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LAND USE STUDIES WITH SKYLAB DATA

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Abstract

This study reports on preliminary analyses of Skylab space photography and multispectral scanner data. S-190A and S-190B high resolution color and color infrared photography have been evaluated for ways in which they may complement ERTS data in land use mapping and for detailed land use sampling studies in regional resource surveys.

Capabilities of Skylab photographic data suggest significant applications for: 1) identification and mapping of all primary, most secondary, and many tertiary land use classes; 2) stratification of the landscape for more detailed sampling; and, 3) rapid updating of existing land use and vegetation maps subscaled at 1:25,000 and smaller with manual interpretation techniques.

Automated thematic mapping of land use categories with electronic data processing techniques is feasible with the S-192 Multispectral Scanner, despite the high noise levels in many channels.

Introduction

Planners are increasingly faced with the need for state and regionwide land use and related data, both to develop land use plans and to monitor their progress. Many ways of acquiring the needed data are being examined. The role of various remote sensing systems - high altitude aircraft, ERTS, and Skylab (the latter particularly as a possible guide to the use of space shuttle in the 1980's) - are of interest to the planning community, as a means for meeting a significant part of their data needs.

The most attractive feature of earth resource satellite systems for planners and resource managers is the capability to rapidly map and update changing land use patterns over large regions, with simultaneously-obtained images. The broad view and potentially many looks with satellite systems can provide new, compact, and in some cases improved information for comprehensive land use planning. Another attractive feature of satellite systems is the provision of information on a common data base, capable of being overlayed on earlier data, and in standard geometric format.

Skylab, which is complementary rather than competitive with ERTS, provides data of higher resolution than that currently available from the ERTS-1 satellite. In general, ERTS-1 imagery should be considered a tool to monitor trends in changes in regional land use and to focus on areas of most rapid change requiring more intensive study. Skylab, on the other hand, foreshadows the use of high resolution systems on space shuttle which will focus on those areas of most rapid change derived from analysis of the ERTS data.

In our studies, we are assessing the accuracy and level of detailed information which may be extracted from Skylab photographs. These data are to be used for comparison with other Skylab sensors for initial stratification of the landscape and for selection of training sets to be used in analysis of electronic data processing of Skylab multispectral scanner imagery.

A major problem associated with electronic data processing is determining the location and number of training classes needed for prediction over the remainder of a large area with acceptable accuracy. This is a very expensive part of any land use mapping project. Different sampling strategies for developing training sets are to be examined along with the degradation of prediction accuracy as one moves away from the training set to varying distances. Working rules for sampling prior to, during, and after spacecraft data are available are being reviewed as well as refinements in sampling strategy. Several computer-based land use discrimination studies have shown that coarse resolution data with resolutions comparable to that recorded on the S-192 multispectral scanner are very useful for mapping broad categories in land use. Accurate discrimination between land use categories can drop off significantly when only a limited number of data channels are available. This frequently is the case in some environments for certain land use classes with ERTS imagery. The 13 channel multispectral scanner on Skylab is expected to permit an examination of questions on sampling and distance decay functions in land use mapping as well as giving insights on the spectral bands needed for acceptable land use classifications.

In our preliminary analyses of Skylab data, significant capabilities are evident for land use mapping. These capabilities include: 1) identification and mapping of land use classes at levels of detail competitive with some aircraft imagery; 2) stratification of the landscape for more detailed sampling; 3) rapid updating of existing land use maps at scales of 1:25,000 and smaller; and 4) automated thematic mapping of land use categories with electronic data processing techniques.

Skylab Orbital Manned Workshop

Skylab was launched in early 1973 at an altitude of approximately 544 kilometers. It was equipped with a number of earth observation sensors, three of particular interest in our studies. These are the S-190A multispectral photographic camera, S-190B Earth Terrain Camera and the S-192 multispectral scanner. The configuration of these sensors is shown in Tables 1, 2, and 3. Skylab photographic and multispectral scanner data obtained over the Washington, D.C. - Baltimore test site on 12 June and 5 August 1973 are examined in this study.

S-190A and S-190B images have been enlarged to various scales from 1:1,000,000 to 1:25,000 for enhancement, interpretation and analysis. False color composites have been prepared from multi-band black and white images recorded with the S-190A camera. S-192 multispectral scanner data are being analyzed using electronic data processing techniques and various image enhancement techniques.

Land Use Classification Scheme

A problem inherent to all land use studies is the selection or development of a suitable land use classification scheme, particularly when dealing with imagery at various scales and resolutions.

The development of a land use classification scheme is not a prime objective of this study, therefore we have adopted a legend proposed by Hardy, et al., 1972, with some modification of secondary and tertiary classes. Table 4 shows the land use classification scheme through the tertiary level being used in this study. Further refinement of the legend is necessary to incorporate more detailed fourth and fifth levels of information.

Analysis of S-190A and S-190B Photographic Data

The first Skylab data available over the Washington, D. C. - Baltimore test site, obtained on 12 June 1973, has clearly shown that such data will provide significant inputs to regional, state, and local land use mapping. All primary and most secondary land use classes can be identified from S-190A multispectral photography.

It is significant to note that no one band permits accurate identification of all land use classes. Black and white infrared photography provides an excellent tool for identifying and mapping coastlines, bays, streams, inland water bodies, coastal wetlands, and inland marshes (Figure 2). Black and white panchromatic photography, 0.5 to 0.6 μm and 0.6-0.7 μm, permits quick and accurate identification and mapping of agricultural, forest, and urban categories (Figure 3). Further detailed classification within these broad categories can be accomplished with color infrared and high resolution color film. For example, color infrared photography permits separation of deciduous, evergreen and mixed forest classes. This is a function of the spectral characteristics of forest vegetation, film spectral sensitivities, and time of year. Agricultural classes are discernible on both color infrared and high resolution color film on June imagery. Most agricultural land under active cultivation images in light tones on both emulsions as these lands are generally freshly plowed or planted. Winter small grains (wheat and barley) are easily identified on color infrared photography in early spring since these small grains reflect strongly in the infrared and image as red or magneta on color infrared film. Pasture lands typically have green vegetation present in the field but are intermixed with other dead or dying plant material. The resultant image appearance on June imagery is a mottled pinkish-bluish tone. A thorough understanding of the characteristics of agricultural classes, reflectance spectra, imaging characteristics and their patterns of change is essential for accurate identification and mapping of these classes.

Urban and built up areas are readily identified on panchromatic imagery in the green and red portions of the spectrum as well as on color infrared and high resolution color film. Our preliminary analysis suggests that within the urban category, more detailed information can be extracted from high resolution color film than from color infrared photography. Resolution appears to be a limiting factor at this time. Figure 4 is a comparative analysis of S-190A color I.R. and high resolution color film for mapping urban land use categories. Single family residential, multi-family residential and commercial service categories are discernible on both image types. Residential density can only be inferred, based on imaging characteristics as related to the presence or absence of lawns and trees, on imagery of this quality. In some cases, older neighborhoods with substantial shade trees are mistaken for parks, wooded areas, or other unimproved open lands. In the area shown in Figure 4, schools and parks are not readily separable from each other although the distribution of these categories within residential areas is such that apparent breaks or openings within a residential community can be inferred as either institutional (schools) or parks. Within the commercial urban categories it is difficult to identify and separate wholesale and retail commercial services except as inferences based on their location and spatial arrangement with respect to other urban categories. The essence of this, is that this quality of satellite data can provide significant information on urban areas particularly when there exists a thorough understanding of the character of spatial arrangements, and relationships of one urban category to another.

Higher resolution photography acquired on Skylab with the S-190B Earth Terrain Camera illustrates the substantial body of information obtainable from satellite photography (Figure 5). Imagery of this quality permits rapid mapping of urban categories to the second and third levels of detail. Density and relative age of single and multi-family residential areas can be inferred from this imagery. Also, schools and parks are separable within the residential areas providing initial ground truth data are available for interpreter training. Most major and secondary concrete and asphalt highways are easily identified on this imagery. The spatial arrangement of homes within residential areas allows inferences to be made of street patterns. The ability to identify and map transportation routes, railroads, and commercial categories permits inferences of wholesale, retail and industrial categories, again based on a thorough understanding of the distribution, location, and character of such categories within the broad urban land use class.

Regional land use maps have been prepared from Skylab S-190A data to demonstrate the rapidity with which such maps can be prepared and to supplement analyses of the S-192 multispectral scanner data. One such map has been prepared for St. Mary's County, Maryland (Figure 6). This map was prepared at an original scale of 1:126,720. Although S-190A color and color I.R. photography can be enlarged to scales of 1:63,360 without significant image breakup, we chose this scale to be compatible with other products being prepared by projecting S-190A Pan-X (0.6-0.7 μm) and color I.R. film to map scale. The county is roughly 420 square miles and required 14 hours for interpretation, mapping, and preparation of the final map. A similar map prepared from RC-10 aircraft color infrared photography at the same scale required 32 hours for completion. Assuming a fully burdened labor rate of $13.50/hour, the use of Skylab data resulted in a cost savings of approximately 43%. The map shown in Figure 6 depicts land use classes to the secondary level. It must be noted that more detailed information at the tertiary level can be interpreted from the S-190A data, but is not adequately displayed on a map scale of 1:126,720. These results clearly show that Skylab data would be extremely valuable in initial preparation of land use maps which can be updated as new imagery becomes available.

It is apparent from our preliminary analyses of Skylab photography that such data can be effectively used to update existing land use maps at a substantial cost savings. Figure 7 is an example of a land use map of Howard County, Maryland. This map was prepared at a scale of 1:63,360 from high altitude aircraft color infrared photography. Maps of this quality and level of detail are readily updated by directly overlaying S-190A or S-190B data at the appropriate scale and mapping those areas where change has occurred. The entire State of Maryland has maps similar to those in Figure 7 for each county. Since these maps were prepared from high altitude aircraft data and displayed on a map base with minimized distortions, they are quite amenable to updating with satellite data.

Maps prepared from uncontrolled mosaics of low altitude photography and from ground surveys often have considerable distortion or boundary misplacement within the map. Such maps are more valuable as aids to preparation of land use maps from satellite photography which will subsequently be displayed on standardized geometric formats. Figure 8 is a forest type map of St. Mary's County, Maryland. This map was prepared from low altitude photography and ground surveys. The county boundary is displayed without significant distortion. However, internal boundaries are quite inconsistent with respect to forest boundaries as mapped from satellite data. Skylab data permits accurate mapping of forest boundaries on a standard geometric format, updating of areas where change within the forest category has occurred, and identification of the primary forest cover (deciduous, evergreen, mixed) based on the imaging characteristics and collateral data from the existing vegetation map. The resultant map is then on a mapping base and at a scale amenable to accurate, rapid updating with subsequent satellite data, or for refinement within categories by detailed sampling.

Electronic Data Processing of S-192 Multispectral Scanner Data

Satellite sensors provide an enormous amount of data. Data handling and rapid interpretation procedures must be developed before optimal use can be made of satellite imagery. To be sure, human interpretation techniques can and will be used extensively. However, land use surveys over very large regions will require that automated techniques be used to complete these surveys within a reasonable amount of time. Development of electronic data processing (EDP) techniques to handle large quantities of multispectral satellite data is in process by numerous government, university, and commercial institutions. Inherent to successful application of computer techniques is the need for procedures to establish the location and quantity of ground data needed to train and test the EDP techniques, as well as, ultimately, the overall reductions in cost now foreshadowed by parallel processing and hardwiring.

The Washington, D. C. - Baltimore test site encompasses several physiographic provinces extending from the Appalachian Plateau, Valley and

Ridge, and Blue Ridge, through the Piedmont and Coastal Plain. This provides a very diverse test site in terms of geology, soils, vegetation, climate, and patterns of cultural land use. This is evidenced on the ERTS-1 mosaic of the test site (Figure 1). The establishment of training sets with respect to size, location, and distribution must be cognizant of the diverse mixture of categories one might encounter within such a test site.

The following discussion is based on our preliminary results from an analysis of a segment of the S-192 data obtained over the Washington, D. C. test site on 12 June 1973. A variety of computer related activities have been performed on the S-192 data. Data processing activities have included tape reformatting, generating Litton film recordings of seven bands of one scene using selected gray scale adjustment functions, and a multispectral classification test.

Computer techniques have been used to generate hard copy prints from the S-192 tapes. These techniques permit gray scale adjustments to maximize picture contrast and can be conducted in a variety of ways. One method is simply a linear stretch, multiplying each digital picture element value by a constant to produce a new, higher contrast picture. A second method is to calculate a mean and standard deviation for the pixel values of an image and to expand the range of the picture elements while retaining the same mean and standard deviation relationship. A third method would increase the contrast of an image by mapping the ogive of the picture to the same ogive over an expanded scale. Each method produces a slightly different picture, enhancing different features. The method used in our first analysis is that of histogram equalization where equal numbers of pixels are assigned to each segment of the gray scale to spread the data over the entire dynamic range available. These data are then presented as hard copy prints on a Litton digital film recorder. Figures 9 and 10 illustrate the histogram for band 11 (1.55-1.75 μm) before and after histogram equalization. Figure 11 shows examples of Litton prints from seven S-192 data channels after histogram equalization. These enhanced images are suitable for locating and identifying ground truth data to be used in training set selection for later work. Also, film positives are easily made from these images and can be used for preparing color composites in color combining viewers.

These techniques allow users to prepare false color images from data in photographic and non-photographic spectral regions. Such images provide enhancement and improved discriminations between features that have only subtle differences on the black and white prints.

As an example of the value of color composite images for site selection <u>after</u> histogram equalization the information on bands 11 and 6 may be compared. Agricultural land images in light tones on band 11 (1.55-1.75 μm). On this band, it is difficult to separate those fields with growing crops from those that were freshly plowed or recently planted. Band 6 (0.68-0.76 μm) imagery shows freshly plowed or planted fields as light toned and fields with growing crops as dark toned. On this band, however, the fields with growing crops present are not easily discriminated from upland brush and adjacent forest lands. A color composite prepared with these bands (0.68-0.76 μm as blue, 1.5-1.8 μm as green and band 0.41-0.46 μm as red) clearly shows the distinction between agricultural fields with growing crops present and those which have been recently plowed or planted.

A major concern in our initial analyses has been with the substantial noise component of the data. Upon inspection of the film recordings of the various bands (Figure 11), several "noise" features stand out. Noise, here, indicates undesirable image features from a utilization point of view whether or not these features can be explained and whether these features originate in the scene, the vehicle, or the processing of data.

Two types of noise predominate during the visual inspection: the circular scan pattern and patches (two dimensional fairly localized obliteration of persumed scene variations). The patches occur in different format locations in different bands. Of the two, the scan pattern is the less serious for several reasons. The first is that for human interpretation the impact is minimal since the interpreter quickly adjusts and can ignore it. Second is that it is systematic and hence suggests that it can be algorithmically compensated.

In the patches, a histogram equalization scale adjustment could be used to minimize the effect of "noise" on the recognition results. Future preprocessing of S-192 data by NASA, before it is sent to users, will hopefully reduce or minimize the noise component in the data.

