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by

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INTRODUCTION

In Spring 1972, the National Aeronautics and Space Administration will launch the first of the earth resource satellites, ERTS-A which will be followed within a year by ERTS-B and Skylab. One of the major purposes of these satellites is to gather synoptic and time-lapse multispectral data of the earth for broad dissemination to be used in the advancement of earth resources management. Of particular interest to many researchers is data produced by multispectral scanner systems (MSS) on board each of the earth resource satellites.

Multispectral scanners similar to the ones proposed for the ERTS and Skylab satellites have become common tools in earth resources research and a great deal of effort has been expended to devise applicable data analysis techniques to handle these data. It has been generally assumed that extensions of these analysis techniques will be applicable to data obtained from the ERTS and Skylab MSS systems.

The purpose of the research was to determine to what extent the assumption of applicability is valid through the simulation of ERTS and Skylab data using available data from aircraft scanner systems. The research technique used compared aircraft multispectral scanner data obtained under nominal conditions at low altitudes with ERTS and Skylab simulations from aircraft data obtained during the same time period over the same terrain at higher altitudes. Maximum likelihood decision criteria algorithms implemented on a digital computer were used to classify training set data as well as certain other test data. These are common techniques used in the analysis of MSS data. Comparisons between percentages of correct classification were made and implications as to the applicability of these techniques to the analysis of satellite MSS data were drawn from these comparisons.

MULTISPECTRAL SCANNER SYSTEMS

Certain fundamental operational principles are common to each MSS system and a basic understanding of these principles is necessary in the analysis of scanner data. Among the principle sub-sections of each scanner are the scanning mechanism, the spectral resolvers, energy detectors and the recording instrumentation. These components and the basic scanning principle are depicted in Figure 1.

The scanning mechanism consists of a rotating mirror and the necessary optical lenses to focus sharply on a resolution or data cell (which is defined by the terrain in the instantaneous field of view of the scanner). The rotation of the mirror causes the field of view of the scanner to move across the flight path and the forward motion of the aircraft produces a raster survey of a swath beneath the sensor. Thus areal measurements are obtained.

The radiant energy entering the aperture of the sensor is focused on a defraction grating thus the energy is spatially separated into its spectral components. These separated energy bands are transmitted generally via fiber optics bundles to semiconductor photodetectors where voltages are produced which are proportional to the incident energy. These voltages are suitably amplified and recorded on multichannel analog magnetic tape. [In the ERTS MSS Systems the data is digitized and transmitted to a ground station.] The analog data is then digitized to provide a data vector with elements proportional to the reflected energy in various spectral bands from resolution cells in the swath viewed by the scanner.

SPECTRAL SIGNATURES

Each object, by its peculiar absorption, transmission and reflectance characteristics alters radiation incident upon it. The spectral distribution of the radiation is altered in a specific way for each object and this distribution becomes a characteristic signature of the object. It is this signature which is measured by the MSS system. If a signature for a particular class of objects is sufficiently different from signatures for other classes of objects, membership in these data classes may be inferred by a comparison of an unknown signatures to the individual class signatures. This, in essence, is the principal objective of standard

MSS data analysis, i.e. the assignment of unknown data resolution cells to specified data classes. Several typical signatures of objects are shown in Figure 2 and the MSS systems obtain discrete measurements of these signatures.

SYSTEM STUDIES

General system comparisons point to major differences between three MSS systems, the University of Michigan M-5 scanner, the ERTS-A system and the Skylab MSS system (S-192). The several system differences which exist between the three are operational altitude, field of view, the resultant spatial resolution and varied spectral resolution.

The most obvious system difference between the three MSS systems is the operational altitude. The nominal operational altitude for the Michigan scanner is 2000 feet. At this altitude, with an angular resolution of approximately 0.003 radians, the nominal resolution cell area is approximately 30 square feet. The operational altitude of the ERTS-A satellite system is approximately 492 nautical miles. The instantaneous field of view of the scanner system is 230 × 230 feet or approximately 53,000 square feet (1.2 acres) causing a considerable degredation in the spatial resolution over the aircraft system. The Skylab S192 Multispectral Scanner system has an operational altitude also near 492 nautical miles. The Skylab MSS system has an instantaneous field of view of approximately 260 × 260 feet which is an area of approximately 74,900 square feet (1.6 acres). In Figure 3 is shown the relative sizes of the resolution elements and the comparative resolution is readily apparent.

The increased operational altitude of the satellite systems also permits a greater intervening atmosphere. This produces greater signal degredation in the ERTS and Skylab systems from the additional atmospheric attenuation and scattering having a possible detremental effect upon the quality of the data.

A third major area of difference in the three systems is spectral resolution. The Michigan M-5 system has 12 spectral bands, the ERTS-A, 4 spectral bands and the Skylab system has 13 spectral bands. The location and bandwidths of the common spectral bands considered are shown in Tables 1-3 and in Figure 4. Thus each system obtains a varying number of measurements of the cell signal.

Based on the three system comparison, the simulation procedure was determined. Atmospheric degredation would be accounted for by using the high altitude Michigan scanner data in simulating the satellite system measurements since a major portion of the atmosphere is below 10,000 feet. Simulation of the satellite systems reduced spatial resolution accomplished by averaging M-5 measurements over an area comparable to the satellite resolution cell. Spectral channels for the satellite systems would be approximated by computing a weighted sum of the M-5 channels where the weights would be determined by the spectral characteristics of the Michigan and satellite scanner systems.

With these procedures outlined, available Michigan M-5 data were surveyed to identify suitable data sets for the simulation. Nearly simultaneous data from two altitudes, acquired over a well documented test site, were desired. Such a data set was flown at Weslaco, Texas in May 1966 when flights were made at 2000 feet and 10,000 feet altitudes. A well documented ground truth summary was also available. In Figures 5 and 6 photographs of the flight line are shown. The digital data was obtained in magnetic tape format from LARS at Purdue through the cooperation of the USDA-ARS at Weslaco, Texas.

ANALYSIS

In the preliminary analysis, grey scale printouts were made of the flight lines, photo mosaics were produced and ground truth, photographs, and data were correlated. During this analysis phase it was determined that the data was degraded in spots by partial cloud cover of the flight lines. A survey of published preprocessing technique was made and a technique reported by Krieglar _et_ _al._ [1969] was selected to remove the shadow effects in the data without severely affecting the channel spectral characteristics. All data were subsequently processed according to the Krieglar algorithm in which the value of each resolution cell channel was divided by the sum of the values of the channels for that data cell. This was in essence a normalization procedure and tended to compensate for varying levels of illumination along the flight line. Corrections for varying scanner amplifier gains were also made at this time.

