GEOGRAPHIC INFORMATION SYSTEM STRATEGIES FOR IMPROVING LANDSAT LAND USE CLASSIFICATION ACCURACY

by

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(ABSTRACT)

This study focuses on POWER Geographic Information System strategies for improving the land use classification and mapping accuracies of Landsat multispectral scanner (MSS) data. The specific strategies are additional-band, class reduction, exclusion, and conditional.

Three classified images served as the basis upon which all accuracy improvements were determined. Generated from 4 bands of Landsat data, each of these 3 images possessed 13-classes and were composed of clusters greater than or equal to 5, 9, and 13 pixels, respectively. Image classification was accomplished through use of the General Image Processing System (GIPSY) at Virginia Tech.

The additional-band method consisted of augmenting each 4-band Landsat image with 5 ancillary bands producing a 9-band image. Only moderate improvements in select class accuracies were realized.

The reduction method involved decreasing the number of land use classes from 13 (Level 2) to 4 (Level 1) in both 4- and 9-band imagery. This resulted in significant increases in overall image

and select class accuracies.

In the exclusion method, 7 data sets were removed sequentially from each 13-class image with 3 data sets removed from 4-class images. These data sets represented land uses with a low probability of consistent classification. Each exclusion produced moderate increases in overall image and select class accuracies.

A conditional classification method, utilizing a hierchical decision-tree structure, was developed to determine its potential for increasing image accuracies. Slope angle, slope aspect, elevation, distance-from-water, and Landsat classified land use were included as environmental parameters. Decreased accuracies resulting from data registration and overlay problems warrant further research into and testing of this method.

Significant efficiencies in assessing subscene accuracies were realized using a distance-from-roads sampling strategy. Ground data, inclusive of 9 pixels from a primary or secondary highway, produced comparable accuracies to those derived from more extensive ground truth.

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INTRODUCTION, JUSTIFICATION, AND OBJECTIVES

Few people are neutral about technology, they see it as either a blessing or an evil (Hite, 1979). For the professional wildlife manager and land use planner, technology is neither; it is a resource to be utilized.

New technologies should be examined for possible application as wildlife management research tools (Parker, 1977). Intelligent, rational answers to many questions require technical information. Technology can be used to secure such information. Policy formulated without reliable information may be ineffective or erroneous. Regional and local losses of wildlife habitat are one result of decisions based on intuition and experience and not on the best available information. Increased benefits may be gained from the wildlife resource and limited funds better spent with more information.

Better resource decisions can be made in terms of accuracy, efficiency, and effectiveness by expanding the existing information base available to wildlifers. One technology available to expand the information base is remote sensing by satellites.

Perhaps the most revolutionary technical development in gathering low cost, large area, land resources information has been the Earth Resources Technology Satellite (ERTS). The ERTS satellite program has since been renamed Landsat, standing for Land Satellite. Landsat has provided a new vantage point for monitoring the Earth's resources and assessing the impact of people upon these resources. As experience is

gained and technical problems are resolved, it is quite possible that Landsat imagery may become a standard information source for much future land-resources planning (Hite, 1979). Parker (1977) stated that without encouragement from wildlife professionals, it is unlikely that advances in the field of remote sensing will enter the realm of traditional ecological studies and wildlife management.

Given the great potential of Landsat, there remain major problems in accurately classifying land use and cover from its image products. The probability of correctly classifying the land use in a Landsat picture element or pixel (a cell on the land surface 79m x 56m or 1.1 acres) is low relative to other remote sensing methods such as aerial photography. Reported accuracies for classifying land use and cover types from Landsat imagery are within the range of 40 to 70 percent (Haralick et al., 1973; Tom, 1978; Tom and Miller, 1980; Tom et al., 1978; Strahler, 1980). The reasons for spectral inaccuracies are easily understood but are usually unacceptable in satisfying planners and resource managers who need to secure and utilize map data from Landsat with a very high accuracy. Another problem is that the potential for Landsat information in large-area planning has only been partially addressed. Greater efficiency and quality from Landsat data would increase its acceptability and use by the land use planner. Planners and resource managers need accurately classified Landsat land use and cover data and the means to store and retrieve it. Large geographic data bases such as POWER (Jones, 1976) can provide this function. This thesis will address both problems of accuracy and large-area data management.

The objectives of this study are:

1. Primary: To develop a machine-assisted procedure for improving land use and cover classification from Landsat data.
2. Secondary:
   a. To create algorithms for improving efficiency and accuracy of land use and cover classification.
   b. To determine whether ancillary data about areas (e.g., elevations, slope, and aspect) can aid in improving land use and cover classification.
   c. To relate the potentials of using Landsat image interpretation to wildlife management and state-level natural resource information systems.

LITERATURE REVIEW

This review is presented in 3 sections. The first section provides a brief overview of the key elements of Landsat analyses for wildlife managers and land use planners unfamiliar with the field. The second part provides a review of Landsat applications in wildlife management and related fields. The final section addresses means used for improving accuracy of Landsat image interpretation.

OVERVIEW

Remote Sensing

Space age technology contains a key to increased knowledge about the resources of Earth (U.S. Dept. of the Interior, 1979). This key is remote sensing. Remote sensing may be broadly defined as the field involved with collecting and analyzing information about an object without actual physical contact with an object (Sabins, 1978). Wildlife managers are familiar with radiotelemetry of animal location and behavior as one aspect of remote sensing. Another major branch of the field is sensing of electromagnetic radiation from objects such as the land. Here, information is acquired by recording devices which are sensitive to wavelengths from the ultraviolet to radio regions (Reeves, 1975). It is this latter branch that is addressed herein.

Remote sensing has many contacts with other fields. Investigators working with remote sensing have referred to it as the "multiscience" because of its many potentials and capabilities (Richason, 1978). Its

information can be used broadly for problem-solving in agriculture, industrial operations, hydrology, geology, transportation, forestry, and wildlife management. One of the principal characteristics of remote-sensor imagery is that it may be obtained simultaneously in several portions of the electromagnetic spectrum which are not normally apparent to the human eye (Richason, 1978).

The problem which is presented to users of remote sensing is one of searching through the electromagnetic spectrum to find those wavelengths which are most suitable for identifying a specific target or event (Richason, 1978). Other aspects of remote sensor images or techniques with which users must be knowledgeable include:

1. the electromagnetic energy which contributed the image of the scene;
2. the capabilities of the instruments that received, transmitted, and stored the data; and
3. the varying filtering properties of the atmosphere between the objects emitting wavelengths of energy (Richason, 1978) and the sensor.

Familiarity with these three items and how they interact with remote sensor systems can aid in understanding the potential uses of Landsat data in wildlife management and other fields.

Landsat

Landsat 1 was launched by the National Aeronautics and Space Administration (NASA) in July 1972. Landsat 1 has since been retired, but replaced by two similar satellites. These satellites, Landsats 2

and 3, launched in 1975 and 1978, have essentially the same instrumentation as the initial platform.

Each Landsat orbits the Earth 14 times each day at an altitude of approximately 920 km (560 mi) (U.S. Geological Survey, 1979a). Two satellites in near polar orbit permit repetitive coverage of any point on the surface of the Earth (excluding polar and cloud covered areas) every 9 days. A single satellite provides coverage once every 18 days.

Landsat presently carries three data acquisition systems:

1. a multispectral scanner (MSS);
2. a return-beam vidicon (RBV), similar to a television sensor, and
3. a data-collection system (DCS) to relay environmental data from ground-based, data-collection platforms (DCP's) (U.S. Department of the Interior, 1975).

The MSS is the primary sensor for wildlife management.

The MSS operates on the general principle that objects produce a spectral reflectance curve from the ultraviolet through the near-infrared portion of the electromagnetic spectrum. These spectral characteristics can be used to identify similar features in an image by comparing, then classifying, known with unknown spectra. The reliability of any spectrally-based classification of land use or cover depends on the certainty with which each signature can be discriminated (Mamula, 1978).

MSS data are acquired in four bands. These extend from the visible (Bands 4 and 5) to the near-infrared (Bands 6 and 7) portions of the electromagnetic spectrum (Watkins, 1978). A short description of each band is reprinted from Richason (1978).

- Band 4 (500-600nm) detects and registers blue-green wavelengths. This band is most useful for studying the characteristics of water bodies. It is subject to atmospheric scattering.

- Band 5 (600-700nm) is sensitive to radiation in the red wavelengths. This band is best for producing images which distinguish topographic and man-made features.

- Band 6 (700-800nm) registers targets whose radiance is at a maximum in the near-infrared spectral region. This band is used to discriminate between land and water interfaces and healthy and stressed vegetation.

- Band 7 (800-1100nm) is sensitive to radiation in the near-infrared spectral region. This band is also useful for identifying land-water interfaces although it is subject to absorption by atmospheric water vapor. Band 7 is the least useable for studying the intrinsic characteristics of water bodies because water appears almost solidly black in the wavelengths to which this band is responsive.

Digital Image Processing

In order to exploit fully the spectral, spatial, and temporal content of Landsat data, computer-assisted digital image processing has become necessary. One advantage of digital processing over photographic is that transformations applied to the data are precisely known, repeatable, and are not subject to the vagaries of complex and often difficult-to-control, chemical processing (Yost et al., 1973). With digital image processing, it is possible to manipulate, combine, and classify large numbers of spectral data while realizing all of the advantages of machine-assistance.

The principal stimulus for applying computer techniques to image analysis is their ability to perform much more complex image classification than have been possible in the past (Lillestrand and Hoyt, 1974). Digital input and output equipment is being improved to provide increased spatial and gray-scale mapping accuracy, consistent with the information

needs of users. The ability to produce cost-effective solutions to land-use decisions using digital image processing has only been partially demonstrated, but significant progress is being made for applications involving large volumes of data (Lillestrand and Hoyt, 1974).

Geographic Information Systems

Technology serves to fragment information into specialized compartments (Hite, 1979). The creation of a geographic information system (GIS), on the other hand, serves to consolidate standardized spatial-environmental information of different sources (Mitchell et al., 1977). A GIS is a system that can receive, manipulate, analyze, and display geographic data in support of the decision making processes within an organization (Salmin et al., 1977). In the past, lack of standardization has prevented immediate success even though good information has been available. The advent of the GIS has served to lessen this standardization problem with more data, including MSS data, being adapted for computer compatibility within a GIS.

Because of large and ever-increasing amounts of Landsat and geo-based data, GISs have been designed to aid people in processing such data into useful information (Hyde, 1980). Such information may include answers to the following questions,

1. how much productive wildlife land is there available within a region?,
2. how are land resources presently being used?, and
3. what have been the changes in land use and cover over time (Soileau et al., 1971)?

A GIS operates on geocoded parameters and interactions which may effect resources. Slope, aspect, elevation, topographic position, and land and use cover are just a few factors which can be integrated and used in solving resource problems with automated techniques. The potential for improved quality and efficiency of natural resource management is so obviously in the direction of a quantitative and semi-quantitative approach that any decision not to utilize the capability of modern GIS techniques should be consciously made and justified (Dean, 1971).

Landsat MSS data may be used in two ways within a GIS. First, because the location of control points can be registered to specific map projections (e.g. Universal Transverse Mercator, Latitude-Longitude, State Plane), it is possible to allign scenes accurately. Second, because of the relatively low cost of computer compatible tapes which store a complete MSS image ($300, October 1981), Landsat has been judged a cost-effective supplement to collecting data with conventional photography.

Landsat data used within a GIS environment can also provide planners and land managers access to large volumes of data and the varied options for manipulation and display. These data may reflect specific environmental characteristics which include:

1. Temporal--the continuous, modifying effects of natural succession on the composition and pattern of surface vegetation,
2. Spatial--the size of the area that is directly or indirectly affected by beneficial or detrimental wildlife-related activities (Mamula, 1978), and

3. Varietal--such as contiguity, extent, and distribution of wildlife habitats and how they may be indicative of a quality environment.

Analyzing Landsat data within a GIS permits innumerable applications and integrations with advanced analytical models and cartographic algorithms developed during recent years (Hite, 1979). Moreover, because these analyses often require composite mapping (i.e. overlaying different sets of resource data planes), large numbers of maps may be needed to evaluate alternative land use schemes. Computer mapping within a GIS can provide such a service quickly and at low cost once the data are stored. Landsat maps themselves can be produced with considerable cost savings in relation to the degree of accuracy obtained (Finch, 1974).

APPLICATIONS

Within recent years MSS data have been used for diverse environmental problem analyses. The following literature review has been structured to present this array of applications to the wildlife manager in 2 parts. The first part seeks to familiarize managers with direct applications in the wildlife field. The latter section reports applications in non-wildlife fields but fields which are nonetheless land-related. As such, both sections would benefit wildlife decision-making by bringing to light inter-disciplinary Landsat data usage and possibilities for better utilizing this present information base. These sections may also assist in clarifying the general capabilities of Landsat.

Wildlife

Accurate land use and cover classification for large areas can be of immense aid to the wildlife manager, since wildlife is a product of the land, and the kinds and numbers of wildlife produced usually are a result of the uses of the land (Foote, 1971). For multi-county management regions, up-to-date land use and cover information may serve as the means by which wildlife population changes are studied. Habitat losses to human development are well-publicized, apparent, and locally important, but they may be small when compared to losses which can occur because of natural changes in plant composition (Yoakum, 1971). Multispectral scanner data coupled with digital processing is one technique for recognizing and estimating these natural changes quickly (Ellefsen et al., 1977).

In wildlife management, specific topics such as habitat assessment, food base estimation, wildlife censusing, and vegetation mapping have been investigated using Landsat data.

Best and Sather (1978) presented Landsat imagery as a technique for assessing the quality and quantity of available wildlife wintering areas. Six classes of winter habitat were interpreted with an overall classification accuracy of 76.6 percent in a test using imagery mosaics. Traylor and Mealor (1978) used Landsat imagery to prepare a wildlife habitat map based upon traditional cartographic and photographic techniques. Studies in North Dakota, by Gilmer et al. (1975) and Gilmer et al. (1978), evaluated Landsat as a tool for predicting annual waterfowl production. Katibah and Graves (1978) outlined a means for identifying potential wild turkey habitat in California. Areas having

established wild turkey populations were used as training sites to identify the vegetation structure that would be suitable for turkey introduction. Successful attempts at recognizing and delineating grizzly bear (Craighead, 1976) and moose (Laperriere et al., 1980) habitats using Landsat data have also been documented.

For studies of forage, Klaas et al. (1978) used Landsat imagery acquired for four dates during September to November to estimate and monitor the amount of food available to lesser snow geese in Iowa and Nebraska. Work and Gilmer (1974) conducted a similar study to extract pond and lake information necessary for formulating management decisions relating to migratory waterfowl.

Sites of actual and potential colonies of Ross' geese in the Central Canadian Arctic had a distinctive signature on Landsat band 6 imagery, as reported by Kerbes and Moore (1975) and Kerbes (1978). Identification of such site facilitated a census inventory of the nesting birds in 1976 and 1977.

O'Neil et al. (1978) used MSS band 7 to map vegetation succession trends in Louisiana's Atchafalaya River Basin. The maps were later used to develop a mathematical model capable of predicting vegetation changes based on hydrologic factors. Applications of Landsat imagery to monitor the extent and rate of snow disappearance from Arctic goose nesting areas were discussed by Reeves (1978). Observing snow disappearance was an effective and economical management tool for assessing gross vegetative conditions and their effects on goose production prospects.

Two factors which prevent extensive application of Landsat information in wildlife management are accuracy and quality. Landsat derived

land cover classifications are, at present, marginally accurate for resource management requirements (Stow and Estes, 1981). Without consistently high land use and cover interpretation accuracies, actual and potential wildlife habitat assessment through Landsat is limited. Landsat information by itself is also not capable of expressing site quality for different land use and cover types (Johnson, 1972). These data from the images do not reflect the potentialities and limitations of areas for sustaining wildlife production. Given the need for evaluating regional habitat suitability, Landsat data alone cannot be utilized to discriminate areas requiring immediate management.

Land Use Investigation and Planning

Problems in properly planning land use have always existed. These problems have limited wildlife populations by not protecting prime lands capable of producing sustained annual crops of wild game. Because of the diverse nature of land use and human demand, effective wildlife management must be compatible and tailored to encourage wildlife productivity. To meet this production goal, information collected in many fields needs to be integrated and evaluated for its applicability. Broad-based information collection techniques, such as those offered by Landsat satellite imagery, can aid in making this possible.

In problems concerning accurate mapping of 100-year flood plains, Henniger et al. (1975) and Harker and Rouse (1977) reported that computer analysis of Landsat digital data had the potential for playing a prominent role in successfully identifying and mapping these areas. They also stated that this method could be used to update and verify

existing United States Army Corps of Engineers (USACE) maps or to produce maps in unsurveyed watersheds.

The potential for using remotely sensed data in hydrology has also been investigated. Fostel, et al. (1978) studied the categorization, location, and quantification of nonpoint source of pollutants using Landsat-derived spatial information. Specific examples were fertilizers and pesticides from agricultural fields, bacteria and nutrients from agricultural feedlots and over-flowing septic tanks, oil and tar residues along road sides and curbs, and salts used in winter-road icing. In order to estimate the location and scale of activity, the land use and cover types were identified. Reduced costs of hydrographic surveys were reported by Warne (1978) when Landsat MSS imagery was employed. Given the need to meet requirements of the Federal Dam Safety Program, staff of the Texas Natural Resource Information System used Landsat and computer-assisted techniques to locate and map constructed reservoirs. These maps were then used to investigate potentially hazardous conditions (National Conference of State Legislatures, 1978). The changing character of water clarity can also be effectively monitored using Landsat data (Brooks 1975).

In geologic and geographic studies, applications of Landsat have proven that digital classification techniques can create a land systems map usable for grazing land management in Australia (Robinove, 1979). Ulaby and McNaughton (1975) produced maps which reflected physiographic differences between regions of Kansas. Seigal and Goetz (1977) studied the influences of vegetation upon discrimination of rock and soil type using Landsat imagery. Parks, et al. (1973) used Landsat imagery for

delineating soil associations and detecting drainage patterns, erosion, and sedimentation. Soil association mapping results from Landgrebe (1974) showed that strong relationships exist between Landsat-data-derived maps and conventional soil maps. Campbell (1980) noted that the usefulness of remote sensing techniques (including satellite imagery) to soil survey is limited as much by an imperfect knowledge of soils as it is by technical limits of the instruments. He added that appling remote sensing to soils carries with it a demand for more complete knowledge of the soil landscape.

Landsat research in the forestry sciences is often directed toward applying images as a supplementary data source to a forest information system. In a preliminary study to access information needs, Coggeshall and Hoffer (1973) found that accurate classification of deciduous and coniferous forest cover can be achieved with the visible plus either the near- or middle-infrared spectral regions. Data from the near-infrared region is available from Landsat. In comparisons of infrared to red reflectance ratios and areas defoliated by gypsy moths (Porthetria dispar), Landsat imagery was shown as an eventual replacement technique to aerial sketch mapping of defoliation (Walker, et al., 1977). This analysis revealed that in areas of high to medium infestation levels, the infrared-to-red reflectance ratio (Band 7/Band 5) was a good, cost effective measure of percent defoliation. In low to medium infestation levels, it was not. In a study by Heller et al. (1974) and Heller (1975), both natural and people-caused forest disturbances could be detected with 90 percent accuracy when Landsat imagery was compared with aerial photos. Classification accuracies of 60 to 70 percent were

reported by Heller, et al. (1974) in classifying aspen, Douglas-fir, lodgepole pine, ponderosa pine, and spruce/fir forest stands. Hall (1973) reported the possibility for delineating 3 degrees of lodgepole pine timber mortality, (i.e., light, medium, and heavy), using enlarged Landsat color composites. Williams (1976) delineated three levels of pine crown closure using MSS data. With automated classification of MSS CCT data, commercial stands of Alaskan cottonwood and white spruce were identified with 80 percent accuracy by McKendrick (1974). Langely and Van Roessel (1973) found that the difference between bands 5 and 7 proved to be of special importance for estimating timber volume.

In order to more accurately predict present and future food production, Landsat technology has been incorporated into some state, regional, and federal agricultural forecasting programs. These food-production acreages potentially relate to farm wildlife population densities, both vertebrate pests as well as game animals. One such federal program was the large area crop inventory experiment (LACIE) from 1974 to 1978 (Macdonald, 1976; National Aeronautics and Space Administration, 1977a; National Aeronautics and Space Administration, 1977b; National Aeronautics and Space Administration, 1978; Bryan, 1979).

Additional agricultural applications of Landsat data range widely. Richardson et al. (1977) used MSS data collected on January 21 and May 27, 1973 for classifying and estimating acreage of various crop and soil categories. Stockton et al. (1975) obtained a classification accuracy of 97 percent for wheat with the resultant county wheat estimate in hectares being within 5 percent of the USDA's Statistical Reporting Service estimate. Nalepka, et al. (1976) identified the red band

(equivalent to Landsat band 5) as the best predictor of wheat yield, with the green band (equivalent to band 4) as next best. Kumar (1977) stated that the red channel (equivalent to band 5) was optimal for statistically separating agricultural cover types in western Indiana. Distinguishing differing vegetation from soil background data was a topic explored by Richardson and Wiegand (1977). Richardson et al. (1975) reported successes in determining plant, soil, and shadow reflectance components of various domesticated food plants. Studies by Wiegand (1973), Wiegand et al. (1974), and Gausman et al. (1975) used multispectral data from ERTS-1 to detect differences in chlorophyll concentration between chlorotic (iron deficient) and green (normal) grain sorghum plants. Chlorotic sorghum areas, 2.8 acres or larger, were identified on a computer printout of band 5 data. Identifying and mapping citrus trees affected with young tree diseases was 89 percent successful using processed Landsat digital data (Edwards et al. 1975). Wiegand et al. (1976) reported that computer-aided variety classification accuracies using Landsat data for a 600-hectare citrus farm were 83 percent for grapefruit and 91 percent for oranges.

The impact of strip mining on environmental quality and on land resource quality and quantity underlies one of the critical problems in land use policy (Johnson, 1972). In the area of strip mine reclamation, Anderson and Schubert (1976) were able to delineate disturbed strip mine areas from surrounding geological and vegetation features by using ERTS-1 data in both analog and digital form. Results from this study indicated that satellites can both monitor and map the extent of strip mining to determine the acreage affected and indicate where future

reclamation and revegetation may be necessary. Anderson et al. (1977) used Landsat digital data processing for producing maps which could be later used in strip mine inventory. Wier et al. (1974) reported similar results for coal refuse site inventory in Indiana. In their study, Landsat data, when combined with coal industry and state agency statistics, were used to compute costs of reclamation for each site. Areas of dead or dying vegetation caused by acid mine drainage are distinctly classified using computer processing techniques on Landsat MSS data (McMurtry et al., 1976). Visual examination of Landsat imagery revealed the location of larger strip mines. However, only by digital analysis is it possible to distinguish subclassifications of mined areas.

In New Jersey, Wobber (1975) reported that integrated Landsat and collateral aircraft imagery were used for management of the coastal zone of the state. Accurately detecting land use changes in coastal areas was one problem investigated in that study.

Christenson et al. (1977) applied Landsat digital data to the delineation of urban area boundaries and to other census related problems. The purpose was to investigate and extract land cover characteristics of the urban fringe. This information is often vital since large areas of prime farmland are lost to industrial, commercial, and suburban growth each year (Rehder, 1971; Fields, 1979). Data on census tract boundaries and other political subdivisions were merged with the satellite data. Area measurements for the various land cover types within these subdivisions were then calculated. Haralick et al. (1973), reported that land use categories for regions over Kansas can be

identified with an accuracy of about 70 percent using the textural-spectral features of the 4 MSS bands. This information was then applied to regionalization studies. In Pennsylvania, forest land, cultivated land, and water, including subcategories, were separable within a 10,117 hectare (25,000 acre) area using Landsat digital data and pattern recognition techniques (McMurtry et al., 1973). Lee (1979) reported compound problems in employing a multiperiod Landsat imagery approach to monitor land use change. Both cloud cover and field checking problems were intensified using 2 data periods.

PROBLEMS OF ACCURACY

The present state-of-the-art for Landsat land use and cover classification yields relatively mediocre accuracies (R. Mead, pers. comm.). This level of accuracy may be below that needed for making management decisions. Inaccuracies result because insufficient spatial and spectral information is present in Landsat images to differentiate among land use and cover types (Strahler et al., 1978).

As stated above, the resolution of the MSS is approximately 79m x 56m (1.1 acres). This low spatial resolution, in part, is among the most important factors affecting Landsat land use and cover classification accuracy. Within this acreage, a less than perfect classification is caused by the mixed spectral response. This response is recorded by the MSS.

Physical components which partake in this spectral mixing include presence of land use and cover type(s), composition, proportion, and orientation; terrain variation; and the relative location of a 79 m by 56 m landscape within the 185 km by 185 km Landsat scene. Component interactions are also possible. An example of the mixing problem is that if one surface cover class is highly transmissive, then there is an increased probability of reflection from other, less transmissive, physical classes. The result is that the response proportion of transmissive components will be lower than their physical proportions (McCloy, 1980). In effect these components produce an average or integrated spectral response of all the surface phenomena within the pixel. If this composite land use and cover spectra is hypothesized as a point in multi-dimensional space, a multiplicity of component axes would represent the factors responsible for shifting the alignment of a "true" response position. This shift can result in an improper classification.

Characteristics of the acquisition and system environments also downgrade Landsat data quality. This is because attempts to quantify spectral response values from the MSS do not convert the original digital data to absolute radiometric units which exclude the effects of atmospheric attenuation and scattering as well as instrument factors. MSS data hence represent less-than-the-absolute radiance that leaves the surface due to atmospheric, molecular, and aerosol absorption and scattering on the way to the sensor. Because of these effects, identical surfaces may not yield similar response values, whether they be on the same or different images.

Recently there has been an increase in research demonstrating the potential uses and applications of supplemental data in a computer information system. These data may be used with Landsat data to augment their interpretation. They have been called "ancillary" for they may serve as an aid to interpreting Landsat data. Examples of Type 1 ancillary data are slope, aspect, elevation, solar irradiation, and topographic shadow. This type represents numeric data which are presently in computer-compatible form or can be derived using mathematical equations. Examples of Type 2 data are map features such as roads, water bodies, cities, and soil associations. These data are locational by definition and require digitizing or other forms of data entry for computer analysis. In effect, both data types may be used as new bands in forming the spectral signature. Research is needed on how to combine such data in a Landsat multispectral data base, create and test various models for predicting land use and cover, and map these land uses. Results by Tom (1978) show relatively high initial increases in classification accuracy with accuracy leveling off as greater numbers of data sets are added. Overall, predictive accuracies have varied, and actual success ratios have depended on the specific level of classification.

Species-specific forest cover type classifications were improved 27 percent by incorporating topographic information from U.S. Geological Survey digital terrain tapes registered to multidate (i.e. 2 or more different time periods) Landsat imagery (Strahler et al., 1978). Elevation data aided in the separation of forest cover types which have similar spectral signatures but different species compositions.

Strahler (1980) demonstrated how prior probabilities can be used to merge continuous variables of multispectral brightness with discrete variables of elevation and aspect class to improve forest cover classification accuracies. Classification using estimated probabilities contingent on both elevation and aspect yielded an accuracy of 77 percent, an improvement of 6 percent over that observed for elevation alone. The initial classification using only Landsat spectral data had yielded an accuracy of 58 percent.

In a study conducted by Tom (1978), 13 ancillary landscape variables were spatially overlaid and registered onto 20 bands of Landsat spectral data and tested for significance in mapping 15 vegetation cover classes in southeastern Montana. Ancillary data added to Landsat bands allowed interpreters to achieve 69 percent accuracy. Total direct cost was estimated at either $10.25 per square mile or $534.22 per 7 1/2 minute USGS quadrangle. Tom et al. (1978), in a similar study, used ancillary and Landsat data to create a spatial land use inventory and projection model for the Denver Metropolitan Area. Seven multivariate land use projection models were used to predict spatial land use changes. These achieved accuracies of from 42 to 57 percent. Using a landscape modeling approach, Tom and Miller (1980) merged Landsat MSS data and 15 ancillary map variables to predict and to map forest site productivity with a supervised nonparametric classifier. A stepwise classification yielded a training set accuracy of 43 percent using only 5 basic ancillary map variables, and 97 percent using all 19 image and map variables.

Hoffer et al. (1975) registered elevation data to 3 Skylab-2 spectral bands. Computer classification of regional forest cover types,

based on these 4 information channels, were improved 23 percent and 32 percent over strictly spectral analysis. Incorporating elevation information into a Landsat data classification scheme should also improve accuracies (Hoffer 1976).

In summary, many fields and sciences have applied Landsat data toward research and in problem solving. Immediate difficulties which have existed rest with the inability to accurately discriminate within Landsat images areas of differing land use and cover. While some work has been done to improve land use interpretation accuracies, an effort has been made to extend this work and to attempt alternative approaches. Existence of a large GIS not only provided unusual resources but also unique opportunities and efficiencies. This thesis seeks to present a method for significantly improving Landsat land use and cover classification.

METHODS

IMAGE DESCRIPTION

The 4-band Landsat image to be used in this project was obtained as a computer compatible tape (CCT). Since this image was already available from the Virginia Polytechnic Institute and State University Department of Forestry, no prior selection of frames was necessary. The scene identification number and exposure date are 8536014502500 and April 13, 1976, respectively. The area covered included a large portion of southeastern West Virginia and southwestern Virginia (Fig. 1). Other relevant scene information is listed in Table 1.

TAPE SUBSETTING

The first step in selecting a tentative study area was to overlay a clear plastic sheet, with appropriate line, sample, and file delineations (Fig. 2) onto the respective band 7 analog image. All of Montgomery County, Virginia was selected. Since the area to be classified was proposed to be less than a full county, this large subset would provide an adequate buffer zone for any inaccuracies encountered in the overlay or processes. Data which were recorded included the 4 sets of line-sample coordinates at the corners of the area and the CCT files where the data were located. This information served as inputs into program PREEX.

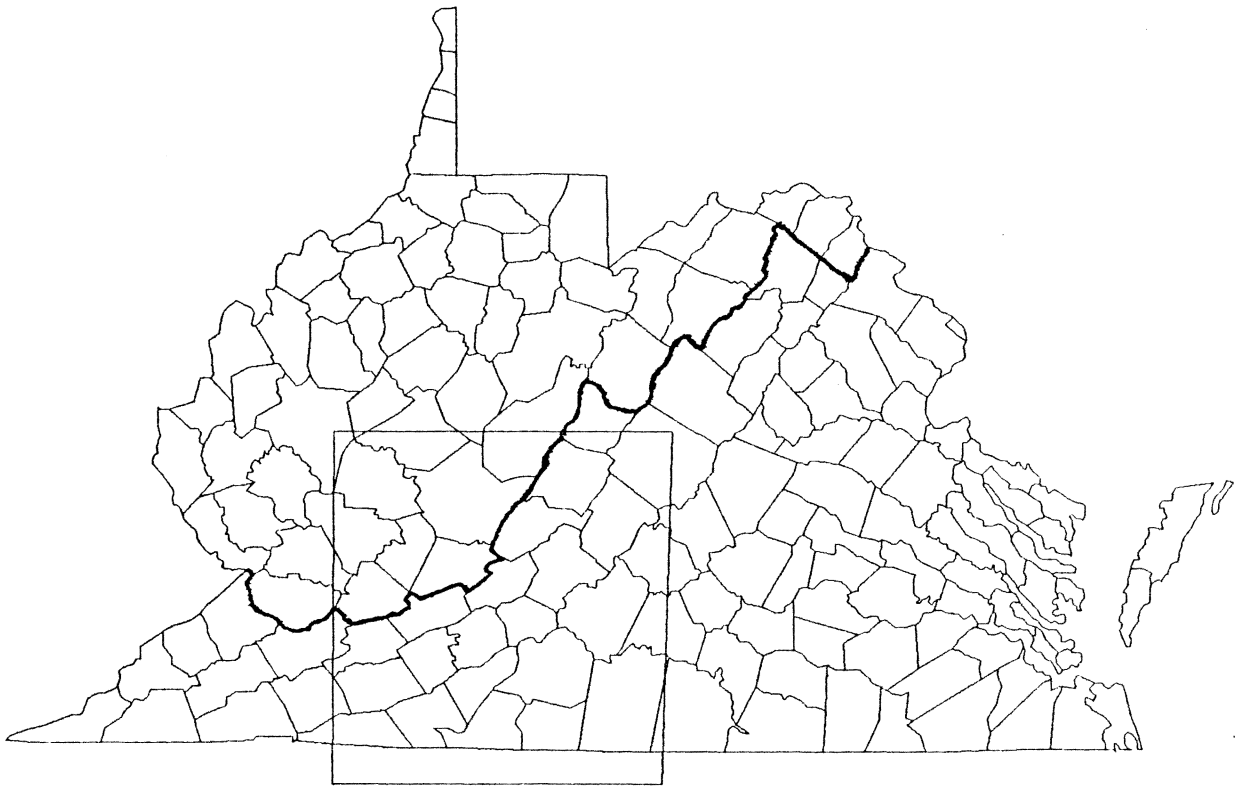


Fig. 1. Approximate coverage of Landsat scene 8536014502500, April 13, 1976.

Table 1. Appropriate parameters for Landsat 1 Scene 8536014502500.

Film-Source:	B & W - 02.1
Band Quality (Bands 4 5 6 7):	8 8 8 8
Cloud Cover:	00%
Exposure Date:	04/13/76
Scene Center Point:	N37D33M00S W080D24M00S
Scene Scale:	1 : 3,369,000
Corner Point Coordinates:	1. N38D01M38S W079D05M09S 2. N38D19M31S W081D07M35S 3. N36D47M35S W081D37M39S 4. N36D30M10S W079D37M36S

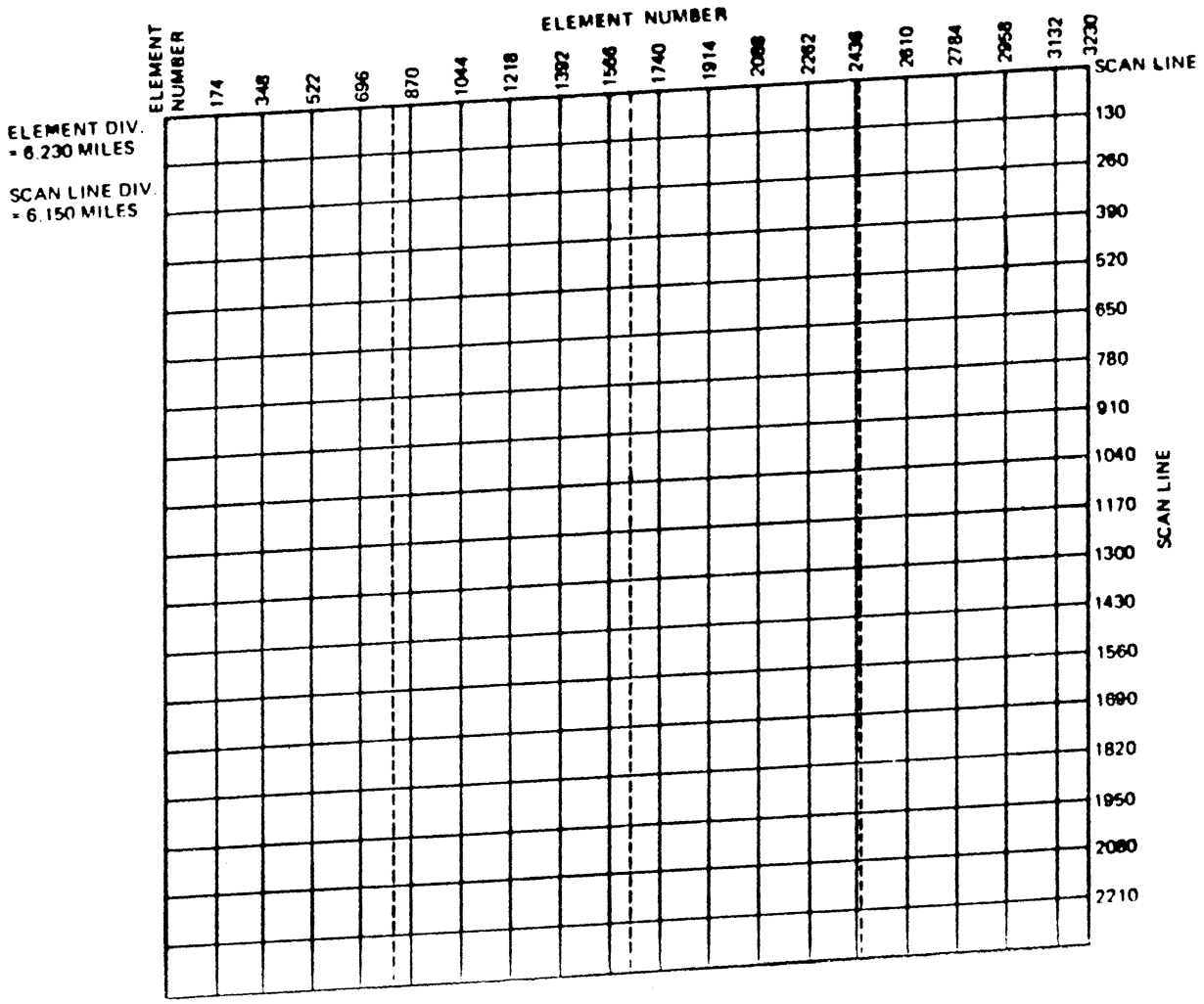


Fig. 2. Overlay used in selecting a tentative study area from a complete Landsat scene.

PREEX is a FORTRAN IV program written by the author which provides tape parameters and input and output format statements for subsetting an area from a Band Interleaved By Pixel Pair (BIP2) format tape. Information which was used to write this program is from Thomas (1975). PREEX outputs, which are used in subsequent tape subsetting programs, are provided on the lineprinter (FORTRAN Unit 6). A listing of program PREEX is provided in Appendix A.

The next step involved extracting the MSS data from the CCT. To accomplish this, a sequence of 4 FORTRAN IV computer programs (B4BLOC, B5BLOC, B6BLOC, and B7BLOC) were written for subsetting a 4-band image from the complete image stored on the CCT. Each of the 4 programs subsets a single band of the MSS data. Outputs include the subset radiance data (written to disk storage in 1-byte binary format) and values for the greatest and least radiance in the subset. Listings for these 4 programs are found in Appendices B, C, D, and E.

Because portions of Montgomery County were located on different CCT files, subsetting the areas required 2 PREEX and 2 B_BLOC runs for each band. This resulted in there being 2 disk data files per MSS band. For purposes of orienting, merging, and storing these bi-volume band data files into single files (i.e., one disk file for each band), FORTRAN IV programs GPCOL and GPROW were written. Differences between these programs are that GPCOL merges 2 data files in a east-west fashion (i.e. grouping by column) with GPROW merging 2 files north-to-south (i.e. grouping by rows). Respective program listings are found in Appendices F and G. The resulting 4 aggregate files, each 700 lines by 836 samples, represented the complete 4-band Landsat image for Montgomery County.

To serve as a precautionary measure, FORTRAN IV program RANK (Appendix H) was written to recheck the largest and smallest radiance values present in each aggregate file. This program was executed proceeding GPCOL and/or GPROW.

GRAY SCALING

To remove the possibility of gray scaling incorrect disk data sets (i.e., sets generated during unsuccessful subset and merge program runs), another validity check was performed prior to gray scaling. This was performed using FORTRAN IV program READCHK (Appendix I). The purpose of READCHK is to audit MSS values at specific column intervals to determine if obvious errors are present. If READCHK outputs proved unsatisfactory (i.e., alphabetic or special characters present in place of MSS numbers), it was then necessary to resubset and remerge the data.

If outputs from program READCHK appeared satisfactory, the next step was to produce representative gray scale images using the Versatec Electrostatic Printer/Plotter. These gray scale images as such were to be used in assessing image distortion due to atmospheric "noise". If necessary, unacceptable MSS bands (i.e. data containing few recognizable features as displayed by gray scaling) would be run through restructuring algorithms prior to image classification.

A maximum of 20 gray scale shades are available using the Versatec. Ranges of pixel radiance values (e.g., 1-5) were assigned a single shading value (1-20) with the number 1 representing white and 20 black. The FORTRAN IV program which uses these ranges and gray scale values as inputs is NASAGRAY (G. Koeln, pers. comm.).

Two methods were tested for producing quality single-band gray scale images. Both were involved with selecting an optimum range of radiance values upon which to assign a gray scale shade. Resulting radiance ranges would be different for each data set.

Method 1 is a manual task which involves dividing the range of radiance values for each band by 20 (the number of gray scales) to find the initial radiance interval. If this interval value includes a fractional remainder, this remainder is then truncated leaving an integer value. The next step is to calculate cut-off bounds for the first 19 gray scale intervals by initially adding the interval value to the smallest pixel MSS value and thereafter (18 repetitions) to the sum. In other words, if the smallest and largest MSS values were 0 and 49, respectively, for a band 7 data set, the range would equal 49. By dividing 49 by 20 the initial interval would equal 2.45, after truncation equaling 2. In calculating bounds, the value 2 would first be added to 0 (=2) and thereafter 2 would be added to respective sums producing bound values such as 2, 4, 6, 8, 10, etc., up to 38 (nineteenth repetition). Each gray scale would be assigned MSS values which are less than (not inclusive of) the next greater bound. Hence, gray scale 1 would be assigned to MSS values 0 and 1, gray scale 2 to values 2 and 3, and so on up to gray scale 19 which would be assigned values 36 and 37. The twentieth gray scale would be assigned to all remaining MSS values.

One decision to be made when using method 1 was whether to use all 20 gray scales or to expand intervals by 2's or 3's and use less than 20 shadings. Experimenting was necessary to produce the most visually defining (in terms of surface-feature location) gray scale image.

The second method proved to produce slightly more discriminating gray scale images. This procedure involved generating a histogram (pixel radiance-frequency; Fig. 3) for the entire subset area so that natural breaks in the data were visible. These conspicuous divisions between peaks and valleys represent the approximate boundaries of separable classes in the relative radiance distribution. By noting the upper and lower radiance-level values associated with each peak and adjacent valley, and assigning a specific gray scale to represent each slope range, a more discriminating image resulted. Locations of peaks and valleys in the unidimensional histogram were determined using FORTRAN IV program PEAKVALY (Appendix J).

If output from program PEAKVALY indicated that more than 20 divisions existed, these were reduced by aggregating neighboring slopes with radiance frequencies less than 500. This involved first combining slopes on the right side of the radiance-frequency distribution, then concentrating on the left and central portions of the histogram. Finally, these aggregates were incorporated within neighboring slopes. The process stopped when the division total was reduced to 20 gray scale classes.

Because of the size and high costs related to a 700 by 836 pixel matrix (pixel size = 0.05 in; 0.125 cm square), only images of bands 5 and 7 were plotted in their entirety. Two 200 x 200 pixel windows, representing only the northwestern portion of Montgomery County, are displayed in Fig. 4 (band 5) and Fig. 5 (band 7). FORTRAN IV program SUBSET (Appendix K) was used for extracting these two 200 x 200 pixel sets from the larger subimage. Gray scaling technique 2 was used for

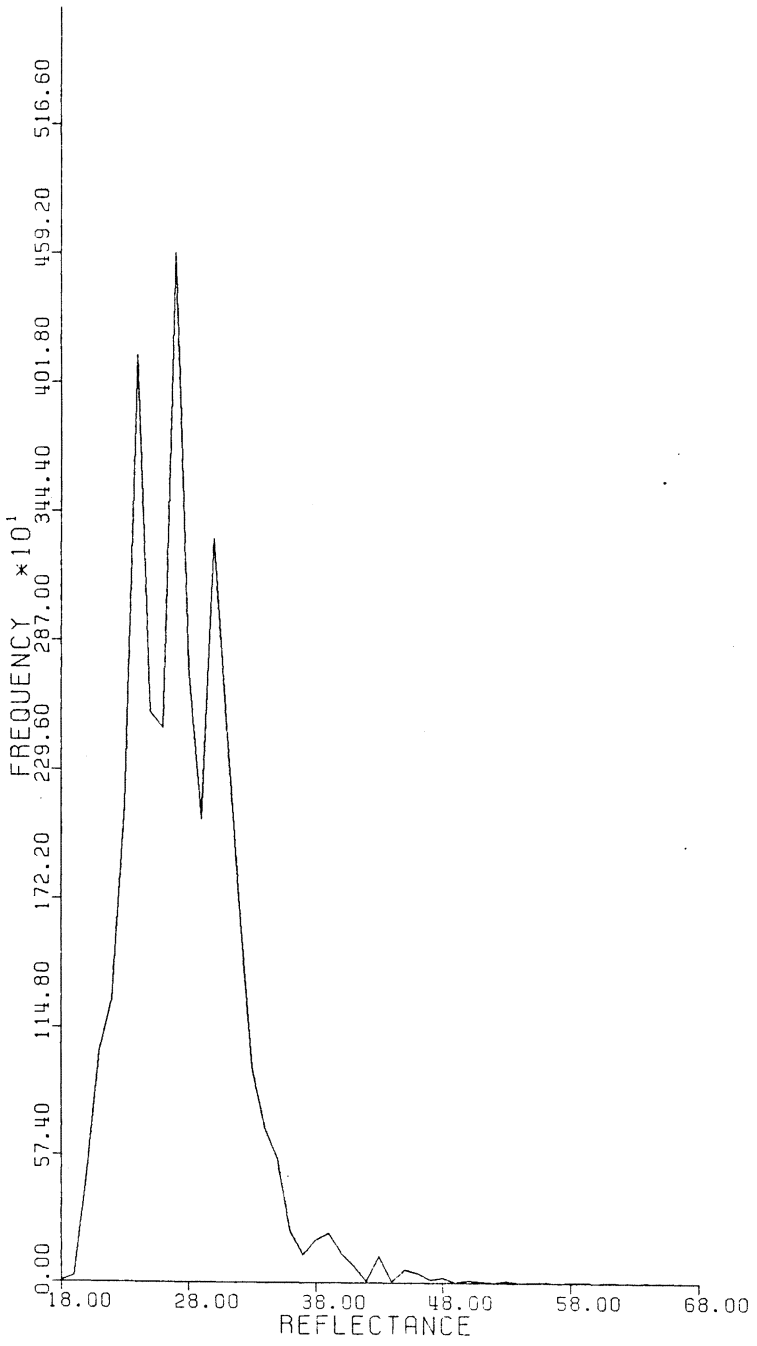


Fig. 3. Example histogram of pixel radiance values and frequencies.

Fig. 4. Gray scale image of MSS band 5 (600 to 700 nm) for northwest Montgomery County, Virginia. Low radiance ranges are assigned dark gray scale shades.

Fig. 5. Gray scale image of MSS band 7 (800 to 1100 nm) for northwest Montgomery County, Virginia. Low radiance ranges are assigned dark gray scale shades.

these two figures. For bands 4 and 6, gray scale images were only produced for areas along CCT file boundaries. This allowed for further error-checking of the merged image. These 2 images are not shown.

ATMOSPHERIC EFFECTS CORRECTION

The atmosphere may affect Landsat data in 2 ways (Taranik, 1978a).

1. Atmospheric absorption subtracts brightness from the longest wavelength, and
2. Atmospheric scattering adds brightness values to the shorter wavelengths, detected by the MSS.

These effects commonly cause data from band 7 to have 0 brightness even when no objects of 0 radiance are in the scene and cause the darkest pixels in bands 4, 5, and 6 to have especially increasing brightness values (J. Campbell, pers. comm.).

Since adjustments for atmospheric absorption are difficult to determine because absorption is largely a function of free water vapor (Taranik, 1978a), no attempt was made to correct band 7 for this effect.

To determine whether high levels of atmospheric scattering detracted from band 4, 5, and 6 image quality (Montgomery County), FORTRAN IV programs ATMCOR (Appendix L) and CNSTRCH (Appendix M) were written. Both computations leave the original content of the image data unaffected.

The purpose of program ATMCOR is to shift the histograms of bands 4, 5, and 6 to the left so that 0 values appear in the data. The displacement of values is accomplished by subtracting the lowest brightness value in a band from all brightness values in the band. This rescaling

was desired because it adjusts radiance data to correct for atmospheric scattering of band 4, 5, and 6 wavelengths (Chavez, 1975).

The purpose of program CNSTRCH is to magnify subtle variations in image radiance values. The operation utilizes a linear stretch algorithm over an 8-bit (0-255) range in order to separate the pixel radiance levels as much as possible. By extending the left histogram tail to 0, results are similar to those of program ATMCOR. Figs. 6 through 14 display the radiance-frequency histograms of bands 4, 5, and 6 (Montgomery County) along with distribution changes proceeding ATMCOR and CNSTRCH procedures.

A past problem with contrast stretch operations has been that cloud-free scenes do not result in images with the same brightness values as scenes with clouds (Taranik, 1978b). This is caused by the much larger range of brightness values initially present (i.e., pre-contrast stretch) in the scenes with clouds. A larger brightness range shows less "stretch-effect" than a smaller brightness range (e.g., cloud-free scene). Since this portion of the study seeks to remove atmospheric "noise" on a single cloud-free scene (non-temporal analysis), this problem was not of immediate importance.

Distortion free gray scale images derived using ATMCOR and CNSTRCH and raw data images were then compared by ocular means. Using this technique there appeared to be no image distortion due to atmospheric "noise". The raw Landsat data as such were to be input into image classification algorithms.

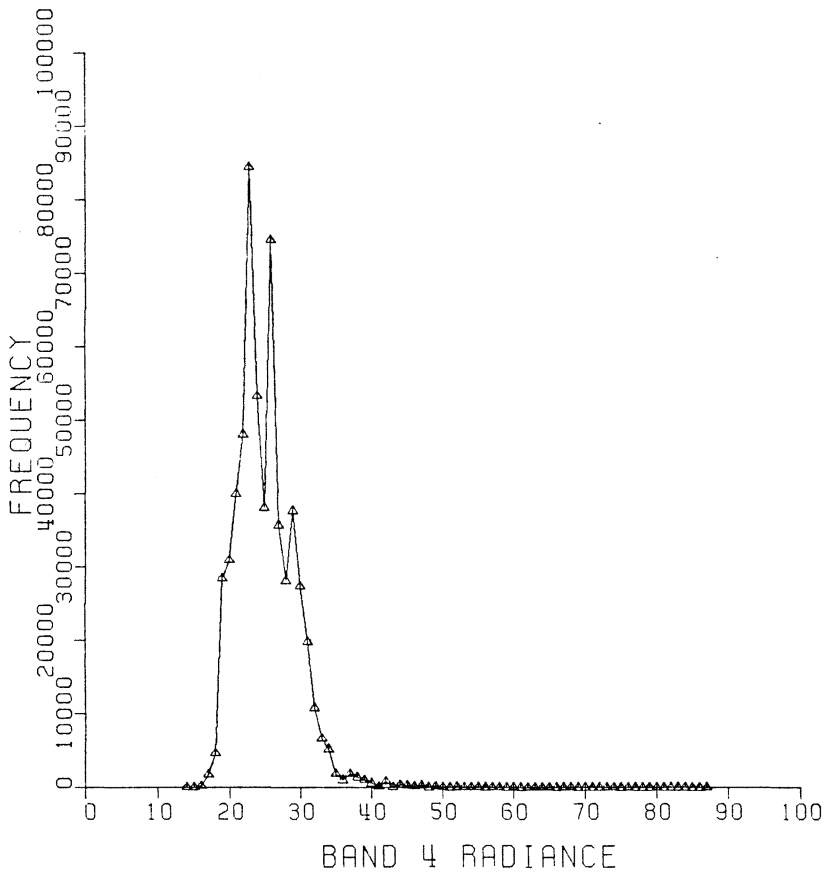


Fig. 6. Histogram of MSS band 4 for Montogomery County, Virginia.

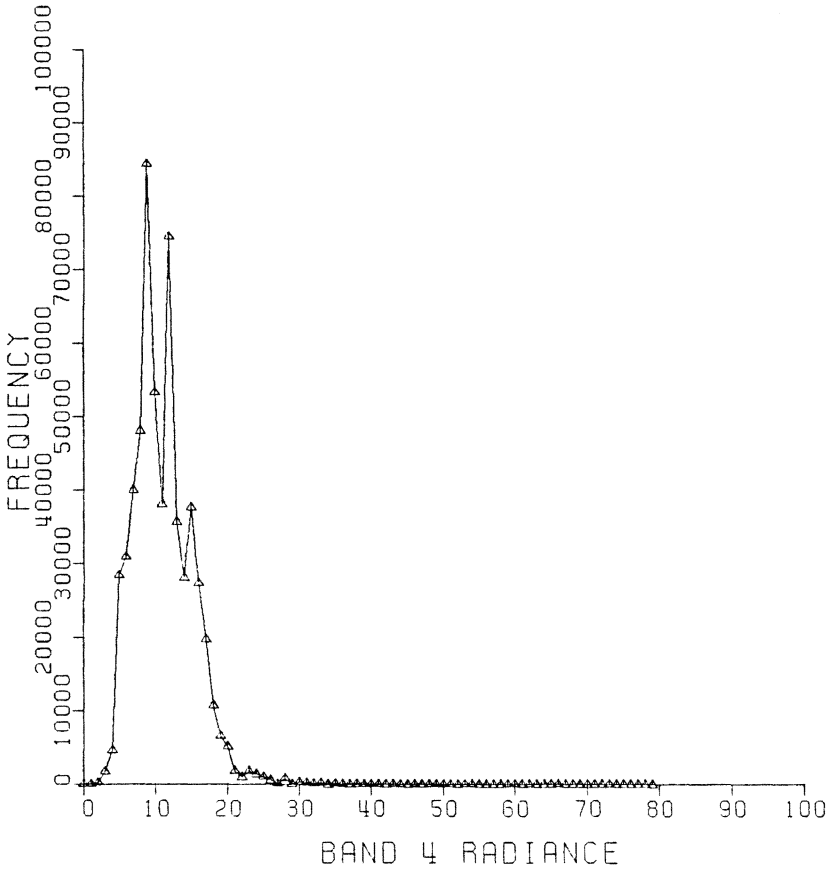


Fig. 7. Histogram of MSS band 4 for Montgomery County, Virginia following an atmospheric scattering correction procedure.

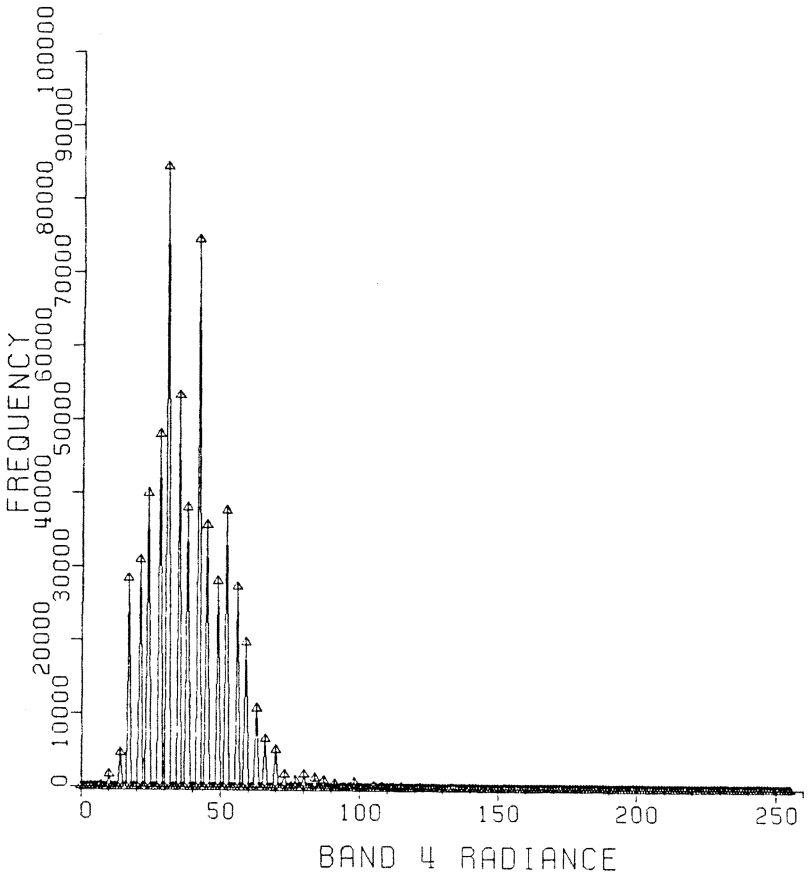


Fig. 8. Histogram of MSS band 4 for Montgomery County, Virginia following a linear contrast stretch procedure.

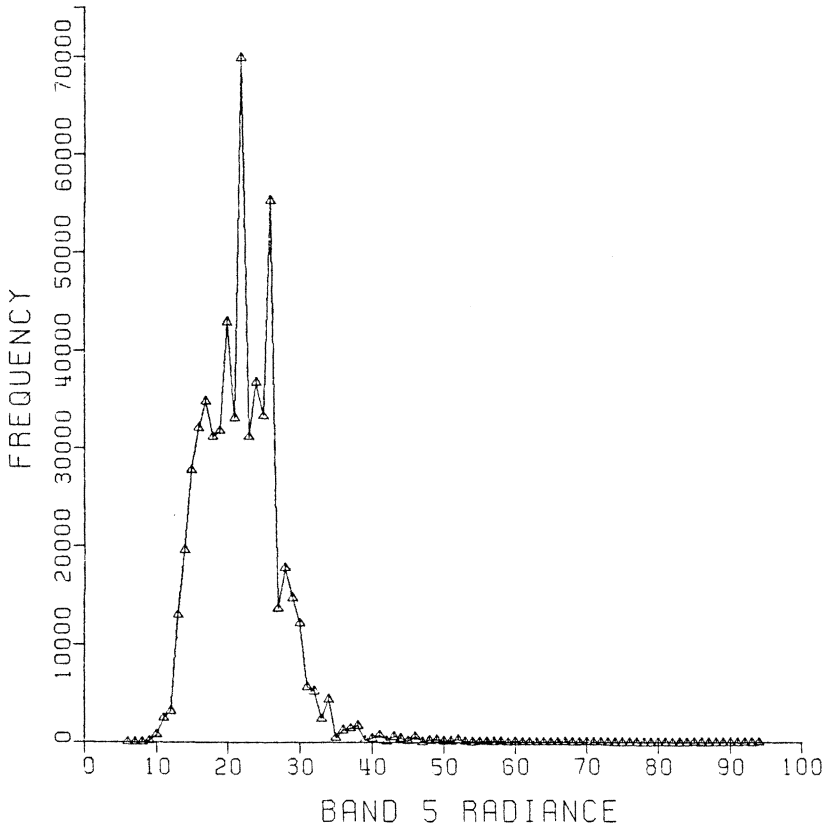


Fig. 9. Histogram of MSS band 5 for Montgomery County, Virginia.

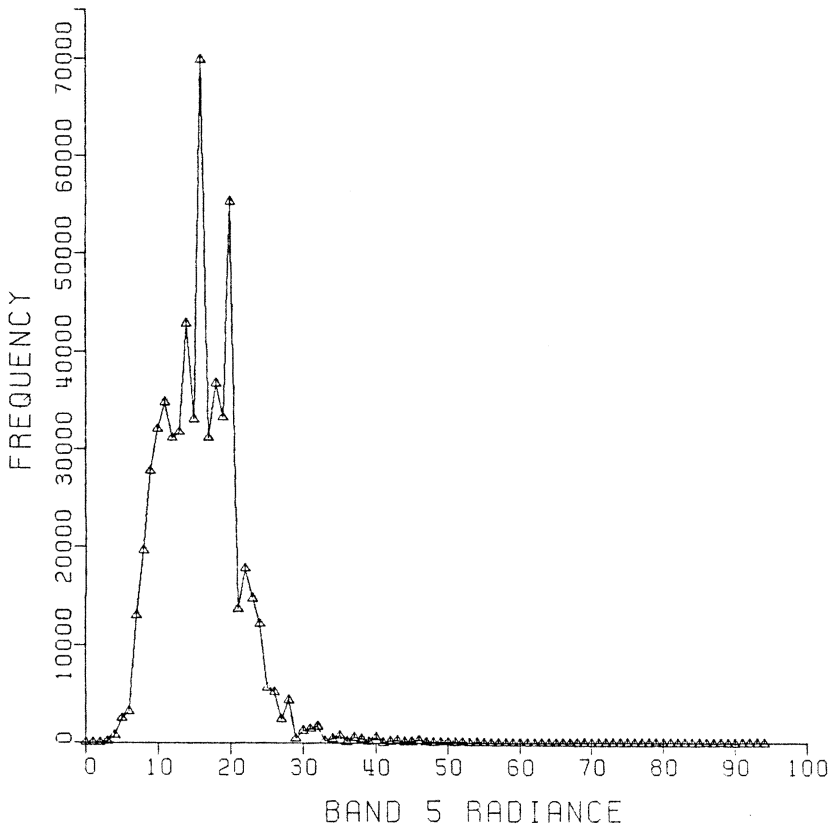


Fig. 10. Histogram of MSS band 5 for Montgomery County, Virginia following an atmospheric scattering correction procedure.

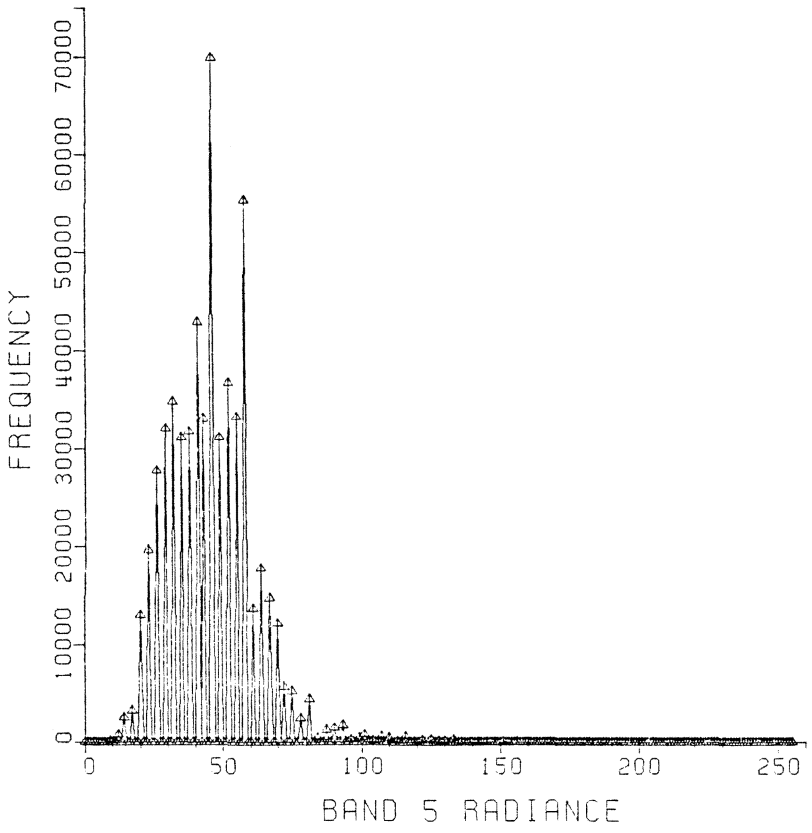


Fig. 11. Histogram of MSS band 5 for Montgomery County, Virginia following a linear contrast stretch procedure.

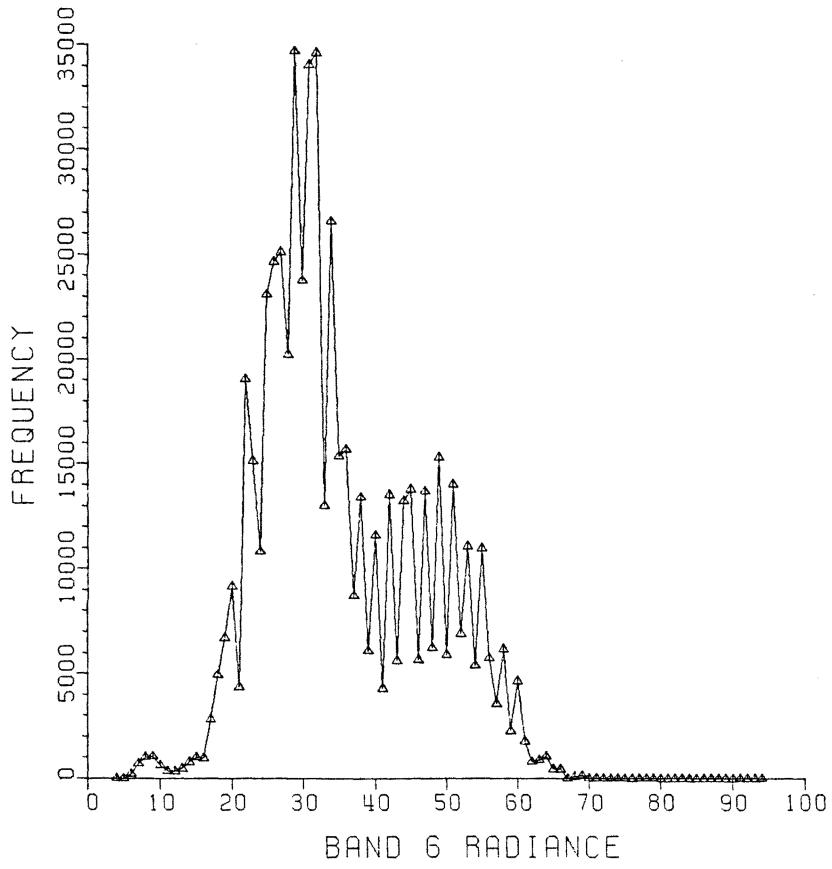


Fig. 12. Histogram of MSS band 6 for Montgomery County, Virginia.

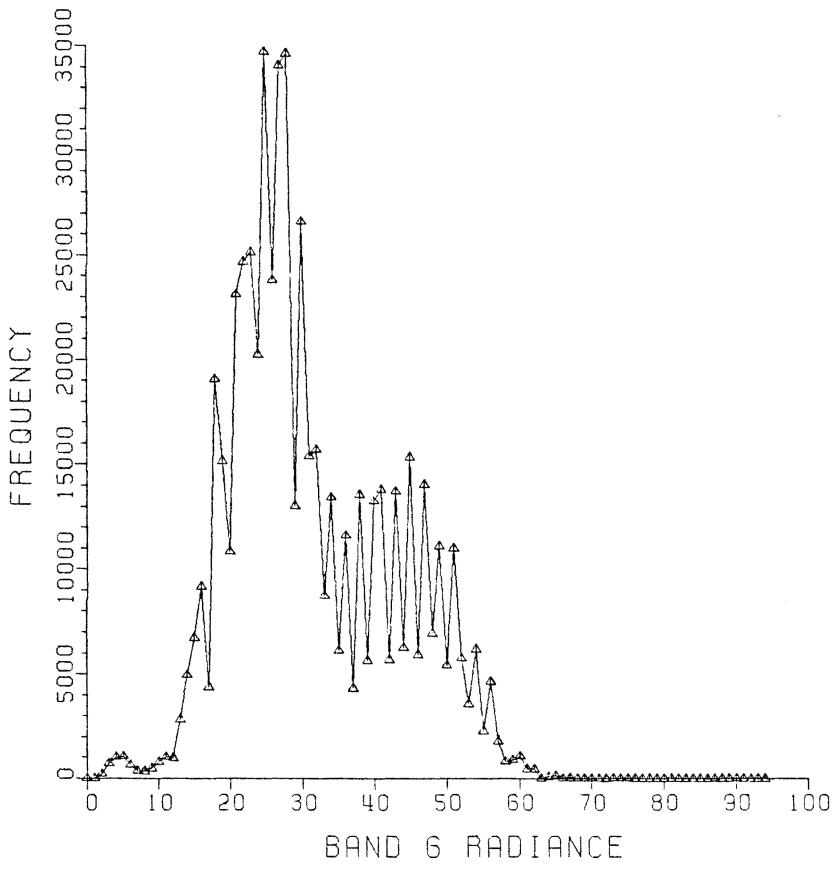


Fig. 13. Histogram of MSS band 6 for Montgomery County, Virginia following an atmospheric scattering correction procedure.

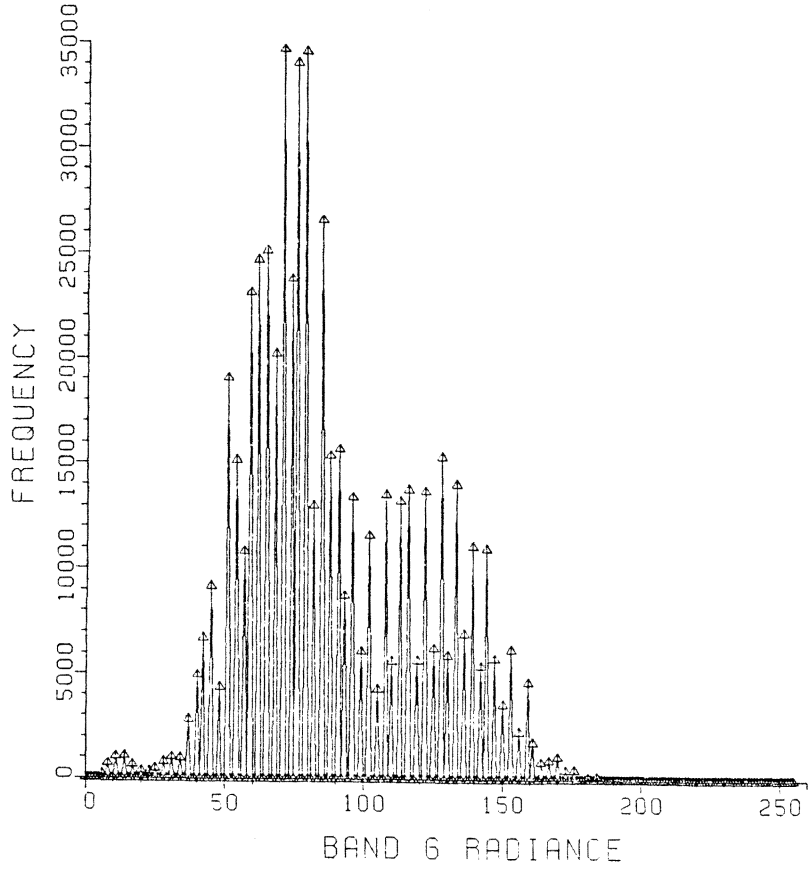


Fig. 14. Histogram of MSS band 6 for Montgomery County, Virginia following a linear contrast stretch procedure.

STUDY AREA SELECTION

Before discussing the next preprocessing step, the study area selected for the land use and cover classification will be described. Because of the vagaries associated with using "land use and cover" to denote each land and water classification category (e.g., deciduous forest, cropland, etc.), I shall use just "land use" as the general term from here on. Due to research cost-constraints, this area was to be smaller (less number of pixels) than the complete Montgomery County subscene.

The area is located in the northeast portion of Montgomery County, Virginia. The complete area is displayed on portions of 4 U.S. Geological Survey 7.5 minute quadrangles: Blacksburg, Eggleston, Newport, and Radford North. The tract is square with edge dimensions of 13.2 km (8.2 mi) and an area of approximately 174.57 km^2 (67.4 mi^2). Universal Transverse Mercator (UTM) boundaries are the 4100000 and 4123213 N lines and the 540000 and 553213 E lines.

A wide variety of Level 1 and 2 land use categories (Anderson, et al., 1976), are present within this area. This diverse pattern is characteristic of large portions of Montgomery County.

There are 3 major landforms within the tract. They are Brush Mountain in the northeast sector, the New River to the west, and Price Mountain in the south central zone. The elevation ranges from approximately 487.7 m (1600 ft) at the New River to 822.9 m (2700 ft) on Brush Mountain.

The following sections on physiography, geology and soils, climate and weather, and major vegetation types are taken from Brooks (1965).

Physiography

The study area is found in the southern Appalachian Ridge and Valley Physiographic Province. This region is composed of well-defined long narrow ridges and intervening valleys that lie between the Blue Ridge and Appalachian Plateau Provinces. The ridges and valleys form a near-continuous band trending northeast to southwest. Few streams cut across the rock trends and rectilinear or trellis drainage patterns are characteristic. Rock outcrops are common with rock strata heavily folded and often ranging from strongly inclined to almost vertical.

Geology and Soils

The dominant forest soils of the steep slopes and ridges are derived from sandstone and shale. Soils in the lower slope position and valleys are often limestone or have a limestone influence. Most of the sandstone- and shale-derived soils are considered somewhat excessively drained, low in natural fertility, and very strongly acid (pH 4.5-5.0) to strongly acid (pH 5.1-5.5). The soils with limestone, most of which are in agricultural uses, are well drained to moderately well drained, of medium fertility and medium to strongly acid (pH 5.1-6.0).

Climate and Weather

The total annual precipitation is 100 cm (40 in). Of this, 52.5 cm (21 in), or 53 percent, usually falls in April through September, which includes the growing season for most crops. Average seasonal snowfall is 70 cm (28 in). In summer, the average temperature is 21 degrees C (69 degrees F), and the average daily maximum temperature is 27 degrees

C (81 degrees F). For winter, the average temperature is 0 degrees C (32 degrees F), and the average daily minimum temperature is -6 degrees C (22 degrees F). The prevailing wind is from the west. Average windspeed is highest, 13 km/h (8 mi/h), in March.

Major Vegetation Types

The study area lies within the Appalachian hardwood subregion. Mixed oak forests occupy all forested tracts. Extremes in slope, aspect, and climate, as well as prior use of the land, result in a wide range of forest cover types and species mixtures. Forest cover types include (proceeding from poorest to best site),

1. Chestnut oak-Scarlet oak type,
2. White oak-Black oak type,
3. Sugar maple-Red oak type, and
4. Yellow-poplar-mixed hardwood type group.

Available moisture for plant growth is probably the most important single factor that directly and indirectly influences stand type productivity.

It is the exception rather than the rule to find pure stands in Appalachian hardwood forests. Many species have a range of environmental conditions under which they are capable of competing. In any one stand it is common to have 10 to 15 overstory species (Appendix PP), as well as numerous understory species, present within a hectare.

LANDSAT IMAGE PREPROCESSING

Image Rectification

Geometric registration of Landsat data to a map projection involves determining the spectral location of a pixel in the gray scale image and calculating a new location value for the pixel. This new value is a specific coordinate within a map projection system. The locational structure within POWER (Jones, 1976) was chosen as the basis for this correction procedure.

POWER

POWER is a cellular based geographic information system developed by the VPI & SU Department of Fisheries and Wildlife Sciences (Jones, 1976). Information is stored as numerical data describing a square cell or parcel of land. One hundred plus variables are currently stored within the POWER structure, all being coded from grid overlaid, 1:24000 scale (7.5 min) USGS topographic maps (Koeln, 1980). Serving as a data management and information system for Virginia, POWER utilizes a cell size of 1/9 km^2 (approximately 1094 feet per side or 27 acres). Capabilities exist for handling square cells of any size (Jones, 1976). Cells are alligned with the Universal Transverse Mercator (UTM) coordinate system.

Within the POWER structure geographic information is stored as a series of mapfiles. The mapfile format is representative of a square or rectangular 2-dimensional array. Each mapfile consists of blocks or maps of 900 cells arranged in a matrix of 30 cells south-to-north (Y

direction) and 30 cells west-to-east (X direction). Increasing Y coordinate values indicate movement north, and increasing X coordinate values correspond to movement east. Mapfiles are composed of individual maps in a similar south-to-north and west-to-east orientation. This data configuration allows access to individual maps, each represented by a sequence number. Cells in each mapfile must represent the same land area throughout a complete set of mapfiles because the POWER modules are independent of cell area. Additional information on the POWER system, its computer routines, and applications in corridor location and airport siting, can be found in Smart (1976), Jones, et al. (1976), Jones (1976), and Koeln (1980).

Registration

The following procedure was used for registering the uncorrected 4-band study area data to the POWER structure. The sequence can be divided into manual and machine-assisted steps. The manual portion (A.) involves collecting appropriate data about the location of control points from both gray scale and topographic maps. The machine-assisted procedure (B.) includes correcting and loading the study area data into the POWER structure.

A. Control Point Location. The steps in the procedure for locating control points are as follows:

   1. Produce a quality gray scale image of dimensions larger than the study area. In this study, the 700 by 836 pixel gray scale plot [pixel size = 0.125 cm (0.05 in)] from band 7 was judged best for spatial interpretation.

2. Define and record initial pixel control points according to line (row) and sample (column) location. This was done by placing an engineering scale registered to 0.125 cm (0.05 in) square pixel onto the gray scale image and recording locations. For this purpose a control point is defined by the author as a feature which can be precisely located on both a Landsat gray scale image and a reference map (e.g., bridges, road intersections, river bends).
3. Check, and if necessary correct (re-define) existing line and sample control point locations. FORTRAN IV program CPPLOT (G. Koeln, pers. comm.) was used to display a 10 by 10 window of radiance values surrounding a control point to assess control point accuracy.
4. Utilizing a minicomputer, graphics terminal, and digitizer, record UTM coordinate locations for control points using respective USGS 7.5 minute quadrangle maps as base maps. This process requires initial digitizing and recording of boundary UTM tick mark locations from quadrangle maps. These locations then serve as inputs to a triangulation program (B. Jones, pers. comm.) which defines transformation factors and the UTM location when the specific control point location is digitized.