Inspection of the Litton prints in Figure 11 shows that although there is substantial noise present, many land use categories are discernible on several bands.

Agricultural lands often image as light tones. Fields with growing crops are distinguishable from freshly plowed or planted fields by comparing two or more bands at different wavelengths. Evergreen forest types can be separated from deciduous forest types particularly on band 11 (1.55-1.75 μm). On this band, evergreen forest types image in darker tones than deciduous forest types. A similar spectral response is recorded on other spectral bands as well. Water, streams, bays, and wetlands are also identifiable on the S-192 imagery, particularly on the infrared bands. A regional land use map was prepared for a portion of the area shown in Figure 11 from RC-10 1:130,000 color infrared photography and ground truth data. This map provides the basis for selecting training sets for testing their efficacy, and for assessing the accuracy of computer recognition results (Figure 12).

Although our investigation is to assess what level of detailed information can be extracted from S-192 data, our initial analyses were based on broad land use classes. Eight discrete land use classes selected for this initial analysis are shown in Table 6. Studies of more detailed land use classes will be made at a later date.

Although seven data channels were available for processing, four channels were selected on the basis of visual inspection, experience in multispectral data processing, and to provide spectral information from discrete portions of the electromagnetic spectrum (Table 6).

A generalized reflectance curve of green vegetation (Figure 13) shows the S-192 spectral bands with respect to the reflectance curve and those parameters which strongly affect reflectance. It is known that reflectance from green vegetation is generally a function of pigmentation, internal leaf structure, and leaf moisture content. Since these parameters vary from one species to another, one would intuitively expect to achieve optimum separation of vegetation types by selecting spectral bands which sample each of those spectral regions related to physiological and morphological characteristics of vegetation.

Obviously, some combinations of channels provide much better information for discriminating different vegetation classes than other combinations.

Coggeshall and Hoffer (1973), working with aircraft data, demonstrated that five channels of data including one thermal band and a mid-infrared band yielded the best test class performance in discriminating deciduous, evergreen, water, and agricultural classes. Band 7 (0.78-0.88 μm) provides data in a portion of the electromagnetic spectrum which is influenced by subtle changes in reflectance characteristics of many terrain classes. Band 11 (1.55-1.75 μm) provides data which is highly correlated with vegetation moisture content, indicative of species on upland or lowland sites, and permits accurate separation of many agricultural crops (Olson, et al., 1971; Richardson, et al., 1969). Optimum spectral bands for discriminating various land use classes have been reported by many authors (Coggeshall and Hoffer, 1973; Weber and Polcyn, 1972; Driscoll and Spencer, 1972; Weber, et al., 1972; Rohde and Olson, 1972; and Mower, 1971). It is known that when four to six bands are being processed, only modest improvement in recognition accuracy can be expected from using additional bands. Thus, in this analysis our selection was restricted to those four bands which were not severely degraded and which sampled discrete segments of the electromagnetic spectrum. In future analyses with S-192 data, we will examine the data for optimum channel selection and the optimum number of channels to be used.

After channel selection and training set selection, statistical parameters for each class were calculated based on an assumed Gaussian distribution and include the mean, standard deviation, covariance and divergence. (Divergence is a statistical measure of the separability of training classes.) Outputs from this procedure include histograms of each training class which show the distribution of data points in various channels (Figures 14 and 15). Coincident spectral plots were also generated which illustrate the mean spectral response, plus or minus one standard deviation. Such plots are prepared for individual classes (Figure 16) or all classes combined (Figure 17). These plots allow one to obtain an indication of the spectral signature characteristics and their "statistical quality" for each class. These plots also provide an indication of the spectral separability of the training classes.

Coincident spectral plots are inherently one dimensional, thus do not lend themselves easily to multidimensional separability analysis. The divergence measure, embedded in n-space and assuming normally distributed training set data, yields an estimate of the interclass separability and allows inference of expected classification accuracy. Divergence is essentially a measure of the distance separating two classes and is merely a method designed to test interclass separability without resorting to classification. We have implemented a divergence program which outputs divergence values for all possible combinations of spectral bands and land use classes. Generally, a divergence value greater than 1600 would suggest good separability of the two classes tested. A more detailed discussion of divergence theory can be found in Swain and King (1973).

Examination of the spectral signature statistics, histograms, spectral plots, and divergence measures, can, when properly interpreted, indicate the "quality" of the training set, i.e., how representative it is of the total population. Sometimes it is necessary to establish new training sets to more accurately define representative spectral signatures for each class.

Once suitable training sets are established, the data are further analyzed using LARSYS multispectral maximum likelihood classification algorithms. Subsequent discrimination between classes is accomplished by establishing decision boundaries in four dimensional space based on the spectral signature statistics generated for each of the training sets. Each individual pixel is then assigned to one of the defined training set classes on a maximum likelihood basis and recorded on tape. All classes can be displayed on a single printout, or displayed individually, or in any combination with other classes.

When displaying the data, it is possible to further restrict the classification of data points into various classes by using thresholding techniques. The classification algorithm establishes in n-dimensional space decision boundaries to define each class. Thresholding permits the researcher to reject data points assigned to a class which in reality do not look sufficiently like the class. This is done by establishing a threshold value, e.g., 10%, and rejecting those points assigned to a particular class which lie in the outer 10% of the decision boundary. In reality, one cannot usually establish training sets for each discrete class recorded on an image. Also, within-class variability in certain instances can be quite high. For example, the variability of spectral signatures from agricultural lands is quite high at the beginning of the growing season when some fields are being tilled, others recently planted, and still others in various stages of growth. Establishing appropriate threshold values would allow one to reduce commission errors. However, it must be noted that, although high threshold values will generally reduce commission errors, there often may be a substantial increase in omission errors. Selection of threshold values is based entirely on experience and judgment of within class and between class variability and must be performed carefully.

The multispectral classification algorithm used in this analysis assumes that the signals received by the S-192 multispectral scanner have multivariate normal distributions. Histograms for each spectral band for the urban and bare soil/cropland training classes are shown in Figures 14 and 15. One can readily see that the distribution is not a perfect normal distribution. It is difficult to assess whether the apparent departures from a normal distribution are significant without conducting non-normality tests. Such tests have not yet been performed on these data. A discussion of non-normality tests as related to multispectral data processing can be found in Malila, et al., 1971.

The coincident spectral plots suggested that separation of the various classes being trained on was possible. For example, Figure 17 suggests that on the basis of these training sets, one could expect to achieve separation of water (B) from all other categories in all bands except 1.55-1.75 μm. Urban (A) classes appear to be separable from other classes in the 1.55-1.75 μm and 0.41-0.46 μm spectral region. Deciduous and evergreen forest classes appear separable on virtually every band although the mixed forest class appears to be spectrally similar to both the deciduous and evergreen forest class. This by definition would be expected. Close examination of Figure 17 illustrates the difficulty in assessing the separability of several classes based on four dimensional data.

The divergence tests provide an estimate of interclass separability. They also provide insight to the optimum set of channels and the contribution each channel makes toward the separation of a given pair of classes. An optimum combination of channels can be selected and ranked on the basis of the highest average divergence value or highest minimum divergence value (Coggeshall and Hoffer, 1973). Given a set of classes to recognize, if two or more classes are felt to be spectrally similar, the optimum combination of channels would be selected on the basis of the highest minimum divergence value. For example, deciduous, evergreen, and mixed forest classes would likely appear spectrally similar. To insure separation of these classes, the combination of channels which provide the highest minimum divergence value would be used. Conversely, if a set of classes are to be identified which are spectrally dissimilar, one would select the combination of spectral bands which provide the highest average divergence value. Generally, this would result in fewer channels being used in the recognition process thereby significantly reducing the computer costs. Figure 18 presents the average divergence values and minimum divergence values for all classes for combinations of spectral bands taken two at a time, three at a time, and all four together. It can be seen that the average divergence value associated with the 0.78-0.88 μm and 1.55-1.75 μm spectral bands is 1794. This suggests good separation of all classes with these two spectral bands. However, the minimum divergence value is 805, suggestive of poor to fair separability. As expected, the minimum interclass divergence value of 805 was associated with the evergreen and mixed forest type. It would be noted that some combination of two bands may yield higher divergence values than certain combinations of three bands. For example, the combination of 0.78-0.88 μm, 12.0-13.0 μm, and 0.41-0.46 μm spectral bands yielded lower divergence values than several combinations of two bands. The best combination of spectral bands based on the highest averge divergence and highest minimum divergence values for the classes trained on included all four spectral bands. Figure 19 is a matrix showing the divergence values for all pairwise combinations of training classes based on spectral signature statistics for the four spectral bands used in this analysis. It appears from the divergence values that good separability of the training classes can be expected. This is particularly encouraging considering the apparent noise component in the data.

A computer recognition map is shown in Figure 20. Outlined in black are the areas used in establishing the training set statistics and decision boundaries used in the classification process. One can see by examining the classified pixels within the training sets that the performance within these areas is quite good in some cases and less accurate in others. Figures 21, 22, and 23 show classification performance within training sets at three different threshold values. The training class performance indicates an overall performance of 84.6% correct identification at the 7% threshold with little change at larger threshold values. The classification performance indicates % correct identification and % commission error, where:

$$\% \text{ Correct} = \frac{\text{\# of fields correctly identified as being in a class}}{\text{total \# of fields in that class in the test area}}$$

$$\% \text{ Commission} = \frac{\text{\# of fields incorrectly identified as belonging to a class}}{\text{total \# of fields identified as belonging to that class}}$$

The accuracy figures associated with the training class performance reflect to some extent the quality of those training sets. The urban, water, and wetlands training classes have relatively low omission and commission errors suggesting a " good" training set. However, the training class (cropland/growing crops present) resulted in only 50% correct identification. This can result from improper training class selection or large within class and between class variations. Note that for this training class, the confusion was with bare soil and deciduous forest. In early June, many fields have winter wheat or barley growing with substantial ground cover while other fields have only recently been planted and have substantial bare soil showing. These conditions could result in the accuracy figures associated with the vegetated cropland class if extreme care is not exercised in selecting the training sets.

The accuracy of the computer classification map was determined by establishing several test fields for each training class. Contingency tables showing the % correct identification and the % commission error at thresholds of 7%, 15%, and 30% are shown in Figures 24, 25 and 26. As expected the overall accuracy was reduced at increasingly higher threshold values. There was no major change in commission error with increasing thresholds except for the wetlands class. The accuracy figures associated with the training classes and the test statistics for wetlands suggests that a misjudgment was made in selecting the wetlands test fields. Again, these accuracy figures give indications of the spectral variability within and between classes. For example, Figure 24 shows that there was little confusion between deciduous and evergreen forest although each was confused with mixed forest. It should be noted that there was little change in accuracy for these forest classes with the three threshold values used in this preliminary study. It is conceivable that with better defined training sets and higher threshold values, these accuracy figures could be improved.

In general, these preliminary results have yielded very promising results. It must be remembered that these data were processed with a substantial noise component present. Future processing will be accomplished on data that has been pre-processed to remove or minimize the noise effect. Also, procedures are being developed to digitally merge ground truth data with satellite digital tape data to insure accurate selection of training classes and test classes. This will allow precise training on specific land use types and to test the accuracy of the classification over a substantially larger portion of the site.

Summary

Our first analyses of Skylab photographs and multispectral scanner data have shown that such data will provide significant inputs to state, regional and local land use planners in the future. Detailed land use mapping to scales of 1:25,000 and 1:63,360 is possible with the quality of data obtained with the S-190B Earth Terrain Camera and the S-190A multi-band camera, respectively. Land use mapping can be completed with S-190A photography in a cost effective manner. Using the alternative cost approach to benefit/cost analyses, the benefit cost ratio in our initial studies is 2.3/1. As people gain more experience in handling and interpreting satellite photographic data, the benefit/cost ratio will likely increase.

Our first results with the S-192 multispectral scanner data have been quite encouraging and indicate that the quality of the data, although somewhat degraded, will permit us to examine several key questions related to electronic data processing techniques for automated land use mapping. Basically our first results have shown that land use mapping can be accomplished with S-192 data. Our future work is being directed toward establishing which spectral bands and how many spectral bands are needed. We also will examine various sampling strategies for establishing training classes, and assess the accuracy of subsequent classification for land use mapping.

Skylab data should not be considered a competitive system with other satellite data from ERTS-1. Skylab has provided resource managers with photographic data of higher resolution than imagery available from ERTS-1 and should be employed for more detailed analyses of areas where significant change has occurred. ERTS-1 imagery is extremely useful for monitoring and identifying those areas where change has occurred.

Satellite systems continue to show great promise for automated thematic mapping and indeed, this is possible now for certain land use features. The multispectral scanner on Skylab provides investigators with data in various discrete portions of the electromagnetic spectrum. This will permit us, for the first time, to examine optimum spectral bands for automated thematic mapping from satellite data, if the effect of noise can be reduced or in most of the channels.

Although the Skylab manned workshop is no longer acquiring earth resource imagery, it has provided data which is and should be considered exemplary of data to be available from future manned earth orbiting space stations.

These systems, to become operational in the not too distant future, will provide land use planners and other resource managers a tool for obtaining information needed for comprehensive land use planning. In particular, the S-190B Earth Terrain Camera study foreshadows the possibilities for detailed land use mapping, until the even higher resolution systems such as Space Shuttle, the space airplane of the 1980's.

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Table 1. S-190A Multispectral Photographic Camera Configuration

- Lenses - Six (6) F/2.8 15.24cm. Focal Length (21.2° FOV)

- Coverage - 163 km square (26585 square km)

Film	Spectral Coverage	Expected Ground Resolution
B&W I.R (EK2424)	0.7 to 0.8 μm	68 Meters
B&W I.R (EK2424)	0.8 to 0.9 μm	68 Meters
Color I.R (EK2443)	0.5 to 0.88 μm	57 Meters
Hi Res Color (SO-356)	0.4 to 0.7 μm	23.8 Meters
B&W Pan-X (SO-022)	0.6 to 0.8 μm	27.8 Meters
B&W Pan-X (SO-022)	0.5 to 0.6 μm	30 Meters

Table 2. S-190B Earth Terrain Camera Configuration

- Lens - F/4 18" Focal Length
- Coverage - 109 km Square
  (11950 square km)

Film	Spectral Coverage	Expected Ground Resolution
Hi Res Color (SO-242)	0.4 - 0.7 μm	15 Meters
B&W High Definition (EK3414)	0.5 - 0.7 μm	15 Meters
Color I.R (EK3443)	0.5 - 0.88 μm	30 Meters

Table 3. S-192 Multispectral Scanner Configuration

- IFOV - 79.3 Meter Square Ground Coverage
- Swath Width - 68.5 km.