The simulated satellite data was computed from this preprocessed data. A satellite scanner resolution cell was determined from the average of aircraft scanner resolution cells over a satellite cell area.

The number of M-5 scanner cells included in a satellite scanner cell was determined by a ground comparison of known ground distances with grey scale computer maps of M-5 data cells. Each aircraft scanner channel was summed and divided by the total number of resolution cells providing a twelve channel data vector for each satellite resolution cell. No attempt was made to select data so that satellite cells fell within specific terrain boundaries. Once this computation was made, simulation of the spatial degredation of the satellite data was completed.

The bandpass characteristics of the aircraft scanner channels were removed from the data by dividing the data value of each channel by the area beneath the bandwidth characteristic curves for that channel, thus calculating the normalized energy within each M-5 channel bandwidth. The contribution of the M-5 channels for each ERTS channel was determined by integrating the normalized energy within the M-5 channel bandwidths over the ERTS channel characteristics. The normalized energy for each of the M-5 channels was weighted by the computed contribution and these values for appropriate channels were summed to provide the simulated ERTS data. The Skylab scanner spectral characteristics were not generally available therefore a triangular bandpass function similar to the M-5 system characterization was assumed for the specular integration. These procedures in essence provided the simulation study data for ERTS and Skylab comparisons.

Determination of relative data worth between the data sets was based on the number of correct classification percentages. Identification procedures were based on the maximum likelihood decision algorithm which is commonly used in the analysis of multispectral scanner data. Data samples of known classification are determined, then statistical characteristics are estimated and these parameter estimates are used to define probability density functions by which data vectors are compared in digital computer implementation.

The first step in this analysis is the identification of data samples (training sets) where the characteristics of the terrain viewed are known sufficiently well so that the mean value and the covariance of the data vectors in each category may be determined. Great care was taken in the selection of the data sets to assure that these data sets were selected only from well identified, homogeneous areas to minimize the effects of crop signature variability within the data training sample. In Table 4 is shown the classes into which the data was divided. Particular crops, where several divisions existed in size and age were subdivided into separate classes to insure maximum homogenity in the training samples. Histograms of these sets of carefully selected data were produced to insure that multimodal distributions were excluded. Fields where only crop type was identified and which were not specifically documented as to size or age, were used as test areas for comparison. Each data set, the Michigan M-5, the ERTS and the Skylab simulations, were examined in exactly the same way consistant within each set. Training samples were selected from homogeneous areas within each data set with reference only to the ground truth summary and not to the other data sets.

The classification training algorithms were implemented on the digital computer and training was accomplished on each of the selected data training sets. The sample means were computed by

$$M_i = \frac{1}{N} \sum_{j=1}^{N} X_j \qquad i = 1, \ldots, K$$

and the sample covariances were determined from

$$V_i = \frac{1}{N-1} \sum_{j=1}^{N} (X_j - M_i)(X - M_i)^T \quad i = 1, \cdots K$$

where: M_i is the sample mean vector in the ith class

N is the number of data cells in the class

X_j is the jth data vector

K is the total number of classes

V_i is the covariance matrix of the ith sample

$(\ )^T$ indicates a matrix transpose operation

In order to make the classification analysis consistant between the three data set formats, a subset of the dimensions of each data cell was selected. A subset of four features was chosen from the M-5 and Skylab simulation data sets to reduce the number of dimensions processed in the classification algorithms and to make the processing consistant with that of the ERTS simulation. The subset was chosen to maximize the average of a defined separability functional over the data classes. The separability between two classes, ω_i and ω_j was defined as

$$S = \frac{1}{K-1} \sum_{i=1}^{K} \sum_{j=1}^{K} [M_i - M_j]^T [V_i + V_j]^{-1} [M_i - M_j]$$

Admittedly this particular definition of separability is largely heuristic in the multidimensional case but is intuitively appealing in the determination of separability. That is, it is "good" when the mean vectors of the data classes are widely separated or the squared distance between them is large; however, it is "not good" when the variance of the classes about their mean vectors is large. Hence, the separability varies directly as the separation between the means $[M_i - M_j]$ and inversely as the sum of their covariances. In addition, Fu (1970) indicates that the selection of any four channels from among the total number available in a similar data set did not appreciably affect the correct classification obtainable from the data. Thus, the heuristic separability criteria provides, at worst, a better subset of channels from among the subsets of channels which are sub-optimal in the sense of correct classification results. The channels selected for each of the M-5 scanner data were channels 2, 3, 10, and 11 and the Skylab channels selected were channels 1, 3, 6, and 7.

The data were classified using a maximum likelihood decision criteria implementation. This procedure assigns the data cell X_0 to the class ω_i

for which the likelihood function $p(X|\omega_i)$ (the probability density function of the ω_i class evaluated at the vector X) is maximum or equivalently the class ω_j for which the discriminant function

$$g_i(X) = \mathrm{Log}_e |V_i| + (X - M_i)^T V_i^{-1} (X - M_i)$$

where: $|V_i|$ is the determinant of V_i

V_i^{-1} is the inverse of V_i

is maximum.

It is generally impractical, if not impossible to define all the classes appearing in a scene and to train the classifier on these classes. It is therefore desirable to define a class "everything else", in which those points not "properly" belonging to the selected classes may be placed. This class can be readily established by defining a threshold T_i for each class. All points placed in the class ω_i by the classifier for which the discriminant function $g_i(X)$ is greater than the threshold would be classified as belonging to that class. All other points for which $g_i(X)$ is less than the threshold would be assigned to the class "everything else".

The setting of the appropriate threshold depends on the criterion used. The specific criteria used here sets a threshold so that at least 95% of the sample vectors from class ω_i would not be rejected by the threshold setting.

The quantity $(X-M_i)^T V_i^{-1}(X-M_i)$ has a χ^2 distribution $C_n(\chi^2)$ of N degrees of freedom. Therefore, for a given threshold setting, the percentage of samples from class ω_i being rejected can be determined from the percentage tabulation of the χ^2 distribution. Thus in this case

$$T_i = \text{Log}_e |V_i| + \{\chi^2 \text{ for which } C_4(\chi^2) = 0.95\}$$

or

$$T_i = \text{Log}_e |V_i| + 9.49$$

and the classification of a point X into ω_i requires jointly that

$$1)\quad g_i(X) > g_j(X) \quad \forall j \neq i$$

and

$$2)\ g_i(X) \geq T_i$$

RESULTS

Classification maps from the Michigan low altitude, the ERTS MSS simulation and the Skylab MSS simulation are shown in Figures 7-9. In Table 5 is compiled the classification results from the training sets. Training sets consisting of varieties within a general grouping have been compiled under that grouping for presentation in the table. Thus, for example, the fields of cotton having varying percentages of ground cover have been grouped under their common class, cotton. In Table 6 is shown the classification results for the test fields.

