						
0.80 0.91	-0.190	-0.392	-0.515	0.985	1.000					
0.98 1.08	-0.185	-0.314	-0.374	0.907	0.962	1.000				
1.09 1.19	-0.097	-0.177	-0.207	0.823	0.895	0.978	1.000			
1.20 1.30	0.156	0.197	0.232	0.504	0.596	0.769	0.881	1.000		
1.55 1.75	0.575	0.807	0.907	-0.629	-0.610	-0.456	-0.276	0.196	1.000	
10.40 12.50	0.078	0.207	0.284	-0.207	-0.199	-0.144	-0.082	0.052	0.312	1.000

Another item of concern about the proposed Thematic Mapper bands is the lack of any bands in the 1.0-1.3μm range. Information in this range may not be available in the other bands. The results for the observations analyzed support the above concern. The channels in the 1.0-1.3μm range were correlated the highest with Thematic Mapper channels 4 and 5. However, the correlation of the 1.09-1.19μm band and Thematic Mapper bands 4 and 5 ranges between .87 and .95. More significantly the correlation of the 1.2-1.3μm band and Thematic Mapper channels 4 and 5 ranges between .50 and .85. The results suggest that useful information may be available in the 1.0-1.3μm range.

In general, Tables 11-13 indicate that Thematic Mapper channel 6, the middle IR channel, and Thematic Mapper channel 7, the thermal channel, are not very correlated with any of the other Thematic Mapper channels. The visible channels tend to be correlated and Thematic Mapper channels 4 and 5 are highly correlated. There may be good reasons to move one of the .74-.80μm or .80-.91μm bands into the 1.0-1.3μm range.

<u>Classifier Parameter</u> - Two different classifiers were compared - the standard maximum likelihood pixel classifier and a spectral-spatial classifier called ECHO[8]. The simulated data over the North Dakota 8/15 flightline and the Kansas 7/6 flightline were again used in the analysis. The training statistics for both classifiers were identical and were obtained as described in the spatial resolution parameter discussion.

The classifiers were compared across the four simulated spatial resolutions for the North Dakota flightline and across four noise levels for the Kansas flightline. The same criteria described before were used to evaluate the classifiers across the spatial resolutions.

The test performances were used across the noise levels. The results are illustrated in Figures 13 thru 16.

There was a slight but consistant increase in test performance for the ECHO classifier over the per point classifier at the smaller IFOV's (Figure 13). This is consistent with the theory behind the ECHO classifier. Better classification accuracy should be obtainable as the number of pixels per object (field) increases. The differences between the classifiers are so small, however, that they may not be significant for this particular case.

A very noticeable difference was observed, however, when comparing the classifiers across the noise levels (Figures 15 and 16). The spatial nature of the ECHO classifier was able to provide enough information to help compensate for the added noise in the data. The difference between the two classifiers became greater as the noise level increased.

The results indicate that this spectral-spatial classifier is an improvement over the per point classifier.

SUMMARY AND CONCLUSIONS

In the introduction, the five sets of parameters which influence the ability to extract information from multispectral data were listed and it was pointed out that the problem of properly selecting scanner parameter values amounts to searching the five dimensional parameter space thus defined relative to the desired index performance. This study was structured, within the constraints imposed by the data sets available, to search a portion of this five dimensional space. The effect of at least some variation in all but the fourth parameter class was tested. Significant features of the study were as follows:

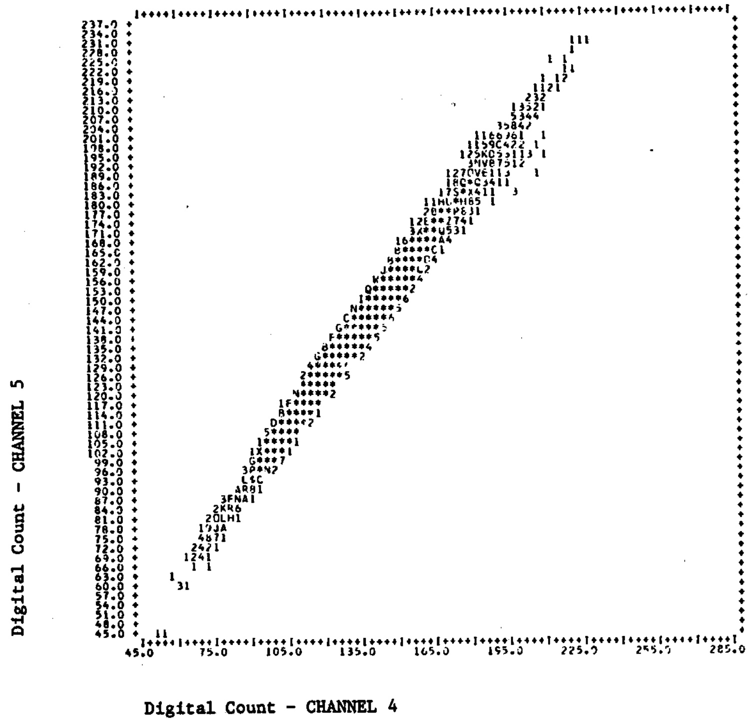

Figure 12. Scatter Diagram Showing Correlation Between Channels 4 and 5.