Band	Description	Spectral Range
1	Violet	0.41 - 0.46 μm
2	Violet-Blue	0.46 - 0.51 μm
3	Blue-Green	0.52 - 0.56 μm
4	Green-Yellow	0.56 - 0.61 μm
5	Orange-Red	0.62 - 0.67 μm
6	Red	0.68 - 0.76 μm
7	Near infrared	0.78 - 0.88 μm
8	Near infrared	0.98 - 1.08 μm
9	Near infrared	1.09 - 1.19 μm
10	Mid infrared	1.20 - 1.30 μm
11	Mid infrared	1.55 - 1.75 μm
12	Mid infrared	2.10 - 2.35 μm
13	Thermal infrared	10.2 - 12.5 μm

TABLE 4

LAND USE CLASSIFICATION SYSTEM

(Adapted from USGS Circular ~~7~~671 and USGS proposed Level III land use classification scheme)

Number and Category

1. Urban and Built-up Land

1.1 Residential

1.1.1 Single-family household units

1.1.2 Multi-family household units

1.1.3 Group quarters (such as rooming and boarding houses, membership lodgings, retirement homes and orphanages, work quarters (labor camps) and other group quarters.

1.1.4 Residential hotels

1.1.5 Mobile home parks or courts

1.1.6 Transient lodging (motels, tourist courts, and non-residential hotels) (Placed under residential in accord with the Standard Land Use Coding Manual)

1.1.9 Other

1.2 Commercial and Services

1.2.1 Wholesale Trade Areas

1.2.2 Retail Trade Areas (Central Business District, Shopping Centers, Strip Commercial and Other Retail Trade Areas

1.2.3 Business, Professional, Personnel Services (except those included in the institutional category)

1.2.4 Cultural, Entertainment, and Recreational Facilities

1.2.9 Other

1.3 Industrial

1.3.1 Mechanical processing (textile mill products, apparel, and other finished products, lumber and wood products, furniture and fixtures, stone, clay, and glass products).

1.3 Industrial

- 1.3.2 Heat processing (primary metal industries, electric power generation).
- 1.3.3 Chemical processing (paper and allied products, petroleum refining, and related industries.
- 1.3.4 Fabrication and assembly (fabricated metal products, professional, scientific and controlling instruments; photographic and optical).
- 1.3.5 Food processing
- 1.3.6 Other

1.4 Extractive

- 1.4.1 Stone quarries
- 1.4.2 Sand and gravel pits
- 1.4.3 Open pit or stip mining
- 1.4.4 Oil, gas, sulphur, salt and other wells
- 1.4.5 Shaft mining
- 1.4.9 Other

1.5 Transportation, Communications, and Utilities

- 1.5.1 Highways, auto parking, bus terminals, motor freight, and other facilities
- 1.5.2 Railroads and associated facilities
- 1.5.3 Airports and associated facilities
- 1.5.4 Marine craft facilities
- 1.5.5 Telecommunications, radio, and television facilities
- 1.5.6 Electric, gas, water, sewage disposal, solid waste, and other utilities
- 1.5.9 Other

1.6 Institutional

- 1.6.1 Educational Facilities
- 1.6.2 Medical and Health Facilities
- 1.6.3 Religious facilities

1.6 Institutional

- 1.6.4 Military areas
- 1.6.4 Correctional
- 1.6.6 Government and Admin Offices
- 1.6.7 Civic, Social, and Fraternal Organizations (YMCA, Scouting groups, etc.)
- 1.6.9 Other

1.7 Strip and Clustered Settlement

(No further breakdown recommended at Level III)

1.8 Mixed

(No further breakdown recommended at Level III)

1.9 Open and Other

- 1.9.1 Improved
- 1.9.2 Unimproved
- 1.9.9 Other

2. Agricultural Land

2.1 Cropland and Pasture

- 2.1.1 Active Cropland
- 2.1.2 Idle Cropland
- 2.1.4 Pasture
- 2.1.9 Other

2.2 Orchards, Groves, Bush Fruits, Vineyards, and Horticultural Areas

- 2.2.1 Fruit and Nut Trees
- 2.2.2 Bush Fruit
- 2.2.3 Vineyard
- 2.2.4 Nurseries and floricultural areas
- 2.2.9 Other

Table 4 (Cont'd)

2.3 Feeding Operations

2.3.1 Cattle feed lots (including holding lots for dairy animals)

2.3.2 Poultry and egg houses

2.3.3 Hog feed lots

2.3.9 Other

3. Rangeland

3.1 Grass

(No further breakdown at Level III required for the study area)

3.2 Savannas (Palmetto praries)

(No further breakdown at Level III required for the study area)

3.3 Desert Shrub

(No further breakdown required at Level III for the study area)

4. Forestland

4.1 Deciduous

4.1.1 Red oak

4.1.2 White oak

4.1.3 Chestnut oak

4.1.4 Scrub oak

4.1.5 Cypress

4.1.6 Aspen - pen cherry

4.1.7 Riverbirch - Sycamore

4.1.8 Cove Hardwoods

4.1.9 Northern Hardwoods

4.1.10 Bottom land Hardwoods

4.1.11 Red gum - yellow poplar

4.2 Evergreen Forest

4.2.1 Whte pine

4.2.2 Loblolly pine

Table 4 (Cont'd)

4.2 Evergreen Forest

- 4.2.3 Oak - White pine
- 4.2.4 S. White cedar
- 4.2.5 Hord pines

4.3 Mixed Forest

- 4.3.1 Northern Hardwoods - White pine
- 4.3.2 White pine - Northern Hardwoods
- 4.3.3 Oak - White pine
- 4.3.4 Hard pine - oak
- 4.3.5 Oak - Hard pine
- 4.3.6 Loblolly pine - Hardwoods
- 4.3.7 Hardwoods - Loblolly pine

4.4 Upland Brush

4.5 Lowland Brush

5. Water

5.1 Streams and Waterways

- 5.1.1 Natural (rivers and creeks)
- 5.1.2 Man-Made (canals, ditches, and aquaducts)

5.2 Lake

- 5.2.1 Natural Lakes and Ponds
- 5.2.2 Man-Made Lakes and Ponds

5.3 Reservoirs

(No further breakdown at Level III required for the CARETS area)

5.4 Bays and Estuaries

- 5.4.1 Bays
- 5.4.2 Estuaries

5.6 Ocean

5.9 Other

Table 4 (Cont'd)

6. Nonforested Wetlands

   6.1 Vegetated

      6.1.1 Brackish marsh

      6.1.2 Fresh water marsh

      6.1.3 Brush covered wetlands

      6.1.9 Other

   6.2 Bare

      6.2.1 Brackish bare areas

      6.2.9 Other

7. Barren Land

   7.1 Salt Flats

   (No further breakdown at Level III required for study area)

   7.2 Beaches

      7.2.1 Sandy beaches

      7.2.2 Gravelly, rocky beaches

      7.2.3 Mud shorelines

   7.3 Sand other than Beaches

   (No further breakdown at Level III required for study area)

   7.4 Bare Exposed Rock

   (No further breakdown at Level III required for study area)

   7.5 Disturbed Land

   (This consists of areas under construction, etc., where the vegetation cover has been removed by mechanical means)

   7.9 Other

8. Tundra

(No further breakdown recommended at this time)

9. Permanent Snow and Icefields

(No further breakdown recommended at this time)

TABLE 5. LAND USE CLASSES AND SYMBOLS USED IN INITIAL TEST OF S-192 MSS DATA

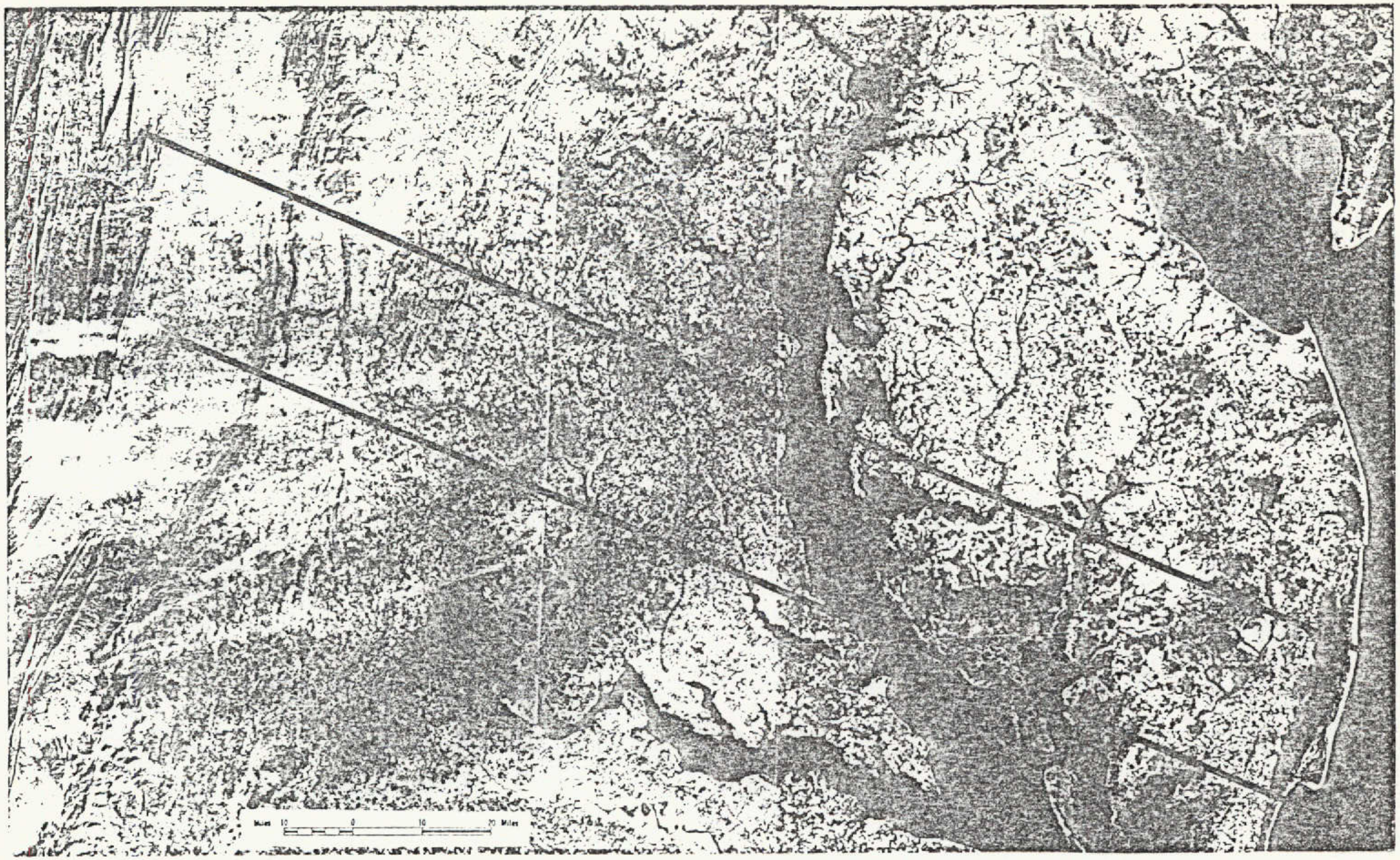
Class	Symbol
Urban	U
Water	W
Wetlands	°
Deciduous Forest	D
Evergreen Forest	E
Mixed Forest	M
Bare Soil/Cropland	S
Cropland/Crop Present	C

TABLE 6. SPECTRAL CHANNELS USED FOR INITIAL LARSYS ANALYSIS

#	Channel	Band	Spectral Band	Description
1	10	7	0.78-0.88 μm	Near Infrared
2	12	11	1.55-1.75 μm	Mid Infrared
3	17	13	12.0-13.0 μm	Thermal Infrared
4	20	1	0.41-0.46 μm	Blue

WASHINGTON, D. C. - BALTIMORE SKYLAB TEST SITE

ERTS-1 MSS5 MOSAIC - WINTER, 1972 IMAGERY



SL/3
5 AUG. 1973

SL/2
12 JUNE 1973

APPROXIMATE GROUND TRACKS (FROM FOV TABULATIONS)

FOR SL/2 AND SL/3 MISSIONS

Figure 1. ERTS-1 Mosaic prepared from MSS 5 winter imagery. This mosaic shows the diverse comples of land use throughout the Washington, D.C. - Baltimore Skylab test site. The test site encompasses several physiographi regions and provides a landscape with quite diverse geology, soils, vegetation and climate.

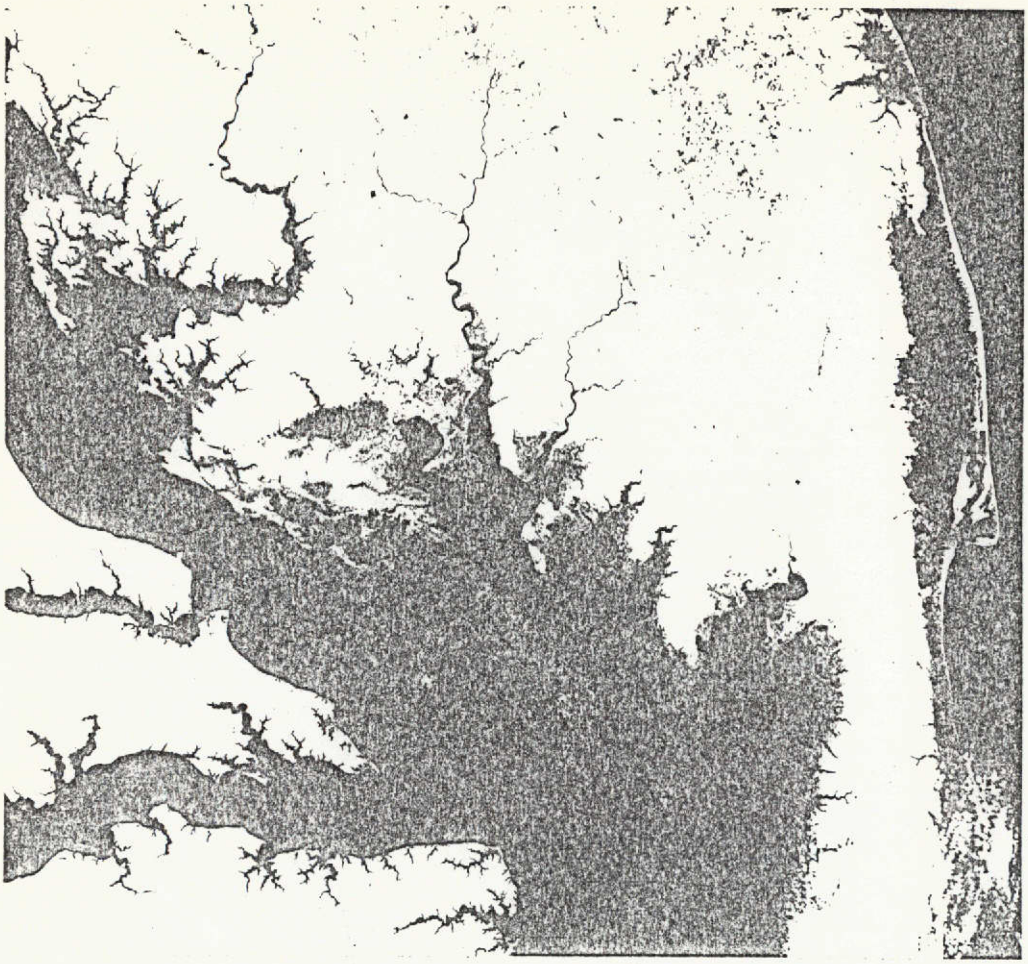


Figure 2. Black and white infrared photography (0.70-0.80 μm) acquired with the S-190A multispectral camera over a portion of the eastern shore area of the Sate of Maryland. Such imagery provides an excellent tool for identifying and mapping coastlines, bays, streams, inland water bodies, coastal wetlands, and inland marshes.