B. Data Transfer to POWER

1. Define characteristics of study area for use in POWER programs. This procedure utilized FORTRAN IV program

DEFINE (Jones, et al., 1976). The purpose of this program is to create a disk file describing a mapfile and the relative portions in the file of maps to be included in the study area. The output file from this program is used to describe the study area.

In defining the actual study area, calculations showed that it would take 16 POWER maps (4 rows by 4 columns) to store the study area data. This area was not to be included as part of the POWER state image.

2. Create a storage area of adequate size to hold the data set. This procedure utilized FORTRAN IV program INITIAL (Jones, et al., 1976). The purpose of this program is to create a mapfile within a study area, as described by program DEFINE, having all cell values assigned the common value 0.

3. Geometrically correct (a.) and resample (b.) data within the POWER-UTM projection. This step utilized FORTRAN IV program BINFIT (G. Koeln, pers. comm.).

   a. Correction

      Prior to the initial subsetting step, the CCT data had not undergone any geometric correction. Before input into POWER, data correction was performed using an Affine transformation within program BINFIT (G. Koeln, pers. comm.). Transformation inputs included line and sample control point locations and their respective UTM coordinates.

The Affine transformation is a geometric correction method which transforms straight lines into lines with altered distance between points and angles between lines (Bendix Aerospace Systems and Colorado State University, 1978).

The transformation used is expressed as:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} c_1 & c_2 \\ c_3 & c_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} c_5 \\ c_6 \end{bmatrix}$$

where x_1 and x_2 are the regularly spaced coordinates in the required output grid, and y_1 and y_2 are the equivalent coordinates (e.g., Landsat line and pixel number) in the input data. The constants c_1 through c_6 are determined by a "least-squares" process from the corresponding (y_1, y_2), (x_1, x_2) coordinates for a series of known points (e.g., ground control points). The Affine transformation process is equivalent to approximating the actual surfaces by "best-fit" planes.

b. Resampling

Since a UTM location on the ground will rarely correspond to an exact Landsat image pixel location, a procedure was necessary to estimate the actual radiance value at UTM ground locations. This procedure is resampling.

The resampling approach utilized in program BINFIT is a "nearest neighbor" interpolation (G. Koeln, pers. comm.). In this technique, a pixel radiance value equal to that of the nearest input pixel is assigned to the output pixel. Advantages for using the "nearest neighbor" approach are:

1. Values of the MSS data, as such, are not altered so the classification for the points will be predictable (Anuta, 1973), and
2. The new point generated by the "nearest neighbor" rule will not be more than one sample space away from its true position in the image.

   Within the actual data, each pixel was resampled to a 1/27 km^2 (3-acre) cell. This cell size allows 9 3-acre cells to be stored within the 1/9 km^2 (27-acre) POWER base.

   Initially, all MSS data sets were composed of the complete Montgomery County image. Registered and resampled data only included a subset of the county (see Study Area Selection) as specified by the Define file parameters.
4. Determine largest and smallest resampled, registered radiance value. This procedure utilized FORTRAN IV program EXTREMES (G. Koeln, pers. comm.). The purpose of this program is to display the largest and smallest radiance

value within the complete mapfile and for each individual POWER map.

5. Create a gray scale image of the data set. Here, FORTRAN IV program RGRAYPWR was used. The purpose of this program is to create a representative gray scale image from data within a POWER mapfile using the Versatec Electrostatic Printer/Plotter (G. Koeln, pers. comm.). Gray scale images and radiance-frequency distributions for bands 4, 5, 6, and 7 (study area data sets) are shown in Figs. 15 through 22.

   Upon completing these steps, bands 4, 5, 6, and 7 were ready to be transferred to the General Image Processing System (GIPSY) for image classification.

GIPSY

A primary interest of this study is to contribute accurate large area land use information to a GIS. To accomplish this a machine-assisted data processing approach was chosen. The specific software package selected is GIPSY developed by Dr. Robert Haralick, students, and colleagues.

GIPSY is an interactive digital image processing system. It is composed of a collection of approximately 150 computer subroutines applicable to land use classification. The subroutines are structured

Fig. 15. Gray scale image of study area MSS band 4 emphasizing low radiance ranges as dark gray shades.

Fig. 15. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
13. - 23.		4325
23. - 25.		1918
25. - 26.		1719
26. - 28.		1892
28. - 29.		1375
29. - 36.		2754
36. - 37.		88
37. - 41.		208
41. - 87.		121

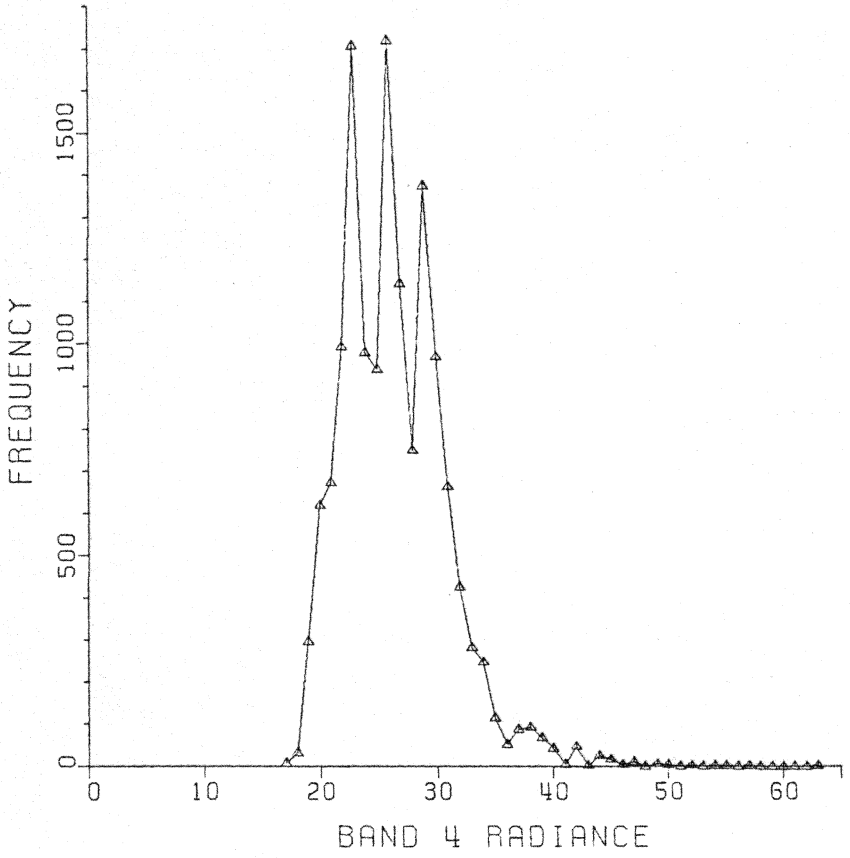


Fig. 16. Histogram of study area MSS band 4.

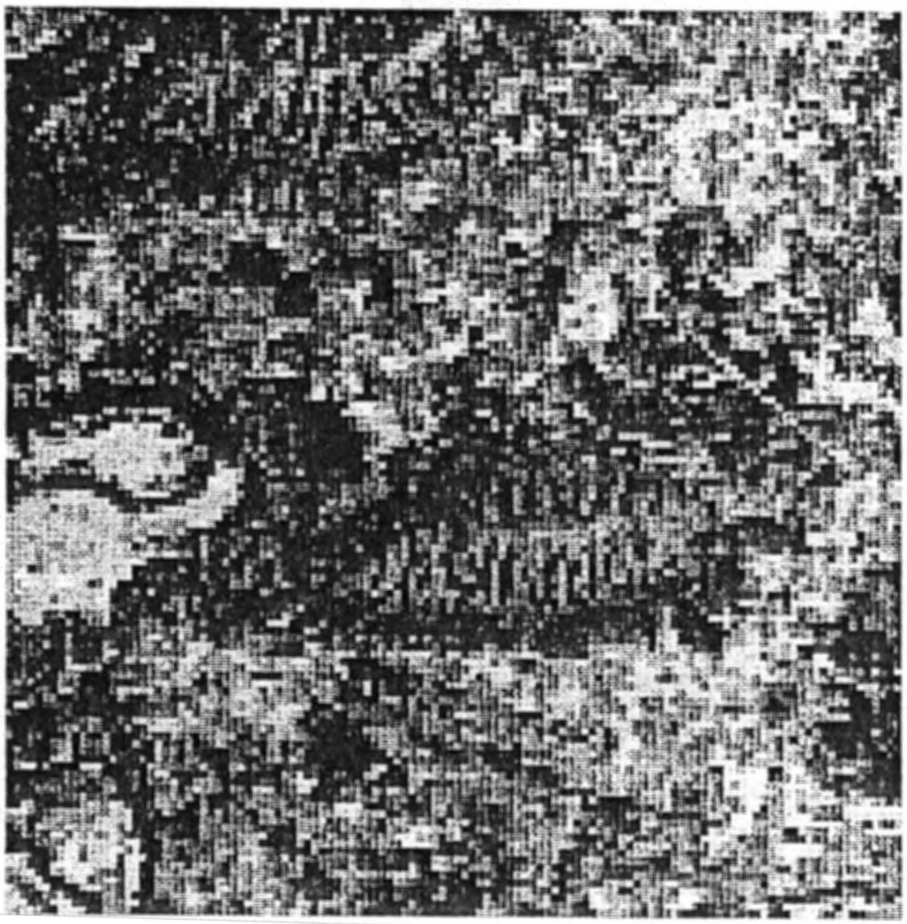


Fig. 17. Gray scale image of study area MSS band 5 emphasizing low radiance ranges as dark gray shades.

Fig. 17. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
5.	- 17.		2550
17.	- 18.		795
18.	- 20.		1871
20.	- 21.		837
21.	- 22.		1756
22.	- 23.		717
23.	- 24.		1013
24.	- 25.		809
25.	- 26.		1357
26.	- 27.		357
27.	- 28.		454
28.	- 33.		1251
33.	- 34.		179
34.	- 35.		20
35.	- 39.		218
39.	- 42.		63
42.	- 43.		39
43.	- 45.		20
45.	- 94.		96

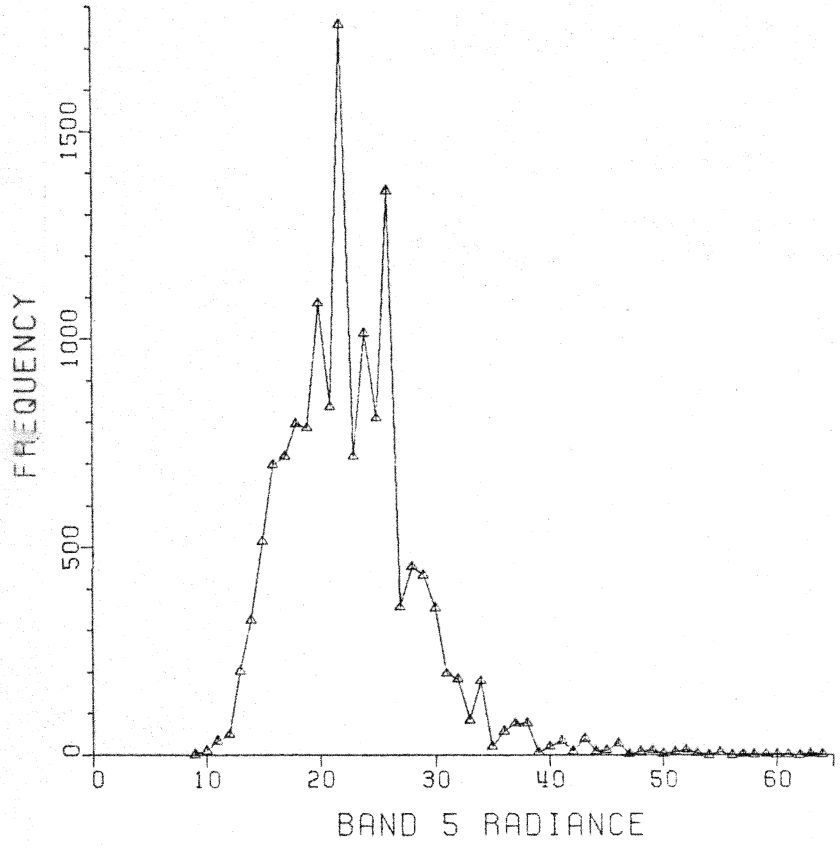


Fig. 18. Histogram of study area MSS band 5.

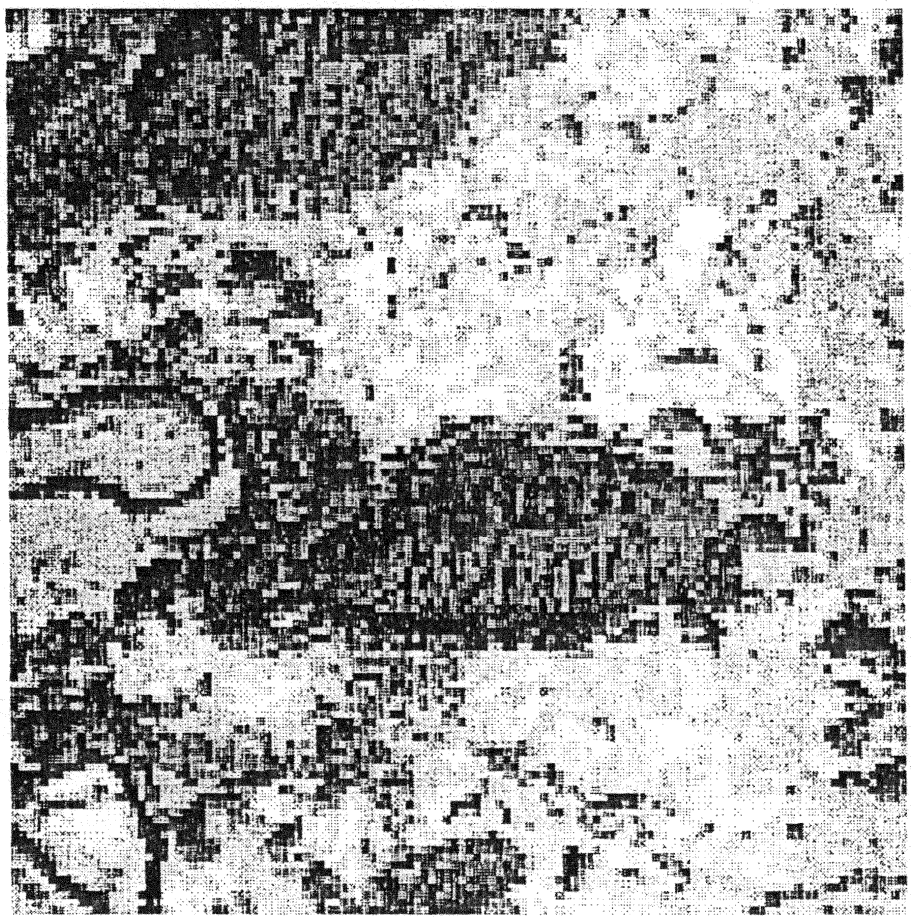
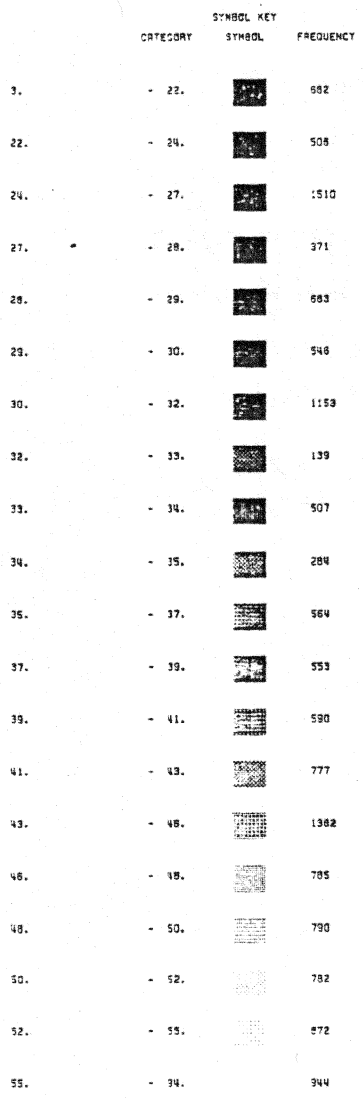


Fig. 19. Gray scale image of study area MSS band 6 emphasizing low radiance ranges as dark gray shades.

Fig. 19. (Continued).



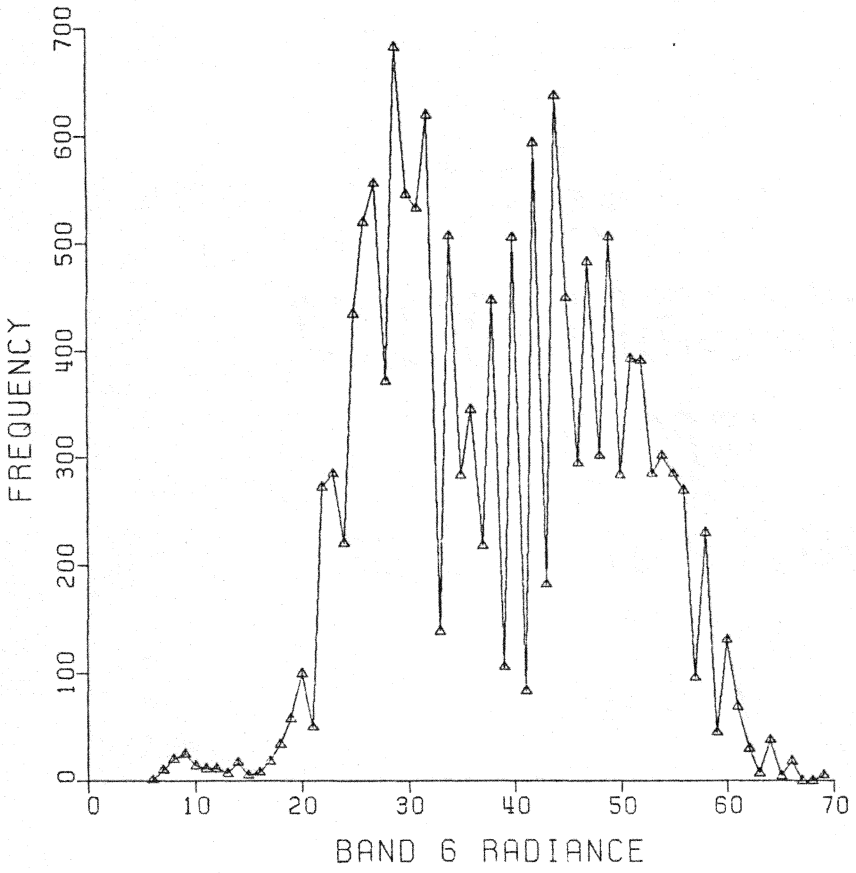


Fig. 20. Histogram of study area MSS band 6.

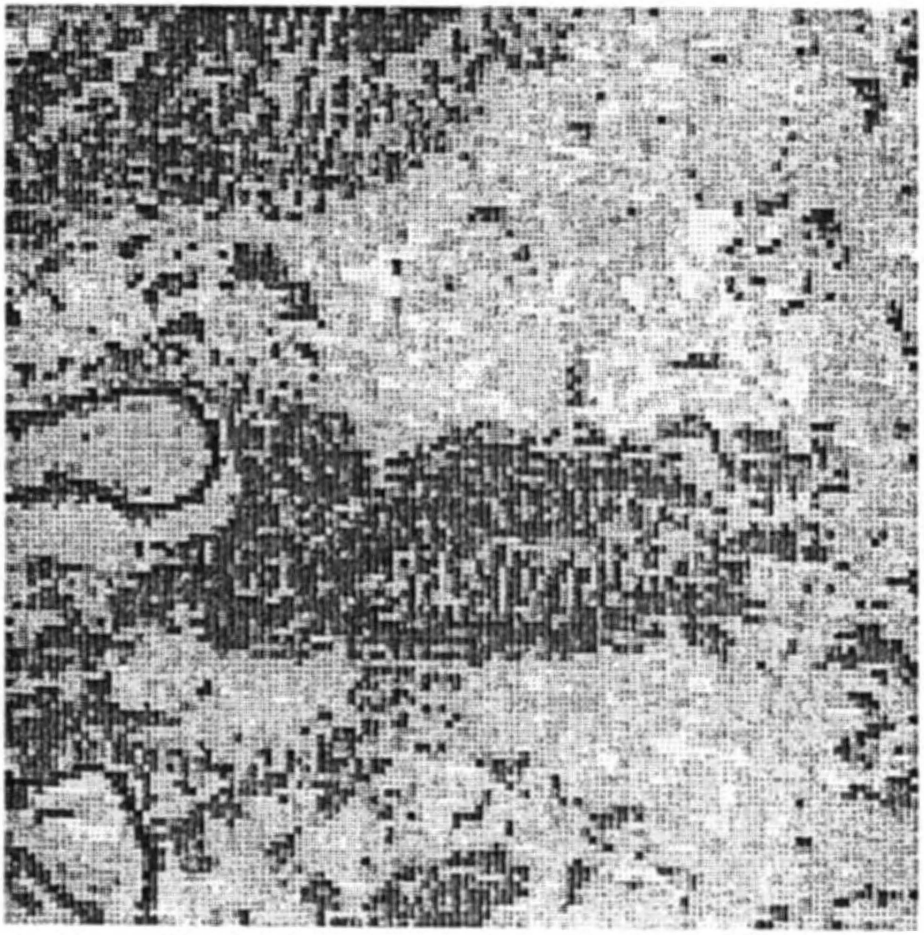


Fig. 21. Gray scale image of study area MSS band 7 emphasizing low radiance ranges as dark gray shades.

Fig. 21. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 1.		10
1. - 4.		80
4. - 14.		2942
14. - 15.		865
15. - 16.		1035
16. - 23.		4635
23. - 24.		674
24. - 31.		3105
31. - 32.		282
32. - 49.		772

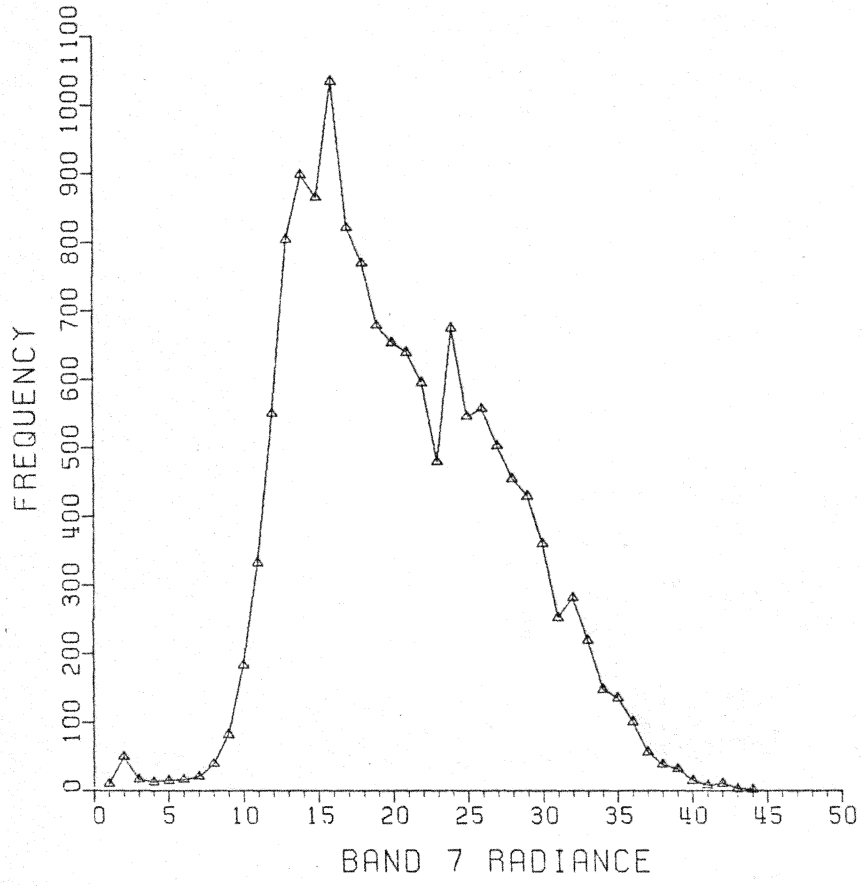


Fig. 22. Histogram of study area MSS band 7.

in a modular fashion, with little dependence of one command upon another. Originally designed for processing MSS digital data, GIPSY modules now have the capabilities of also utilizing ancillary information in its classification and display schemes. Additional information concerning GIPSY can be found in Krusemark (1981).

Data Transfer: POWER to GIPSY

Landsat data transfer from POWER to GIPSY involved 4 steps.

1. Removing the POWER structure from the data sets. Restructuring was accomplished using FORTRAN IV program PWRDUMP (G. Koeln, pers. comm.). The purpose of this program is to take a POWER data set with a 4-byte binary format and reformat it to an ordinary 1-byte binary data set. The restructuring procedure itself involves deleting all file and map descriptor records and outputing only the matrix data to temporary disk storage.
2. Writing the restructured data to magnetic tape. IBM utility program IEBGENER was used to write the restructured data sets to an unlabeled tape (1600 bits per inch). IEBGENER is set up in exec form for interactive processing. Statements and prompts are given for the names and characteristics of each input data set and the specific type and name of the output medium. Results showed each disk data set occupying a single tape file.
3. Delivering the tape to the VPI & SU Spatial Data Analysis (SDA) Laboratory wherein GIPSY is operated.

4. Loading the individual data sets into the VAX computer system in GIPSY standard image format. This last step was done by members of the SDA staff.

LANDSAT IMAGE CLASSIFICATION

Multispectral Classification

For each pixel in a Landsat image, the spectral radiance is recorded at 4 different wavelengths (i.e., bands 4, 5, 6 and 7). A pixel may be characterized by its spectral signature, which is derived from the radiance in the different wavelengths. Multispectral classification is an information extraction process that analyzes the spectral signatures and then assigns pixels to classes based on similar signatures (Sabins, 1978). The two general types of classification schemes are supervised and unsupervised. According to Sabins (1978) they possess the following differences:

1. Supervised classification uses independent information to define training data that are used to establish classification categories. The independent information may be spectral reflectance data for the classification categories or knowledge of the location of areas within the image that typify each of the desired classification categories (i.e., training areas).
2. Unsupervised classification uses only the statistical properties of the image data as a basis for classification. The computer alone defines the classification categories. This method is potentially useful for classifying images where the analyst has no independent information about the scene.

Unsupervised Classification

To facilitate the large-area land use classification requirements of this thesis, an unsupervised method of analysis was used (Su and Cummings, 1972; Haralick and Kelly, 1969). Unsupervised classification has several distinct advantages over supervised methods as listed in Morain (1978).

1. No "a priori" knowledge of the study site is required. This negates supervised classification problems associated with obtaining costly and sizeable pure samples of an information class (Swain, 1978). Such samples (i.e., training sets) are needed to estimate adequately the mode and variance statistics for a land use analysis;
2. Human bias and machine-assistance is minimized since the statistics of the data govern the analysis;
3. Classes are, generally, more homogenous and it is easier to select a class title or description after reviewing all members of a class than it is to identify a class and then have the computer search for the class number; and
4. The method allows for the identification of those data in the set that are unique or residual. These entities may then have additional inquiry assigned to them in the future.

Cluster Analysis

Cluster analysis was chosen as the specific technique to be used in the unsupervised classification. Through clustering it is possible to detect a tendency for a set of Landsat radiance and/or ancillary group

values to accumulate or group near a mode. In theory, spectrally distinct classes cannot have a multimodal probability function (i.e., have more than a single maximum) (Swain, 1978). If multimodality exists, cluster analysis subdivides the offending class or classes into subclasses which each have unimodal and approximately normal probability functions.

Computer implementation of clustering algorithms within GIPSY extend capabilities beyond the 2- or 3-dimensional limitations which are inherent in visual analysis. If it is necessary to specify how many clusters are to be created, the algorithm selects the appropriate number of clusters thought by the analyst to be an adequate representation of differing land use signatures in the study area. The series of GIPSY commands leading up to and including cluster analysis will be presented in Appendix Z.

Because of the large number of spectral bands to be used in the clustering procedure and the desire to keep computing costs low, preliminary processing included using a principal components transformation. The purpose of a principal components transformation was to reduce the inherent dimensionality of data by removing redundant or highly correlated information (Morain, 1978; Swain, 1978; Hielkema, 1979; R. Haralick, pers. comm.).

Using FORTRAN IV program REGRESS (Appendix N), each of the 4 raw Landsat bands was compared to each other to find the degree of positive relation. The population for this test included the complete 700 line by 836 sample matrix for Montgomery County (sample size = 585,200).

Results are shown in Table 2. The bands exhibiting the lowest correlation were bands 5 and 7 with the highest correlation being of bands 6 and 7.

After initial clustering of the 4-band data set, it became apparent that an inflated number of clusters (> 200) would be necessary to represent adequately the study area. The reason was that many pixel radiance values were so spectrally different from other pixel values, they constituted single pixel clusters. Since the information derived from these single pixel clusters would not be worth the computer costs to derive and process them, an alternate strategy was chosen.

The strategy selected involved using GIPSY command ELIMRG which removes and reassigns pre-cluster regions possessing a number of pixels less than a specific threshold. Since the original objectives of the clustering procedure were oriented toward large area land use classification, it was felt that the loss of information present within a single pixel pre-cluster region would be minimal.

Three levels of region removal and reassignment were selected upon which to process the 4-band image. These levels were:

≥ 5, ≥ 9, and ≥ 13.

All region sizes greater than or equal to 5, 9, or 13 pixels were to remain intact, all others were to be removed and reassigned. In other words, 3 classified images were to be generated from the 4 bands of Landsat data. The first classified image would be composed of only those clusters possessing 5 or more pixels, the second image would be composed of only clusters possessing 9 or more pixels, and the third made up of clusters possessing 13 or more pixels.

Table 2. Regression analysis showing the degree of positive similarity among each pair of Landsat bands.

X	Y	R	R^2
Band 7	Band 5	0.56	0.31
Band 6	Band 5	0.65	0.42
Band 7	Band 4	0.70	0.49
Band 6	Band 4	0.78	0.61
Band 5	Band 4	0.90	0.81
Band 7	Band 6	0.96	0.91

It was hoped that the resultant accuracies derived from the 3 images would indicate the largest cluster size which could be removed and reassigned without lowering the corresponding classification accuracy. The smaller number of total clusters might also reduce computing costs.

Classification System

The system proposed by Anderson et al. (1976) was chosen as the basis for all land use definition and classification. Advantages of this system in wildlife related land use classification include the:

1. Applicability to regional and statewide land inventories,
2. Category definition(s) which permit land use(s) to be used as indicators of potential wildlife presence,
3. Year round (temporal) classification suitability,
4. Allowable options for aggregation or segregation of land use types within a GIS,
5. Standardized basis for comparison with other or future classification data, and
6. General acceptance and extensive use of the system.

Here, the objective was, first, to perform very accurate classifications within Level 2 and then to achieve as great as possible accuracy within Level 1.

Prior to Landsat land use classification, 2 slight modifications were made on the Anderson et al. (1976) system. These included:

1. To facilitate the classifiability of water, Level 2 water categories were merged and generalized into 1 category, water, and

2. To encourage agricultural-type separability, the Level 2 category Cropland and Pasture was divided into 2 classes.

Table 3 displays those classes, which were chosen for the land use and cover classification.

Accuracy Assessment

A necessary first step in the accuracy assessment was to prepare a type map for a portion of the study area. Information which was used in the typing included:

1. 9 by 9-inch, 1:40,000 scale black and white aerial photos. These were available for almost all of Montgomery County and were dated October, 1976, and
2. 9 by 9-inch, 1:24,000 scale natural color aerial photos covering U.S. Forest Service Lands (Jefferson National Forest) on Brush Mountain. These photos had an exposure date of April, 1975.

Photographs made more recently than the above to the April 13, 1976 Landsat image data were not available.

Type Mapping

A series of 7 steps were used in the type mapping. Steps 1 through 4 were originally outlined in Baker et al. (1979):

1. Using an overlay for delineating categories. A semi-transparent sheet of drafting film was cut to the 9 x 9-inch format of the photo print and taped to one photo of each stereoscopic pair,

Table 3. List of Level 1 and 2 categories and code numbers which were chosen for the Landsat land use classification.

Level 1	Level 2
1 Built-up Land	5 Water
2 Agriculture	8 Cropland
4 Forest	9 Pasture
5 Water	11 Residential
	12 Services
	13 Industrial
	14 Transportation
	17 Other Urban
	22 Orchards
	41 Hardwoods
	42 Conifer
	43 Mixed
	76 Transitional

2. Putting the effective area and accessory information (e.g., scale, photo ID number, exposure date, collimation marks) on the photo overlay. Delineating the effective area allows for minimum displacement of points from their map overlay position,
3. Delineating planimetric detail. This included existing roads, intersections, and water bodies which acted as control points.
4. Delineating type categories using stereoscopic coverage. Category definitions were representative of those Level 2 land use(s) and cover(s) listed in Anderson et al. (1976).
5. Transferring photo-overlay delineations to a transparent drafting film overlaid 1:24000 scale (7.5 min) USGS topographic map of the area. This procedure utilized a Bausch and Lomb Zoom Transfer Scope in the information transfer step.
6. Using field surveys conducted along roadways to assess the accuracy of the categorization. Since these surveys were done in April, 1981, category reassignment was performed only if drastic differences existed (e.g., Level 1 aerial interpretation contrasting with Level 1 ground interpretation).
7. Enhancing the location of all categories. Here, felt tip markers of different shades of ink were used, one shade denoting a single land use type.

The initial transfer of Level 2 cover type information to the POWER system involved overlaying a 1/9 km^2 (3-acre) grid sheet onto the type map-topographic map combination. Utilizing a graphics terminal, minicomputer, digitizer, and a modified version of FORTRAN IV, program PWR3030 (G. Koeln, pers. comm.), category assignment was based on the

majority (color dominant) Level 2 land use and cover within each cell. Numerical identifiers for categories were those used in Anderson et al. (1976) (e.g., 41 = Deciduous Forest Land). Areas within the study plot which were not mapped were assigned a null value. Only 1 file of information was created. Using FORTRAN IV program TEKCELLS (G. Koeln, pers. comm.), this information was then loaded into the POWER structure. The Level 2 ground truth image is displayed in Fig. 23.

To create the corresponding Level 1 ground truth data set, FORTRAN IV program CATEGORY (Jones, 1976) was used to aggregate Level 2 classes to their Level 1 representatives. Table 4 displays the various Level 2 categories and Level 1 counterparts. Inputs to program CATEGORY consist primarily of Level 1 and 2 numerical category identifiers. The execution process is simply a relabeling/renumbering procedure taking Level 2 identifiers (e.g., 41 = Deciduous Forest Land) and changing the values to those representative of Level 1 (e.g., 4 = Forest Land). The Level 1 image is not shown.

Analysis and Confusion

A. Confusion Matrices

A confusion matrix is a 2-axis matrix or table that shows on 1 axis the known classes (i.e., ground truth) and on the other axis the classes that have been interpreted or classified in an analysis (i.e., clustered and classified Landsat image). The matrix itself indicates both similarities that exist between Landsat and ground truth classes (i.e., correct classifications) and where "confusion" or misclassification (i.e., incorrect classifications) of land use(s) may exist. Factors

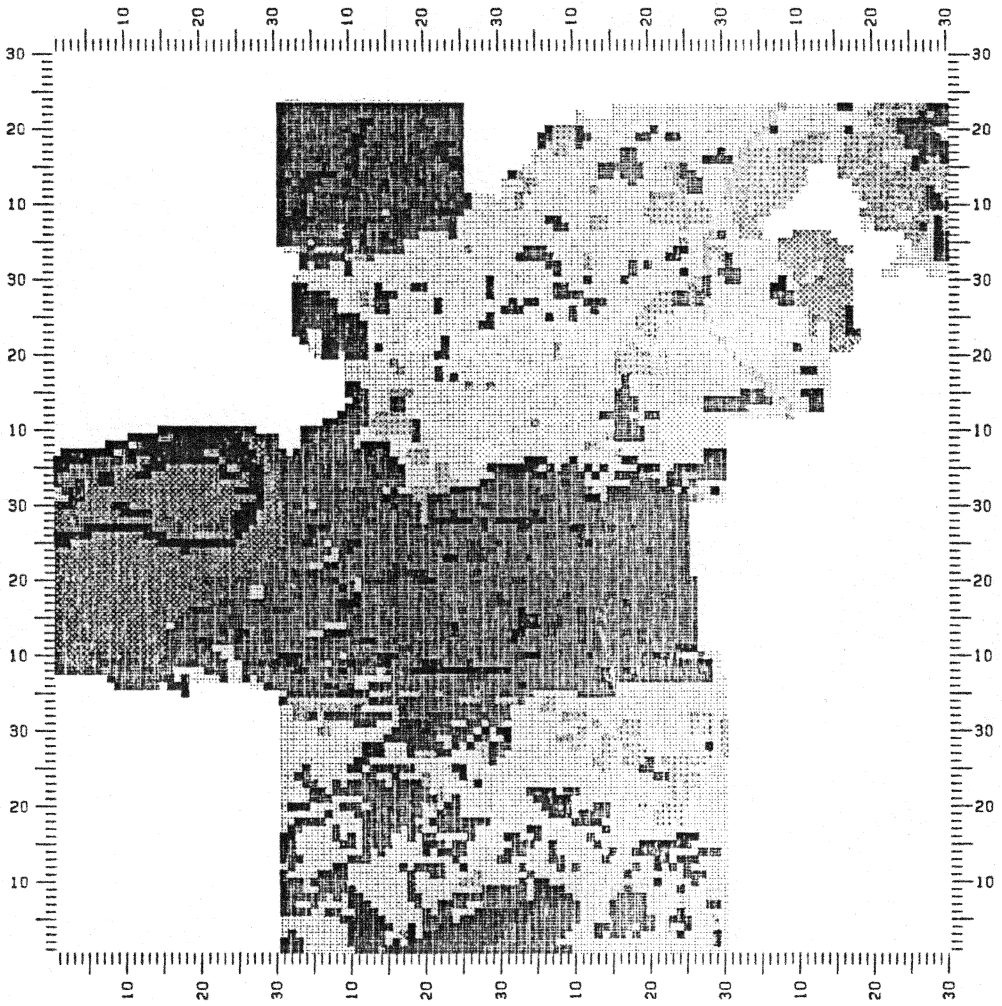


Fig. 23. Gray scale image of study area ground truth. Each land use is assigned a single gray shade.

Fig. 23. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		6129
5.	- 5.		83
8.	- 8.		115
9.	- 9.		3323
11.	- 11.		519
12.	- 12.		116
13.	- 13.		519
14.	- 14.		40
17.	- 17.		1
22.	- 22.		11
41.	- 41.		2587
42.	- 42.		410
43.	- 43.		536
76.	- 76.		11

Table 4. Land use classes were aggregated form Level 2 to Level 1 in the following groups.

Level 2	Level 1
Water	Water
Cropland	Agriculture
Pasture	
Orchards	
Residential	Built-up Land
Services	
Industrial	
Transportation	
Other Urban	
Transitional	
Hardwoods	Forest
Conifer	
Mixed	

which collectively contribute to land use misclassifications within Landsat data are found in McCloy (1980).

For this portion of the data processing, classification accuracies were calculated in the form of confusion tables as produced by FORTRAN IV program CONFUS (G. Koeln, pers. comm.). Prior to program execution, CONFUS requires 2 inputs:

1. a fully-clustered Landsat image; clusters having already been assigned numerical Anderson et al. (1976) land use codes, and
2. a similarly coded ground truth image of known land use locations.

Utilizing these inputs, program CONFUS was run twice for each classified scene, once according to a Level 2 categorization and the other for Level 1.

One option within CONFUS allows for specific image pixels to be omitted from the computation of an accuracy statistic. These classified pixels are those for which no ground truth data exist.

The approach used in assessing accuracy by way of program CONFUS is similar to a modified cluster routine. In this way, CONFUS compares the classified Landsat image to the ground truth image by recording the omissions (i.e., pixel losses to an incorrect class), commissions (i.e., incorrect pixel additions from other classes), and correct classifications (i.e., pixels which possess a classification equivalent to ground truth) as based on the ground truth class which comprises the greatest portion of a specific cluster. In this way if the location of 1 Landsat image cluster (9 pixels) is associated with a ground truth area made up of 7 water cells and 2 forest cells, the complete cluster is categorized

as just water. As part of the accuracy assessment for this cluster, 7 pixels are correctly classified as water and 2 are not. More specifically, these 2 misclassified pixels would be considered as being both omitted from the water class (i.e., water omission error) and committed to the forest class (i.e., forest commission error). Overall, the accuracy assessment for the complete image is conducted on a cluster by cluster basis for only those clusters with associated ground truth data.

Program CONFUS provides several specific indices as outputs. These include:

1. Pixel totals for all information classes,
2. Numbers of pixels accurately classified within an information class,
3. Number and percentage of both omissions and commissions within an information class, and
4. Overall study area classification accuracy.

Overall classification accuracy can be defined as a point-by-point (i.e., pixel-by-pixel) image accuracy measure which is based strictly on errors of omission. Omission error is produced when classified pixels are not assigned a correct land use categorization as determined by ground truth observations. Results for the overall classification accuracy index are calculated from the diagonal of a confusion matrix, and expressed in terms of percentage pixels correctly classified.

Overall classification accuracy is calculated using the following equation:

$$K = \frac{\sum_{I=1}^{n} N_I}{\sum_{I=1}^{n} T_I} \; 100$$

where: K = overall study area classification accuracy (in percent)

$\sum_{I=1}^{n} N_I$ = total number of correctly classified pixels in all n classes

$\sum_{I=1}^{n} T_I$ = total number of pixels in all n classes

Based on this equation, if K equalled 47 percent, this would indicate that 47 percent of all pixels possessed a correct land use classification, with 53 percent assigned to incorrect land use classes. Fifty-three percent would hence represent the degree of omission error (i.e., overall omission error from all classes).

B. Mapping Indices

While the confusion table is an accepted way to express classification accuracy, it is inadequate for the expression of mapping accuracy, i.e., the error in class location on a map (Kalensky and Scherk, 1976). This error requires both omissions and commissions to be combined since it must evaluate and assess accuracy by losses (omissions) to, as well as additions (commissions) from other classes.

To satisfy this requirement, 2 mapping measures were included in the accuracy evaluation. They are class mapping accuracy (CMA) and overall mapping accuracy (OMA).

Class mapping accuracy can be defined as the number of correctly classified pixels (= size of correctly classified area) expressed in terms of all pixels affected by its classification (= size of displayed area which includes commissions plus omissions) (Kalensky and Scherk, 1976). The equation is:

$$M(I) = \frac{N(I)}{N(I) + E(I)} \quad 100$$

where: M(I) = mapping accuracy of class I (in percent)

N(I) = number of correctly classified pixels in class I

E(I) = number of erroneous pixels in class I (= sum of omissions and commissions).

In brief, this index serves to consolidate registration and classification accuracies into a single percentage value. This value can be interpreted as the degree of locational congruence between Landsat and ground truth classes.

Although the CMA algorithm utilizes a pixel-by-pixel accuracy calculation similar to overall classification accuracy (OCA), results are expressed differently. Instead of the percentage values being expressed in terms of overall image accuracy as with OCA, values for CMA are expressed relative to individual class pattern. The CMA index, as such, is a better indicator of image accuracy since it does not overestimate positional class accuracy as does the OCA index (i.e., OCA considers only omissions while CMA evaluates omission and commission errors) (Kalensky and Sherk, 1976). Based on this equation, if M equalled 47 percent for the deciduous forest class, this would indicate that 47 percent of the area which ground truth determined to be this forest

type was correctly classified and positioned (i.e., mapped) using Landsat data.

Overall mapping accuracy is defined as the weighted arithmetic mean of the mapping accuracies of all participating classes (Kalensky and Scherk, 1976). The weights are defined from ground truth data of the identified classes. The equation is:

$$M = \frac{\sum_{I=1}^{n} P_I \, M_I}{\sum_{I=1}^{n} P_I} \; 100$$

where: M = overall mapping accuracy (in percent)

M(I) = mapping accuracy of class I

$$P_I = \frac{T_I}{\sum_{I=1}^{n} T_I}$$

T(I) = correct number of pixels in class I

$\sum_{I=1}^{n} T_I$ = total number of pixels in all n classes

If results from the OMA calculation equalled 47 percent, this would indicate that 47 percent of the overall Landsat image area was correctly classified and positioned (i.e., mapped) as determined through ground truth.

Proceeding the accuracy assessments, improvements were to be sought for accuracies in the 13-category and 4-category classified images. The methods used included:

1. Additional-band method,
2. Exclusion method, and
3. Exclusion-conditional method.

LANDSAT IMAGE POSTPROCESSING

Accuracy Improvement Methods

One important premise about the MSS instrument is that it must collect adequate radiance measurements to characterize distinctly a point on the land surface. This implies proper classification of the spectral, spatial, and temporal variations of such a surface (Landgrebe, 1978). Additional quantitative data from sensor-derived or non-sensor sources can often increase the extraction of scene information. Such data can be referred to as being either from an ancillary source or simply as ancillary data. Three methods used in this research to improve accuracies employed ancillary data.

Three criteria were used in selecting ancillary data. They were data availability, cost, and past success.

Data availability and cost relate to whether or not the data are already commercially produced and if so, what is the price? If the data are not provided, can such data be gained in a cost-effective manner? Past successes acknowledge data which have increased land use classification accuracies.

The Additional-Band Method

The first approach which utilized the information-bearing attributes of ancillary data was the additional-band method. This approach uses

additional MSS bands. Although these bands are not direct sensor measurements as are Landsat bands 4, 5, 6, and 7, they are weighted equally in terms of potential information content and quality. Utilizing additional data is an attempt to increase the intrinsic dimensionality of the data and thus the scene information that can be extracted. Intrinsic dimensionality refers to the smallest number of variables which could be used to represent the data set accurately (Landgrebe, 1978). In this sense, utilizing ancillary data attempts to maximize the smallest number of quality variables (i.e., megafactors) which essentially characterize a data set.

The additional band method itself consists of adding specific additional bands to the 4 Landsat bands (4, 5, 6, and 7) in order to create combinations that may increase classification accuracy. Changes are monitored by noting the differences in accuracy levels of each combination compared to the 4-band data sets. A change in accuracy may be attributed to the effects of the additional data.

To demonstrate the potential increases in classification accuracy using additional bands, several types of data sets were assembled. The types included:

1. Ratio,
2. Linear Combination,
3. Texture, and
4. Experimental.

All of the additional data sets are based on manipulation of the 4 raw Landsat spectral bands. Their image sizes (700 by 836 pixels) covered all of Montgomery County. Because ground control points for the

ancillary bands were equivalent to those of band 7, one run of the BINFIT program was all that was required to register, resample, and load each new data set into the POWER structure, provided that a storage area had been allocated using program INITIAL. Utilizing both gray scaling methods initially, each data set image used for display was selected according to the degree of visual contrast. The sequence of steps used in transferring "additional" data sets from POWER to GIPSY was similar to bands 4, 5, 6, and 7. (See Methods section, Data Transfer: POWER to GIPSY).

The following is a list of types of spectral data considered for use in additional-band tests and a description of each.

1. Ratios

Ratios are simply the division of the digital value of 1 MSS band by that of another, pixel-by-pixel. The result is a ratio band. The ratio band is a quotient value which tends to accentuate differences between bands, and likewise, surface radiance values (Morain, 1978). Division by zero is not allowed.

An advantage of ratio images is that a material has the same ratio value, regardless of variations in illumination. Shadowed and sunlit areas are nearly identical using this technique. This allows similar covers to have similar ratio signatures (Sabins, 1978). Hypothetically, ratio bands reduce the illumination differences present in a Landsat scene, thus deemphasizing the expression of topography.

Although Otterman et al. (1979) found that poor atmospheric conditions can reduce the range of ratio values within a scene, it is hoped that since the selected Landsat scene had 0% cloud cover, such effects are minimal.

Three FORTRAN IV programs were written to generate ratio-biomass band data. They are BIBLOC, BIBLOC1, and VEGBLOC.

The algorithm used in program BIBLOC (Appendix O) is:

RAT45 = BAND 4/BAND 5;

band 4 is the green band (0.5 to 0.6 um) and band 5 the red band (0.6 to 0.7 um). The usefulness of this ratio is that as vegetal cover (leaf area) increases, the green radiance will increase. Conversely, as vegetal cover increases, radiance in the red channel will decline because of greater absorption of red wavelengths by chlorophyll. A simple ratio of the pixel values for these 2 channels over an entire cropping season, should correlate well to estimates of leaf area index (LAI) and crop vigor (Morain, 1978). A scatterplot showing the relationship between band 4 and band 5 radiance values (study area) is provided as Fig. 24.

Fig. 25 displays the Band 4/5 ratio image. Areas exhibiting a high LAI have a light gray scale, those with low LAI have dark-color pixels. Fig. 26 displays the frequency distribution for the Band 4/5 ratio values.

The second ratio data set was computed using program BIBLOC1 (Appendix P). Here, the algorithm was:

RAT57 = BAND 5/BAND 7;

band 5 is the red band and band 7 (0.8 to 1.1 um) is from the near-infrared region. This ratio is used for interpreting areas of healthy vegetation. Healthy vegetation characteristically absorbs in the red region and radiates in the near-infrared. Lower ratio values would thus be more evident for areas of healthy vegetation. The relationship

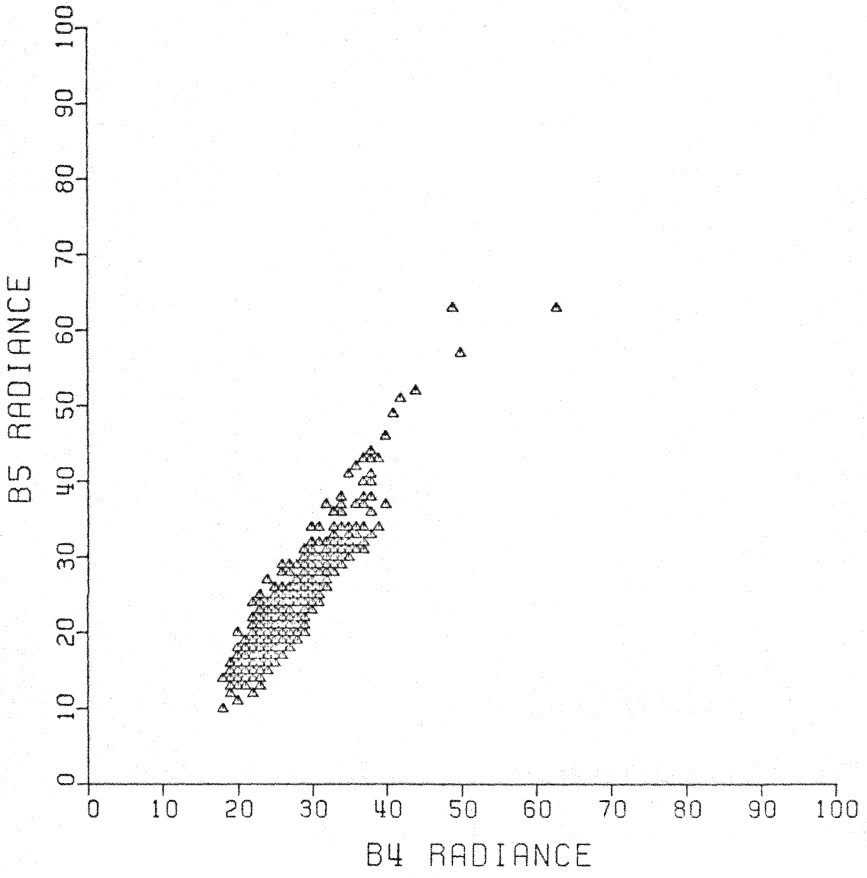


Fig. 24. Plot of study area band 4 versus band 5.

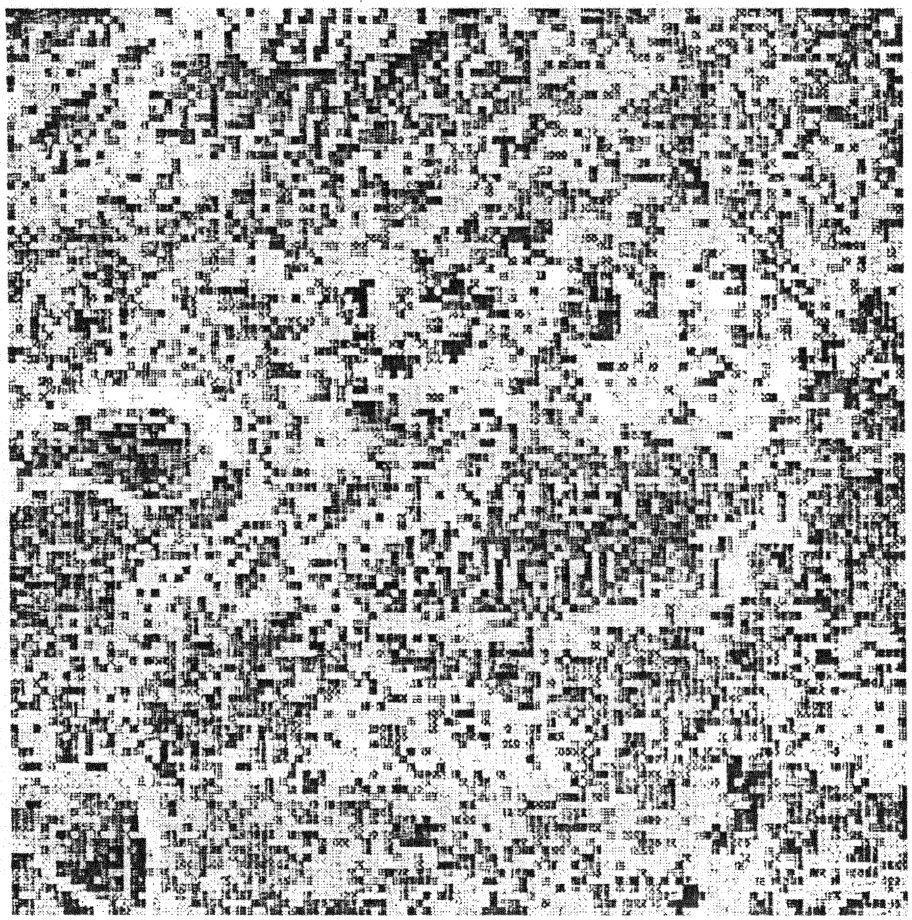


Fig. 25. Gray scale image of study area band 4 to band 5 emphasizing low ratio ranges as dark gray shades.

Fig. 25. (Continued).

CATEGORY		SYMBOL KEY SYMBOL	FREQUENCY
34.	- 46.		293
46.	- 47.		110
47.	- 49.		262
49.	- 51.		610
51.	- 52.		1213
52.	- 53.		317
53.	- 55.		1575
55.	- 56.		1025
56.	- 57.		906
57.	- 58.		743
58.	- 59.		796
59.	- 62.		2044
62.	- 63.		675
63.	- 66.		1280
66.	- 68.		960
68.	- 72.		815
72.	- 74.		248
74.	- 133.		528

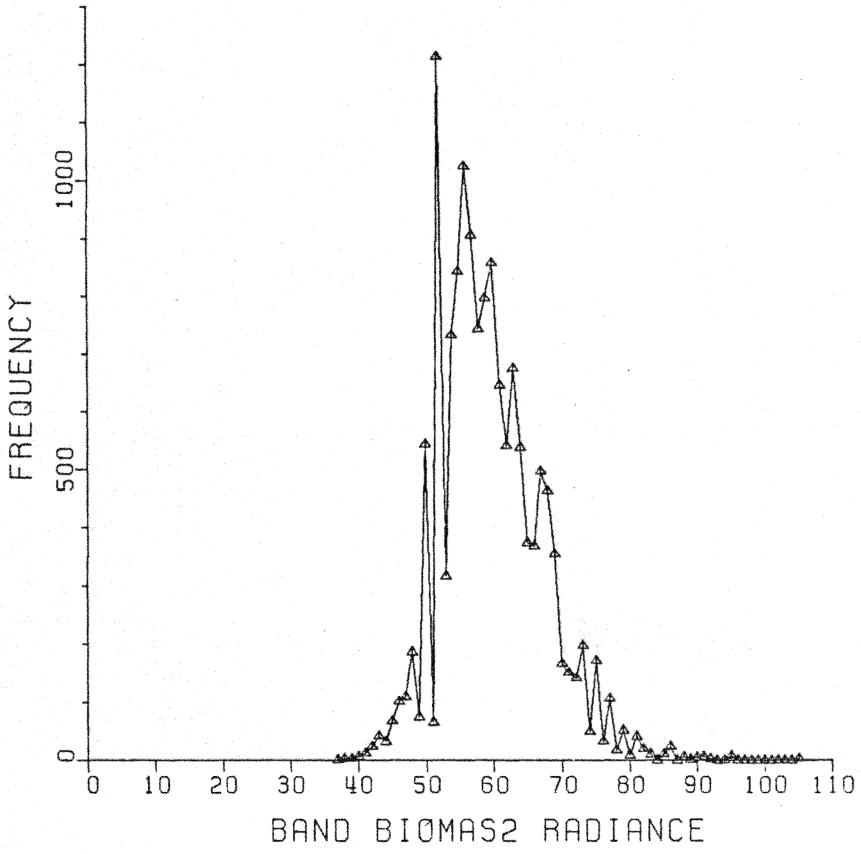


Fig. 26. Histogram of study area band 4/5 ratio.

between band 5 and band 7 radiance values (study area) is shown in Fig. 27.

Fig. 28 displays the results of the Band 5/7 ratio. Areas of healthy vegetation are believed to have a lower ratio than other areas and have been assigned a light gray scale. The frequency distribution is shown in Fig. 29.

Index values for the third ratio data set were calculated using program VEGBLOC (Appendix Q). Called a vegetation index, this ratio was somewhat similar to the B5/B7 ratio but slightly modified to remove the undesirable effects of the atmosphere or variable scene illumination. The algorithm is:

$$VI = (BAND\ 7 - BAND\ 5) / (BAND\ 7 + BAND\ 5).$$

Rouse, et al. (1973) noted that the resulting values for this index seem to correlate well with actual ground measurements of biomass but the reasons why this should be were not clear.

For this band ratio (Fig. 30), light gray scales represent areas of high biomass. The frequency distribution for this ratio is displayed in Fig. 31.

2. Linear Combinations

Large area vegetation types vary by location. In many instances, these spatial changes in vegetation can be correlated to differences in soil type. Since existing vegetation is often the main characteristic determining land use, it would seem logical that soils data may be of assistance in improving land use classification. Augmenting raw Landsat data with a spectral soils band offers one possibility

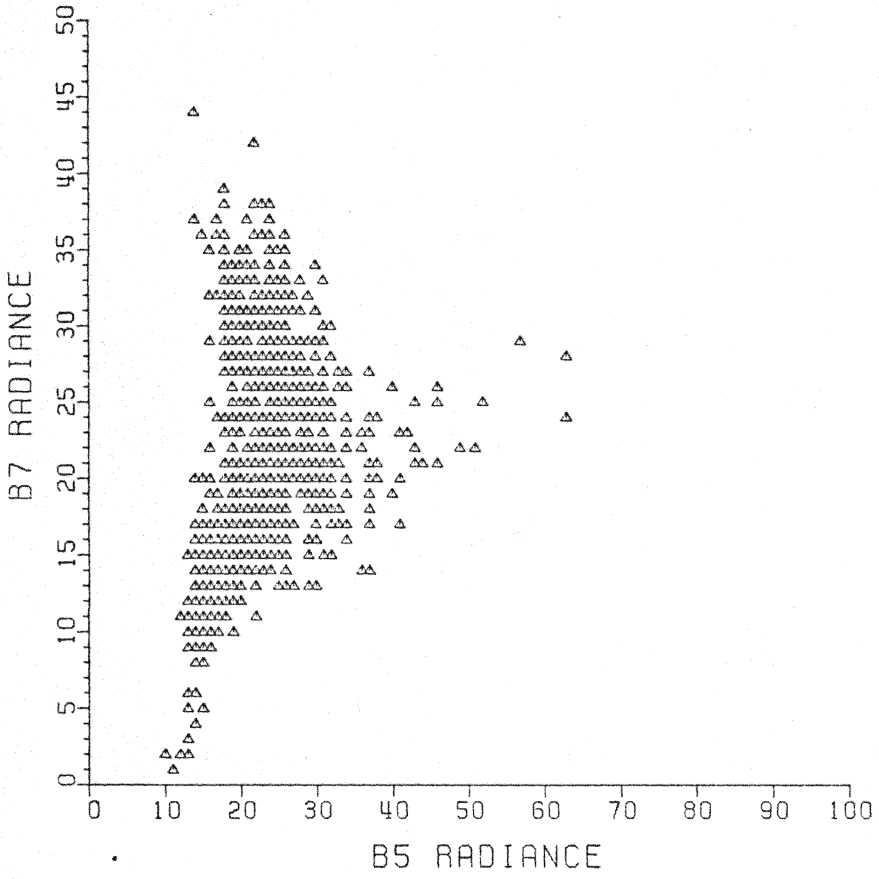


Fig. 27. Plot of study area band 5 versus band 7.

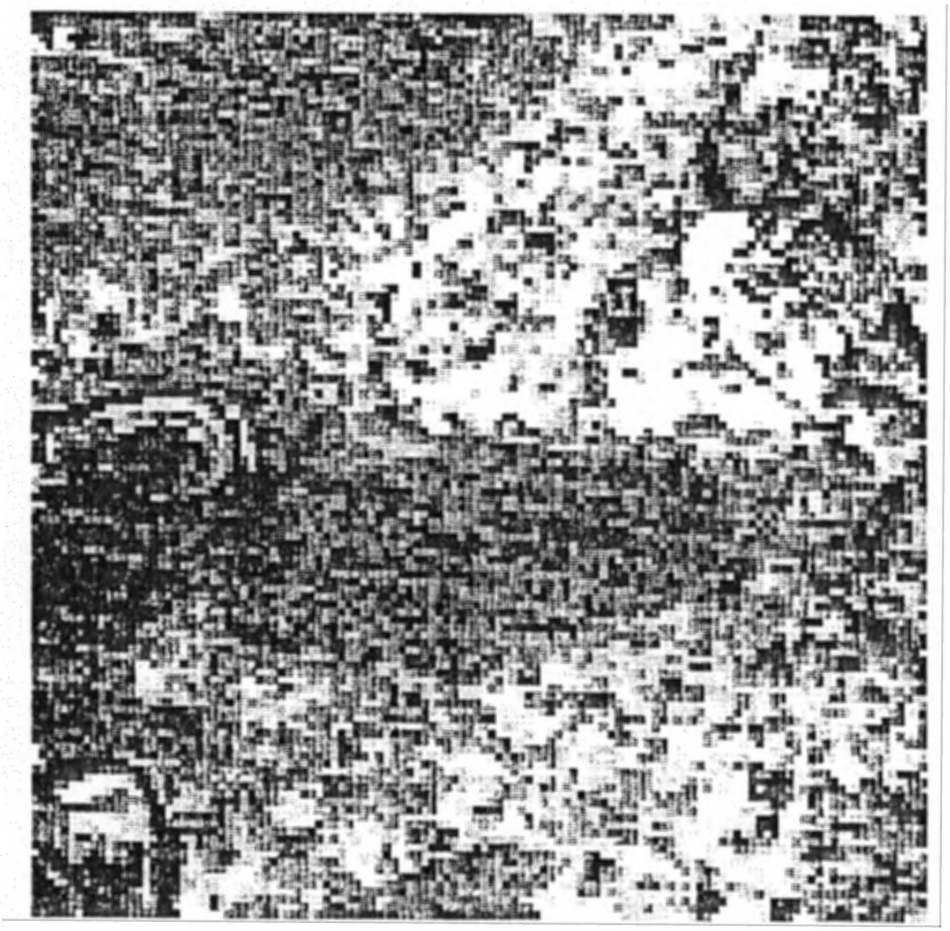
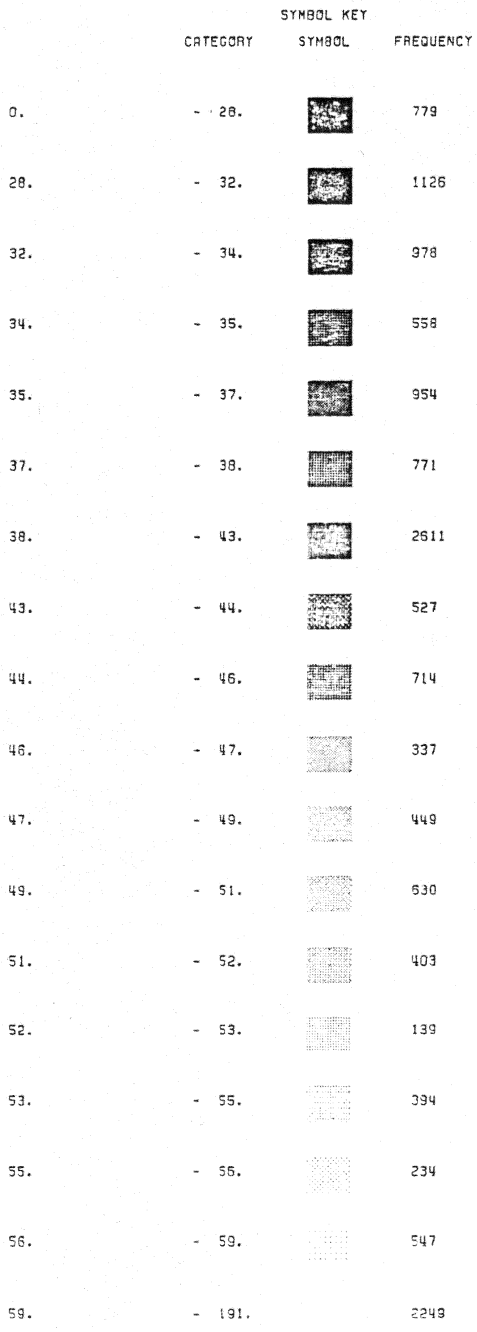


Fig. 28. Gray scale image of study area band 5 to band 7 emphasizing low ratio ranges as light gray shades.

Fig. 28. (Continued).



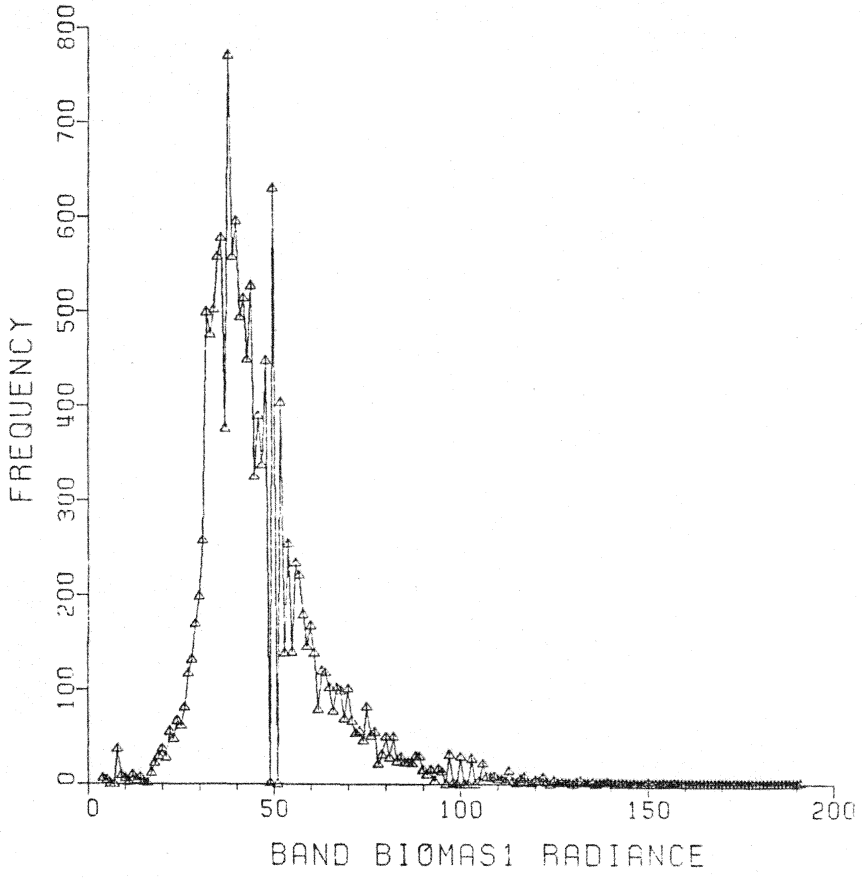


Fig. 29. Histogram of study area band 5/7 ratio.

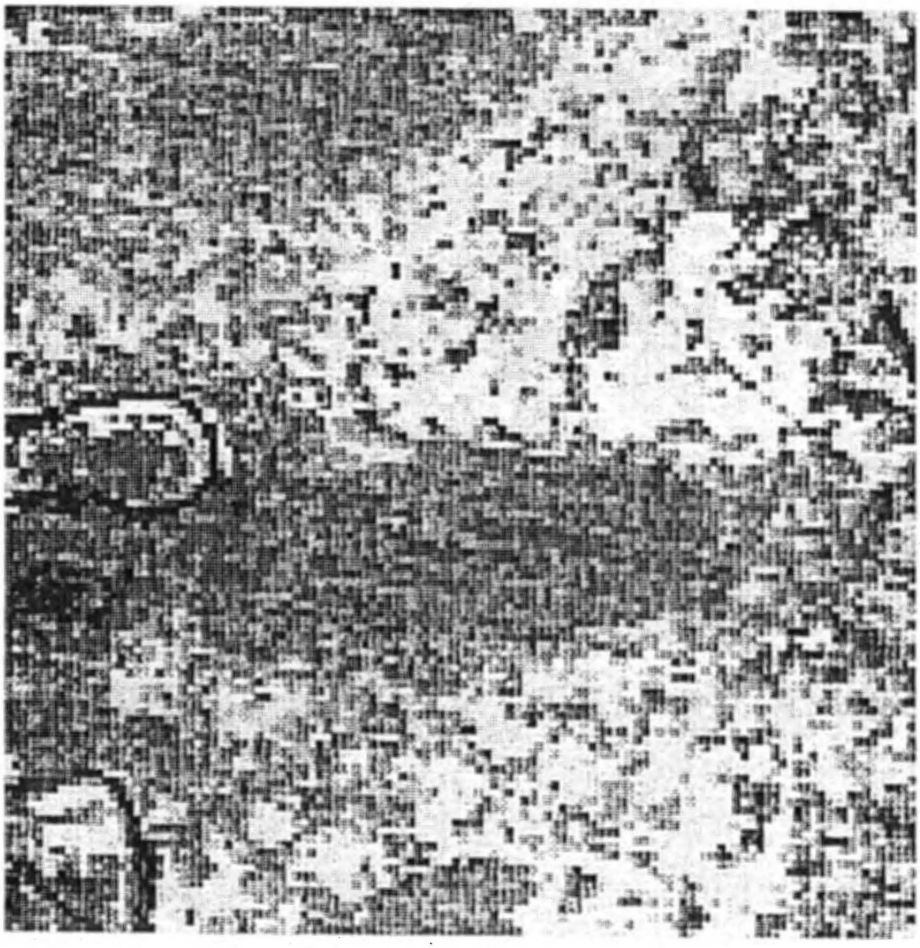


Fig. 30. Gray scale image of study area vegetation index emphasizing low ratio ranges as dark gray shades.

Fig. 30. (Continued).

CATEGORY			SYMBOL KEY SYMBOL	FREQUENCY
0.	-	52.		33
52.	-	80.		316
80.	-	81.		38
81.	-	89.		1994
89.	-	90.		612
90.	-	93.		2349
93.	-	94.		813
94.	-	95.		831
95.	-	97.		1552
97.	-	98.		706
98.	-	99.		560
99.	-	100.		630
100.	-	101.		471
101.	-	102.		455
102.	-	109.		2188
109.	-	110.		209
110.	-	116.		508
116.	-	117.		49
117.	-	126.		86

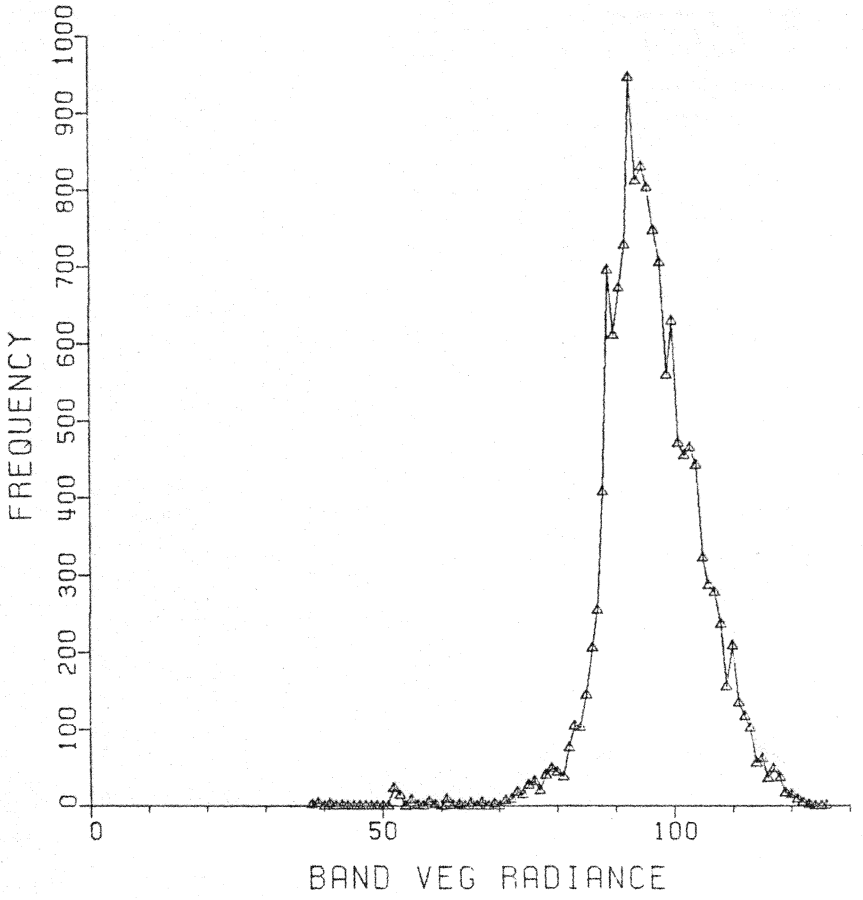


Fig. 31. Histogram of study area vegetation index.

for increasing classification accuracies over levels recorded using only bands 4, 5, 6, and 7.

One algorithm used for identifying different types of soil signatures uses linear combinations of Landsat visible and infrared radiation data (Tucker, 1979). Labeled as the "Soil Brightness Index" by Kauth and Thomas (1976), this algorithm is presented as:

$$SBI = (0.43) \times (MSS4) + (0.63) \times (MSS5) + (0.59) \times (MSS6) + (0.26) \times (MSS7).$$

This algorithm was empirically derived from Landsat data through spectral reflectance experiments.

Linear combinations have certain advantages over other "additional" data types (Kauth and Thomas, 1976).

1. Potentially there is significantly less land use information in some Landsat bands than in others. Linear combinations allow weights to be assigned to bands, indicative of their importance in a particular application.

2. Linear combinations allow certain diagnostic features to be extracted from data which are symptomatic of external effects such as haze, H_2O vapor, illumination angle, and viewing angle.

Fortran IV program SBIBLOC (Appendix R) was written to compute the soil brightness index using the stated algorithm and inputs from Landsat bands 4, 5, 6, and 7.

In Fig. 32, the lightest gray scales indicate that a specific pixel may be largely composed of bare soil. Fig. 33 displays the frequency distribution for the SBI image.

Fig. 32. Gray scale image of study area soil brightness index emphasizing low index ranges as dark gray shades.

Fig. 32. (Continued).