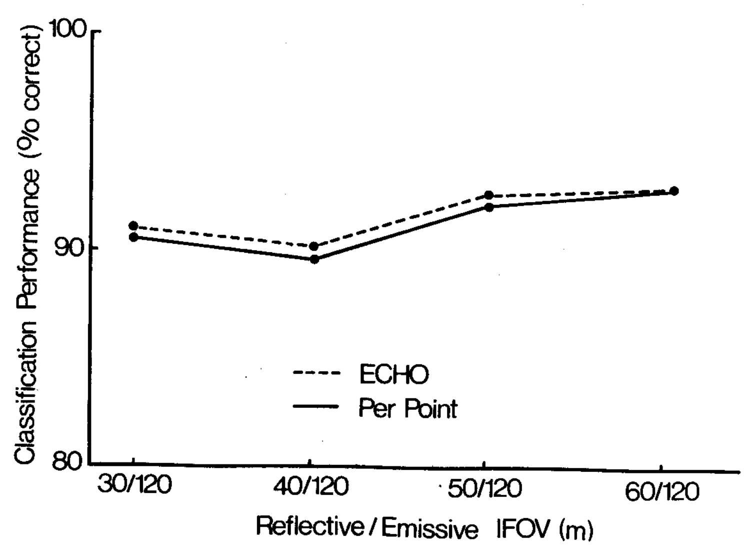

Figure 13. Classification Performance vs. Spatial Resolution Using ECHO and Per Point Classifiers for the 8/15 North Dakota Data Sets. Channels 2, 3, 4, 5, 6, and 7 were used for the Classifications.

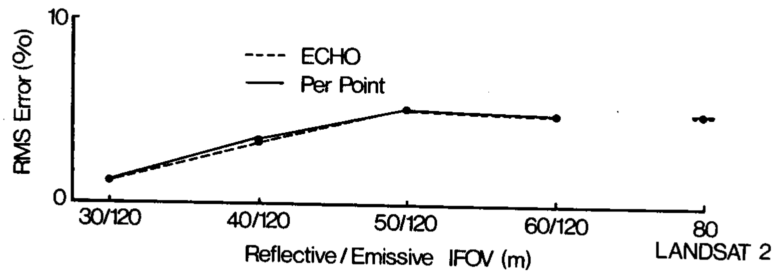

Figure 14. RMS Error vs. Resolution Using ECHO and Per Point Classifiers for the 8/15 North Dakota Data Set.

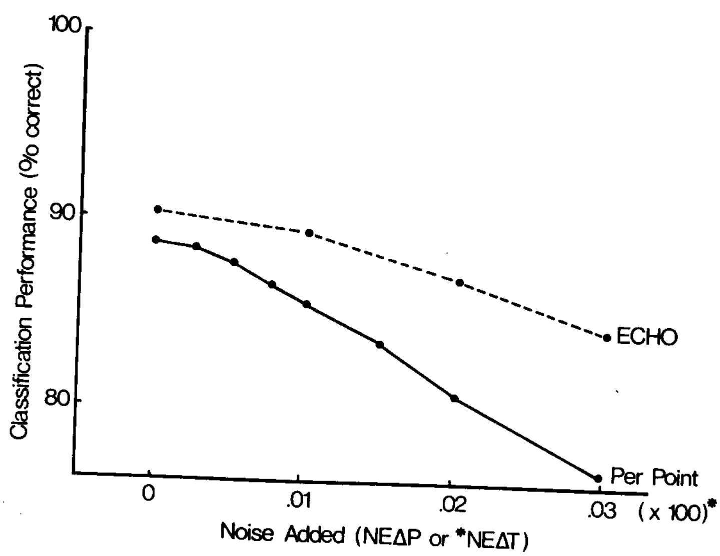

Figure 15. Classification Performance vs. Noise Added Using ECHO and Per Point Classifiers for the 7/6 Kansas, 30/120 Meter Spectral Resolution Data Set. Channels 2, 3, 4, 5, 6, and 7 were used in the Classifications.