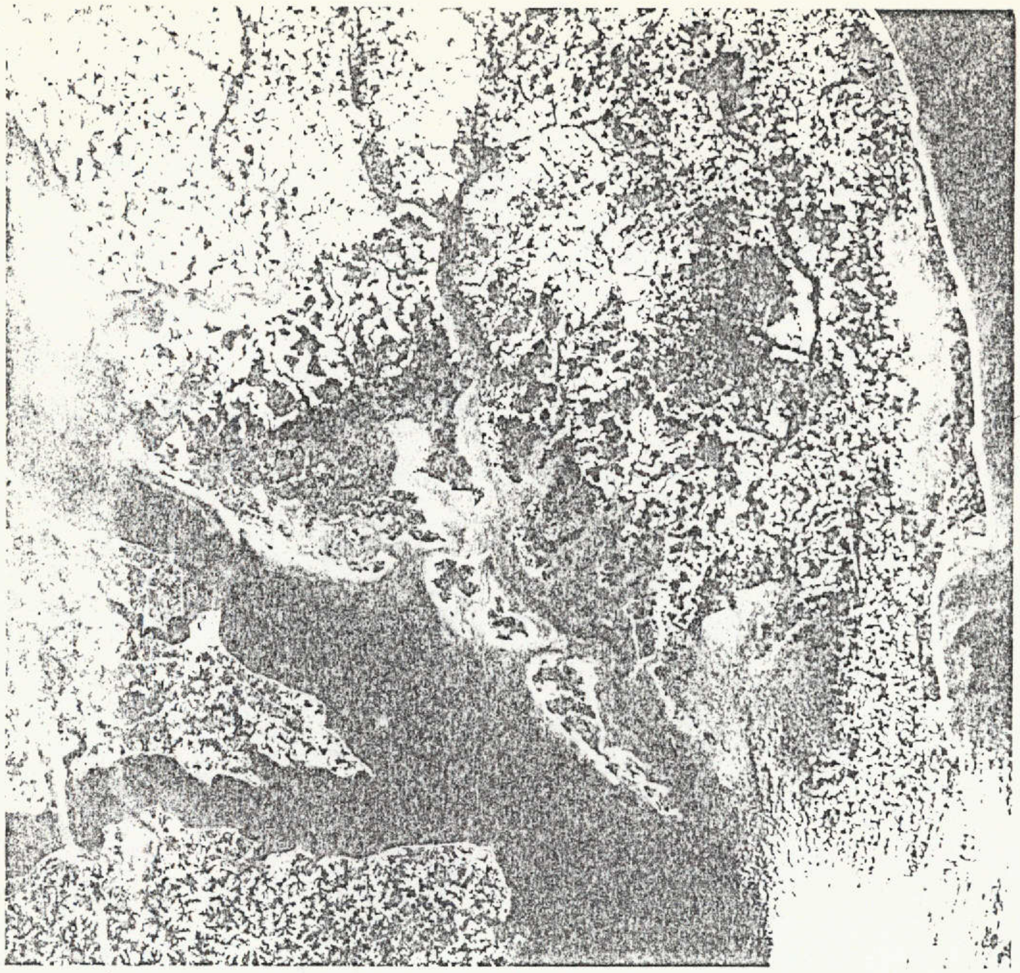
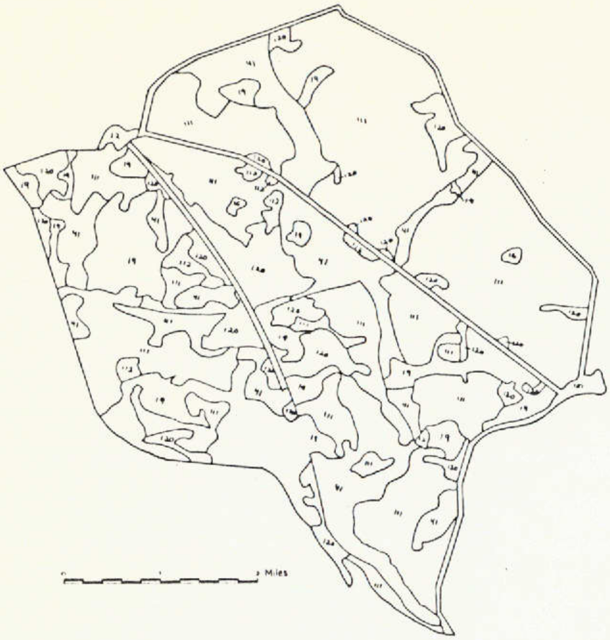
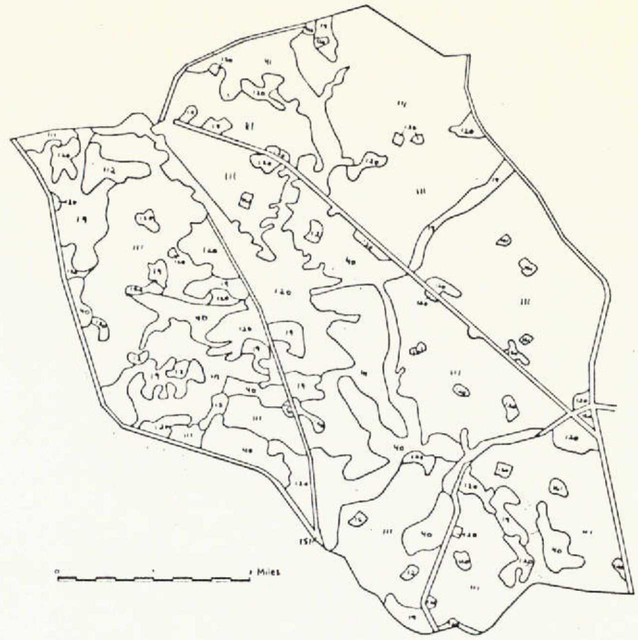


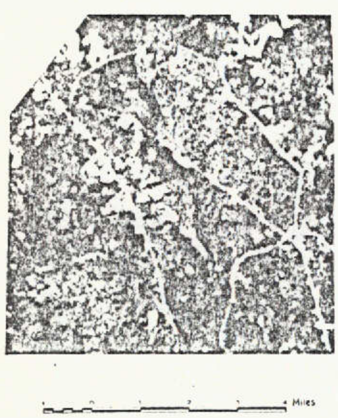
Figure 3. Black and white panchromatic photography (o.50 -0.60 μm) acquired with the S-190A multispectral camera over a portion of the eastern shore area of the State of Maryland. This image acquired in early June, 1973 permits quick and accurate identification of agricultural, forest, and urban land use.

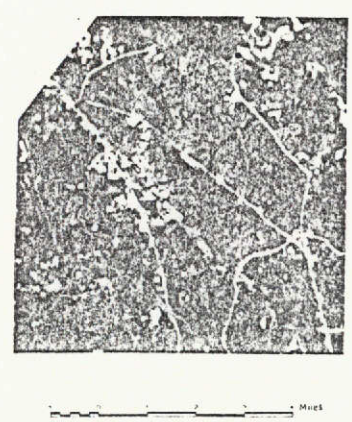




S-190A COLOR I.R. 5 AUG 73

S-190A HI RES COLOR 5 AUG 73





LEGEND

1.0 URBAN AND BUILT-UP
- 110 - Residential
  - 111 - Single Unit, Residential
  - 112 - Multi-Unit Residential
  - 113 - Mobile Homes and Trailer Parks
- 120 - Retail and Wholesale Services
  - 121 - Retail sales and services
  - 122 - Wholesale and services
  - 124 - Recreational Facilities
- 130 - Industrial
- 140 - Extractive
- 150 - Transportation
  - 151 - Highways
  - 152 - Railroads
  - 153 - Airports
- 160 - Institutional
  - 161 - Schools
  - 162 - Medical
  - 163 - Religious
  - 164 - Military
- 170 - Strip and Clustered
- 190 - Open and Other

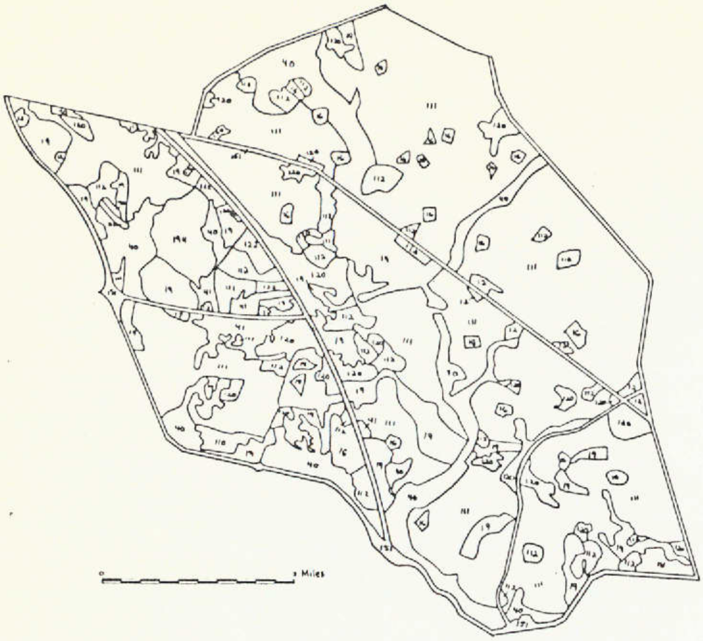
2.0 AGRICULTURAL LAND
- 210 - Crop and Pasture Land
  - 211 - Crop land
  - 212 - Pasture lands
- 220 - Orchards
- 230 - Feeding Operations
  - 231 - Cattle seed lots
  - 232 - Poultry and Egg houses
  - 233 - Hog feed lots

4.0 FOREST LAND
- 410 - Deciduous
- 420 - Evergreen
- 430 - Mixed
- 440 - Upland Brush

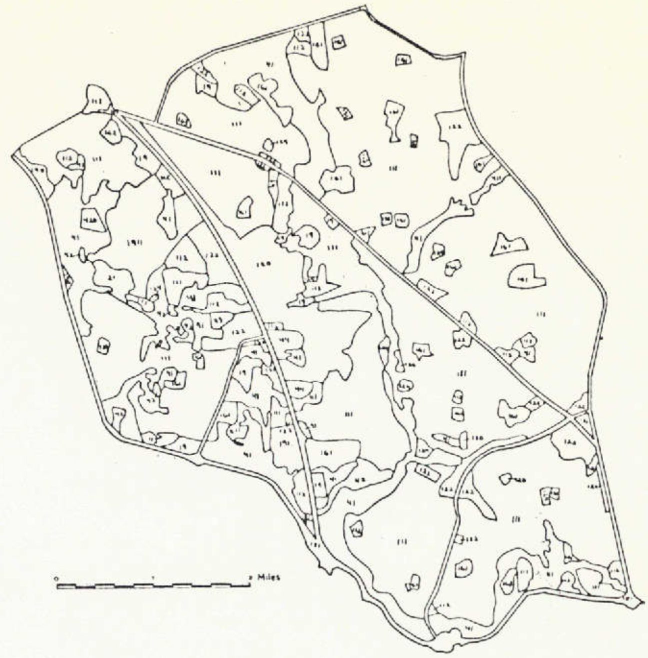
5.0 WATER
- 510 - Rivers
- 540 - Bays and Estuaries
- 560 - Ocean

6.0 WETLANDS
- 610 - Vegetated Wetlands
- 620 - Non-Vegetated Wetlands

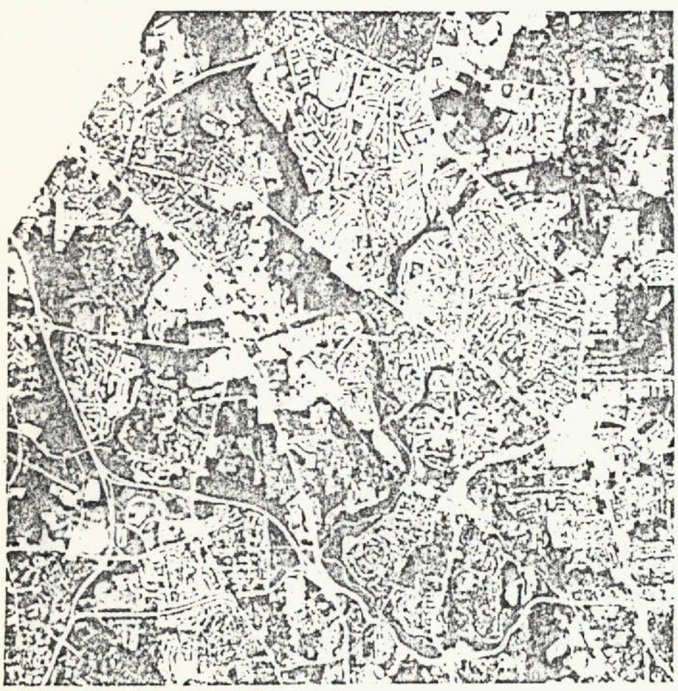
Figure 4. Land use maps have been prepared from color infrared and normal color photography acquired with the S-190A multispectral camera over a portion of Montgomery County, Maryland. These two image types can provide interpreters significant information about urban land use if the interpreter has a thorough understanding of the character of spatial arrangements and relationships of one urban category to another.