CATEGORY			SYMBOL KEY SYMBOL	FREQUENCY
12.	-	22.		49
22.	-	23.		17
23.	-	40.		2283
40.	-	41.		383
41.	-	42.		464
42.	-	43.		388
43.	-	44.		408
44.	-	45.		363
45.	-	46.		398
46.	-	50.		1292
50.	-	51.		269
51.	-	55.		1018
55.	-	56.		299
56.	-	57.		259
57.	-	63.		2807
63.	-	65.		1089
65.	-	66.		494
66.	-	158.		2122

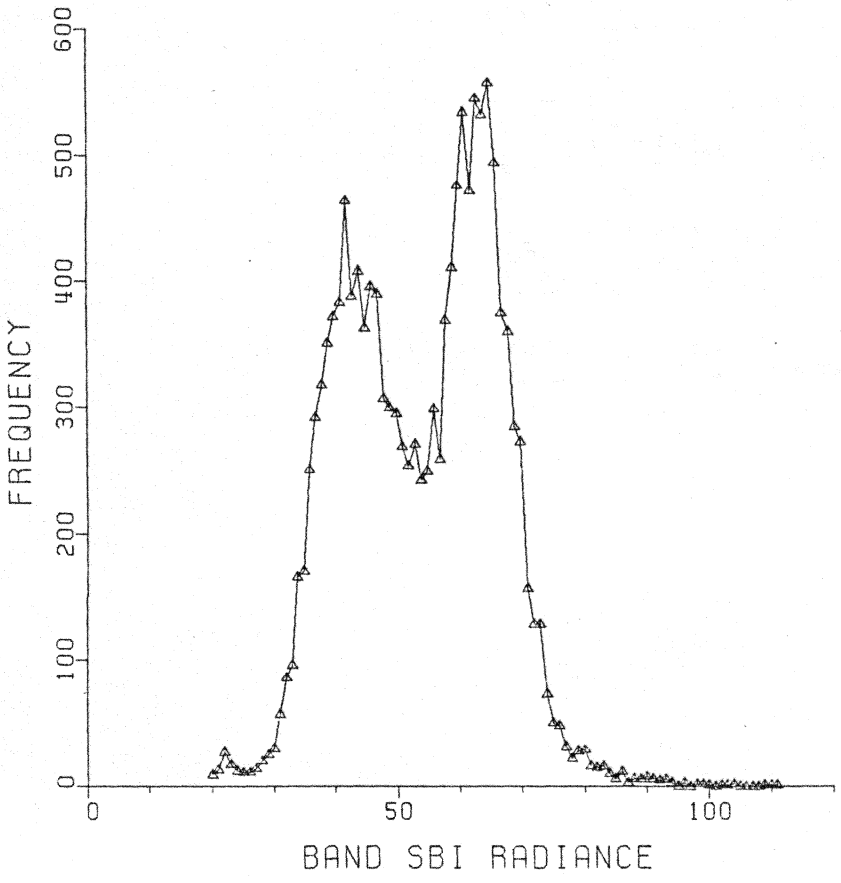


Fig. 33. Histogram of study area soil brightness index.

3. Texture

Analysis of spectral texture as based on Landsat data (i.e., bands 4, 5, 6, and 7) can provide information useful in discriminating numerous land use classes (Logan, et al. 1979; Iisaka, 1979). While radiance data, in itself, is informative about reflectance or emissive qualities, a texture dimension can address these 2 characteristics, along with distributions and sizes.

Texture data sets for bands 5 and 7 were created using FORTRAN IV program TEXTURE (Appendix S). Bands 5 and 7 were selected over bands 4 and 6 respectively because of their longer wavelengths, thus offering a lower probability of atmospheric degradation to the texture data. The algorithm is structured to calculate the standard deviation of density values within a 3-by-3 pixel moving window. The calculated standard deviation in each window is assigned to the center location of the 3-by-3 window.

For interpreting the gray scale displays of the textural index in Fig. 34 (i.e., the moving standard deviation of band 5) and Fig. 35 (i.e., the textural index for band 7), lighter shades are areas of continuous cover while darker areas have discontinuous cover. As such, Figs. 34 and 35 represent potential image data (i.e., textural) which may serve as ancillary bands. Figs. 36 and 37 display the respective frequency distributions.

4. Experimental

An experimental ratio was the final Landsat derived ancillary band. This ratio utilized Landsat band 7 and the soil brightness index

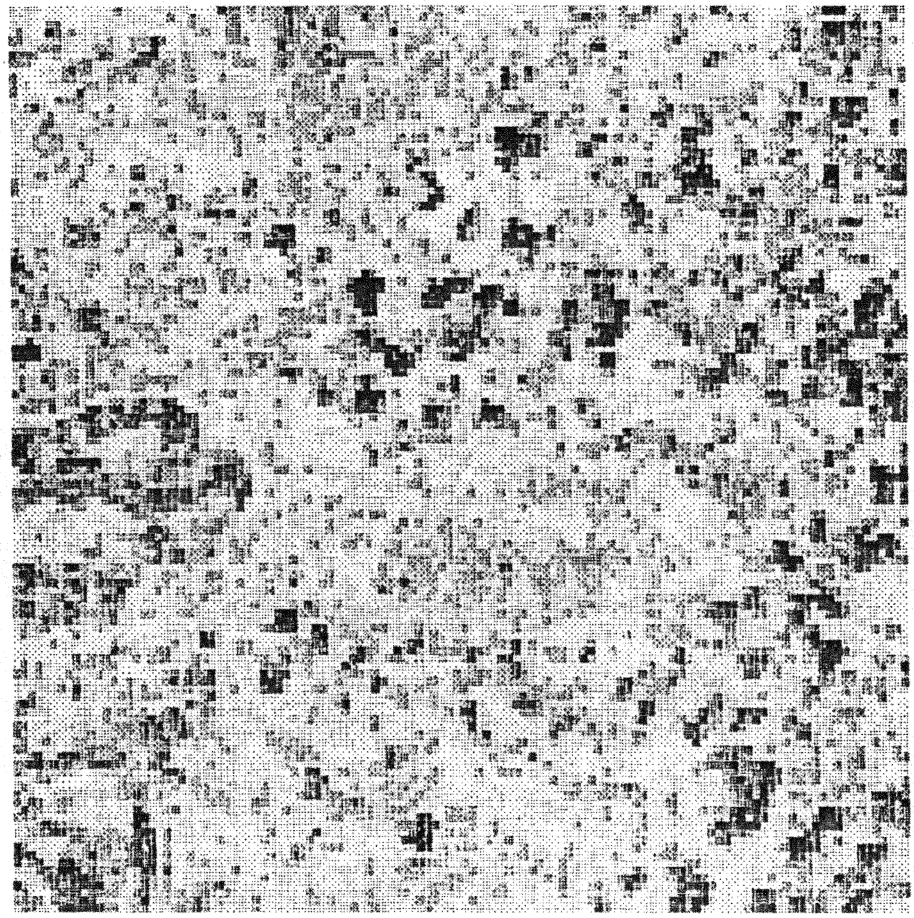


Fig. 34. Gray scale image of study area texture band 5 emphasizing low texture ranges or continuous cover as light gray shades.

Fig. 34. (Continued)

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		6
0.	- 1.		659
1.	- 2.		3045
2.	- 3.		3492
3.	- 4.		2589
4.	- 5.		1813
5.	- 6.		995
6.	- 7.		550
7.	- 8.		356
8.	- 10.		455
10.	- 12.		211
12.	- 14.		92
14.	- 56.		157

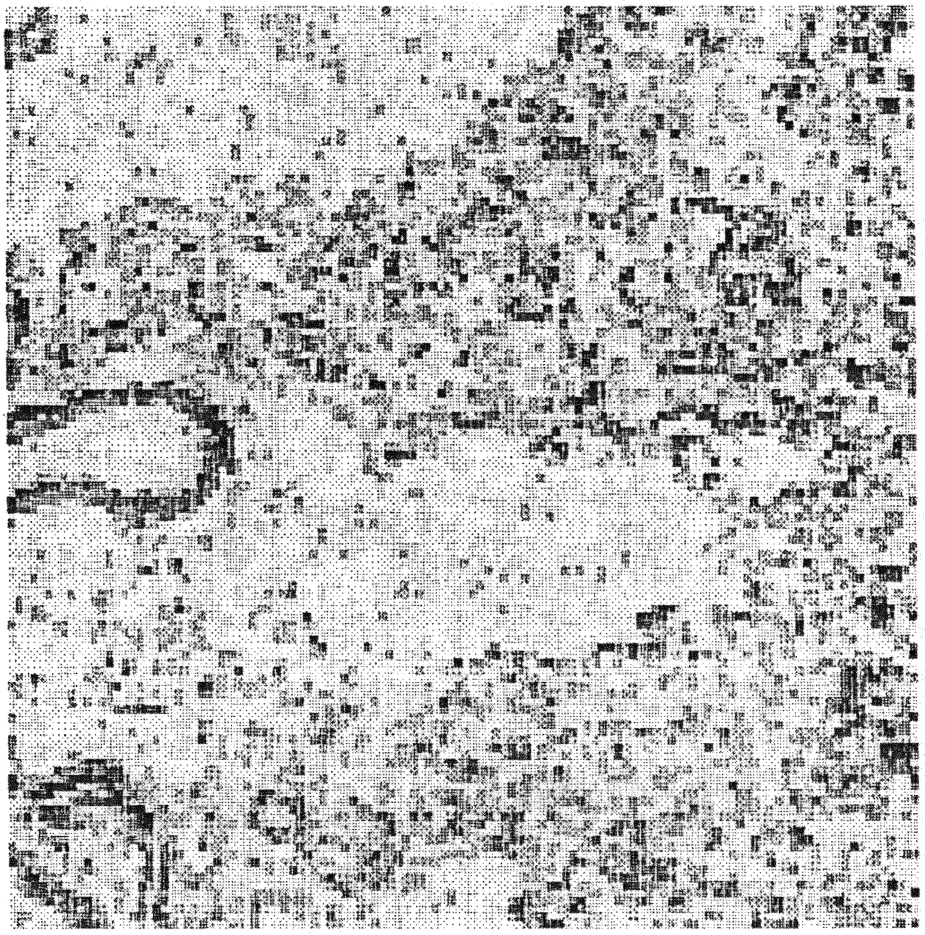


Fig. 35. Gray scale image of study area texture band 7 emphasizing low texture ranges or continuous cover as light gray shades.

Fig. 35. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		4
0.	- 1.		919
1.	- 2.		2938
2.	- 3.		3272
3.	- 4.		2504
4.	- 5.		1790
5.	- 6.		1139
6.	- 7.		759
7.	- 8.		471
8.	- 10.		404
10.	- 12.		139
12.	- 14.		47
14.	- 56.		14

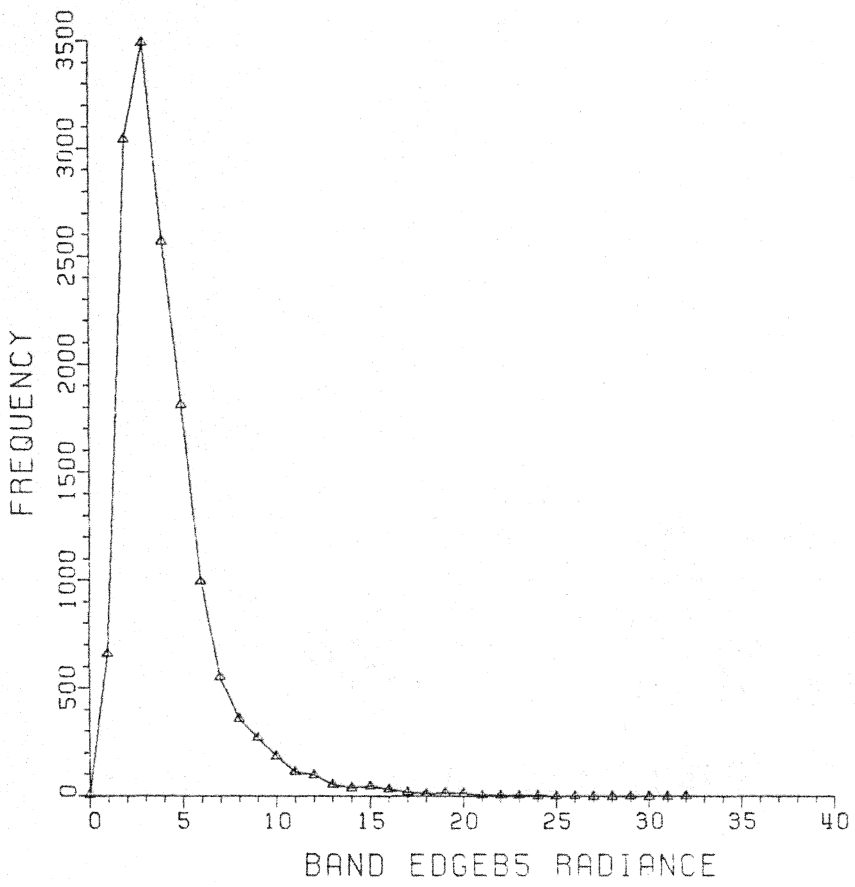


Fig. 36. Histogram of study area texture band 5.

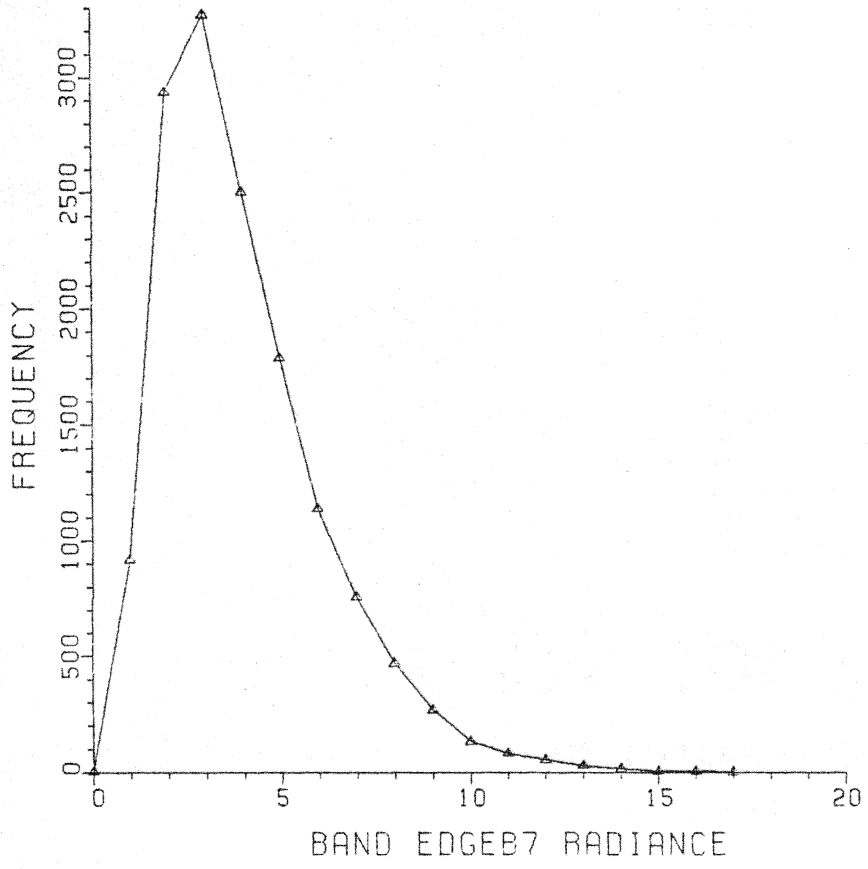


Fig. 37. Histogram of study area texture band 7.

as inputs. Reference to this ratio or a similar one was not noted in any literature which had been reviewed. It was formulated on the general notion that healthy vegetation radiates highly in the near-infrared region (i.e., high band 7 radiance) and is most often located on non-exposed soils (i.e., low SBI index). Higher ratio values would hence be more characteristic of quality vegetative cover.

FORTRAN IV program BI1BLOC (Appendix T) was written to compute this index with the specific algorithm being:

BI1 = BAND 7/SBI.

The relationship between band 7 and soil brightness values (study area) is shown in Fig. 38. A theoretical basis for the ratio values is unknown at present but the gray scale image (Fig. 39) is similar to the ratio 5/7 and vegetation index.

The gray scale image of the BI1 index displays higher index values as lighter gray scales. The BI1 index was the only ratio possessing a unimodal frequency distribution (Fig. 40).

In this thesis, topographic data were not used as "additional" data.

In summary, 5 data sets were chosen to add to the 4 standard Landsat bands. These were:

1. Band 5/7 Ratio,
2. Vegetation Index,
3. Soil Brightness Index,
4. Band 7 Texture, and
5. Experimental Index.

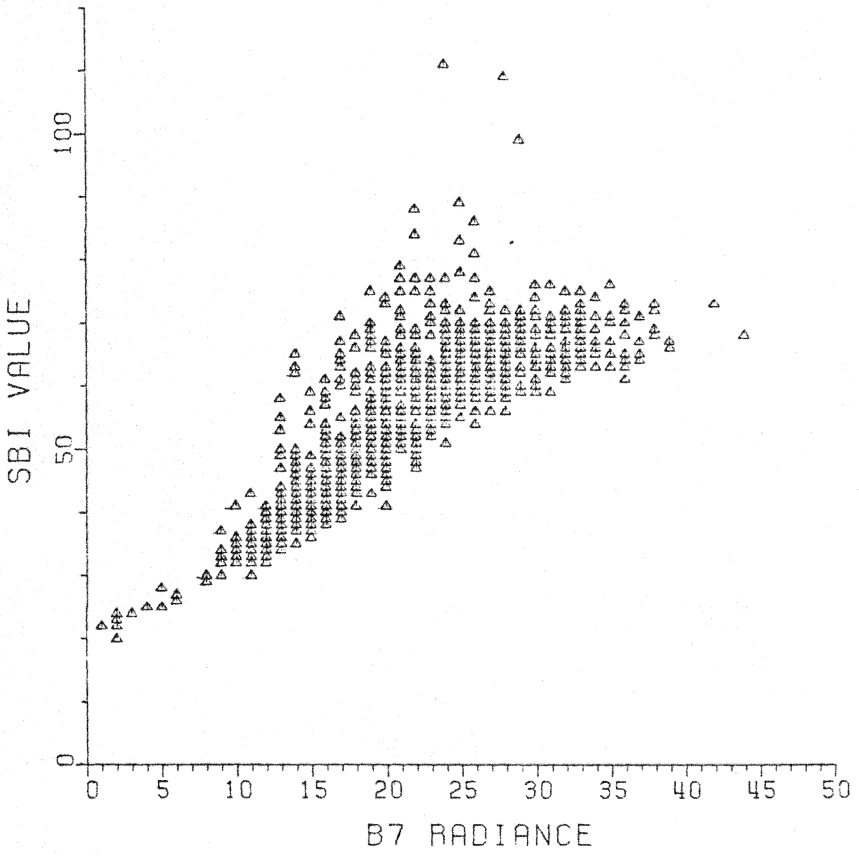


Fig. 38. Plot of study area band 7 versus soil brightness index.

Fig. 39. Gray scale image of study area band 7 to soil brightness index emphasizing low ratio ranges as dark gray shades.

Fig. 39. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 11.		204
11.	- 12.		97
12.	- 13.		213
13.	- 14.		400
14.	- 15.		925
15.	- 16.		1460
16.	- 17.		2203
17.	- 18.		1989
18.	- 19.		1760
19.	- 20.		1419
20.	- 21.		1037
21.	- 22.		876
22.	- 23.		630
23.	- 24.		372
24.	- 25.		344
25.	- 26.		185
26.	- 27.		124
27.	- 34.		162

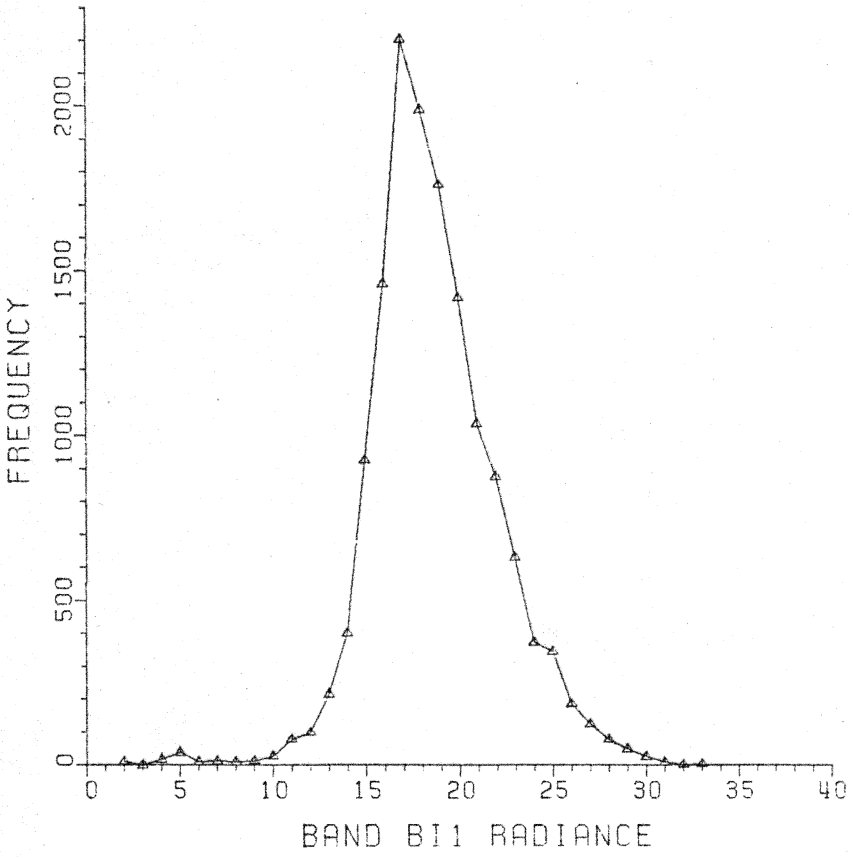


Fig. 40. Histogram of study area band 7/SBI ratio.

The selection criteria for these "additional" bands were based on (1) the ocular information bearing quality of the gray scale map that was produced, and (2) a minimal tonal degradation (i.e., low salt-and-pepper effect). A 9-band image (the 5 new bands and the 4 standard bands) was then classified using steps similar to those for the 4-band data set. Accuracy assessments were also performed in a manner similar to that for the 4-band classifications.

Exclusion Method

Each land use exhibits some variation in the amount of electromagnetic radiation it reflects and radiates. The extent of this variability is dependent on many factors, including:

1. Maturity or age,
2. Moisture content,
3. Health or vigor,
4. Underlying soil type, and
5. Variety.

Reducing improper classifications because of varietal factors is the purpose of the exclusion method. Furthermore, this method demonstrates that improvements in Landsat land use classification accuracy can be expected from incorporating non-spectral topographic information into the process (Strahler et al., 1978).

Variety, in a spectral sense, can be defined as a collection of different signatures within an area designated as a pixel. Certain land uses are more likely to exhibit these varietal-or mixed-signature effects than others. Three specific classes which have a high likelihood are

water, urban, and road. Size, structure, composition, position, and their interactions are only a few factors which result in composite signatures lacking class similarity. Mixed signature pixels or mixed pixels are thus inclusive of more than 1 land use. Such pixels cannot be categorized consistently into a single class.

The premise of the exclusion method is that removing "noisy" scene information may be as effective in increasing accuracy as adding information. The information to be removed is selected according to the likelihood of it being noisy or prone to erroneous classification as influenced by spectral variety. The information to be excluded will, for the most part, be classified pixels at predetermined locations.

The method used is to collect topographic map locational information about the presence of water, urban, and road classes and subsequently to remove classified pixels occupying those locations. Although it will not be demonstrated in this thesis, these classes could also be removed prior to any classification. Accuracy testing is then done only on the remaining pixels. The ability to see the effects of excluding classes on the overall scene classification accuracy will be plotted to show the change in accuracy with each individual class removal.

All data to be used in the exclusion procedure were coded from 1:24000 scale (7.5 min.) USGS topographic maps. Features of interest included those areas possessing water, urban, and/or road characteristics. Table 5 parallels the association between these exclusion features and the classification categories chosen.

Data collection and storage were made according to land use type and assigned codes resembling those used in the POWER system. The types

Table 5. Association between exclusion type and Level 1 and 2 classification categories.

Exclusion Type	Level 1 classes	Level 2 classes
Water	Water	Water
Road	Built-up Land	Transportation
Urban	Build-up Land	Residential Services Industrial Other Urban Transitional

and codes used are shown in Table 6. The actual coding technique utilized a transparent grid overlay, digitizer, minicomputer, and graphics terminal. Using a modified version of FORTRAN IV program PWR3030 (Jones, pers. comm.), 1/27 km^2 (3-acre) cells were coded to a specific exclusion type if a majority of the cell exhibited that characteristic.

Following the digitizing sequence, codes were transferred from the minicomputer flexible disk to IBM data storage (disk). FORTRAN IV program TEKCELLS (Jones, pers. comm.) was used for loading codes into the POWER structure.

The exclusion approach for the Level 2 classificaton was conducted on classified images, both 4-band and 9-band. The procedure itself utilizes single exclusion sets (i.e., water, urban sites, and roads) as well as their combinations (i.e., water + urban, water + roads, urban + roads, and water + urban + roads). This amounted to 7 exclusion steps total for each Level 2 classified image. Each step consisted of 1 single or 1 combination set being excluded at a time. FORTRAN IV program DROPPWR (Appendix U) was responsible for excluding each set. Combination exclusion sets utilized FORTRAN IV programs AGPWR2 (Appendix V) and AGPWR3 (Appendix W) for merging single sets. An accuracy assessment (program CONFUS) proceeded each exclusion. Resulting accuracy changes were credited to the type of data set excluded, single or combination. Figs. 41 through 43 display the single exclusion data sets according to type. Combination sets (Figs. 44-47) are displayed according to presence/absence of a single data set in a cell.

Tests of Level 1 classification accuracy change, according to exclusion type, were conducted using a lesser number of sets. Here, the

Table 6. POWER land use types and coding scheme.

Water	Type
0	No water
2	Large river
9	Pond or lake

Urban	Type
0	None
1	Urban (Pink on map)
2	Residential (5 or more houses per cell)
3	Residential (> 1 house but < 5 per cell)
4	Industrial

Road	Type
0	None
1	Dual highway, dividing strip > 7.62 m (25 ft)
2	Dual highway, dividing strip ≤ 7.62 m (25 ft)
3	Airport runway
4	Mine or quarry
5	Railroad

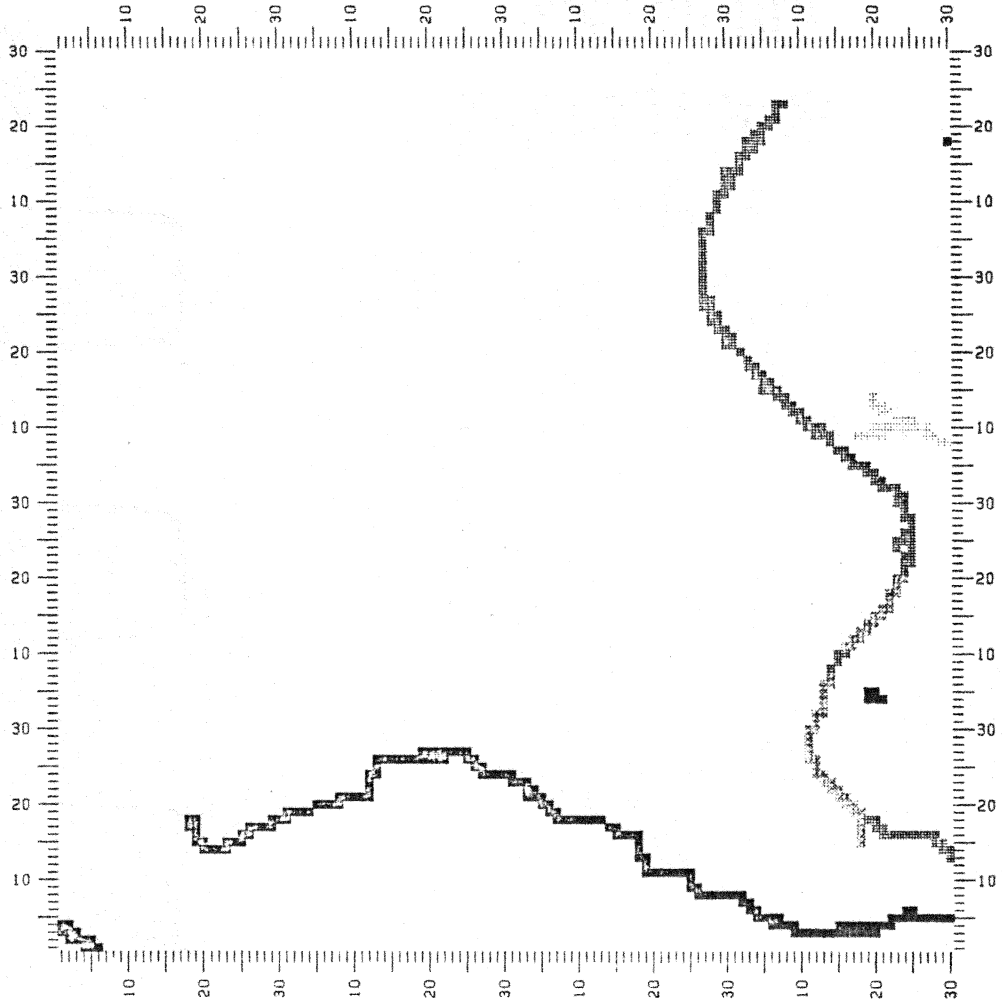


Fig. 41. Gray scale image of study area level 2 roads exclusion data set.

Fig. 41. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		14014
1. - 1.		135
2. - 2.		51
3. - 3.		25
4. - 4.		6
5. - 5.		169

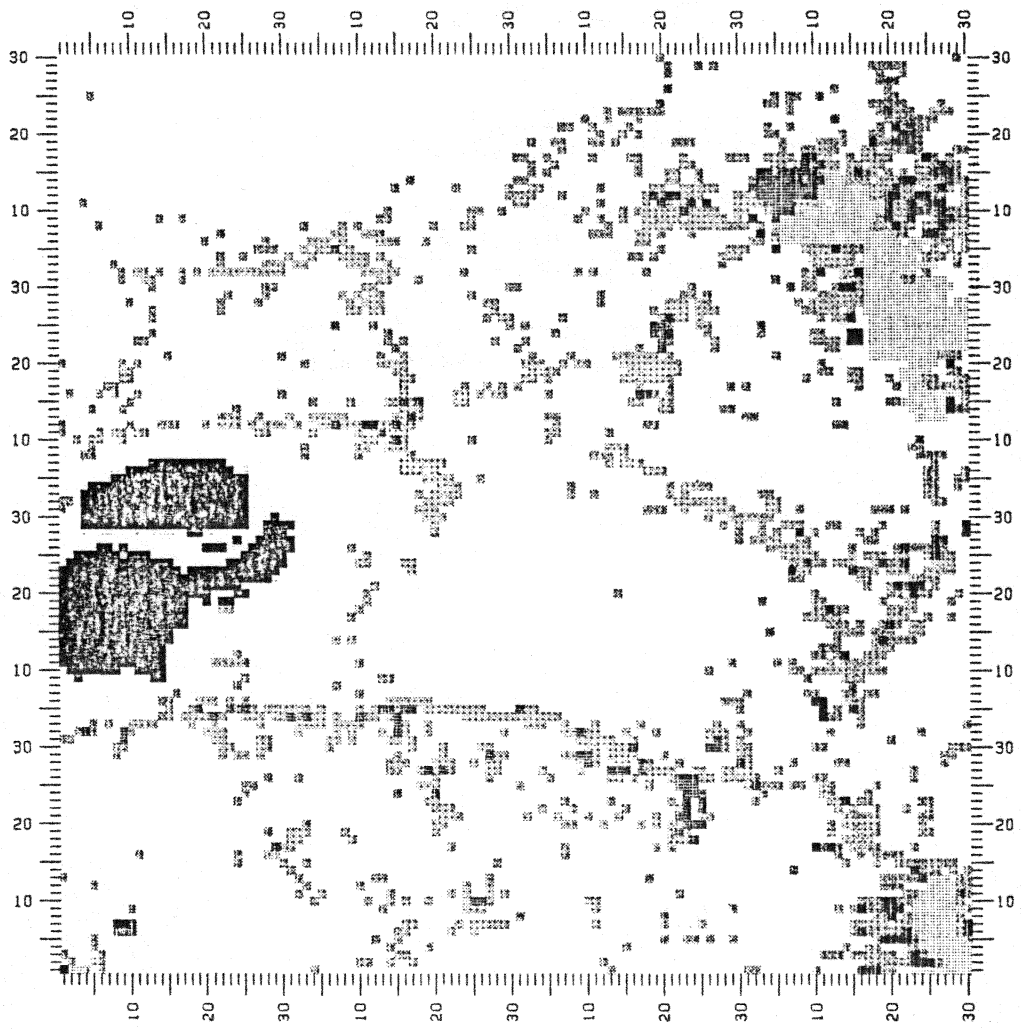


Fig. 42. Gray scale image of study area level 2 urban exclusion data set.

Fig. 42. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		11536
1.	- 1.		376
2.	- 2.		220
3.	- 3.		1742
4.	- 4.		526

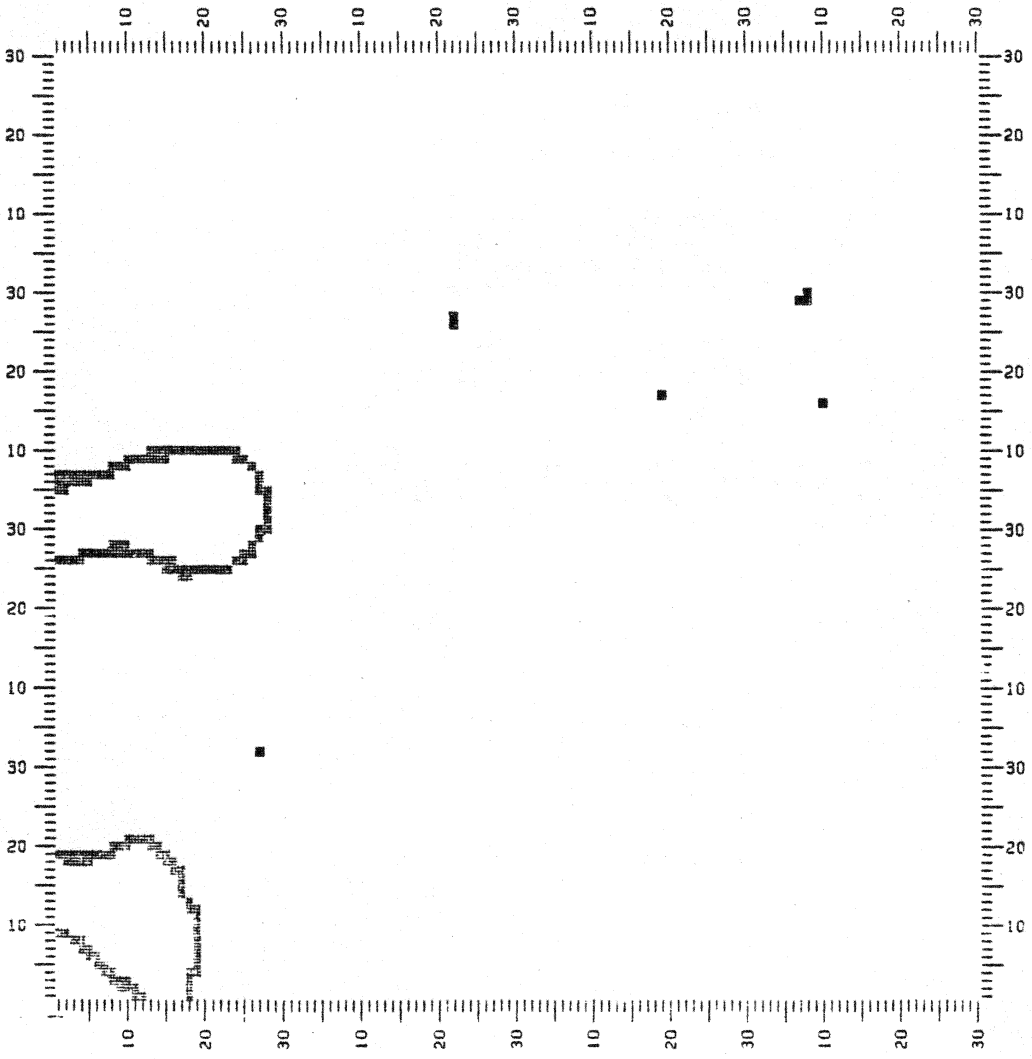


Fig. 43. Gray scale image of study area level 2 water exclusion data set.

Fig. 43. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		14240
2. - 2.		152
9. - 9.		8

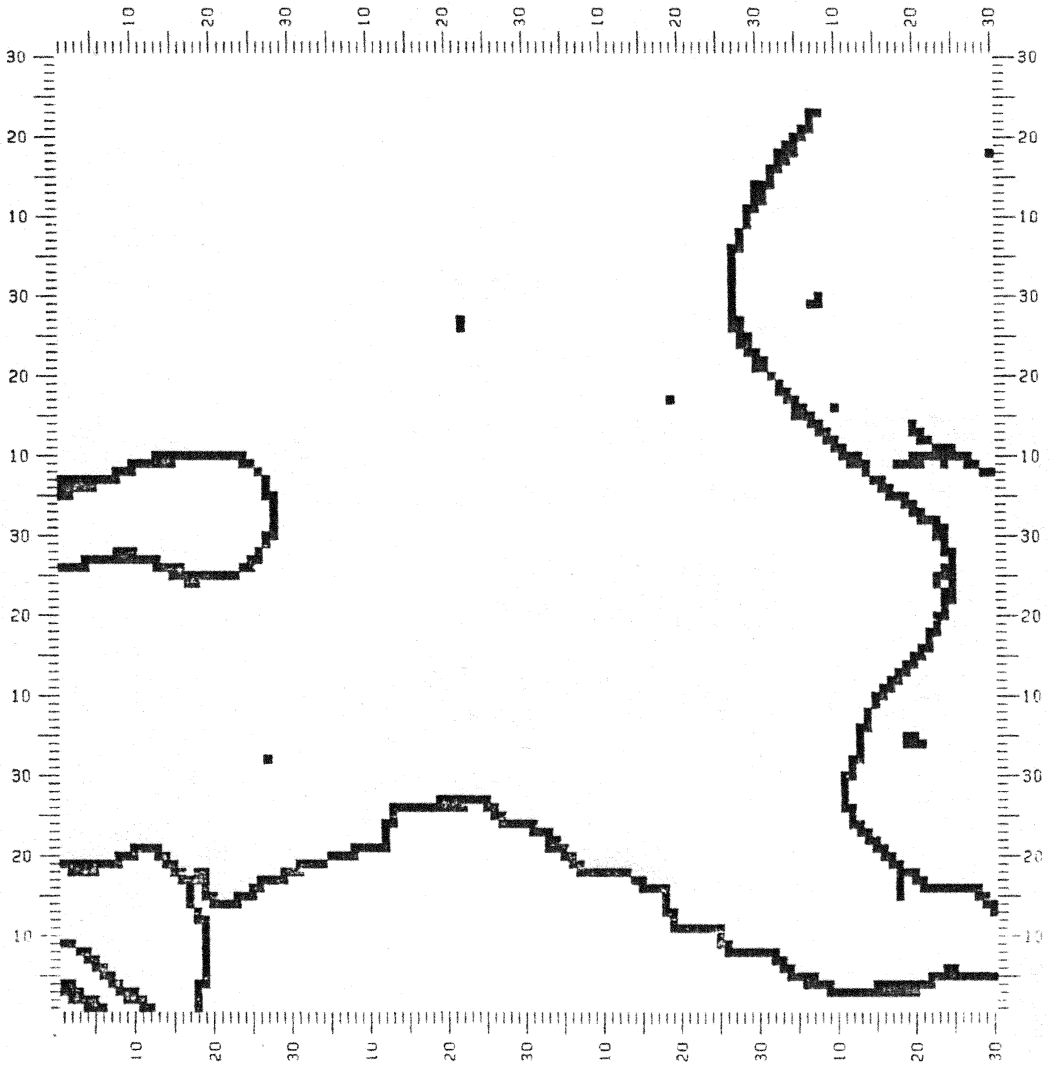


Fig. 44. Gray scale image of study area level 2 roads plus water exclusion data set.

Fig. 44. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		546
0.	-	0.		13854

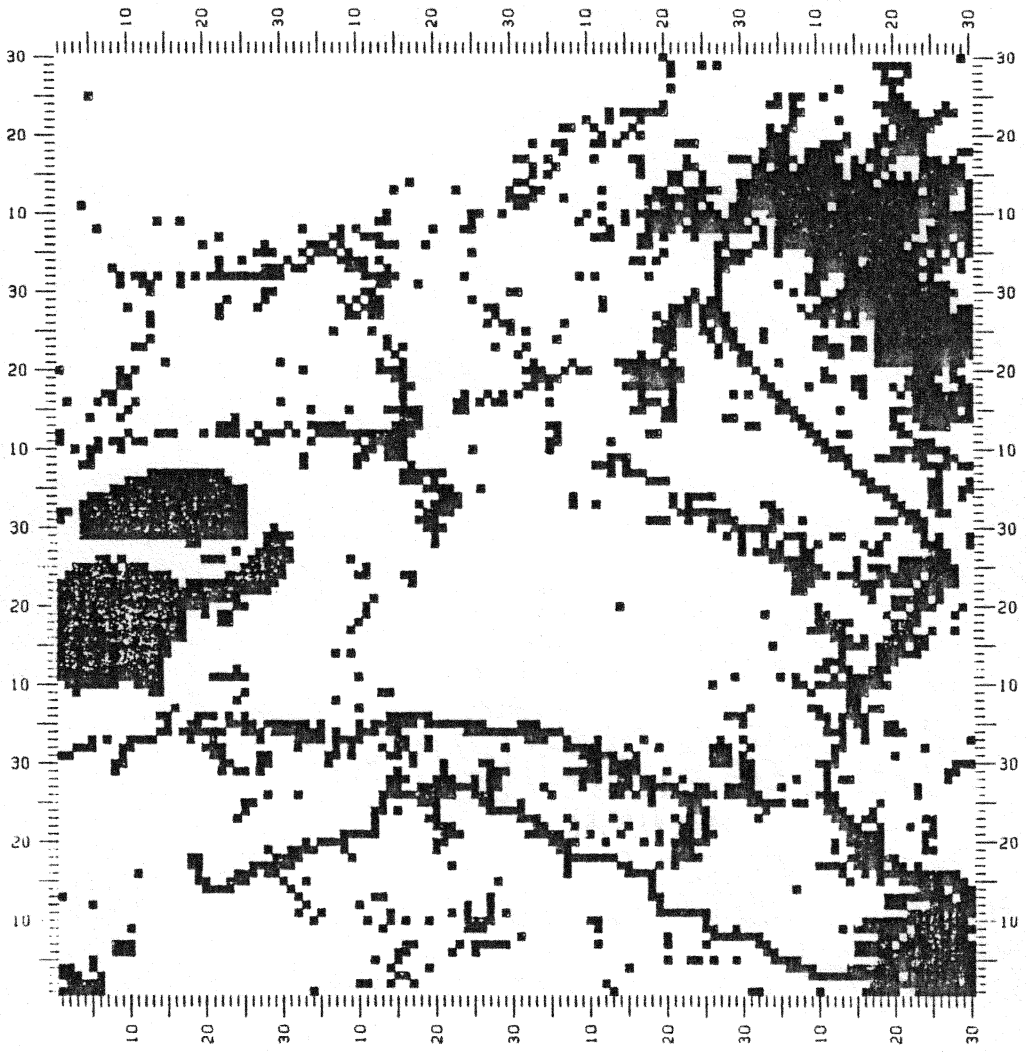


Fig. 45. Gray scale image of study area level 2 roads plus urban exclusion data set.

Fig. 45. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
-9999.	- -9999.		3144
0.	- 0.		11256

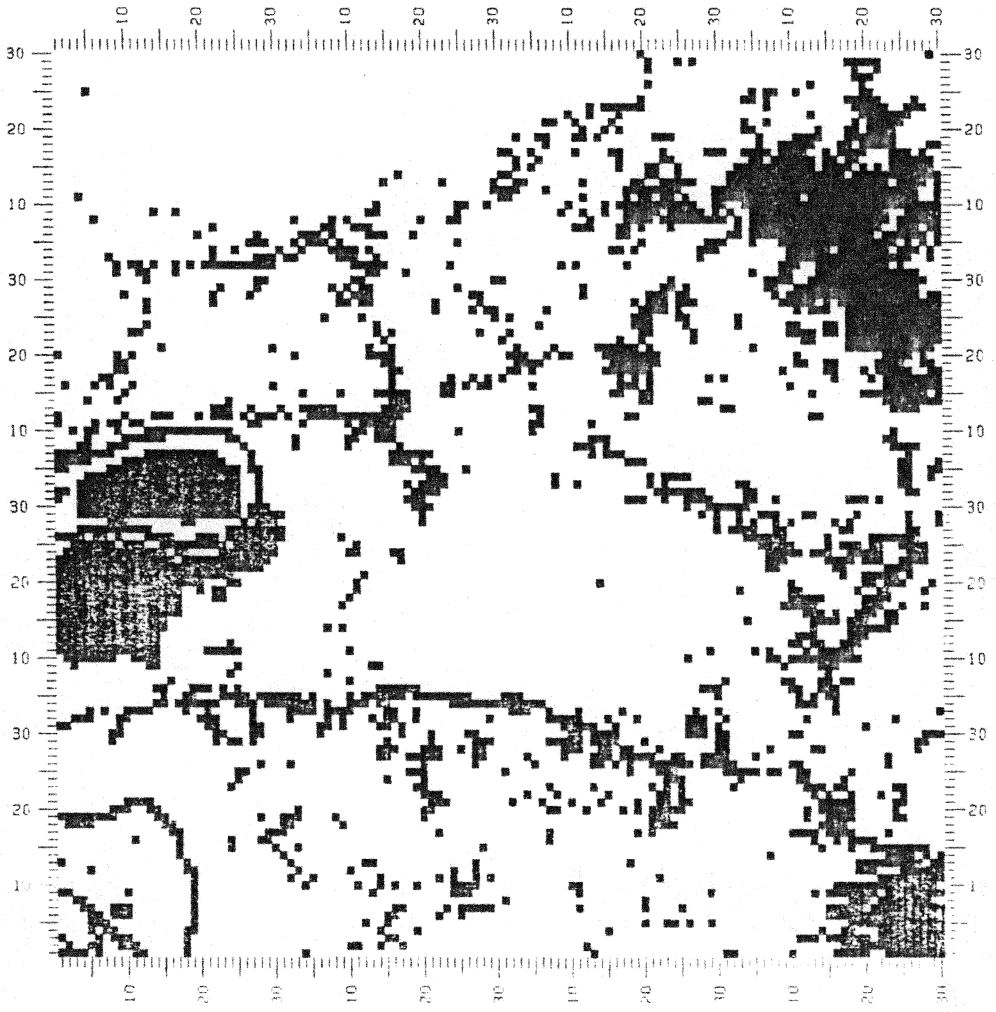


Fig. 46. Gray scale image of study area level 2 urban plus water exclusion data set.

Fig. 46. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3024
0.	-	0.		11376

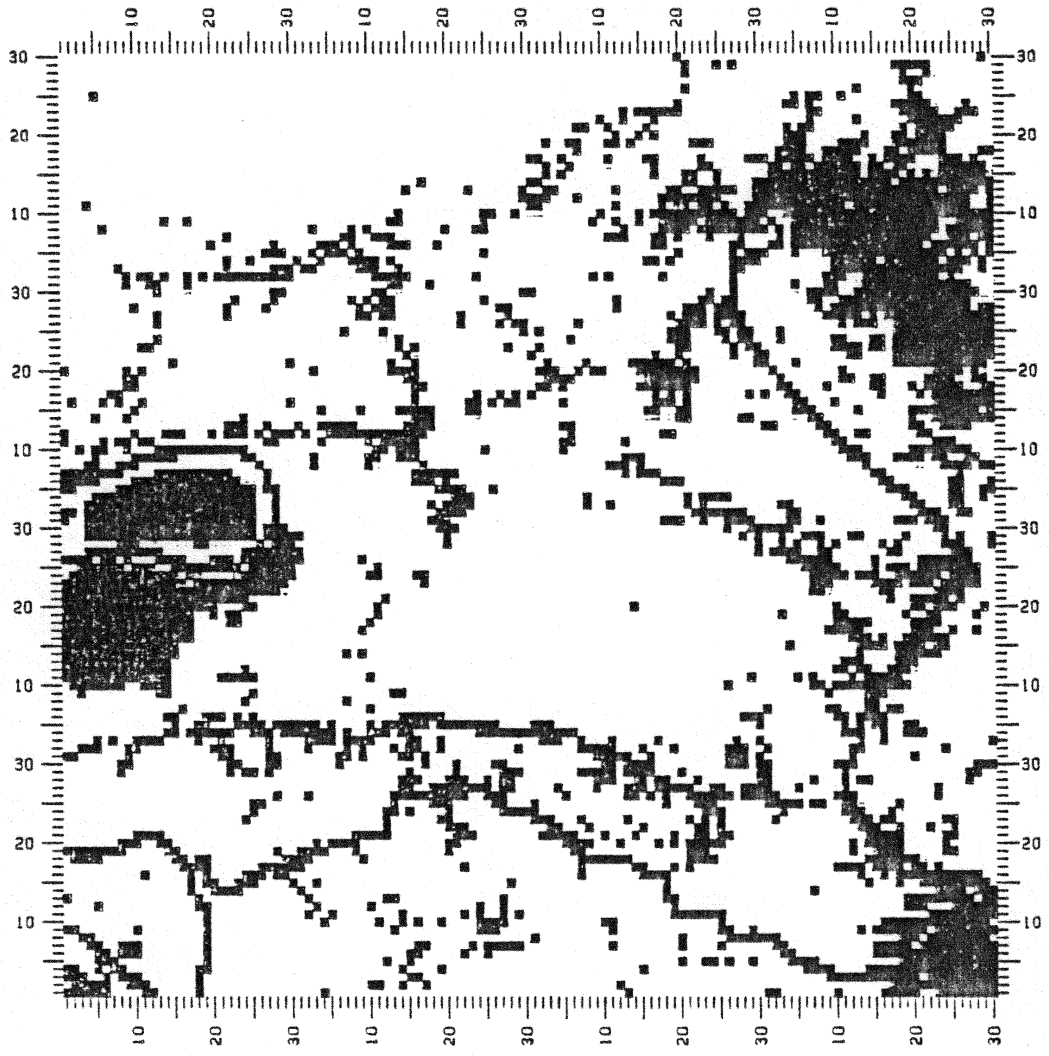


Fig. 47. Gray scale image of study area level 2 roads plus urban plus water exclusion data set.

Fig. 47. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
0.	-	0.		11096

urban and roads sets were combined. This combination was made because urban and roads are both included in the Level 1 class, "built-up land". As such, conducting 2 single exclusions (i.e., urban and roads) on a Level 1 classified image was felt to be inefficient given the physical, and to a lesser degree spectral, similarities of the data sets. Three exclusion sets (i.e., water, urban, and water + urban) were excluded from each Level 1 classified image using the same procedure as for Level 2. Accuracy changes were assessed after each step. Figs. 48 through 50 display the 3 sets used in the Level 1 exclusion sequence.

Exclusion-Conditional Method

Decision theory constitutes the basis for an exclusion-conditional approach. In terms of information extraction, this approach introduces a logical branching arrangement of decision processes (involving classes, features, and decision rules) which allow information class-membership decisions to be made in sequential steps. This operation can be visualized as a decision-tree (Hauska and Swain, 1975), with decisions moving along the tree from multi-alternative branches to few alternative nodes.

The reasoning behind the exclusion-conditional approach is that if registered ancillary data do not concur with the classification a pixel possesses, this classification can be changed so that it does. One example is that if elevation, slope angle, and slope aspect for an area in southwestern Virginia are 610 m (2000 ft), 40 degrees, and southwest, respectively, and if a classified Landsat image indicates this area to be deciduous forest, the classification is probably incorrect. More likely, as based on intuition, deduction, and/or probability, this area

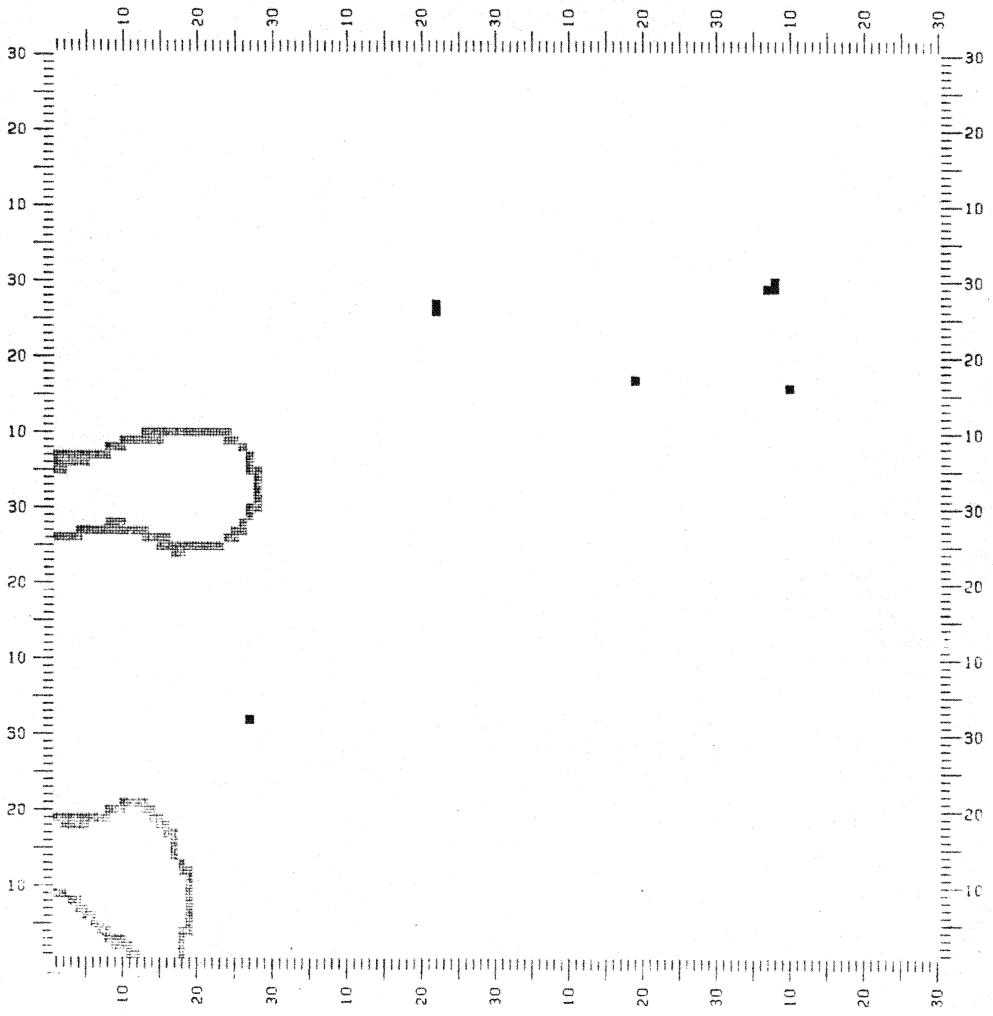


Fig. 48. Gray scale image of study area level 1 water exclusion data set.

Fig. 48. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		14240
2. - 2.		152
9. - 9.		8

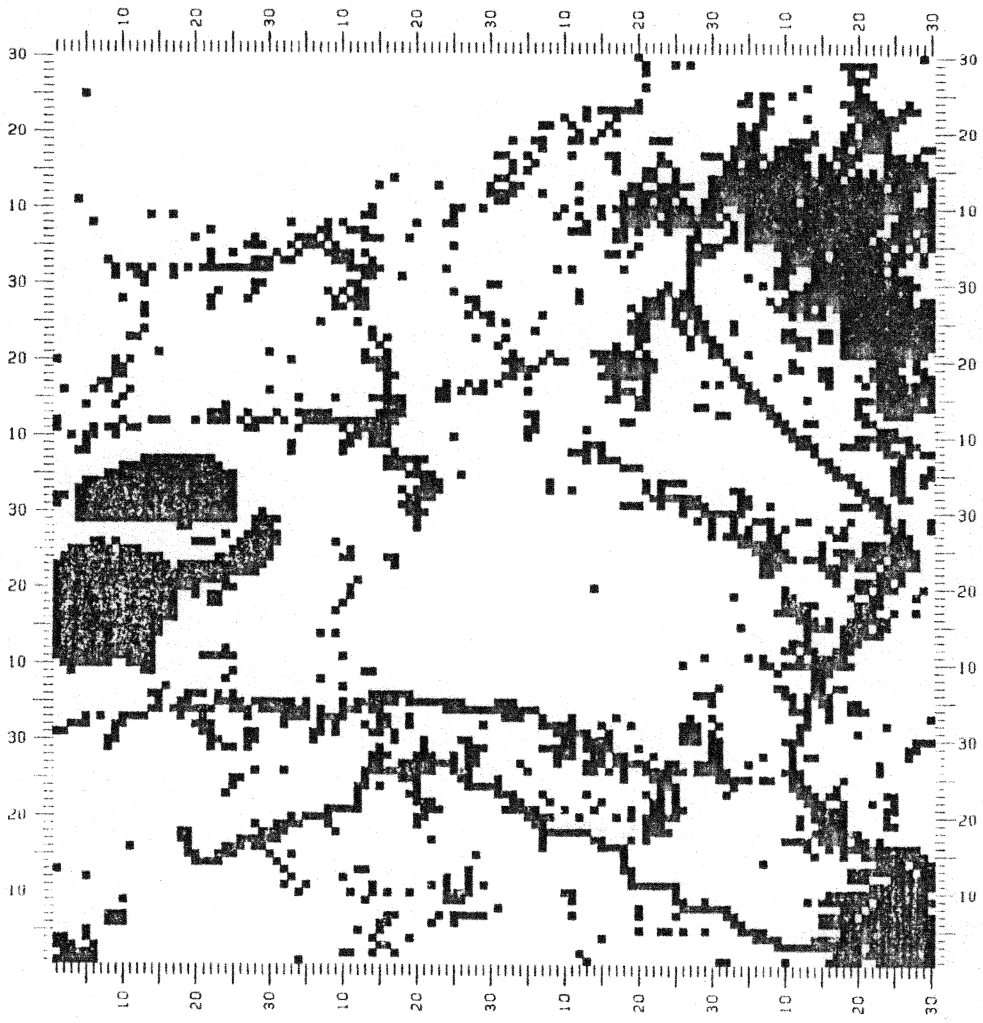


Fig. 49. Gray scale image of study area level 1 urban exclusion data set.

Fig. 49. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3144
0.	-	0.		11256

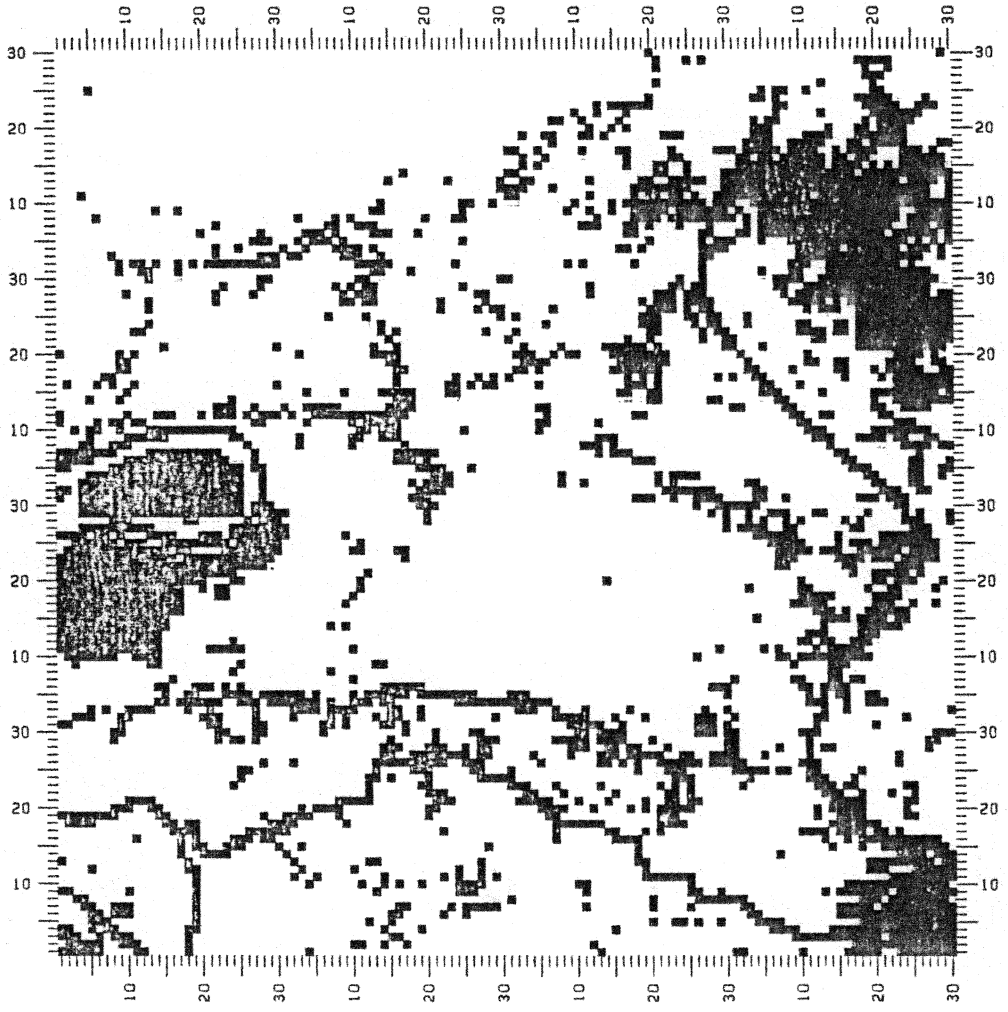


Fig. 50. Gray scale image of study area level 1 water plus urban exclusion data set.

Fig. 50. (Continued).

SYMBOL KEY

	CATEGORY	SYMBOL	FREQUENCY
-9999.	- -9999.		3304
0.	- 0.		11096

is conifer forest. Structuring a computer program to recognize ranges of ancillary data and reclassify image pixels accordingly is one means to achieve a maximum likelihood of ancillary data-pixel classification agreement. Of course, if there is concurrence between ancillary data and the classification a pixel possesses, no reclassification is necessary. Overall, using a conditional sequence creates a decision hierarchy with some individual ancillary data sets assigned more importance in terms of land use classification, than other sets.

In this thesis, an attempt was made to show that the potential exists for increasing land use classification accuracy through using a conditional sequence. The decision-tree branching pattern, characteristic of the exclusion-conditional method, was structured within FORTRAN IV program CONDITN (Appendix X) using a series of logical-if type statements.

With one exception, all of the ancillary data sets serving as input to the conditional method were non-spectral. These sets included:

1. Elevation-height above sea level (in feet),
2. Degree of slope-rate of elevation change (in degrees),
3. Degree of aspect-compass direction of maximum decreasing slope (in degrees),
4. Nearness-to-water-distance in terms of meters, from any water which constitutes a major portion of a 3-acre cell, and
5. Level 2 classified land use.

Given the structure of the conditional classification algorithm within program CONDITN, there were 2 restrictions associated with the exclusion-conditional method. These were:

1. the conditional classification of cells into Level 2 land use types was performed only on 13-category images, and
2. the 13-category images must have previously undergone a complete 3-set exclusion (i.e., roads, urban areas, and water).

More specifically, restriction 1 was necessary since program CONDITN only accepted 13-category land use classification codes as input. Serving as the basis for restriction 2 were the limitations associated with using applied ecological principles for identifying land use types. As such, an effort was made to structure the conditional sequence to identify only those land use types whose locations were ecologically based (i.e., deciduous, conifer, and mixed forests, pastureland, cropland, and water areas). Types for which placements were only weakly related to ecological conditions (i.e., roads and urban areas) were excluded. Ancillary data relevant to those cells were disregarded. Water areas which served as the framework upon which the nearness-to-water data set was calculated were excluded for a different reason. This was because the nearness-to-water data essentially represented correctly classified water bodies. Identifying water areas in the conditional sequence was oriented to those waters which occupied less than 50 percent of the 1/27 km^2 (3-acre) cell and thus were not originally identified.

The conditional classification selection algorithm is displayed in Fig. 51.

Conditional Topographic Data

In many cases, associations exist between specific land uses (e.g., cropland, pastureland, and forest) and certain topographic features

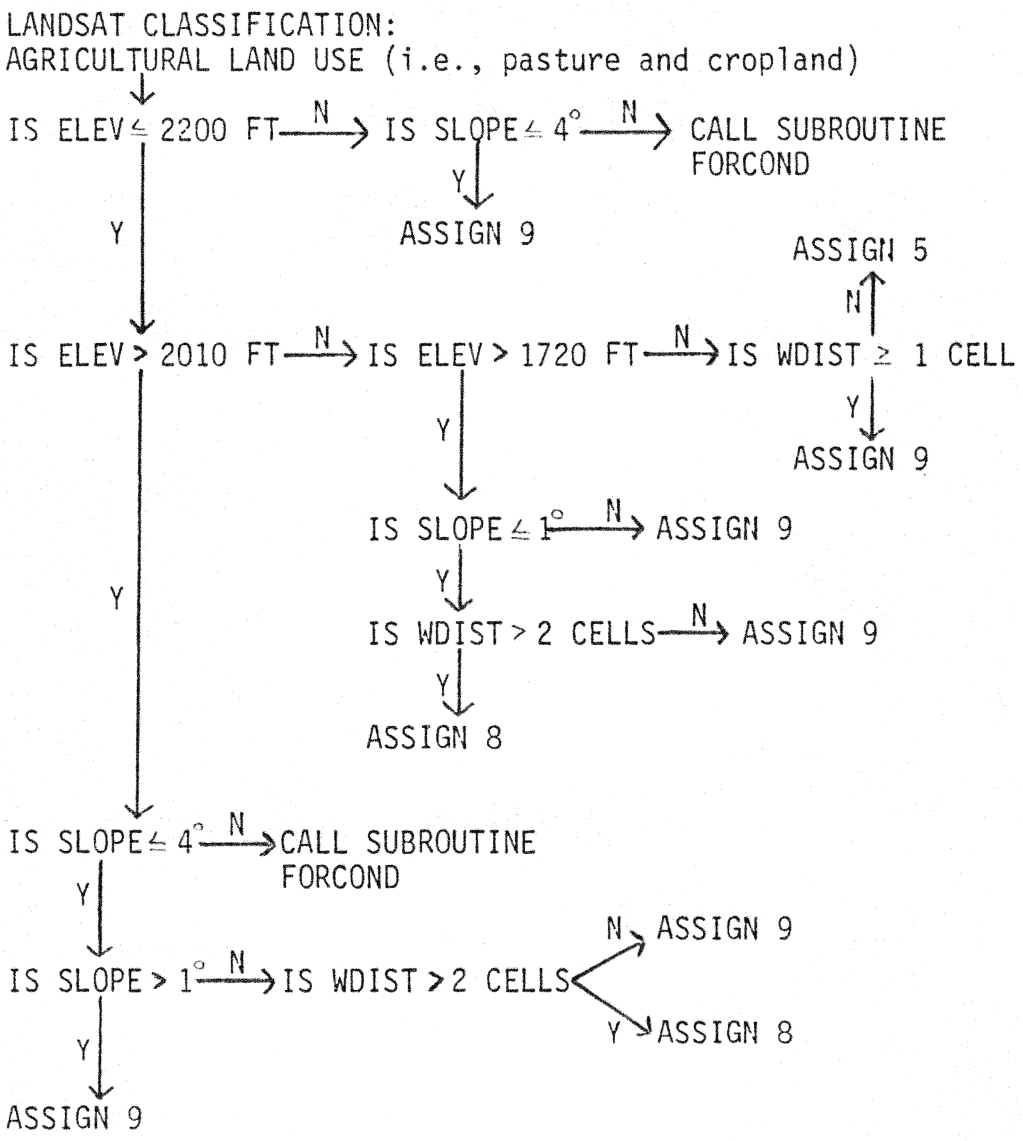
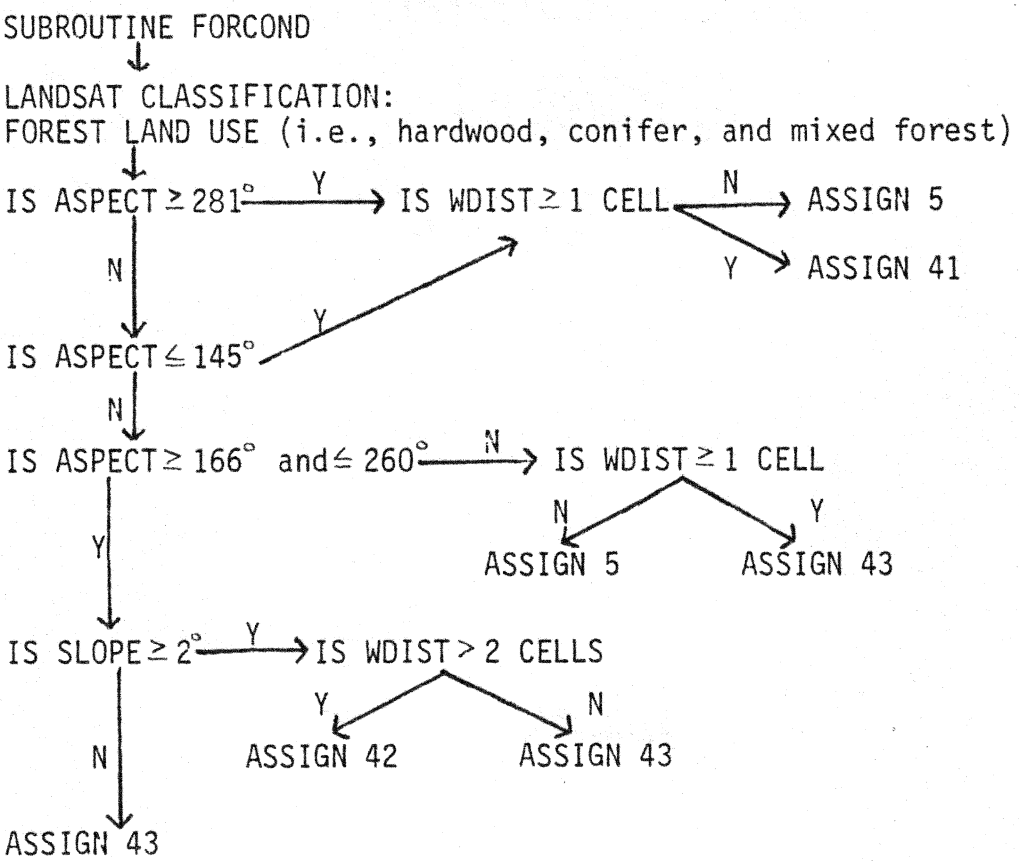


Fig. 51. Decision-tree diagram of the land use classification algorithm used in FORTRAN IV program CONDITN.

Fig. 51. continued.



and/or settings (e.g., slope, aspect, and elevation). The opportunity exists, therefore, to utilize such information about associations as parameters in a conditional approach to classification.

One source of topographic data is the Defense Mapping Agency (DMA) Digital Terrain Tapes (DDTs) available from the National Cartographic Information Center (NCIC), U.S. Geological Survey, Reston, Virginia.

NCIC Digital Terrain Tapes are multiple track tapes containing elevation data. Each file corresponds to one half of a USGS 1:250000 scale map sheet. The data are obtained by digitizing elevation contours (100 ft intervals) on a 1:250000 scale topographic map and interpolating between contours at a spacing of 0.025 cm (0.01 in) map scale or roughly 63.5 meters on the ground (U.S. Geological Survey, 1979b). Map control points are provided with the terrain file for registration within a geocoded data base. Elevation data for the study area in Montgomery County are located on the eastern half of the 1:250000 scale Bluefield map.

Elevation, slope, and aspect were all computed directly or indirectly from the DTT data.

Topographic Data Generation

The following sequence of steps was used in generating the topographic data sets:

1. Define size and location of elevation data to be stored in the data structure,
2. Create adequate storage for this data,
3. Create subsets of elevation data from digital terrain tape to disk,

4. Load elevation data (disk) into the POWER system structure,
5. Compute slope and aspect data using FORTRAN IV program TOPO-III (Grender, 1976),
6. Load topographic data files into defined study area storage.

The initial step in this procedure called for increasing the study area in terms of individual POWER maps from a 16 map-file of elevations (4 by 4) to a 36 map-file (6 by 6). POWER program DEFINE was executed to create and store the new mapfile specifications. This enlargement was decided on due to the mode of calculation for slope and aspect which requires a 8-way nearest-elevation search before assigning a value to the central cell. If only a 4 by 4 mapfile was originally defined, all 480 cells composing the outer boundary of the study area (120 cells on a side) would have no topographic values (i.e., slope and aspect) assigned. Later, after all calculations had been completed for the 6 by 6 mapfiles (i.e., elevation, slope, and aspect), all 3 would be subset back into 4 by 4 mapfiles representative of the study area. These 4 x 4 mapfiles would hence contain a respective topographic value for each inner and boundary cell.

In the next step, POWER program INITIAL was executed using those specifications for the 6 by 6 define file. This resulted in values of 0 being assigned to all 3-acre cells within the 36 map-file.

FORTRAN IV program DIGTAPES was used for extracting the study area elevation data from the NCIC digital terrain tapes. Inputs to this program include the minimum X UTM, minimum Y UTM, maximum X UTM, and maximum Y UTM coordinates for the 6 by 6 mapfile area (G. Koeln, pers. comm.). Elevations for each pixel in the study area are output to disk storage.

The purpose of FORTRAN IV program DIGPOWER was to load the disk-stored elevation into the 6 by 6 mapfile. DIGPOWER inputs included the minimum UTM X and Y coordinates of the extreme southwest map within the 36 map area and the resampled cell width (i.e., distance along X) and length (i.e., distance along Y), both being in meters. Distances of 111.111 meters in both the X and Y directions were specified to represent a 3-acre cell. The resampling approach utilized in program DIGPOWER is a "nearest neighbor" interpolation (G. Koeln, pers. comm.). The file used for storing this data had previously been defined using program INITIAL.

Calculations of topographic slope and aspect were based on algorithms found in program TOPO-III (Grender, 1976). The name of the specific POWER program which performs these calculations is TOPO. Elevation data are the primary input to this program. Outputs consist of 2 mapfiles, one each for slope and aspect.

To restructure the 6 by 6 topographic mapfiles to a 4 by 4 study area format, FORTRAN IV program GETAREA was executed. This 4 by 4 format represented the number of POWER maps (i.e., 16) composing the study area. The purpose of program GETAREA is to redefine individual POWER map coordinate positions within a mapfile. The specific procedure for restructuring the topographic data involved reassigning mapfile map 2,2 as 1,1 and map 5,5 as 4,4, then using the original study area define file, subsetting only those 16 respective maps to previously initialized 4 by 4 POWER mapfiles. Output mapfiles of elevation, slope, and aspect were thus representative of only that topography within the study area. Gray scale images of elevation, slope, and aspect are displayed in Figs. 52, 53, and 54, respectively.

Fig. 52. Gray scale image of study area elevation (in feet) emphasizing high elevation ranges as dark gray shades.

Fig. 52. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
1600.	-	1720.		400
1720.	-	1840.		1499
1840.	-	1960.		2685
1960.	-	2080.		5487
2080.	-	2200.		3183
2200.	-	2320.		604
2320.	-	2440.		303
2440.	-	2560.		157
2560.	-	2680.		79
2680.	-	2800.		3

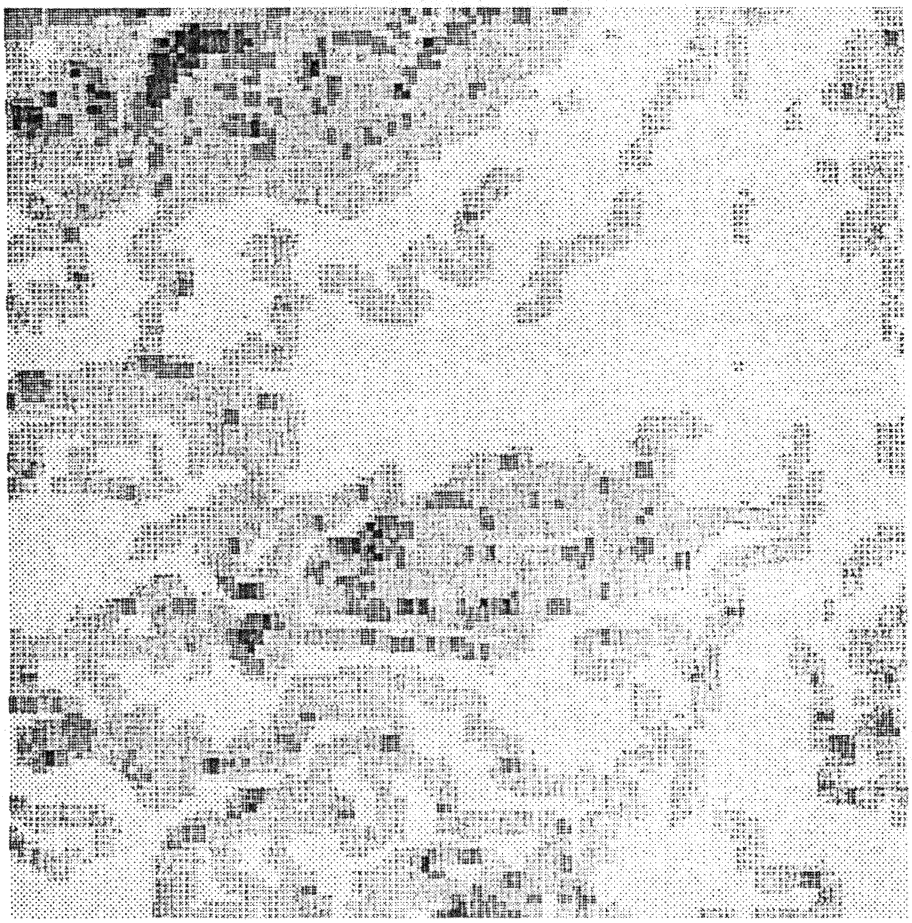


Fig. 53. Gray scale image of study area slope (in degrees) emphasizing extreme slope ranges as dark gray scales.