Generally the classification results for the training fields, which were carefully chosen homogeneous areas, do not show the strong bias toward the M-5 system with its increased spectral and spatial resolution which might at first be suspected. Rather each system classifies well in some areas and less well in others. However, on the test fields, which were not necessarily homogeneous in the subclasses of general categories although they were the same crop throughout, there appears to be consistant bias in favor of the M-5 system. This bias is strong in the two classes "sorghum" and "cotton" where variability with the class would be reduced. In the class "fallow" where the variability of points would necessarily be large, the percentage of correct recognition is consistantly low.

The results of this study show that for carefully chosen homogeneous data training classes, where data variability within classes is low, classification results are generally equivalent among data sets from varying altitudes and that the spectral and spatial degredations do not appreciably affect the classification results. However, it also appears that the variability in the data produced jointly by class uncertainty, spectral averaging and spatial averaging determines some unspecified variability threshold beyond which classification is seriously impaired.

This study points to the need for the increased investigation of this threshold phenomena through rigid comparisons of data sets similar to those described and for the development of methods to effectively reduce the impact of this threshold of degredation.

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TABLE 1

SPECTRAL BANDS OF THE MICHIGAN M-5 MULTISPECTRAL SCANNER

Range	Channel Number	Spectral Response (Microns)
ultraviolet	0	0.32 to 0.38
visible (violet)	1	0.40 to 0.44
visible (blue)	2	0.44 to 0.46
visible	3	0.46 to 0.48
visible (blue-green)	4	0.48 to 0.50
visible	5	0.50 to 0.52
visible (green)	6	0.52 to 0.55
visible	7	0.55 to 0.58
visible (yellow)	8	0.58 to 0.62
visible (red)	9	0.62 to 0.66
visible (red)	10	0.66 to 0.72
near infrared (reflective)	11	0.72 to 0.80
near infrared (reflective)	12	0.80 to 1.00
near infrared (reflective)	13	1.50 to 1.80
near infrared (reflective)	14	2.00 to 2.60
middle infrared (thermal)	15	3.00 to 4.10
middle infrared (thermal)	16	4.50 to 5.50
far infrared (thermal)	17	8.00 to 14.0

TABLE 2

SPECTRAL BANDS OF THE ERTS-A MULTISPECTRAL SCANNER

Range	Channel Number	Spectral Response (Microns)
visible	1	0.50 to 0.60
visible (red)	2	0.60 to 0.70
near infrared (reflective)	3	0.70 to 0.80
near infrared (reflective)	4	0.80 to 1.10
far infrared (thermal)	5	10.4 to 12.6

TABLE 3

SPECTRAL BANDS OF THE SKYLAB MULTISPECTRAL SCANNER

Range	Channel Number	Spectral Response (Microns)
visible (blue-violet)	1	0.410 to 0.460
visible (blue-green)	2	0.460 to 0.510
visible (green)	3	0.520 to 0.556
visible (yellow)	4	0.565 to 0.609
visible (red)	5	0.620 to 0.670
visible (red)	6	0.680 to 0.762
near infrared (reflective)	7	0.783 to 0.880
near infrared (reflective)	8	0.980 to 1.080
near infrared (reflective)	9	1.090 to 1.190
near infrared (reflective)	10	1.200 to 1.300
near infrared (reflective)	11	1.550 to 1.750
near infrared (reflective)	12	2.100 to 2.350
far infrared (thermal)	13	10.20 to 12.50

TABLE 4

DATA TRAINING CLASSES AND KEY

	KEY		
Class	2000'	ERTS	Skylab
Water	1	1	1
Sorghum (25%)	2	2	2
Corn	3	3	3
Cotton 17-38%	A	4	4
Cabbage	5	5	5
Cotton 50-63%	9	6	6
Weeds	B	7	7
Sorghum 30-50%	6, 8	8	8
Cotton 70-85%	7	9	9
Trees	-	A	A
Fallow	C	B	B
Sorghum 96%	4	-	-

TABLE 5

DATA TRAINING SETS

Weslaco 5/66

2,000'

	M-5		ERTS-A		SKYLAB	
Water	376	93.4%	4	0%	4	0%
Sorghum	3077	62.7%	82	63.4%	82	68.3%
Cotton	2679	82.3%	63	66.7%	63	73.0%
Fallow	1950	67.7%	52	63.5%	52	67.3%
Corn	408	83.8%	22	86.4%	22	63.6%
Cabbage	1000	82.2%	21	81.0%	21	85.7%
Trees	-	-	-	-	-	-

10,000'

	M-5		ERTS-A		SKYLAB	
Water	203	56.2%	18	44.4%	18	55.6%
Sorghum	707	69.3%	79	84.8%	79	79.8%
Cotton	1649	71.4%	141	60.3%	141	70.2%
Fallow	751	34.1%	59	71.2%	59	57.6%
Corn	101	91.1%	5	100.0%	5	100.0%
Cabbage	207	88.9%	24	79.2%	24	83.3%
Trees	1000	97.8%	174	94.2%	174	93.1%

TABLE 6

DATA TEST SETS

Weslaco 5/66

2,000'

	M-5		ERTS-A		SKYLAB	
Water	169	72.2%	-	-	-	-
Sorghum	480	76.9%	12	58.3%	12	66.7%
Cotton	3056	66.8%	86	67.4%	86	62.8%
Fallow	1458	42.4%	24	33.3%	24	33.3%
Corn	-	-	-	-	-	-
Cabbage	-	-	-	-	-	-
Trees	-	-	-	-	-	-

10,000'

	M-5		ERTS-A		SKYLAB	
Water	-	-	-	-	-	-
Sorghum	707	59.3%	21	38.1%	21	38.1%
Cotton	1920	54.11%	175	40.6%	175	56.57%
Fallow	1035	19.23%	101	40.6%	101	37.6%
Corn	-	-	-	-	-	-
Cabbage	-	-	-	-	-	-
Trees	1360	61.4%	130	94.6%	130	86.2%