S-190B ETC HI RES COLOR 5 AUG 73



RC-10 COLOR I.R. 14 JUNE 73



LEGEND

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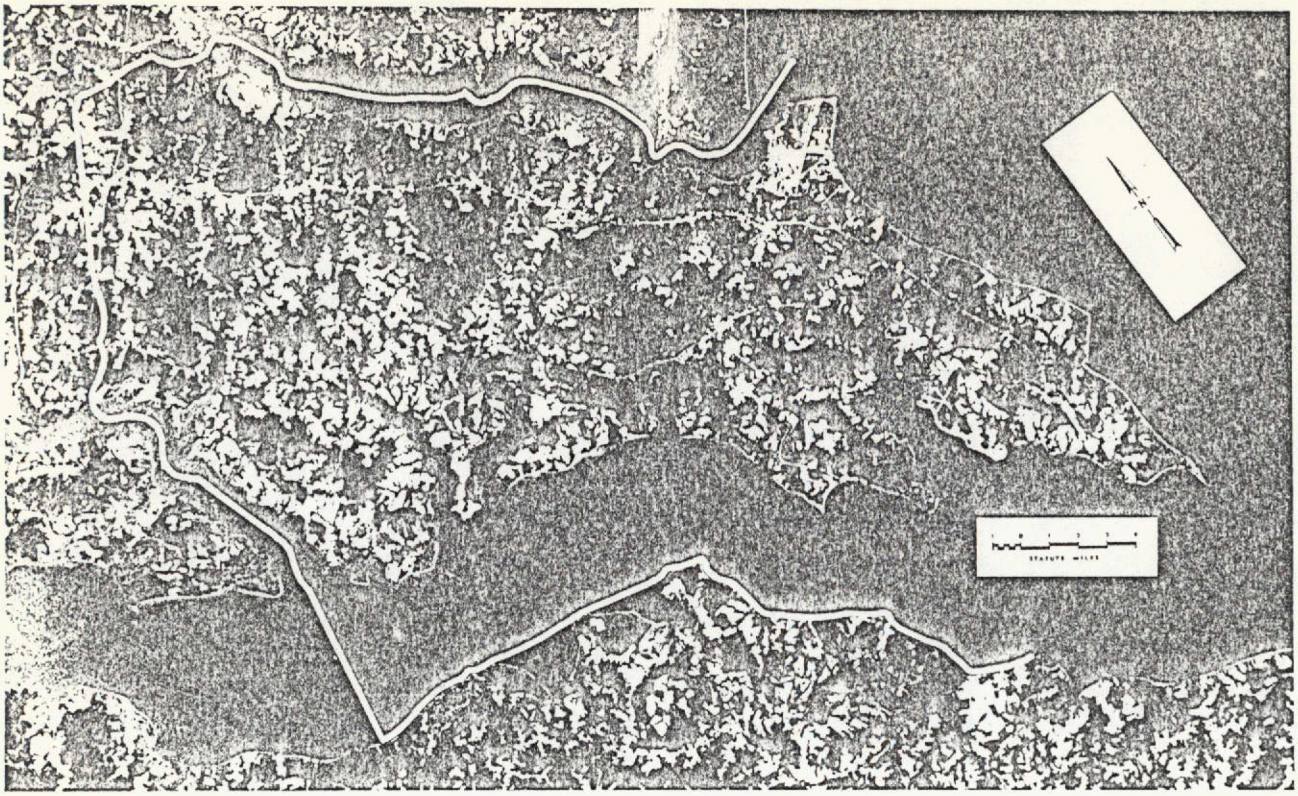
- 560 - Ocean

6.0 WETLANDS
- 610 - Vegetated Wetlands
- 620 - Non-Vegetated Wetlands

Figure 5. Land use maps prepared from high resolution S-190B Earth Terrain Camera photography and aircraft RC-10 color infrared photography over a portion of Montgomery County, Maryland. Satellite photography at this resolution will provide land planners a substantial body of information. For example, density and relative age of residential areas, location of schools and parks, location of commerical development and accurate delineations of transportation patterns can be made.



S-190A PAN-X AERIAL B/W (SO-022) 0.6-0.7um 12 JUNE 1972

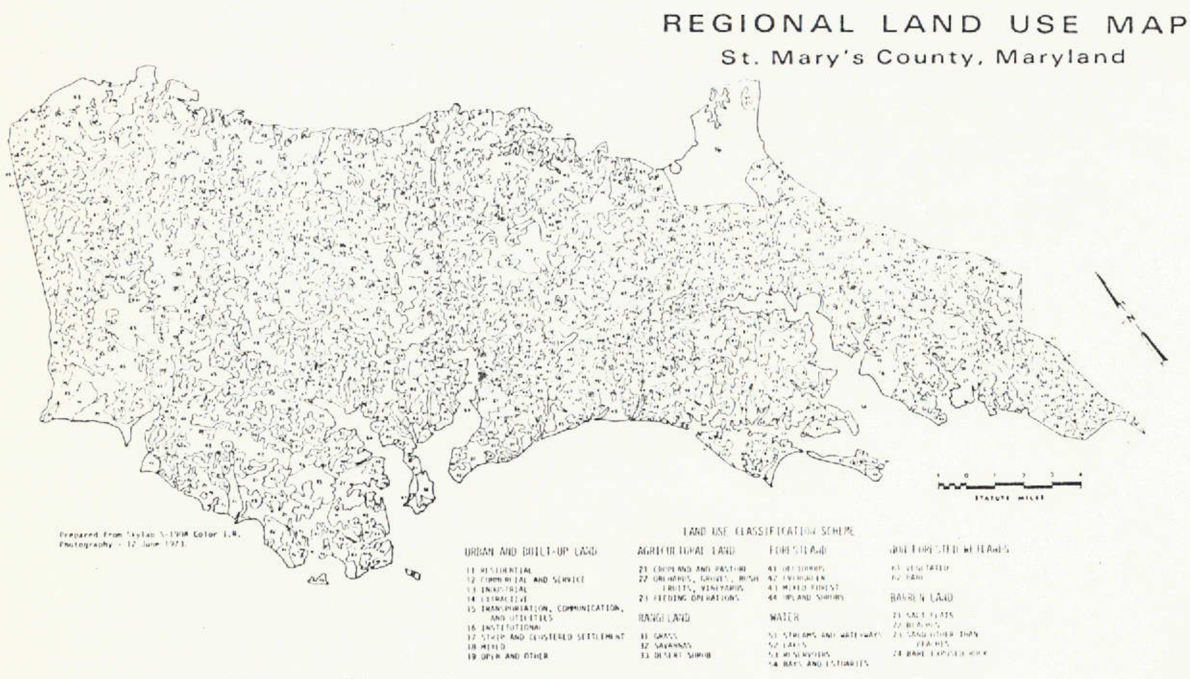


Figure 6. Regional land use map prepared from S-190A black and white and color infrared photography over St. Mary's County, Maryland. This map, approximately 420 square miles, was prepared in approximately 14 hours.

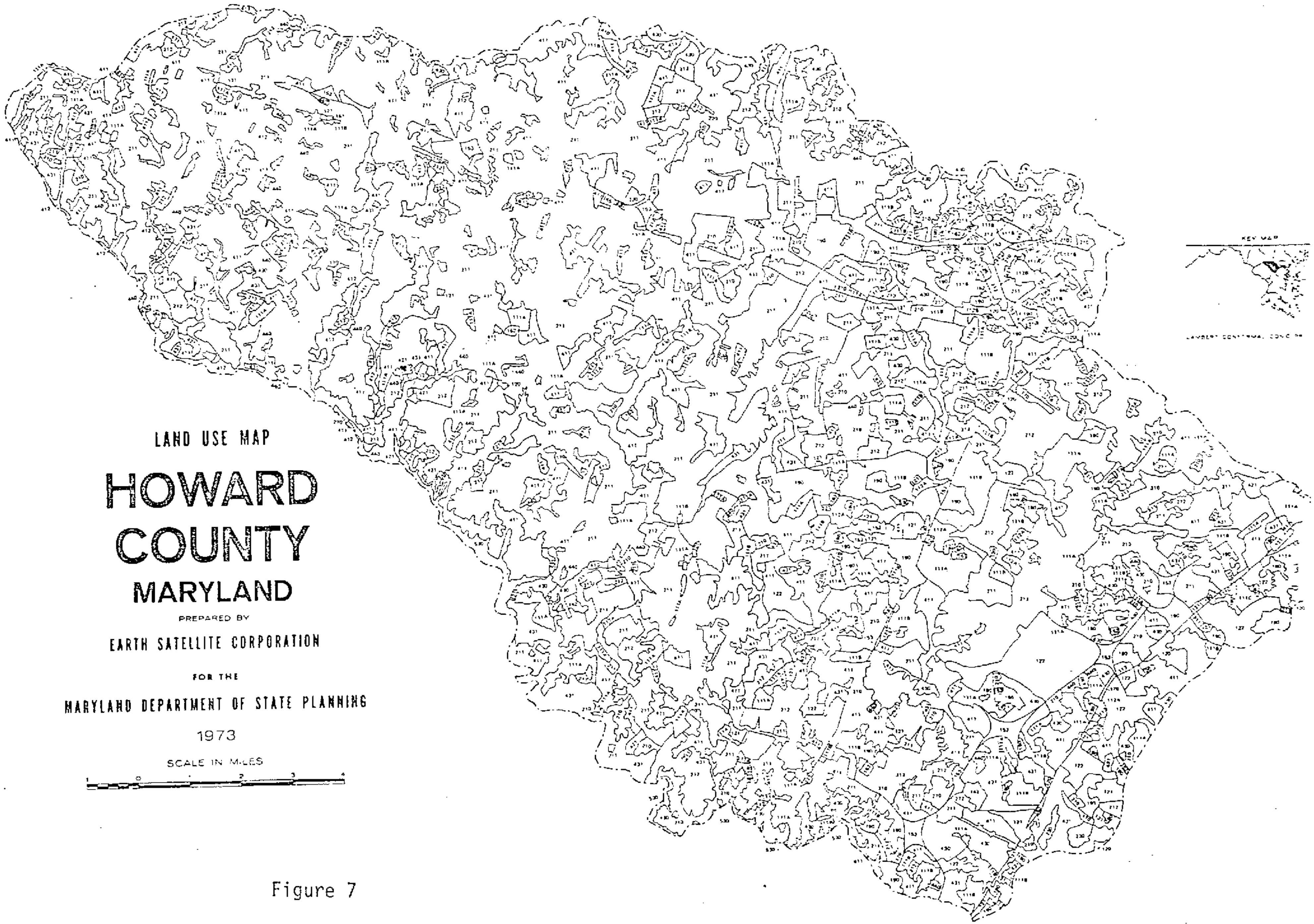

LAND USE MAP
HOWARD
COUNTY
MARYLAND
PREPARED BY
EARTH SATELLITE CORPORATION
FOR THE
MARYLAND DEPARTMENT OF STATE PLANNING
1973
SCALE IN MILES
KEY MAP

Figure 7

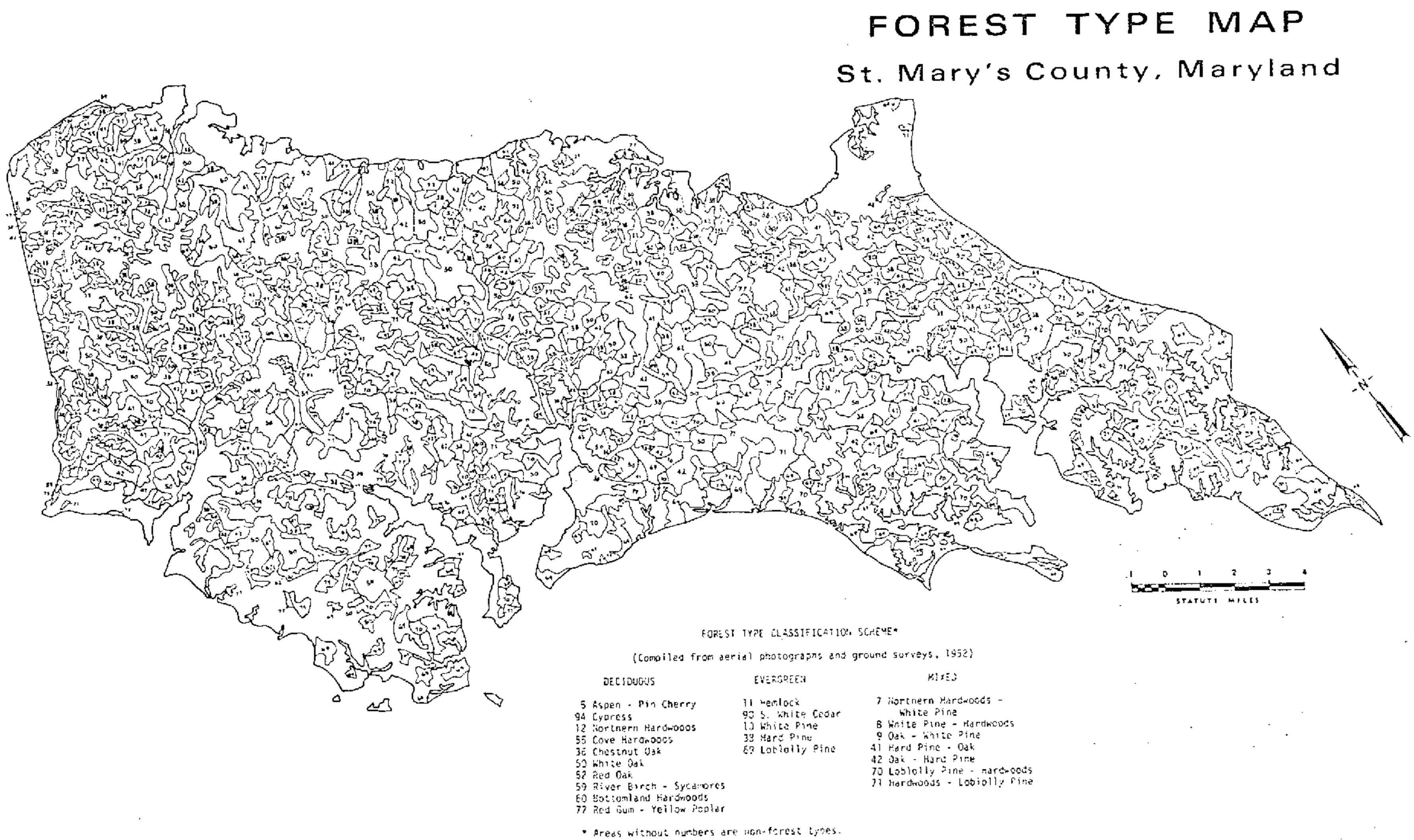


Figure 8. Forest vegetation map of St. Mary's County, Maryland. This map was compiled from un-compiled from uncontrolled aerial photographs and ground surveys.