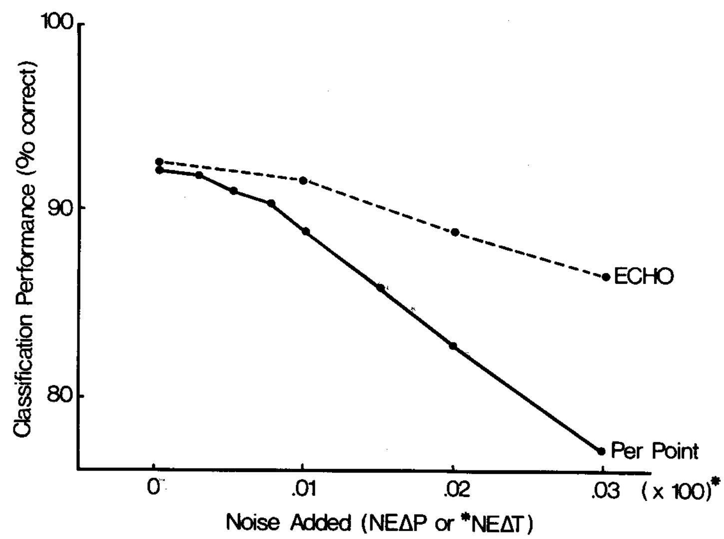

Figure 16. Classification Performance vs. Noise Added using ECHO and Per Point Classifiers for the 7/6 Kansas 40/120 Meter Spatial Resolution Data Set. Channels 2, 3, 4, 5, 6, and 7 were used in the Classifications.

1. The index of performance used encompassed both identification accuracy and mensuration accuracy.

2. Data from two times of the year was used.

3. Data from two quite different parts of the U.S. Wheat Belt was used. Even so only a small part of the world agriculture and world vegetation was sampled.

4. The impact of the affect of a human analyst was allowed in the study in that two different analysts, using slightly different analysis techniques, were used. As would be desired, there is no indication that this affected the results.

Both training sample accuracy and test sample accuracy were considered for purposes of evaluating the various tests, the former because it tends to minimize the impact of variations in the scene. However, it was decided to use test sample accuracy for this purpose since it appears to provide the more reliable indicator of the impact of the various parameters on identification accuracy*. The RMS proportion estimation error indicator was devised to provide an indication of combined identification and mensuration performance.

The major conclusions from the study are as follows:

1. There was a very small but consistent increase in identification accuracy as the IFOV was enlarged. This is presumed to stem primarily from the small increase in signal-to-noise ratio with increase in IFOV.

2. There was a more significant decrease in the mensuration accuracy as the IFOV was enlarged.

3. The noise parameter study proved somewhat inconclusive due to the greater amount of noise present in the original MSDS data than desired. For example, viewing Figure 8 moving from right to left, it is seen that the classification performance continues to improve as the amount of noise added is decreased until the point is reached where the noise added approximately equals that already initially present due to the MSDS operation. Thus, it is difficult to say for what signal-to-noise ratio a point of diminishing return would have been reached had the initial noise not been present.

*Training sample accuracies for the various results are given in reference 4.

4. The result of the spectral band classification studies may also be clouded by the noise originally present in the MSDS data. The relative amount of that change in performance due to using different combinations of the .45 - .52μm, .74 - .80μm, .80 - .91μm and .74 - .91μm bands is slight but there appears to be a slight preference for the .45 - .52μm band. The performance improvement of the Thematic Mapper channels over those approximating Landsat I/II is clear however.

5. Using spectrometer data it was verified that the .74 - .80μm and .80 - .91μm bands are highly correlated.

6. Correlation studies also showed that the range from 1.0 - 1.3μm is likely to be an important area in discriminating between earth surface features. Further, it is noted that the absolute calibration procedure described above results in a global atmospheric correction of a linear type in that assuming a uniform atmosphere over the test site, the calibration procedure permits a digital count number at the airborne scanner output to be related directly to the percent reflectance of a scene element.

Although much has been learned in this study about the selection of parameters for the Thematic Mapper, it is clear that this problem cannot be now regarded as entirely solved. Further studies of this and other types are needed to develop a convincing set of facts regarding scanner system parameters selection. This study also illustrates very clearly the value of both field gathered and airborne multispectral data in continuing research efforts.

ACKNOWLEDGEMENTS

The authors would like to recognize the many individuals who were involved in this project. Beginning with the staff of the Laboratory for Applications of Remote Sensing (LARS) who were directly involved: Forest E. Goodrick, Keith Steva, and Daniel Wiersma performed the major portion of the computer analysis; Keith Philipp, Jim Kast, Phil Alenduff, and Bill Freestone programmed the simulation algorithms and processed the simulated data. Professor Phillip Swain, Professor LeRoy Silva, Dr. Marvin Bauer, Terry Phillips, Paul Anuta, and Barbara Davis assisted in the several phases of the project.

We also wish to acknowledge the assistance from those outside LARS who helped define the simulated parameters: Dr. Steve Ungar of Goddard Institute of Space Sciences (GISS), New York, New York; Sid Whitley of Earth Resources Laboratory (ERL), Bay St. Louis, Mississippi; Ruth Whitman of NASA Headquarters, Washington, D.C.; Gerry Kenney and Ken Demel of NASA-Johnson Space Center, Houston, Texas; and John Barker of Goddard Space Flight Center, Greenbelt, Maryland.

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LIST OF FIGURES

LIST OF TABLES