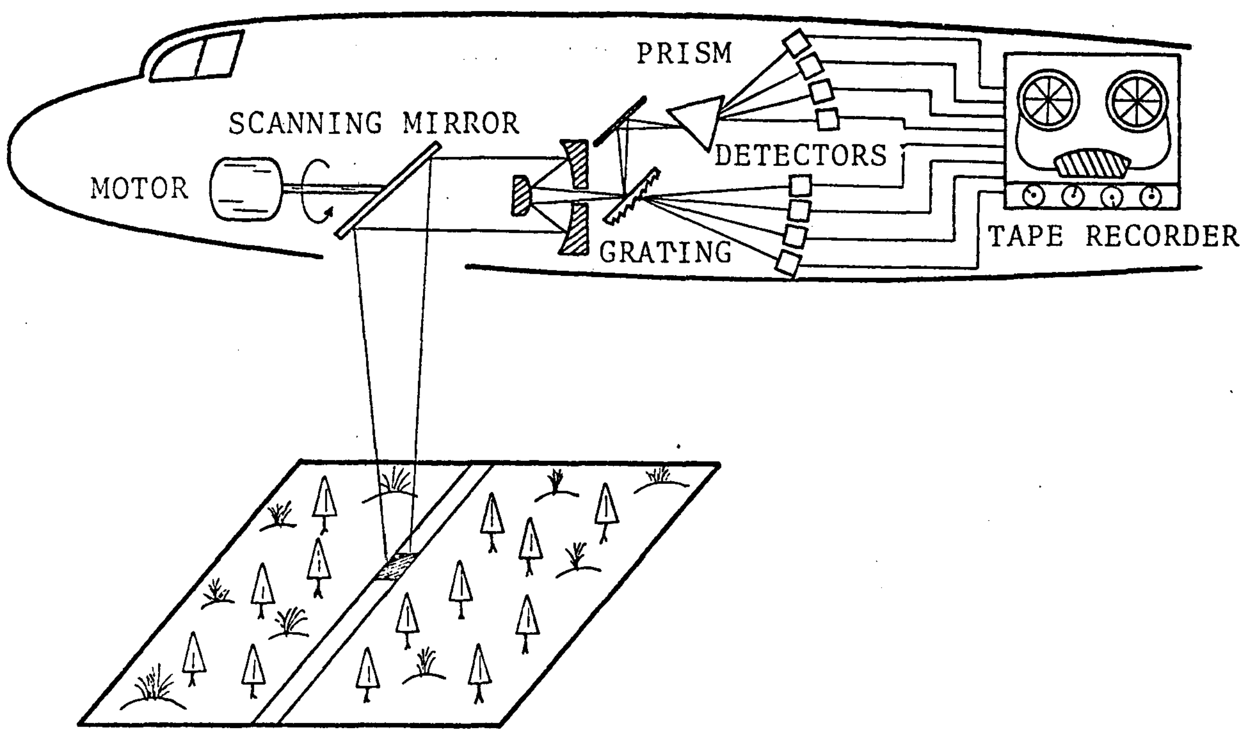

Figure 1. A multi-channel optical mechanical scanner (mounted in aircraft).

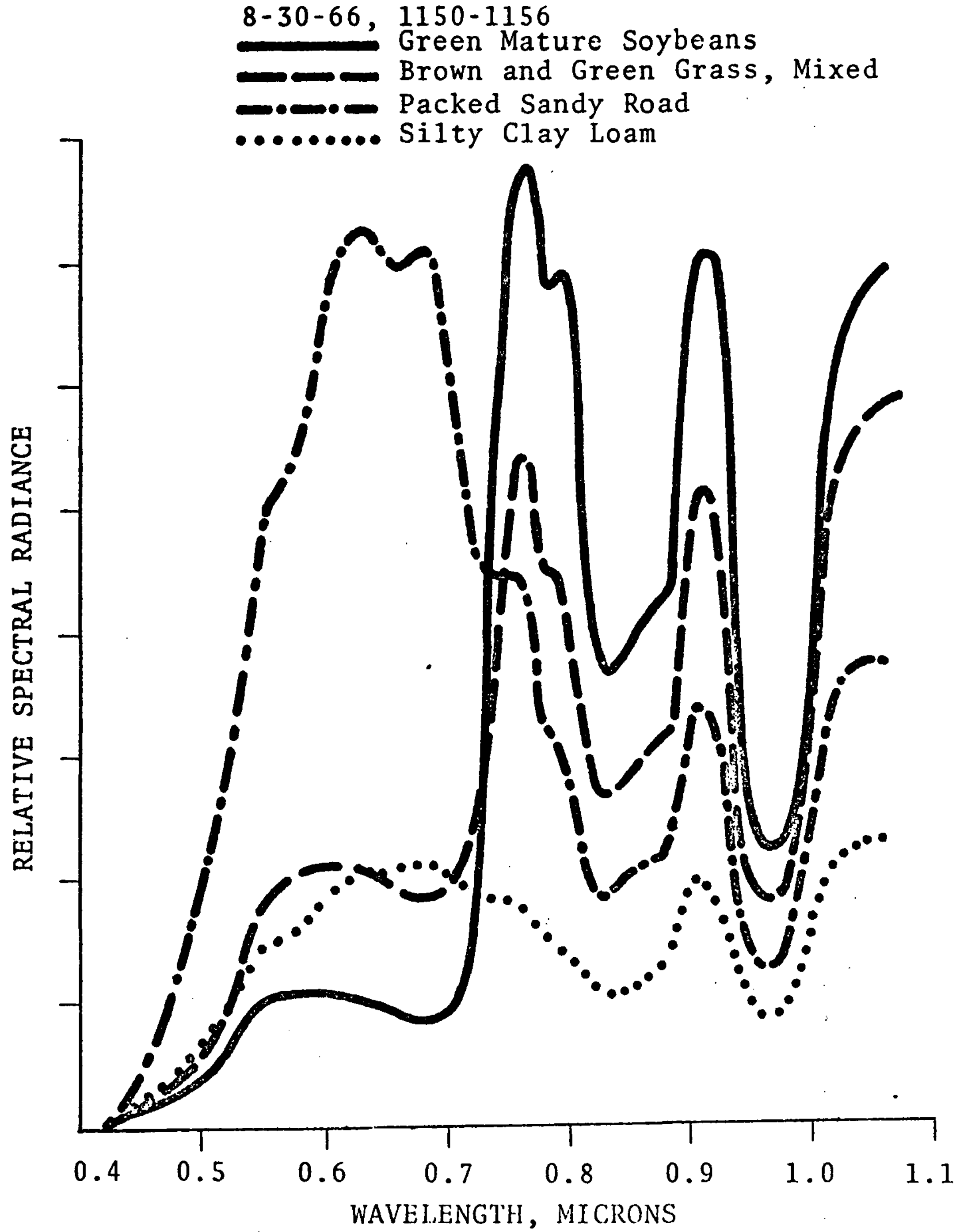

Figure 2. Relative spectral radiance spectra showing the marked rise in vegetation reflectance at 0.72 micron.