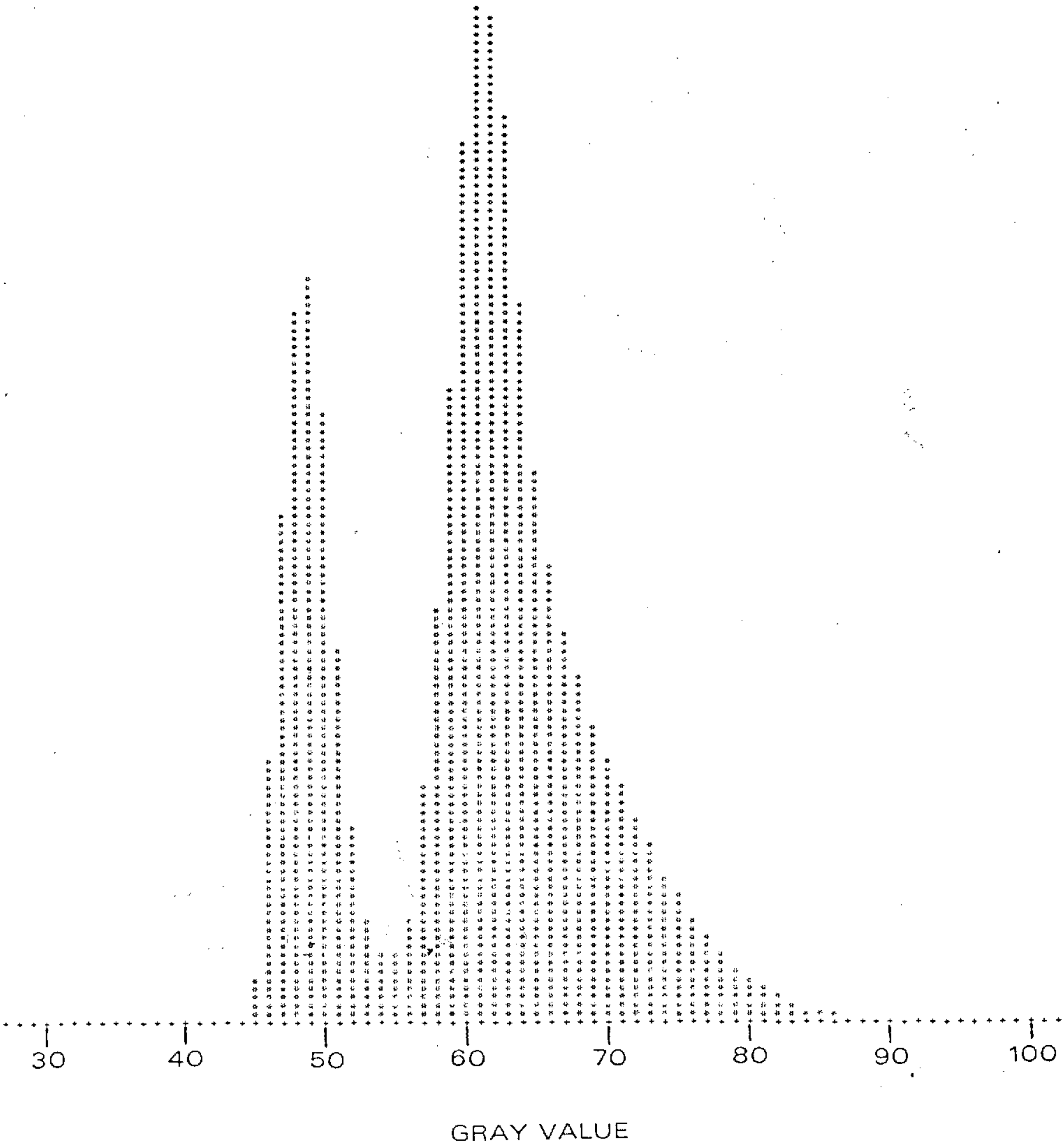


FIGURE 9. Histogram of S-192 data. Channel 12 - Band 11 (1.55-1.75 um). This is the histogram before histogram equalization. Data are generally compressed within small range of gray values.

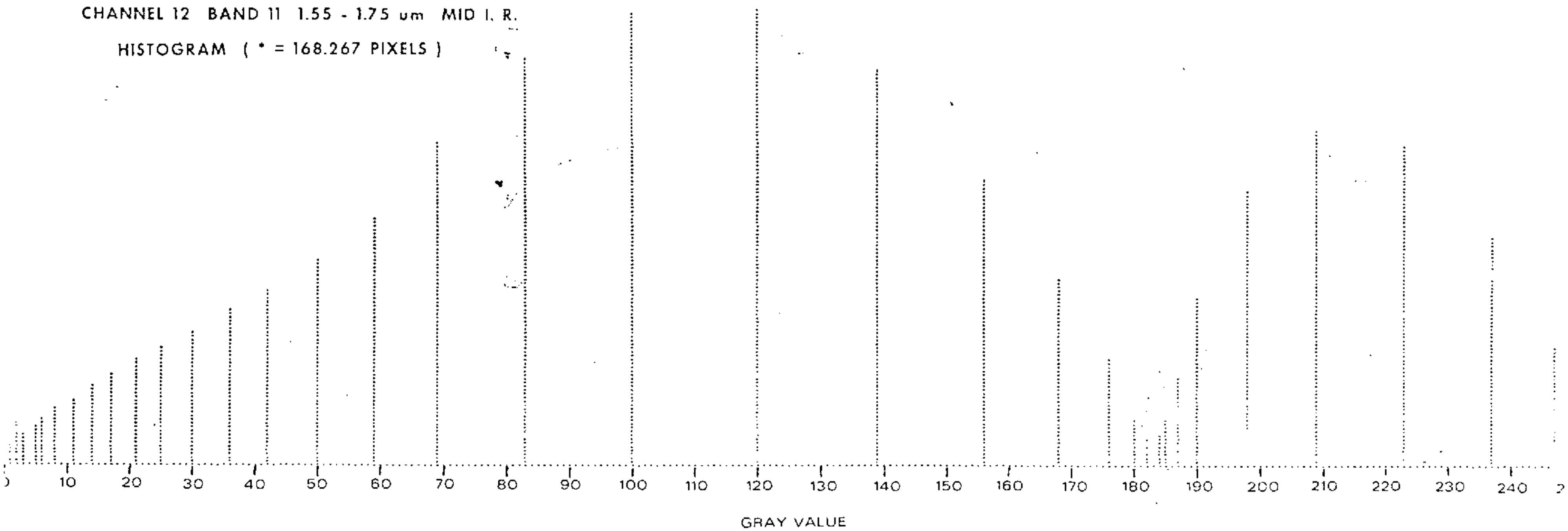


Figure 10. Histogram of S-192 data Channel 12-Band 11 (1.55-1.75). This is the histogram after equalization. Equal numbers of pixels are assigned to each segment of the gray scaleq The data are then spread out over the entire dynamic range available.

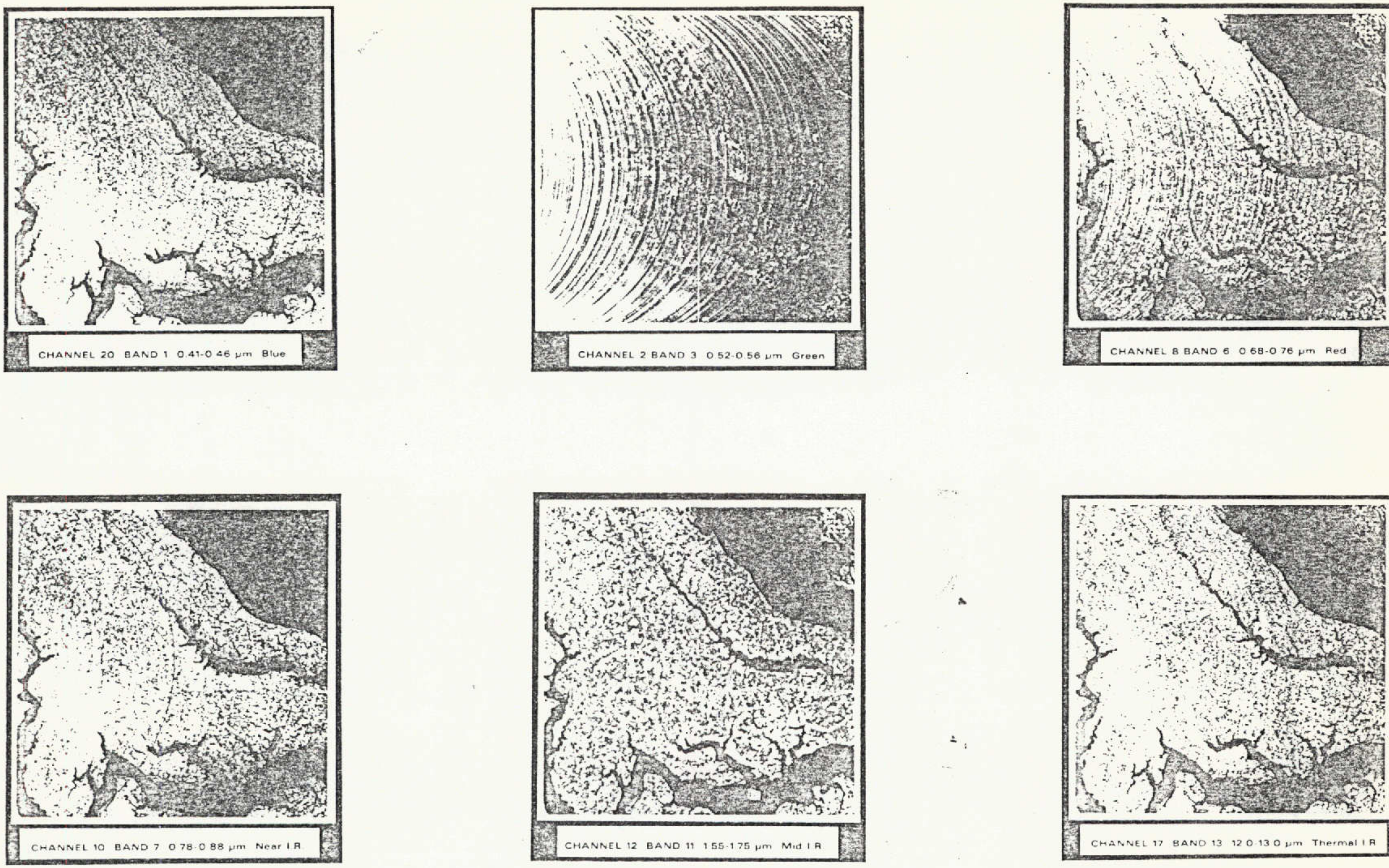
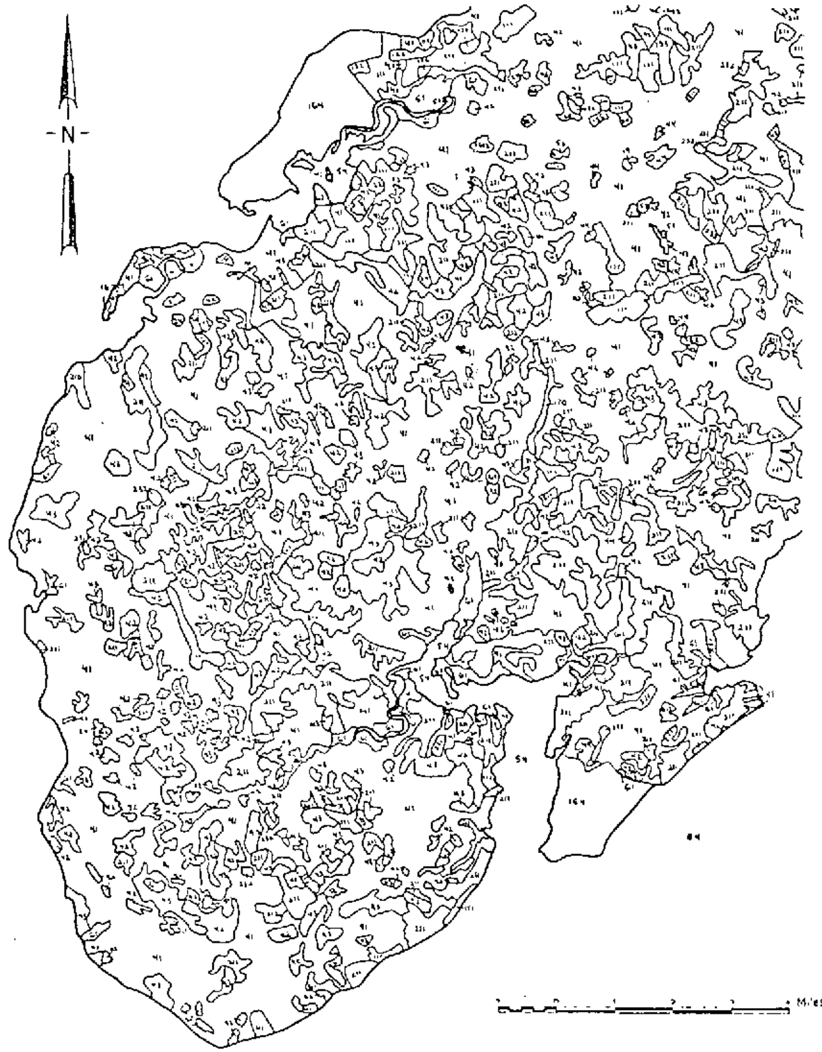


Figure 11. S-192 computer produced imagery. The above images were produced from S-192 digital tapes on a modified litton digital film recorder. Computer techniques permit gray scale adjustments to maximize picture contrast. S-192 data acquired on SL/2 on June 12, 1973 has noise problems as evidenced in this imagery. Techniques to remove the noise or normalize the data to minimize the noise effect are being investigated.

REGIONAL LAND USE MAP

SOUTHERN CHARLES COUNTY, MARYLAND



LEGEND

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- 110 - Residential
  - 111 - Single Unit, Residential
  - 112 - Multi-Unit Residential
  - 113 - Mobile Homes and Trailer Parks
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- 170 - Strip and Clustered
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2.0 AGRICULTURAL LAND

- 210 - Crop and Pasture Land
  - 211 - Crop land
  - 212 - Pasture lands
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  - 231 - Cattle seed lots
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- 440 - Upland Brush

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- 510 - Rivers
- 540 - Bays and Estuaries
- 560 - Ocean