Fig. 53. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
0.	-	1.		7342
1.	-	3.		4456
3.	-	4.		1720
4.	-	6.		764
6.	-	9.		111
9.	-	999999.		7

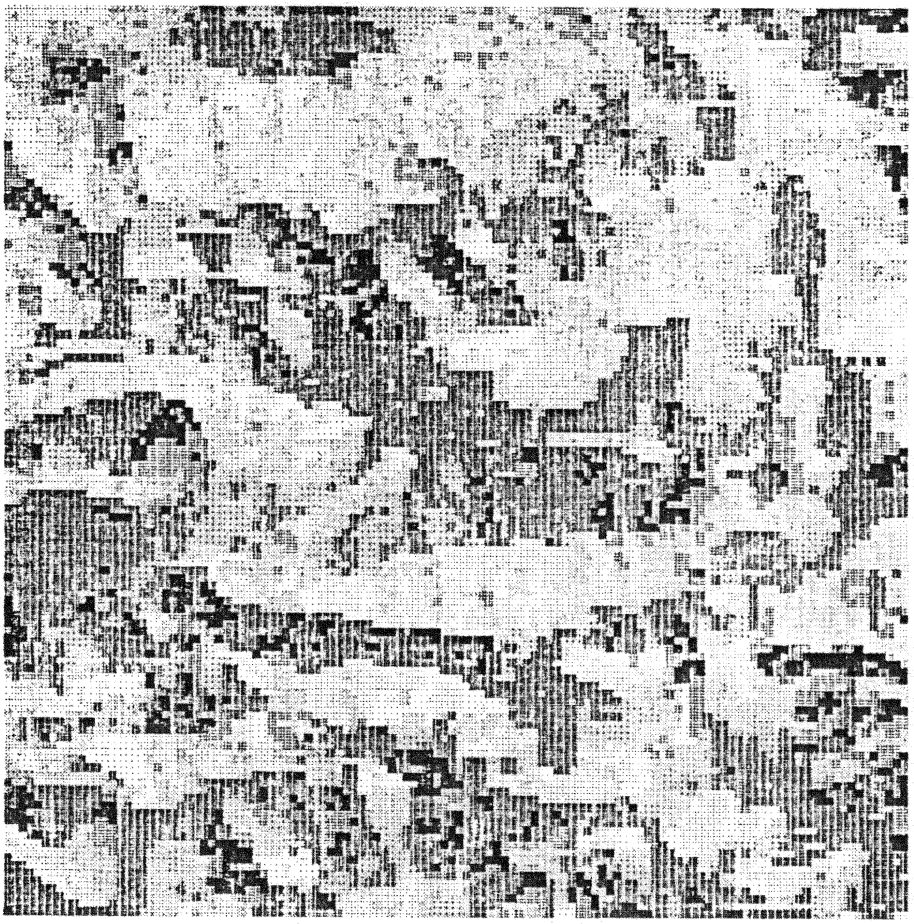


Fig. 54. Gray scale image of study area aspect (in degrees) emphasizing northern and eastern aspects as darker gray scales.

Fig. 54. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 45.		709
45. - 90.		835
90. - 135.		1512
135. - 180.		2357
180. - 225.		1284
225. - 270.		1900
270. - 315.		1745
315. - 360.		4058

Distance-From-Water Data

Calculations of distance from water (i.e., cellular distance) were based on only those water areas which occupied over 50% of a representative 1/27 km^2 (3-acre) cell present on a 1:24000 scale USGS quadrangle. Water area data were those which had been used previously in the exclusion method.

FORTRAN IV program DIST4 was used for calculating cellular water distance. Inputs to this program include the water area data set and values which indicate the smallest, largest, and total number of actual distances to be calculated (G. Koeln, pers. comm.). For this application, actual distances calculated were 0 to 15 cells from water (i.e., 16 actual distances) with cells greater than 15 being assigned a value of 15.

Fig. 55 displays the results of the DIST4 program computations.

The intent of using distance from water as a conditional parameter was to help distinguish between areas of a) cropland, b) pasture, and c) forests.

All classification decisions based on conditional parameters will appear in terms of greatest likelihood of occurrence. These likelihoods will correlate with established ecological and applied ecological principles in the study area.

Results may indicate that an already grossly classified Landsat scene (i.e., few categories) could be classified into more categories, or a highly classified image (i.e., many categories) could be aggregated.

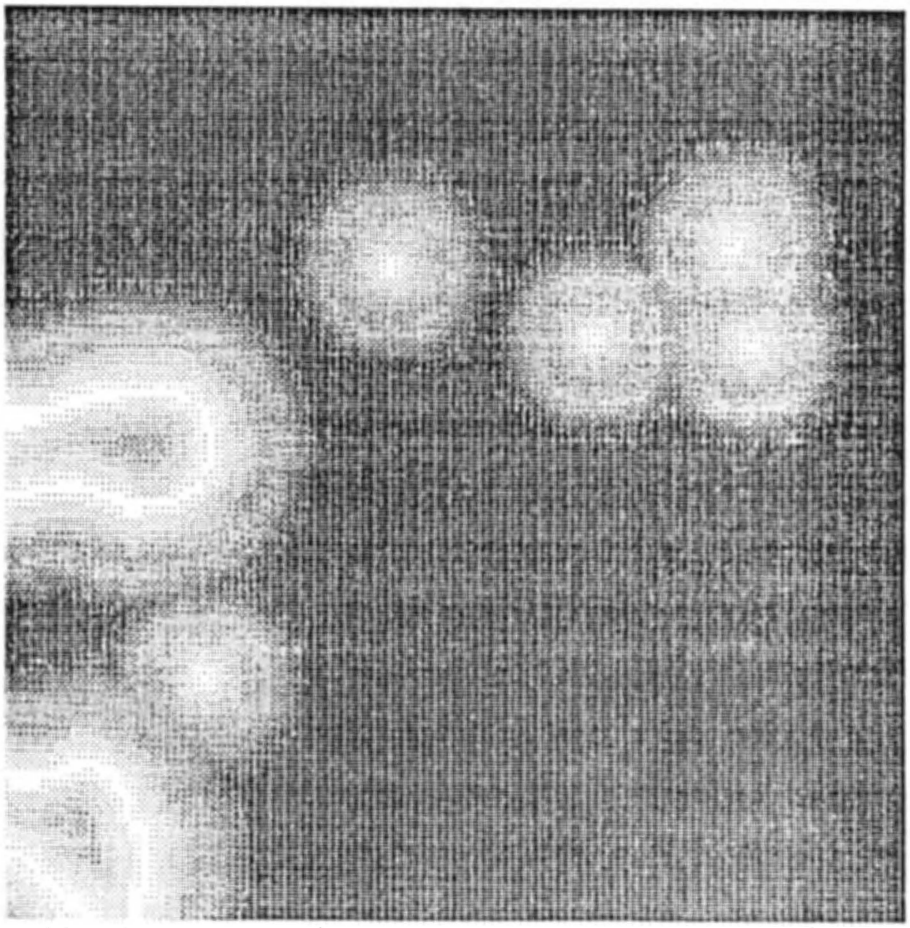


Fig. 55. Gray scale image of study area distance-from-water (in cells) emphasizing great distances as dark gray shades.

Fig. 55. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 1.		160
1. - 2.		329
2. - 3.		484
3. - 4.		308
4. - 5.		382
5. - 6.		324
6. - 7.		326
7. - 8.		373
8. - 9.		406
9. - 10.		422
10. - 11.		383
11. - 12.		368
12. - 13.		448
13. - 14.		396
14. - 15.		9291

Field Validation

Quality ground measurements (i.e., ground truth) are an essential element of all field validation procedures involving remotely sensed data. The importance of these measurements rest with their ability to help identify and explain anomalous classified image signatures. Presently, these measurements are most practical for surveys of small areas that can be covered with a single flight line (Sabins, 1978). Relative to large area land use surveys (e.g., those utilizing classified Landsat MSS imagery) measurements are often overly costly in terms of hours and dollars allocated, opposed to accuracy assessment benefits. Determining a GIS sampling strategy which would increase the ratio of accuracy assessment benefits to ground truth costs was the purpose of this portion of the research.

Distance-From-Roads Sampling Strategy

Similar to other sampling strategies, the purpose of the distance-from-roads method is to use sample data (i.e., areal ground truth) to make an inference about a population. Here, the population of interest is an extensive ground truth data set collected for use in assessing the accuracy of a classified Landsat image (Fig. 23). Calculating the smallest representative sample of ground truth data which could be used to infer correctly the accuracy of a classified Landsat image (also being comparable to that accuracy derived from more extensive ground truth) was the goal of this strategy.

The focus of distance-from-roads sampling is upon ground truth nearness (in cells) to digitized primary and secondary highway locations.

Here, ground data to be used in accuracy assessments are sampled at relative cell distances from highways. Landsat classified image accuracies are calculated at these varying distances and compared to an extensive ground truth accuracy assessment to determine the smallest distance (i.e., smallest sample) which produces Landsat accuracies closest to the extensive accuracy assessment. Overall, this "best" (i.e., smallest) distance value may reveal that classification accuracies can be derived just as efficiently and effectively from limited ground truth operations near highways as from extensive surveys. In terms of dollars spent, the smaller the ground truth sample required to conduct an acceptable accuracy assessment, the lower the costs of a complete unsupervised classification procedure.

Road cells which were used in the distance-from-roads strategy were digitized and stored similarly to those of the "roads-only" Level 2 exclusion set. The only difference which existed between these two road sets was that the exclusion set (i.e., "roads-only") was composed of only primary highway locations, with the distance-from-roads set composed of both primary and secondary highways. Fig. 56 displays the road network from which distance-from-roads calculations were based.

Five distances were randomly chosen upon which to base the distance-from-roads sampling strategy. These distances included =1, ≤ 2, ≤ 3, ≤ 6, and ≤ 9 cells from primary and secondary highways. In this case, =1 represents the sample of only those ground truth cells which were adjacent to roads. Those cells which occupied the same locations as the digitized roads (i.e., distance = 0) were nullified and not included in any of the 5 distance samples. Distance sample ≤ 2 represents the

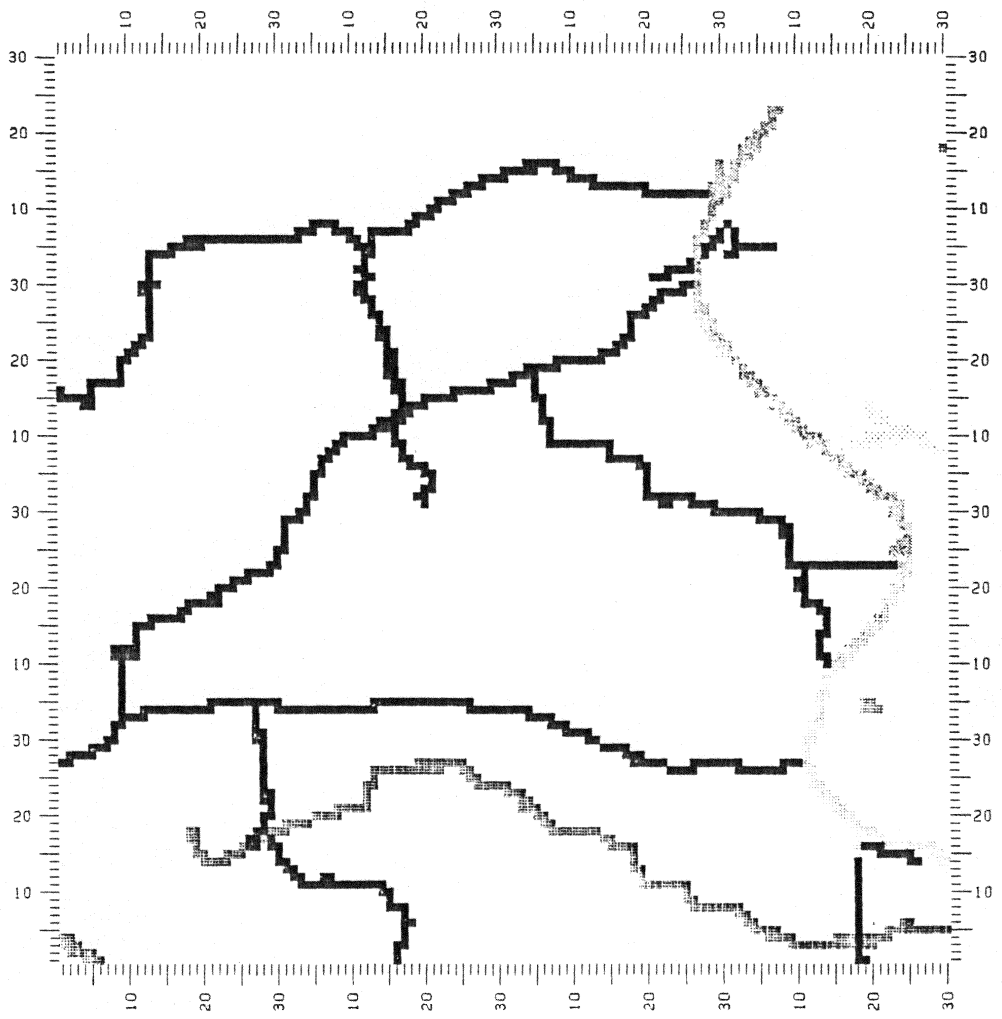


Fig. 56. Gray scale image of study area primary and secondary road network.

Fig. 56. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		13350
1. - 1.		138
2. - 2.		51
3. - 3.		25
4. - 4.		6
5. - 5.		163
6. - 6.		667

sample inclusive of ground truth cells adjacent to roads (i.e., distance = 1) and those cells lying 2 cells beyond highway cells. The largest sample, ≤ 9, was inclusive of cells 1 through 9 cells beyond a highway cell.

Two computer programs were utilized in the distance-from-roads strategy. The first was FORTRAN IV Program DIST4. The purpose of this program was to calculate the minimum distance of each cell in the study area from those cells associated with the location of a primary or secondary highway (G. Koeln, pers. comm.). Distance values are assigned to each cell based on how many cells removed it is from a highway cell. The specific range of distances to be calculated in DIST4 were from 0 through 10. Here, 0 would indicate an existing primary or secondary highway cell with 10 representing a cell greater than or equal to 10 cells from a highway. These distance calculations were stored on disk as a new cellular data set.

Inputs to FORTRAN IV program DROPPWR2 (Appendix Y) included (a) the distance-from-roads data set and (b) the extensive ground truth image. The purpose of DROPPWR2 was to overlay the 2 input images (a and b) creating a third image (c) of only those ground truth cells which were in the specific distance-from-roads zone. The width of the zone was required as a program input. As mentioned previously, cell-width zones were 1, ≤ 2, ≤ 3, ≤ 6, and ≤ 9. An accuracy assessment was performed upon each of the 5 sample sets. Accuracy assessments were limited to the Level 1 and 2 Landsat images possessing the greatest overall classification accuracy prior to any exclusion.

RESULTS

The Results section is presented in 4 parts. Part 1 will cover accuracies associated with each classified Landsat image. Where appropriate, comparisons will be made between images. Changes produced by the sequence of analyses for improving image accuracy are presented in tables. Part 2 will be a summary of inter- and intra-image accuracy assessments. This summary will include additional observations and comparisons not made in Part 1. Part 3 will examine results from the distance-from-roads sampling strategy and accuracy assessments. Finally, Part 4 will discuss those aspects of computer processing determined to be significant in this research.

PART 1

Table 7 lists classified images to be examined in Part 1 along with brief comments. As shown in this table, each image is differentiated according to parameters used during its processing. "Classified Landsat image" will here be defined by the author as the final product of multispectral data processing in which pixels have been categorized on the basis of reflectance and radiance characteristics.

Table 7. Sequence of classified Landsat images to be presented and characterized in Part 1 of the Results section.

Image Identifier	No. of Input Bands	No. of Classification Categories	Comments
1(A.)	4	13	Region elimination size prior to clustering (RESPC): < 13 pixels Output clusters (OC): 70
1(B.)	4	4	Same as 1(A.)
2(A.)	4	13	RESPC: < 9 pixels OC: 90
2(B.)	4	4	Same as 2(A.)
3(A.)	4	13	RESPC: < 5 pixels OC: 120
3(B.)	4	4	Same as 3(A.)
4(A.)	9	13	RESPC: < 13 pixels OC: 70
4(B.)	9	4	Same as 4(A.)
5(A.)	9	13	RESPC: < 9 pixels OC: 90
5(B.)	9	4	Same as 5(A.)
6(A.)	9	13	RESPC: < 5 pixels OC: 160
6(B.)	9	4	Same as 6(A.)

I. IMAGE NO. 1

A. 13 classes

1. Complete Image

Image No. 1 (Fig. 57) was prepared from the 4 raw Landsat bands. This data set had been clustered to include 70 spectrally-distinct areas. Previous analysis on the GIPSY system had removed and reassigned those pre-cluster regions of less than 13 pixels. The confusion matrix for the complete image no. 1 is displayed in Table 8. To prevent problems associated with improperly interpreting confusion matrix results, Table 9 is provided as a key.

For this image, the overall classification accuracy (OCA) was 67.3 percent. This is the percentage of the total number of pixels in all land use classes that were correctly classified. A 49.0 percent overall mapping accuracy (OMA) was achieved with this OCA. This means that 49 percent of the area in the Landsat image was corrected classified and positioned (i.e., mapped) according to land use class (see Methods, page 86, for additional information).

As shown in the Omissions columns [i.e., Total, No., and Percent (%)] of Table 8, there was difficulty identifying 8 out of 13 land use classes (i.e., water, cropland, transportation, other urban, orchards, conifer forest, mixed forest, and transitional) within image no. 1. This means that these 8 classes did not possess a distinct enough signature to prevent them from being assigned to other land use classes. The "Omissions Percent" column of Table 8 show all of these 8 classes possessing omission errors of 85 percent or higher. A level of 85 percent or greater was chosen somewhat arbitrarily to represent severe

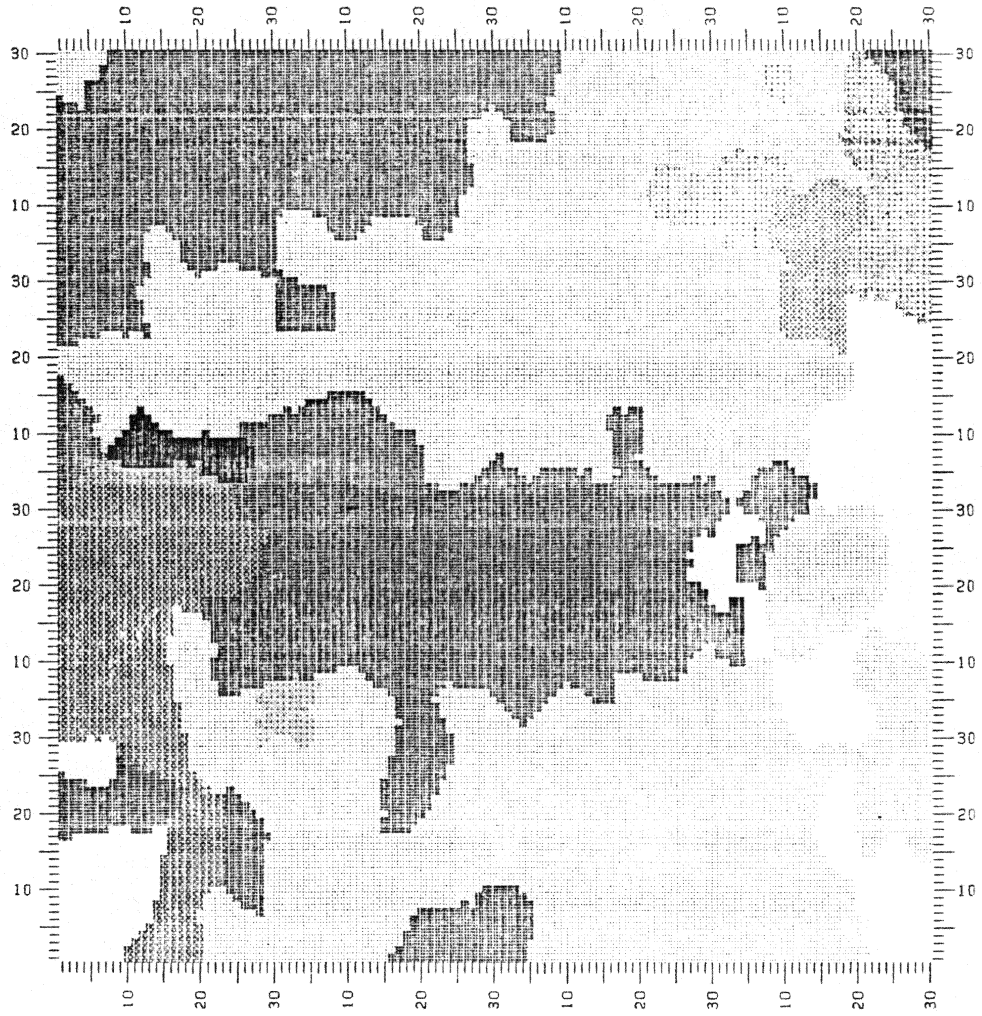


Fig. 57. Gray scale representation of classified Landsat image no. 1. Each land use is assigned a single gray scale shade.

Fig. 57. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		1261
8.	- 8.		30
9.	- 9.		6876
11.	- 11.		540
12.	- 12.		207
13.	- 13.		971
41.	- 41.		4416
42.	- 42.		99

Table 8. Confusion table and mapping accuracies of the complete 13-class, image no. 1. This image was originally classified using the 4 raw Landsat bands. All regions with less than 13 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	12 0	1 20	0 16	34 0	83	83	100.0	0.0
CROPLAND	8	0 0 0	11 0	97 0	0 7	0 0	0 0	115	104	90.4	8.9
PASTURE	9	0 0 0	2 0	3002 0	102 191	21 2	3 0	3323	321	9.7	64.0
RESIDENTIAL	11	0 0 0	0 0	270 0	189 46	14 0	0 0	519	330	63.6	26.4
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	53.2
INDUSTRIAL	13	0 0 0	0 0	4 0	0 38	0 11	466 0	519	53	10.2	68.0
TRANSPORTATION	14	0 0 0	0 0	34 0	6 0	0 0	0 0	40	40	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	8 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	0 0 0	7 0	636 0	67 1769	5 6	97 0	2587	818	31.6	50.9
CONIFER	42	0 0 0	0 0	126 0	2 205	0 48	29 0	410	362	88.3	10.8
MIXED	43	0 0 0	0 0	148 0	0 384	0 1	3 0	536	536	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		0 0	20 0	4366 0	386 2660	123 84	632 0				

Table 8. (Continued).

		0					
COMMISSIONS	NO.	0	9	1364	197	40	166
		0	0	0	891	36	0
		0					
COMMISSIONS	%	0.0	45.0	31.2	51.0	32.5	26.3
		0.0	0.0	0.0	33.5	42.9	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) = 67.3							
OVERALL MAPPING ACCURACY(OMA) = 49.0							

Table 9. A table for use in reading and interpreting confusion matrices.

A EXPECTED OR KNOWN LAND USE		B INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO. F	NO. G	% H	*
WATER	5	0 0 0	0 0	12 0	1 20	0 16	34 0	83 F1	83 G1	100.0 H1	0.0
CROPLAND	8	0 0 0	E 11 0	C 97 0	0 7	0 0	0 0	115	104	90.4	8.9
PASTURE	9	0 0 0	2 0	3002 0	102 191	21 2	D 3 0	3323	321	9.7	64.0
RESIDENTIAL	11	0 0 0	0 0	270 0	189 46	14 0	0 0	519	330	63.6	26.4
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	53.2
INDUSTRIAL	13	0 0 0	0 0	4 0	0 38	0 11	466 0	519	53	10.2	68.0
TRANSPORTATION	14	0 0 0	0 0	34 0	6 0	0 0	0 0	40	40	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	8 0	0 0	0 0	11	11	100.0	0.0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
TOTAL NO. OF CELLS I		0 0 0	I1 20 0	4366 0	386 2660	123 84	632 0				
COMMISSIONS NO. J		0 0 0	J1 9 0	1364 0	197 891	40 36	166 0				
COMMISSIONS % K		0.0 0.0 0.0	K1 45.0 0.0	31.2 0.0	51.0 33.5	32.5 42.9	26.3 0.0				

* OVERALL CLASSIFICATION ACCURACY(OCA) = 67.3

* OVERALL MAPPING ACCURACY(OMA) = 49.0

Table 9. (Continued).

A - Observed ground truth land use classes. Field classes are found immediately under this heading bordering the left table margin. A numeric class identifier is placed to the right of each category name.

B - Landsat image land use classes. To conserve table space, only numeric class identifiers are located under this heading. Classes are arranged in two lines of 6 identifiers and one line of 1 identifier.

C - Ninety-seven (97) pixels were omitted (i.e., omission error) from the cropland class and committed (i.e., commission error) to a pasture classification. (Class omissions are identified moving left to right across the appropriate ground truth class row. Class commissions are identified moving up or down under the appropriate Landsat image class column.)

D - Three (3) pixels were omitted from the pasture class and committed to an industrial classification.

E - Eleven (11) Landsat pixels were correctly classified as cropland based on ground truth observations. The point of intersection between ground truth row and Landsat image column possessing equivalent class identifiers always represents the number of correctly classified pixels (i.e., matrix diagonal).

F - Total number of pixels field observed and assigned to each ground truth class.

F1 - Eighty-three (83) pixels classed as water were included in the ground truth sample.

G - Total number of Landsat image pixels which did not possess (i.e., were omitted from) a correct land use classification. Omission error results when a pixel does not possess a classification similar to that of ground truth.

G1 - Eighty-three (83) pixels were omitted from a correct water classification.

H - Percentage of Landsat image pixels omitted from a correct land use classification.

H1 - One-hundred (100) percent of the pixels ground truthed to be water were omitted from a water classification.

Table 9. (Concluded).

I - Total number of Landsat image pixels classified according to each land use.

I1 - Twenty (20) Landsat image pixels were classified as cropland.

J - Total number of Landsat image pixels assigned to (i.e., committed to) an incorrect land use classification. Commission error results when a pixel is classified as an incorrect land use.

J1 - Nine (9) pixels were incorrectly committed to the cropland class.

K - Percentage of Landsat image pixels committed to an incorrect land use.

K1 - Forty-five (45) percent of the pixels classified as cropland were incorrectly committed from non-cropland classes.

* - For a detailed discussion of this heading, the reader is referred to the Methods: Analysis and Confusion section.

omission errors. This percentage appeared to separate those land uses which were fairly from poorly classifiable. "Percent omissions" represents the percentage of pixels that were classified to an incorrect land use (i.e., omitted from a "true" class as determined from ground truth observations).

Commission problems occur when land use signatures mimic those of other land use classes and are thus incorrectly classified. As denoted in the "Commissions" rows [i.e., No. and Percent (%)] of Table 8, this error was greatest for the residential class. This means that the residential class signature was likely to be variously assigned to a variety of classes. The specific percentage was 51.0. [Values shown in the Commissions No. and Percent (%) rows correspond to the original sequence of land uses as listed in the Expected or Known Land Use row.] The cause was probably that the residential land use class (i.e., the specific Level 2 residential class) possessed a variety of signatures (e.g., wooded areas as well as densely built areas). A great number of non-residential pixels were therefore classed as residential.

The greatest mapping accuracies in image no. 1 were for industrial (68.0) and pasture (64.0).

2. Incremental Exclusions

The order of classes which were excluded in sequence was arbitrarily chosen. The sequence began with single-class exclusions. The series of confusion matrices corresponding to the exclusions are displayed in Tables 10 through 16. Table 17 is provided to summarize the OCA and OMA changes resulting from the exclusions.

Table 10. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding road cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	12 0	1 20	0 16	34 0	83	83	100.0	0.0
CROPLAND	8	0 0 0	11 0	97 0	0 7	0 0	0 0	115	104	90.4	8.9
PASTURE	9	0 0 0	2 0	2918 0	93 183	21 2	3 0	3222	304	9.4	64.3
RESIDENTIAL	11	0 0 0	0 0	270 0	187 43	14 0	0 0	514	327	63.6	26.8
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	53.2
INDUSTRIAL	13	0 0 0	0 0	4 0	0 38	0 11	466 0	519	53	10.2	68.0
TRANSPORTATION	14	0 0 0	0 0	7 0	1 0	0 0	0 0	8	8	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	8 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	0 0 0	7 0	622 0	67 1768	5 6	97 0	2572	804	31.3	51.2
CONIFER	42	0 0 0	0 0	121 0	2 205	0 48	29 0	405	357	88.1	10.9
MIXED	43	0 0 0	0 0	147 0	0 382	0 1	3 0	533	533	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		0 0 0	20 0	4235 0	370 2646	123 84	632 0				

Table 10. (Continued).

		0					
COMMISSIONS	NO.	0	6	1032	119	16	128
		0	0	0	751	25	0
		0					
COMMISSIONS	%	0.0	35.3	28.2	85.6	53.3	70.7
		0.0	0.0	0.0	30.6	45.5	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				68.3			
OVERALL MAPPING ACCURACY(OMA) =				50.6			

Table 11. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding urban cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	12 0	1 20	0 16	34 0	83	83	100.0	0.0
CROPLAND	8	0 0 0	11 0	96 0	0 5	0 0	0 0	112	101	90.2	9.3
PASTURE	9	0 0 0	2 0	2630 0	62 144	12 2	1 0	2853	223	7.8	67.7
RESIDENTIAL	11	0 0 0	0 0	57 0	20 9	0 0	0 0	86	66	76.7	9.8
SERVICES	12	0 0 0	0 0	12 0	6 0	14 0	0 0	32	18	56.3	29.2
INDUSTRIAL	13	0 0 0	0 0	2 0	0 18	0 2	53 0	75	22	29.3	26.1
TRANSPORTATION	14	0 0 0	0 0	31 0	3 0	0 0	0 0	34	34	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	1 0	4 0	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	4 0	567 0	41 1707	4 5	84 0	2412	705	29.2	54.0
CONIFER	42	0 0 0	0 0	115 0	2 192	0 30	7 0	346	316	91.3	8.1
MIXED	43	0 0 0	0 0	133 0	0 363	0 0	2 0	498	498	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	17 0	3662 0	139 2458	30 55	181 0				

Table 11. (Continued).

COMMISSIONS	NO.	0 0 0	9 0	1317 0	183 878	40 36	166 0
COMMISSIONS	%	0.0 0.0 0.0	45.0 0.0	31.1 0.0	49.5 33.2	32.5 42.9	26.3 0.0
OVERALL CLASSIFICATION ACCURACY(OCA) =				67.6			
OVERALL MAPPING ACCURACY(OMA) =				49.3			

Table 12. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding water cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	0 0	1 1	0 0	5 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	11 0	97 0	0 7	0 0	0 0	115	104	90.4	8.9
PASTURE	9	0 0 0	2 0	3000 0	102 191	21 2	3 0	3321	321	9.7	64.2
RESIDENTIAL	11	0 0 0	0 0	270 0	189 46	14 0	0 0	519	330	63.6	26.4
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	53.2
INDUSTRIAL	13	0 0 0	0 0	4 0	0 38	0 11	462 0	515	53	10.3	71.4
TRANSPORTATION	14	0 0 0	0 0	34 0	6 0	0 0	0 0	40	40	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	8 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	0 0 0	7 0	636 0	67 1769	5 5	94 0	2583	814	31.5	51.2
CONIFER	42	0 0 0	0 0	126 0	2 203	0 48	27 0	406	358	88.2	11.3
MIXED	43	0 0 0	0 0	148 0	0 384	0 1	3 0	536	536	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		0 0	20 0	4352 0	386 2639	123 67	594 0				

Table 12. (Continued).

		0					
COMMISSIONS	NO.	0	9	1352	197	40	132
		0	0	0	870	19	0
		0					
COMMISSIONS	%	0.0	45.0	31.1	51.0	32.5	22.2
		0.0	0.0	0.0	33.0	28.4	0.0
		0.0					

OVERALL CLASSIFICATION ACCURACY(OCA) = 68.0

OVERALL MAPPING ACCURACY(OMA) = 49.8

Table 13. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding road plus water cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	0 0	1 1	0 0	5 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	11 0	97 0	0 7	0 0	0 0	115	104	90.4	8.9
PASTURE	9	0 0 0	2 0	2916 0	93 183	21 2	3 0	3220	304	9.4	64.4
RESIDENTIAL	11	0 0 0	0 0	270 0	187 43	14 0	0 0	514	327	63.6	26.8
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	53.2
INDUSTRIAL	13	0 0 0	0 0	4 0	0 38	0 11	462 0	515	53	10.3	71.4
TRANSPORTATION	14	0 0 0	0 0	7 0	1 0	0 0	0 0	8	8	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	8 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	0 0 0	7 0	622 0	67 1768	5 5	94 0	2568	800	31.2	51.6
CONIFER	42	0 0 0	0 0	121 0	2 203	0 48	27 0	401	353	88.0	11.4
MIXED	43	0 0 0	0 0	147 0	0 382	0 1	3 0	533	533	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		0 0	20 0	4221 0	370 2625	123 67	594 0				

Table 13. (Continued).

		0					
COMMISSIONS	NO.	0	9	1305	183	40	132
		0	0	0	857	19	0
		0					
COMMISSIONS	%	0.0	45.0	30.9	49.5	32.5	22.2
		0.0	0.0	0.0	32.6	28.4	0.0
		0.0					

OVERALL CLASSIFICATION ACCURACY(OCA) = 68.3

OVERALL MAPPING ACCURACY(OMA) = 50.2

Table 14. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding road plus urban cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	12	1	0	34	83	83	100.0	0.0
		0	0	0	20	16	0				
		0									
CROPLAND	8	0	11	96	0	0	0	112	101	90.2	9.3
		0	0	0	5	0	0				
		0									
PASTURE	9	0	2	2554	55	12	1	2763	209	7.6	68.1
		0	0	0	137	2	0				
		0									
RESIDENTIAL	11	0	0	57	20	0	0	86	66	76.7	10.3
		0	0	0	9	0	0				
		0									
SERVICES	12	0	0	12	6	14	0	32	18	56.3	29.2
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	2	0	0	53	75	22	29.3	26.1
		0	0	0	18	2	0				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URABN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	1	4	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	4	555	41	4	84	2400	693	28.9	54.3
		0	0	0	1707	5	0				
		0									
CONIFER	42	0	0	110	2	0	7	341	311	91.2	8.2
		0	0	0	192	30	0				
		0									
MIXED	43	0	0	132	0	0	2	496	496	100.0	0.0
		0	0	0	362	0	0				
		0									
TRANSITIONAL	76	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
TOTAL NO. OF CELLS		0	17	3542	129	30	181				
		0	0	0	2450	55	0				

Table 14. (Continued).

		G					
COMMISSIONS	NO.	0 0 0	6 0	988 0	109 743	16 25	128 0
COMMISSIONS	%	0.0 0.0 0.0	35.3 0.0	27.9 0.0	84.5 30.3	53.3 45.5	70.7 0.0
OVERALL CLASSIFICATION ACCURACY(OCA) =			68.5				
OVERALL MAPPING ACCURACY(OMA) =			50.9				

Table 15. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding urban plus water cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	0 0	1 1	0 0	5 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	11 0	96 0	0 5	0 0	0 0	112	101	90.2	9.3
PASTURE	9	0 0 0	2 0	2628 0	62 144	12 2	1 0	2851	223	7.8	67.9
RESIDENTIAL	11	0 0 0	0 0	57 0	20 9	0 0	0 0	86	66	76.7	9.8
SERVICES	12	0 0 0	0 0	12 0	6 0	14 0	0 0	32	18	56.3	29.2
INDUSTRIAL	13	0 0 0	0 0	2 0	0 18	0 2	49 0	71	22	31.0	29.7
TRANSPORTATION	14	0 0 0	0 0	31 0	3 0	0 0	0 0	34	34	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	1 0	4 0	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	4 0	567 0	41 1707	4 4	81 0	2408	701	29.1	54.4
CONIFER	42	0 0 0	0 0	115 0	2 190	0 30	5 0	342	312	91.2	8.6
MIXED	43	0 0 0	0 0	133 0	0 363	0 0	2 0	498	498	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	17 0	3648 0	139 2437	30 38	143 0				

Table 15. (Continued).

		0					
COMMISSIONS	NO.	0	6	1020	119	16	94
		0	0	0	730	8	0
		0					
COMMISSIONS	%	0.0	35.3	28.0	85.6	53.3	65.7
		0.0	0.0	0.0	30.0	21.1	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				69.1			
OVERALL MAPPING ACCURACY(OMA) =				51.5			

Table 16. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding road plus urban plus water cells.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	0 0	1 1	0 0	5 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	11 0	96 0	0 5	0 0	0 0	112	101	90.2	9.3
PASTURE	9	0 0 0	2 0	2552 0	55 137	12 2	1 0	2761	209	7.6	68.3
RESIDENTIAL	11	0 0 0	0 0	57 0	20 9	0 0	0 0	86	66	76.7	10.3
SERVICES	12	0 0 0	0 0	12 0	6 0	14 0	0 0	32	18	56.3	29.2
INDUSTRIAL	13	0 0 0	0 0	2 0	0 18	0 2	49 0	71	22	31.0	29.7
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URABN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	1 0	4 0	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	4 0	555 0	41 1707	4 4	81 0	2396	689	28.8	54.7
CONIFER	42	0 0 0	0 0	110 0	2 190	0 30	5 0	337	307	91.1	8.7
MIXED	43	0 0 0	0 0	132 0	0 362	0 0	2 0	496	496	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	17 0	3528 0	129 2429	30 38	143 0				

Table 16. (Continued).

		0					
COMMISSIONS	NO.	0	6	976	109	16	94
		0	0	0	722	8	0
		0					
COMMISSIONS	%	0.0	35.3	27.7	84.5	53.3	65.7
		0.0	0.0	0.0	29.7	21.1	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				69.4			
OVERALL MAPPING ACCURACY(OMA) =				51.9			

Table 17. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 1.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	67.3	49.0
Roads	67.6	49.3
Urban	68.3	50.6
Water	68.0	49.8
Roads + Water	68.3	50.2
Roads + Urban	68.5	50.9
Urban + Water	69.1	51.5
Roads + Urban + Water	69.4	51.9

Roads

Upon excluding the initial class, "roads-only", both OCA and OMA increased 0.3 percent over those of the complete image no. 1 to 67.6 percent and 49.3 percent respectively (Table 17). The greatest increase in mapping accuracies, after excluding roads, occurred for the residential land use (26.4 to 26.8; i.e., +0.4%) (Table 10). In this section (2.), all resulting accuracies are based on/compared to the complete image no. 1.

Urban

The next set of excluded cells was the "urban-only" class. Results from this step showed OCA having increased 0.7 percent over the previous exclusion (roads only) to 68.3 percent with OMA increasing 1.3 percent to 50.6 percent (Table 17). These accuracy levels were 1.0 percent and 1.6 percent greater than the complete image no. 1. The greatest step increase in mapping accuracy for land use classes occurred for pasture (64.0 to 67.7; i.e., +3.7%) (Table 11). The largest decrease from an exclusion, also shown in Table 11, was for the industrial class (68.0 to 26.1; i.e., -41.9%). Since digitized industrial areas were part of the "urban-only" exclusion class, this significant decrease can be attributed to the exclusion of some industrial pixels which were correctly classified. Post-exclusion, industrial mapping accuracy was hence based on remaining and incorrectly classified pixels.

Water

After excluding "water-only", OCA and OMA decreased 0.3 percent and 0.8 percent from the level of accuracy achieved when "urban-only" cells were excluded. The results were 68.0 percent and 49.8 percent respectively (Table 17). These levels still represented an increase of 0.7 percent for OCA and 0.8 percent for OMA when compared to the complete image no. 1. In eliminating water cells, the largest increase in mapping accuracy occurred in the industrial class (68.0 to 71.4; +3.4%) (Table 12).

Roads Plus Water

The next exclusions were combined "roads-only" plus "water-only" sets. This resulted in OCA increasing to 68.3 percent (Table 17); OMA increased to 50.2 percent. These levels were 1.0 percent and 1.2 percent higher than the OCA and OMA of the complete, image no. 1. The largest increases in mapping accuracy within classes occurred for industrial (68.0 to 71.4; i.e., +3.4%) (Table 13). There were no decreases in class mapping accuracies.

Roads Plus Urban

After excluding the "road-only" plus "urban-only" pairs, OCA and OMA increased 1.2 percent and 1.9 percent over the complete image no. 1 (Table 17). The largest increase in mapping accuracy during this step

occurred in pasture (64.0 to 68.1; i.e., +4.1%) (Table 14). The largest decrease in accuracy occurred for the industrial class (68.0 to 26.1; i.e., -41.9%) and can be attributed to the same factors which caused the large decrease during the "urban-only" exclusion.

Urban Plus Water

When the "urban-only" and "water-only" combination was excluded, OCA and OMA were 1.8 percent and 2.5 percent higher than the complete image no. 1 (Table 17). During this exclusion, the accuracy of the pasture class increased the greatest (64.0 to 67.9; i.e., +3.9%) (Table 15). The industrial class showed the greatest decrease (68.0 to 29.7; i.e., -38.3%).

Roads Plus Urban Plus Water

When the set of "roads-only" "urban-only" and "water-only" were excluded, both OCA and OMA increased to their highest levels (Table 17). OCA and OMA levels were 69.4 percent and 51.9 percent respectively. These levels were 2.1 percent and 2.9 percent greater than the accuracies reported for the complete image no. 1. For this step, accuracies for the pasture class increased the greatest (64.0 to 68.3; i.e., +4.3%), with industrial possessing the largest overall decrease (68.0 to 29.7; i.e., -38.3%) (Table 16). Table 18 summarizes the principal class accuracy effects which resulted from specific exclusions.

Table 18. Greatest increases in image no. 1 (13 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Residential	-
Urban	Pasture	Industrial
Water	Industrial	-
Roads + Water	Industrial	-
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	Mixed (Forest)	Hardwoods

Overall Exclusion Changes (+ and -): Pasture (64.0 to 68.3; i.e., +4.3%)
Industrial (68.0 to 29.7; i.e., -38.3%)

Per Pixel Accuracy

Accuracy changes per pixel excluded are summarized in Table 19 for the 13-class, image no. 1. Changes are expressed per-pixel because the pixel seemed to be the most basic analysis/decision element for both accuracy improvement and cost evaluations. For this image, excluding water resulted in the greatest per-pixel accuracy improvements. Being more specific, this means that based on the number of cells in the "water-only" exclusion class, and the resulting post-exclusion changes in image no. 1 OCA and OMA, excluding "water-only" produced a larger increase in accuracy per-pixel excluded than any other exclusion strategy used. Values for these respective indexes are 0.0078 (OCA) and 0.0089 (OMA) (Table 19) and are shown in Fig. 58. Roads possessed the next greatest single-factor OCA (0.0019) and OMA (0.0019) improvement values (Table 19). These values along with the multiple-exclusion index values, are displayed in Fig. 58.

3. Conditional classification

The final approach used a conditional classification method to improve the image no. 1 accuracies. This method [i.e., utilizing registered ancillary data sets (elevation, slope, aspect, nearness to water, and land use) within a decision-tree classification algorithm to verify, and if necessary, reclassify each pixel's land use] was used on image no. 1 only after the "roads plus urban plus water" combination had been excluded (Fig. 59). Results showed accuracies of 56.6 percent and 41.7 percent for OCA and OMA respectively (Table 20). Both accuracies were below those levels reported for the complete image no. 1 and the sequence of exclusion steps.

Table 19. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 1.

1	2	3	4	5	6	7	8
1. Roads	161	67.6	+0.3	0.0019	49.3	+0.3	0.0019
2. Urban	1729	68.3	+1.0	0.0006	50.6	+1.6	0.0009
3. Water	90	68.0	+0.7	0.0078	49.8	+0.8	0.0089
4. Roads + Water	251	68.3	+1.0	0.0040	50.2	+1.2	0.0048
5. Roads + Urban	1867	68.5	+1.2	0.0006	50.9	+1.9	0.0010
6. Urban + Water	1819	69.1	+1.8	0.0010	51.5	+2.5	0.0014
7. Roads + Urban + Water	1957	69.4	+2.1	0.0011	51.9	+2.9	0.0015

Image 1; 13 classes OCA = 67.3% OMA = 49.0%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

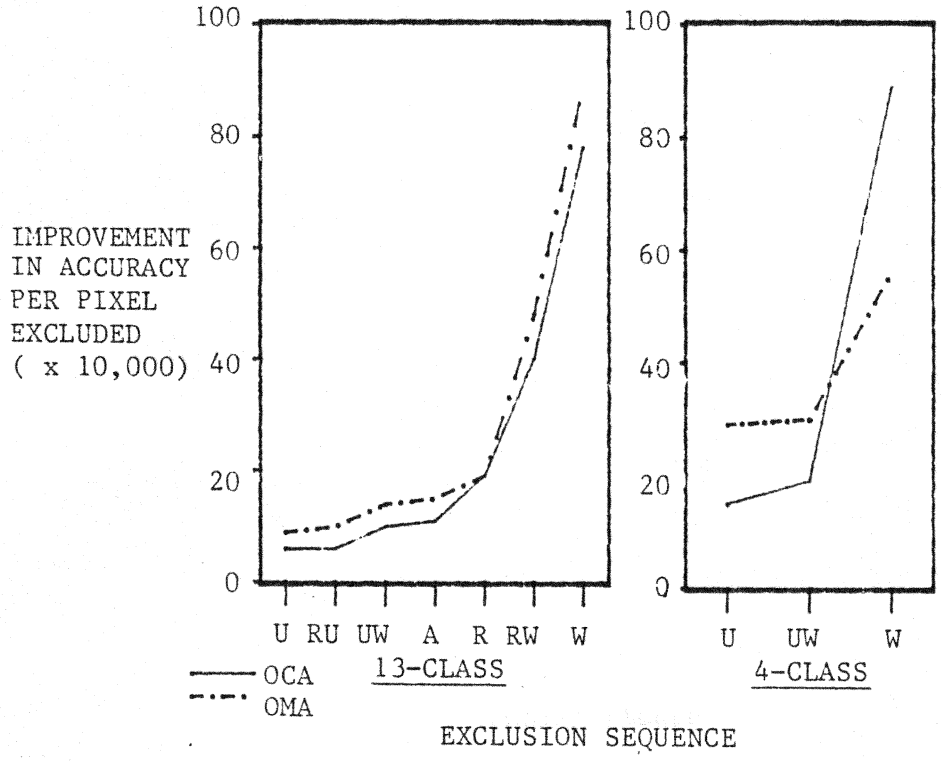


Fig. 58. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 1 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

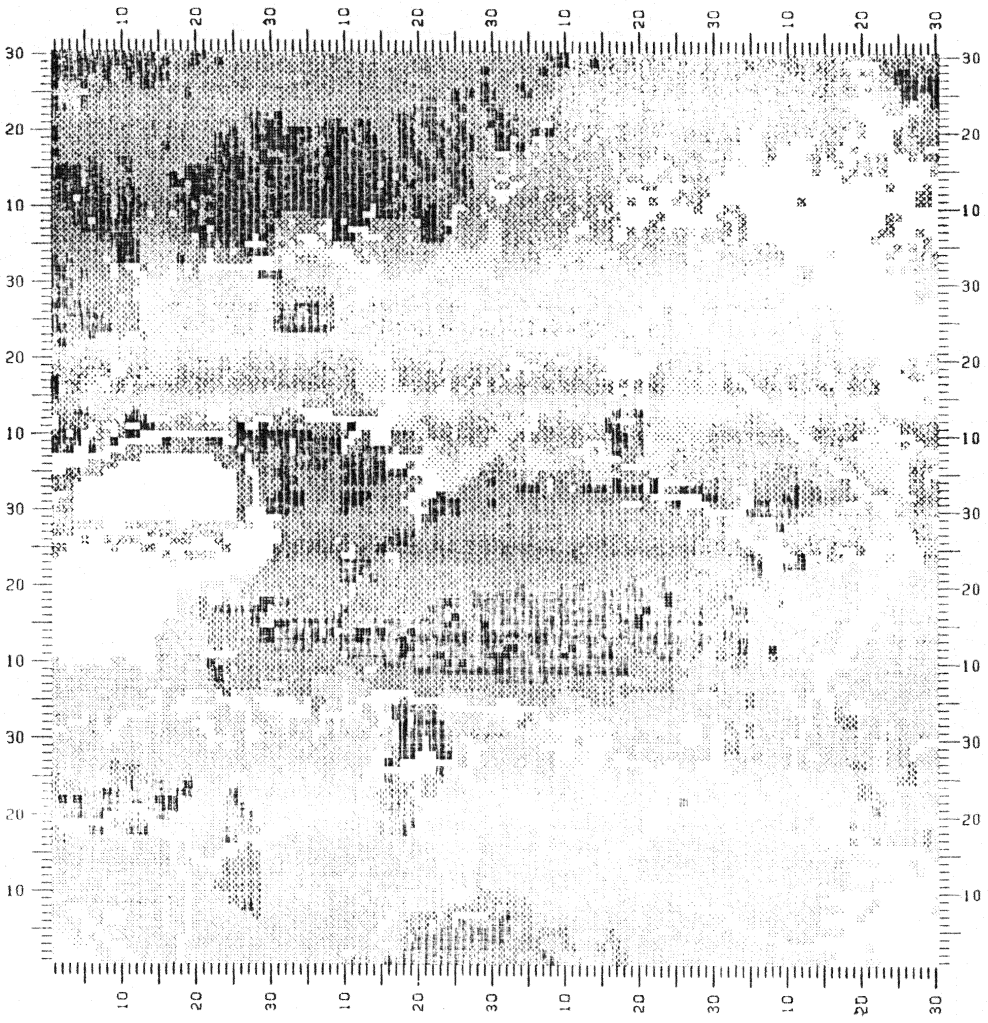


Fig. 59. Gray scale representation of conditional classification image no. 1. Each land use is assigned a single gray scale shade.

Fig. 59. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
8.	-	8.		895
9.	-	9.		5902
41.	-	41.		2872
42.	-	42.		138
43.	-	43.		1289

Table 20. Confusion table and mapping accuracies of the 13-class, image no. 1 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	6	0	0	0	7	7	100.0	0.0
		0	0	0	1	0	0				
		0									
CROPLAND	8	0	57	50	0	0	0	112	55	49.1	9.5
		0	0	0	4	0	1				
		0									
PASTURE	9	0	412	2196	0	0	0	2761	565	20.5	57.7
		0	0	0	126	0	27				
		0									
RESIDENTIAL	11	0	11	65	0	0	0	86	86	100.0	0.0
		0	0	0	6	0	4				
		0									
SERVICES	12	0	7	25	0	0	0	32	32	100.0	0.0
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	51	0	0	0	71	71	100.0	0.0
		0	0	0	14	0	6				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	43	598	0	0	0	2396	1247	52.0	39.8
		0	0	0	1149	54	552				
		0									
CONIFER	42	0	5	111	0	0	0	337	335	99.4	0.5
		0	0	0	151	2	68				
		0									
MIXED	43	0	7	124	0	0	0	496	325	65.5	14.8
		0	0	0	187	7	171				
		0									
TRANSITIONAL	76	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
TOTAL NO. OF CELLS		0	542	3242	0	0	0				
		0	0	0	1638	63	829				

Table 20. (Continued).

		0					
COMMISSIONS	NO.	0 0 0	485 0	1046 0	0 489	0 61	0 658
COMMISSIONS	%	0.0 0.0 0.0	89.5 0.0	32.3 0.0	0.0 29.9	0.0 96.8	0.0 79.4
OVERALL CLASSIFICATION ACCURACY(OCA) = 56.6							
OVERALL MAPPING ACCURACY(OMA) = 41.7							

As shown in the Omissions columns [i.e., Total, No., and Percent (%)] of Table 20, there were very high errors of omission in trying to identify conifer forest (99.4%) and mixed forest (65.5%) using the conditional methodology. These results might indicate that the 5 conditional inputs (i.e. elevation, slope, aspect, distance to water, and land use) did not constitute adequate information to identify those land areas where mixed or conifer forest existed. An alternative explanation is that problems with accurately aligning data from Landsat and maps prevented accurate classification.

As shown in the Commissions rows [i.e., No. and Percent (%)] of Table 20, commission error was highest for cropland (89.5%), mixed forest (79.4%), and conifer forest (96.8%). This might indicate that either the conditional parameters which were used to characterize these areas are also common to areas of differing land use, or, again, overlay errors caused information assignment problems.

As shown in Tables 20 and 18, when compared to the accuracy levels reported for the complete image no. 1, the greatest increase in mapping accuracy for classes using the conditional approach, was for mixed forest (0.0 to 14.8; i.e., +14.8%) (Table 20); the largest decrease was for the hardwoods class (50.9 to 39.8; i.e., -11.1%). The reason for this substantial decrease in hardwoods accuracy was because of the imperfect and incomplete environmental decision rules present in the conditional methodology. Based on the ancillary data used in this approach, decision rules reclassified many hardwoods pixels to mixed forest, although hardwoods was the correct classification to begin with. This indicates that the conditional classification criteria were not strict or inclusive enough (e.g., did not include soil differences).

Fig. 60 displays the step-by-step changes in OCA and OMA for 9 analyses of image no. 1 as based on 13 land use classes.

B. 4 Classes

1. Complete Image

After reducing the number of image no. 1 classes from 13 to 4, and holding region and cluster parameters the same, both OCA and OMA increased significantly when compared to the 13-class, complete image. Table 21 shows the results of the accuracy assessment for this 4-class image. Specific values for OCA and OMA were 76.1 percent and 62.5 percent respectively. Accuracy differences, when comparing the complete 4-class image to the complete 13-class image no. 1 (Table 8) were +8.8 percent (67.3 to 76.1) for OCA and +13.5 percent (49.0 to 62.5) for OMA. Extending this comparison to the 13-class image no. 1 when "roads-only", "urban-only", and "water-only" were excluded (Table 16), the complete 4-class image possessed a greater OCA (69.4 to 76.1; i.e., +6.7%) and OMA (51.9 to 62.5; i.e., +10.6%). As shown in Table 21, the agriculture class had the greatest mapping accuracy for this image.

2. Incremental Exclusions

The order in which classes were excluded for the 4-class image was chosen arbitrarily. In the following sequence of exclusions, "roads-only" and "urban-only" were combined into one set, "urban", in keeping with the gross nature of the classification scheme. Table 22 summarizes OCA and OMA after exclusions were made.

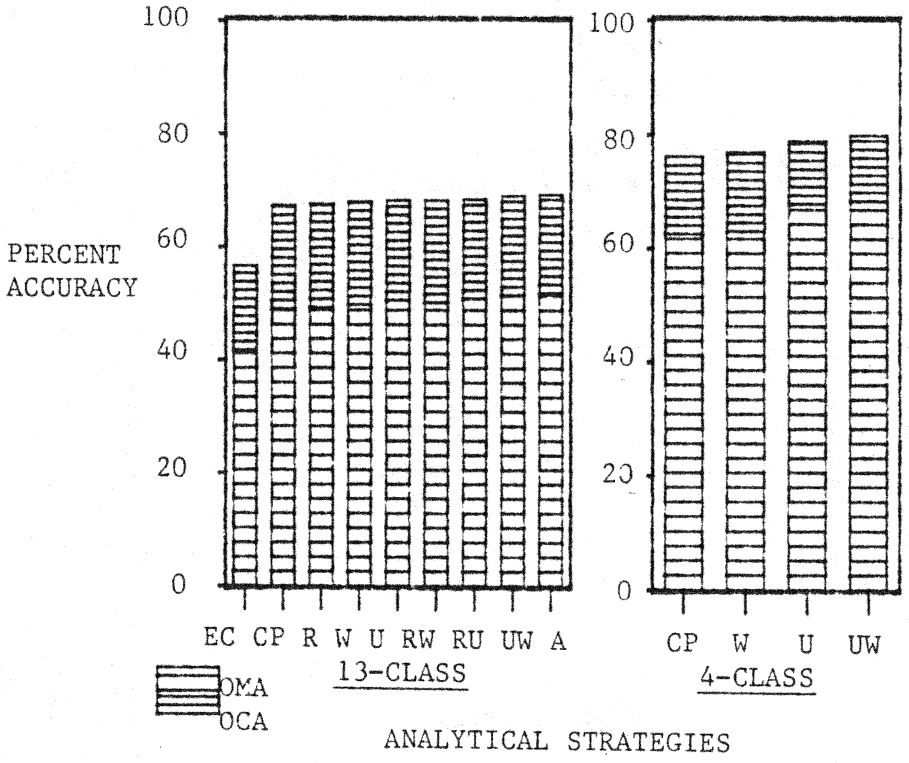


Fig. 60. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 1 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

Table 21. Confusion table and mapping accuracies of the complete 4-class, image no. 1. This classification was based on the 4 raw Landsat bands. All regions of less than 13-pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	769	342	95	0	1206	437	36.2	48.7
Agriculture	2	134	3115	200	0	3449	334	9.7	66.0
Forest	4	203	917	2413	0	3533	1120	31.7	62.4
Water	5	35	12	36	0	83	83	100.0	0
Total No. of Cells		1141	4386	2744	0				
Commissions No.		372	1271	331	0				
Commissions %		32.6	29.0	12.1	0				

Overall Classification Accuracy (OCA) = 76.1
Overall Mapping Accuracy (OMA) = 62.5

Table 22. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 1.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	76.1	62.5
Water	76.9	63.0
Urban	78.9	67.9
Water + Urban	79.9	68.4

Water

When "water-only" was excluded, OCA increased 0.8 percent over the original 4-class image no. 1 to 76.9 percent. OMA increased 0.5 percent to 63.0 percent (Table 22). The greatest increase in class mapping accuracy after excluding water was for built-up land (48.7 to 49.7; i.e., +1.0%) (Table 23). There were no decreases in class mapping accuracies as a result of excluding water.

Urban

When the "urban" set (composed of combined roads and urban sets from the 13-class exclusion sequence) was excluded, OCA increased 2.0 percent from the previous step to 78.9 percent (Table 22). OMA increased 4.9 percent to 67.9 percent. These levels were 2.8 percent and 5.4 percent higher than the complete 4-class image no. 1 OCA and OMA, respectively. [Up to this point, the 4-class exclusion results showed slightly higher overall accuracy increases per exclusion step than for the 13-class sequence. These increases indicate that it is possible to increase the accuracies of a lower level classification (4-class) just as for a higher level (13-class).] Mapping accuracy increases during this urban exclusion step were greatest for agriculture (66.0 to 70.6; i.e., +4.6%) (Table 24). The largest decrease was for built-up land (48.7 to 20.6; i.e., -28.1%).

Table 23. Confusion table and mapping accuracies of the 4-class, image no. 1 after excluding water cells.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	765	342	95	0	1202	437	36.4	49.7
Agriculture	2	134	3113	200	0	3447	334	9.7	66.1
Forest	4	198	917	2410	0	3525	1115	31.6	63.1
Water	5	6	0	1	0	7	7	100.0	0
Total No. of Cells		1103	4372	2706	0				
Commissions No.		338	1259	296	0				
Commissions %		30.6	28.8	10.9	0				

Overall Classification Accuracy (OCA) = 76.9
Overall Mapping Accuracy (OMA) = 63.0

Table 24. Confusion table and mapping accuracies of the 4-class, image no. 1 after excluding urban cells.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	93	82	29	0	204	111	54.4	20.6
Agriculture	2	72	2664	144	0	2880	216	7.5	70.6
Forest	4	140	801	2296	0	3237	941	41.0	66.6
Water	5	35	12	36	0	83	83	100.0	0
Total No. of Cells		340	3559	2505	0				
Commissions No.		247	895	209	0				
Commissions %		72.6	25.1	8.3	0				

Overall Classification Accuracy (OCA) = 78.9
Overall Mapping Accuracy (OMA) = 67.9

Water Plus Urban

When "water-only" plus "urban" classes were excluded (equivalent to the 3-set exclusion for the 13-class image no. 1; i.e., "roads-only", "urban-only", "water-only" combination), OCA and OMA levels reached their highest point for both 4-class and 13-class accuracy levels. Here, OCA was 79.9 percent with an OMA of 68.4 percent (Table 22). These levels were 1.0 percent (OCA) and 0.5 percent (OMA) greater than the previous "urban" exclusion step and 3.8 percent and 5.9 percent higher than non-exclusion, 4-class image no. 1 levels. When compared to the complete 4-class image no. 1 (Table 21), forest was the class possessing the greatest overall increase for the 2-set exclusion (62.4 to 67.4; i.e., +5.0%); built-up land had the greatest decrease (48.7 to 21.5; i.e., -27.2%) (Table 25). Table 26 summarizes the principal class accuracy effects which resulted from the exclusions.

Changes in OCA and OMA for the 4-class image no. 1 exclusion sequence are displayed in Fig. 60.

Per-Pixel Accuracy

Similar to the 13-class exclusion procedure, water in the 4-class exclusion sequence produced the highest improvements per-pixel in accuracies expressed as OCA and OMA. These values were 0.0089 and 0.0056 respectively (Table 27). Fig. 58 displays the improvement indexes per-pixel for all 4-class image no. 1 exclusion steps.

Table 25. Confusion table and mapping accuracies of the 4-class, image no. 1 after excluding water plus urban cells.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	89	82	29	0	200	111	55.5	21.5
Agriculture	2	72	2662	144	0	2878	216	7.5	70.8
Forest	4	135	801	2293	0	3229	936	29.0	67.4
Water	5	6	0	1	0	7	7	100.0	0
Total No. of Cells		302	3545	2467	0				
Commissions No.		213	883	174	0				
Commissions %		70.5	24.9	7.1	0				

Overall Classification Accuracy (OCA) = 79.9
Overall Mapping Accuracy (OMA) = 68.4

Table 26. Greatest increases in image no. 1(4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up Land	-
Urban	Agriculture	Built-up Land
Water + Urban	Forest	Built-up Land

Overall Exclusion Changes (+ and -): Forest (62.4 to 67.4; i.e., +5.0%)
Built-up Land (48.7 to 21.5; i.e., -27.2%)

Table 27. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 1.

1	2	3	4	5	6	7	8
1. Water	90	76.9	+0.8	0.0089	63.0	+0.5	0.0056
2. Urban	1867	78.9	+2.8	0.0015	67.9	+5.4	0.0029
3. Water + Urban	1957	79.9	+3.8	0.0019	68.4	+5.9	0.0030

Image 1; 4 classes OCA = 76.1% OMA = 62.5%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

II. IMAGE NO. 2

A. 13 classes

1. Complete Image

Image no. 2 (Fig. 61) also represents a classification derived from the 4 raw Landsat bands. This image possessed 90 clusters as compared to 70 clusters for image no. 1. Analysis using the GIPSY system had removed and reassigned all regions of less than 9 pixels before clustering this image. The confusion matrix for the complete image no. 2 is displayed in Table 28.

As summarized in Table 29, overall classification results for image no. 2 were very similar to those of image no. 1. Besides the small differences in overall accuracy which favored image 2, only parameters 4 (the largest class commission error %) and 6 (the no. of classes with 0% mapping accuracy) showed any real changes. Both these changes seemed directly caused by the increased capability of the GIPSY system to classify water in image no. 2 (Table 28). Water could not be classified at all (i.e., 0% mapping accuracy) in image no. 1 (Table 8).

In this image, there were a very large number of classes with high errors of omission (> 85%) and commission (Table 28). Although being repetitive, a > 85 percent omission error means that greater than 85 percent of the pixels which were ground determined (i.e., ground observed) to be a specific land use class (e.g., water) did not possess a distinct enough spectral signature among the 4 Landsat bands, to be classified as that specific land class. A high commission error, on the other hand, means that a high percentage of pixels which were observed

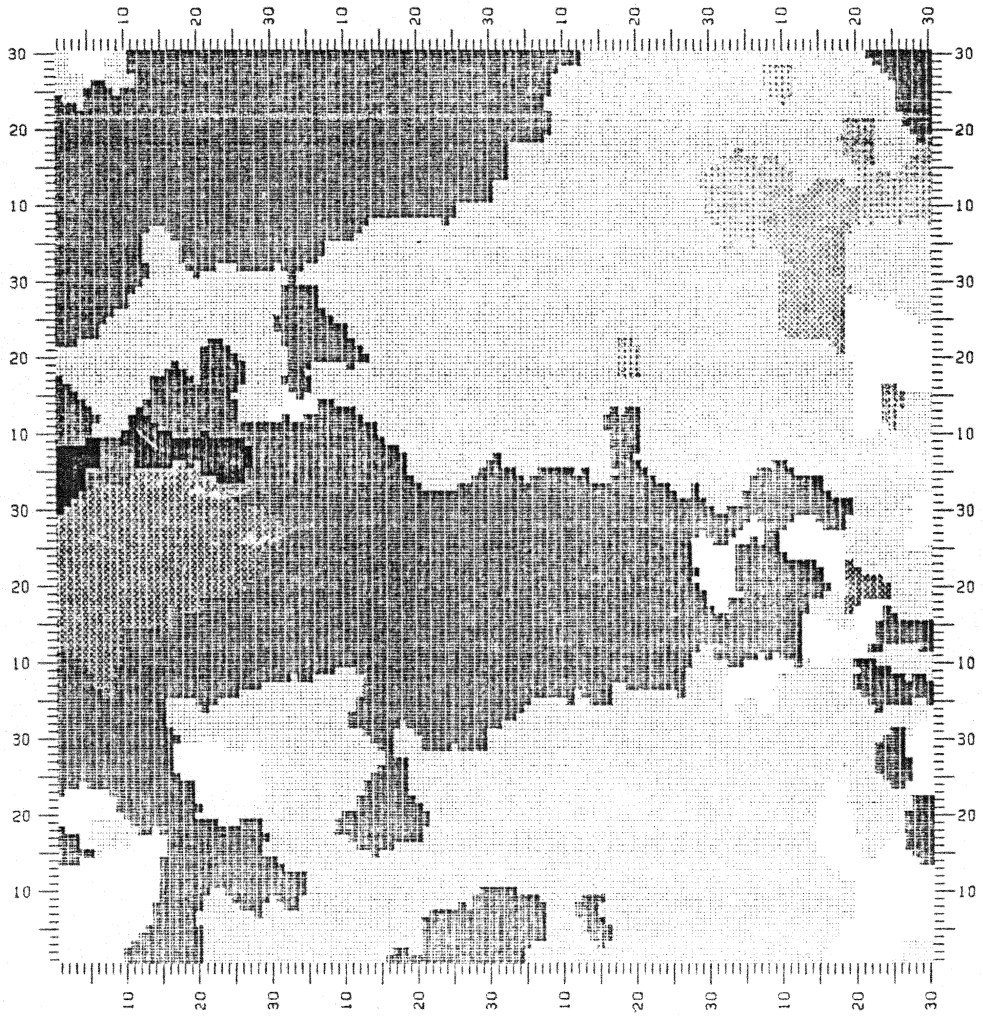


Fig. 61. Gray scale representation of classified Landsat image no. 2. Each land use is assigned a single gray scale shade.

Fig. 61. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		1048
5. - 5.		38
8. - 8.		11
9. - 9.		6740
11. - 11.		243
12. - 12.		204
13. - 13.		577
41. - 41.		5450
42. - 42.		89

Table 28. Confusion table and mapping accuracies of the complete 13-class, image no. 2. This image was originally classified using the 4 raw Landsat bands. All regions with less than 9 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	12 0 0	0 0	6 0	0 18	0 12	35 0	83	71	85.5	12.0
CROPLAND	8	0 0 0	8 0	100 0	0 7	0 0	0 0	115	107	93.0	6.8
PASTURE	9	3 0 0	1 0	3040 0	41 216	21 1	0 0	3323	283	8.5	66.0
RESIDENTIAL	11	0 0 0	0 0	327 0	138 43	11 0	0 0	519	381	73.4	23.5
SERVICES	12	0 0 0	0 0	22 0	11 0	83 0	0 0	116	33	28.4	54.2
INDUSTRIAL	13	1 0 0	0 0	0 0	0 69	0 11	438 0	519	81	15.6	69.5
TRANSPORTATION	14	0 0 0	0 0	35 0	5 0	0 0	0 0	40	40	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	11 0 0	2 0	535 0	11 1971	5 4	48 0	2587	616	23.8	55.1
CONIFER	42	2 0 0	0 0	106 0	0 229	0 46	27 0	410	364	88.8	10.5
MIXED	43	0 0 0	0 0	129 0	0 405	0 1	1 0	536	536	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	10 0	0 1	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		29 0	11 0	4322 0	206 2959	120 75	549 0				

Table 28. (Continued).

		0					
COMMISSIONS	NO.	17 0 0	3 0	1282 0	68 988	37 29	111 0
COMMISSIONS	%	58.6 0.0 0.0	27.3 0.0	29.7 0.0	33.0 33.4	30.8 38.7	20.2 0.0
OVERALL CLASSIFICATION ACCURACY(OCA) = 69.4							
OVERALL MAPPING ACCURACY(OMA) = 51.1							

Table 29. A select comparison between 13-class (complete) images nos. 1, 2, and 3.

Parameter	Image No. 1	Image No. 2	Image No. 3
1. Overall classification accuracy (%)	67.3	69.4	68.0
2. Overall mapping accuracy (%)	49.0	51.1	49.5
3. No. of classes with > 85% omission error	8	8	8
4. Largest class commission error %	Residential (51.0)	Water (58.6)	Water (58.6)
5. Largest class mapping accuracies (%)	Industrial (68.0) Pasture (64.0)	Industrial (69.5) Pasture (66.0)	Industrial (70.3) Pasture (65.1)
6. No. of classes with 0% mapping accuracy	6	5	5

in the field to be of a specific land use (e.g., water) possessed spectral signatures which mimiced or were similar to a completely different class (e.g., hardwoods) resulting in an improper classification. These signatures were also the product of the 4 Landsat bands. In this sense, an omission error in one class is a commission error in another.

2. Incremental Exclusions

The same order of exclusions which were conducted on image no. 1 were likewise performed on image no. 2. This sequence will also be used on all remaining complete images (e.g., images 3, 4, 5, and 6).

Presented in Tables 30 and 31 are summaries of the results for the exclusion sequence performed on image no. 2. A comparison of these tables with those of image no. 1 (Table 17 and Table 18) shows only a few differences. The first, comparing Table 30 with Table 17, identifies that all OCA's and OMA's for the image no. 2 exclusion sequence were higher than those for the image no. 1 sequence. These increases in the exclusion accuracy levels were the result of higher accuracies recorded for the complete 13-class image no. 2 over those of image no. 1. Another difference, identified in Table 31, shows that as a result of the "water" and "roads plus water" exclusions performed on image no. 2, the water class showed the largest accuracy decrease. This differed from image no. 1 (Table 18) where no class showed an accuracy decrease during either exclusion. Water could not show corresponding decreases in image no. 1 since it could not be classified (i.e., mapping accuracy = 0%).

Accuracy changes per pixel excluded for image no. 2 are displayed in Table 32. Again, "water" and "roads plus water" were the two exclusion strategies with the largest corresponding OCA and OMA improvement

Table 30. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 2.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	69.4	51.1
Roads	69.6	51.4
Urban	71.0	53.5
Water	69.9	51.9
Roads + Water	70.1	52.1
Roads + Urban	71.2	53.8
Urban + Water	71.7	54.3
Roads + Urban + Water	72.0	54.6

Table 31. Greatest increases in image no. 2 (13 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Residential	-
Urban	Pasture	Industrial
Water	Industrial	Water
Roads + Water	Industrial	Water
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	Mixed (Forest)	Hardwoods

Overall Exclusion Changes (+ and -): Pasture (66.0 to 70.9; i.e., +4.9%)
Industrial (69.5 to 36.4; i.e., -33.1%)

Table 32. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 2.

1	2	3	4	5	6	7	8
1. Roads	161	69.6	+0.2	0.0012	51.4	+0.3	0.0019
2. Urban	1729	71.0	+1.6	0.0009	53.5	+2.4	0.0014
3. Water	90	69.9	+0.5	0.0056	51.9	+0.8	0.0089
4. Roads + Water	251	70.1	+0.7	0.0028	52.1	+1.0	0.0040
5. Roads + Urban	1867	71.2	+1.8	0.0010	53.8	+2.7	0.0014
6. Urban + Water	1819	71.7	+2.3	0.0013	54.3	+3.2	0.0018
7. Roads + Urban + Water	1957	72.0	+2.6	0.0013	54.6	+3.5	0.0018

Image 2; 13 classes OCA = 69.4% OMA = 51.1%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

indices values. One interesting difference between these improvement index values and those for image no. 1 (Table 19), is that only with strategies where "urban" was excluded (i.e., "urban-only", "roads plus urban", "urban plus water", and "roads plus urban plus water") did increases occur during the image no. 2 procedure. All other exclusion strategies showed results equal to or less than those of image no. 1. This difference is noticeable in Fig. 62 where the "urban-only" and "road plus water" exclusion columns have traded the positions they held for the image no. 1 sequence (Fig. 60). This effect might possibly be linked to the classifiability of water in image no. 2 (12.0% vs. 0% mapping accuracy in image no. 1). Water, when excluded, had previously resulted in large increases in urban-related (i.e., residential, services, and industrial) mapping accuracies. Fig. 63 shows the sequence of OCA and OMA improvement indices values for image no. 2.

3. Conditional Classification

Results from the conditional classification performed on the complete-exclusion (i.e., "roads plus urban plus water") image no. 2 were similar to those of image no. 1. Fig. 64 displays the conditional image no. 2.

For this classification, although OCA and OMA (Table 33) were slightly higher than corresponding accuracies for image no. 1 (Table 20), these were the result of the higher image no. 2 complete-exclusion input accuracies (as compared to image no. 1), not the classification procedure itself. Fig. 62 shows that for the conditional approach, classification accuracies were still less than those for the complete (CP) and full-exclusion (A) image no. 2. As displayed in Table 31, mixed (forest) and hardwoods again experienced the largest changes in accuracy.