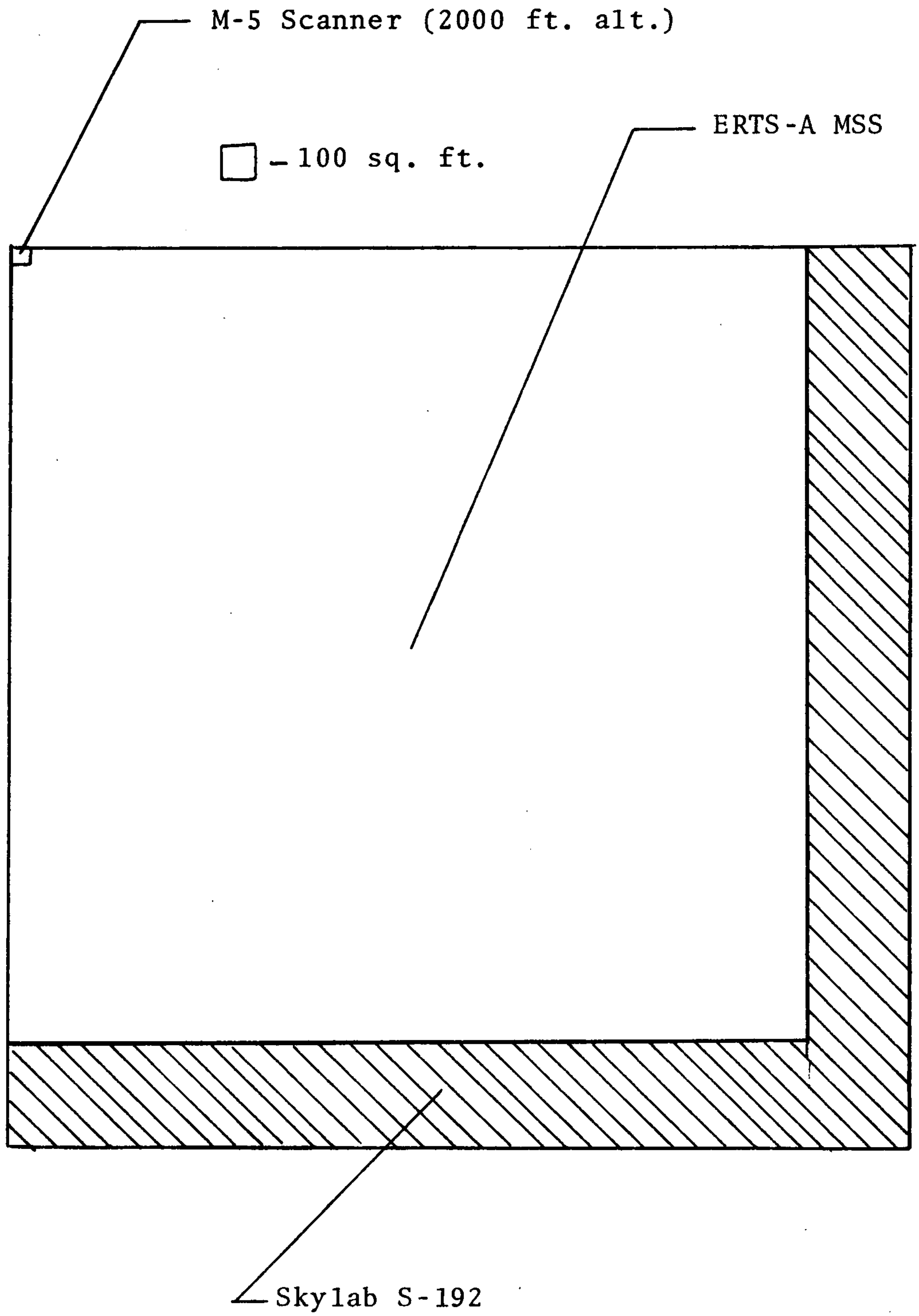

Figure 3. Relative Size of MSS Resolution Elements.

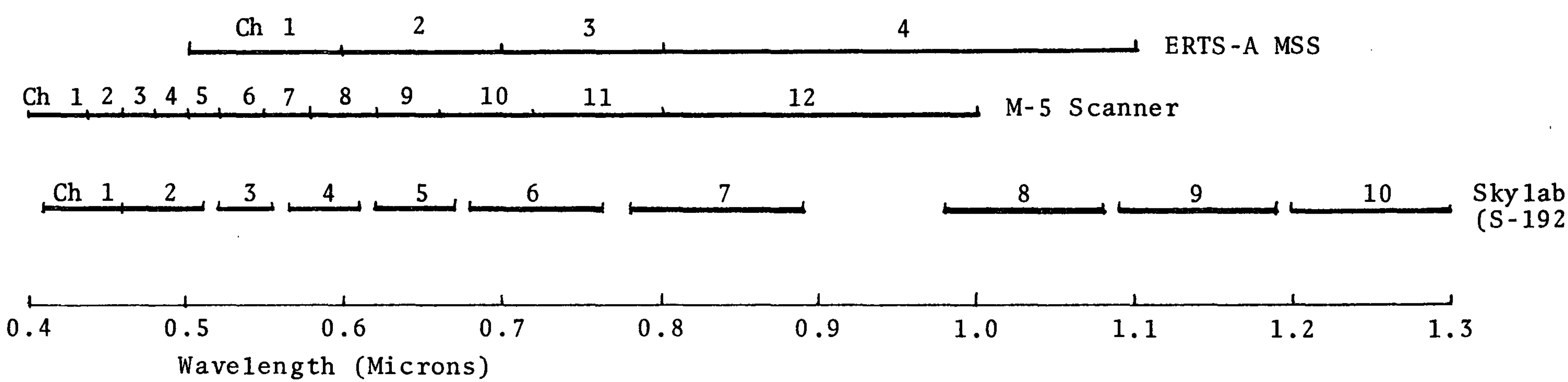

Figure 4. Location and Bandwidths of MSS Spectral Bands.

Figure 5. Weslaco, Texas Flight Line May, 1966 (Part I).