6.0 WETLANDS

- 610 - Vegetated Wetlands
- 620 - Non-Vegetated Wetlands

Figure 12

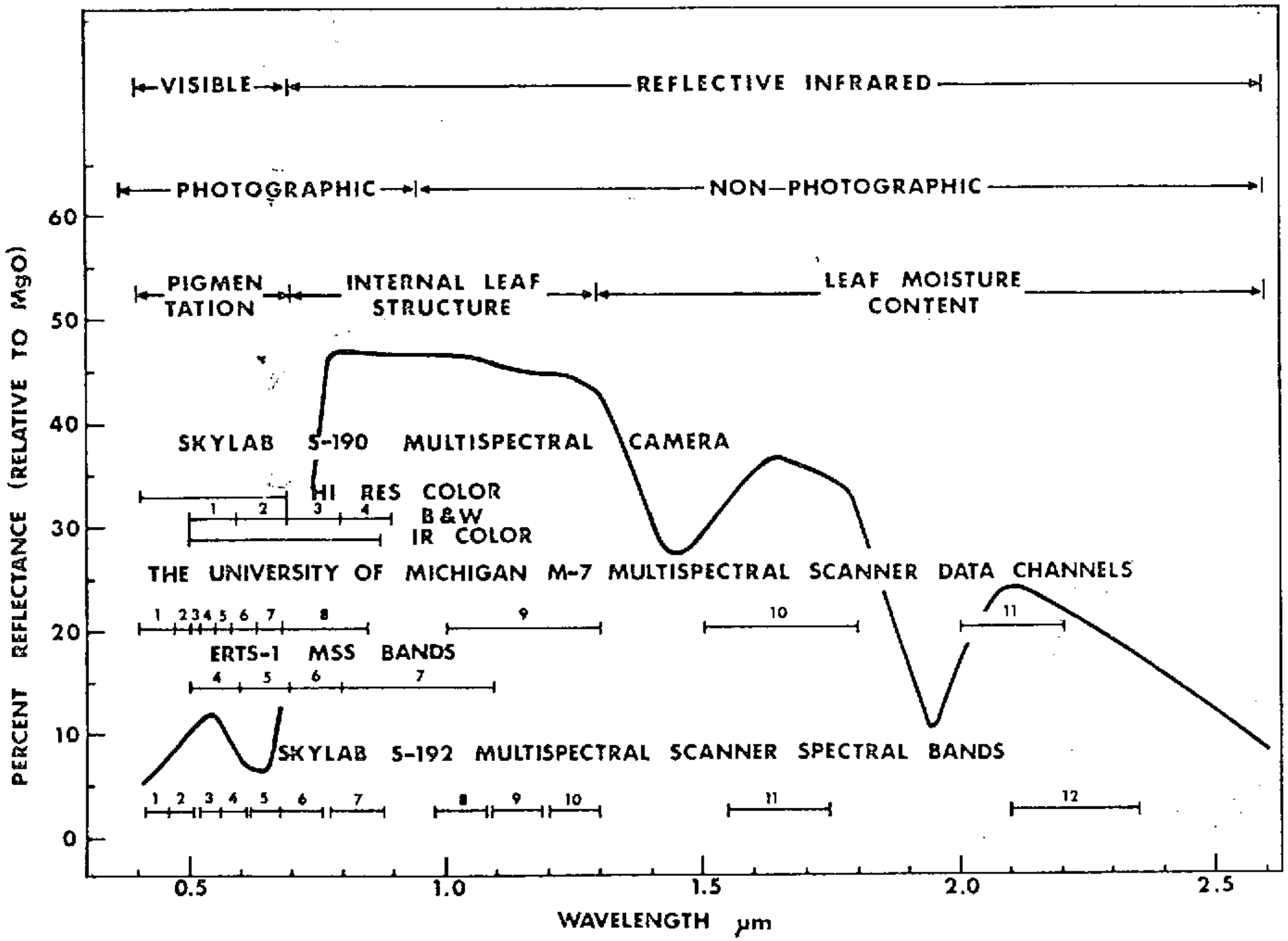

Figure 13. Generalized laboratory reflectance curve of green vegetation. The above illustrates the spectral coverage of orbital and aircraft multispectral sensing systems. Skylab S-192 multispectral scanner provides satellite data over discrete segments of the electromagnetic spectrum as they are influenced by vegetation characteristics.

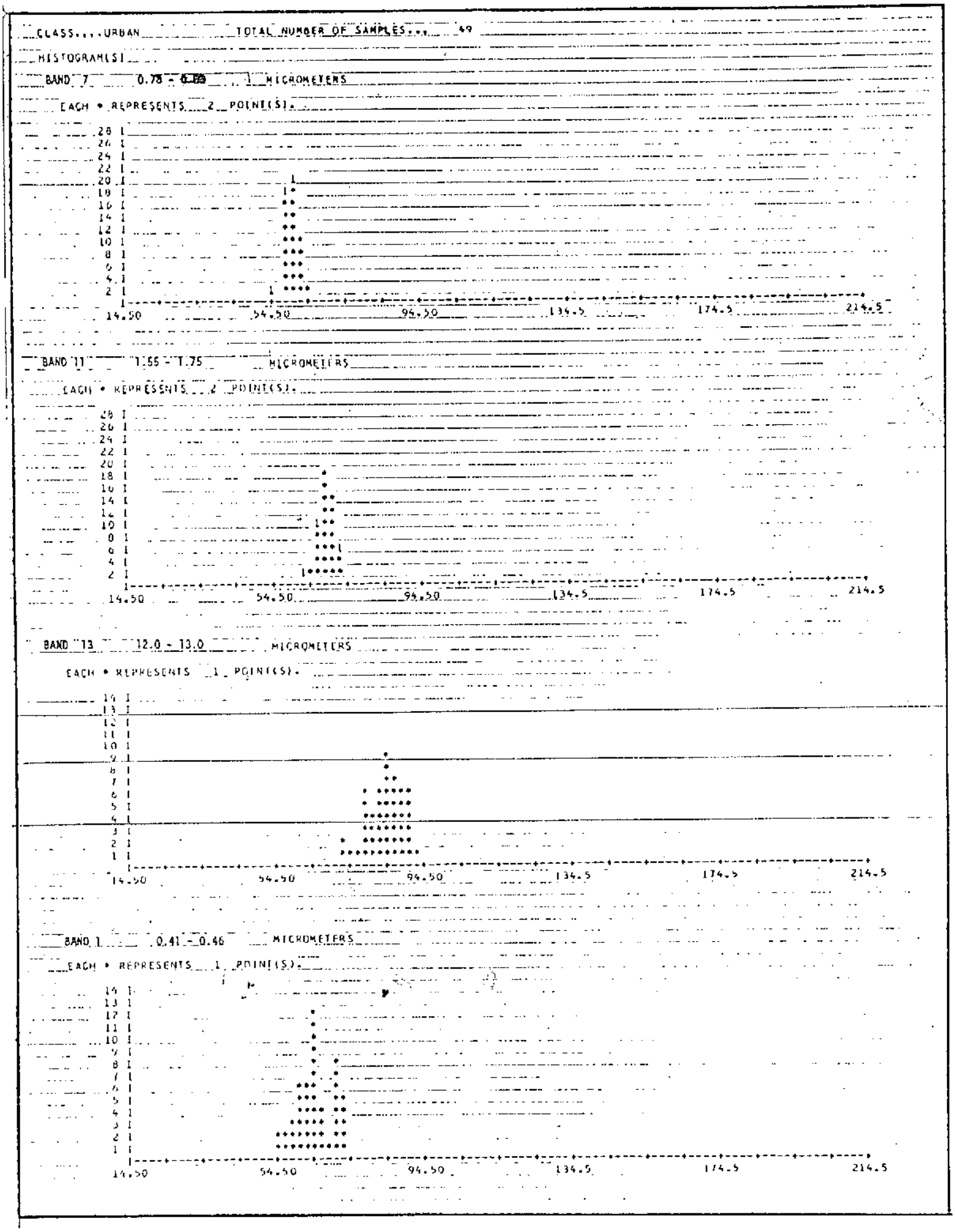

Figure 14. Histograms for each S-192 spectral band illustrating the distribution of data points within an urban training set.

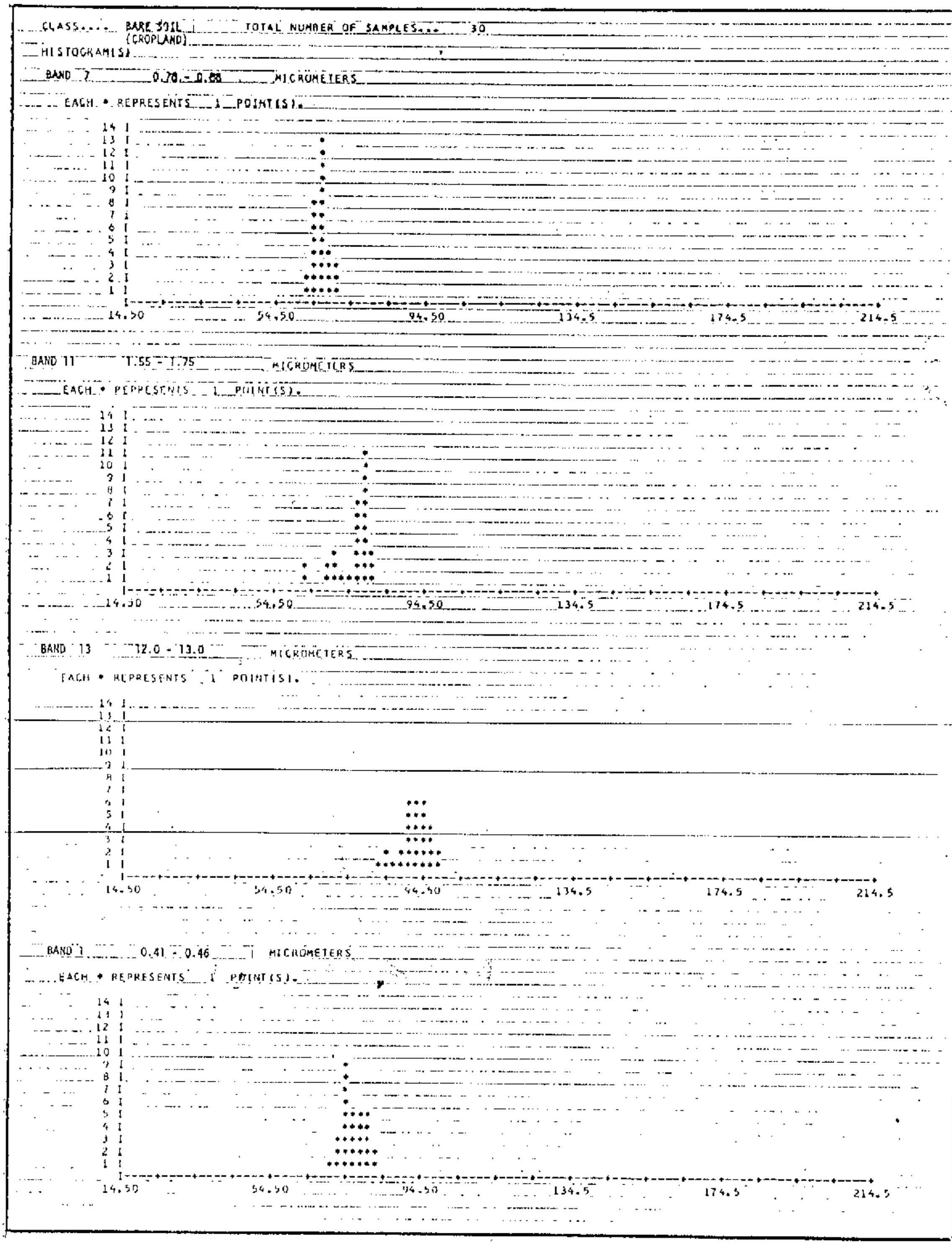

Figure 15. Histograms for each S-192 spectral band illustrating the distribution of data points within a bare soil training set.

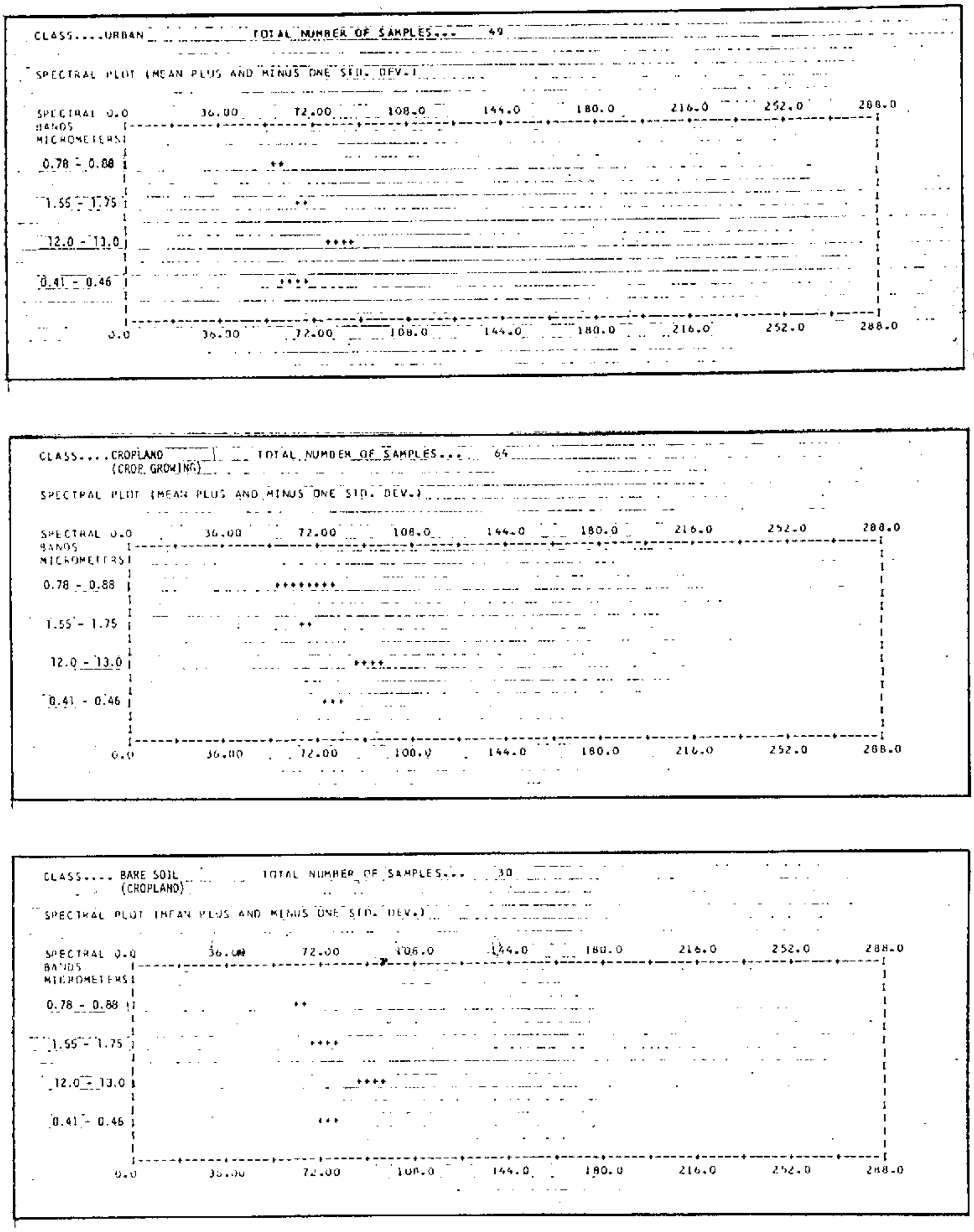

Figure 16. Coincident spectral polts for three training sets used in this initial analysis. These plots illustrate the mean spectral response plus or minus one standard deviation for each training set.