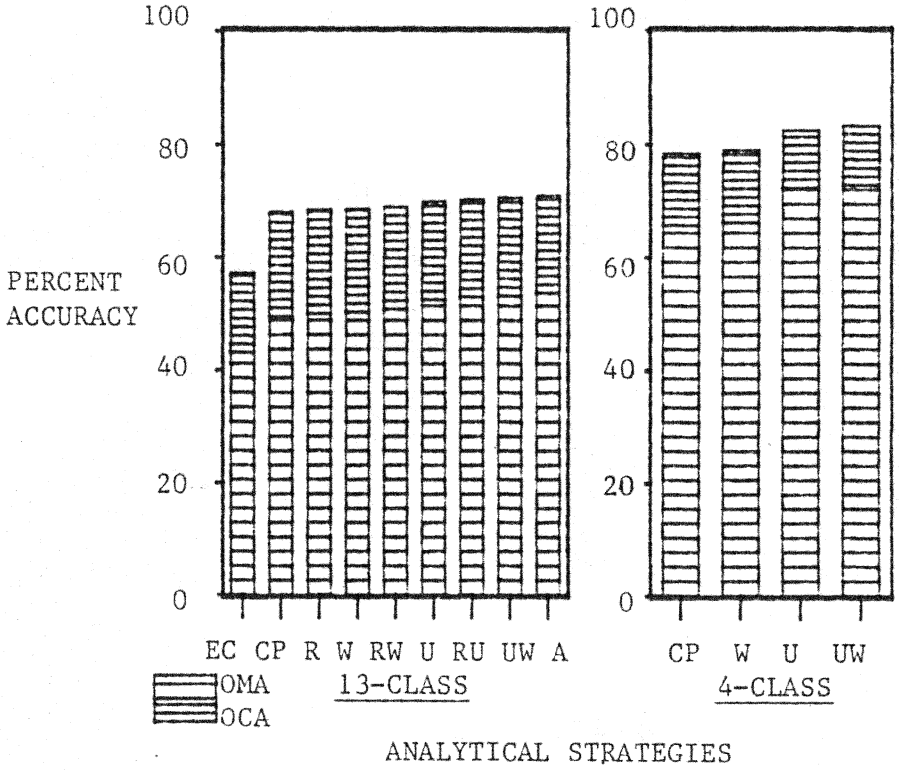


Fig. 62. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 2 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

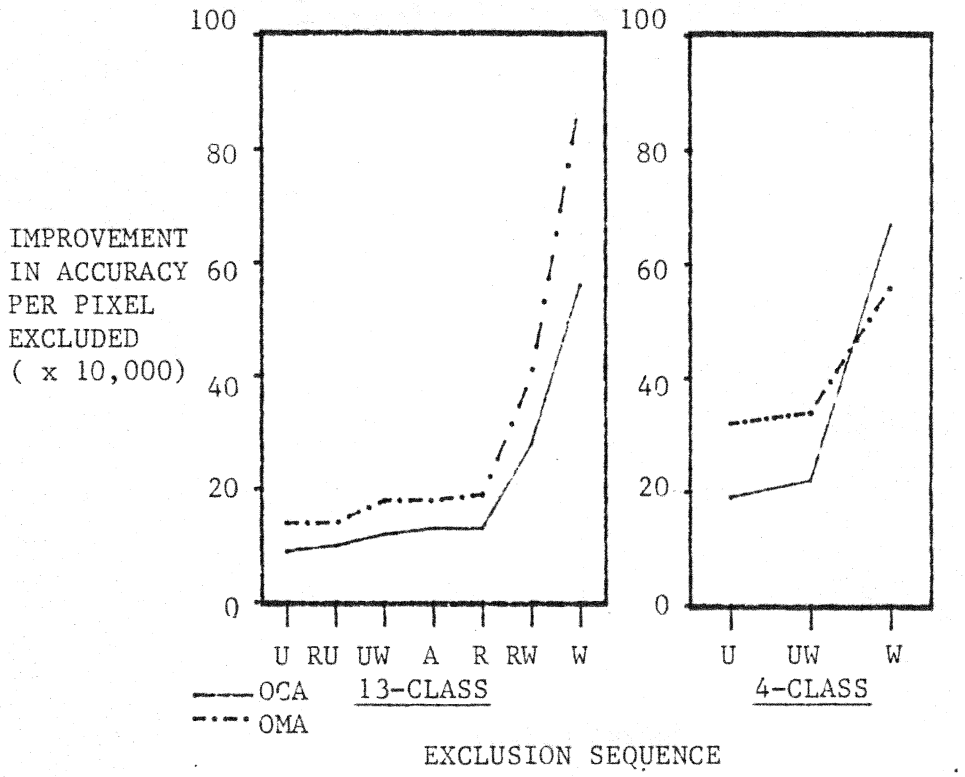


Fig. 63. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 2 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

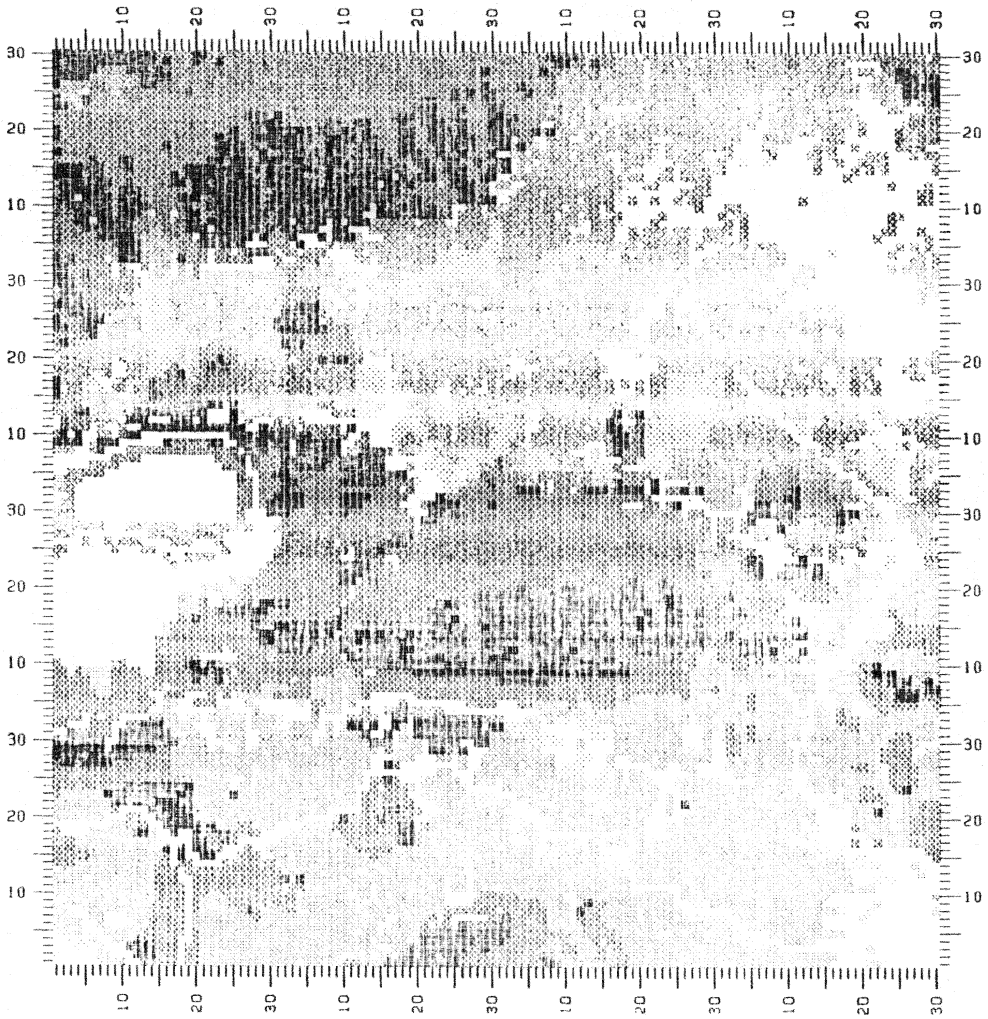


Fig. 64. Gray scale representation of conditional classification image no. 2. Each land use is assigned a single gray scale shade.

Fig. 64. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
8.	-	8.		837
9.	-	9.		5137
41.	-	41.		3503
42.	-	42.		147
43.	-	43.		1472

Table 33. Confusion table and mapping accuracies of the 13-class, image no. 2 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.	NO.	%	
WATER	5	0 0 0	0 0	6 0	0 1	0 0	0 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	57 0	50 0	0 4	0 0	0 1	112	55	49.1	9.6
PASTURE	9	0 0 0	414 0	2167 0	0 144	0 0	0 36	2761	594	21.5	60.1
RESIDENTIAL	11	0 0 0	11 0	65 0	0 6	0 0	0 4	86	86	100.0	0.0
SERVICES	12	0 0 0	7 0	25 0	0 0	0 0	0 0	32	32	100.0	0.0
INDUSTRIAL	13	0 0 0	0 0	45 0	0 20	0 0	0 6	71	71	100.0	0.0
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	36 0	446 0	0 1280	0 56	0 578	2396	1116	46.6	43.4
CONIFER	42	0 0 0	5 0	94 0	0 161	0 2	0 75	337	335	99.4	0.5
MIXED	43	0 0 0	7 0	98 0	0 214	0 7	0 170	496	326	65.7	14.2
TRANSITIONAL	76	0 0 0	0 0	4 0	0 1	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	537 0	3011 0	0 1831	0 65	0 870				

Table 33. (Continued).

		0					
COMMISSIONS	NO.	0	480	844	0	0	0
		0	0	0	551	63	700
		0					
COMMISSIONS	%	0.0	89.4	28.0	0.0	0.0	0.0
		0.0	0.0	0.0	30.1	96.9	80.5
		0.0					

OVERALL CLASSIFICATION ACCURACY(OCA) = 58.2

OVERALL MAPPING ACCURACY(OMA) = 44.1

B. 4 classes

1. Complete Image

The same reduction grouping of 13 classes to 4 classes was conducted on image no. 2 as for image no. 1. An equivalent grouping format will be used in constructing all remaining complete, 4-class images from those of 13-class origin.

Upon reducing the complete, 13-class image no. 2 to 4 classes, accuracies increased significantly. As shown in Table 34, the OCA and OMA were greater than all 13-class, image no. 2 levels.

Just as for the complete 13-class image nos. 1 and 2, there were also similarities between the 4-class counterparts. Table 35 shows a comparison of both images. The only differences, besides accuracy, were caused by the classifiability of water in image no. 2. Water could not be classified in image no. 1 (i.e., 100.0 percent omission), hence it possessed both a 0 percent commission error and mapping accuracy.

2. Incremental Exclusions

The same order of exclusions which were made on the 4-class, image no. 1 were also made for image no. 2. This sequence would be used on all remaining complete 4-class images.

Results of the exclusion sequence performed on image no. 2 (Table 36) were very similar in magnitude to those of image no. 1 (Table 22). As displayed in Fig. 62, these results showed, in order, "water", "urban", and "urban plus water" exclusions bringing about increasingly larger accuracy gains. After excluding the urban cells, results showed for the first time an OCA of greater than 80.0 percent.

Table 34. Confusion table and mapping accuracies of the complete 4-class, image no. 2. This classification was based on the 4 raw Landsat bands. All regions of less than 9 pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	686	395	124	1	1206	520	43.1	49.2
Agriculture	2	62	3160	224	3	3449	289	8.4	68.4
Forest	4	92	772	2656	13	3533	877	24.8	67.9
Water	5	35	6	30	12	83	71	85.5	12.0
Total No. of Cells		875	4333	3034	29				
Commissions No.		189	1173	378	17				
Commissions %		21.6	27.1	12.5	58.6				

Overall Classification Accuracy (OCA) = 78.8
Overall Mapping Accuracy (OMA) = 66.1

Table 35. A select comparison between 4-class (complete) image nos. 1, 2, and 3.

Parameter	Image No. 1	Image No. 2	Image No. 3
1. Overall classification accuracy (%)	76.1	78.8	78.3
2. Overall mapping accuracy (%)	62.5	66.1	65.6
3. No. of classes with > 85% omission error	1	1	1
4. Largest class commission error %	Build-up Land (32.6)	Water (58.6)	Water (58.6)
5. Largest class mapping accuracies (%)	Agriculture (66.0) Forest (62.4)	Agriculture (68.4) Forest (67.9)	Forest (68.5) Agriculture (67.3)
6. No. of classes with 0% mapping accuracy	1	0	0

Table 36. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 2.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	78.8	66.1
Water	79.4	66.6
Urban	82.3	72.1
Water + Urban	83.2	72.7

As shown in Table 37, classes exhibiting the largest accuracy increases following the "water" and "urban" exclusions were equivalent to those of image no. 1 (Table 26). Differing from image no. 1, the water class possessed the largest accuracy decreases following the "water" exclusion. Reasons for this decrease are similar to those mentioned for the 13-class, image no. 2 exclusion sequence.

Agriculture realized the largest overall accuracy gain after the complete exclusion (i.e., "water plus urban"). This differed from image no. 1 where forest had the greatest overall increase. As portrayed in Table 38, this forest-to-agriculture overall accuracy shift was probably influenced by the greater per-pixel change in accuracy (represented through the OCA and OMA improvement index values) for the image no. 2 "urban" exclusion over those of image no. 1 (Table 27). This shift is substantiated in Table 37 where a prior "urban" exclusion had resulted in increasing agriculture accuracy.

Fig. 63 displays OCA and OMA improvement indices values for the exclusion sequence.

Table 37. Greatest increases in image no. 2 (4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up Land	Water
Urban	Agriculture	Built-up Land
Water + Urban	Agriculture	Built-up Land

Overall Exclusion Changes (+ and -): Agriculture (68.4 to 73.8; i.e., +5.4%)
Built-up Land (49.2 to 24.6; i.e., -24.6%)

Table 38. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 2.

1	2	3	4	5	6	7	8
1. Water	90	79.4	+0.6	0.0067	66.6	+0.5	0.0056
2. Urban	1867	82.3	+3.5	0.0019	72.1	+6.0	0.0032
3. Water + Urban	1957	83.2	+4.4	0.0022	72.7	+6.6	0.0034

Image 2; 4 classes OCA = 78.8% OMA = 66.1%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

III. IMAGE NO. 3

A. 13 classes

1. Complete Image

Image no. 3 (Fig. 65) was the final image composed of only the 4 raw Landsat bands. This image possessed 120 clusters. Analysis with the GIPSY system had removed and reassigned all regions of less than 5 pixels before the clustering step. As compared to image nos. 1 and 2, this image possessed the finest classification resolution achievable by the ELIMRG command. In other words, at this resolution classified cluster sizes were the smallest of the 3-4-band images. Classification resolution refers to the minimum size (in pixels) of a spectrally distinct class which was detected through computer processing. Because of its association with the image processing/ classification function, classification resolution differs from general resolution (the smallest area at which data can accurately be identified) and Landsat or MSS resolution (a land area 79m x 56m or 1.1 acres). The confusion matrix for the complete image no. 3 is displayed in Table 39.

As shown in Table 29, overall accuracies for image no. 3 were slightly higher than image no. 1 but less than image no. 2. Results shown in Table 39 indicate that only the industrial class increased in accuracy (e.g., to 70.3%) above both previous complete image classifications. As compared to image no. 2 (Table 28), all image no. 3 classes which could be identified, excluding industrial, (i.e., water, cropland, pasture, residential, services, hardwoods, and conifer), possessed accuracies less than or equal to image no. 2 levels. Four image no. 3

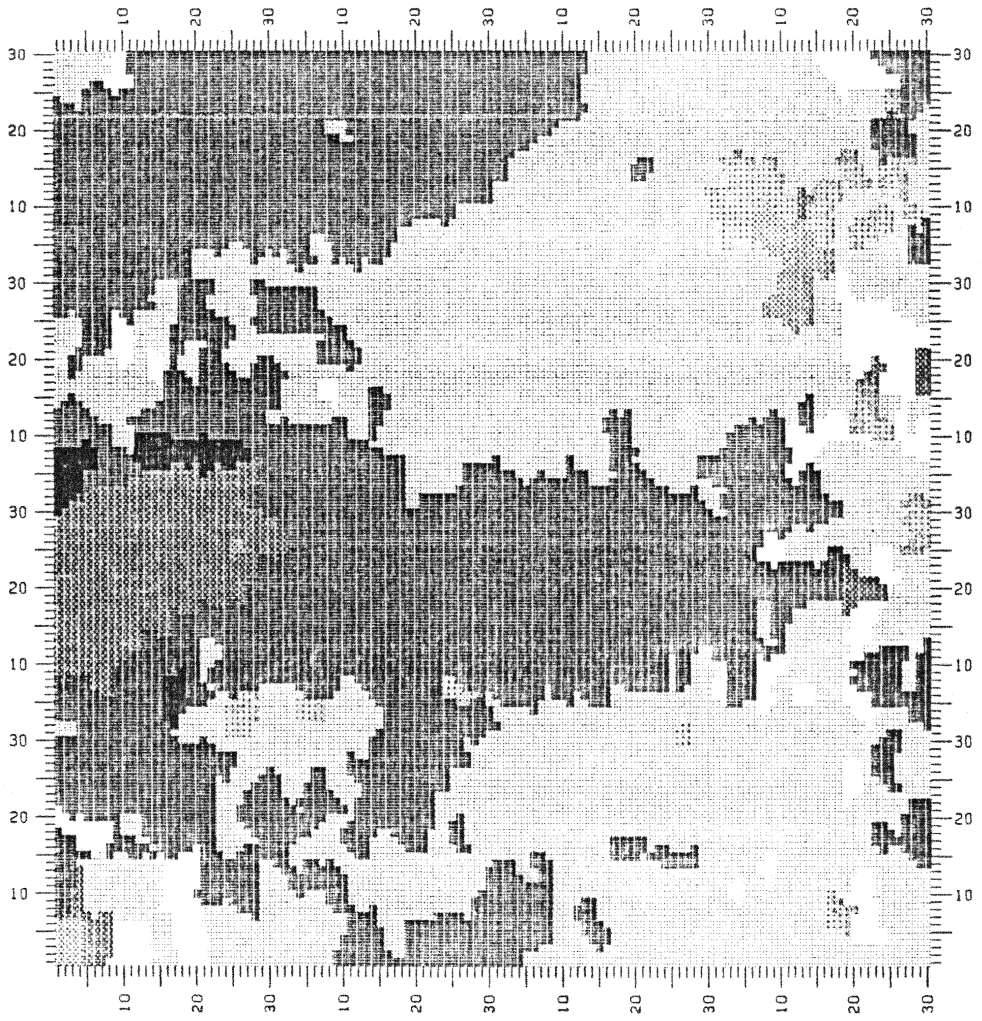


Fig. 65. Gray scale representation of classified Landsat image no. 3. Each land use is assigned a single gray scale shade.

Fig. 65. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		611
5. - 5.		37
8. - 8.		11
9. - 9.		6588
11. - 11.		320
12. - 12.		123
13. - 13.		681
41. - 41.		5946
42. - 42.		83

Table 39. Confusion table and mapping accuracies of the complete 13-class, image no. 3. This image was originally classified using the 4 raw Landsat bands. All regions with less than 5 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	12 0 0	0 0	7 0	0 16	1 10	37 0	83	71	85.5	12.0
CROPLAND	8	0 0 0	8 0	98 0	0 9	0 0	0 0	115	107	93.0	6.8
PASTURE	9	3 0 0	1 0	2935 0	24 346	11 3	0 0	3323	388	11.7	65.1
RESIDENTIAL	11	0 0 0	0 0	355 0	109 54	1 0	0 0	519	410	79.0	18.8
SERVICES	12	0 0 0	0 0	44 0	14 0	58 0	0 0	116	58	50.0	42.3
INDUSTRIAL	13	1 0 0	0 0	0 0	0 48	4 5	461 0	519	58	11.2	70.3
TRANSPORTATION	14	0 0 0	0 0	35 0	3 2	0 0	0 0	40	40	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	0 0	0 1	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	7 0	0 4	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	11 0 0	2 0	491 0	17 1995	4 7	60 0	2587	592	22.9	52.7
CONIFER	42	2 0 0	0 0	76 0	2 247	0 45	38 0	410	365	89.0	10.3
MIXED	43	0 0 0	0 0	64 0	1 468	0 1	2 0	536	536	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	10 0	0 1	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		29 0	11 0	4122 0	170 3191	79 71	598 0				

Table 39. (Continued).

		0					
COMMISSIONS	NO.	17	3	1187	61	21	137
		0	0	0	1196	26	0
		0					
COMMISSIONS	%	58.6	27.3	28.8	35.9	26.6	22.9
		0.0	0.0	0.0	37.5	36.6	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				68.0			
OVERALL MAPPING ACCURACY(OMA) =				49.5			

classes (i.e., cropland, residential, services, and conifer) had accuracies less than those of image no. 1 (Table 8). These results indicated that even though the classification resolution of image no. 3 was greater than for image nos. 1 and 2, this did not augment the capability to discriminate accurately between spectral signatures recorded in the 4 data bands. The classification resolution in image no. 2 (i.e., a reassignment area of less than 9 pixels), although being less intense than image no. 3, was the most classification-effective (i.e., produced the greatest OMA and OCA), for the 4-band images.

Given the differences between image nos. 2 and 3 (i.e., classification-effectiveness vs. resolution intensity), this may indicate that even at greater levels of classification resolution the additional information provided by classifying smaller clusters may not be justified in terms of increased accuracies. This would infer the possibility of there being limits to how precisely the areal extent of land use can be classified using the 4 Landsat bands.

2. Incremental Exclusions

As shown in Table 40, OCAs and OMAs proceeding each image no. 3 exclusion always occupied levels intermediate to those of image no. 1 (Table 17) and image no. 2 (Table 30). These results were consistent with the pattern of overall accuracy values for the 3 complete images (i.e., image nos. 1, 2, and 3).

During the image no. 3 exclusion sequence, only results from the "roads-only" exclusion differed from those for image nos. 1 and 2. As represented in Table 41, this difference shows hardwoods possessing the largest positive change in class accuracy. Previously in images no. 1

Table 40. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 3.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	68.0	49.5
Roads	68.4	50.0
Urban	69.9	52.5
Water	68.5	50.3
Roads + Water	68.9	50.8
Roads + Urban	70.3	53.0
Urban + Water	70.6	53.2
Roads + Urban + Water	71.0	53.7

Table 41. Greatest increases in image no. 3 (13 classes) class accuracy as related to the exclusive strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Hardwoods	-
Urban	Pasture	Industrial
Water	Industrial	Water
Roads + Water	Industrial	Water
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	Mixed (Forest)	Hardwoods

Overall Exclusion Changes (+ and -): Pasture (65.1 to 70.9; i.e., +5.8%)
Industrial (70.3 to 36.0; i.e., -34.3%)

(Table 18) and no. 2 (Table 31), residential had recorded the largest increase from this exclusion. Reasons which explain why hardwoods realized this increase during the image no. 3 exclusion sequence are unsettled.

The remainder of exclusion-caused class accuracy changes for image no. 3 (Table 41) were similar to those for image no. 2 (Table 31).

As displayed in Table 42, 5 OCA and 6 OMA improvement index values were greater than respective levels obtained from image nos. 1 (Table 19) and 2 (Table 32). The 11 index values were representative of the following exclusion strategies, "roads-only", "urban-only", "roads plus water" (only OMA index), "roads plus urban", "urban plus water", and "roads plus urban plus water". These results might reflect the increased utility of the exclusion procedure on a higher resolution image possessing a greater number of clusters (e.g., image no. 3). In other words, excluding select pixels from an image with a high classification resolution or many clusters (e.g., image no. 3) might increase accuracies more than excluding pixels from an image possessing a low classification resolution or few clusters (e.g., image no. 1).

Also for image no. 3, the "roads-only" exclusion showed the most significant improvement indices increases over previous image no. 1 and no. 2 highs (i.e., OCA index = + 0.0006 and OMA index = + 0.0012).

The series of OCA and OMA improvement index values for image no. 3 are displayed in Fig. 66.

3. Conditional Classification

Overall accuracies for the conditional classification performed on the complete-exclusion image no. 3 were greater than those for image

Table 42. Accuracy expressed changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 3.

1	2	3	4	5	6	7	8
1. Roads	161	68.4	+0.4	0.0025	50.0	+0.5	0.0031
2. Urban	1729	69.9	+1.9	0.0011	52.5	+3.0	0.0017
3. Water	90	68.5	+0.5	0.0056	50.3	+0.8	0.0089
4. Roads + Water	251	68.9	+0.9	0.0036	50.8	+1.3	0.0052
5. Roads + Urban	1867	70.3	+2.3	0.0012	53.0	+3.5	0.0019
6. Urban + Water	1819	70.6	+2.6	0.0014	53.2	+3.7	0.0020
7. Roads + Urban + Water	1957	71.0	+3.0	0.0015	53.7	+4.2	0.0021

Image 3; 13 classes OCA = 68.0% OMA = 49.5%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

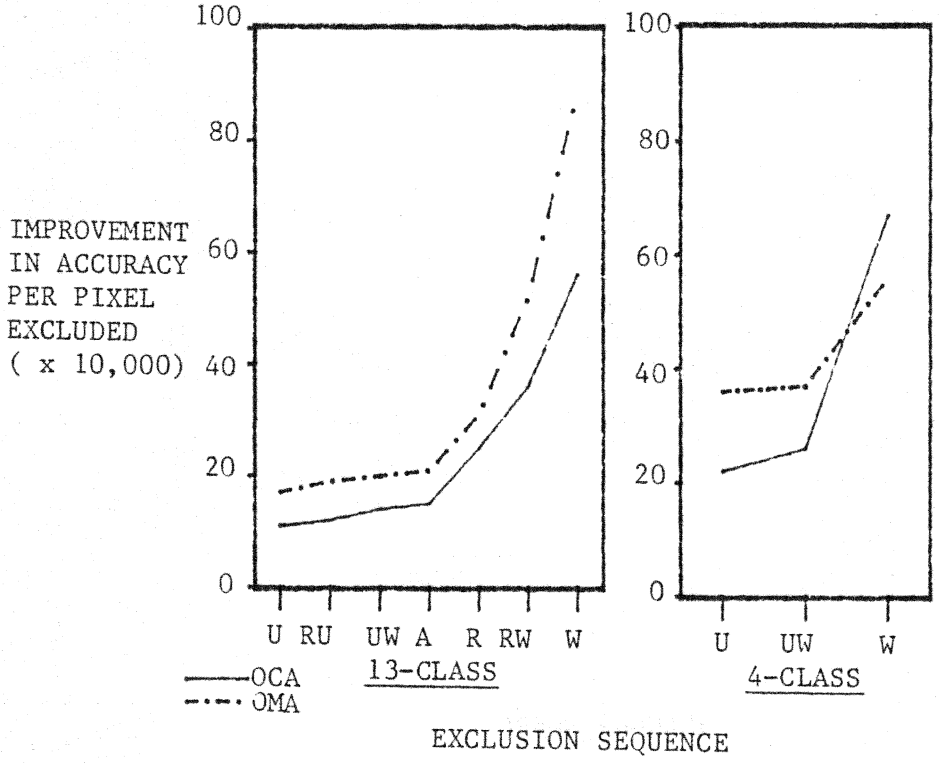


Fig. 66. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 3 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

no. 1 but less than image no. 2. Class mapping accuracy increases and decreases (Table 41) were similar to previous conditional classification results. Conditional image no. 3 is displayed in Fig. 67 with the corresponding confusion matrix found in Table 43.

Fig. 68 shows the results of the complete sequence of accuracy improving strategies performed on image no. 3.

B. 4 classes

1. Complete Image

Reducing image no. 3 from 13 classes (Table 39) to 4 classes (Table 44) produced results which were similar to image nos. 1 and 2 (i.e., significant increases in OCA and OMA). These levels were only slightly below the image no. 2 highs.

As shown in Table 35, image no. 3 differed from image no. 2 only according to the largest class map accuracies (parameter 5). Here, forest possessed the largest class mapping accuracy. Among all 4-class images (complete image), the image no. 3 accuracy for built-up land was lowest for that class (Table 44).

2. Incremental Exclusions

OCA and OMA values proceeding the complete image no. 3 exclusion (i.e., "water plus urban") were the highest among all 13-and 4-class (4-band) image variations (Table 45, Fig. 68). Both these values were only 0.1% larger than levels for image no. 2 (Table 36, Fig. 62). In this case, excluding pixels from a grossly classified, high resolution, highly clustered image (e.g., 4-class, image no. 3) produced larger increases in accuracy than for images with few clusters (e.g., 4-class, image no. 1). This supports similar results mentioned previously for exclusions performed on 13-class images.

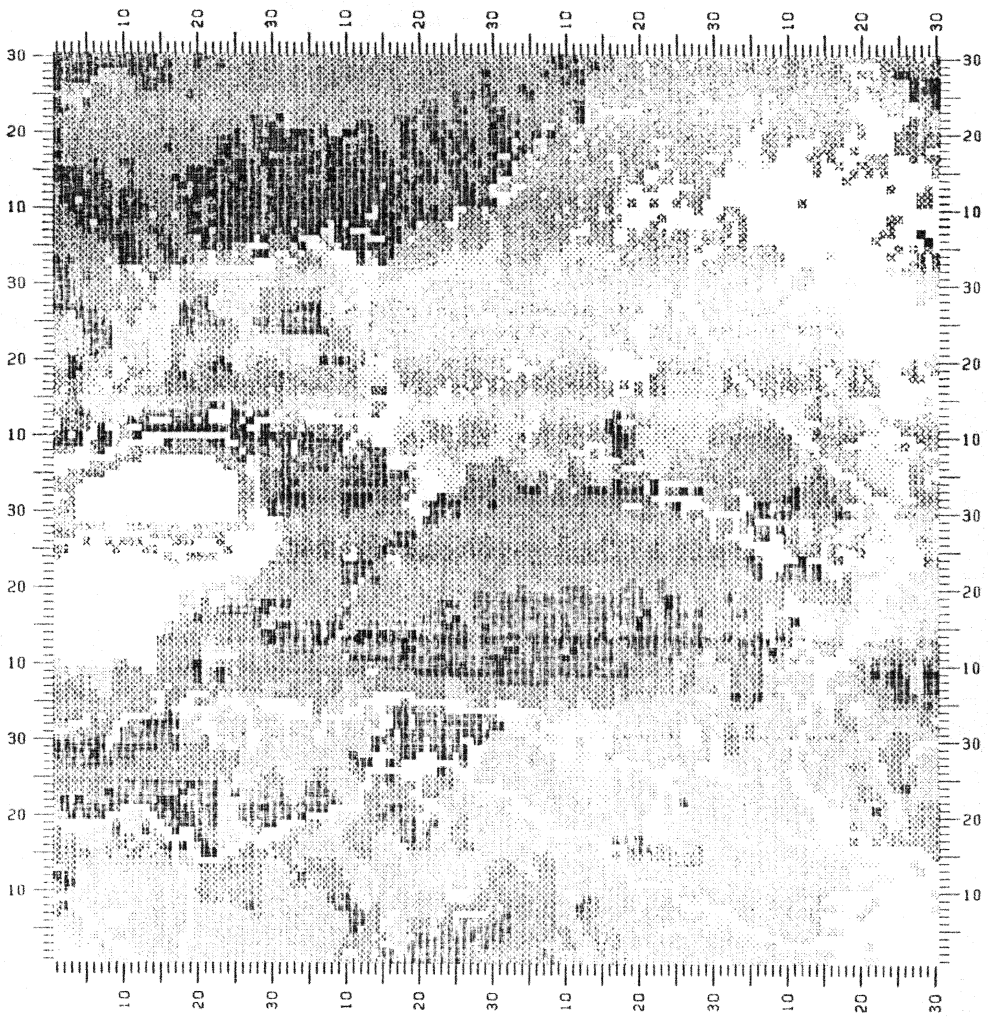


Fig. 67. Gray scale representation of conditional classification image no. 3. Each land use is assigned a single gray scale shade.

Fig. 67. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
8.	-	8.		813
9.	-	9.		4711
41.	-	41.		3807
42.	-	42.		151
43.	-	43.		1614

Table 43. Confusion table and mapping accuracies of the 13-class, image no. 3 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	6 0	0 1	0 0	0 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	55 0	50 0	0 6	0 0	0 1	112	57	50.9	9.4
PASTURE	9	0 0 0	407 0	2075 0	0 222	0 0	0 57	2761	686	24.8	58.9
RESIDENTIAL	11	0 0 0	12 0	65 0	0 4	0 0	0 5	86	86	100.0	0.0
SERVICES	12	0 0 0	7 0	25 0	0 0	0 0	0 0	32	32	100.0	0.0
INDUSTRIAL	13	0 0 0	0 0	51 0	0 15	0 0	0 5	71	71	100.0	0.0
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	0 0	0 1	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	3 0	0 2	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	35 0	429 0	0 1286	0 55	0 591	2396	1110	46.3	42.0
CONIFER	42	0 0 0	5 0	74 0	0 173	0 2	0 83	337	335	99.4	0.5
MIXED	43	0 0 0	7 0	52 0	0 238	0 7	0 192	496	304	61.3	15.5
TRANSITIONAL	76	0 0 0	0 0	4 0	0 1	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	528 0	2839 0	0 1949	0 64	0 934				

Table 43. (Continued).

		0					
COMMISSIONS	NO.	0 0 0	473 0	764 0	0 663	0 62	0 742
COMMISSIONS	%	0.0 0.0 0.0	89.6 0.0	26.9 0.0	0.0 34.0	0.0 96.9	0.0 79.4
OVERALL CLASSIFICATION ACCURACY(OCA) =				57.2			
OVERALL MAPPING ACCURACY(OMA) =				43.1			

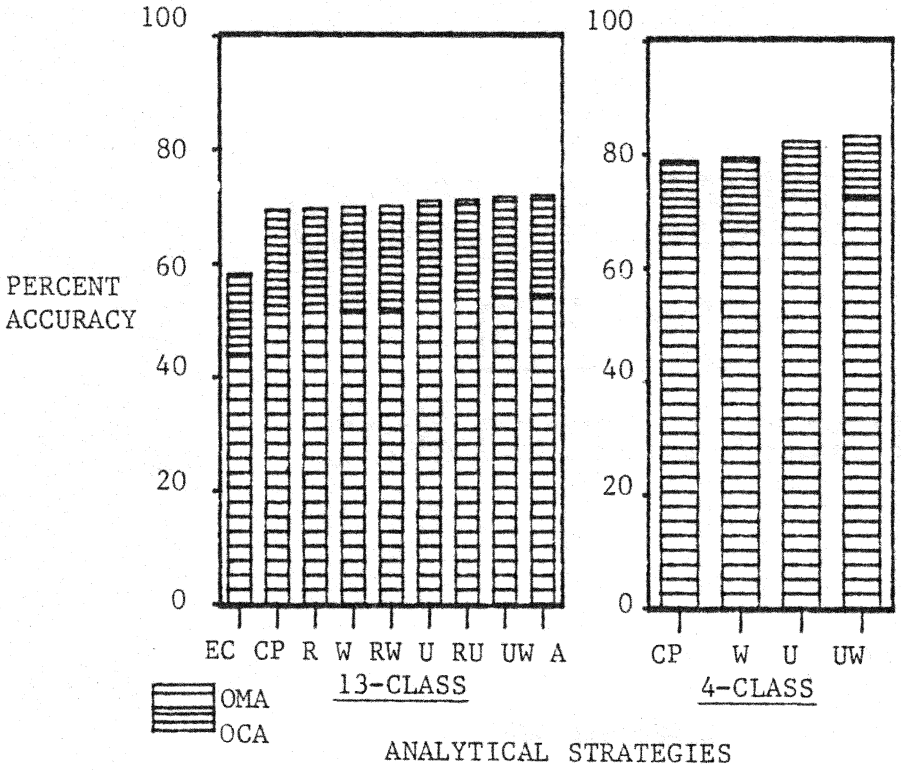


Fig. 68. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 3 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

Table 44. Confusion table and mapping accuracies of the complete 4-class, image no. 3. This classification was based on the 4 raw Landsat bands. All regions of less than 5 pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	650	444	111	1	1206	556	46.1	46.3
Agriculture	2	35	3049	362	3	3449	400	11.6	67.3
Forest	4	124	633	2763	13	3533	770	21.8	68.5
Water	5	38	7	26	12	83	71	85.5	12.0
Total No. of Cells		847	4133	3262	29				
Commissions No.		197	1084	499	17				
Commissions %		23.3	26.2	15.3	58.6				

Overall Classification Accuracy (OCA) = 78.3
Overall Mapping Accuracy (OMA) = 65.6

Table 45. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 3.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	78.3	65.6
Water	78.9	66.1
Urban	82.5	72.3
Water + Urban	83.3	72.8

As shown in Table 46, increases in image no. 3 class accuracies produced by the various exclusions were similar to those for image no. 2 (Table 37).

Improvement index values (OCA and OMA) for the image no. 3 exclusion sequence are displayed in Fig. 66. Specific index values for the "urban" and "water plus urban" exclusions (Table 47) were highest among the 3-4-class images.

Table 46. Greatest increases in image no. 3 (4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up Land	Water
Urban	Agriculture	Built-up Land
Water + Urban	Agriculture	Built-up Land

Overall Exclusion Changes (+ and -): Agriculture (67.3 to 73.4; i.e., +6.1%)
Built-up Land (46.3 to 26.0; i.e., -20.3%)

Table 47. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 3.

1	2	3	4	5	6	7	8
1. Water	90	78.9	+0.6	0.0067	66.1	+0.5	0.0056
2. Urban	1867	82.5	+4.2	0.0022	72.3	+6.7	0.0036
3. Water + Urban	1957	83.3	+5.0	0.0026	72.8	+7.2	0.0037

Image 3; 4 classes OCA = 78.3% OMA = 65.6%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

IV. IMAGE NO. 4

A. 13 classes

1. Complete Image

Image no. 4 (Fig. 69) was the first image produced from 9 bands of Landsat data. These bands included the 4 raw Landsat bands (i.e., Bands 4, 5, 6, and 7) and 5 ancillary bands (i.e., Band 5-7 Ratio, Vegetation Index, Soil Brightness Index, Band 7 Texture data, and an Experimental Index). The objective of adding the ancillary data was to determine if it would aid in increasing overall, mapping, and/or class accuracies.

Image no. 4 possessed 70 clusters. Analysis using the GIPSY system had removed and reassigned all regions of less than 13 pixels before clustering. The confusion matrix for this image is displayed in Table 48.

As shown in Table 49, image no. 4 parameters were comparable to those of the 3-4 band images (i.e., image nos. 1, 2, and 3; Table 29). Overall accuracies for image no. 4, however, were slightly lower than for all 3-4 band images.

Although the total number of image no. 4 classes with > 85% omission error was equivalent to all 4-band images, classes constituting the total were not. Two classes, residential and services, which had previously realized less than 85 percent omission errors in complete image classification nos. 1, 2, and 3 (Tables 8, 28, and 39), realized errors greater than 85 percent in image no. 4 (Table 48). Omission errors for water and cropland classes on the other hand, were less than 85 percent in image no. 4, unlike results for image nos. 1, 2, and 3.

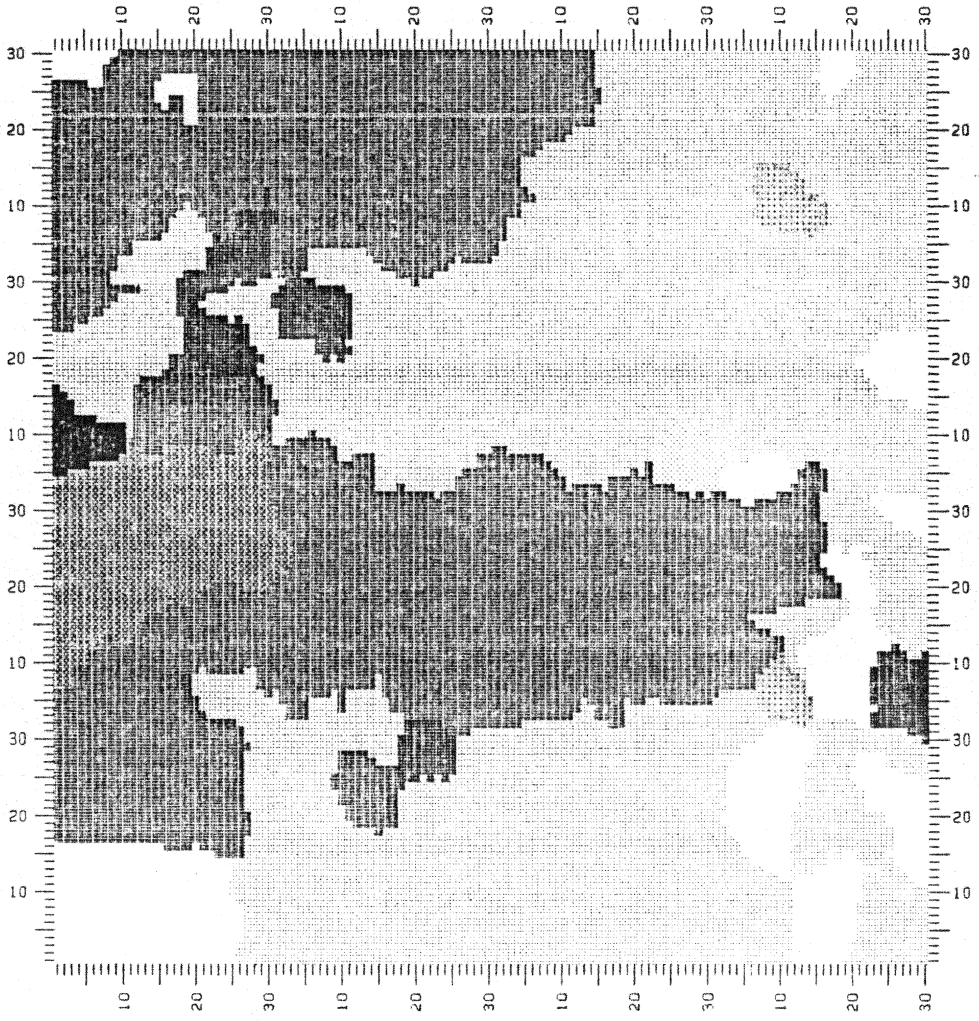


Fig. 69. Gray scale representation of classified Landsat image no. 4. Each land use is assigned a single gray scale shade.

Fig. 69. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		1228
5. - 5.		71
8. - 8.		81
9. - 9.		6785
11. - 11.		121
13. - 13.		687
41. - 41.		5070
43. - 43.		357

Table 48. Confusion table and mapping accuracies of the complete 13-class, image no. 4. This image was originally classified using the 4 raw Landsat bands and 5 ancillary bands. All regions with less than 13 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	17 0 0	0 0	6 0	0 16	0 0	44 0	83	66	79.5	20.2
CROPLAND	8	0 0 0	37 0	74 0	0 4	0 0	0 0	115	78	67.8	25.9
PASTURE	9	1 0 0	6 0	2969 0	0 302	0 0	4 41	3323	354	10.7	60.1
RESIDENTIAL	11	0 0 0	2 0	439 0	24 51	0 0	0 3	519	495	95.4	4.6
SERVICES	12	0 0 0	0 0	115 0	1 0	0 0	0 0	116	116	100.0	0.0
INDUSTRIAL	13	0 0 0	0 0	0 0	0 59	0 0	460 0	519	59	11.4	62.1
TRANSPORTATION	14	0 0 0	0 0	40 0	0 0	0 0	0 0	40	40	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	11 0	0 0	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	0 0 0	20 0	652 0	0 1808	0 0	99 8	2587	779	30.1	51.1
CONIFER	42	0 0 0	0 0	84 0	0 244	0 0	73 9	410	410	100.0	0.0
MIXED	43	0 0 0	0 0	184 0	0 275	0 0	2 75	536	461	86.0	12.6
TRANSITIONAL	76	0 0 0	0 0	8 0	0 3	0 0	0 0	11	11	100.0	0.0
TOTAL NO. OF CELLS		18 0	65 0	4583 0	25 2762	0 0	682 136				

Table 48. (Continued).

		0					
COMMISSIONS	NO.	1	28	1614	1	0	222
		0	0	0	954	0	61
		0					
COMMISSIONS	%	5.6	43.1	35.2	4.0	0.0	32.6
		0.0	0.0	0.0	34.5	0.0	44.9
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				65.2			
OVERALL MAPPING ACCURACY(OMA) =				45.7			

Table 49. A select comparison between 13-class (complete) image nos. 4, 5, and 6.

	Parameter	Image No. 4	Image No. 5	Image No. 6
1.	Overall classification accuracy (%)	65.2	66.9	67.8
2.	Overall mapping accuracy (%)	45.7	48.5	49.1
3.	No. of classes with > 85% omission error	8	6	6
4.	Largest class commission error (%)	Mixed (Forest) (44.9)	Mixed (Forest) (59.9)	Mixed (Forest) (73.3)
5.	Largest class mapping mapping accuracies (%)	Industrial (62.1) Pasture (60.1)	Industrial (63.9) Pasture (62.1)	Industrial (69.4) Pasture (63.7)
6.	No. of classes with 0% mapping accuracy	6	4	3

As shown in Table 49, although the total number of classes with 0 percent mapping accuracy (parameter 6) were equivalent to those of image no. 1 (Table 29), the classes themselves differed. Here, water and mixed (forest) could be classified in image no. 4 (Table 48) but not in image no. 1 (Table 8). These results were opposite those for services and conifer mapping accuracies (i.e., services and conifer could be identified in complete image nos. 1, 2, and 3 but not in image no. 4).

Overall, class accuracies for water, cropland, and mixed (forest) were better in image no. 4 than corresponding image nos. 1, 2, and 3. Accuracies for residential, services, and conifer decreased as compared to the previous 3-4-band image levels. In summary, this reflects the initial ability of the ancillary bands to produce larger changes in some individual class accuracies rather than overall accuracies.

2. Incremental Exclusions

Table 50 shows the overall accuracy changes throughout the image no.4 exclusion sequence. Accuracy differences between the complete image and the full exclusion (i.e., "roads plus urban plus water") (i.e., OCA = +3.8%, OMA = +5.5%) were only slightly greater than the high observed for the 4-band image (i.e., image 3: OCA = +3.0%, OMA = +4.2%). In total, these differences are not substantial enough to imply that 4-band classifications which are supplemented by ancillary data will be more responsive to the exclusion sequence (in terms of increased accuracy) than when other data are not added.

Only one significant difference can be found in Table 51 which distinguishes it from the previous 4-band tables. This is the loss in accuracy for mixed (forest) upon excluding "roads-only". Previously for

Table 50. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 4.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	65.2	45.7
Roads	65.3	45.8
Urban	68.2	50.5
Water	65.6	46.3
Roads + Water	65.7	46.4
Roads + Urban	68.4	50.7
Urban + Water	68.8	51.0
Roads + Urban + Water	69.0	51.2

Table 51. Greatest increases in image no. 4 (13 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Pasture Residential Hardwoods	Mixed (Forest)
Urban	Pasture	Industrial
Water	Industrial	Water
Roads + Water	Industrial	Water
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	Conifer	Cropland

Overall Exclusion Changes (+ and -): Pasture (60.1 to 66.1; i.e., +6.0%)
Industrial (62.1 to 26.4; i.e., -35.7%)

image nos. 1 (Table 18), 2 (Table 31), and 3 (Table 41) there had never been a class exhibiting a drop in accuracy proceeding the "roads-only" exclusion. This can be correlated with the fact that mixed (forest) had never been correctly classified in image nos. 1, 2, and 3 (i.e., map accuracy = 0%).

Similar to all 4-band images, "water-only" possessed the highest OCA and OMA improvement indexes for the image no. 4 exclusion sequence (Table 52). Differing from image nos. 1 (Table 19), 2 (Table 32), and 3 (Table 42), all exclusions conducted on image no. 4 (Table 52), composed in whole or part of the "urban" set (i.e., "urban-only", "roads plus urban", "urban plus water", and "roads plus urban plus water"), produced larger improvement indices. These index increases can probably be attributed to the lower classification accuracy of residential, services, and industrial classes in image no. 4 as compared to the 3-4-band images. Fig. 70 displays the respective improvement indexes for each exclusion.

3. Conditional Classification

The only class which showed an accuracy increase as a result of the conditional classification performed on image no. 4 was conifer (i.e., +0.5%; Table 51). The conditional classification image and confusion matrix are displayed in Fig. 71 and Table 53, respectively.

Fig. 72 shows the sequential increases in accuracies as based on the strategies performed on image no. 4.

Table 52. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 4.

1	2	3	4	5	6	7	8
1. Roads	161	65.3	+0.1	0.0006	45.8	+0.1	0.0006
2. Urban	1729	68.2	+3.0	0.0017	50.5	+4.8	0.0028
3. Water	90	65.6	+0.4	0.0044	46.3	+0.6	0.0067
4. Roads + Water	251	65.7	+0.5	0.0020	46.4	+0.7	0.0028
5. Roads + Urban	1867	68.4	+3.2	0.0017	50.7	+5.0	0.0027
6. Urban + Water	1819	68.8	+3.6	0.0020	51.0	+5.3	0.0029
7. Roads + Urban + Water	1957	69.0	+3.8	0.0019	51.2	+5.5	0.0028

Image 4; 13 classes OCA = 65.2% OMA = 45.7%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% _ or -- percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing COL. 4 by COL. 2.
6. OMA% - overall mapping accuracy level (%) after excluding a specific set (x 100).
7. OMA% + or --OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8. OMA improvement index - OMA change per pixel excluded; computed by dividing COL. 7 by COL. 2.

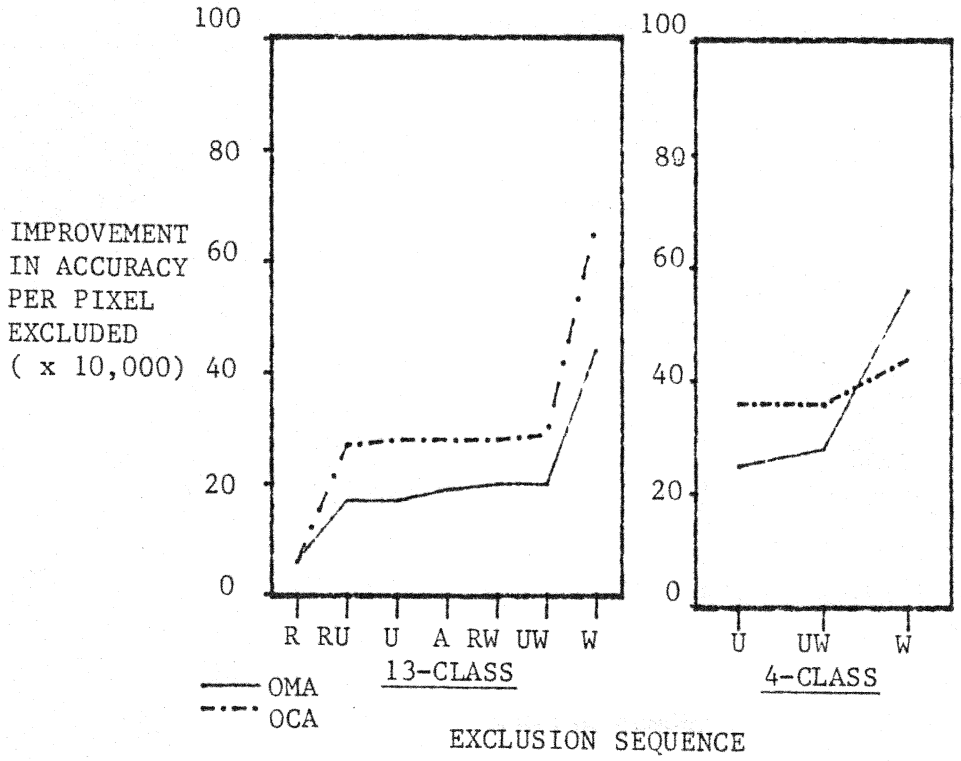


Fig. 70. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 4 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

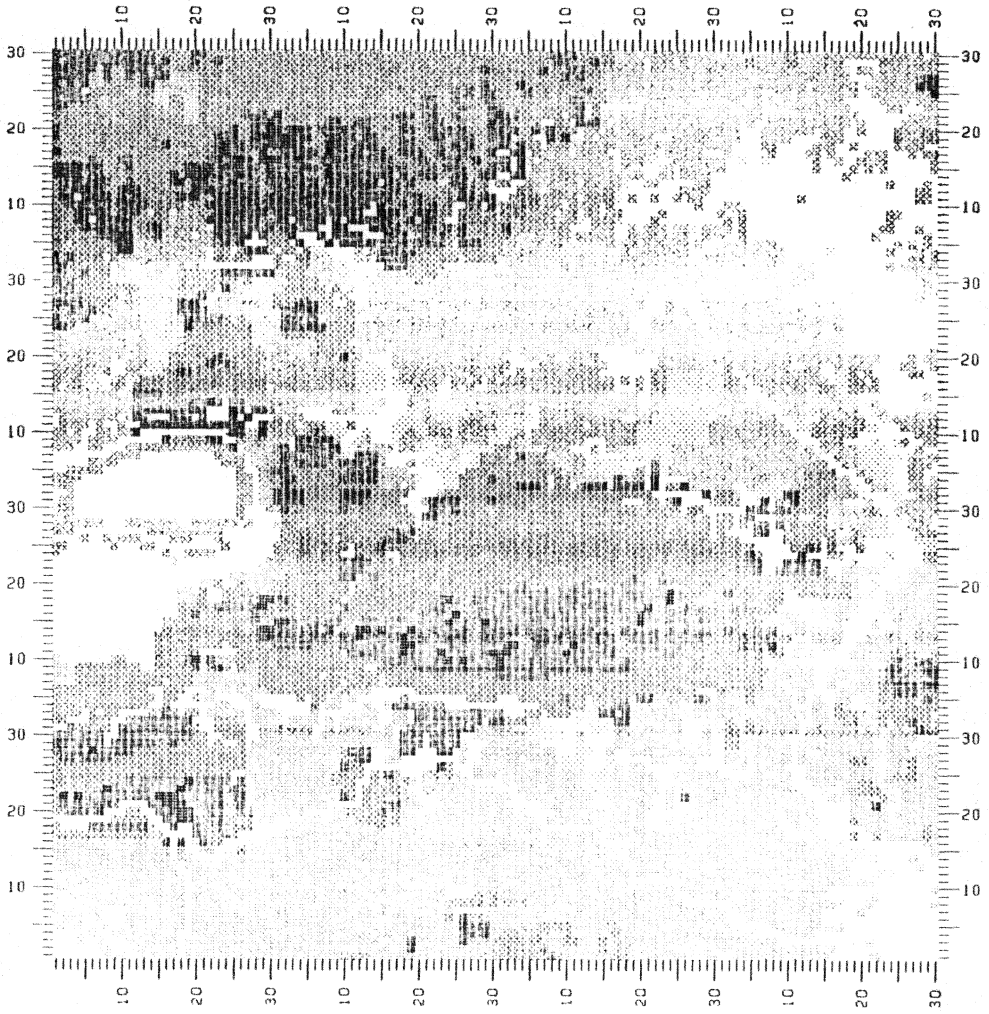


Fig. 71. Gray scale representation of conditional classification image no. 4. Each land use is assigned a single gray scale shade.

Fig. 71. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
8.	-	8.		813
9.	-	9.		5190
41.	-	41.		3445
42.	-	42.		141
43.	-	43.		1507

Table 53. Confusion table and mapping accuracies of the 13-class, image no. 4 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.	NO.	%	
WATER	5	0 0 0	0 0	6 0	0 1	0 0	0 0	7	7	100.0	0.0
CROPLAND	8	0 0 0	57 0	51 0	0 4	0 0	0 0	112	55	49.1	10.1
PASTURE	9	0 0 0	374 0	2088 0	0 235	0 0	0 64	2761	673	24.4	55.5
RESIDENTIAL	11	0 0 0	12 0	55 0	0 12	0 0	0 7	86	86	100.0	0.0
SERVICES	12	0 0 0	7 0	25 0	0 0	0 0	0 0	32	32	100.0	0.0
INDUSTRIAL	13	0 0 0	0 0	52 0	0 19	0 0	0 0	71	71	100.0	0.0
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
HARDWOODS	41	0 0 0	45 0	559 0	0 1173	0 53	0 566	2396	1223	51.0	38.9
CONIFER	42	0 0 0	3 0	98 0	0 159	0 2	0 75	337	335	99.4	0.5
MIXED	43	0 0 0	10 0	143 0	0 187	0 7	0 149	496	347	70.0	12.3
TRANSITIONAL	76	0 0 0	0 0	2 0	0 3	0 0	0 0	5	5	100.0	0.0
TOTAL NO. OF CELLS		0 0	508 0	3090 0	0 1793	0 62	0 861				

Table 53. (Continued).

		0					
COMMISSIONS	NO.	0	451	1002	0	0	0
		0	0	0	620	60	712
		0					
COMMISSIONS	%	0.0	88.8	32.4	0.0	0.0	0.0
		0.0	0.0	0.0	34.6	96.8	82.7
		0.0					

OVERALL CLASSIFICATION ACCURACY(OCA) = 54.9

OVERALL MAPPING ACCURACY(OMA) = 40.2

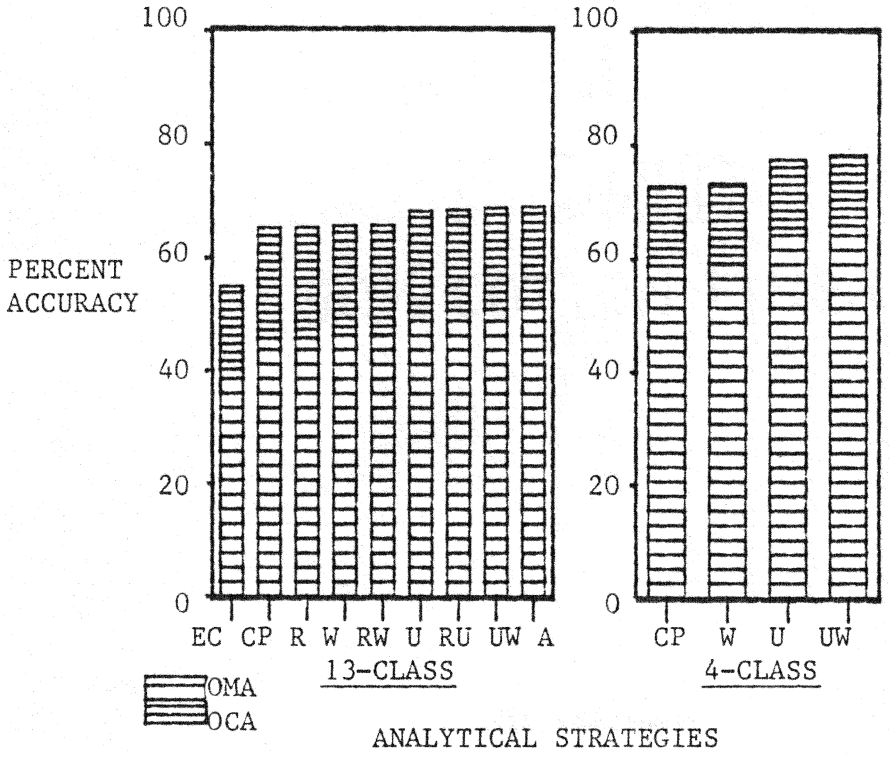


Fig. 72. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 4 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

B. 4 classes

1. Complete Image

As shown in Table 54, overall accuracies for the 9-band, 4-class, image no. 4 were less than those for all 4-band, 4-class images (Table 35). This indicates that even at a grosser classification scale (i.e., 4 classes), the ancillary data used could not increase overall image accuracies. Values for OCA and OMA (Table 55) were actually 3.3 percent and 3.6 percent less than for image no. 1 (Table 21), which possessed the lowest accuracies of the 4-band images.

Differences relating to agriculture and water distinguish image no. 4 (4-class) from the 3 previous 4-class images (nos. 1, 2, and 3). Here, agriculture possessed the largest commission error (Table 54) replacing built-up land or water which had previously in image nos. 1, 2, and 3 (Table 35). This increased agriculture error was most likely caused by the additional data which directed more built-up land and forest pixels to be incorrectly classed as agriculture. Water was the only class among the 4 (Table 55) which possessed accuracies higher than those in image nos. 1, 2, and 3. Ancillary data were thus most effective for increasing the classifiability of water.

2. Incremental Exclusions

Table 56 summarizes the results of the exclusions performed on image no. 4.

As shown in columns 4 and 7 of Table 57, the increases in OCA following exclusions of "urban" and "water plus urban" sets were slightly larger than the 3-4-band images (Tables 27, 38, and 47). The large increases following these two exclusions are partially the result of the

Table 54. A select comparison between 4-class (complete) image nos. 4, 5, and 6.

	Parameter	Image No. 4	Image No. 5	Image No. 6
1.	Overall classification accuracy (%)	72.8	74.7	76.0
2.	Overall mapping accuracy (%)	58.9	60.8	62.5
3.	No. of classes with > 85% omission error	0	0	0
4.	Largest class commission error (%)	Agriculture (33.4)	Agriculture (31.4)	Water (57.1)
5.	Largest class mapping accuracies (%)	Agriculture (61.9) Forest (61.8)	Agriculture (63.9) Forest (64.0)	Agriculture (65.2) Forest (60.3)
6.	No. of classes with 0% mapping accuracy	0	0	0

Table 55. Confusion table and mapping accuracies of the complete 4-class, image no. 4. This classification was based on the 4 raw Landsat bands and 5 ancillary bands. All regions of less than 13 pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	485	605	116	0	1206	721	59.8	34.0
Agriculture	2	4	3097	347	1	3449	352	10.2	61.9
Forest	4	174	940	2419	0	3533	1114	31.5	60.3
Water	5	44	6	16	17	83	66	79.5	20.2
Total No. of Cells		707	4648	2898	18				
Commissions No.		222	1551	479	1				
Commissions %		31.4	33.4	16.5	5.6				

Overall Classification Accuracy (OCA) = 72.8
Overall Mapping Accuracy (OMA) = 58.9

Table 56. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 4.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	72.8	58.9
Water	73.3	59.3
Urban	77.5	65.6
Water + Urban	78.3	66.0

Table 57. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 4.

1	2	3	4	5	6	7	8
1. Water	90	73.3	+0.5	0.0056	59.3	+0.4	0.0044
2. Urban	1867	77.5	+4.7	0.0025	65.6	+6.7	0.0036
3. Water + Urban	1957	78.3	+5.5	0.0028	66.0	+7.1	0.0036

Image 4; 4 classes OCA = 72.8% OMA = 58.9%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing COL. 4 by COL. 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing COL. 7 by COL. 2.

initially low, image no. 4 (complete image) built-up land classification accuracy (Table 55). Overall, image no. 4 OMA increases per exclusion (Table 56) were very similar to those of image no. 3 (Table 45).

Class accuracy increases proceeding each exclusion (Table 58) followed the same pattern as for image nos. 2 (Table 37) and 3 (Table 46). The largest overall positive exclusion change belonged to agriculture which was similar to image nos. 2 (Table 37) and 3 (Table 46). Differing from results for image nos. 1, 2, and 3, water was the class which had the largest overall negative change (Table 58).

Although water possessed the largest OCA and OMA improvement index values for the image no. 4 exclusion sequence (Table 57), these values were less than all previous 4-band water improvement indices. Except for the image no. 3, "water plus urban" OMA improvement index (Table 47), all image no. 4 improvement indices resulting from the "urban" and "water plus urban" exclusions (Table 57) were slightly greater than or equal to the corresponding indices for the 3-4-band images. Fig. 70 displays the range of the improvement indices values for each exclusion.

Fig. 72 displays the sequence of image no. 4 accuracy improvements.

Table 58. Greatest increases in image no. 4 (4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up land	Water
Urban	Agriculture	Built-up land
Water + Urban	Agriculture	Water

Overall Exclusion Changes (+ and -): Agriculture (61.9 to 68.2; i.e., +6.3%)
Water (20.2 to 0.0; i.e., -20.2%)

V. IMAGE NO. 5

A. 13 classes

1. Complete Image

Further work was done with the 9 Landsat bands (i.e., Landsat bands 4, 5, 6, and 7 and the 5 ancillary bands). Classification no. 5 (Fig. 73) was the second image produced from them. This image possessed 90 clusters. Analysis using the GIPSY system had removed and reassigned all regions of less than 9 pixels before clustering.

Compared to the first 9-band classification (image no. 4), image no. 5 possessed greater overall accuracies. Mapping accuracies for pasture, residential, services, industrial, hardwoods, conifer, and mixed were also higher in image no. 5 (Table 59) than in image no. 4 (Table 48). Only 2 classes from among the 13, water and cropland (Table 59), decreased in accuracy relative to image no. 4 classes (Table 48). These differences are most likely the result of the decreased GIPSY removal/reassignment factor from 13 to 9 [This reduced threshold (i.e., 13 to 9) had previously caused similar accuracy increases in the complete image no. 2 (4-band) relative to those of image no. 1 (4-band)]. As shown in Table 49, these image no. 5 results are substantiated by increased accuracies in parameters 1, 2, and 5 and decreased values for parameters 3 and 6 when compared to image no. 4. Classes which exhibited the largest omission error or greatest mapping accuracies remained consistent.

Similar to image no. 4, overall accuracies for image no. 5 were less than all complete 4-band images (i.e., nos. 1, 2, and 3) (Table 29).

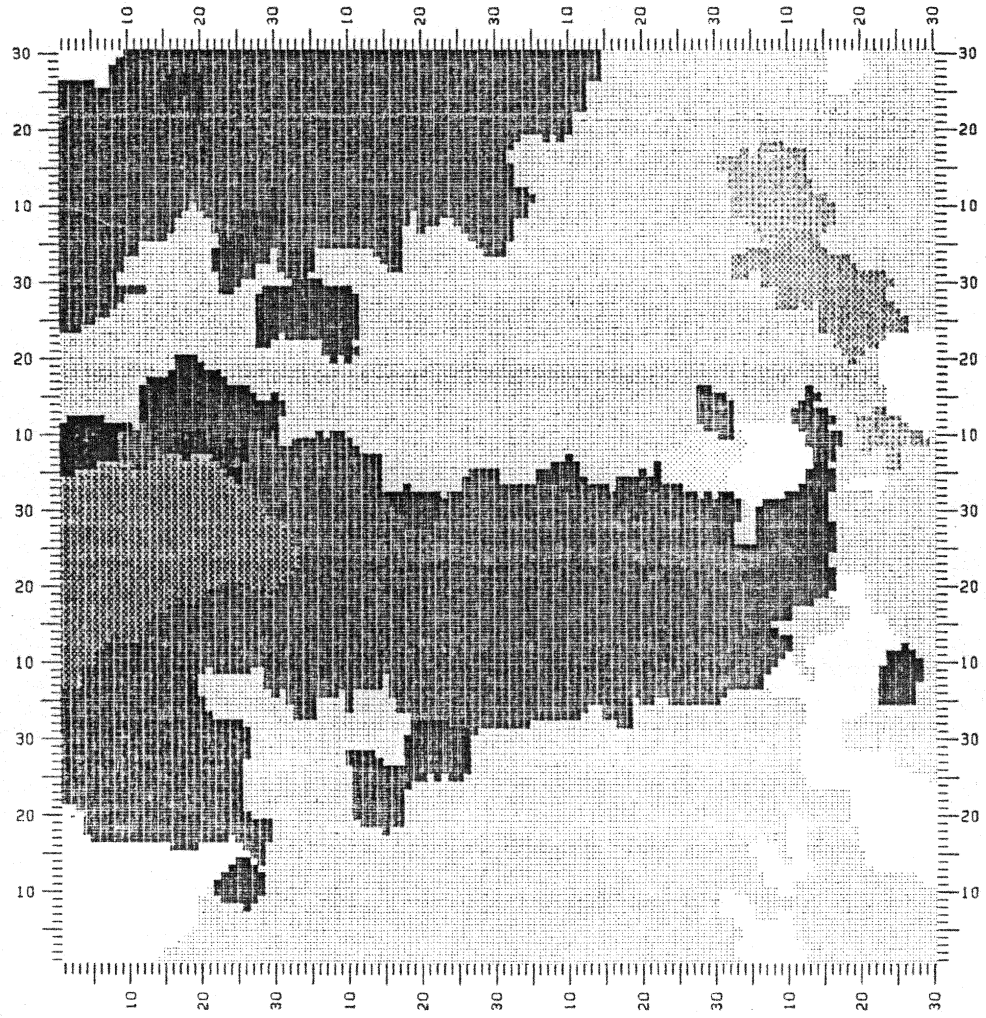


Fig. 73. Gray scale representation of classified Landsat image no. 5. Each land use is assigned a single gray scale shade.

Fig. 73. (Continued).

SYMBOL KEY

	CATEGORY	SYMBOL	FREQUENCY
0.	- 0.		1115
5.	- 5.		53
8.	- 8.		72
9.	- 9.		6842
11.	- 11.		174
12.	- 12.		189
13.	- 13.		615
41.	- 41.		4475
42.	- 42.		33
43.	- 43.		832

Table 59. Confusion table and mapping accuracies of the complete 13-class, image no. 5. This image was originally classified using the 4 raw Landsat bands and 5 ancillary bands. All regions with less than 9 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	15	0	5	0	1	36	83	68	81.9	18.1
		0	0	0	12	5	9				
		0									
CROPLAND	8	0	28	79	0	0	0	115	87	75.7	19.6
		0	0	0	6	0	2				
		0									
PASTURE	9	0	6	2993	10	30	3	3323	330	9.9	62.1
		0	0	0	221	0	60				
		0									
RESIDENTIAL	11	0	2	405	64	0	0	519	455	87.7	11.9
		0	0	0	36	0	12				
		0									
SERVICES	12	0	0	37	3	76	0	116	40	34.5	49.4
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	0	0	0	441	519	78	15.0	63.9
		0	0	0	74	4	0				
		0									
TRANSPORTATION	14	0	0	37	3	0	0	40	40	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	11	0	0	0	11	11	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	20	635	1	7	82	2587	784	30.3	52.8
		0	0	0	1803	1	38				
		0									
CONIFER	42	0	0	93	0	0	50	410	388	94.6	5.2
		0	0	0	224	22	21				
		0									
MIXED	43	0	0	186	0	0	0	536	441	82.3	14.0
		0	0	0	254	1	95				
		0									
TRANSITIONAL	76	0	0	8	0	0	0	11	11	100.0	0.0
		0	0	0	3	0	0				
		0									
TOTAL NO. OF CELLS		15	56	4490	81	114	612				
		0	0	0	2633	33	237				

Table 59. (Continued).

		0					
COMMISSIONS	NO.	0	28	1497	17	38	171
		0	0	0	830	11	142
		0					
COMMISSIONS	%	0.0	50.0	33.3	21.0	33.3	27.9
		0.0	0.0	0.0	31.5	33.3	59.9
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				66.9			
OVERALL MAPPING ACCURACY(OMA) =				48.5			

This demonstrates that even with a reduced removal and reassignment factor (i.e., increased classification resolution), the additional bands did not aid in increasing overall accuracies. Only one class, mixed (forest) (Table 59), had a mapping accuracy greater than those recorded for the complete 4-band images (Tables 8, 28, and 39).

Overall accuracies for image no. 5 most closely compared to image no. 1 of the 4-band classifications.

2. Incremental Exclusions

Accuracy changes resulting from the image no. 5 exclusion sequence are shown in Table 60. Although accuracy levels proceeding each exclusion were greater than for image no. 4 (Table 50), when all were excluded, overall accuracy differences were greatest for image no. 4 ["roads plus urban plus water" exclusion minus complete image accuracy for image no. 5 (i.e., OCA = +3.0%, OMA = +4.2%) were less than those for image no. 4 (i.e., OCA = +3.8%, OMA = +5.5%)]. Compared to fully excluded image nos. 1, 2, and 3, overall accuracy changes following the image no. 5 full exclusion were greater than those for image nos. 1 (Table 17) and 2 (Table 30) and equivalent to image no. 3 (Table 40).

For image no. 5, the majority of exclusion/class accuracy increases (Table 61) were similar to those obtained in analyzing images nos. 1 (Table 18), 2 (Table 31), 3 (Table 41), and 4 (Table 51). Differences which existed were limited to the "roads-only" exclusion. For image no. 5, 4 classes (i.e., pasture, residential, hardwoods, and conifer) possessed equal increases proceeding the exclusion of roads as compared to with only 3 classes (i.e., pasture, residential, and hardwoods) for image no. 4 and 1 each for image nos. 3 (i.e., hardwoods), 2 (i.e.,

Table 60. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 5.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	66.9	48.5
Roads	67.1	48.7
Urban	69.0	51.8
Water	67.4	49.1
Roads + Water	67.6	49.3
Roads + Urban	69.2	52.1
Urban + Water	69.6	52.5
Roads + Urban + Water	69.9	52.7

Table 61. Greatest increases in image no. 5 (13 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Pasture Residential Hardwoods Conifer	-
Urban	Pasture	Industrial
Water	Industrial	Water
Roads + Water	Industrial	Water
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	-	Hardwoods

Overall Exclusion Changes (+ and -): Pasture (62.1 to 67.0; i.e., +4.9%)
Industrial (63.9 to 25.0; i.e., -38.9%)

residential), and 1 (i.e., residential). Mixed (forest) did not show a decrease in accuracy as a result of the image no. 5 "roads-only" exclusion as it had in image no. 4. This indicates that areas classified as mixed (forest) in image no. 4 were dissimilar to those in image no. 5.

For image no. 5, 3 exclusions (i.e., "roads-only", "water-only", and "roads plus water"; Table 62) produced improvement indices greater than for respective image no. 4 exclusions (Table 52). The increases in improvement indices that were associated with a "water" exclusion were probably produced as a result of the lower water classification accuracy for image no. 5 than image no. 4. Analogous to results for image no. 4, exclusions performed on image no. 5 (Table 62), composed in whole or part of the "urban" set, possessed improvement indices greater than those for the 4-band images (Tables 19, 32, and 42). Two exceptions, the "roads plus urban" and "roads plus urban plus water" exclusions, did not possess improvement indices greater than those for image no. 3 (Table 42). Reasons for these increases are the same as those mentioned for image no. 4. Fig. 74 displays the respective improvement index values for image no. 5.

3. Conditional Classification

As shown in Table 61, no classes increased in accuracy as a result of the conditional classification performed on image no. 5. Classification accuracy of hardwoods decreased the most. The conditional classification image and confusion matrix are shown in Fig. 75 and Table 63 respectively.

Fig. 76 shows the sequence of accuracy changes generated by the strategies performed on image no. 5.

Table 62. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 5

1	2	3	4	5	6	7	8
1. Roads	161	67.1	+0.2	0.0012	48.7	+0.2	0.0012
2. Urban	1729	69.0	+2.1	0.0012	51.8	+3.3	0.0019
3. Water	90	67.4	+0.5	0.0056	49.1	+0.6	0.0067
4. Roads + Water	251	67.6	+0.7	0.0028	49.3	+0.8	0.0032
5. Roads + Urban	1867	69.2	+2.3	0.0012	52.1	+3.6	0.0019
6. Urban + Water	1819	69.6	+2.7	0.0015	52.5	+4.0	0.0022
7. Roads + Urban + Water	1957	69.9	+3.0	0.0015	52.7	+4.2	0.0021

Image 5; 13 classes OCA = 66.9% OMA = 48.5%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

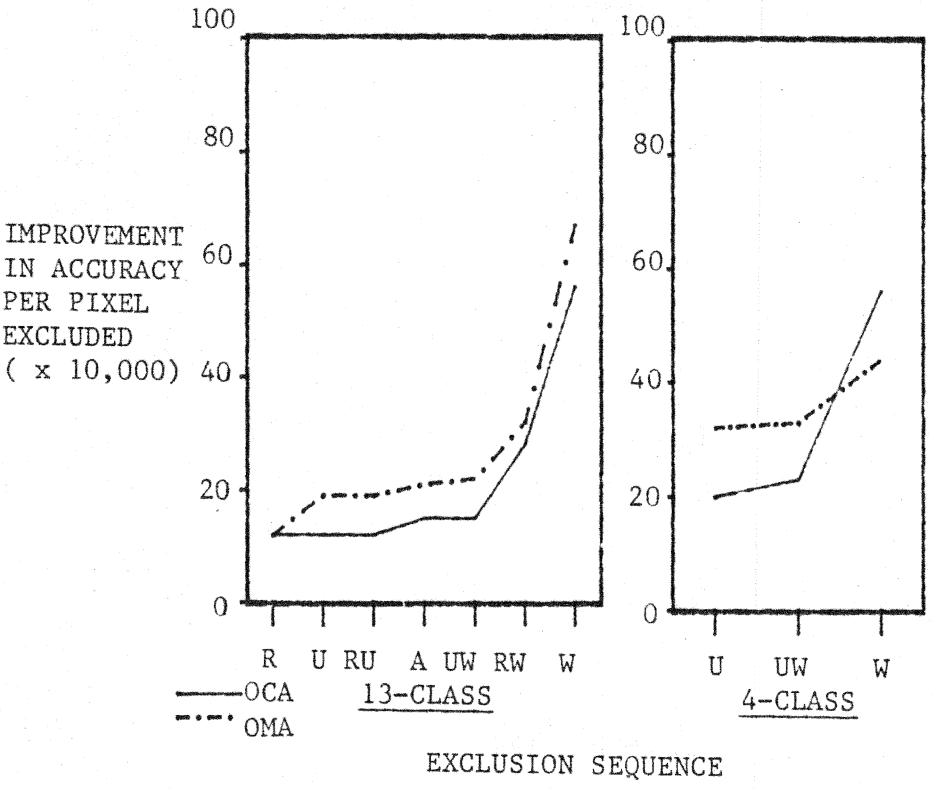


Fig. 74. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 5 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

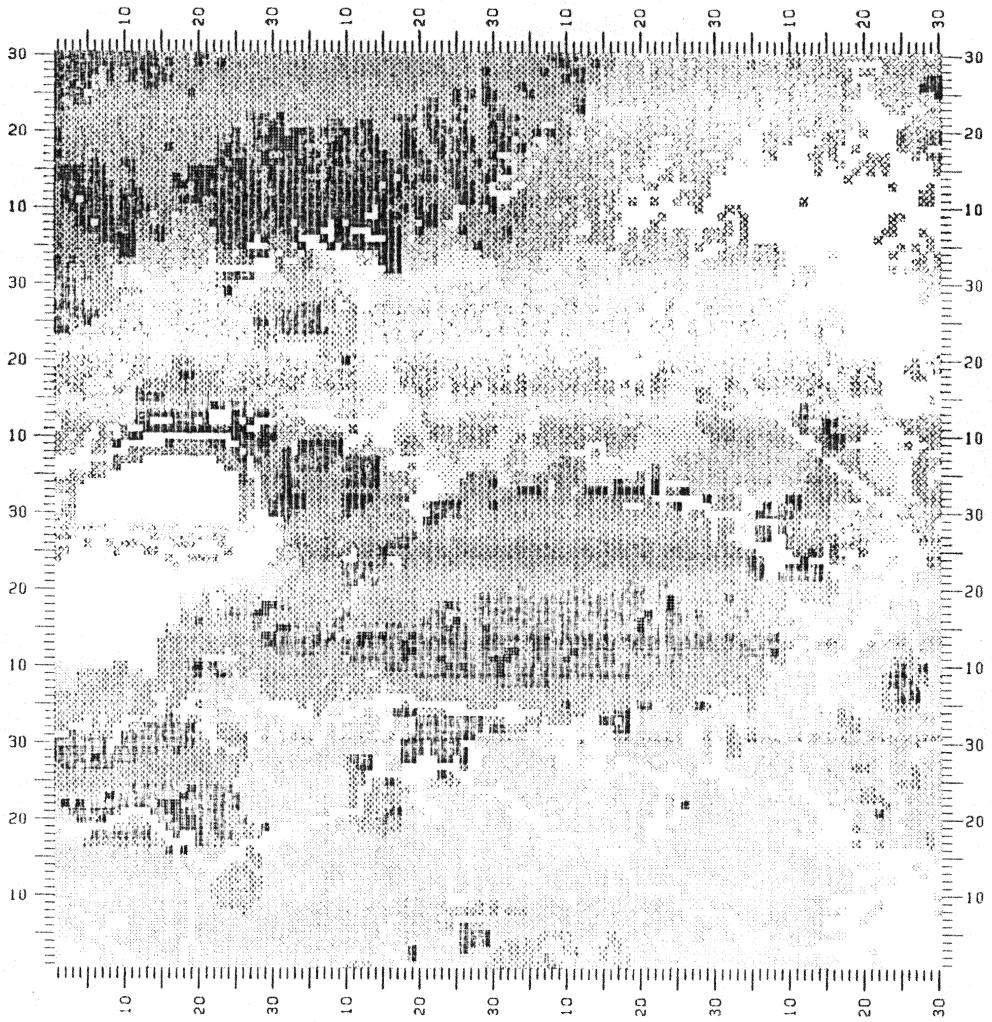


Fig. 75. Gray scale representation of conditional classification image no. 5. Each land use is assigned a single gray scale shade.