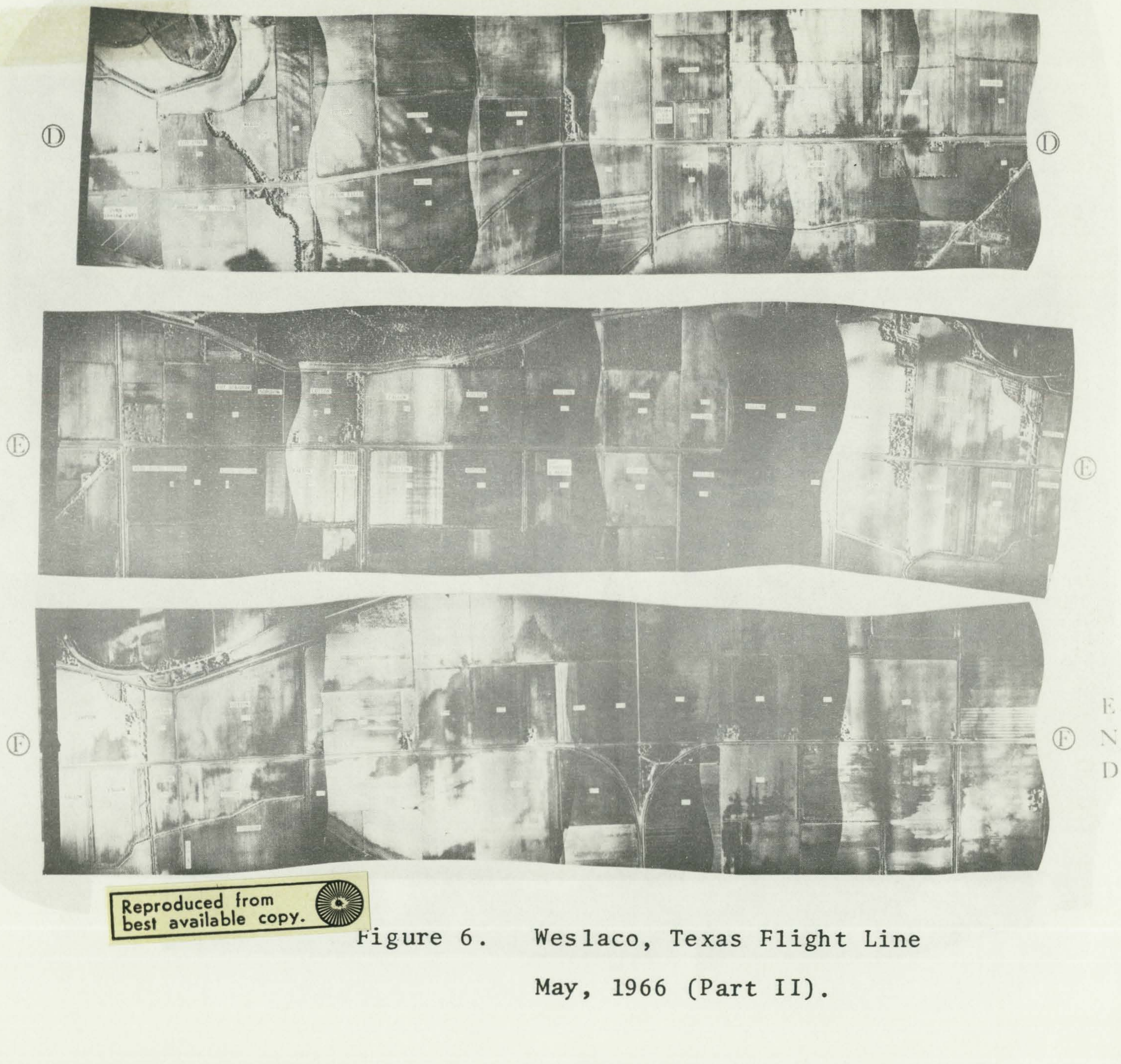

Figure 6. Weslaco, Texas Flight Line May, 1966 (Part II).

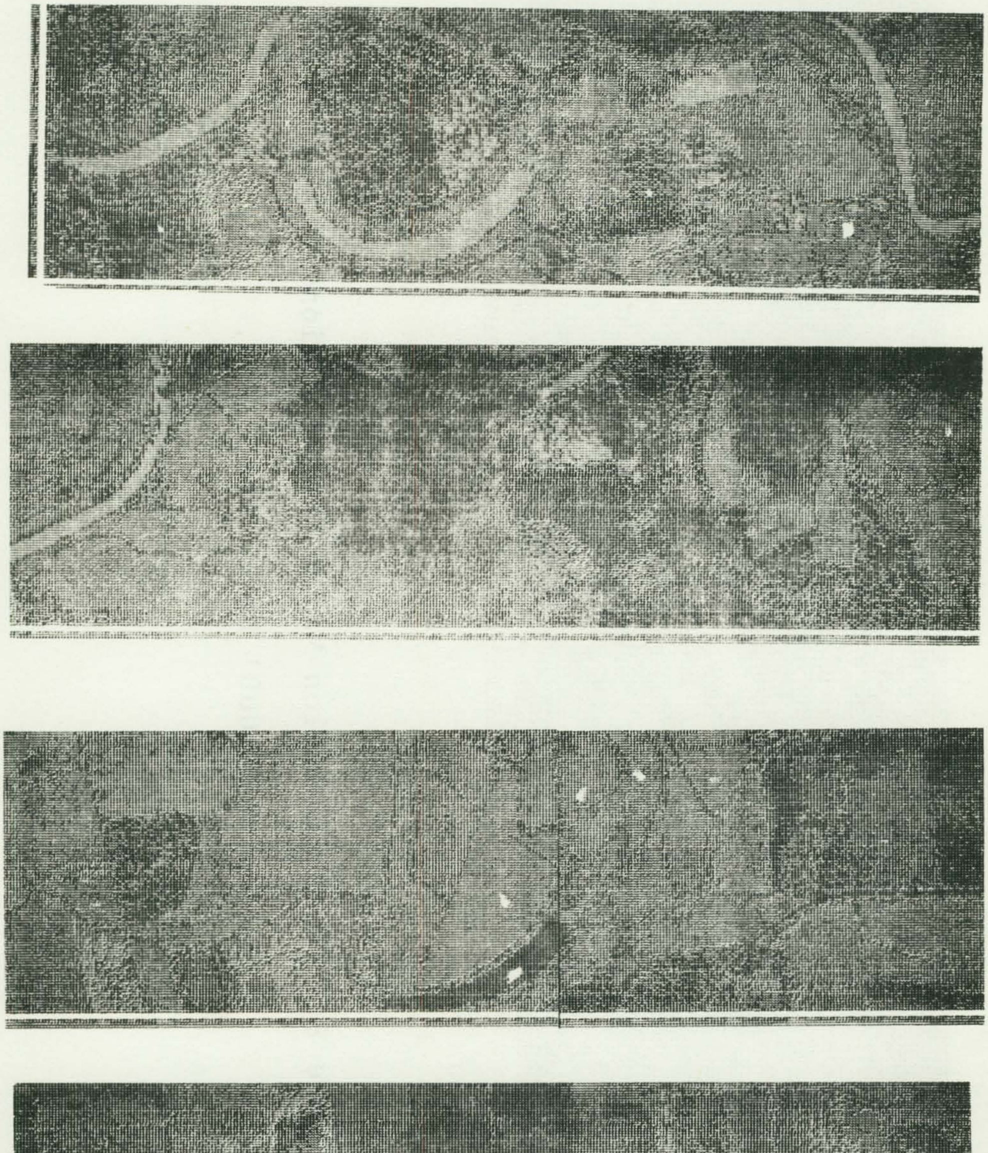

Figure 7. Classification Map 2,000' Weslaco Data, May, 1966.