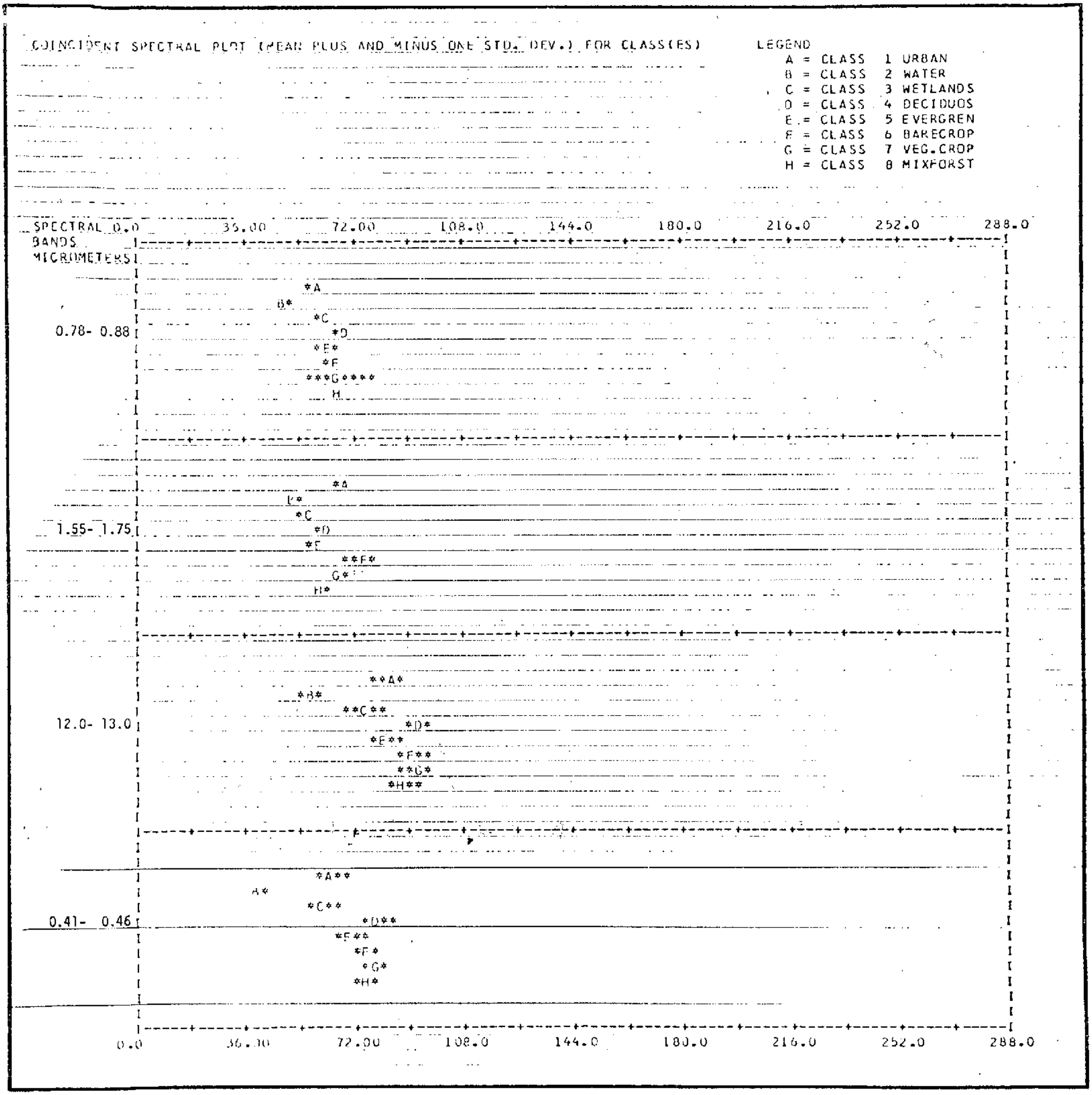

Figure 17. Coincident spectral plots for all classes illustrating the mean spectral response plus or minus one standard deviation. These plots provide an indication of the spectral separability of the training classes.

COMBINATION OF SPECTRAL BANDS	AVERAGE DIVERGENCE	MINIMUM DIVERGENCE
0.78 - 0.88, 1.55-1.75	1794	805
1.55 - 1.75, 0.41 - 0.46	1774	655
1.55 - 1.75, 12.0 - 13.0	1702	517
0.78 - 0.88, 0.41 - 0.46	1562	148
0.78 - 0.88, 12.0 - 13.0	1511	298
12.0 - 13.0, 0.41 - 0.46	1326	106
0.78 - 0.88, 1.55 - 1.75, 0.41 - 0.46	1881	875
0.78 - 0.88, 1.55 - 1.75, 12.0 - 13.0	1846	953
1.55 - 1.75, 12.0 - 13.0, 0.41 - 0.46	1811	822
0.78 - 0.88, 12.0 - 13.0, 0.41 - 0.46	1661	374
0.78 - 0.88, 1.55 - 1.75, 12.0 - 13.0, 0.41 - 0.46	1903	1009

Figure 18. Average divergence and minimum divergence values for various combinations of spectral bands for all combination of classes.

	1 Urban	2 Water	3 Wetlands	4 Deciduous Forest	5 Evergreen Forest	6 Mixed Forest	7 Cropland/ Bare Soil	8 Cropland/ Crop Present
1. Urban								
2. Water	2000							
3. Wetlands	2000	2000						
4. Deciduous Forest	1996	2000	1996					
5. Evergreen Forest	1986	2000	1620	1762				
6. Mixed Forest	2000	2000	1972	1009	1228			
7. Cropland/Bare Soil	1902	2000	2000	1996	2000	2000		
8. Cropland/Crop Present	1994	2000	2000	1885	1985	1999	1980	

FIGURE 19. Divergence and feature analysis based on spectral signature statistics for spectral channels 0.79-0.88 μm, 1.55-1.75 μm, 12.0-13.0 μm, and 0.41-0.45 μm. The divergence value for any two classes indicates the expected degree of separability based on training set data. These data suggest that quite accurate separation of these classes can be achieved.

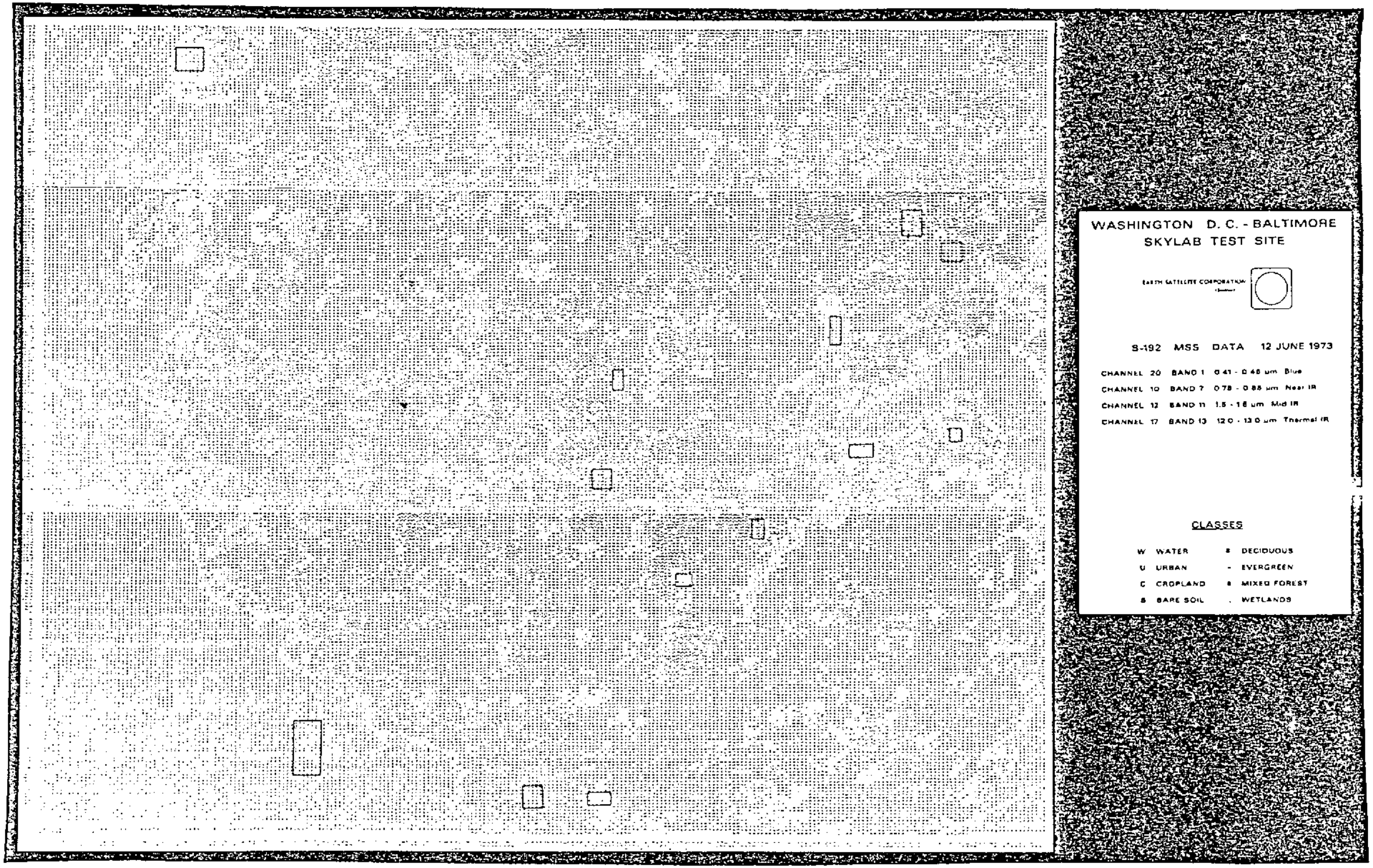

Figure 20. Computer generated land use recognition map. The areas outlined in black were used for deriving training lass spectral signatures to be used in the classification process. Classification performance tests indicated an overall accuracy of 84.6%. Techniques have been developed to output classification results such as those above on a digital film recorder.

	TRAINING SET CLASSIFICATION PERFORMANCE										
GROUND TRUTH	URBAN	WATER	WETLANDS	DECIDUOUS FOREST	EVER-GREEN FOREST	CROPLAND BARE SOIL	CROPLAND GROWING CROP	MIXED FOREST	THRESHOLD	TOTAL	PERCENT Correct
URBAN	48					1			1	49	98
WATER		119								119	100
WETLANDS			26		1					27	96
DECIDUOUS FOREST				51		1	2	11		65	78
EVERGREEN FOREST			3		50			5		58	86
CROPLAND BARE SOIL				1	1	26	2			30	87
CROPLAND GROWING CROP				10		21	32		1	64	50
MIXED FOREST				5	3			22		30	73
TOTAL	48	119	29	67	55	48	36	38	2		
PERCENT COMMISSION	0	0	10	24	9	46	11	42			374/442

THRESHOLD - 7% OVERALL PERFORMANCE - 84.6

Figure 21.

	TRAINING SET CLASSIFICATION PERFORMANCE										
GROUND TRUTH	URBAN	WATER	WETLANDS	DECIDUOUS FOREST	EVER-GREEN FOREST	CROPLAND BARE SOIL	CROPLAND GROWING CROP	MIXED FOREST	THRESHOLD	TOTAL	PERCENT Correct
URBAN	48					1				49	98
WATER		118							1	119	99
WETLANDS			26		1					27	96
DECIDUOUS FOREST				51		1	2	11		65	78
EVERGREEN FOREST			3		50			5		58	86
CROPLAND BARE SOIL				1	1	26	2			30	87
CROPLAND GROWING CROP				10		21	32			64	50
MIXED FOREST				5	3			22		30	73
TOTAL	48	118	29	67	55	49	36	38			
PERCENT COMMISSION	0	0	10	24	9	47	11	42			373/442

THRESHOLD - 15% OVERALL PERFORMANCE - 84.4%

Figure 22.

		TRAINING SET CLASSIFICATION PERFORMANCE										
		URBAN	WATER	WETLANDS	DECIDUOUS FOREST	EVER-GREEN FOREST	CROPLAND BARE SOIL	CROPLAND GROWING CROP	MIXED FOREST	THRESHOLD	TOTAL	PERCENT Correct
GROUND TRUTH	URBAN	47					1			1	49	96
	WATER		117							2	119	98
	WETLANDS			25		1				1	27	93
	DECIDUOUS FOREST				50		1	2	11	1	65	77
	EVERGREEN FOREST			3		49			4	2	58	84
	CROPLAND BARE SOIL				1	1	26	2			30	87
	CROPLAND GROWING CROP				10		21	32		1	64	50
	MIXED FOREST				5	3			22		30	73
	TOTAL	47	117	28	66	54	49	36	37			
	PERCENT COMMISSION	0	0	11	24	9	47	11	41			368 / 442

THRESHOLD - 30%   OVERALL PERFORMANCE - 83.3%

Figure 23.

Ground Truth	Test Class Performance: Urban	Water	Wetlands	Deciduous Forest	Ever-green Forest	Cropland Bare Soil	Cropland Growing Crop	Mixed Forest	Threshold	Total	Percent Correct
URBAN	20			9	2	4	6			41	49
WATER		1101	11						73	1185	93
WETLANDS	8		3	5	19	1	2	4	11	53	6
DECIDUOUS FOREST				100		1	6	19	1	127	79
EVERGREEN FOREST			7	3	75			9		94	80
CROPLAND BARE SOIL	1					84	3		2	90	93
CROPLAND GROWING CROP	2			23	1	6	47		3	82	57
MIXED FOREST				41	10		3	34		88	39
TOTAL	31	1101	21	181	107	96	67	66			
PERCENT COMMISSION	35	0	86	45	30	13	30	48			1464 / 1760

THRESHOLD - 7%   OVERALL PERFORMANCE - 83.1%

Figure 24.

	TEST CLASS PERFORMANCE										
GROUND TRUTH	URBAN	WATER	WETLANDS	DECIDUOUS FOREST	EVER-GREEN FOREST	CROPLAND BARE SOIL	CROPLAND GROWING CROP	MIXED FOREST	THRESHOLD	TOTAL	PERCENT Correct
URBAN	19			9	2	4	6		1	41	46
WATER		1012	9						164	1185	85
WETLANDS	5		2	5	16	1	2	4	18	53	4
DECIDUOUS FOREST				100		1	6	19	1	127	79
EVERGREEN FOREST			7	3	75			9		94	80
CROPLAND BARE SOIL						79	2		9	90	88
CROPLAND GROWING CROP	2			21	1	6	47		5	82	57
MIXED FOREST				41	10		3	34		88	39
TOTAL	26	1012	18	179	104	91	66	66			
PERCENT COMMISSION	27	0	50	44	28	13	29	48			1368 / 1760

THRESHOLD - 15%   OVERALL PERFORMANCE - 77.7%

Figure 25.

		URBAN	WATER	WETLANDS	DECIDUOUS FOREST	EVER-GREEN FOREST	CROPLAND BARE SOIL	CROPLAND GROWING CROP	MIXED FOREST	THRESHOLD	TOTAL	PERCENT Correct
		TEST CLASS PERFORMANCE										
GROUND TRUTH	URBAN	17			7	2	4	6		5	41	41
	WATER		886	3						296	1185	75
	WETLANDS	1		1	5	13	1	2	4	26	53	2
	DECIDUOUS FOREST				94		1	6	17	9	127	74
	EVERGREEN FOREST			7	3	73			9	2	94	78
	CROPLAND BARE SOIL						69	2		19	90	77
	CROPLAND GROWING CROP	2			15		6	42		17	82	51
	MIXED FOREST				41	9		3	29	6	88	33
	TOTAL	20	886	11	165	97	81	61	59			
	PERCENT COMMISSION	15	0	91	43	25	15	31	51			1211 / 1760

THRESHOLD - 30% OVERALL PERFORMANCE - 68.8%

Figure 26.