Fig. 75. (Continued).

SYMBOL KEY

	CATEGORY	SYMBOL	FREQUENCY
-9999.	- -9999.		3304
8.	- 8.		819
9.	- 9.		5271
41.	- 41.		3403
42.	- 42.		144
43.	- 43.		1459

Table 63. Confusion table and mapping accuracies of the 13-class, image no. 5 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	6	0	0	0	7	7	100.0	0.0
		0	0	0	1	0	0				
		0									
CROPLAND	8	0	55	49	0	0	0	112	57	50.9	9.5
		0	0	0	8	0	0				
		0									
PASTURE	9	0	394	2125	0	0	0	2761	636	23.0	57.0
		0	0	0	199	0	43				
		0									
RESIDENTIAL	11	0	13	58	0	0	0	86	86	100.0	0.0
		0	0	0	11	0	4				
		0									
SERVICES	12	0	7	25	0	0	0	32	32	100.0	0.0
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	40	0	0	0	71	71	100.0	0.0
		0	0	0	25	0	6				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	37	547	0	0	0	2396	1209	50.5	39.6
		0	0	0	1187	55	570				
		0									
CONIFER	42	0	6	85	0	0	0	337	335	99.4	0.5
		0	0	0	168	2	76				
		0									
MIXED	43	0	11	144	0	0	0	496	348	70.2	12.4
		0	0	0	186	7	148				
		0									
TRANSITIONAL	76	0	0	2	0	0	0	5	5	100.0	0.0
		0	0	0	3	0	0				
		0									
TOTAL NO. OF CELLS		0	523	3092	0	0	0				
		0	0	0	1788	64	847				

Table 63. (Continued).

		0					
COMMISSIONS	NO.	0	468	967	0	0	0
		0	0	0	601	62	699
		0					
COMMISSIONS	%	0.0	89.5	31.3	0.0	0.0	0.0
		0.0	0.0	0.0	33.6	96.9	82.5
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				55.7			
OVERALL MAPPING ACCURACY(OMA) =				41.1			

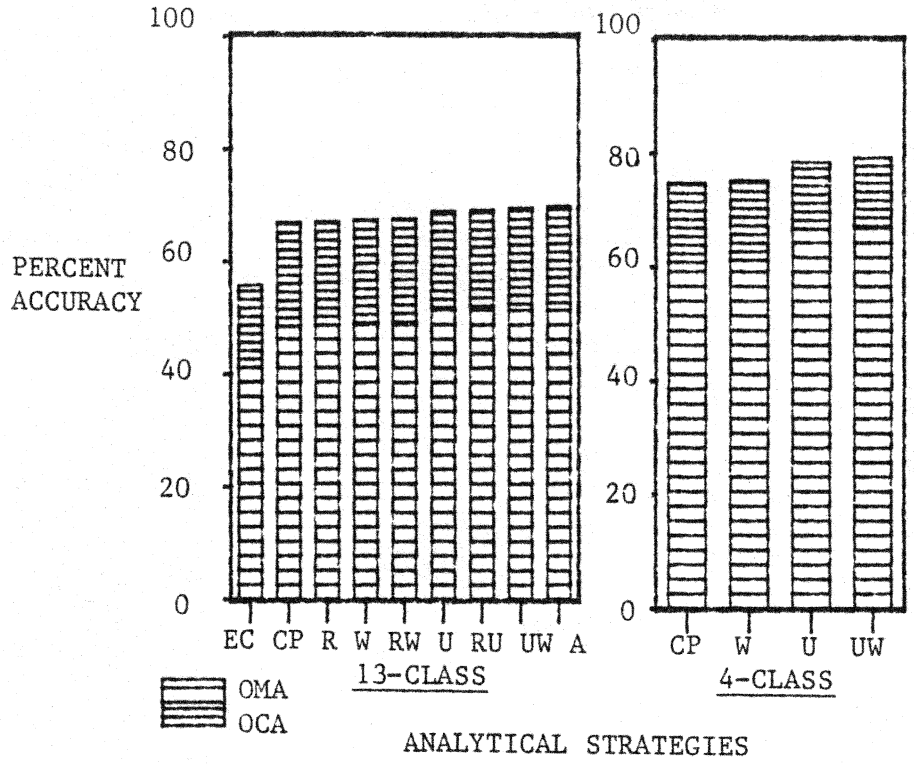


Fig. 76. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 5 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

B. 4 classes

1. Complete Image

As shown in Table 54, image no. 5 possessed classification accuracies greater than image no. 4 but less than image nos. 1, 2, and 3 (Table 35). Only 1 class, water, possessed a lesser accuracy in image no. 5 (Table 64) than in image no. 4 (Table 55). Conversely, water was the only class in image no. 5 which had an accuracy greater than the water class of image nos. 1 (Table 21), 2 (Table 34), and 3 (Table 44).

2. Incremental Exclusions

Table 65 summarizes overall accuracy changes proceeding each exclusion performed on image no. 5. Individual accuracies were greater than for image no. 4 (Table 56) but relative increases over the 3-step exclusion sequence were less. Image no. 3 (Table 45) was the only 4-band image which had a larger relative accuracy increase, over the exclusion sequence, than image no. 5. As portrayed in Table 66, classes which exhibited the greatest positive change in accuracy (post-exclusion) for image no. 5, were equivalent to those of image no. 4 (Table 58), image no. 3 (Table 46), and image no. 2 (Table 37).

Table 67 displays the improvement index values per image no. 5 exclusion strategy. All values were equal to or less than respective levels for image no. 4 (Table 57). These decreases for image no. 5 were most likely caused by the greater image accuracy that occurred when no exclusions were made. In other words, a lesser number of incorrectly classified pixels were present to be excluded, resulting in a smaller increase in accuracy. Among the 4-band images, only image no. 3 (Table 47) possessed improvement index values consistently greater than those

Table 64. Confusion table and mapping accuracies of the complete 4-class, image no. 5. This classification was based on the 4 raw Landsat bands and 5 ancillary bands. All regions of less than 9 pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	587	490	129	0	1206	619	51.3	41.2
Agriculture	2	43	3117	289	0	3449	332	9.6	63.9
Forest	4	140	934	2459	0	3533	1074	30.4	61.8
Water	5	37	5	26	15	83	68	81.9	18.1
Total No. of Cells		807	4546	2903	15				
Commissions No.		220	1429	444	0				
Commissions %		27.3	31.4	15.3	0				

Overall Classification Accuracy (OCA) = 74.7
Overall Mapping Accuracy (OMA) = 60.8

Table 65. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 5.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	74.7	60.8
Water	75.2	61.2
Urban	78.4	66.7
Water + Urban	79.2	67.2

Table 66. Greatest increases in image no. 5 (4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up Land	Water
Urban	Agriculture	Built-up Land
Water + Urban	Agriculture	Built-up Land

Overall Exclusion Changes (+ and -): Agriculture (63.9 to 69.0; i.e., +5.1%)
Built-up Land (41.2 to 17.2; i.e., -24.0%)

Table 67. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 5.

1	2	3	4	5	6	7	8
1. Water	90	75.2	+0.5	0.0056	61.2	+0.4	0.0044
2. Urban	1867	78.4	+3.7	0.0020	66.7	+5.9	0.0032
3. Water + Urban	1957	79.2	+4.5	0.0023	67.2	+6.4	0.0033

Image 5; 4 classes OCA = 74.7% OMA = 60.8%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

for image no. 5. Fig. 74 displays the improvement index values for image no. 5.

The sequence of 4-class, image no. 5 overall accuracy increases are displayed in Fig. 76.

VI. IMAGE NO. 6

A. 13 classes

1. Complete Image

Image no. 6 (Fig. 77) was the final image derived from the 9-band data set. It possessed 160 clusters. This represented the most precisely clustered, 13-class image of the 6 classifications. Analysis using the GIPSY system had removed and reassigned all regions of less than 5 pixels before clustering.

As shown in Table 49, image no. 6 possessed the greatest overall classification accuracies of the 3 images augmented with ancillary data (i.e., image nos. 4, 5, and 6). This pattern of overall accuracy increases given greater classification resolution (i.e., overall accuracies being lowest for image no. 4, 13-pixel resolution; middle for the image no. 5, 9-pixel resolution; and greatest for the image no. 6, 5-pixel resolution) differed from results for image nos. 1, 2, and 3. (As mentioned previously for the 4-band images, overall accuracies were highest for image no. 2 which had a 9-pixel resolution). This greater classification resolution-higher accuracy outcome for image nos. 4, 5, and 6 may indicate that for images supplemented by ancillary data, greater resolutions would allow for larger numbers of recognizable clusters to be correctly classified (e.g., comparison of parameters 3, 5, and 6 in Table 49). Also, these results suggest that for 4-band images (i.e., classifications composed only of Landsat bands 4, 5, 6, and 7) there are classification resolution and clustering limits (e.g., image no. 2, 9-pixel resolution having 90 clusters), after which the

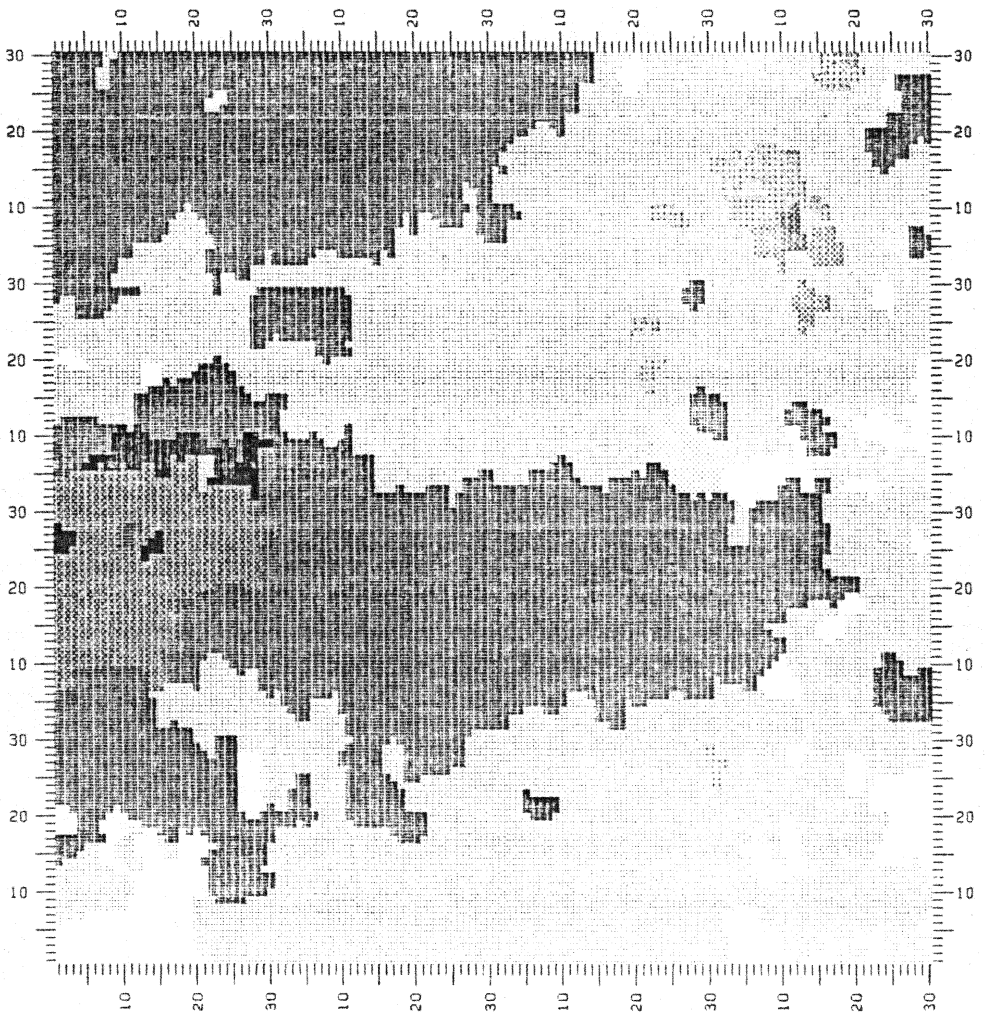


Fig. 77. Gray scale representation of classified Landsat image no. 6. Each land use is assigned a single gray scale shade.

Fig. 77. (Continued).

	SYMBOL KEY		
	CATEGORY	SYMBOL	FREQUENCY
0.	- 0.		802
5.	- 5.		43
8.	- 8.		95
9.	- 9.		7234
11.	- 11.		149
12.	- 12.		57
13.	- 13.		617
41.	- 41.		5291
42.	- 42.		87
43.	- 43.		15
76.	- 76.		10

quality of classification decreases (e.g., overall accuracies in image no. 3). For images supplemented with ancillary data, these resolution and clustering limits may also exist but may require more testing to determine because of the greater quantity of data and subsequent interactions that are possible.

The inability to determine classification resolution and cluster limits for images with additional data may be one reason why neither image nos. 4, 5, or 6 possessed accuracies greater than for the highest 4-band image (i.e., image no. 2). Only by fine-tuning the quality of ancillary data (i.e. through resolution and cluster manipulation) would it be possible to maximize the intrinsic dimensionality of the data and thus the scene information that can be accurately extracted. Unrefined ancillary data thus may not offer a capability to increase classification accuracies above a certain level. Another possibility which could have contributed to the inability of the ancillary data to increase accuracies may rest with the lower quality of the data as based on the season (early spring) in which it was collected.

The confusion matrix for image no. 6 is displayed in Table 68. Here, class accuracies for cropland, pasture, residential, industrial, hardwoods, conifer, and transitional were all greater than respective levels for image nos. 4 (Table 48) and 5 (Table 59). Exclusive of image no. 6, the transitional class present in 13-category images had never before been correctly identified (i.e., map accuracy never greater than 0%).

2. Incremental Exclusions

Presented in Table 69 are the results of the exclusion strategies performed on image no. 6. Complete exclusion-non-exclusion accuracy

Table 68. Confusion table and mapping accuracies of the complete 13-class, image no. 6. This image was originally classified using the 4 raw Landsat bands and 5 ancillary bands. All regions with less than 5 pixels were removed and reassigned prior to clustering.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	18 0 0	0 0	6 0	0 24	0 11	24 0	83	65	78.3	16.8
CROPLAND	8	0 0 0	48 0	57 0	0 6	0 0	0 4	115	67	58.3	32.9
PASTURE	9	0 0 5	12 0	3031 0	13 251	2 4	3 2	3323	292	8.8	63.7
RESIDENTIAL	11	0 0 0	2 0	383 0	71 63	0 0	0 0	519	448	86.3	13.2
SERVICES	12	0 0 0	0 0	74 0	2 0	34 0	6 0	116	82	70.7	28.8
INDUSTRIAL	13	11 0 0	0 0	6 0	0 36	0 6	460 0	519	59	11.4	69.4
TRANSPORTATION	14	0 0 0	0 0	35 0	3 2	0 0	0 0	40	40	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	8 0	0 3	0 0	0 0	11	11	100.0	0.0
HARDWOODS	41	9 0 0	17 0	590 0	1 1889	0 8	70 3	2587	698	27.0	53.2
CONIFER	42	4 0 0	0 0	90 0	0 226	0 48	40 2	410	362	88.3	10.9
MIXED	43	0 0 0	0 0	183 0	0 347	0 1	1 4	536	532	99.3	0.7
TRANSITIONAL	76	0 0 5	0 0	3 0	0 3	0 0	0 0	11	6	54.5	31.3
TOTAL NO. OF CELLS		42 0	79 0	4467 0	90 2850	36 78	604 15				

Table 68. (Continued).

		10					
COMMISSIONS	NO.	24	31	1436	19	2	144
		0	0	0	961	30	11
		5					
COMMISSIONS	%	57.1	39.2	32.1	21.1	5.6	23.8
		0.0	0.0	0.0	33.7	38.5	73.3
		50.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				67.8			
OVERALL MAPPING ACCURACY(OMA) =				49.1			

Table 69. Summary of exclusion strategy effects on accuracy for the 13-class, image no. 6.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	67.8	49.1
Roads	68.0	49.3
Urban	69.9	52.2
Water	68.3	49.7
Roads + Water	68.5	49.9
Roads + Urban	70.0	52.4
Urban + Water	70.5	52.9
Roads + Urban + Water	70.6	53.1

differences for this image (i.e., OCA = + 2.8%, OMA = + 4.0%) were the lowest among the 3-9-band classifications. These accuracy differences were consistently lower progressing from image no. 4 to image no. 6. This may indicate that the higher the complete image accuracies, the lower are accuracies resulting from exclusion strategies.

Multi-class accuracy changes, characteristic of the "roads-only" exclusion for images no. 4 (Table 51) and no. 5 (Table 61), did not occur in image no. 6. As shown in Table 70, only the accuracy of classifying hardwoods increased greatly after the exclusion was made.

In image no. 6, accuracy of classifying the conifer class decreased after the "roads-only" exclusion (Table 70). This was distinct from exclusion results for image nos. 1 (Table 18), 2 (Table 31), 3 (Table 41), 4 (Table 51), and 5 (Table 61).

Table 71 displays the respective indices of improvement for the image no. 6 exclusion sequence. Compared to values for image no. 5 (Table 62), these results are essentially equivalent. The largest deviation between corresponding image nos. 5 and 6 exclusion indices was 0.0001. Although these results are inconclusive, this may indicate that either climatic or stable improvement index levels have been reached, given the level of non-exclusion classification accuracy. Figure 78 displays the range of improvement indices for image no. 6.

3. Conditional Classification

Results from the conditional method of classification performed on image no. 6 (Fig. 79) are found in Table 72. As compared to class accuracies for the complete image (Table 68), mixed (forest) showed the most significant increase in accuracy. Cropland possessed the greatest decrease.

Table 70. Greatest increases in image no. 6 (13 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Roads	Hardwoods	Conifer
Urban	Pasture	Industrial
Water	Industrial	Water
Roads + Water	Industrial	Water
Roads + Urban	Pasture	Industrial
Urban + Water	Pasture	Industrial
Roads + Urban + Water	Pasture	Industrial
Conditional	Mixed (Forest)	Cropland

Overall Exclusion Changes (+ and -): Pasture (63.7 to 68.9; i.e., +5.2%)
Industrial (69.4 to 25.0; i.e., -44.4%)

Table 71. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 13-class, image no. 6.

1	2	3	4	5	6	7	8
1. Roads	161	68.0	+0.2	0.0012	49.3	+0.2	0.0012
2. Urban	1729	69.9	+2.1	0.0012	52.2	+3.1	0.0018
3. Water	90	68.3	+0.5	0.0056	49.7	+0.6	0.0067
4. Roads + Water	251	68.5	+0.7	0.0028	49.9	+0.8	0.0032
5. Roads + Urban	1867	70.0	+2.2	0.0012	52.4	+3.3	0.0018
6. Urban + Water	1819	70.5	+2.7	0.0015	52.9	+3.8	0.0021
7. Roads + Urban + Water	1957	70.6	+2.8	0.0014	53.1	+4.0	0.0020

Image 6; 13 classes OCA = 67.8% OMA = 49.1%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

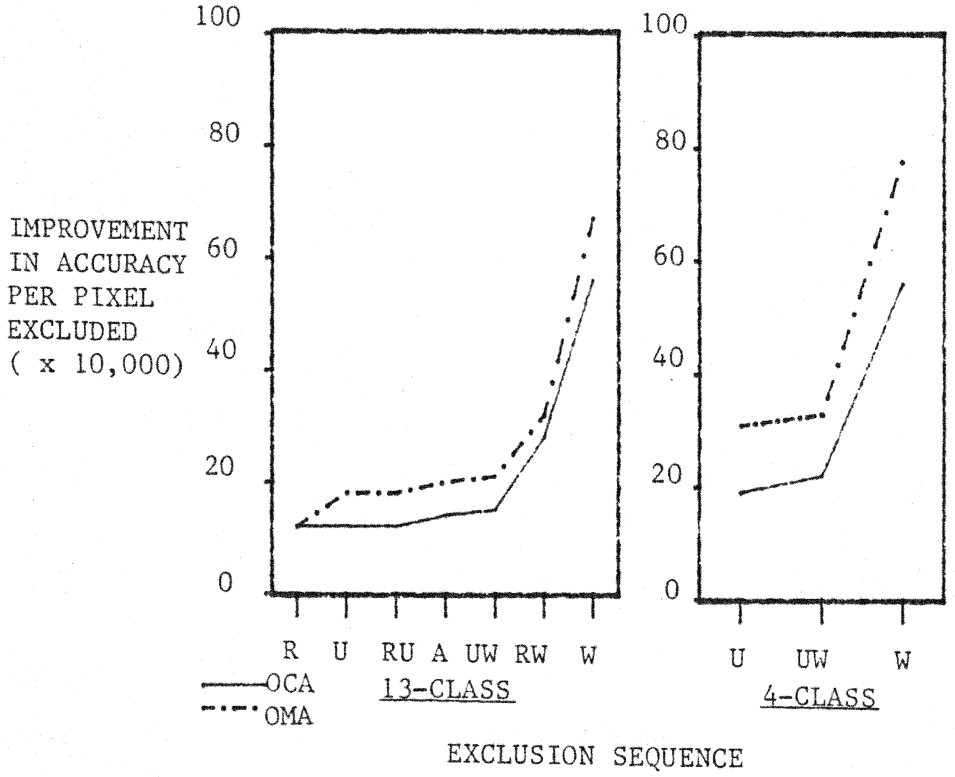


Fig. 78. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) improvement indices changes for the 13-class and 4-class, image no. 6 exclusion sequence [R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

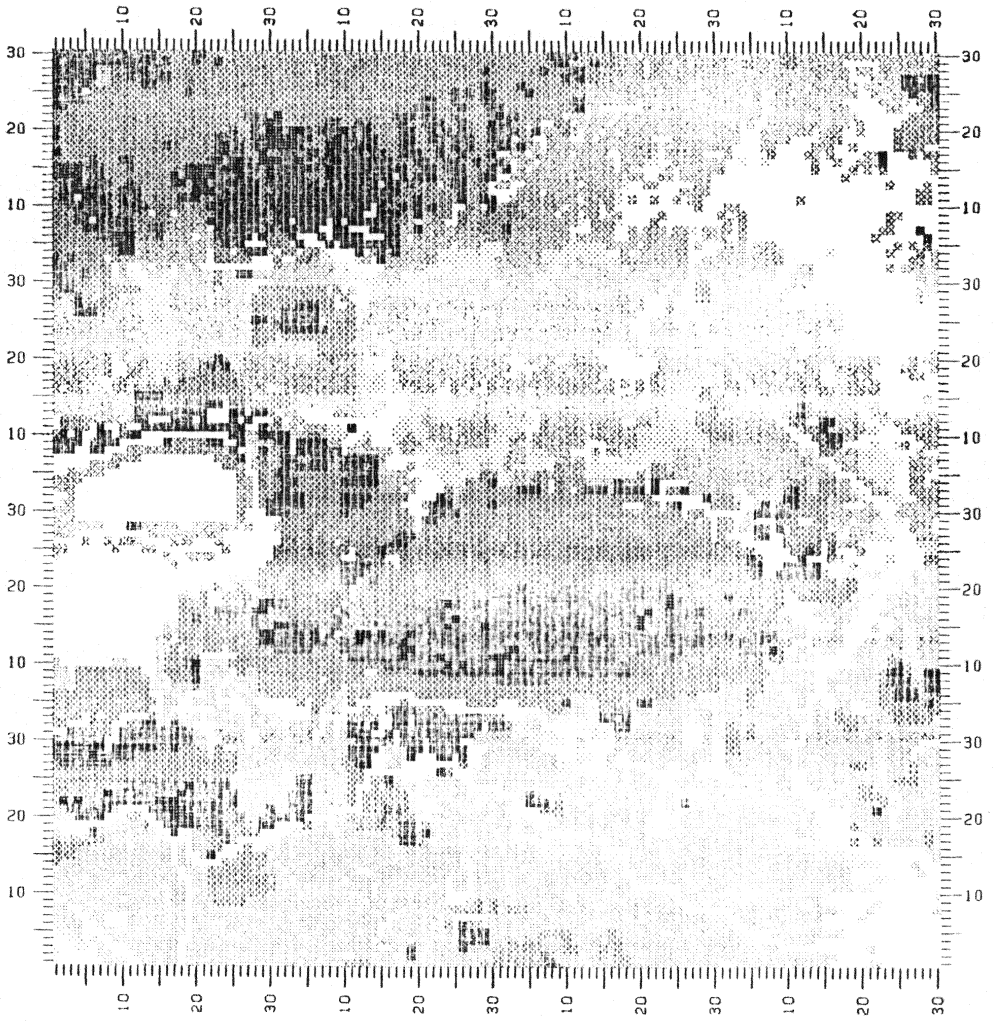


Fig. 79. Gray scale representation of conditional classification image no. 6. Each land use is assigned a single gray scale shade.

Fig. 79. (Continued).

SYMBOL KEY

CATEGORY			SYMBOL	FREQUENCY
-9999.	-	-9999.		3304
8.	-	8.		847
9.	-	9.		5243
41.	-	41.		3370
42.	-	42.		142
43.	-	43.		1494

Table 72. Confusion table and mapping accuracies of the 13-class, image no. 6 after excluding road plus urban plus water cells then performing a conditional classification on the remaining pixels.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	6	0	0	0	7	7	100.0	0.0
		0	0	0	1	0	0				
		0									
CROPLAND	8	0	53	49	0	0	0	112	59	52.7	8.9
		0	0	0	10	0	0				
		0									
PASTURE	9	0	410	2139	0	0	0	2761	622	22.5	57.9
		0	0	0	156	0	56				
		0									
RESIDENTIAL	11	0	11	63	0	0	0	86	86	100.0	0.0
		0	0	0	8	0	4				
		0									
SERVICES	12	0	7	25	0	0	0	32	32	100.0	0.0
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	46	0	0	0	71	71	100.0	0.0
		0	0	0	22	0	3				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	4	0	0	0	5	5	100.0	0.0
		0	0	0	1	0	0				
		0									
HARDWOODS	41	0	41	501	0	0	0	2396	1180	49.2	41.3
		0	0	0	1216	53	585				
		0									
CONIFER	42	0	6	88	0	0	0	337	335	99.4	0.5
		0	0	0	163	2	78				
		0									
MIXED	43	0	11	144	0	0	0	496	346	69.8	12.3
		0	0	0	184	7	150				
		0									
TRANSITIONAL	76	0	0	2	0	0	0	5	5	100.0	0.0
		0	0	0	3	0	0				
		0									
TOTAL NO. OF CELLS		0	539	3073	0	0	0				
		0	0	0	1764	62	876				

Table 72. (Continued).

		0					
COMMISSIONS	NO.	0	486	934	0	0	0
		0	0	0	548	60	726
		0					
COMMISSIONS	%	0.0	90.2	30.4	0.0	0.0	0.0
		0.0	0.0	0.0	31.1	96.8	82.9
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =			56.4				
OVERALL MAPPING ACCURACY(OMA) =			42.1				

Overall accuracies for the sequence of strategies performed on image no. 6 are displayed in Fig. 80.

B. 4 classes

1. Complete Image

Supported by results from image no. 6, a pattern of overall accuracy increases given greater classification resolution was established for the 4-class, 9-band classifications (i.e., image nos. 4, 5, and 6). This greater resolution-higher accuracy relationship was similar to results exhibited by the 13-class, 9-band classifications. Although the accuracy increases were small (Table 54), they do express important differences over the sequence of accuracy changes for 4-band classification nos. 1, 2, and 3. These differences had been mentioned previously along with results for the 13-class, image no. 6.

As shown in Table 54, only small differences existed between results for classification nos. 4, 5, and 6. The most evident shows water possessing the largest commission error in image no. 6 as compared to agriculture in image nos. 4 and 5. Given the increased resolution of image no. 6, the signature for water often became confused with built-up land and forest signatures (Table 73).

Overall improvements in accuracy, as displayed in the image no. 6 confusion matrix (Table 73), occurred for built-up land, agriculture, and forest. These were greater than in either image no. 4 (Table 55) or no. 5 (Table 64). Only the water class showed a decrease in class accuracy progressing from image no. 4 to image no. 6. In this respect, although accuracies of the water class were higher in 9-band images (i.e., nos. 4, 5, and 6) than in corresponding 4-band images (i.e.,

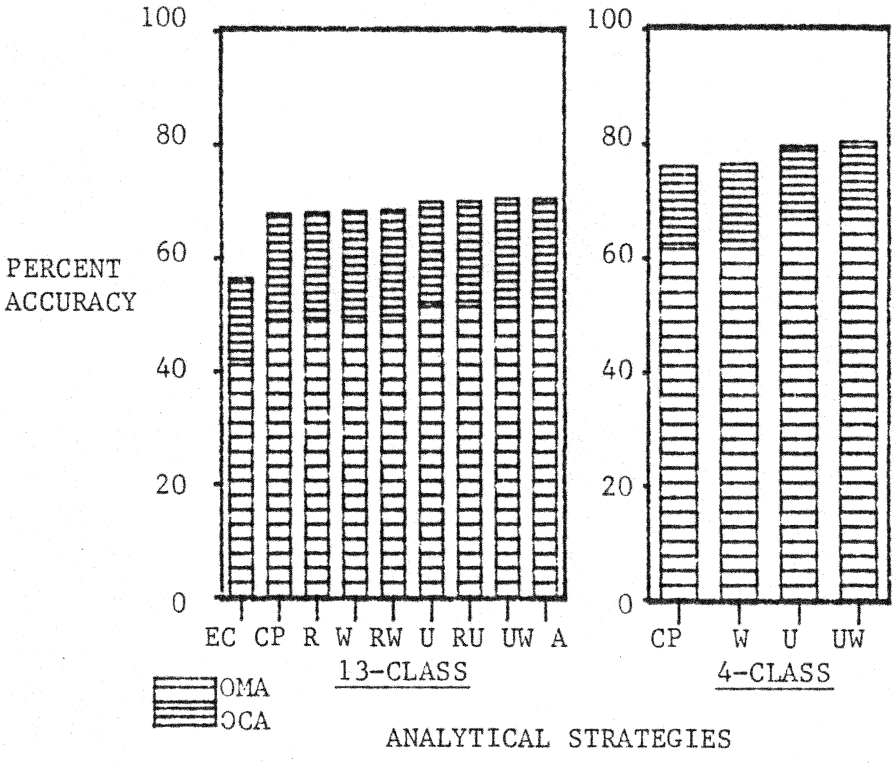


Fig. 80. Overall classification accuracy (OCA) and overall mapping accuracy (OMA) for the 13-class and 4-class, image no. 6 resulting from the use of selected exclusion strategies for increasing accuracy [EC=Exclusion-conditional, CP=Complete image, R=Roads, W=Water, U=Urban, RW=Roads plus Water, RU=Roads plus Urban, UW=Urban plus Water, A=Roads plus Urban plus Water (all)].

Table 73. Confusion table and mapping accuracies of the complete 4-class, image no. 6. This classification was based on the 4 raw Landsat bands and 5 ancillary bands. All regions of less than 5 pixels were removed and reassigned prior to clustering.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	581	504	110	11	1206	625	51.8	42.6
Agriculture	2	23	3156	270	0	3449	293	8.5	65.2
Forest	4	112	880	2528	13	3533	1005	28.4	64.0
Water	5	24	6	35	18	83	65	78.3	16.8
Total No. of Cells		740	4546	2943	42				
Commissions No.		159	1390	415	24				
Commissions %		21.5	30.6	14.1	57.1				

Overall Classification Accuracy (OCA) = 76.0
Overall Mapping Accuracy (OMA) = 62.5

nos. 1, 2, and 3), these results were offset by slight decreases in accuracy progressing from the low resolution image no. 4 (13-pixel resolution) to the high resolution image no. 6 (5-pixel resolution). In other words, increasing resolution reduced the positive relationship between the addition of ancillary data and the classifiability of water.

Given the advantages of classifying 9-band Landsat images at higher resolutions (i.e., high OCA and OMA), results have shown that an increased resolution can also reduce the benefits of some ancillary data useful in identifying specific classes (e.g., water). This infers that as the quality or resolution of some data sources increase, this can decrease the utility of others. If left present in the analyses, this lower quality data may give rise to a net decrease in overall data effectiveness. Performing an analysis of covariance on ancillary data pairs which may or may not be positively correlated could increase proficiency in eliminating some sources of extraneous variance before the classification process.

2. Incremental Exclusions

Table 74 displays the results of the exclusion strategies performed on image no. 6. Except for increases in overall mapping accuracy proceeding the "water-only" exclusion, all accuracy changes for image no. 6 (columns 4 and 7; Table 75) were within 0.1 percent of image no. 5 (Table 67). These results correspond with improvement index values for image nos. 5 (Table 67; Fig. 74) and 6 (Table 75; Fig. 78). Classes of land use which exhibited the largest accuracy change after each exclusion performed on image no. 6 are shown in Table 76.

Overall accuracies for the image no. 6 exclusion sequence are displayed in Fig. 80.

Table 74. Summary of exclusion strategy effects on accuracy for the 4-class, image no. 6.

Exclusion Strategies	Accuracy Indexes (%)	
	Overall Classification Accuracy	Overall Mapping Accuracy
None	76.0	62.5
Water	76.5	63.2
Urban	79.6	68.3
Water + Urban	80.4	68.9

Table 75. Accuracy expressed as changes per pixel excluded for each exclusion strategy conducted on the 4-class, image no. 6.

1	2	3	4	5	6	7	8
1. Water	90	76.5	+0.5	0.0056	63.2	+0.7	0.0078
2. Urban	1867	79.6	+3.6	0.0019	68.3	+5.8	0.0031
3. Water + Urban	1957	80.4	+4.4	0.0022	68.9	+6.4	0.0033

Image 6; 4 classes OCA = 76.0% OMA = 62.5%

Column 1: Exclusion step/set - digitized data set which is to be excluded (in sequence).
2: Pixels excluded - number of pixels contained in each specific exclusion set.
3: OCA% - overall classification accuracy level (%) after excluding a specific set (x 100).
4: OCA% + or - - percent increase or decrease when comparing that exclusion step OCA to the complete (non-exclusion) image OCA (x 100).
5: OCA improvement index - OCA change per pixel excluded; computed by dividing Column 4 by Column 2.
6: OMA % - overall mapping accuracy level (%) after excluding a specific set (x 100).
7: OMA % + or - - OMA percent increase or decrease when comparing that exclusion step OMA to the complete image OMA (x 100).
8: OMA improvement index - OMA change per pixel excluded; computed by dividing Column 7 by Column 2.

Table 76. Greatest increases in image no. 6 (4 classes) class accuracy as related to the exclusion strategy used.

Exclusion Strategy	Largest Class Accuracy Change per Strategy Step	
	Positive (+)	Negative (-)
Water	Built-up Land	Water
Urban	Agriculture	Built-up Land
Water + Urban	Agriculture	Built-up Land

Overall Exclusion Changes (+ and -): Agriculture (65.2 to 70.7; i.e., +5.5%)
Built-up Land (42.6 to 17.4; i.e., -25.2%)

PART 2

VII. IMAGE SUMMARY

A. 13 classes

1. Complete Image

A summary of the accuracy assessments for all 6 images showed that:

- 4-band image nos. 1, 2, and 3 had significantly better CMAs for the residential class than did 9-band image nos. 4, 5, and 6.
- all 9-band images had significantly better CMAs for the water, cropland, and mixed forest classes than did 4-band images.
- in no images, could the transportation, other urban, and orchards classes be identified.
- for both 4-band and 9-band images, as the number of image clusters increased (i.e., the more precise the classification resolution) more land use signatures could be correctly identified (CMA > 0%).
- for 4-band images, unlike 9-band images, increasing the total number of clusters did not always result in corresponding increase in OCA and OMA.

2. Single class exclusion

- excluding road cells in image nos. 1, 2, and 3 had the largest positive effect on residential and hardwood CMAs.

In image nos. 4, 5, and 6, this exclusion produced the greatest overall CMA increases in the residential, pasture, hardwood, and conifer classes.

- for all images, excluding urban cells was the best strategy for increasing pasture CMA.
- for all images, the greatest increase in accuracy for the industrial class was obtained by excluding water cells.
- for all images, to exclude one class only, urban had the greatest effect in increasing OCA and OMA.
- water was the single exclusion factor which resulted in the greatest OCA and OMA improvement index values.

3. Bi- and Multi-class exclusion

- for all images, excluding a combination of roads plus water cells produced the largest accuracy increase for the industrial class.
- for all images, excluding a combination of roads plus urban cells had the largest effect for increasing pasture accuracy.
- for all images, excluding a combination of urban plus water cells had the greatest positive effect for increasing pasture accuracy.
- for all images, exclusions of urban plus water cells produced the largest positive effects on OCA and OMA of all 2-factor exclusion strategies.
- for all images, excluding the complete set of road plus urban plus water cells resulted in pasture CMA possessing the largest increase.

- for all images, excluding the roads plus urban plus water combination resulted in the greatest overall increases in OCA and OMA.
- except for image no. 4, the exclusion combination which resulted in the greatest increase in both the OCA and OMA improvement indexes was roads plus water.

D. Conditional classification

- for image nos. 1, 2, and 3, the conditional approach resulted in significantly increasing only accuracies in the cropland and mixed forest classes.
- except for mixed forest in image no. 6, there were minimal or no significant increases in class accuracy using the conditional approach in image nos. 4, 5, and 6.

B. 4 classes

1. Complete Image

- for all images, when the number of land use classes were reduced from 13 to 4, OCA and OMA for all 4-class images increased significantly (for OCA x = + 8.68%, for OMA x = + 13.92%).
- except for water CMA, 4-band images possessed higher built-up land, agriculture, and forest accuracies than did corresponding 9-band images.
- for 4-band images, unlike 9-band images, increasing the total number of clusters did not always result in a corresponding increase in OCA and OMA.
- all 4-band images possessed higher OCAs and OMAs than corresponding 9-band images.

2. Single class exclusion

   - for all images, excluding water cells produced the largest increase in built-up land accuracy.
   - for all images, excluding urban cells had the largest effect on increasing agriculture accuracy.
   - water was the exclusion set which resulted in the largest increase in the OCA and OMA improvement indexes.

3. Bi- and Multi-class exclusion

   - with the exception of image no. 1, excluding the combination set of water plus urban cells produced the largest accuracy increase in the agriculture class.
   - for all images, the water plus urban exclusion produced the greatest effect in increasing OCA and OMA above complete, 4-class image levels.

PART 3

Distance from Roads Accuracy Test

A. 13 classes

Confusion matrices for those accuracy assessments performed at respective distances from primary and secondary highways are displayed in Tables 77 through 81. All results are based on the complete 13-class, image no. 2 (Fig. 61) which possessed the highest OCA and OMA of the 6 complete, 13-class images (Table 28). The initial OCA and OMA for the complete image no. 2 were based on 8271 "truth" points derived from field observations. (Table 82 is presented as a supplement to the following discussion.)

Basing the overall scene accuracies (OCA and OMA) on only those cells adjacent to roads (i.e. a sample composed of cells which lie 1 cell beyond a road border) (Fig. 81), had the lowest values for the distance accuracy test (Table 77). This sample included 698 total "truth" cells or 8.4 percent of the ground truth sample. For this distance, OCA was 6.5 percent lower than the image no. 2 accuracy and OMA was 8.0 percent under (Table 82). Due to the limited cell sample, 9 land use classes recorded a 0 percent mapping accuracy at distance 1 (Table 77). Besides the 5 original unclassifiable land uses in the complete image no. 2, (i.e., transportation, other urban, orchards, mixed forest, and transitional), water, cropland, services, and conifer forest also possessed 0 percent mapping accuracies.

At 2 cells away from roads (i.e. a sample inclusive of those cells adjacent to and 2 beyond the road border; Fig. 82), accuracies increased

Table 77. Confusion table and mapping accuracies of the 13-class, image no. 2 as based on only those pixels which were one beyond (adjacent to) the border of primary and secondary highways.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	0 0	0 0	0 0	0 0	0	0	0.0	0.0
CROPLAND	8	0 0 0	0 0	9 0	0 3	0 0	0 0	12	12	100.0	0.0
PASTURE	9	0 0 0	0 0	295 0	5 22	0 0	0 0	322	27	8.4	60.8
RESIDENTIAL	11	0 0 0	0 0	61 0	6 8	0 0	0 0	75	69	92.0	7.1
SERVICES	12	0 0 0	0 0	7 0	5 0	0 0	0 0	12	12	100.0	0.0
INDUSTRIAL	13	0 0 0	0 0	0 0	0 13	0 0	32 0	45	13	28.9	58.2
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	0 0	0 0	0 0	0 0	0	0	0.0	0.0
ORCHARDS	22	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
HARDWOODS	41	0 0 0	0 0	54 0	0 106	0 0	10 0	170	64	37.6	43.1
CONIFER	42	0 0 0	0 0	15 0	0 12	0 0	0 0	27	27	100.0	0.0
MIXED	43	0 0 0	0 0	11 0	0 18	0 0	0 0	29	29	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	0 0	0 0	0 0	0 0	0	0	0.0	0.0
TOTAL NO. OF CELLS		0 0	0 0	458 0	16 182	0 0	42 0				

Table 77. (Continued).

		0					
COMMISSIONS	NO.	0	0	163	10	0	10
		0	0	0	76	0	0
		0					
COMMISSIONS	%	0.0	0.0	35.6	62.5	0.0	23.8
		0.0	0.0	0.0	41.8	0.0	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				62.9			
OVERALL MAPPING ACCURACY(OMA) =				43.1			

Table 78. Confusion table and mapping accuracies of the 13-class, image no. 2 as based on only those pixels which were one and two beyond the border of primary and secondary highways.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5 14 76	8 17	9 22	11 41	12 42	13 43	TOTAL NO.		%	
WATER	5	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
CROPLAND	8	0 0 0	0 0	17 0	0 3	0 0	0 0	20	20	100.0	0.0
PASTURE	9	0 0 0	0 0	582 0	7 49	0 0	0 0	638	56	8.8	62.1
RESIDENTIAL	11	0 0 0	0 0	107 0	14 11	0 0	0 0	132	118	89.4	9.5
SERVICES	12	0 0 0	0 0	10 0	8 0	1 0	0 0	19	18	94.7	5.3
INDUSTRIAL	13	0 0 0	0 0	0 0	0 19	0 0	63 0	82	19	23.2	65.6
TRANSPORTATION	14	0 0 0	0 0	5 0	0 0	0 0	0 0	5	5	100.0	0.0
OTHER URBAN	17	0 0 0	0 0	1 0	0 0	0 0	0 0	1	1	100.0	0.0
ORCHARDS	22	0 0 0	0 0	2 0	0 0	0 0	0 0	2	2	100.0	0.0
HARDWOODS	41	0 0 0	0 0	110 0	0 225	0 0	13 0	348	123	35.3	45.4
CONIFER	42	0 0 0	0 0	25 0	0 29	0 0	0 0	54	54	100.0	0.0
MIXED	43	0 0 0	0 0	21 0	0 36	0 0	1 0	58	58	100.0	0.0
TRANSITIONAL	76	0 0 0	0 0	0 0	0 1	0 0	0 0	1	1	100.0	0.0
TOTAL NO. OF CELLS		0 0	0 0	881 0	29 373	1 0	77 0				

Table 78. (Continued).

		0					
COMMISSIONS	NO.	0	0	299	15	0	14
		0	0	0	148	0	0
		0					
COMMISSIONS	%	0.0	0.0	33.9	51.7	0.0	18.2
		0.0	0.0	0.0	39.7	0.0	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				65.0			
OVERALL MAPPING ACCURACY(OMA) =				45.7			

Table 79. Confusion table and mapping accuracies of the 13-class, image no. 2 as based on only those pixels which were up to and inclusive of 3 pixels beyond the border of primary and secondary highways.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
CROPLAND	8	0	0	25	0	0	0	28	28	100.0	0.0
		0	0	0	3	0	0				
		0									
PASTURE	9	0	0	904	11	0	0	979	75	7.7	64.4
		0	0	0	64	0	0				
		0									
RESIDENTIAL	11	0	0	142	25	0	0	181	156	86.2	12.3
		0	0	0	14	0	0				
		0									
SERVICES	12	0	0	13	11	2	0	26	24	92.3	7.7
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	0	0	0	97	123	26	21.1	69.8
		0	0	0	26	0	0				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	2	0	0	0	2	2	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	0	166	0	0	15	544	181	33.3	47.6
		0	0	0	363	0	0				
		0									
CONIFER	42	0	0	28	0	0	0	78	78	100.0	0.0
		0	0	0	50	0	0				
		0									
MIXED	43	0	0	40	0	0	1	102	102	100.0	0.0
		0	0	0	61	0	0				
		0									
TRANSITIONAL	76	0	0	2	0	0	0	3	3	100.0	0.0
		0	0	0	1	0	0				
		0									
TOTAL NO. OF CELLS		0	0	1329	47	2	113				
		0	0	0	582	0	0				

Table 79. (Continued).

		0					
COMMISSIONS	NO.	0	0	425	22	0	16
		0	0	0	219	0	0
		0					
COMMISSIONS	%	0.0	0.0	32.0	46.8	0.0	14.2
		0.0	0.0	0.0	37.6	0.0	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				67.1			
OVERALL MAPPING ACCURACY(OMA) =				48.2			

Table 80. Confusion table and mapping accuracies of the 13-class, image no. 2 as based on only those pixels which were up to and inclusive of 6 pixels beyond the border of primary and secondary highways.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL NO.		%	
		14	17	22	41	42	43				
		76									
WATER	5	0	0	3	0	0	12	19	19	100.0	0.0
		0	0	0	4	0	0				
		0									
CROPLAND	8	0	0	62	0	0	0	65	65	100.0	0.0
		0	0	0	3	0	0				
		0									
PASTURE	9	0	0	1693	12	0	0	1828	135	7.4	67.2
		0	0	0	123	0	0				
		0									
RESIDENTIAL	11	0	0	186	58	0	0	261	203	77.8	20.4
		0	0	0	17	0	0				
		0									
SERVICES	12	0	0	17	11	17	0	45	28	62.2	37.8
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	0	0	0	176	218	42	19.3	68.2
		0	0	0	42	0	0				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	2	0	0	0	2	2	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	0	0	274	0	0	20	1049	294	28.0	49.8
		0	0	0	755	0	0				
		0									
CONIFER	42	0	0	48	0	0	7	171	171	100.0	0.0
		0	0	0	116	0	0				
		0									
MIXED	43	0	0	86	0	0	1	249	249	100.0	0.0
		0	0	0	162	0	0				
		0									
TRANSITIONAL	76	0	0	9	0	0	0	10	10	100.0	0.0
		0	0	0	1	0	0				
		0									
TOTAL NO. OF CELLS		0	0	2386	81	17	216				
		0	0	0	1223	0	0				

Table 80. (Continued).

		0					
COMMISSIONS	NO.	0	0	693	23	0	40
		0	0	0	468	0	0
		0					
COMMISSIONS	%	0.0	0.0	29.0	28.4	0.0	18.5
		0.0	0.0	0.0	38.3	0.0	0.0
		0.0					

OVERALL CLASSIFICATION ACCURACY(OCA) = 68.8

OVERALL MAPPING ACCURACY(OMA) = 50.2

Table 81. Confusion table and mapping accuracies of the 13-class, image no. 2 as based on only those pixels which were up to and inclusive of 9 pixels beyond the border of primary and secondary highways.

EXPECTED OR KNOWN LAND USE		INTERPRETED OR CLASSIFIED LAND USE						OMISSIONS			MAP ACCURACY
		5	8	9	11	12	13	TOTAL	NO.	%	
		14	17	22	41	42	43				
		76									
WATER	5	10	0	6	0	0	18	50	40	80.0	19.2
		0	0	0	11	5	0				
		0									
CROPLAND	8	0	8	97	0	0	0	108	100	92.6	7.2
		0	0	0	3	0	0				
		0									
PASTURE	9	0	1	2216	12	8	0	2402	186	7.7	68.2
		0	0	0	164	1	0				
		0									
RESIDENTIAL	11	0	0	212	65	3	0	297	232	78.1	20.3
		0	0	0	17	0	0				
		0									
SERVICES	12	0	0	17	11	41	0	69	28	40.6	51.2
		0	0	0	0	0	0				
		0									
INDUSTRIAL	13	0	0	0	0	0	258	311	53	17.0	70.5
		0	0	0	50	3	0				
		0									
TRANSPORTATION	14	0	0	5	0	0	0	5	5	100.0	0.0
		0	0	0	0	0	0				
		0									
OTHER URBAN	17	0	0	1	0	0	0	1	1	100.0	0.0
		0	0	0	0	0	0				
		0									
ORCHARDS	22	0	0	2	0	0	0	2	2	100.0	0.0
		0	0	0	0	0	0				
		0									
HARDWOODS	41	2	2	336	0	0	29	1543	369	23.9	53.3
		0	0	0	1174	0	0				
		0									
CONIFER	42	0	0	60	0	0	7	233	230	98.7	1.2
		0	0	0	163	3	0				
		0									
MIXED	43	0	0	99	0	0	1	353	353	100.0	0.0
		0	0	0	252	1	0				
		0									
TRANSITIONAL	76	0	0	10	0	0	0	11	11	100.0	0.0
		0	0	0	1	0	0				
		0									
TOTAL NO. OF CELLS		12	11	3061	88	52	313				
		0	0	0	1835	13	0				

Table 81. (Continued).

		0					
COMMISSIONS	NO.	2	3	845	23	11	55
		0	0	0	661	10	0
		0					
COMMISSIONS	%	16.7	27.3	27.6	26.1	21.2	17.6
		0.0	0.0	0.0	36.0	76.9	0.0
		0.0					
OVERALL CLASSIFICATION ACCURACY(OCA) =				70.1			
OVERALL MAPPING ACCURACY(OMA) =				51.9			

Table 82. Summary of accuracy changes for the complete 13-class, image no. 2 on varying distances from roads.

Distance	OCA	±OCA	ΔOCA	OMA	±OMA	ΔOMA	Sample Points	% of total sample
0 (image no. 2)	69.4	-	-	51.1	-	-	8271	100.0
1	62.9	-6.5	-	43.1	-8.0	-	698	8.4
2	65.0	-4.4	+2.1	45.7	-5.4	+2.6	1361	16.5
3	67.1	-2.3	+2.1	48.2	-2.9	+2.5	2073	25.1
6	68.8	-0.6	+1.7	50.2	-0.9	+2.0	3923	47.4
9	70.1	+0.7	+1.3	51.9	+0.8	+1.7	5385	65.1

OCA/OMA - Overall Classification Accuracy/Overall Mapping Accuracy.

±OCA/±OMA - Respective distance OCA/OMA increase or decrease as compared to complete image no. 2 values.

ΔOCA/ΔOMA - Respective distance OCA/OMA increase or decrease as compared to previous distance values.

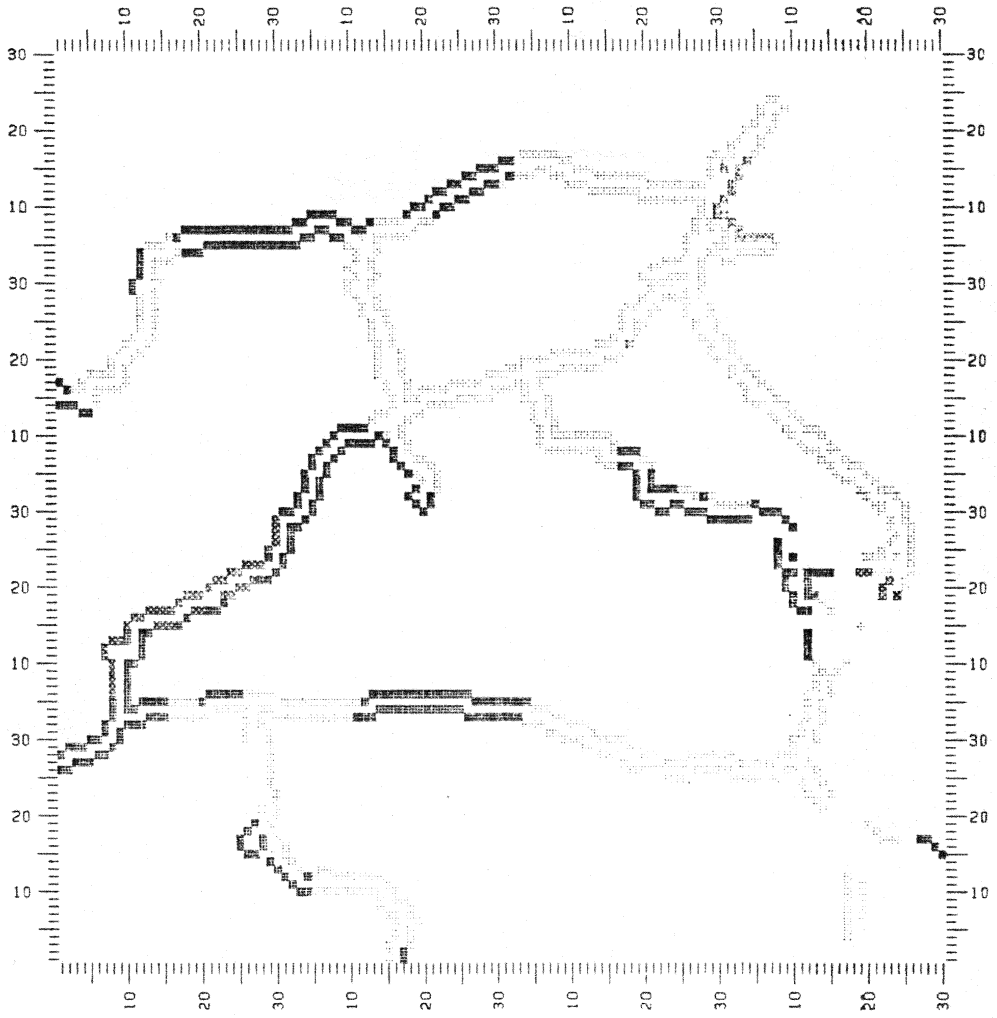


Fig. 81. Gray scale image of study area land use adjacent to (1 cell beyond) a primary or secondary highway. Each land use is assigned a single gray scale shade.

Fig. 81. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		13321
9.	- 9.		685
11.	- 11.		18
13.	- 13.		49
41.	- 41.		327

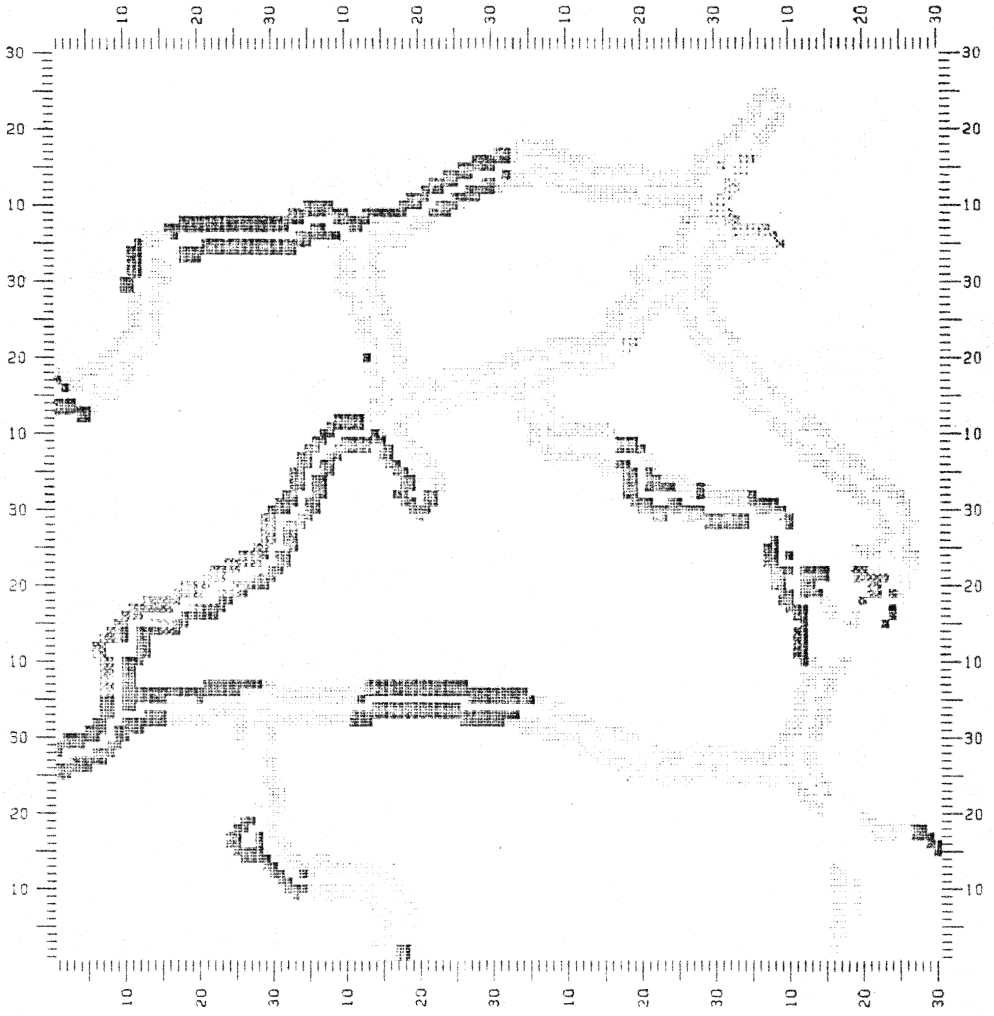


Fig. 82. Gray scale image of study area land use adjacent to and 2 cells beyond a primary or secondary highway. Each land use is assigned a single gray scale shade.

Fig. 82. (Continued).

SYMBOL KEY

CATEGORY	SYMBOL	FREQUENCY
0. - 0.		12308
9. - 9.		1310
11. - 11.		33
12. - 12.		2
13. - 13.		94
41. - 41.		653

over those for 1 cell beyond. For this distance, OCA was 65.0 percent and OMA reached 45.7 percent (Table 78). These results were only 4.4 percent and 5.4 percent lower than values recorded for complete image no. 2 OCA and OMA, respectively (Table 82). This represented an increase of 2.1 percent for OCA and 2.6 percent for OMA over that for the distance 1 test. There were 1361 total cells or 16.5 percent of the complete truth sample included in this distance step. Except for services, all land uses possessing a 0 percent mapping accuracy at distance 1 still had 0 percent accuracy at distance 2 (Table 78).

Another accuracy assessment was based on those cells less than and inclusive of 3 cells beyond a road border (Fig. 83). This sample produced an OCA at 67.1 percent and an OMA of 48.2 percent (Table 79). At this distance OCA was 2.3 percent lower than that for image no. 2, with OMA 2.9 percent less (Table 82). Percent differences, when compared to distance 2 showed an increase of 2.1 percent for OCA and 2.5 percent for OMA. All land use classes possessing no mapping accuracy at distance 2 also had none at distance 3 (Table 79).

As summarized in Table 82, for the final 2 analyses, distances 6 (Fig. 84) (Table 80) and 9 (Fig. 85) (Table 81), a similar trend continued. This trend showed OCA and OMA increasing given larger cell sample sizes. At distance 9, OCA and OMA surprisingly surpassed those levels for the complete image no. 2. Also at that distance, land use classes exhibiting a 0 percent mapping accuracy were equivalent to those in the complete image no. 2.

Figs. 86 and 87 summarize the cumulative and incremental distance changes for OCA and OMA.

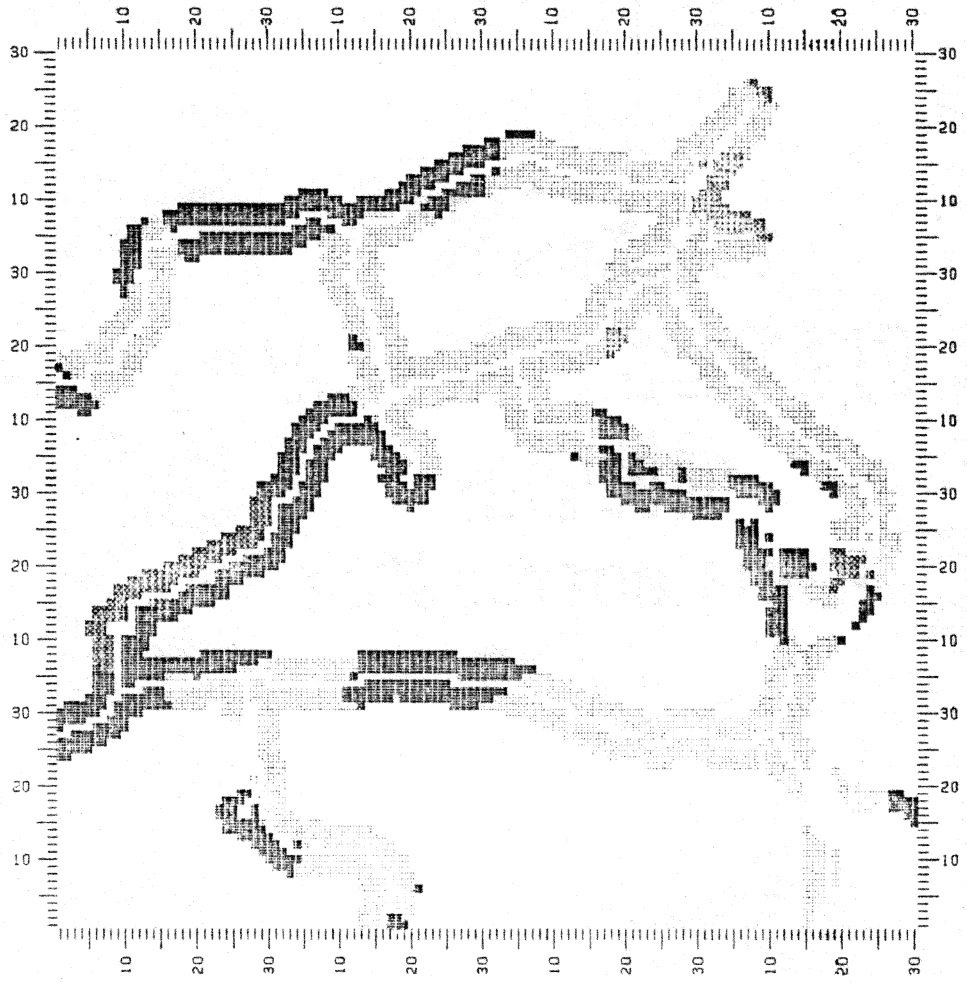


Fig. 83. Gray scale image of study area land use 1 through 3 cells beyond a primary or secondary highway. Each land use is assigned a single gray scale shade.

Fig. 83. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		11219
9.	- 9.		1963
11.	- 11.		57
12.	- 12.		6
13.	- 13.		136
41.	- 41.		1019

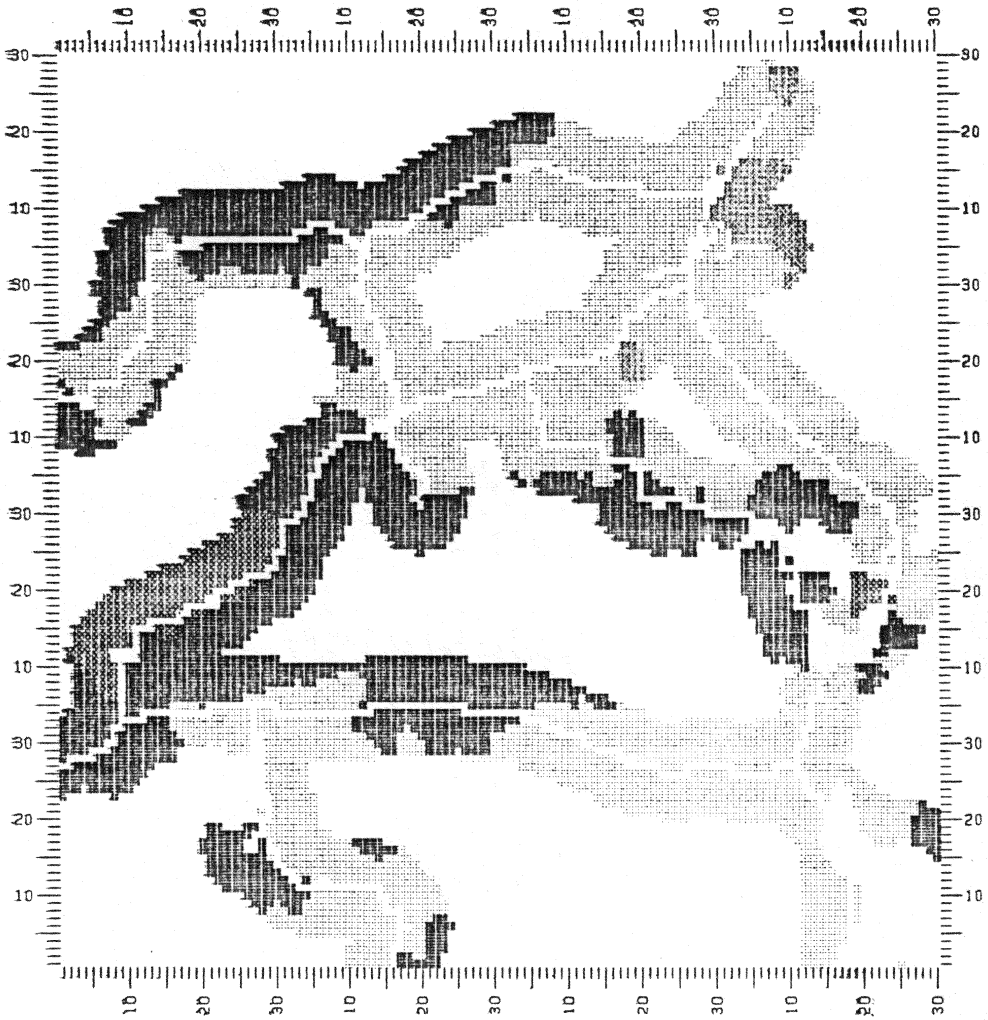


Fig. 84. Gray scale image of study area land use 1 through 6 cells beyond a primary or secondary highway. Each land use is assigned a single gray scale shade.

Fig. 84. (Continued).

SYMBOL KEY

	CATEGORY	SYMBOL	FREQUENCY
0.	- 0.		8386
5.	- 5.		4
9.	- 9.		3525
11.	- 11.		105
12.	- 12.		34
13.	- 13.		240
41.	- 41.		2103
42.	- 42.		3

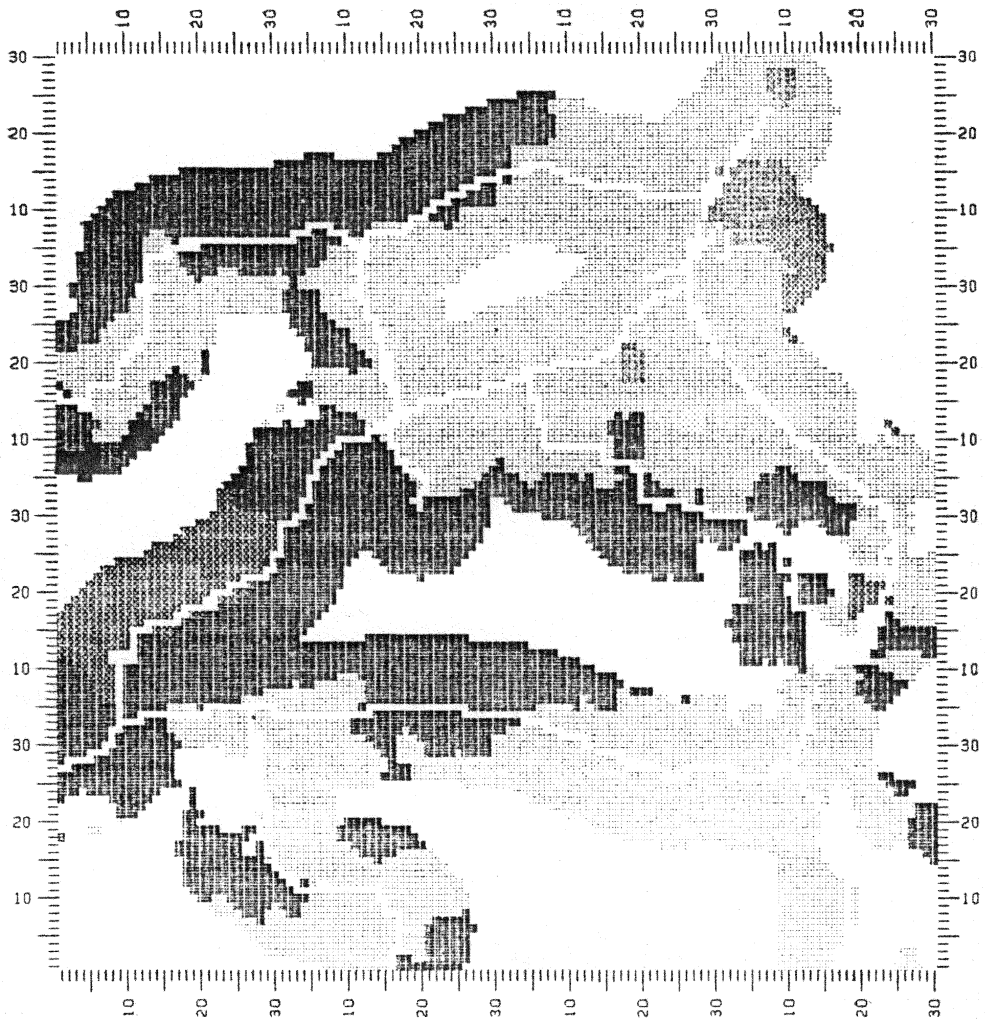


Fig. 85. Gray scale image of study area land use 1 through 9 cells beyond a primary or secondary highway. Each land use is assigned a single gray scale shade.

Fig. 85. (Continued).

SYMBOL KEY

CATEGORY		SYMBOL	FREQUENCY
0.	- 0.		6126
5.	- 5.		21
8.	- 8.		11
9.	- 9.		4597
11.	- 11.		114
12.	- 12.		90
13.	- 13.		337
41.	- 41.		3077
42.	- 42.		27

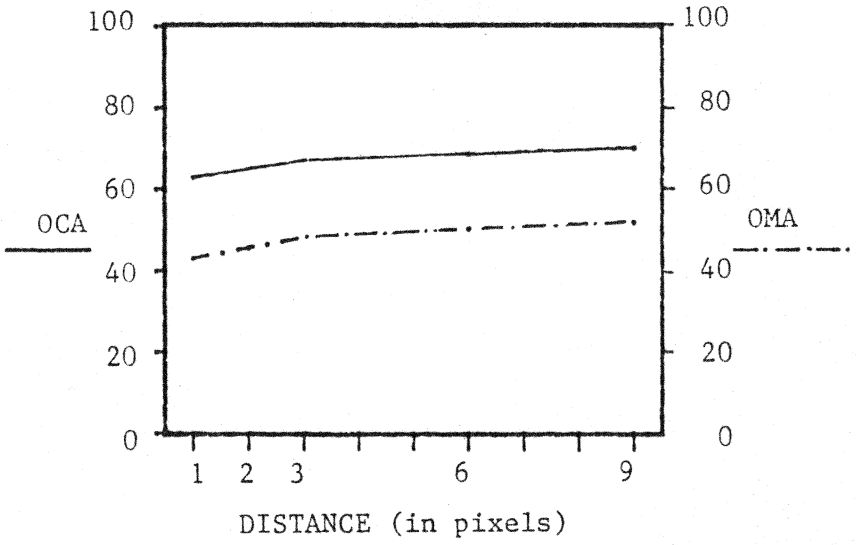


Fig. 86. Accuracies of the 13-class, image no. 2 as based on distance-from-roads sampling.

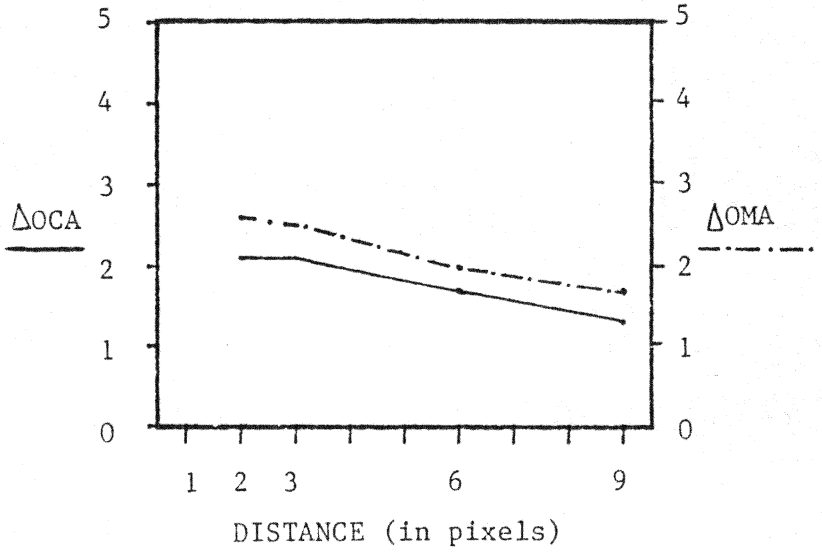


Fig. 87. Incremental accuracy changes for the 13-class, image no. 2 as based on distance-from-roads sampling.

B. 4 classes

Results for this second set of distance analyses are based on the complete 4-class, image no. 2 accuracies (Table 34). Respective distance accuracies are displayed in Tables 83 through 87. Sample size increases and percentages per distance increment are equivalent to those for the 13-class, distance accuracy assessment. (Table 88 is presented as a supplement to the following discussion.)

For this set of distance analyses, the results were similar to those for the 13-class image. Although overall OCA and OMA were higher for this image than for the 13-class, OCA and OMA again generally increased along with the larger cell sample sizes at greater distance from roads (Table 88). Up until the final distance 9 assessment (Table 87), water was the lone land use recording a 0 percent mapping accuracy. This was because of the limited number of water cells within the sampled areas. As with the distance 9 assessment for the complete 13-class image no. 2, distance 9 accuracies for the 4-class image were higher than those for the original complete 4-class image no. 2.

Figs. 88 and 89 show the cumulative and incremental distance changes for the 4-class OCA and OMA.