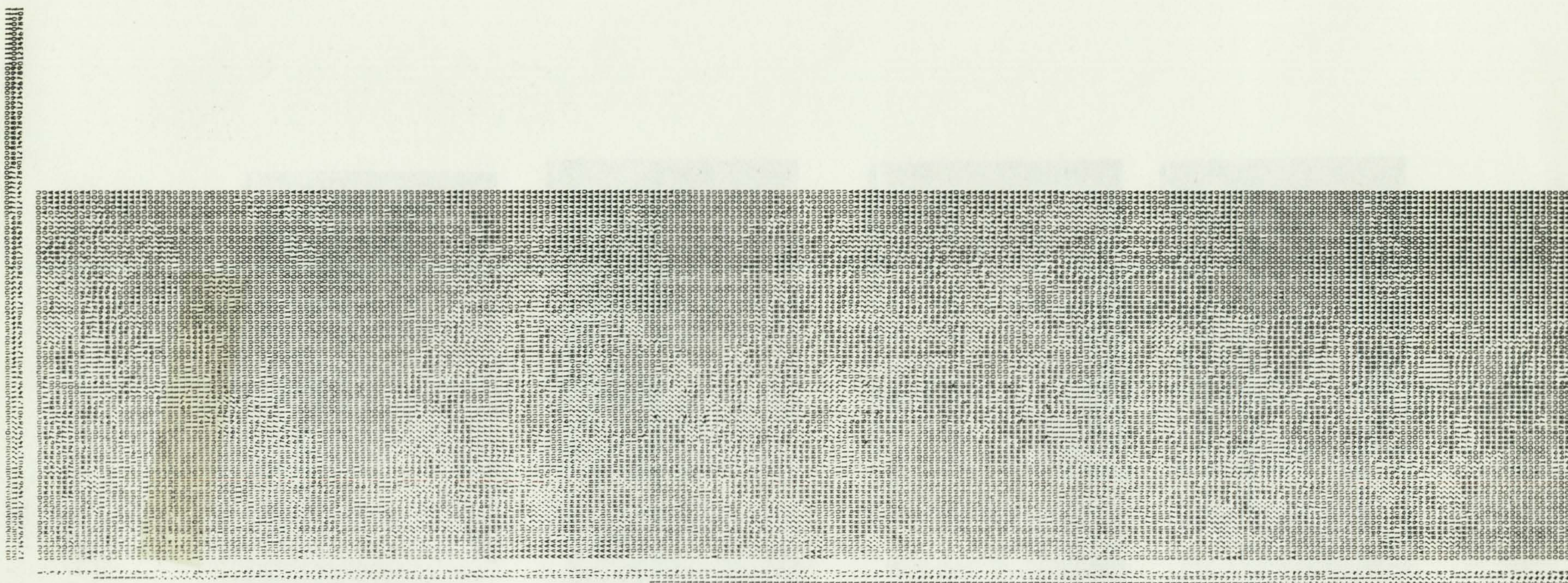

Figure 8. Classification Map ERTS Simulation Weslaco 10,000' Data, May, 1966.

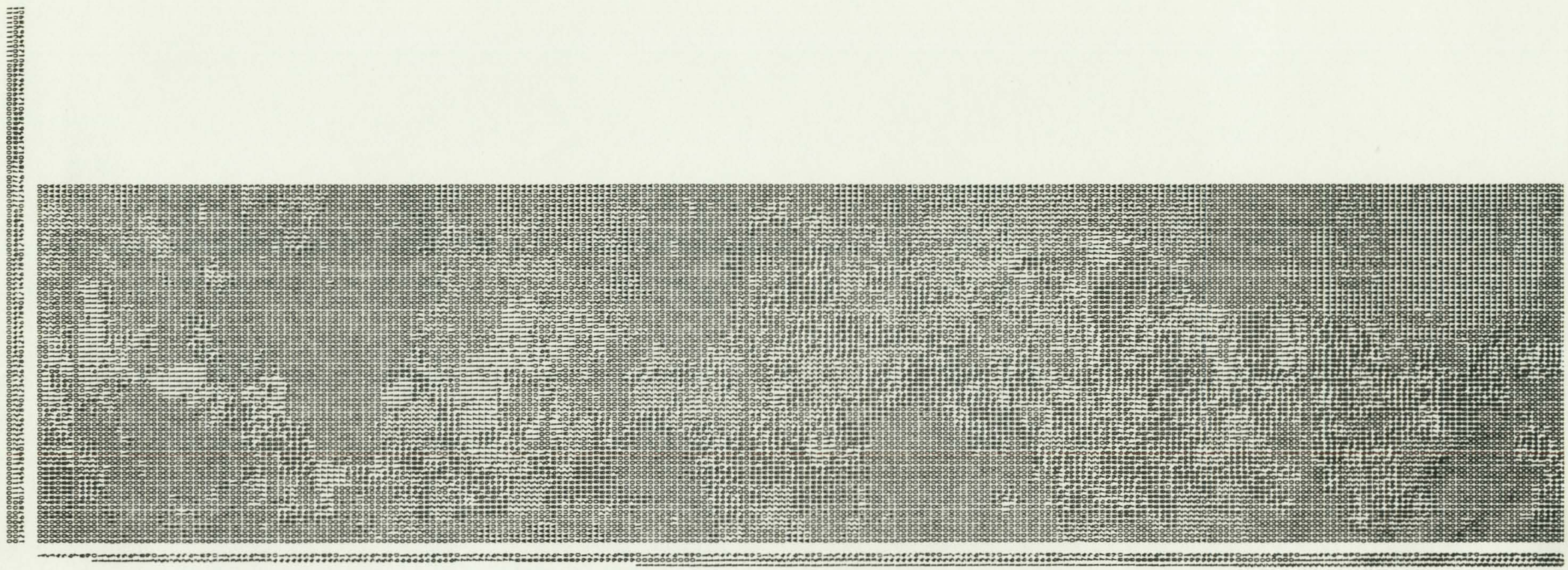

Figure 9. Classification Map Skylab Simulation Weslaco 10,000' Data, May, 1966.

APPENDIX A

GROUND TRUTH SUMMARY

GROUND TRUTH SUMMARY

WESLACO, TEXAS

5/31/66

(White, 1971)

Field	Crop	Maturity	Color	% Cover	Ht(cm)	Row	Remarks
42	sorghum	headout milk	Lg	25	100	N-S	
44A	cotton	prebloom	Lg	17/31	87/72	N-S	
44B	cotton	early	g	17	75	N-S	
45	corn	preharvest	dg	100	250	N-S	soil very wet irrigated ver recently
47	cotton	prebloom	Lg-g	33	65/55	E-W	
47A	cotton	early	g	38	58	E-W	
52	sorghum	headout, dough	dg	96	136	W-SE	irrigated
53	sorghum	headout, milky	g-dg	96	110	E-W	irrigated
54	cotton	prebloom	Lg	40	50	N-S	being irrigat water standin
58	cotton	prebloom	Lg	50	14	E-W	dry
60	sorghum	preboot	g	30	68	E-W	north of site much younger sorghum
61	cotton	prebloom	Lg	70	30	N-S	cultivated an insecticides added
63	cotton	prebloom	Lg	50	40	N-S	
66	cotton	prebloom	Lg	50	44	N-S	cultivation a fertilizer
69	sorghum	preboot	Lg	29	70	N-S	prob. irrigati and fertilizat
71	cotton	prebloom	Lg	50	40	N-S	

Field	Crop	Maturity	Color	% Cover	Ht(cm)	Row	Remarks
78	cotton	prebloom	Lg	63	32	N-S	young and uniform
83	cotton	prebloom	Lg	70	28	N-S	
87	sorghum	preboot	Lg	50	50	N-S	very young, clea and cultivated
89	cotton	prebloom	Lg	85	24	N-S	
92A	cotton	prebloom	Lg	70	24	N-S	cultivated
92B	cotton	prebloom	Lg	65	36	N-S	
96A	mustard green	new flush	gg	26	33	N-S	
97A	cotton	prebloom	Lg	10	17	N-S	poor stand
97B	cotton	prebloom	Lg	65	36	N-S	good stand
104	cotton	prebloom	Lg	60	37	N-S	
105	cotton	prebloom	Lg	50	45/56	N-S	
112	cotton	prebloom	Lg	80	16/20	N-S	
118	cotton	prebloom	Lg	66	24	N-S	

APPENDIX B

TRAINING AND TEST FIELD SPECIFICATIONS

WESLACO 2000' (WF1)

5/30/66

(Training Fields, White, 8/71)

Field	Class	Row Start	Row End	Column Start	Column End
		Water			
-	1	198	260	23	29
-	1	410	448	159	169
-	1	540	544	103	133
-	1	556	594	49	55
		Sorghum 25% Headout Milk			
42	2	1385	1448	121	181
		Corn			
45	3	1504	1550	79	111
		Cotton (Young) 17-38%			
43B	4	1454	1472	31	57
43A	4	1474	1498	99	143
47	4	1572	1593	133	211
		Sorghum 96% Headout (Milk & Dough)			
53	5	1634	1650	111	167
52	5	1652	1676	181	205
		Fallow			
55	6	1764	1789	105	181
64	6	2060	2082	7	83

Field	Class	Row Start	Row End	Column Start	Column End
		Cotton 70%			
61	7	1990	2040	7	65
		Sorghum 30%			
60	8	1918	1976	9	69
		Sorghum 30%			
69	9	2266	2322	39	87
		Cotton 50-63%			
58	10	1872	1894	19	59
66	10	2204	2238	113	143
71	10	2348	2376	105	133
78	10	2548	2576	113	145
		Cabbage			
56	11	1808	1846	107	205
		Weeds			
57	12	1904	1928	105	181
62	12	2004	2026	105	181

WESLACO 10,000' (WAF)

5/31/66

(Training Fields, ERTS-SKYLAB Simulation, White, 8/71)

Field	Class	Row Start	Row End	Column Start	Column End
		Water			
-	1	9	13	35	35
-	1	18	18	44	44
-	1	66	69	35	35
-	1	8	81	42	45
-	1	83	85	36	35
-	1	95	95	43	43
		Sorghum 25% Headout Milk			
42	2	101	105	29	34
		Corn			
45	3	108	108	25	26
45	3	109	111	28	29
		Cotton 17-38%			
47	4	114	114	32	36
		Cabbage			
56	5	128	130	32	39

Field	Class	Row Start	Row End	Column Start	Column End
		Cotton 50-63%			
58	6	133	134	24	28
65	6	149	150	32	35
66	6	152	157	29	35
71	6	164	167	31	31
78	6	178	179	33	38
		Weeds			
57	7	135	136	30	35
62	7	143	143	31	38
79	7	183	186	28	31
		Sorghum 30-50%			
60	8	138	140	26	28
69	8	160	163	25	28
87	8	202	205	35	40
		Cotton 70-85%			
83	9	193	196	31	33
89	9	213	214	36	40
92A	9	223	228	30	34
97B	9	231	232	37	40
		Trees			
998	10	236	241	46	74
		Fallow			
53	11	125	126	29	38
64	11	148	150	28	29

WESLACO 2000' (WFI)

5/30/66

(Test Fields, White, 8/71)

Field	Class	Row Start	Row End	Column Start	Column End
199	1	30	56	89	99
199	1	686	694	147	179
38	2	1234	1264	119	177
39A	12	1288	1314	81	145
41	10	1362	1426	1	55
46	10	1544	1558	147	197
54	4	1758	1856	63	85
59	10	1942	1966	105	197
59A	6	1974	1994	105	199
76	10	2508	2528	51	75
80	7	2596	2624	83	157
79	12	2600	2624	1	71

WESLACO 10,000' (WAF)

5/31/66

(Test Fields, ERTS-SKYLAB Simulation, White, 8/71)

Field	Class	Row Start	Row End	Column Start	Column End
59	6	138	139	30	36
59A	11	140	141	30	36
59B	6	138	141	38	40
63	6	145	147	31	39
80	9	182	185	34	37
82	11	188	190	35	37
83A	2	194	196	27	29
62A	2	142	147	40	41
98	7	203	209	29	33
90	9	216	218	36	40
99	11	236	238	30	34
98	11	235	238	37	40
100	6	240	243	31	34
101	9	240	243	37	40
105	9	247	250	38	39
112	9	268	272	39	41
113	11	269	270	32	37
999	10	230	234	49	74
117	6	276	279	34	42

The REMOTE SENSING CENTER was established by authority of the Board of Directors of the Texas A&M University System on February 27, 1968. The CENTER is a consortium of four colleges of the University; Agriculture, Engineering, Geosciences, and Science. This unique organization concentrates on the development and utilization of remote sensing techniques and technology for a broad range of applications to the betterment of mankind.