C. Summary

Results from this analysis demonstrate that a ground truth sample which includes only those pixels (1.22 h or 3 acre pixels) a distance of ≤ 9 away from a primary or secondary highway is adequate for representing subscene accuracies. This is significant since if there is a need in the future to reclassify the same study area or a neighboring area using Landsat data, ground truthing to a maximum distance of 9 pixels from a

Table 83. Confusion table and mapping accuracies of the 4-class, image no. 2 as based on only those pixels which were one beyond (adjacent to) the border of primary and secondary highways.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	43	73	21	0	137	94	68.6	28.3
Agriculture	2	5	305	25	0	335	30	9.0	62.5
Forest	4	10	80	136	0	226	90	39.8	50.0
Water	5	0	0	0	0	0	0	0	0
Total No. of Cells		58	458	182	0				
Commissions No.		15	153	46	0				
Commissions %		25.9	33.4	25.3	0				

Overall Classification Accuracy (OCA) = 69.3
Overall Mapping Accuracy (OMA) = 55.9

Table 84. Confusion table and mapping accuracies of the 4-class, image no. 2 as based on only those pixels which were one and two beyond the border of primary and secondary highways.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	86	123	31	0	240	154	64.2	33.0
Agriculture	2	7	601	52	0	660	59	9.0	63.9
Forest	4	14	156	290	0	460	170	37.0	53.4
Water	5	0	1	0	0	1	1	100.0	0
Total No. of Cells		107	881	373	0				
Commissions No.		21	280	83	0				
Commissions %		19.6	31.8	22.3	0				

Overall Classification Accuracy (OCA) = 71.8
Overall Mapping Accuracy (OMA) = 58.1

Table 85. Confusion table and mapping accuracies of the 4-class, image no. 2 as based on only those pixels which were up to and inclusive of 3 pixels beyond the border of primary and secondary highways.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	135	163	41	0	339	204	60.1	36.9
Agriculture	2	11	931	67	0	1009	78	7.7	66.2
Forest	4	16	234	474	0	724	250	34.5	57.0
Water	5	0	1	0	0	1	1	100.0	0
Total No. of Cells		162	1329	582	0				
Commissions No.		27	398	108	0				
Commissions %		16.7	29.9	18.6	0				

Overall Classification Accuracy (OCA) = 74.3
Overall Mapping Accuracy (OMA) = 60.8

Table 86. Confusion table and mapping accuracies of the 4-class, image no. 2 as based on only those pixels which were up to and inclusive of 6 pixels beyond the border of primary and secondary highways.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	262	218	60	0	540	278	51.5	44.3
Agriculture	2	12	1757	126	0	1895	138	7.3	69.6
Forest	4	28	408	1033	0	1469	436	29.7	62.3
Water	5	12	3	4	0	19	19	100.0	0
Total No. of Cells		314	2386	1223	0				
Commissions No.		52	629	190	0				
Commissions %		16.6	26.4	15.5	0				

Overall Classification Accuracy (OCA) = 77.8
Overall Mapping Accuracy (OMA) = 65.0

Table 87. Confusion table and mapping accuracies of the 4-class, image no. 2 as based on only those pixels which were up to and inclusive of 9 pixels beyond the border of primary and secondary highways.

Expected or Known Land Use		Interpreted or Classified Land Use 1	2	4	5	Omissions Total	No.	%	Map Accuracy(%)
Built-up Land	1	378	245	71	0	694	316	45.5	49.2
Agriculture	2	20	2324	168	0	2512	188	7.5	71.3
Forest	4	37	497	1593	2	2129	536	25.2	66.8
Water	5	18	6	16	10	50	40	80.0	19.2
Total No. of Cells		453	3072	1848	12				
Commissions No.		75	748	255	2				
Commissions %		16.6	24.3	13.8	16.7				

Overall Classification Accuracy (OCA) = 79.9
Overall Mapping Accuracy (OMA) = 67.0

Table 88. Summary of accuracy changes for the complete 4-class, image no. 2 as based on varying distances from roads.

Distance	OCA	±OCA	ΔOCA	OMA	±OMA	ΔOMA	Sample Points	% of total sample
0 (image no. 2)	78.8	-	-	66.1	-	-	8271	100.0
1	69.3	-9.5	-	55.9	-10.2	-	698	8.4
2	71.8	-7.0	+2.5	58.1	-8.0	+2.2	1361	16.5
3	74.3	-4.5	+2.5	60.8	-5.3	+2.7	2073	25.1
6	77.8	-1.0	+3.5	65.0	-1.1	+4.2	3923	47.4
9	79.9	+1.1	+2.1	67.0	+0.9	+2.0	5385	65.1

OCA/OMA - Overall Classification Accuracy/Overall Mapping Accuracy.

±OCA/±OMA - Respective distance OCA/OMA increase or decrease as compared to complete image no. 2 values.

ΔOCA/ΔOMA - Respective distance OCA/OMA increase or decrease as compared to previous distance values.

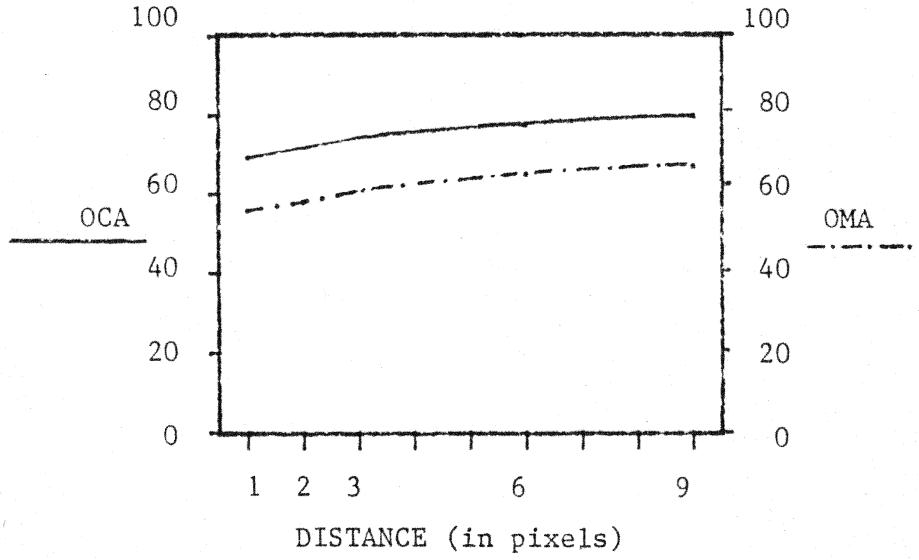


Fig. 88. Accuracies of the 4-class, image no. 2 as based on distance-from-roads sampling.

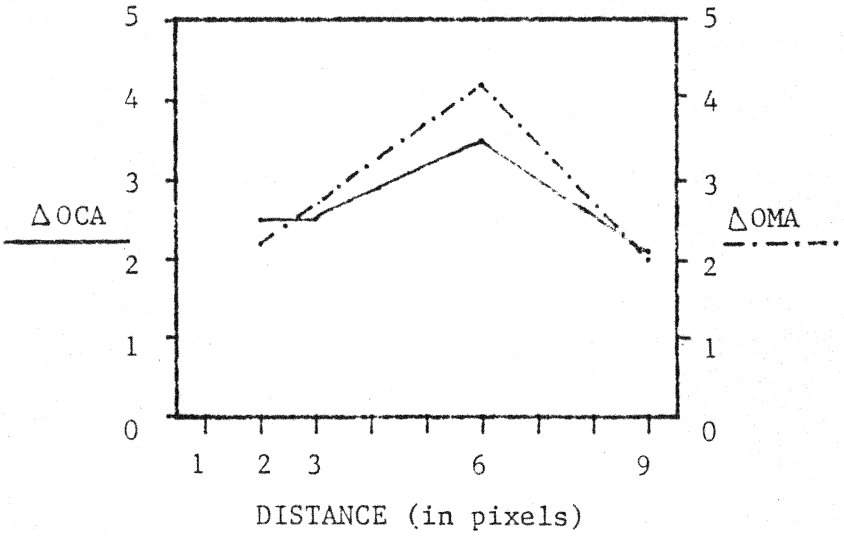


Fig. 89. Incremental accuracy changes for the 4-class, image no. 2 as based on distance-from-roads sampling.

select highway would be adequate for assessing the overall accuracy. Substantial savings in time and money and equivalent classification accuracies would be at least 3 times more advantageous than using a more extensive ground truth operation.

PART 4

Computer Processing

For both the 4-band and 9-band images (13-class), there was a direct relationship between cluster totals, image processing time (complete), and segmentation region removal and reassignment. As shown in Figs. 90 and 91, as the size of the removed/reassigned region increased, the number of appropriate image clusters and image processing time decreased. "Appropriate image clusters" refers to the number of clusters felt to be an adequate representation of differing land use signatures in the study area. For all 13-class images (4- and 9-band), the area of the reassigned region, the number of clusters in each final image, and the approximate processing time from raw image input to the GIPSY system to clustered image are shown in Table 89.

Fig. 92 shows that for the 4-band images, as the size of the region to be removed/reassinged increased, the number of segmentation regions (post-elimination) decreased. Post-reassignment computer processing time also decreased since there were fewer distinct regions prior to clustering. Although similar data for 9-band images were not collected, the results are assumed to be the same. For the 4-band images, the number of segmentation regions, and the post-reassignment processing time are located at the bottom of Table 89.

Figs. 93 and 94 show the relation of the complete 13-class, 4-band and 9-band image accuracies to complete image processing times.

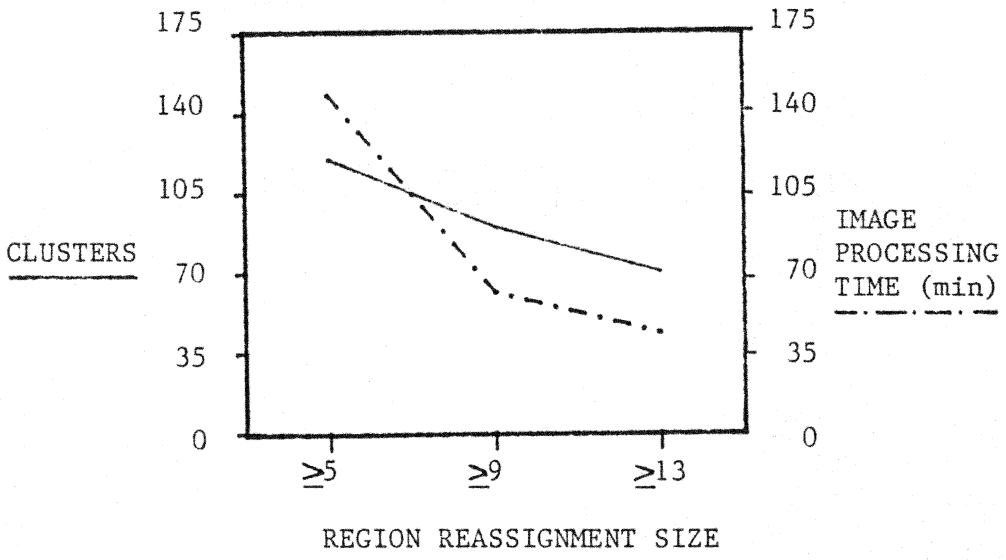


Fig. 90. Relationship between cluster total, image processing time (complete), and region removal and reassignment for the 4-band, 13-class images.

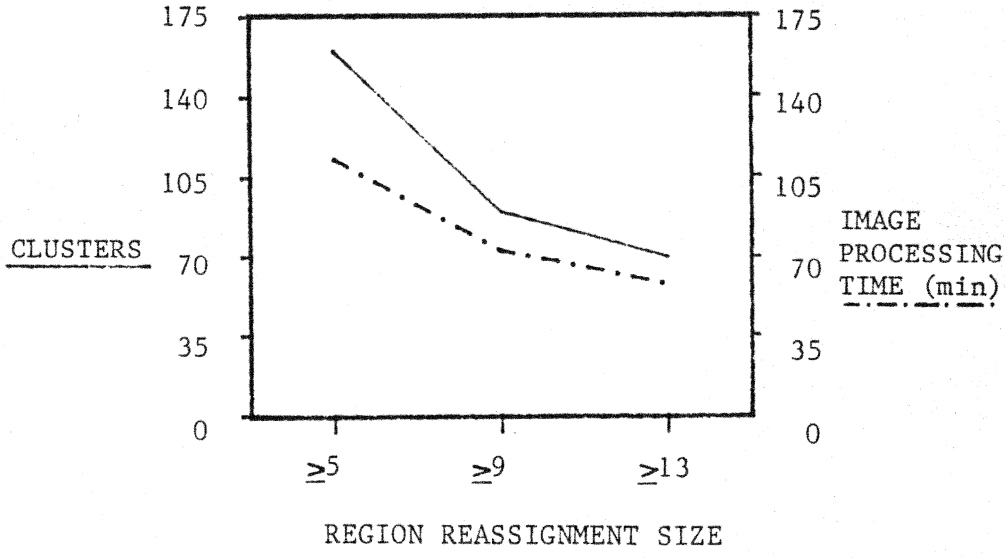


Fig. 91. Relationship between cluster total, image processing time (complete), and region removal and reassignment for the 9-band, 13-class images.

Table 89. Computer processing summary for 13-class imagery.

	Image	Region reassignment size (in pixels)	Output cluster total	Time in minutes
4-Band	1	≥13	70	43.5
	2	≥ 9	90	61.5
	3	≥ 5	120	148.5
9-Band	4	≥13	70	57.5
	5	≥ 9	90	73.0
	6	≥ 5	160	113.0
4-Band	1	≥13	161	11.5
	2	≥ 9	262	29.5
	3	≥ 5	603	116.5

Image 1: ≥13 refers to all segmentation regions less than 13 pixels being removed and reassigned prior to the clustering step.

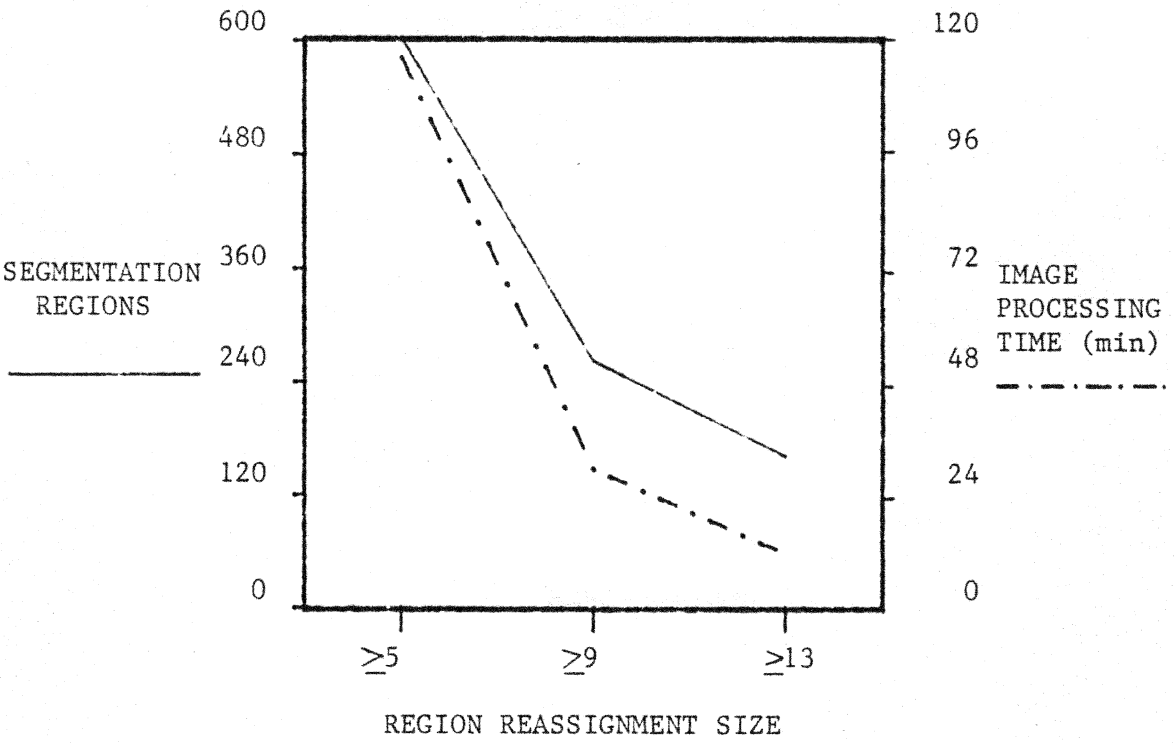


Fig. 92. Relationship between segmentation region total, image processing time (complete), and region removal and reassignment for 4-band, 13-class images.

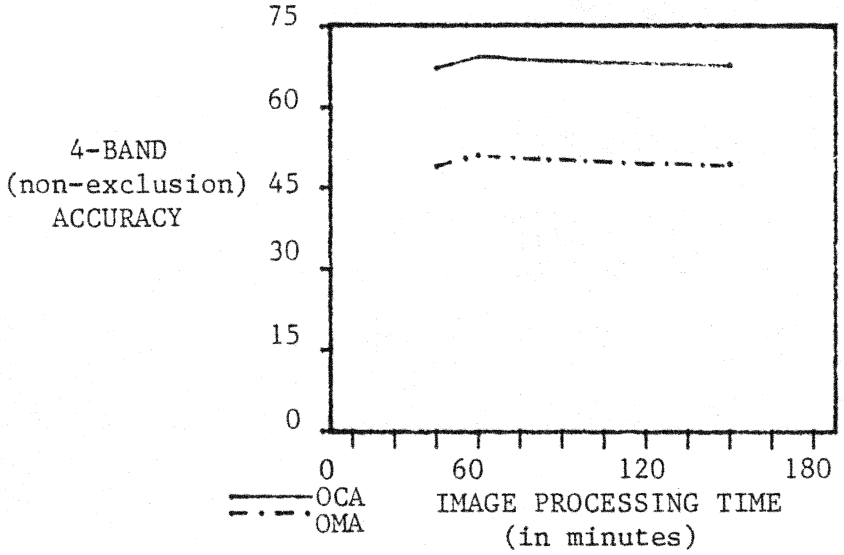


Fig. 93. Relationship of 4-band image accuracy to complete computer processing time.

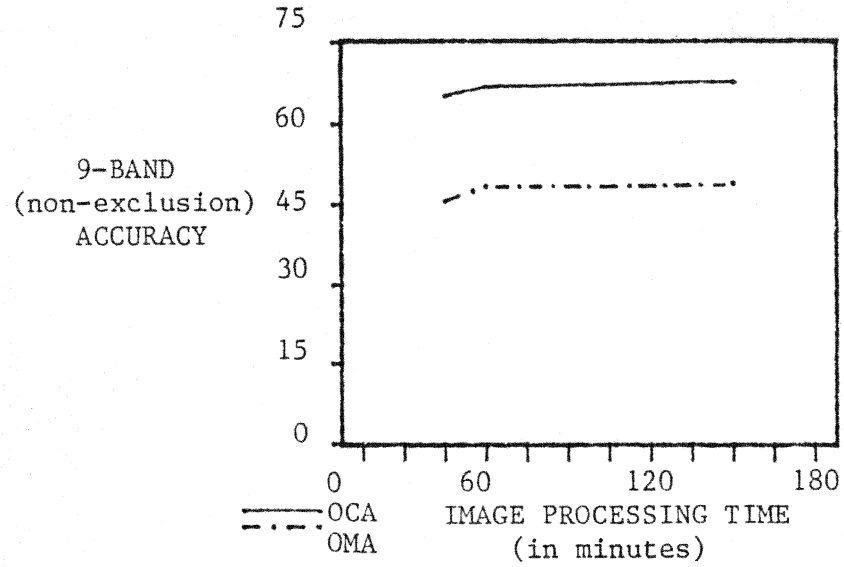


Fig. 94. Relationship of 9-band image accuracy to complete computer processing time.

DISCUSSION

Land management is an information-intensive discipline. Although specific sources of information may be important for short term decision making, a diverse GIS network (one composed of interconnected input, manipulative, analytic, and display channels) may be very important for long range planning. This research has sought to demonstrate that, although limitations are evident, the potential exists for improving and using Landsat satellite information within this GIS network.

One major cost within any resource information structure is that of gathering or acquiring raw, yet accurate data. These data will, for the most part, directly contribute to the availability of refined information. Presently, all land use data stored within POWER and other GISs are derived from digitized 1:24,000 scale USGS topographic maps. Problems in collecting up-to-date information are encountered when maps have not been revised so as to express present land patterns, or when maps are nonexistent.

This limitation suggests the question of whether Landsat land use information accuracies in the range of 65 to 85 percent can be judged worse, equal to, or better than outdated topographic map information. The accuracy of these maps are certainly less than 100%, expecially in areas of rapid change (e.g., growing cities). For these areas, the question is whether moderately accurate Landsat information is better than no information at all? Possible future research can be directed

toward comparing Landsat accuracies with those of outdated topographic maps, emphasizing a cost-benefit analysis. Results may provide a more equitable assessment (those considering factors in addition to accuracy such as data availability, timeliness, cost, and computer-compatibility) of Landsat's role in modern Geographic Information Systems.

In this research, three techniques were used to improve Landsat classification accuracy. The exclusion and class reduction methods were successful, the conditional was not. Future research into each can be justified.

Exclusion: To expand the usefulness of the exclusion procedure in future Landsat applications, it may be necessary to determine quickly and accurately the sequence of land use categories to be excluded. By developing a procedure to indicate those land uses which are most likely to increase accuracies significantly, the exclusion strategy can be facilitated. One possibility would be to develop a class variability index. The purpose of this index would be to determine those land use signatures most likely to be excluded with resulting increases in accuracy. Using a modified clustering approach, this index could be calculated using an equation similar to

$$\text{Index} = \sum_{J=1}^{N} \left(\sum_{I=1}^{N} \text{Difference (-) of Class (J) and Class (I)} \right)^2 \times \text{Number of cells or pixels incorrectly assigned to Class (I)} \times \frac{1}{\text{importance value}}$$

Here, the class difference could be denoted as the difference between a appropriate mean single or multi-band radiance for a class (J) and a similar mean for each class (I) to which it is incorrectly assigned.

This value would be intensified by multiplying it by the number of pixels which are incorrectly classed in those corresponding N land uses. The importance value could quantitatively indicate the need for information pertaining to a specific class and would be user defined. Higher index values would be assigned to those classes expressing a high exclusion potential.

Reduction: Classification accuracies are class dependent. For Landsat scenes, these accuracies will differ given the level of specificity for a classification scheme.

As shown in the Results, as a greater number of more specific classification categories are used (e.g., Level 2; Anderson et al., 1976), accuracies are reduced. Fewer, more general classes (e.g., Level 1) achieve higher accuracies. To create a set of robust land use categories which are the most informative to the land manager and which provide for the highest classification accuracy, would be another consideration for future study. Such a system, provided the classes allow for geographic variation, may be the ultimate means for increasing the accuracy of large-area, vegetation type mapping.

Conditional: Although the results from the conditional methodology were mediocre at best, the basic principles still seem to be sound. These principles involved integrating epistemological decision rules and models into a GIS.

Epistemology itself is the study of how we know what we know. Given several epistemological bases, a more "true" classification of land use and cover may result if computer support is used along with these bases. In this way, machine assistance would aid in characterizing

the most logical land use, given the best available land data (e.g., slope, aspect, distance to water, insolation, and a Level 1 Landsat classification). Possible epistemological bases which may be used in future research include:

1. Sensory - land information derived from aerial photos and/or maps (e.g., knowledge that land use diversities increase near urban areas);
2. Inductive - information provided from study plots and areas serving as training fields (e.g., knowledge of where specific land uses already exist);
3. Deductive - species or cover type presence or absence based on ecological knowledge (e.g., presence of forest types on areas of a particular quality); and
4. Probability - numerical or statistic assessment of a qualitative, physical element, occurrence, or stage (e.g., high likelihood of intensive farming on flat, limestone-derived soils).

Using these bases together may clarify land signatures more accurately than those using only nonsupervised clustering.

Conditional Parameter Registration and Overlay

Elevation, together with its derivatives, slope and aspect data, are essential elements of the conditional classification. It is of major importance that these data be properly registered to and overlaid on a classified Landsat scene before conditional processing. Only then will land characteristics be assigned to appropriate ground locations.

Such alignment was not always possible during this research and is a major problem, in the author's opinion, in almost all large area Landsat analyses. Surveyed registration points, improved fitting and "rubber sheeting" methods, selection of study areas with good registration points, and more attention to the problem may help in the future.

To prevent registration and overlay problems in the future, alternative elevation data sources need to be developed to replace the inaccurate 1:250,000 scale Defense Maping Agency digital terrain tapes. Three proposed options include:

1. The proposed Stereosat, with a 17-m^2 pixel, appears promising for studies requiring slope, strike, and/or dip data (Doyle, 1978; Henderson and Ondrejka, 1978);
2. The digital terrain model elevation data digitized from 1:24,000 scale USGS topographic maps. Only a few areas of the country are available at this time; and
3. Using bilinear interpolation or bicubic or cubic spline techniques on the 27-acre hand-coded POWER elevation data in order to provide estimated elevations for representative 3-acre cells (shown to have promise by Ziewitz 1982).

Ancillary Inputs

Utilizing additional ancillary data inputs in the conditional classification scheme offers another means for improving accuracies. The most obvious landscape variables (e.g., elevation, slope, aspect, land use, and distance to water) have already been incorporated into the conditional algorithm, but other data sources also exist. Two examples

include, soil survey maps, expressing the location of limestone vs. sandstone derived soils, and ground water maps, delineating areas with a high water table. Such data could also contribute toward developing and expanding the multivariate nature of the existing POWER system and its ability to handle diverse management, planning, and research problems.

Maximum Accuracy and Minimum Cost Considerations

Accuracy and cost considerations are an important element of Landsat image processing. To the wildlife manager and land use planner, these considerations can be expressed in terms of:

A. What is the highest (i.e., maximum) level of land use accuracy which can be obtained from classified Landsat data?, and,

B. What is the most cost-effective data processing strategy for obtaining an acceptable accuracy?

Given the relevance of these questions in Landsat/GIS research and applications, the following discussion seeks to examine and provide in-sight to these questions (A. and B.) based on the preceeding research results. Fig. 95 serves as a supplement to this discussion.

To prevent a misinterpretation of terms in this section, "maximum accuracy" will describe the exclusion strategy which produced the largest OCA and OMA percentage values. "Cost-effectiveness" will be based on the degree of OCA and OMA change (positive percentage) per pixel excluded. Given the time and cost associated with performing each strategy, the one producing the largest positive OCA and OMA changes per pixel excluded will be judged as the most "cost-effective" strategy.

Relative to "maximum accuracy" (question A), if a manager is interested in the highest possible image accuracies regardless of cost,

results from this research show strategies 2A (roads plus urban plus water exclusion; 13-class image no. 2) and 3UW (urban plus water exclusion; 4-class image no. 3) as the most successful (Fig. 95). Strategies determined to be the most "cost-effective" (question B) in terms of OCA are 1A (roads plus urban plus water exclusion; 13-class image no. 1) and 1UW (urban plus water exclusion; 4-class image no. 1) (Fig. 95).

Combining the two questions (A. and B.), if a manager was interested in maximum accuracy but preferred the strategy which was the most cost effective, he would have to choose between strategies 2A and 1A for the 13-class images and 1UW and 6UW for the 4-class images. Before making a final decision, the manager would want to consider if it was better to base cost-effectiveness on either an OCA or OMA index. The appropriateness of using either index would relate to definitions of OCA and OMA presented in the Methods section. Strategy tradeoffs would have to be made except in one case (2A). Here, provided cost-effectiveness is based on the OCA index, strategy 2A produced the largest final accuracy with the best cost-effectiveness. On the other hand, if a strategy was to be chosen based on the highest image accuracy and OMA cost-effectiveness, 1A would be selected given the tradeoffs of a high OMA cost-effectiveness for a slightly lower image accuracy. Similar interpretations and tradeoffs would be realized in selecting the optimum 4-class image strategy. Given the more extensive error considerations (i.e., omission and commission) used in calculating OMA, use of this index may be more appropriate for basing cost-effectiveness.

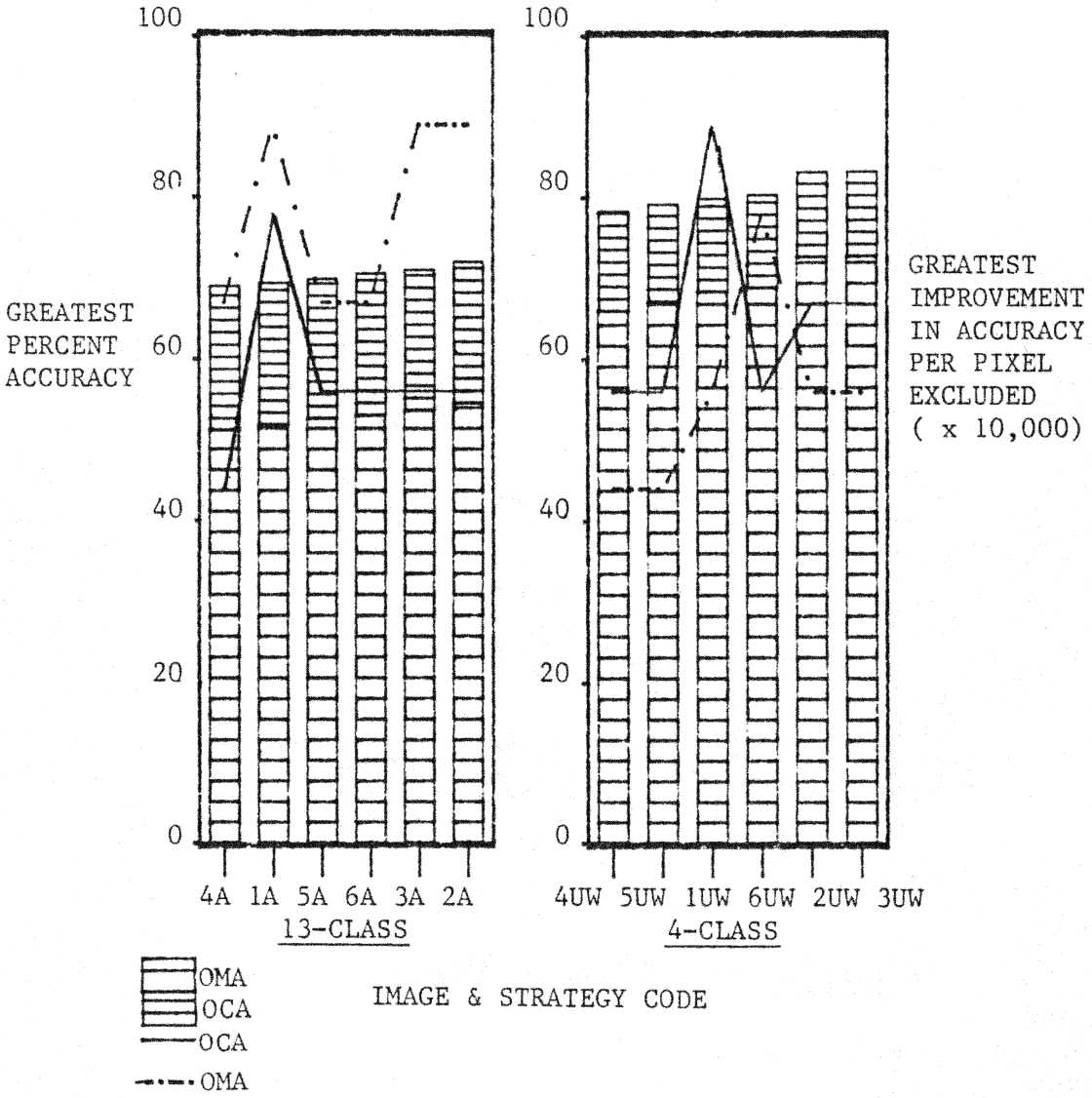


Fig. 95. Comparison of the 12 most effective accuracy improvement strategies and respective cost-efficiencies [A=Roads plus Urban plus Water exclusion (13-class images), UW=Urban plus Water exclusion (4-class images)].

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APPENDIX A

```
C                          PROGRAM PREEX (JSZ-1980)
C
C  **  THIS PROGRAM IS TO BE EXECUTED BEFORE USING ANY (ALL) BAND
C  **  EXTRACTION PROGRAM(S) (E.G., B_BLOC SEQUENCE).
C  **  OUTPUT VALUES WILL BE USED IN THE BAND EXTRACTION PROGRAM
C  **  FORMAT STATEMENTS FOR READING AND WRITING RAW LANDSAT DATA
C  **  FROM BIP2 TAPES.
C
C  **  VARIABLES:
C
C  **  COL1:    LEFT SIDE SAMPLE BOUNDARY OF THE STUDY AREA
C  **  COL2:    RIGHT SIDE SAMPLE BOUNDARY OF THE STUDY AREA
C  **  FILE:    LANDSAT TAPE FILE WHERE STUDY AREA IS LOCATED
C  **  FLAG:    NUMERIC INDICATOR OF WHICH SUBROUTINE HAS BEEN
C               ACCESSED IN THE COURSE OF PROGRAM EXECUTION
C  **  FORM:    ARRAY STORING THE ALPHANUMERIC FORMAT STATEMENT
C               FOR THE BAND TO BE SUBSET FROM TAPE
C  **  IBYTSK:  AMOUNT OF NON-STUDY AREA INFORMATION (IN BYTES)
C               SKIPPED ON EACH DESIGNATED DATA ROW
C  **  IVAL:    X FORMAT CODE COEFFICIENT
C  **  I2PGRP:  NUMBER OF 2 PIXEL GROUPS TO BE SKIPPED BEFORE STORING
C               STUDY AREA DATA
C  **  KCSKIP:  NUMBER OF COLUMNS OF NON-STUDY AREA INFORMATION
C               (IN BYTES) TO BE SKIPPED ON EACH DATA RECORD
C  **  KGPWDT:  NUMBER OF 2 PIXEL GROUPS ACROSS THE UPPER BOUNDARY OF
C               THE STUDY AREA
C  **  KRSKIP:  NUMBER OF DATA RECORDS SKIPPED ON THE DESIGNATED FILE
C               TO REACH THE STUDY AREA
C  **  LENG:    LENGTH OF THE STUDY AREA (IN PIXELS)
C  **  MAX;MAX1: PRECURSOR TO X FORMAT COEFFICIENT (LARGEST VALUE
C                POSSIBLE - 255)
C  **  ROW1:    UPPER BOUNDARY LINE OF THE STUDY AREA
C  **  ROW2:    LOWER BOUNDARY LINE OF THE STUDY AREA
C  **  WIDTH:   WIDTH OF THE STUDY AREA (IN PIXELS)
C
      INTEGER ROW1,ROW2,COL1,COL2,WIDTH,FILE,KGP2,MAX,MAX1,IVAL
      REAL KGP1,FLAG
C  **  CONSTANTS:
      DATA MAX/255/,MAX1/255/,IVAL/0/
C  **  ROWS 1 AND 2 AND COLUMNS 1 AND 2 ARE TO BE ASSIGNED FROM AN
C      OVERLAID (LINE AND SAMPLE PLASTIC OVERLAY) LANDSAT IMAGE.
C  **  COLUMN LIMITS WHEN REQUESTING A SPECIFIC FILE ARE AS FOLLOWS:
C  **  FILE 1 :  COLUMNS 1 THRU 810,
C  **  FILE 2 :  COLUMNS 811 THRU 1620,
```

```
C  **  FILE 3 :  COLUMNS 1621 THRU 2430,
C  **  FILE 4 :  COLUMNS 2431 THRU 3240,
C  **  IF THE WIDTH OF A CHOSEN AREA EXTENDS INTO 2 OR MORE ADJACENT
C      TAPE FILES, THIS PROGRAM WILL HAVE TO BE RUN ONCE FOR EACH
C      FILE THE DATA SET ENCOUNTERS.
C  **  ESSENTIALLY, THIS PROGRAM WILL PROVIDE THE FORMAT VARIABLES
C      TO EXTRACT THE DATA ONE TAPE FILE AT A TIME.
C  **  ROW LIMITS ARE NOT DEPENDENT ON WHICH FILE IS BEING REQUESTED.
C  **  THE ROW LIMITS ARE 1 TO 2340.
C  **  READ TAPE FILE ON WHICH DATA IS FOUND AND BEGINNING AND END
C      ROW AND COLUMN COORDINATES RESPECTIVELY FOR THE SUBSET IMAGE.
      READ (5,*) FILE,ROW1,ROW2,COL1,COL2
C  **  READ APPROPRIATE FORMAT USED IN EXTRACTING SINGLE BAND DATA
C  **  FROM TAPE.  FORMATS FOR EACH BAND ARE:
C      BAND4 :  (2A1,6X)
C      BAND5 :  (2X,2A1,4X)
C      BAND6 :  (4X,2A1,2X)
C      BAND7 :  (6X,2A1)
      READ (5,110) FORM,FORM1,FORM2
  100 FORMAT (3A4)
      FLAG=FLOAT(MAX1)
      PRINT *,MAX,MAX1,FLAG
C  **  ROW AND COLUMN VALUES ARE CHECKED, AND IF NECESSARY, ADJUSTED,
C      TO OPTIMIZE DATA EXTRACTION.
      CALL ODD(ROW1,COL1)
      CALL EVEN(ROW2,COL2)
C  **  OUTPUT VALUES ARE CALCULATED FOR USE IN THE BAND EXTRACTION
C      PROGRAMS.
      KRSKIP=ROW1-1
      KCSKIP=COL1-((810*(FILE=1))+1)
      I2PGRP=KCSKIP/2
      LENG=(ROW2-ROW1)+1
      WIDTH=(COL2-COL1)+1
      KGPWDT=WIDTH/2
      IBYTSK=I2PGRP*8
      CALL MULT(IBYTSK,MAX,IVAL)
      PRINT *,KGPWDT,MAX1
      IF (KGPWDT.GT.MAX1) GO TO 41
C  **  INPUT STATEMENT FORMAT FOR B_BLOC FORTRAN PROGRAM IS WRITTEN
C      OUT.
      CALL WRITE (IVAL,MAX,KGPWDT,FORM,FORM1,FORM2)
      GO TO 51
C  **  FURTHER CALCULATIONS ARE NECESSARY TO PRODUCE INPUT AND OUTPUT
C      FORMAT STATEMENTS FOR PROGRAM(S) B_BLOC.
   41 CALL PRECIS (MAX1,KGPWDT,FLAG,KGP1,KGP2)
      CALL PRECI2 (MAX1,KGPWDT,FLAG,X1,X2)
   51 IF (FLAG.EQ.255.) GO TO 49
```

```
C  **  WRITE INPUT FORMAT STATEMENT 555 FOR B_BLOC PROGRAM(S) GIVEN
C       THE APPROPRIATE FLAG.
       WRITE (6,107) IVAL,MAX,X1,FORM,FORM1,FORM2,X2,FORM,FORM1,FORM2
  107 FORMAT (1HO,3X,'((',I3,'(',I3,'X)),',I3,3A4,',',I3,3A4,')')
       GO TO 52
C  **  WRITE INPUT FORMAT STATEMENT.
   49 WRITE (6,111) IVAL,MAX,X1,FORM,FORM1,FORM2,X2,FORM,FORM1,FORM2
  111 FORMAT (1HO,3X,'((',I3,'(',I3,'X)),',I3,3A4,',(',I3,3A4,')')
C  **  VARIABLE NAMES AND VALUES ARE PRINTED OUT FOR USE IN THE BAND
C       EXTRACTION PROGRAM(S).
    52 WRITE (6,99)
    99 FORMAT (1H1,67X,'*')
       WRITE (6,100)
  100 FORMAT (1H ,10X,'ROW1',10X,'ROW2',10X,'COL1',10X,'COL2',10X,
     &'FILE')
       WRITE (6,101) ROW1,ROW2,COL1,COL2,FILE
  101 FORMAT (1HO,5(10X,I4),//)
       WRITE (6,104)
  104 FORMAT (1HO,5X,'*',20X,'*',9X,'*',9X,' ',20X,' ',7X,' ')
       WRITE (6,102)
  102 FORMAT (1H ,3X,'KRSKIP',5X,'KCSKIP',5X,'LENG',5X,'WIDTH',5X,
     &'KGPWDT',5X,'IBYTSK',5X,'MAX',5X,'IVAL')
        WRITE (6,103) KRSKIP,KCSKIP,LENG,WIDTH,KGPWDT,IBYTSK,MAX,IVAL
  103 FORMAT (1HO,3X,I6,5X,I6,5X,I4,5X,I5,5X,I6,5X,I6,5X,I3,5X,I4,
     &///)
       WRITE (6,105)
  105 FORMAT (1HO,3X,'VARIABLE VALUES WITH A STAR ABOVE THEM WILL BE
     &USED DIRECTLY IN THE SPECIFIED'/5X, 'B_BLOC PROGRAM(S).')
       WRITE (6,106)
  106 FORMAT (1HO,3X,'IF THE VALUES FOR VARIABLES MAX AND IVAL ARE
     &BOTH 0, THEY ARE TO BE OMITTED FROM THE READ FORMAT'/5X,
     &'STATEMENT OF ANY B_EXTRA FORTRAN PROGRAM(S) REQUESTED.')
       STOP
       END
C
C                          --------------------
C                          ***SUBROUTINE ODD***
C                       ------------------------------
C******THIS SUBROUTINE CHECKS, AND IF NECESSARY, ADJUSTS ROW1 AND
C   ***COL1 TO EVEN VALUES.  THIS FORM WILL ALLOW FOR MORE EFFICIENT
C     *DATA EXTRACTION.
C                       ------------------------------
C                                 VARIABLES
C                       ------------------------------
C  **  CLCK AND ICLCK:  VARIABLES USED TO DETERMINE IF COL1 IS AN
C       ODD VALUE
C  **  IRWCK AND RWCK:  VARIABLES USED TO DETERMINE IF ROW1 IS AN
```

```
C      ODD VALUE
C      ------------------------------------------------------------
       SUBROUTINE ODD(ROW1,COL1)
       INTEGER ROW1,COL1
       WRITE (6,100)
  100  FORMAT ('0','ODD ACCESSED')
       PRINT *,ROW1,COL1
       RWCK=(FLOAT(ROW1))/2.
       IRWCK=ROW1/2
       IF (RWCK.EQ.IRWCK) ROW1=ROW1-1
       CLCK=(FLOAT(COL1))/2
       ICLCK=COL1/2
       IF (CLCK.EQ.ICLCK) COL1=COL1-1
       PRINT *,ROW1,COL1
       WRITE (6,101)
  101  FORMAT ('0','ODD LEFT')
       RETURN
       END
C
C                    ---------------------
C                    ***SUBROUTINE EVEN***
C                  -------------------------------
C******THIS SUBROUTINE CHECKS,AND IF NECESSARY, ADJUSTS ROW2 AND COL2
C   ***TO ODD VALUES.  THIS WILL ALLOW FOR MORE EFFICIENT DATA
C     *RETRIEVAL.
C                  -------------------------------
C                             VARIABLES
C                  -------------------------------
C  **  CLCK2 AND ICLCK2:  VARIABLES USED TO DTERMINE IF COL2 IS AN
C      EVEN VALUE
C  **  IRWCK2 AND RWCK2:  VARIABLES USED TO DETERMINE IF ROW2 IS AN
C      EVEN VALUE
C      ------------------------------------------------------------
       SUBROUTINE EVEN (ROW2,COL2)
       INTEGER ROW2,COL2
       WRITE (6,100)
  100  FORMAT ('0','EVEN ACCESSED')
       PRINT *,ROW2,COL2
       RWCK2=(FLOAT(ROW2))/2
       IRWCK2=ROW2/2
       IF (RWCK2.NE.IRWCK2) ROW2=ROW2+1
       CLCK2=(FLOAT(COL2))/2.
       ICLCK2=COL2/2
       IF (CLCK2.NE.ICLCK2) COL2=COL2+1
       PRINT *,ROW2,COL2
       WRITE (6,101)
  101  FORMAT ('0','EVEN LEFT')
```

```
      RETURN
      END
C
C                    --------------------
C                    ***SUBROUTINE MULT***
C                  -------------------------------
C******THIS SUBROUTINE CALCULATES 2 VALUES, MAX AND IVAL.  WHEN THESE
C   ***2 VALUES ARE MULTIPLIED BY ONE ANOTHER THEY REPRESENT THE
C     *NUMBER OF BYTES TO BE SKIPPED (IBYTSK) IN A RECORD BEFORE
C     *STORING DATA.
C                  -------------------------------
C                            VARIABLES
C                  -------------------------------
C  **  VAL;IVAL:  VARIABLES WHICH INDICATE WHETHER THE PREVIOUS
C                 DIVISION HAS RESULTED IN AN INTEGER VALUE.
C     ------------------------------------------------------------------
      SUBROUTINE MULT(IBYTSK,MAX,IVAL)
      INTEGER IBYTSK,MAX,IVAL
      WRITE (6,100)
  100 FORMAT ('0','MULT ACCESSED')
    1 VAL=(FLOAT(IBYTSK))/(FLOAT(MAX))
      IVAL=IFIX(VAL)
      IF(VAL.EQ.IVAL) GO TO 2
      MAX=MAX-1
      GO TO 1
    2 IF(IVAL) 5,5,6
    5 MAX=0
      IVAL=0
    6 WRITE (6,101)
  101 FORMAT ('0','MULT LEFT')
      RETURN
      END
C                    --------------------
C                    **SUBROUTINE PRECIS**
C                  -------------------------------
C******THIS SUBROUTINE DETERMINES WHETHER THE KGPWDT VALUE (>255) HAS
C *****2 DIVISORS WHICH PRODUCE INTEGER VALUES BOTH BEING < 255.
C  ****IF NO DIVISORS EXIST, A LABEL WILL BE PRINTED OUT. ALSO
C   ***PRINTED IS THE OUTPUT FORMAT STATEMENT 1000 (B_BLOC PROGRAM)
C     *FOR WRITING LANDSAT DATA TO DISK.
C                  -------------------------------
C                            VARIABLES
C                  -------------------------------
C  **  NEW1 AND NEW2 : INTEGER FORMATTED DIVISOR VALUES.
C  **  WR1 AND WR2: OUTPUT FORMAT STATEMENT VARIABLES.
C     ------------------------------------------------------------------
      SUBROUTINE PRECIS (MAX1,KGPWDT,FLAG,NEW1,NEW2)
```

```
      INTEGER MAX1,KGPWDT,NEW2,NEW,WR1,WR2
      REAL NEW1,FLAG
      WRITE (6,99)
   99 FORMAT ('0','PRECIS ACCESSED')
      PRINT *,MAX1,KGPWDT
      DO 1 J=1,MAX1
      NEW1=FLOAT(KGPWDT)/FLOAT(J)
      PRINT *,NEW1
      NEW=IFIX(NEW1)
      IF (NEW1.EQ.NEW) GO TO 30
      GO TO 1
   30 IF (NEW1.LE.MAX1) GO TO 40
    1 CONTINUE
   40 NEW2=J
      IF (NEW2.EQ.255) GO TO 49
      PRINT *,NEW1,NEW2
      WR1=NEW1*2
      WR2=NEW2*2
      WRITE (6,100) WR1,WR2
  100 FORMAT (1H0,3X,'(',I3,'(',I3,'A1))')
      FLAG=1.
      PRINT *,WR1,WR2
      GO TO 50
   49 WRITE (6,101)
  101 FORMAT (1H0,'KGPWDT CANNOT BE DIVIDED SO TO BE < 255')
   50 WRITE (6,102)
  102 FORMAT ('0','PRECIS LEFT')
      RETURN
      END
C
C                    ---------------------
C                    **SUBROUTINE PRECI2**
C                  -------------------------------
C******THIS SUBROUTINE PRINTS OUTPUT FORMAT STATEMENT 1000 FOR B_BLOC
C   ***PROGRAMS GIVEN THE APPROPRIATE FLAG.
C                  -------------------------------
C                             VARIABLES
C                  -------------------------------
C  **  X1 AND X2:  OUTPUT FORMAT STATEMENT VARIABLES.
C     ------------------------------------------------------------
      SUBROUTINE PRECI2 (MAX1,KGPWDT,FLAG,X1,X2)
      INTEGER MAX1,KGPWDT,X1,X2
      WRITE (6,99)
   99 FORMAT ('0','PRECI2 ACCESSED')
      X1=KGPWDT-MAX1
      X2=MAX1
      PRINT *,X1,X2,MAX1,KGPWDT
```

```
      IF (FLAG.EQ.1.) GO TO 10
      WRITE (6,100) X1,X2
  100 FORMAT (1H0,3X,'(2(',I3,'A1)',',2(',I3,'A1))')
   10 WRITE (6,101)
  101 FORMAT ('0','PRECI2 LEFT')
      RETURN
      END
C
C                    --------------------
C                    **SUBROUTINE WRITE**
C                  ------------------------------
C******THIS SUBROUTINE PRINTS OUT THE APPROPRIATE INPUT FORMAT
C   ***(I.E., STATEMENT 555) FOUND IN PROGRAM(S) B_BLOC.
C     ------------------------------------------------------------------
      SUBROUTINE WRITE (IVAL,MAX,KGPWDT,FORM,FORM1,FORM2)
      WRITE (6,99)
   99 FORMAT ('0','WRITE ACCESSED')
      WRITE (6,100) IVAL,MAX,KGPWDT,FORM,FORM1,FORM2
  100 FORMAT (1H0,3X,'((',I3,'(',I3,'X)),',I3,3A4,')')
   10 WRITE (6,101)
  101 FORMAT ('0','WRITE LEFT')
      RETURN
      END
```

APPENDIX B

```
C                          PROGRAM B4BLOC (JSZ-1980)
C
C  **  THIS PROGRAM READS BAND 4 RADIANCE VALUE OFF OF A LANDSAT CCT
C  **  FOR AN AREA OF INTEREST.  SPECIFIC FORMAT INFORMATION HAD
C  **  PREVIOUSLY BEEN OUTPUT FROM PROGRAM PREEX.  RADIANCE VALUES
C  **  AREA ORIGINALLY READ OFF TAPE IN THE A-FORMAT BECAUSE OF
C  **  THEIR HEXIDECIMAL FORMAT ON TAPE.  AFTER STORING THE RADIANCE
C  **  VALUES IN ARRAY B4, THE VALUES ARE CONVERTED TO AN INTEGER
C  **  FORMAT AND STORED IN ARRAY ISAMPL.  WHILE IN INTEGER FORMAT,
C  **  THESE DIGITAL VALUES ARE RANKED TO DETERMINE THE GREATEST
C  **  (G) AND SMALLEST (T) RADIANCE VALUES.  ARRAY B4 IS THEN
C  **  WRITTEN TO DISK.
C
C      VARIABLES:
C
C      *B4         :  STORAGE ARRAY WHICH CONTAINS LANDSAT BAND 4
C                     RADIANCE VALUES IN BINARY FORMAT.
C      *BIN        :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE STORAGE
C                     ALLOCATION.)
C      *G          :  LARGEST RADIANCE VALUE IN ARRAY RANK.
C                     (ORIGINALLY ASSIGNED DUMMY VALUE 25.)
C      *H          :  OVERLAY ARRAY WHEN CONVERTING FROM BINARY TO
C                     INTEGER FORMAT.
C      *H(1)       :  FIRST STORAGE POSITION OF ARRAY H.
C      *H(4)       :  FINAL STORAGE POSITION OF ARRAY H.  (1-BYTE
C                     STORAGE ALLOCATION.)
C      *INT        :  INDIVIDUAL VALUE'S INTEGER FORM.
C      *ISAMPL     :  STORAGE ARRAY WHICH CONTAINS RADIANCE VALUES IN
C                     INTEGER FORMAT.
C      *KK         :  OVERLAY VARIABLE WHICH IS EQUIVALENT TO H(1).
C                     ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C      *KRSKIP     :  NUMBER OF DATA RECORDS SKIPPED ON THE DESIGNATED
C                     LENGTH (IN PIXELS) OF THE STUDY AREA.
C      *LENG       :  LENGTH OF THE STUDY AREA (IN PIXELS).
C      *M          :  COUNT VARIABLE.
C      *RANK       :  STORAGE ARRAY WHICH HOLDS RADIANCE VALUES IN
C                     DESCENDING ORDER.
C      *T          :  SMALLEST RADIANCE VALUES IN ARRAY RANK.
C                     (ORIGINALLY ASSIGNED DUMMY VALUE 999999.)
C      *WIDTH      :  WIDTH (IN PIXELS) OF THE STUDY AREA.
C
C  **  INDIVIDUAL VALUES FOR ARRAYS H AND B4 AREA ASSIGNED A STORAGE
C  **  ALLOCATION OF 1-BYTE (8 BIT).
      LOGICAL * 1 H(4)
```

```
      LOGICAL * 1 B4(560)
      EQUIVALENCE (H(1),KK)
C  **  STORAGE
      DIMENSION ISAMPL(560)
C  **  INTEGER DECLARATION
      INTEGER G,ISAMPL,KRSKIP,LENG,RANK,T,WIDTH
C  **  ASSIGNMENTS
      DATA T/999999/,G/25/
C  **  READ VALUE LENG,WIDTH, AND KRSKIP.  THEY ARE OUTPUT VALUES
C  **  FROM PROGRAM PREEX.
      READ (5,*) LENG,WIDTH,KRSKIP
C  **  TAPE IS REWOUND
      REWIND 8
C  **  FIRST 2 ANNOTATION RECORDS ON CCT ARE SKIPPED.
      READ (8,40)
      READ (8,40)
C  **  KRSKIP=0 ONLY IF WORKING WITH 1ST ROW (RECORD 3) OF BIP2
C  **  DIGITAL DATA.
      IF (KRSKIP .EQ. 0) GO TO 5
C  **  SKIP APPROPRIATE NUMBER OF RECORDS TO REACH STUDY AREA.
      DO 8 J=1,KRSKIP
      READ (8,40)
   40 FORMAT (1X)
    8 CONTINUE
C  **  STUDY AREA IS READ OFF CCT ONE SCAN LINE AT A TIME.
    5 DO 1 I=1,LENG
      READ (8,555) (B4(J),J=1,WIDTH)
C  **  FORMAT STATEMENT SPECIFICATIONS ARE OBTAINED FROM PROGRAM
C  **  PREEX.
  555 FORMAT (140(2A1,6X),140(2A1,6X))
C  **  BINARY VALUES ARE CONVERTED TO INTEGER FORMAT ONE LINE AT A
C  **  TIME USING SUBROUTINE B1INT.  INTEGER VALUES ARE RETURNED AND
C  **  STORED IN ARRAY ISAMPL.
      DO 2 J=1,WIDTH
      CALL B1INT (B4(J),INT)
      ISAMPL(J)=INT
    2 CONTINUE
C  **  LARGEST AND SMALLEST VALUES IN EACH LINE ARE DETERMINED USING
C  **  SUBROUTINE RANK.
      CALL RANKA1 (ISAMPL,WIDTH,T,G)
C  **  ARRAY B4 IS WRITTEN TO DISK USING THE SPECIFIED FORMAT.
      WRITE (10,1000) (B4(J),J=1,WIDTH)
 1000 FORMAT (10(56A1))
C  **  CYCLE INCOMPLETE UNTIL I = LENG.
    1 CONTINUE
C  **  LARGEST AND SMALLEST RADIANCE VALUES ARE WRITTEN TO UNIT 6.
      WRITE (6,1001) T,G
```

```
 1001 FORMAT (1H1,'T=',I3,5X,'G=',I3)
      STOP
      END
C                      --------------------
C                     ***SUBROUTINE B1INT***
C                    ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                    ------------------------------
C                              VARIABLES
C                    ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                      ---------------------
C                     ***SUBROUTINE RANKA1***
C                    --------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                    --------------------------------
C                              VARIABLES
C                      ----------------------
C     *G            :  LARGEST RATIO VALUE.
C     *ISAMPL       :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                      FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK         :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
```

```
C                       DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :    PROGRAM SUBROUTINE.
C     *T           :    SMALLEST RATIO VALUE.
C     *WIDTH       :    WIDTH (IN PIXELS) OF DATA STRIP.
C                       ----------------------
      SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
      DIMENSION ISAMPL(560),RANK(560)
      INTEGER G,ISAMPL,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISAMPL(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX C

```
C                          PROGRAM B5BLOC (JSZ-1980)
C
C  **  THIS PROGRAM READS BAND 5 RADIANCE VALUE OFF OF A LANDSAT CCT
C  **  FOR AN AREA OF INTEREST.  SPECIFIC FORMAT INFORMATION HAD
C  **  PREVIOUSLY BEEN OUTPUT FROM PROGRAM PREEX.  RADIANCE VALUES
C  **  AREA ORIGINALLY READ OFF TAPE IN THE A-FORMAT BECAUSE OF
C  **  THEIR HEXIDECIMAL FORMAT ON TAPE.  AFTER STORING THE RADIANCE
C  **  VALUES IN ARRAY B5, THE VALUES ARE CONVERTED TO AN INTEGER
C  **  FORMAT AND STORED IN ARRAY ISAMPL.  WHILE IN INTEGER FORMAT,
C  **  THESE DIGITAL VALUES ARE RANKED TO DETERMINE THE GREATEST
C  **  (G) AND SMALLEST (T) RADIANCE VALUES.  ARRAY B5 IS THEN
C  **  WRITTEN TO DISK.
C
C      VARIABLES:
C
C      *B5         :  STORAGE ARRAY WHICH CONTAINS LANDSAT BAND 5
C                     RADIANCE VALUES IN BINARY FORMAT.
C      *BIN        :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE STORAGE
C                     ALLOCATION.)
C      *G          :  LARGEST RADIANCE VALUE IN ARRAY RANK.
C                     (ORIGINALLY ASSIGNED DUMMY VALUE 25.)
C      *H          :  OVERLAY ARRAY WHEN CONVERTING FROM BINARY TO
C                     INTEGER FORMAT.
C      *H(1)       :  FIRST STORAGE POSITION OF ARRAY H.
C      *H(4)       :  FINAL STORAGE POSITION OF ARRAY H.  (1-BYTE
C                     STORAGE ALLOCATION.)
C      *INT        :  INDIVIDUAL VALUE'S INTEGER FORM.
C      *ISAMPL     :  STORAGE ARRAY WHICH CONTAINS RADIANCE VALUES IN
C                     INTEGER FORMAT.
C      *KK         :  OVERLAY VARIABLE WHICH IS EQUIVALENT TO H(1).
C                     ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C      *KRSKIP     :  NUMBER OF DATA RECORDS SKIPPED ON THE DESIGNATED
C                     LENGTH (IN PIXELS) OF THE STUDY AREA.
C      *LENG       :  LENGTH OF THE STUDY AREA (IN PIXELS).
C      *M          :  COUNT VARIABLE.
C      *RANK       :  STORAGE ARRAY WHICH HOLDS RADIANCE VALUES IN
C                     DESCENDING ORDER.
C      *T          :  SMALLEST RADIANCE VALUES IN ARRAY RANK.
C                     (ORIGINALLY ASSIGNED DUMMY VALUE 999999.)
C      *WIDTH      :  WIDTH (IN PIXELS) OF THE STUDY AREA.
C
C  **  INDIVIDUAL VALUES FOR ARRAYS H AND B5 AREA ASSIGNED A STORAGE
C  **  ALLOCATION OF 1-BYTE (8 BIT).
      LOGICAL * 1 H(4)
```

```
      LOGICAL * 1 B5(512)
      EQUIVALENCE (H(1),KK)
C  **  STORAGE
      DIMENSION ISAMPL(512)
C  **  INTEGER DECLARATION
      INTEGER G,ISAMPL,KRSKIP,LENG,RANK,T,WIDTH
C  **  ASSIGNMENTS
      DATA T/999999/,G/25/
C  **  READ VALUE LENG,WIDTH, AND KRSKIP.  THEY ARE OUTPUT VALUES
C  **  FROM PROGRAM PREEX.
      READ (5,*) LENG,WIDTH,KRSKIP
C  **  TAPE IS REWOUND
      REWIND 8
C  **  FIRST 2 ANNOTATION RECORDS ON CCT ARE SKIPPED.
      READ (8,40)
      READ (8,40)
C  **  KRSKIP=0 ONLY IF WORKING WITH 1ST ROW (RECORD 3) OF BIP2
C  **  DIGITAL DATA.
      IF (KRSKIP .EQ. 0) GO TO 5
C  **  SKIP APPROPRIATE NUMBER OF RECORDS TO REACH STUDY AREA.
      DO 8 J=1,KRSKIP
      READ (8,40)
   40 FORMAT (1X)
    8 CONTINUE
C  **  STUDY AREA IS READ OFF CCT ONE SCAN LINE AT A TIME.
    5 DO 1 I=1,LENG
      READ (8,555) (B5(J),J=1,WIDTH)
C  **  FORMAT STATEMENT SPECIFICATIONS ARE OBTAINED FROM PROGRAM
C  **  PREEX.
  555 FORMAT (8(149X),128(2X,2A1,4X),128(2X,2A1,4X))
C  **  BINARY VALUES ARE CONVERTED TO INTEGER FORMAT ONE LINE AT A
C  **  TIME USING SUBROUTINE B1INT.  INTEGER VALUES ARE RETURNED AND
C  **  STORED IN ARRAY ISAMPL.
      DO 2 J=1,WIDTH
      CALL B1INT (B5(J),INT)
      ISAMPL(J)=INT
    2 CONTINUE
C  **  LARGEST AND SMALLEST VALUES IN EACH LINE ARE DETERMINED USING
C  **  SUBROUTINE RANK.
      CALL RANKA1 (ISAMPL,WIDTH,T,G)
C  **  ARRAY B5 IS WRITTEN TO DISK USING THE SPECIFIED FORMAT.
      WRITE (10,1000) (B5(J),J=1,WIDTH)
 1000 FORMAT (4(128A1))
C  **  CYCLE INCOMPLETE UNTIL I = LENG.
    1 CONTINUE
C  **  LARGEST AND SMALLEST RADIANCE VALUES ARE WRITTEN TO UNIT 6.
      WRITE (6,1001) T,G
```

```
 1001 FORMAT (1H1,'T=',I3,5X,'G=',I3)
      STOP
      END
C                      --------------------
C                     ***SUBROUTINE B1INT***
C                   ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                   ------------------------------
C                              VARIABLES
C                   ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                      --------------------
C                     ***SUBROUTINE RANKA1***
C                   ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                   ---------------------------------
C                              VARIABLES
C                      ----------------------
C     *G            :  LARGEST RATIO VALUE.
C     *ISAMPL       :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                      FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK         :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
```

```
C                       DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :    PROGRAM SUBROUTINE.
C     *T           :    SMALLEST RATIO VALUE.
C     *WIDTH       :    WIDTH (IN PIXELS) OF DATA STRIP.
C                       ------------------------
      SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
      DIMENSION ISAMPL(512),RANK(512)
      INTEGER G,ISAMPL,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISAMPL(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX D

```
C                          PROGRAM B6BLOC (JSZ-1980)
C
C  **  THIS PROGRAM READS BAND 6 RADIANCE VALUE OFF OF A LANDSAT CCT
C  **  FOR AN AREA OF INTEREST.  SPECIFIC FORMAT INFORMATION HAD
C  **  PREVIOUSLY BEEN OUTPUT FROM PROGRAM PREEX.  RADIANCE VALUES
C  **  AREA ORIGINALLY READ OFF TAPE IN THE A-FORMAT BECAUSE OF
C  **  THEIR HEXIDECIMAL FORMAT ON TAPE.  AFTER STORING THE RADIANCE
C  **  VALUES IN ARRAY B6, THE VALUES ARE CONVERTED TO AN INTEGER
C  **  FORMAT AND STORED IN ARRAY ISAMPL.  WHILE IN INTEGER FORMAT,
C  **  THESE DIGITAL VALUES ARE RANKED TO DETERMINE THE GREATEST
C  **  (G) AND SMALLEST (T) RADIANCE VALUES.  ARRAY B6 IS THEN
C  **  WRITTEN TO DISK.
C
C      VARIABLES:
C
C      *B6          :  STORAGE ARRAY WHICH CONTAINS LANDSAT BAND 6
C                      RADIANCE VALUES IN BINARY FORMAT.
C      *BIN         :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE STORAGE
C                      ALLOCATION.)
C      *G           :  LARGEST RADIANCE VALUE IN ARRAY RANK.
C                      (ORIGINALLY ASSIGNED DUMMY VALUE 25.)
C      *H           :  OVERLAY ARRAY WHEN CONVERTING FROM BINARY TO
C                      INTEGER FORMAT.
C      *H(1)        :  FIRST STORAGE POSITION OF ARRAY H.
C      *H(4)        :  FINAL STORAGE POSITION OF ARRAY H.  (1-BYTE
C                      STORAGE ALLOCATION.)
C      *INT         :  INDIVIDUAL VALUE'S INTEGER FORM.
C      *ISAMPL      :  STORAGE ARRAY WHICH CONTAINS RADIANCE VALUES IN
C                      INTEGER FORMAT.
C      *KK          :  OVERLAY VARIABLE WHICH IS EQUIVALENT TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C      *KRSKIP      :  NUMBER OF DATA RECORDS SKIPPED ON THE DESIGNATED
C                      LENGTH (IN PIXELS) OF THE STUDY AREA.
C      *LENG        :  LENGTH OF THE STUDY AREA (IN PIXELS).
C      *M           :  COUNT VARIABLE.
C      *RANK        :  STORAGE ARRAY WHICH HOLDS RADIANCE VALUES IN
C                      DESCENDING ORDER.
C      *T           :  SMALLEST RADIANCE VALUES IN ARRAY RANK.
C                      (ORIGINALLY ASSIGNED DUMMY VALUE 999999.)
C      *WIDTH       :  WIDTH (IN PIXELS) OF THE STUDY AREA.
C
C  **  INDIVIDUAL VALUES FOR ARRAYS H AND B6 AREA ASSIGNED A STORAGE
C  **  ALLOCATION OF 1-BYTE (8 BIT).
      LOGICAL * 1 H(4)
```

```
      LOGICAL * 1 B6(560)
      EQUIVALENCE (H(1),KK)
C  **  STORAGE
      DIMENSION ISAMPL(560)
C  **  INTEGER DECLARATION
      INTEGER G,ISAMPL,KRSKIP,LENG,RANK,T,WIDTH
C  **  ASSIGNMENTS
      DATA T/999999/,G/25/
C  **  READ VALUE LENG,WIDTH, AND KRSKIP.  THEY ARE OUTPUT VALUES
C  **  FROM PROGRAM PREEX.
      READ (5,*) LENG,WIDTH,KRSKIP
C  **  TAPE IS REWOUND
      REWIND 8
C  **  FIRST 2 ANNOTATION RECORDS ON CCT ARE SKIPPED.
      READ (8,40)
      READ (8,40)
C  **  KRSKIP=0 ONLY IF WORKING WITH 1ST ROW (RECORD 3) OF BIP2
C  **  DIGITAL DATA.
      IF (KRSKIP .EQ. 0) GO TO 5
C  **  SKIP APPROPRIATE NUMBER OF RECORDS TO REACH STUDY AREA.
      DO 8 J=1,KRSKIP
      READ (8,40)
   40 FORMAT (1X)
    8 CONTINUE
C  **  STUDY AREA IS READ OFF CCT ONE SCAN LINE AT A TIME.
    5 DO 1 I=1,LENG
      READ (8,555) (B6(J),J=1,WIDTH)
C  **  FORMAT STATEMENT SPECIFICATIONS ARE OBTAINED FROM PROGRAM
C  **  PREEX.
  555 FORMAT (140(4X,2A1,2X),140(4X,2A1,2X))
C  **  BINARY VALUES ARE CONVERTED TO INTEGER FORMAT ONE LINE AT A
C  **  TIME USING SUBROUTINE B1INT.  INTEGER VALUES ARE RETURNED AND
C  **  STORED IN ARRAY ISAMPL.
      DO 2 J=1,WIDTH
      CALL B1INT (B6(J),INT)
      ISAMPL(J)=INT
    2 CONTINUE
C  **  LARGEST AND SMALLEST VALUES IN EACH LINE ARE DETERMINED USING
C  **  SUBROUTINE RANK.
      CALL RANKA1 (ISAMPL,WIDTH,T,G)
C  **  ARRAY B6 IS WRITTEN TO DISK USING THE SPECIFIED FORMAT.
      WRITE (10,1000) (B6(J),J=1,WIDTH)
 1000 FORMAT (10(56A1))
C  **  CYCLE INCOMPLETE UNTIL I = LENG.
    1 CONTINUE
C  **  LARGEST AND SMALLEST RADIANCE VALUES ARE WRITTEN TO UNIT 6.
      WRITE (6,1001) T,G
```

```
 1001 FORMAT (1H1,'T=',I3,5X,'G=',I3)
      STOP
      END
C                      -------------------
C                     ***SUBROUTINE B1INT***
C                    ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                    ------------------------------
C                              VARIABLES
C                    ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ---------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                      ---------------------
C                     ***SUBROUTINE RANKA1***
C                    ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                    ---------------------------------
C                              VARIABLES
C                      ----------------------
C     *G            :  LARGEST RATIO VALUE.
C     *ISAMPL       :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                      FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK         :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
```

```
C                       DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :    PROGRAM SUBROUTINE.
C     *T           :    SMALLEST RATIO VALUE.
C     *WIDTH       :    WIDTH (IN PIXELS) OF DATA STRIP.
C                       ----------------------
      SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
      DIMENSION ISAMPL(560),RANK(560)
      INTEGER G,ISAMPL,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISAMPL(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX E

```
C                              PROGRAM B7BLOC (JSZ-1980)
C
C  **  THIS PROGRAM READS BAND 7 RADIANCE VALUE OFF OF A LANDSAT CCT
C  **  FOR AN AREA OF INTEREST.  SPECIFIC FORMAT INFORMATION HAD
C  **  PREVIOUSLY BEEN OUTPUT FROM PROGRAM PREEX.  RADIANCE VALUES
C  **  AREA ORIGINALLY READ OFF TAPE IN THE A-FORMAT BECAUSE OF
C  **  THEIR HEXIDECIMAL FORMAT ON TAPE.  AFTER STORING THE RADIANCE
C  **  VALUES IN ARRAY B7, THE VALUES ARE CONVERTED TO AN INTEGER
C  **  FORMAT AND STORED IN ARRAY ISAMPL.  WHILE IN INTEGER FORMAT,
C  **  THESE DIGITAL VALUES ARE RANKED TO DETERMINE THE GREATEST
C  **  (G) AND SMALLEST (T) RADIANCE VALUES.  ARRAY B7 IS THEN
C  **  WRITTEN TO DISK.
C
C      VARIABLES:
C
C      *B7          :  STORAGE ARRAY WHICH CONTAINS LANDSAT BAND 7
C                      RADIANCE VALUES IN BINARY FORMAT.
C      *BIN         :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE STORAGE
C                      ALLOCATION.)
C      *G           :  LARGEST RADIANCE VALUE IN ARRAY RANK.
C                      (ORIGINALLY ASSIGNED DUMMY VALUE 25.)
C      *H           :  OVERLAY ARRAY WHEN CONVERTING FROM BINARY TO
C                      INTEGER FORMAT.
C      *H(1)        :  FIRST STORAGE POSITION OF ARRAY H.
C      *H(4)        :  FINAL STORAGE POSITION OF ARRAY H.  (1-BYTE
C                      STORAGE ALLOCATION.)
C      *INT         :  INDIVIDUAL VALUE'S INTEGER FORM.
C      *ISAMPL      :  STORAGE ARRAY WHICH CONTAINS RADIANCE VALUES IN
C                      INTEGER FORMAT.
C      *KK          :  OVERLAY VARIABLE WHICH IS EQUIVALENT TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C      *KRSKIP      :  NUMBER OF DATA RECORDS SKIPPED ON THE DESIGNATED
C                      LENGTH (IN PIXELS) OF THE STUDY AREA.
C      *LENG        :  LENGTH OF THE STUDY AREA (IN PIXELS).
C      *M           :  COUNT VARIABLE.
C      *RANK        :  STORAGE ARRAY WHICH HOLDS RADIANCE VALUES IN
C                      DESCENDING ORDER.
C      *T           :  SMALLEST RADIANCE VALUES IN ARRAY RANK.
C                      (ORIGINALLY ASSIGNED DUMMY VALUE 999999.)
C      *WIDTH       :  WIDTH (IN PIXELS) OF THE STUDY AREA.
C
C  **  INDIVIDUAL VALUES FOR ARRAYS H AND B7 AREA ASSIGNED A STORAGE
C  **  ALLOCATION OF 1-BYTE (8 BIT).
      LOGICAL * 1 H(4)
```

```
      LOGICAL * 1 B7(120)
      EQUIVALENCE (H(1),KK)
C  **  STORAGE
      DIMENSION ISAMPL(120)
C  **  INTEGER DECLARATION
      INTEGER G,ISAMPL,KRSKIP,LENG,RANK,T,WIDTH
C  **  ASSIGNMENTS
      DATA T/999999/,G/25/
C  **  READ VALUE LENG,WIDTH, AND KRSKIP.  THEY ARE OUTPUT VALUES
C  **  FROM PROGRAM PREEX.
      READ (5,*) LENG,WIDTH,KRSKIP
C  **  TAPE IS REWOUND
      REWIND 8
C  **  FIRST 2 ANNOTATION RECORDS ON CCT ARE SKIPPED.
      READ (8,40)
      READ (8,40)
C  **  KRSKIP=0 ONLY IF WORKING WITH 1ST ROW (RECORD 3) OF BIP2
C  **  DIGITAL DATA.
      IF (KRSKIP .EQ. 0) GO TO 5
C  **  SKIP APPROPRIATE NUMBER OF RECORDS TO REACH STUDY AREA.
      DO 8 J=1,KRSKIP
      READ (8,40)
   40 FORMAT (1X)
    8 CONTINUE
C  **  STUDY AREA IS READ OFF CCT ONE SCAN LINE AT A TIME.
    5 DO 1 I=1,LENG
      READ (8,555) (B7(J),J=1,WIDTH)
C  **  FORMAT STATEMENT SPECIFICATIONS ARE OBTAINED FROM PROGRAM
C  **  PREEX.
  555 FORMAT (120A1)
C  **  BINARY VALUES ARE CONVERTED TO INTEGER FORMAT ONE LINE AT A
C  **  TIME USING SUBROUTINE B1INT.  INTEGER VALUES ARE RETURNED AND
C  **  STORED IN ARRAY ISAMPL.
      DO 2 J=1,WIDTH
      CALL B1INT (B7(J),INT)
      ISAMPL(J)=INT
    2 CONTINUE
C  **  LARGEST AND SMALLEST VALUES IN EACH LINE ARE DETERMINED USING
C  **  SUBROUTINE RANK.
      CALL RANKA1 (ISAMPL,WIDTH,T,G)
C  **  ARRAY B7 IS WRITTEN TO DISK USING THE SPECIFIED FORMAT.
      WRITE (10,1000) (B7(J),J=1,WIDTH)
 1000 FORMAT (120A1)
C  **  CYCLE INCOMPLETE UNTIL I = LENG.
    1 CONTINUE
C  **  LARGEST AND SMALLEST RADIANCE VALUES ARE WRITTEN TO UNIT 6.
      WRITE (6,1001) T,G
```

```
 1001 FORMAT (1H1,'T=',I3,5X,'G=',I3)
      STOP
      END
C                      --------------------
C                        ***SUBROUTINE B1INT***
C                     ----------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                     ----------------------------
C                                VARIABLES
C                     ----------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                      --------------------
C                        ***SUBROUTINE RANKA1***
C                     ----------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                     ----------------------------------
C                                VARIABLES
C                      ----------------------
C     *G            :  LARGEST RATIO VALUE.
C     *ISAMPL       :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                      FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK         :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
```

```
C                       DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C      *RANKA1      :   PROGRAM SUBROUTINE.
C      *T           :   SMALLEST RATIO VALUE.
C      *WIDTH       :   WIDTH (IN PIXELS) OF DATA STRIP.
C                       ----------------------
       SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
       DIMENSION ISAMPL(120),RANK(120)
       INTEGER G,ISAMPL,RANK,T,WIDTH
       DO 3 J=1,WIDTH
       RANK(J)=ISAMPL(J)
     3 CONTINUE
       DO 4 L=1,WIDTH
       IF (G .GE. RANK(L)) GO TO 24
       IF (G .LT. T) T=G
       G=RANK(L)
       GO TO 4
    24 IF (RANK(L) .GE. T) GO TO 4
       T=RANK(L)
     4 CONTINUE
       RETURN
       END
```

APPENDIX F

```
C                        PROGRAM GPCOL (JSZ-1980)
C
C  **  THIS PROGRAM MERGES 2 SEQUENTIAL DATA SETS. MERGING IS DONE
C  **  ON A HORIZONTAL (COLUMNAR) FORMAT.  DATA VALUES FOR RECORD 1
C  **  OF DATA SET 1 ARE COMBINED WITH DATA VALUES FOR RECORD 1 OF
C  **  DATA SET 2 TO PRODUCE A COMBINED RECORD 1 FOR A NEW COMPLETE
C  **  DATA SET.  THIS NEW DATA SET IS WRITTEN TO DISK STORAGE,
C  **  RECORD BY RECORD.
C
C     VARIABLES:
C
C     B6DAT1        :  INITIAL RECORD OF PIXEL RADIANCE VALUES TO BE
C                      COMBINED AND WRITTEN TO DISK (LEFT SIDE).
C     B6DAT2        :  NEXT RECORD OF PIXEL RADIANCE VALUES TO BE
C                      COMBINED AND WRITTEN TO DISK (RIGHT SIDE).
C     LENG          :  LENGTH OF EACH COMPONENT DATA SET (IN PIXELS).
C     WIDTH1        :  WIDTH OF COMPONENT DATA SET 1 (IN PIXELS).
C     WIDTH2        :  WIDTH OF COMPONENT DATA SET 2 (IN PIXELS).
C
      LOGICAL * 1 B6DAT1(276),B6DAT2(560)
      INTEGER LENG,WIDTH1,WIDTH2
C  **  READ:  1. LENGTH OF EACH DATA SET (IN PIXELS),
C  **  2. WIDTH OF DATA SET 1 (IN PIXELS), AND 3. WIDTH OF DATA
C  **  SET 2 (IN PIXELS).
      READ (5,*) LENG,WIDTH1,WIDTH2
      DO 1 I=1,LENG
C  **  VALUES FOR RECORD 1 OF DATA SET 1 ARE READ.
      READ (9,1000) B6DAT1
 1000 FORMAT (2(138A1))
C  **  VALUES FOR RECORD 1 OF DATA SET 2 ARE READ.
      READ (10,1001) B6DAT2
 1001 FORMAT (10(56A1))
C  **  VALUES ARE WRITTEN TO DISK IN A COMBINED FORMAT.
      WRITE (12,1002) (B6DAT1(J),J=1,WIDTH1),(B6DAT2(K),K=1,WIDTH2)
 1002 FORMAT (2(138A1),10(56A1))
    1 CONTINUE
      STOP
      END
```

APPENDIX G

```
C                        PROGRAM GPROW (JSZ-1980)
C
C  **  THIS PROGRAM MERGES 2 SEQUENTIAL DATA SETS.  MERGING IS DONE
C  **  ON A VERTICAL (ROW) FORMAT.  ALL VALUES FOR DATA SET 1 ARE
C  **  WRITTEN TO DISK STORAGE FIRST, FOLLOWED BY THOSE VALUES FOR
C  **  DATA SET 2.
C
C     VARIABLES:
C
C     B7MONT       :  SECOND ARRAY OF PIXEL RADIANCE VALUES TO BE
C                     WRITTEN TO DISK (LOWER).
C     B7MTOP       :  FIRST ARRAY OF PIXEL RADIANCE VALUES TO BE
C                     WRITTEN TO DISK (UPPER).
C     LENG1        :  LENGTH OF COMPONENT DATA SET 1 (IN PIXELS).
C     LENG2        :  LENGTH OF COMPONENT DATA SET 2 (IN PIXELS).
C     WIDTH        :  WIDTH OF EACH COMPONENT DATA SET (IN PIXELS).
C
      LOGICAL * 1 B7MTOP(776),B7MONT(776)
      INTEGER LENG1,LENG2,WIDTH
C  **  READ :  1. LENGTH OF DATA SET 1 (IN PIXELS),
C  **  2. LENGTH OF DATA SET 2 (IN PIXELS), 3. WIDTH OF EACH DATA SET
C  **  IN PIXELS).
      READ (5,*) LENG1,LENG2,WIDTH
      DO 1 I=1,LENG1
C  **  DATA SET 1 IS READ FROM DISK STORAGE (12) AND IMMEDIATELY
C  **  WRITTEN TO ANOTHER DISK UNIT (13).
      READ (12,1000) B7MTOP
 1000 FORMAT (194(4A1))
      WRITE (13,1001) (B7MTOP(K),K=1,WIDTH)
 1001 FORMAT (194(4A1))
    1 CONTINUE
      DO 2 J=1,LENG2
C  **  DATA SET 2 IS READ FROM DISK STORAGE (11) AND ALSO WRITTEN TO
C  **  DISK UNIT 13.
      READ (11,1002) B7MONT
 1002 FORMAT (194(4A1))
      WRITE (13,1003) (B7MONT(L), L=1,WIDTH)
 1003 FORMAT (194(4A1))
    2 CONTINUE
      STOP
      END
```

APPENDIX H

```
C                        PROGRAM RANK (JSZ-1980)
C
C  **  THIS PROGRAM CALCULATES THE LARGEST AND SMALLEST RADIANCE
C  **  VALUES WITHIN A LANDSAT SCENE.
C
C      VARIABLES:
C
C      BX            :  RAW LANDSAT SINGLE-BAND PIXEL RADIANCE VALUE
C                       (BINARY)
C      ISAMBX        :  INTEGER FORMATTED SINGLE BAND LANDSAT DATA
C      LENG          :  LENGTH OF THE DATA SET (IN PIXELS)
C      WIDTH         :  WIDTH OF THE DATA SET (IN PIXELS)
C
      DIMENSION ISAMBX(836)
      LOGICAL * 1 BX(836)
      LOGICAL * 1 H(4)
      EQUIVALENCE (H(1),KK)
      INTEGER G,INT,ISAMBX,LENG,T,WIDTH
C  **  DATA STATEMENT INCLUDES:  CONSTANTS; 'T'=999999 AND 'G'=20.
      DATA T/999999/,G/20/
C  **  READ LENGTH AND WIDTH OF DATA SET (IN PIXELS).
      READ (5,*) LENG,WIDTH
      DO 1 I=1,LENG
C  **  LANDSAT DATA IS READ OFF DISK ONE RECORD AT A TIME.  ONE BYTE
C  **  STORAGE ASSIGNMENTS ARE MADE FOR EACH DATA VALUE.
      READ (9,1000) BX
      DO 2 J=1,WIDTH
      CALL B1INT (BX(J),INT)
C  **  INDIVIDUAL DATA VALUES ARE ASSIGNED SEQUENTIALLY TO ARRAY
C  **  ISAMBX.
      ISAMBX(J)=INT
    2 CONTINUE
      CALL RANKA1 (ISAMBX,WIDTH,T,G)
    1 CONTINUE
C  **  LARGEST AND SMALLEST REFLECTANCE VALUES ARE PRINTED TO UNIT 6.
      PRINT *,T,G
      STOP
 1000 FORMAT (209(4A1))
      END
C                    -------------------
C                   ***SUBROUTINE B1INT***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
```

```
C                  ------------------------------
C                              VARIABLES
C                  ------------------------------
C     *BIN         :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                     STORAGE ALLOCATION.)
C     *B1INT       :  PROGRAM SUBROUTINE.
C     *H(1)        :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)        :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                     BYTE STORAGE ALLOCATION.)
C     *INT         :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK          :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                     ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    ---------------------
C                   ***SUBROUTINE RANKA1***
C                  ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                  ---------------------------------
C                              VARIABLES
C                     ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISAMBX      :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                     ----------------------
      SUBROUTINE RANKA1 (ISAMBX,WIDTH,T,G)
      DIMENSION ISAMBX(836),RANK(836)
      INTEGER G,ISAMBX,RANK,T,WIDTH
```

```
      DO 3 J=1,WIDTH
      RANK(J)=ISAMBX(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX I

```
C                        PROGRAM READCHK (JSZ-1980)
C
C  **  THIS PROGRAM IS A CHECK TO DETERMINE IF TEST DATA STORED ON
C  **  DISK APPEAR VALID.  THIS WILL PREVENT ADDITIONAL MANIPULATIONS
C  **  ON INCORRECT DATA.
C
C     VARIABLES:
C
C     INCR          :  INCREMENT VALUE SPECIFYING EVERY 'TH VALUE TO
C                      PRINT TO UNIT 6.
C     ISUB          :  INTEGER FORMATTED SINGLE BAND LANDSAT DATA
C     LENG          :  LENGTH OF DATA SET (IN PIXELS)
C     SUB           :  RAW LANDSAT SINGLE BAND PIXEL RADIANCE VALUE
C                      (BINARY)
C     WIDTH         :  WIDTH OF DATA SET (IN PIXELS)
C
      LOGICAL * 1 SUB(120),H(4)
      INTEGER ISUB(120),LENG,WIDTH,INCR
      EQUIVALENCE (H(1),KK)
C  **  READ CHECK VARIABLES.
      READ (5,*) LENG,WIDTH,INCR
      DO 1 I=1,LENG
C  **  READ SUBSET DATA RECORD.
      READ (9,1000) SUB
      DO 2 J=1,WIDTH
      CALL B1INT (SUB(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISUB(J)=INT
    2 CONTINUE
C  **  WRITE EVERY 'INCR-TH' VALUE TO UNIT 6.
      WRITE (6,1001) (ISUB(J),J=1,WIDTH,INCR)
    1 CONTINUE
      STOP
 1000 FORMAT (120A1)
 1001 FORMAT (40(1X,I2))
      END
C                      --------------------
C                     ***SUBROUTINE B1INT***
C                   ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                   ------------------------------
C                              VARIABLES
C                   ------------------------------
```

```
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
```

APPENDIX J

```
C                        PROGRAM PEAKVALY (JSZ-1981)
C
C  **  THIS PROGRAM COMPUTES THE DISTRIBUTION OF RADIANCE VALUES
C  **  WITHIN A SUBSCENE AND WHETHER THE INDIVIDUAL RADIANCE VALUES
C  **  ARE AT PEAK, VALLEY, OR SLOPE POSITIONS.  THE MEAN RADIANCE
C  **  VALUE FOR THE SUBSCENE IS ALSO COMPUTED.
C
C     VARIABLES:
C
C     BV            :  RAW LANDSAT SINGLE-BAND PIXEL RADIANCE VALUES
C                      (BINARY)
C     IBV           :  INTEGER FORMATTED RAW LANDSAT SINGLE-BAND PIXEL
C                      RADIANCE VALUES
C     K             :  CONSTANT WHICH INITIALIZES BEGINNING OF
C                      RADIANCE FREQUENCY SEARCH AND INCREMENT
C     KOUNT         :  FREQUENCY OF EACH LANDSAT RADIANCE VALUE
C     LENG          :  LENGTH OF THE DATA SET (IN PIXELS)
C     MEAN          :  MEAN DATA SET RADIANCE
C     N             :  TOTAL NUMBER OF PIXELS IN THE DATA SET
C     TOTAL         :  SUM OF ALL RADIANCE VALUES
C     UPLMT         :  GREATEST PIXEL RADIANCE IN THE DATA SET
C     WIDTH         :  WIDTH OF THE DATA SET (IN PIXELS)
C
      DIMENSION IBV(120),KOUNT(71)
      LOGICAL * 1 BV(120)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER TOTAL,N,KOUNT,IBV,LENG,WIDTH,UPLMT
      REAL*8 MEAN
C  **  DATA STATEMENT INCLUDES:  1.  NUMBER OF INDEPENDENT
C  **  RADIANCE VALUES IN THE SPECIFIC BAND SUBSCENE (E.G., VALUES
C  **  FOR BAND 6 RANGE FROM 4-94.  EVEN THOUGH THE RANGE OF VALUES
C  **  IS 91, USE THE UPPER VALUE LIMIT PLUS ONE (94+1) FOR THE
C  **  RANGE VARIABLE 'UPLMT'=95 (RANGE CAN BE DETERMINED BY
C  **  EXECUTING PROGRAM RANK), AND 2. AND 3. N AND TOTAL ARE
C  **  SUMMATION AND INCREMENT VARIABLES RESPECTIVELY, ORIGINALLY
C  **  INITIATED TO 0.
C  **  NOTE:  BE SURE THAT THE VALUE ASSIGNED TO VARIABLE 'UPLMT' IS
C  **  ALSO THE MULTIPLE FOR VARIABLE 'KOUNT' IN THE DATA STATEMENT.
      DATA KOUNT/71*0/,N/0/,TOTAL/0/
C  **  READ: 1. LENGTH OF THE DATA SET (IN PIXELS), 2. WIDTH OF THE
C  **  DATA SET (IN PIXELS), AND 3. GREATEST SUBSCENE RADIANCE VALUE
C  **  PLUS ONE.
      READ (5,*) LENG,WIDTH,UPLMT
```

```
      DO 1 I=1,LENG
C  **  VALUES ARE READ ONE RECORD AT A TIME.
      READ (9,1000) BV
      DO 2 J=1,WIDTH
      CALL B1INT (BV(J),INT)
C  **  INTEGER ASSIGNMENT.
      IBV(J)=INT
      K=0
C  **  FREQUENCY OF EACH RADIANCE VALUE (K) IS DETERMINED AND STORED
C  **  AS K+1.  ARRAY VALUE K CANNOT = 0.
    4 IF(IBV(J).EQ.K) GO TO 5
      K=K+1
      GO TO 4
    5 KOUNT(K+1)=KOUNT(K+1)+1
C  **  SUMMING OF RADIANCE VALUES.
      TOTAL=TOTAL+IBV(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
    2 CONTINUE
    1 CONTINUE
C  **  MEAN RADIANCE COMPUTED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  NUMBER OF PIXELS PROCESSED, TOTAL SUM OF RADIANCES, AND
C  **  RADIANCE MEAN IS WRITTEN TO UNIT 6
      PRINT *,N,TOTAL,MEAN
      DO 6 J=1,UPLMT
C  **  ARRAY STORAGE FACTOR (K + 1) IS REMOVED.
      M=J-1
C  **  EACH RADIANCE VALUE AND CORRESPONDING FREQUENCY IS WRITTEN TO
C  **  UNIT 6.
      WRITE (6,1001) M,KOUNT(J)
C  **  THE FOLLOWING 3 STATEMENTS DETERMINE WHAT THE BAND RADIANCE
C  **  VALUE IS AND WHERE IT IS LOCATED (E.G., FIRST, LAST, ETC...)
C  **  IN RELATION TO OTHER RADIANCE VALUES.  THE MAIN PROGRAM THEN
C  **  TRANSFERS TO AN APPROPRIATE SUBROUTINE FOR PEAK OR VALLEY
C  **  ASSIGNMENTS. IF THE VALUE IS FOUND ON A SLOPE, NO ASSIGNMENT
C  **  IS MADE.
      IF ((J-1).LT.1) CALL SETUP1 (M,KOUNT(J),KOUNT(J+1))
      IF ((J+1).GT.UPLMT) CALL SETUP2 (M,KOUNT(J),KOUNT(J-1))
      IF ((J-1).GE.1.AND.(J+1).LE.UPLMT) CALL SETUP3 (M,KOUNT(J),
     &KOUNT(J-1),KOUNT(J+1))
    6 CONTINUE
      STOP
 1000 FORMAT (4(209A1))
 1001 FORMAT (1H ,'KOUNT',I3,3X,I6)
      END
C                    --------------------
```

```
C                    ***SUBROUTINE B1INT***
C                   ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                   ------------------------------
C                             VARIABLES
C                   ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C
C                     -------------------
C                     *SUBROUTINE SETUP1*
C                    ----------------------
C******THIS SUBROUTINE DETERMINES THE APPROPRIATE ASSIGNMENT (PEAK OR
C   ***VALLEY) FOR THE FIRST (I.E., SMALLEST) RADIANCE VALUE.
C                    ----------------------
C                          VARIABLES
C                    ----------------------
C     *M            :  RADIANCE VALUE
C     *ICV          :  FREQUENCY OF RADIANCE VALUE M.
C     *ICV1         :  FREQUENCY OF RADIANCE VALUE M+1.
C     ------------------------------------------------------------------
      SUBROUTINE SETUP1 (M,ICV,ICV1)
      INTEGER M,ICV,ICV1
      IF (ICV.EQ.0.AND.ICV1.EQ.0) GO TO 1
      IF (ICV.LE.ICV1) WRITE (6,100)M
      IF (ICV.GT.ICV1) WRITE (6,102)M
  100 FORMAT (1H ,5X,I3,2X,'VALLEY')
  102 FORMAT (1H ,5X,I3,2X,'PEAK')
    1 RETURN
```

```
      END
C                    ------------------
C                     *SUBROUTINE SETUP2*
C                    ----------------------
C******THIS SUBROUTINE DETERMINES THE APPROPRIATE ASSIGNMENT (PEAK OR
C   ***VALLEY) FOR THE LAST (I.E., GREATEST) RADIANCE VALUE.
C                    ----------------------
C                          VARIABLES
C                    ----------------------
C     *M              :  RADIANCE VALUE
C     *ICV            :  FREQUENCY OF RADIANCE VALUE M.
C     *ICV1           :  FREQUENCY OF RADIANCE VALUE M+1.
C     ------------------------------------------------------------------
      SUBROUTINE SETUP2 (M,ICV,ICV0)
      INTEGER M,ICV,ICV0
      IF (ICV .LE. ICV0) WRITE (6,100)M
      IF (ICV .GT. ICV0) WRITE (6,102)M
  100 FORMAT (1H ,5X,I3,2X,'VALLEY')
  102 FORMAT (1H ,5X,I3,2X,'PEAK')
      RETURN
      END
C                     ------------------
C                     *SUBROUTINE SETUP3*
C                    ----------------------
C******THIS SUBROUTINE DETERMINES THE APPROPRIATE ASSIGNMENT (PEAK OR
C   ***VALLEY) FOR THE REMAINDER OF RADIANCE VALUES.
C                   --------------------------
C                          VARIABLES
C                   --------------------------
C     *M             :  RADIANCE VALUE
C     *ICV           :  FREQUENCY OF RADIANCE VALUE M.
C     *ICV0          :  FREQUENCY OF RADIANCE VALUE M-1.
C     *ICV1          :  FREQUENCY OF RADIANCE VALUE M+1.
C     ------------------------------------------------------------------
      SUBROUTINE SETUP3 (M,ICV,ICV0,ICV1)
      INTEGER V1,V2,P1,P2,M,ICV,ICV0,ICV1
      V1=0
      V2=0
      P1=0
      P2=0
      IF (ICV .LE. ICV0) V1=1
      IF (ICV .LT. ICV1) V2=2
      IF (ICV .GT. ICV0) P1=1
      IF (ICV .GE. ICV1) P2=2
      IF (V1.EQ.1.AND.V2.EQ.2) WRITE (6,100)M
  100 FORMAT (1H ,5X,I3,2X,'VALLEY')
      IF (P1.EQ.1.AND.P2.EQ.2) WRITE (6,102)M
```

```
102 FORMAT (1H ,5X,I3,2X,'PEAK')
    RETURN
    END
```

APPENDIX K

```
C                        PROGRAM SUBSET (JSZ-1980)
C
C  **  THIS PROGRAM SUBSETS A LARGE DATA SET STORED ON DISK.
C
C     VARIABLES:
C
C     KRSKIP        :  NUMBER OF RECORDS TO SKIP BEFORE REACHING
C                      AREA TO SUBSET.
C     LENG          :  LENGTH OF SUBSET AREA (IN PIXELS)
C     SUB           :  RAW LANDSAT SINGLE-BAND PIXEL RADIANCE VALUE
C                      (BINARY)
C     WIDTH         :  WIDTH OF SUBSET AREA (IN PIXELS)
C
      LOGICAL * 1 SUB(185)
      INTEGER KRSKIP,LENG,WIDTH
C  **  READ SUBSET VARIABLES.
      READ (5,*) KRSKIP,LENG,WIDTH
C  **  CHECK IF SUBSET BEGINS AT TOP OF DATA SET.
      IF (KRSKIP .EQ. 0) GO TO 5
      DO 8 J=1,KRSKIP
C  **  SKIP APPROPRIATE NUMBER OF DATA RECORDS.
      READ (9,1000)
    8 CONTINUE
    5 DO 1 I=1,LENG
C  **  READ SUBSET DATA RECORD FROM DISK.
      READ (9,1001) (SUB(J),J=1,WIDTH)
C  **  WRITE SUBSET DATA RECORD TO DISK.
      WRITE (10,1002) (SUB(J),J=1,WIDTH)
      WRITE (6,100)
    1 CONTINUE
      STOP
  100 FORMAT (1H1,'ONE RECORD WRITTEN TO DISK')
 1000 FORMAT (1X)
 1001 FORMAT (2(145X),185A1)
 1002 FORMAT (185A1)
      END
```

APPENDIX L

```
C                        PROGRAM ATMCOR (JSZ-1980)
C
C  **  THIS PROGRAM USES THE ATMOSPHERIC EFFECTS CORRECTION ALGORITHM
C  **  TO REMOVE THE INHERENT ATMOSPHERIC SCATTERING PRESENT IN A
C  **  SPECTRAL BAND.
C
C       VARIABLES:
C
C       B4MONT       :  BINARY FORMATTED PRE- AND POST-ATMOSPHERICALLY
C                       CORRECTED RADIANCE DATA
C       IB4          :  INTEGER FORMATTED SINGLE-BAND LANDSAT RADIANCE
C                       DATA
C       LENG         :  LENGTH OF THE DATA SET (IN PIXELS)
C       NB4          :  ATMOSPHERIC ATTENUATION CORRECTED RADIANCE DATA
C       T            :  BIAS OR THE AMOUNT OF OFFSET IN A SPECTRAL BAND
C       WIDTH        :  WIDTH OF THE DATA SET (IN PIXELS)
C
      DIMENSION IB4(836),NB4(836)
      LOGICAL * 1 B4MONT(836)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,IB4,T,NB4
C  **  READ:  1.LENGTH OF THE DATA SET IN PIXELS,
C  **  2.  WIDTH OF THE DATA SET IN PIXELS, AND 3.  BIAS OR THE
C  **  AMOUNT OF OFFSET IN A SPECTRAL BAND (EX. BIAS = MIN).
C  **  THE MIN VALUE CAN BE OBTAINED FROM PROGRAM RANK.
      READ (5,*) LENG,WIDTH,T
      DO 1 I=1,LENG
C  **  VALUES ARE READ ONE RECORD AT A TIME.
      READ (9,1000) B4MONT
      DO 2 J=1,WIDTH
      CALL B1INT (B4MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      IB4(J)=INT
C  **  ATMOSPHERIC EFFECTS CORRECTION.
      NB4(J)=IB4(J)-T
      CALL INTB1 (NB4(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      B4MONT(J)=BIN
    2 CONTINUE
C  **  CORRECTED VALUE IS WRITTEN TO DISK.
      WRITE (10,1000) (B4MONT(J),J=1,WIDTH)
    1 CONTINUE
      STOP
```

```
 1000 FORMAT (209(4A1))
      END
C                    --------------------
C                      ***SUBROUTINE B1INT***
C                    ----------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                    ----------------------------
C                              VARIABLES
C                    ----------------------------
C     *BIN           :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                       STORAGE ALLOCATION.)
C     *B1INT         :  PROGRAM SUBROUTINE.
C     *H(1)          :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)          :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                       BYTE STORAGE ALLOCATION.)
C     *INT           :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK            :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                       ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                      ***SUBROUTINE INTB1***
C                    ----------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY
C   ***FORM THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C   ***INFORMATION.
C                    ----------------------------
C                              VARIABLES
C                    ----------------------------
C     *BIN           :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                       STORAGE ALLOCATION.)
C     *H(1)          :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)          :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                       BYTE STORAGE ALLOCATION.)
C     *INT           :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1         :  PROGRAM SUBROUTINE.
C     *KK            :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
```

```
C                    ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      KK=INT
      BIN=H(4)
      RETURN
      END
```

APPENDIX M

```
C                        PROGRAM CNSTRCH (JSZ-1980)
C
C  **  THIS PROGRAM REASSIGNS SUBSCENE RADIANCE VALUES ON A PIXEL-BY-
C  **  PIXEL BASIS.  BASICALLY, THE PROGRAM SEPARATES (STRETCHES) THE
C  **  PIXEL VALUES AS MUCH AS POSSIBLE TO FILL THE COMPLETE
C  **  RANGE OF THE DISPLAY MEDIUM.  (RANGE 0 -255)
C
C     VARIABLES:
C
C     BBV          :  BINARY FORMATTED LINEAR CONTRAST STRETCH OUTPUT
C                     VALUE
C     BV           :  RAW LANDSAT SINGLE-BAND PIXEL RADIANCE DATA
C                     (BINARY)
C     C            :  CONSTANT = 255.  UPPER LIMIT OF STRETCHED
C                     VALUES.
C     IBV          :  INTEGER FORMATTED SINGLE-BAND LANDSAT DATA
C     LCV          :  LINEAR CONTRAST STRETCH OUTPUT VALUE
C     LENG         :  LENGTH OF THE DATA SET (IN PIXELS)
C     MAX          :  GREATEST RADIANCE VALUE IN THE SINGLE BAND
C                     SCENE
C     MIN          :  SMALLEST RADIANCE VALUE IN THE SINGLE BAND
C                     SCENE
C     WIDTH        :  WIDTH OF THE DATA SET (IN PIXELS)
C
      DIMENSION IBV(836),LCV(836)
      LOGICAL * 1 BV(836),BBV(836)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER G,IBV,LCV,LENG,MAX,MIN,T,WIDTH
      REAL C
C  **  DATA STATEMENT INCLUDES:  CONSTANTS; 'C'=255., 'T'=999999,
C  **  AND 'G'=1.
      DATA C/255./,T/999999/,G/1/
C  **  READ:  1. LENGTH OF THE DATA SET (IN PIXELS),
C  **  2. WIDTH OF THE DATA SET (IN PIXELS), 3. MINIMUM BAND RADIANCE
C  **  VALUE (E.G., B7=0) IN THE SUBSCENE, AND 4. MAXIMUM BAND
C  **  RADIANCE VALUE IN THE SUBSCENE.
      READ (5,*) LENG,WIDTH,MIN,MAX
      DO 1 I=1,LENG
C  **  VALUES FOR RAW UNSTRETCHED DATA ARE READ IN ONE RECORD AT A
C  **  TIME.
      READ (9,1000) BV
      DO 2 J=1,WIDTH
      CALL B1INT (BV(J),INT)
```

```
C  **  VALUES ARE PLACED IN AN INTEGER FORMATTED ARRAY.
      IBV(J)=INT
C  **  CONTRAST STRETCH ALGORITHM.
      LCV(J)=(((FLOAT(IBV(J)-MIN))/(FLOAT(MAX-MIN)))*C)+.5
      CALL INTB1 (LCV(J),BIN)
C  **  STRETCHED VALUES ARE FORMATTED TO 1 BYTE STORAGE.
      BBV(J)=BIN
    2 CONTINUE
      CALL RANKA1 (LCV,WIDTH,T,G)
C  **  STRETCHED VALUES ARE WRITTEN TO DISK.
      WRITE (10,1000) (BBV(J),J=1,WIDTH)
    1 CONTINUE
C  **  LARGEST AND SMALLEST RADIANCE VALUES ARE PRINTED TO UNIT 6.
      PRINT *,T,G
      STOP
 1000 FORMAT (4(209A1))
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                  ----------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                  ----------------------------
C                            VARIABLES
C                  ----------------------------
C     *BIN         :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                     STORAGE ALLOCATION.)
C     *B1INT       :  PROGRAM SUBROUTINE.
C     *H(1)        :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)        :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                     BYTE STORAGE ALLOCATION.)
C     *INT         :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK          :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                     ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE INTB1***
C                  ----------------------------
```

```
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C    ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C    ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C     **INFORMATION.
C                  ------------------------------
C                              VARIABLES
C                  ------------------------------
C      *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                       STORAGE ALLOCATION.)
C      *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C      *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                       BYTE STORAGE ALLOCATION.)
C      *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C      *INTB1        :  PROGRAM SUBROUTINE.
C      *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                       ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C      ------------------------------------------------------------------
       SUBROUTINE INTB1(INT,BIN)
       INTEGER INT,KK
       LOGICAL * 1 BIN,H(4)
       EQUIVALENCE (H(1),KK)
       KK=0
       KK=INT
       BIN=H(4)
       RETURN
       END
C                     ---------------------
C                    ***SUBROUTINE RANKA1***
C                  --------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                  ---------------------------------
C                              VARIABLES
C                     ----------------------
C      *G           :  LARGEST RATIO VALUE.
C      *LCV          : ARRAY CONTAINING RATIO VALUES IN INTEGER
C                       FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C      *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                       DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C      *RANKA1      :  PROGRAM SUBROUTINE.
C      *T           :  SMALLEST RATIO VALUE.
C      *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
```

```
C                    ----------------------
      SUBROUTINE RANKA1 (LCV,WIDTH,T,G)
      DIMENSION LCV(836),RANK(836)
      INTEGER G,LCV,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=LCV(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX N

```
C                        PROGRAM REGRESS (JSZ-1980)
C
C  **  THIS PROGRAM PERFORMS A SIMPLE LINEAR REGRESSION ON 2 MSS
C  **  BANDS TO DETERMINE THEIR APPROPRIATE RELATION.
C
C  **  VARIABLES:
C
C     BOHAT          :  Y-INTERCEPT.
C     B1HAT          :  SLOPE OF THE REGRESSION LINE.
C     BBV1           :  BINARY FORMATTED RADIANCE VALUES FROM DATA
C                       SET 1.
C     BBV2           :  BINARY FORMATTED RADIANCE VALUES FROM DATA
C                       SET 2.
C     CIB1HT         :  CONFIDENCE INTERVAL FOR B1HAT.
C     CIYHAT         :  CONFIDENCE INTERVAL FOR Y-HAT.
C     LENG           :  LENGTH OF THE DATA SET (IN PIXELS).
C     LINREL         :  VALUE WHICH INDICATES WHETHER A LINEAR TREND
C                       EXISTS BETWEEN THE 2 DATA SETS.
C     MNX            :  INDEPENDENT VARIABLE MEAN.
C     MNY            :  DEPENDENT VARIABLE MEAN.
C     R              :  COEFFICIENT OF CORRELATION.
C     R2             :  COEFFICIENT OF DETERMINATION.
C     RBV1           :  REAL FORMATTED RADIANCE VALUES FROM DATA SET 1.
C     RBV2           :  REAL FORMATTED RADIANCE VALUES FROM DATA SET 2.
C     S              :  STANDARD DEVIATION.
C     S2             :  VARIANCE.
C     SSE            :  SUM OF SQUARES FOR ERROR.
C     SSX            :  SUM OF SQUARES FOR X.
C     SSXY           :  SUM OF SQUARES FOR XY.
C     SSY            :  SUM OF SQUARES FOR Y.
C     SX             :  SQUARE ROOT OF THE SUM OF SQUARES.
C     T              :  T-STATISTIC.
C     T025           :  APPROPRIATE T-VALUE AT A CHOSEN CONFIDENCE
C                       INTERVAL.
C     TLN            :  TOTAL NUMBER OF PIXELS IN EACH DATA SET.
C     TLX            :  TOTAL SUM OF INDEPENDENT VARIABLE VALUES.
C     TLX2           :  TOTAL OF SQUARED INDEPENDENT VARIABLE VALUES.
C     TLXY           :  TOTAL OF INDEPENDENT-DEPENDENT MULTIPLICATION.
C     TLY            :  TOTAL SUM OF DEPENDENT VARIABLE VALUES.
C     TLY2           :  TOTAL OF SQUARED INDEPENDENT VARIABLE VALUES.
C     WIDTH          :  WIDTH OF DATA SET (IN PIXELS).
C     XEX            :  A SPECIFIED X VALUE FOR USE IN THE Y-HAT
C                       COMPUTATION (E.G., 50).
C     YHAT           :  Y-HAT.
```

```
C
      DIMENSION RBV1(836),RBV2(836)
      LOGICAL * 1 BBV1(836),BBV2(836)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,LINREL
      REAL * 8 RBV1,RBV2,TLX,TLY,TLX2,TLXY,TLY2,MNY,MNX,B1HAT,BOHAT,
     &TLN,TLSX2,TLSXY,TLSY2,R2,R,SSX,SSXY,SX,S,SSY,SSE,S2,T,CIB1HT,
     &CIYHAT,YHAT,PI,T025,XEX
      DATA TLX,TLY,TLX2,TLXY,TLY2/5*0.0/,LINREL/0/
C  **  READ INCLUDES:  1.  LENGTH OF DATA SET (IN PIXELS), 2.  WIDTH
C  **  OF DATA SET (IN PIXELS), 3.  TOTAL AREA OF DATA SET IN
C  **  PIXELS (ROW * COLUMN), 4.  APPROPRIATE T-VALUE AT A CHOSEN
C  **  CONFIDENCE INTERVAL, AND 5.  A SPECIFIED X VALUE FOR USE IN
C  **  THE Y-HAT COMPUTATION.
      READ (5,*) LENG,WIDTH,T025,XEX
      TLN=FLOAT(LENG*WIDTH)
      DO 1 I=1,LENG
C  **  READ IN X AND Y DATA RECORDS, RESPECTIVELY.
      READ (9,1000) BBV1
      READ (10,1000) BBV2
      DO 2 J=1,WIDTH
      CALL B1INT (BBV1(J),INT)
C  **  REAL ASSIGNMENT.
      RBV1(J)=DFLOAT(INT)
      CALL B1INT (BBV2(J),INT)
C  **  REAL ASSIGNMENT.
      RBV2(J)=DFLOAT(INT)
C  **  X VARIABLE SUMMATION.
      TLX=TLX+RBV1(J)
C  **  Y VARIABLE SUMMATION.
      TLY=TLY+RBV2(J)
C  **  X**2 SUMMATION.
      TLX2=TLX2+(RBV1(J)**2)
C  **  X*Y SUMMATION.
      TLXY=TLXY+(RBV1(J)*RBV2(J))
C  **  Y**2 SUMMATION.
      TLY2=TLY2+(RBV2(J)**2)
    2 CONTINUE
    1 CONTINUE
C  **  CALCULATE MEAN Y.
      MNY=TLY/TLN
C  **  CALCULATE MEAN X.
      MNX=TLX/TLN
C  **  CALCULATE SUM OF SQUARES FOR X.
      SSX=TLX2-((TLX**2)/TLN)
C  **  CALCULATE SUM OF SQUARES FOR XY.
```

```
      SSXY=TLXY-((TLX*TLY)/TLN)
C  **  CALCULATE SLOPE OF THE REGRESSION LINE.
      B1HAT=SSXY/SSX
C  **  CALCULATE THE Y-INTERCEPT.
      BOHAT=MNY-(B1HAT*MNX)
      WRITE (6,1001) BOHAT,B1HAT
C  **  CALCULATE SUM OF SQUARES FOR Y.
      SSY=TLY2-((TLY**2)/TLN)
C  **  CALCULATE SUM OF SQUARES FOR ERROR.
      SSE=SSY-(B1HAT*SSXY)
C  **  CALCULATE THE VARIANCE.
      S2=SSE/(TLN-2)
      WRITE (6,1003) S2
C  **  TAKE SQUARE ROOT OF SUM OF SQUARES FOR X.
      SX=DSQRT(SSX)
C  **  CALCULATE THE STANDARD DEVIATION.
      S=DSQRT(S2)
C  **  CALCULATE THE TEST OR T-STATISTIC.
      T=(B1HAT/S)*SX
C  **  DETERMINE IF THE RELATION IS LINEAR.
      IF (T.GT.T025.OR.T.LT.-(T025)) LINREL=1
      WRITE (6,1004) LINREL
C  **  DETERMINE THE CONFIDENCE INTERVAL FOR B1HAT.
      CIB1HT=(T025*S)/SX
      WRITE (6,1005) B1HAT,CIB1HT
C  **  DETERMINE THE CONFIDENCE INTERVAL FOR Y-HAT.
      CIYHAT=(T025*S)*(DSQRT (1/TLN)+(((XEX-MNX)**2)/SSX))
C  **  CALCULATE Y-HAT.
      YHAT=BOHAT+(B1HAT*XEX)
      WRITE (6,1006) XEX
      WRITE (6,1007) YHAT,CIYHAT
C  **  CALCULATE THE COEFFICIENT OF CORRELATION.
      R=SSXY/(DSQRT(SSX*SSY))
C  **  CALCULATE THE COEFFICIENT OF DETERMINATION.
      R2=(SSY-SSE)/SSY
      WRITE (6,1002) R2,R,T
      STOP
 1000 FORMAT (4(209A1))
 1001 FORMAT (1H1,10X,'Y-HAT = ',F6.2,' + ',F6.2,' X')
 1002 FORMAT (1H0,10X,'R2 = ',F4.2,'  R = ',F4.2,'  T = ',F7.2)
 1003 FORMAT (1H0,10X,'S2 = ',F7.2)

 1005 FORMAT (1H0,10X,'THE 95% C.I. FOR B1 IS ',F4.2,' + - ',F4.2)
 1006 FORMAT (1H0,10X,'C.I. FOR E(Y)',F3.0,')')
 1007 FORMAT (1H ,9X,F5.1,' + - ',F7.2)
      END
C                    --------------------
```

```
C                    ***SUBROUTINE B1INT***
C                   ----------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                   ----------------------------
C                             VARIABLES
C                   ----------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
```

APPENDIX O

```
C                          PROGRAM BIBLOC (JSZ-1981)
C
C  **  THIS PROGRAM CREATES A BIOMASS INDEX FROM LANDSAT BANDS 4
C  **  AND 5.
C
C      VARIABLES:
C
C      B4MONT       :  LANDSAT BAND 4 DATA SET (BINARY)
C      B5MONT       :  LANDSAT BAND 5 DATA SET (BINARY)
C      BI           :  REAL FORMATTED PRELIMINARY 4/5 INDEX VALUE
C      BIVAL        :  BINARY FORMATTED 4/5 INDEX OUTPUT
C                      VALUE
C      IBI          :  INTEGER FORMATTED 4/5 INDEX OUTPUT VALUE
C      INCR         :  INCREMENT VALUE WHICH SPECIFIES EVERY 'TH
C                      VALUE(S) BEING WRITTEN TO DISK
C      ISAMB4       :  LANDSAT BAND 4 PIXEL RADIANCE (INTEGER)
C      ISAMB5       :  LANDSAT BAND 5 PIXEL RADIANCE (INTEGER)
C      LENG         :  LENGTH OF EACH DATA SET (IN PIXELS)
C      MEAN         :  MEAN 4/5 INDEX VALUE FOR THE OUTPUT SCENE
C      N            :  AREA OF EACH DATA SET (IN PIXELS)
C      TOTAL        :  SUM OF 4/5 INDEX VALUES FOR THE COMPLETE
C                      OUTPUT SCENE
C      WIDTH        :  WIDTH OF EACH DATA SET (IN PIXELS)
C
      DIMENSION IBI(120),ISAMB4(120),ISAMB5(120)
      LOGICAL * 1 B4MONT(120),B5MONT(120),BIVAL(120)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,ISAMB4,ISAMB5,IBI,T,G,TOTAL,INCR
      REAL BI,MEAN
C  **  DATA STATEMENT INCLUDES:  1. TOTAL, AND 2. N, ARE
C  **  SUMMATION AND INCREMENT VARIABLES, RESPECTIVELY, ORIGINALLY
C  **  ASSIGNED TO 0, 3. DUMMY VALUE WHICH REPRESENTS THE SMALLEST
C  **  RATIO VALUE, AND 4. DUMMY VALUE WHICH REPRESENTS THE LARGEST
C  **  RATIO VALUE.
      DATA TOTAL/0/,N/0/,T/999999/,G/75/
C  **  READ LENGTH AND WIDTH OF DATA SET (IN PIXELS) AND INCREMENT
C  **  VALUE (INC VAL - USED TO SUBSET A SAMPLE OF RADIANCE VALUES
C  **  FOR PLOTALL PROGRAM).
      READ (5,*) LENG,WIDTH,INCR
      DO 1 I=1,LENG
C  **  EACH DATA SET IS READ ONE RECORD AT A TIME.
      READ (9,1000) B4MONT
      READ (10,1000) B5MONT
```

```
      DO 2 J=1,WIDTH
      CALL B1INT (B4MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB4(J)=INT
      CALL B1INT (B5MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB5(J)=INT
C  **  CHECK DENOMINATOR FOR 0 VALUE.
      IF (ISAMB5(J) .NE. 0) GO TO 10
C  **  CONDITIONAL ASSIGNMENT.
      BI=0.
      GO TO 20
C  **  BIOMASS INDEX IS CALCULATED.
   10 BI=(FLOAT(ISAMB4(J))/FLOAT(ISAMB5(J))) * 50.
C  **  ROUNDING OFF STEP.
   20 IBI(J)=IFIX(BI+.5)
C  **  SUMMATION OF INDEX VALUES.
      TOTAL=TOTAL+IBI(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
      CALL INTB1 (IBI(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      BIVAL(J)=BIN
    2 CONTINUE
      CALL RANKA1 (IBI,WIDTH,T,G)
C  **  BIOMASS INDEX VALUES ARE WRITTEN TO DISK.
      WRITE (13,1000) (BIVAL(J),J=1,WIDTH)
C  **  THE 'INCR' VALUE FOR BOTH ISAMB4 AND ISAMB5 IS WRITTEN TO
C  **  DISK FOR USE WITH THE PLOTALL SCATTERPLOT PROGRAM.
      DO 3 K=1,WIDTH,INCR
      WRITE (11,1001) ISAMB4(K),ISAMB5(K)
    3 CONTINUE
    1 CONTINUE
C  **  AVERAGE INDEX VALUE IS CALCULATED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  SMALLEST AND LARGEST INDEX VALUE, SUBSCENE AREA IN PIXELS,
C  **  MEAN INDEX VALUE, AND BIOMASS INDEX SUM ARE WRITTEN TO UNIT 6.
      PRINT *,T,G,N,MEAN,TOTAL
      STOP
 1000 FORMAT (120A1)
 1001 FORMAT (I3,1X,I3)
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
```

```
C                 ------------------------------
C                           VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE INTB1***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                 ------------------------------
C                           VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
```

```
      KK=INT
      BIN=H(4)
      RETURN
      END
C                    ---------------------
C                   ***SUBROUTINE RANKA1***
C                 ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                 ---------------------------------
C                             VARIABLES
C                            ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISAMPL      :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                     ----------------------
      SUBROUTINE RANKA1 (IBI,WIDTH,T,G)
      DIMENSION IBI(120),RANK(120)
      INTEGER G,IBI,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=IBI(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX PP

NATIVE TREES OF MONTGOMERY COUNTY: Blacksburg locale.
version 1.2

Information compiled by John S. Zack

This listing includes those forest trees which are native to Montgomery County, Virginia. Existance of the following species in this area is based on the work of Massey (1961) and silvicultural range maps from Fowells (1965). If a species could not be differentiated as to its large shrub or small tree status, it was not included. Trees which have become naturalized in this county were also excluded.

Abbreviations:
(SA) - present only in select areas.

1. Family Aceraceae — Maple Family
   - Acer negundo: boxelder
   - Acer pensylvanicum: striped maple (SA)
   - Acer rubrum: red maple
   - Acer saccharinum: silver maple
   - Acer saccharum: sugar maple

2. Family Betulaceae — Birch Family
   - Betula lenta: black (sweet) birch
   - Betula nigra: river birch (SA)
   - Carpinus caroliniana: American hornbeam (musclewood)
   - Ostrya virginiana: eastern hophornbeam (ironwood)

3. Family Cornaceae — Dogwood Family
   - Cornus florida: flowering dogwood

4. Family Cupressaceae — Cypress or Cedar Family
   - Juniperus virginiana: eastern redcedar
   - Thuja occidentalis: northern white-cedar (SA)

5. Family Ebenaceae — Ebony Family
   - Diospyros virginiana: common persimmon

6. Family Ericaceae — Heath Family
   - Oxydendrum arboreum: sourwood

7. Family Fagaceae Beech Family
   Fagus grandifolia: American beech
   Quercus alba: white oak
   Quercus bicolor: swamp white oak (SA)
   Quercus coccinea: scarlet oak
   Quercus muehlenbergii: chinquapin oak (SA)
   Quercus prinus: chestnut oak
   Quercus rubra: northern red oak
   Quercus stellata: post oak
   Quercus velutina: black oak

8. Family Hippocastanaceae Buckeye Family
   Aesculus octandra: yellow buckeye (SA)

9. Family Juglandaceae Walnut Family
   Carya cordiformis: bitternut hickory
   Carya glabra: pignut hickory
   Carya laciniosa: shellbark hickory (SA)
   Carya ovalis: red hickory
   Carya tomentosa: mockernut hickory
   Juglans cinerea: butternut (SA)
   Juglans nigra: black walnut

10. Family Lauraceae Laurel Family
    Sassafras albidum: sassafras

11. Family Leguminosae Pulse or Pea Family
    Robinia pseudoacacia: black locust

12. Family Magnoliaceae Magnolia Family
    Liriodendron tulipifera: yellow-poplar
    Magnolia acuminata: cucumbertree (SA)

13. Family Moraceae Mulberry Family
    Morus rubra: red mulberry

14. Family Nyssaceae Tupelo Family
    Nyssa sylvatica: blackgum (black tupelo)

15. Family Oleaceae Olive Family
    Fraxinus americana: white ash
    Fraxinus pennsylvanica: green ash

16. Family Pinaceae Pine Family
Pinus echinata: shortleaf pine (SA)
Pinus pungens: table-mountain pine
Pinus rigida: pitch pine
Pinus strobus: eastern white pine
Pinus virginiana: Virginia pine
Pinus canadensis: eastern hemlock
Pinus caroliniana: Carolina hemlock (SA)

17. Family Platanaceae Sycamore or Planetree Family
Platanus occidentalis: American sycamore

18. Family Rosaceae Rose Family
Amelanchier arborea: downy serviceberry
Prunus pennsylvanica: pin cherry
Prunus serotina: black cherry

19. Family Salicaceae Willow or Poplar Family
Populus grandidentata: bigtooth aspen (SA)
Salix nigra: black willow

20. Family Tiliaceae Linden Family
Tilia americana: American basswood (SA)
Tilia heterophylla: white basswood (SA)

21. Family Ulmaceae Elm Family
Celtis occidentalis: hackberry (SA)
Ulmus americana: American elm (SA)
Ulmus rubra: slippery elm (SA)

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APPENDIX P

```
C                        PROGRAM BIBLOC1 (JSZ-1980)
C
C  **  THIS PROGRAM CREATES A BIOMASS INDEX FROM LANDSAT BANDS 5
C  **  AND 7.
C
C      VARIABLES:
C
C      B5MONT       :  LANDSAT BAND 5 DATA SET (BINARY)
C      B7MONT       :  LANDSAT BAND 7 DATA SET (BINARY)
C      BI           :  REAL FORMATTED PRELIMINARY 5/7 INDEX VALUE
C      BIVAL        :  BINARY FORMATTED 5/7 INDEX OUTPUT
C                      VALUE
C      IBI          :  INTEGER FORMATTED 5/7 INDEX OUTPUT VALUE
C      INCR         :  INCREMENT VALUE WHICH SPECIFIES EVERY 'TH
C                      VALUE(S) BEING WRITTEN TO DISK
C      ISAMB5       :  LANDSAT BAND 5 PIXEL RADIANCE (INTEGER)
C      ISAMB7       :  LANDSAT BAND 7 PIXEL RADIANCE (INTEGER)
C      LENG         :  LENGTH OF EACH DATA SET (IN PIXELS)
C      MEAN         :  MEAN 5/7 INDEX VALUE FOR THE OUTPUT SCENE
C      N            :  AREA OF EACH DATA SET (IN PIXELS)
C      TOTAL        :  SUM OF 5/7 INDEX VALUES FOR THE COMPLETE
C                      OUTPUT SCENE
C      WIDTH        :  WIDTH OF EACH DATA SET (IN PIXELS)
C
      DIMENSION IBI(120),ISAMB5(120),ISAMB7(120)
      LOGICAL * 1 B5MONT(120),B7MONT(120),BIVAL(120)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,ISAMB5,ISAMB7,IBI,T,G,TOTAL,INCR
      REAL BI,MEAN
C  **  DATA STATEMENT INCLUDES:  1. TOTAL, AND 2. N, ARE
C  **  SUMMATION AND INCREMENT VARIABLES, RESPECTIVELY, ORIGINALLY
C  **  ASSIGNED TO 0, 3. DUMMY VALUE WHICH REPRESENTS THE SMALLEST
C  **  RATIO VALUE, AND 4. DUMMY VALUE WHICH REPRESENTS THE LARGEST
C  **  RATIO VALUE.
      DATA TOTAL/0/,N/0/,T/999999/,G/75/
C  **  READ LENGTH AND WIDTH OF DATA SET (IN PIXELS) AND INCREMENT
C  **  VALUE (INC VAL - USED TO SUBSET A SAMPLE OF RADIANCE VALUES
C  **  FOR PLOTALL PROGRAM).
      READ (5,*) LENG,WIDTH,INCR
      DO 1 I=1,LENG
C  **  EACH DATA SET IS READ ONE RECORD AT A TIME.
      READ (9,1000) B5MONT
      READ (10,1000) B7MONT
```

```
      DO 2 J=1,WIDTH
      CALL B1INT (B5MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB5(J)=INT
      CALL B1INT (B7MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB7(J)=INT
C  **  CHECK DENOMINATOR FOR 0 VALUE.
      IF (ISAMB5(J) .NE. 0) GO TO 10
C  **  CONDITIONAL ASSIGNMENT.
      BI=0.
      GO TO 20
C  **  BIOMASS INDEX IS CALCULATED.
   10 BI=(FLOAT(ISAMB7(J))/FLOAT(ISAMB5(J))) * 20.
C  **  ROUNDING OFF STEP.
   20 IBI(J)=IFIX(BI+.5)
C  **  SUMMATION OF INDEX VALUES.
      TOTAL=TOTAL+IBI(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
      CALL INTB1 (IBI(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      BIVAL(J)=BIN
    2 CONTINUE
      CALL RANKA1 (IBI,WIDTH,T,G)
C  **  BIOMASS INDEX VALUES ARE WRITTEN TO DISK.
      WRITE (13,1000) (BIVAL(J),J=1,WIDTH)
C  **  THE 'INCR' VALUE FOR BOTH ISAMB5 AND ISAMB7 IS WRITTEN TO
C  **  DISK FOR USE WITH THE PLOTALL SCATTERPLOT PROGRAM.
      DO 3 K=1,WIDTH,INCR
      WRITE (11,1001) ISAMB5(K),ISAMB7(K)
    3 CONTINUE
    1 CONTINUE
C  **  AVERAGE INDEX VALUE IS CALCULATED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  SMALLEST AND LARGEST INDEX VALUE, SUBSCENE AREA IN PIXELS,
C  **  MEAN INDEX VALUE, AND BIOMASS INDEX SUM ARE WRITTEN TO UNIT 6.
      PRINT *,T,G,N,MEAN,TOTAL
      STOP
 1000 FORMAT (120A1)
 1001 FORMAT (I3,1X,I3)
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
```

```
C                 ------------------------------
C                           VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE INTB1***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                 ------------------------------
C                           VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
```

```
      KK=INT
      BIN=H(4)
      RETURN
      END
C                    ---------------------
C                   ***SUBROUTINE RANKA1***
C                 ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                 ---------------------------------
C                             VARIABLES
C                            ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISAMPL      :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                     ----------------------
      SUBROUTINE RANKA1 (IBI,WIDTH,T,G)
      DIMENSION IBI(120),RANK(120)
      INTEGER G,IBI,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=IBI(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX Q

```
C                        PROGRAM VEGBLOC (JSZ-1981)
C
C  **  THIS PROGRAM CREATES A VEGETATION INDEX FROM LANDSAT BANDS 5
C  **  AND 7.
C
C      VARIABLES:
C
C      B5MONT       :  LANDSAT BAND 5 DATA SET (BINARY)
C      B7MONT       :  LANDSAT BAND 7 DATA SET (BINARY)
C      BIVAL        :  BINARY FORMATTED VEGETATION INDEX OUTPUT
C                      VALUE
C      DENOM        :  DENOMINATOR FOR VEGETATION INDEX RATIO
C      ISAMB5       :  LANDSAT BAND 5 PIXEL RADIANCE (INTEGER)
C      ISAMB7       :  LANDSAT BAND 7 PIXEL RADIANCE (INTEGER)
C      IVI          :  INTEGER FORMATTED VEGETATION INDEX OUTPUT
C                      VALUE.
C      LENG         :  LENGTH OF EACH DATA SET (IN PIXELS)
C      MEAN         :  MEAN VEGETATION INDEX VALUE FOR THE OUTPUT
C                      SCENE.
C      N            :  AREA OF EACH DATA SET (IN PIXELS)
C      NUM          :  NUMERATOR FOR VEGETATION INDEX RATIO
C      PVINDX       :  PRELIMINARY VEGETATION INDEX VALUE
C      TOTAL        :  SUM OF VEGETATION INDEX VALUE FOR THE COMPLETE
C                      OUTPUT SCENE
C      WIDTH        :  WIDTH OF EACH DATA SET (IN PIXELS)
C      X;X1         :  TRANSFORMED VEGETATION INDEX VALUES BEFORE
C                      FINAL ASSIGNMENT TO BINARY FORMAT
C
      DIMENSION IVI(836)
      LOGICAL * 1 B5MONT(836),B7MONT(836),BIVAL(836)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,ISAMB5,ISAMB7,IVI,T,G,TOTAL,DENOM,NUM
      REAL PVINDX,MEAN
C  **  DATA STATEMENT INCLUDES:  1. TOTAL, AND 2. N, ARE
C  **  SUMMATION AND INCREMENT VARIABLES, RESPECTIVELY, ORIGINALLY
C  **  ASSIGNED TO 0, 3. DUMMY VALUE WHICH REPRESENTS THE SMALLEST
C  **  RATIO VALUE, AND 4. DUMMY VALUE WHICH REPRESENTS THE LARGEST
C  **  RATIO VALUE.
      DATA TOTAL/0/,N/0/,T/999999/,G/75/
C  **  READ LENGTH AND WIDTH OF DATA SET (IN PIXELS).
      READ (5,*) LENG,WIDTH
      DO 1 I=1,LENG
C  **  EACH DATA SET IS READ ONE RECORD AT A TIME.
```

```
      READ (9,1000) B5MONT
      READ (10,1000) B7MONT
      DO 2 J=1,WIDTH
      CALL B1INT (B5MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB5=INT
      CALL B1INT (B7MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB7=INT
C  **  VEGETATION INDEX DENOMINATOR IS CALCULATED.
      DENOM =ISAMB7+ISAMB5
C  **  CHECK DENOMINATOR FOR 0 VALUE.
      IF (DENOM .NE. 0) GO TO 10
C  **  CONDITIONAL ASSIGNMENT.
      PVINDX=0.
      GO TO 20
C  **  VEGETATION INDEX NUMERATOR IS CALCULATED.
   10 NUM=ISAMB7-ISAMB5
C  **  PRELIMINARY VEGETATION INDEX IS CALCULATED.
      PVINDX=FLOAT(NUM)/FLOAT(DENOM)
C  **  PVINDX VALUE IS TRANSFORMED TO ELIMINATE NEGATIVE VALUES FROM
C  **  THE ANALYSIS.
   20 X=PVINDX+1.
      X1=SQRT(X)
C  **  EXPANSION AND ROUNDING OFF STEP.
      IVI(J)=IFIX((X1*100.)+.5)
C  **  SUMMATION OF INDEX VALUES.
      TOTAL=TOTAL+IVI(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
      CALL INTB1 (IVI(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      BIVAL(J)=BIN
    2 CONTINUE
      CALL RANKA1 (IVI,WIDTH,T,G)
C  **  VEGETATION INDEX VALUES ARE WRITTEN TO DISK.
      WRITE (13,1000) (BIVAL(J),J=1,WIDTH)
    1 CONTINUE
C  **  AVERAGE INDEX VALUE IS CALCULATED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  SMALLEST AND LARGEST INDEX VALUE, SUBSCENE AREA IN PIXELS,
C  **  MEAN INDEX VALUE, AND INDEX SUM ARE WRITTEN TO UNIT 6.
      PRINT *,T,G,N,MEAN,TOTAL
      STOP
 1000 FORMAT (4(209A1))
      END
C                    --------------------
```

```
C                    ***SUBROUTINE B1INT***
C                  ------------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                  ------------------------------
C                             VARIABLES
C                  ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE INTB1***
C                  ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                  ------------------------------
C                             VARIABLES
C                  ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
```

```
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      KK=INT
      BIN=H(4)
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE RANKA1***
C                 ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                 ---------------------------------
C                             VARIABLES
C                           ----------------------
C     *G          :  LARGEST RATIO VALUE.
C     *ISAMPL     :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                    FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK       :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                    DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1     :  PROGRAM SUBROUTINE.
C     *T          :  SMALLEST RATIO VALUE.
C     *WIDTH      :  WIDTH (IN PIXELS) OF DATA STRIP.
C                    ----------------------
      SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
      DIMENSION ISAMPL(836),RANK(836)
      INTEGER G,ISAMPL,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISAMPL(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX R

```
C                          PROGRAM SBIBLOC (JSZ-1980)
C
C  **  THIS PROGRAM CREATES A SOIL BRIGHTNESS INDEX FROM LANDSAT
C  **  BANDS 4,5,6, AND 7.
C
C      VARIABLES:
C
C      B4MONT       :  LANDSAT BAND 4 DATA SET (BINARY)
C      B5MONT       :  LANDSAT BAND 5 DATA SET (BINARY)
C      B6MONT       :  LANDSAT BAND 6 DATA SET (BINARY)
C      B7MONT       :  LANDSAT BAND 7 DATA SET (BINARY)
C      ISAMB4       :  LANDSAT BAND 4 PIXEL RADIANCE VALUE (INTEGER)
C      ISAMB5       :  LANDSAT BAND 5 PIXEL RADIANCE VALUE (INTEGER)
C      ISAMB6       :  LANDSAT BAND 6 PIXEL RADIANCE VALUE (INTEGER)
C      ISAMB7       :  LANDSAT BAND 7 PIXEL RADIANCE VALUE (INTEGER)
C      ISBV         :  INTEGER FORMATTED SBI INDEX OUTPUT VALUE
C      LENG         :  LENGTH OF EACH DATA SET (IN PIXELS)
C      MEAN         :  MEAN SOIL BRIGHTNESS INDEX VALUE FOR THE OUTPUT
C                      SCENE
C      N            :  AREA OF EACH DATA SET (IN PIXELS)
C      SBIVAL       :  BINARY FORMATTED SOIL BRIGHTNESS INDEX OUTPUT
C                      VALUE
C      SBV          :  REAL FORMATTED PRELIMINARY SOIL BRIGHTNESS
C                      INDEX VALUE
C      TOTAL        :  SUM OF 5/7 INDEX VALUES FOR THE COMPLETE
C                      OUTPUT SCENE
C      WIDTH        :  WIDTH OF EACH DATA SET (IN PIXELS)
C
       DIMENSION ISBV(836)
       LOGICAL * 1 B4MONT(836),B5MONT(836),B6MONT(836),B7MONT(836),
      &SBIVAL(836)
       LOGICAL * 1 H(4),BIN
       EQUIVALENCE (H(1),KK)
       INTEGER LENG,WIDTH,ISAMB4,ISAMB5,ISAMB6,ISAMB7,T,G,TOTAL,ISBV
       REAL SBV,MEAN
C  **   DATA STATEMENT INCLUDES:  1. TOTAL, AND 2. N, ARE
C  **   SUMMATION AND INCREMENT VARIABLES, RESPECTIVELY, ORIGINALLY
C  **   ASSIGNED TO 0, 3. DUMMY VALUE WHICH REPRESENTS THE SMALLEST
C  **   RATIO VALUE, AND 4. DUMMY VALUE WHICH REPRESENTS THE LARGEST
C  **   RATIO VALUE.
       DATA TOTAL/0/,N/0/,T/999999/,G/98/
C  **   READ LENGTH AND WIDTH OF DATA SET (IN PIXELS).
       READ (5,*) LENG,WIDTH
       DO 1 I=1,LENG
```

```
C  **  EACH DATA SET IS READ ONE RECORD AT A TIME.
      READ (9,1000) B4MONT
      READ (10,1000) B5MONT
      READ (11,1000) B6MONT
      READ (12,1000) B7MONT
      DO 2 J=1,WIDTH
      CALL B1INT (B4MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB4(J)=INT
      CALL B1INT (B5MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB5(J)=INT
      CALL B1INT (B6MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB6=INT
      CALL B1INT (B7MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB7=INT
C  **  SOIL BRIGHTNESS INDEX IS CALCULATED.
      SBV=(FLOAT(ISAMB4)*.43)+(FLOAT(ISAMB5)*.63)+(FLOAT(ISAMB6)*.59)
     &+(FLOAT(ISAMB7)*.26)
C  **  ROUNDING OFF STEP.
      ISBV(J)=IFIX(SBV+.5)
C  **  SUMMATION OF INDEX VALUES.
      TOTAL=TOTAL+ISBV(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
      CALL INTB1 (ISBV(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      SBIVAL(J)=BIN
    2 CONTINUE
      CALL RANKA1 (ISBV,WIDTH,T,G)
C  **  SOIL BRIGHTNESS INDEX VALUES ARE WRITTEN TO DISK.
      WRITE (13,1000) (SBIVAL(J),J=1,WIDTH)
    1 CONTINUE
C  **  AVERAGE SOIL BRIGHTNESS INDEX VALUE IS CALCULATED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  SMALLEST AND LARGEST INDEX VALUES, SUBSCENE AREA IN PIXELS,
C  **  MEAN INDEX VALUE, AND SOIL BRIGHTNESS INDEX SUM ARE WRITTEN
C  **  TO UNIT 6.
      PRINT *,T,G,N,MEAN,TOTAL
      STOP
 1000 FORMAT (209(4A1))
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                 ------------------------------
```

```
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                  ------------------------------
C                             VARIABLES
C                  ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE INTB1***
C                  ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                  ------------------------------
C                             VARIABLES
C                  ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
```

```
      EQUIVALENCE (H(1),KK)
      KK=0
      KK=INT
      BIN=H(4)
      RETURN
      END
C                    ---------------------
C                   ***SUBROUTINE RANKA1***
C                 ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                 ---------------------------------
C                             VARIABLES
C                           ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISBV        :  ARRAY CONTAINING INDEX VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                     ----------------------
      SUBROUTINE RANKA1 (ISBV,WIDTH,T,G)
      DIMENSION ISBV(836),RANK(836)
      INTEGER G,ISBV,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISBV(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX S

```
C                        PROGRAM TEXTURE (JSZ-1980)
C
C  **  THIS PROGRAM PERFORMS AND CALCULATES EDGE ENHANCEMENT FOR A
C  **  SPECTRAL BAND SUBSCENE USING A BOX FILTERING TECHNIQUE.
C
C     VARIABLES:
C
C     B1            :  FIRST LINE OF THE OUTPUT TEXTURE IMAGE (BINARY)
C                      EQUIVALENT TO BF.
C     B700          :  LAST LINE OF THE OUTPUT TEXTURE IMAGE (BINARY).
C                      EQUIVALENT TO BL.
C     BF            :  FIRST LINE OF THE OUTPUT TEXTURE IMAGE.
C                      COMPLETE RECORD IS COMPOSED OF 0'S BECAUSE OF
C                      THE LACK OF 8 NEAREST NEIGHBORS TO COMPUTE
C                      SNDEV.
C     BL            :  LAST LINE OF THE OUTPUT TEXTURE IMAGE.
C                      COMPLETE IMAGE IS COMPOSED OF 0'S BECAUSE OF
C                      THE LACK OF 8 NEAREST NEIGHBORS TO COMPUTE
C                      SNDEV.
C     BSNDEV        :  BINARY FORMATTED OUTPUT TEXTURE VALUE FOR EACH
C                      PIXEL.
C     BV1           :  FIRST LINE OF LANDSAT RADIANCE DATA (BINARY).
C     BV2           :  SECOND LINE OF LANDSAT RADIANCE DATA (BINARY).
C     BV3           :  THIRD LINE OF LANDSAT RADIANCE DATA (BINARY).
C     LENG          :  LENGTH OF THE DATA SET (IN PIXELS).
C     SNDEV         :  INTEGER FORMATTED OUTPUT TEXTURE VALUE FOR EACH
C                      PIXEL.
C     WIDTH         :  WIDTH OF THE DATA SET (IN PIXELS).
C
      DIMENSION RBV1(836),RBV2(836),RBV3(836),SNDEV(836),BF(836),
     &BL(836)
      LOGICAL * 1 BV1(836),BV2(836),BV3(836),B1(836),B700(836),
     &BSNDEV(836)
      LOGICAL * 1 H(4),BIN
      EQUIVALENCE (H(1),KK)
      INTEGER BF,BL,WIDTH,LENG,SNDEV,SNDEV1,T,G
      REAL RBV1,RBV2,RBV3
C  **  DATA STATEMENT INCLUDES:  1.  DUMMY VALUE WHICH REPRESENTS THE
C  **  SMALLEST DEVIATE (EDGE) VALUE, 2.  DUMMY VALUE WHICH REPRE-
C  **  SENTS THE LARGEST DEVIATE (EDGE) VALUE, AND 3. AND 4., WHICH
C  **  ARE THE FIRST (BF) AND LAST (BL) FILL LINES FOR THE OUTPUT
C  **  MATRIX.  NOTE:  BE SURE THAT THE VALUE ASSIGNED TO VARIABLE
C  **  'WIDTH' IS ALSO THE MULTIPLE FOR DATA STATEMENT VARIABLES
C  **  'BF' AND 'BL'.
```

```
      DATA T/999999/,G/0/,BF/836*0/,BL/836*0/
C  **  READ:  1.  LENGTH OF THE DATA SET (IN PIXELS), AND 2.  WIDTH
C  **  OF DATA SET (IN PIXELS).
      READ (5,*) LENG,WIDTH
C **** LINES 1,2, AND 3 OF LANDSAT SUBSCENE DATA ARE READ FROM
C  *** DISK.  1-BYTE STORAGE ASSIGNMENTS ARE MADE FOR EACH DATA
C   ** VALUE.
      READ (9,1000) BV1
      READ (9,1000) BV2
      READ (9,1000) BV3
      DO 1 I=1,WIDTH
C **** LOGICAL * 1 ARRAYS BV1, BV2, AND BV3 ARE ASSIGNED TO EQUIV-
C  *** ALENT REAL ARRAYS RBV1, RBV2, AND RBV3, RESPECTIVELY.
      CALL B1INT (BV1(I),INT)
      RBV1(I)=FLOAT(INT)
      CALL B1INT (BV2(I),INT)
      RBV2(I)=FLOAT(INT)
      CALL B1INT (BV3(I),INT)
      RBV3(I)=FLOAT(INT)
C **** REAL ARRAYS BF AND BL ARE ASSIGNED TO EQUIVALENT LOGICAL * 1
C  *** ARRAYS B1 AND B700.
      CALL INTB1 (BF(I),BIN)
      B1(I)=BIN
      CALL INTB1 (BL(I),BIN)
      B700(I)=BIN
    1 CONTINUE
C **** ARRAY B1 IS WRITTEN TO DISK.
      WRITE (10,1000) (B1(J),J=1,WIDTH)
      DO 7 K=2,LENG
      DO 2 J=1,WIDTH
C **** SIGNATURE DEVIATIONS ARE COMPUTED BEGINNING WITH LINE 2 AND
C  *** ENDING WITH LINE LENG-1.  WITHIN A LINE, EACH PIXEL IS
C   ** ANALYZED BEGINNING WITH SAMPLE 2 AND ENDING WITH SAMPLE
C    * WIDTH-1.
      IF (J.EQ.1.OR.J.EQ.WIDTH) GO TO 10
      CALL DEV (J,RBV1,RBV2,RBV3,SNDEV1)
      SNDEV(J)=SNDEV1
      GO TO 3
   10 SNDEV(J)=0
    3 CALL INTB1 (SNDEV(J),BIN)
      BSNDEV(J)=BIN
    2 CONTINUE
C **** THE STANDARD DEVIATION FOR EACH PIXEL ARE WRITTEN TO DISK
C  *** 1 LINE AT A TIME.
      WRITE (10,1000) (BSNDEV(J),J=1,WIDTH)
      CALL RANKA1 (SNDEV,WIDTH,T,G)
      IF (K.EQ.(LENG-1)) GO TO 100
```

```
      DO 4 J=1,WIDTH
C **** EACH DATA ARRAY IS ASSIGNED TO THE CORRESPONDING ARRAY ONE-UP.
      RBV1(J)=RBV2(J)
      RBV2(J)=RBV3(J)
    4 CONTINUE
C **** THE NEXT DATA ARRAY IS READ FROM DISK.
      READ (9,1000) BV3
      DO 5 J=1,WIDTH
      CALL B1INT (BV3(J),INT)
      RBV3(J)=FLOAT(INT)
    5 CONTINUE
    7 CONTINUE
C **** ARRAY B700 IS WRITTEN TO DISK.
  100 WRITE (10,1000) (B700(J),J=1,WIDTH)
C **** SMALLEST AND LARGEST DEVIATION VALUES ARE PRINTED TO UNIT 6.
      PRINT *,T,G
      STOP
 1000 FORMAT (4(209A1))
      END
C
C                        ------------------------
C                           **SUBROUTINE DEV**
C                     ---------------------------------
C**SUBROUTINE DEV ACCEPTS THE CURRENT 3 LINES OF SUBSCENE INPUT,
C**CALCULATES THE VALUE DIFFERENCES (+ OR -) OF THE 8 SURROUNDING
C**CELLS FROM A CENTRAL PIXEL, AND SENDS THE DIFFERENCE VALUES TO
C**SUBROUTINE SUMDEV.  UPON RETURN, VALUEPROC IS ASSIGNED
C**SEQUENTIALLY TO ARRAY SNDEV.
C                     ---------------------------------
C                              VARIABLES
C                           ----------------------
C     *J              :  CURRENT COUNT VALUE FOR VARIABLE 'WIDTH'.
C     *RBV1           :  FIRST LINE OF CURRENT SUBSCENE INPUT.
C     *RBV2           :  SECOND LINE OF CURRENT SUBSCENE INPUT.
C     *RBV3           :  THIRD LINE OF CURRENT SUBSCENE INPUT.
C     *DIFF(1-8)      :  DIFFERENCES IN REFLECTANCE VALUES FOR EACH OF
C                        8 SURROUNDING PIXELS FROM A CENTRAL PIXEL.
C     *SNDEV1         :  STANDARD DEVIATION A CENTRAL PIXEL EXHIBITS
C                        WITH RESPECT TO THE REFLECTANCE VALUES OF ITS
C                        8 SURROUNDING CELLS.
C     *PRO            :  SUBROUTINE COUNTERPART OF VARIABLE 'SNDEV'.
C                           ----------------------
      SUBROUTINE DEV (J,RBV1,RBV2,RBV3,SNDEV1)
      DIMENSION DIFF(8),RBV1(836),RBV2(836),RBV3(836)
      REAL RBV1,RBV2,RBV3,DIFF
      INTEGER J,SNDEV1,PROC
      DIFF(1)=RBV2(J+1)-RBV2(J)
```

```
      DIFF(2)=RBV3(J+1)-RBV2(J)
      DIFF(3)=RBV3(J)-RBV2(J)
      DIFF(4)=RBV3(J-1)-RBV2(J)
      DIFF(5)=RBV2(J-1)-RBV2(J)
      DIFF(6)=RBV1(J-1)-RBV2(J)
      DIFF(7)=RBV1(J)-RBV2(J)
      DIFF(8)=RBV1(J+1)-RBV2(J)
      CALL SUMDEV (DIFF,PROC)
      SNDEV1=PROC
      RETURN
      END
C                    ------------------------
C                     **SUBROUTINE SUMDEV**
C                   ---------------------------------
C**SUBROUTINE SUMDEV ACCEPTS ALL DIFFERENCE (DEVIATION) VALUES FOR A
C**SINGLE CENTRAL PIXEL FROM SUBPROGRAM DEV, CALCULATES THE TOTAL
C**DIFFERENCE OF THE SURROUNDING CELLS, CALCULATES THE STANDARD
C**DEVIATION (VARIABLE-PROC) FOR THE PIXEL, AND RETURNS THE VALUE
C**'PROC' TO SUBPROGRAM DEV.
C                   ---------------------------------
C     *DIFF(1-8)    :  DIFFERENCES IN REFLECTANCE VALUES FOR EACH OF
C                      8 SURROUNDING PIXELS FROM A CENTRAL PIXEL.
C     *PRO          :  SUBROUTINE COUNTERPART OF VARIABLE 'SNDEV' IN
C                      SUBPROGRAM DEV.
C     *TOTAL        :  TOTAL SUM OF DIFF(1) THROUGH DIFF(8).
C                      ------------------------
      SUBROUTINE SUMDEV (DIFF,PROC)
      DIMENSION DIFF(8)
      REAL DIFF,TOTAL
      INTEGER PROC
      TOTAL=0.
      DO 3 I=1,8
      TOTAL=(DIFF(I)**2)+TOTAL
    3 CONTINUE
      PROC=IFIX((SQRT(TOTAL/7.))+.5)
      RETURN
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                   ----------------------------
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FOR
C   ***THROUGH AN OVERLAYING PROCESS.
C                   ----------------------------
C                             VARIABLES
C                   ----------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
```

```
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ---------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                      --------------------
C                    ***SUBROUTINE INTB1***
C                   ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                   ------------------------------
C                              VARIABLES
C                   ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ---------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      KK=INT
      BIN=H(4)
      RETURN
      END
C                      --------------------
```

```
C                    ***SUBROUTINE RANKA1***
C                  --------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                  --------------------------------
C                              VARIABLES
C                           ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISAMPL      :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                           ----------------------
      SUBROUTINE RANKA1 (ISAMPL,WIDTH,T,G)
      DIMENSION ISAMPL(836),RANK(836)
      INTEGER G,ISAMPL,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=ISAMPL(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX T

```
C                          PROGRAM BI1BLOC (JSZ-1980)
C
C  **  THIS PROGRAM CREATES AN EXPERIMENTAL INDEX FROM LANDSAT BAND 7
C  **  AND A SOIL BRIGHTNESS INDEX.
C
C      VARIABLES:
C
C     B7MONT         :  LANDSAT BAND 7 DATA SET (BINARY)
C     BI1            :  PRELIMINARY BI1 INDEX VALUE FOR EACH PIXEL
C     BI1VAL         :  BINARY FORMATTED BI1 INDEX OUTPUT VALUE
C                       ASSIGNED TO A PIXEL
C     IBI1           :  INTEGER FORMATTED BI1 INDEX OUTPUT VALUE
C                       ASSIGNED TO A PIXEL
C     INCR           :  INCREMENT VALUE WHICH SPECIFIES EVERY 'TH
C                       VALUE(S) BEING WRITTEN TO DISK
C     ISAMB7         :  LANDSAT BAND 7 PIXEL RADIANCE VALUE (INTEGER)
C     ISBVL          :  SOIL BRIGHTNESS INDEX VALUE (INTEGER)
C     LENG           :  LENGTH OF EACH DATA SET (IN PIXELS)
C     MEAN           :  MEAN BI1 INDEX VALUE FOR THE OUTPUT SCENE
C     N              :  AREA OF EACH DATA SET (IN PIXELS)
C     SBIVAL         :  SOIL BRIGHTNESS INDEX DATA SET (BINARY)
C     TOTAL          :  SUM OF BI1 INDEX VALUES FOR THE COMPLETE
C                       OUTPUT SCENE
C     WIDTH          :  WIDTH OF EACH DATA SET (IN PIXELS)
C
      DIMENSION IBI1(120),ISAMB7(120),ISBVL(120)
      LOGICAL * 1 B7MONT(120),SBIVAL(120),BI1VAL(120)
      LOGICAL * 1 H(4),BI1N
      EQUIVALENCE (H(1),KK)
      INTEGER LENG,WIDTH,ISAMB7,ISBVL,IBI1,T,G,TOTAL,INCR
      REAL BI1,MEAN
C  **  DATA STATEMENT INCLUDES:  1. TOTAL, AND 2. N, ARE
C  **  SUMMATION AND INCREMENT VARIABLES, RESPECTIVELY, ORIGINALLY
C  **  ASSIGNED TO 0, 3. DUMMY VALUE WHICH REPRESENTS THE SMALLEST
C  **  RATIO VALUE, AND 4. DUMMY VALUE WHICH REPRESENTS THE LARGEST
C  **  RATIO VALUE.
      DATA TOTAL/0/,N/0/,T/999999/,G/75/
C  **  READ LENGTH AND WIDTH OF DATA SET (IN PIXELS) AND INCREMENT
C  **  VALUE (INC VAL - USED TO SUBSET A SAMPLE OF RADIANCE VALUES
C  **  FOR PLOTALL PROGRAM).
      READ (5,*) LENG,WIDTH,INCR
      DO 1 I=1,LENG
C  **  EACH DATA SET IS READ ONE RECORD AT A TIME.
      READ (9,1000) B7MONT
```

```
      READ (10,1000) SBIVAL
      DO 2 J=1,WIDTH
      CALL B1INT (B7MONT(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISAMB7(J)=INT
      CALL B1INT (SBIVAL(J),INT)
C  **  INTEGER ASSIGNMENT.
      ISBVL(J)=INT
C  **  CHECK DENOMINATOR FOR 0 VALUE.
      IF (ISBVL(J) .NE. 0) GO TO 10
C  **  CONDITIONAL ASSIGNMENT.
      BI1=0.
      GO TO 20
C  **  EXPERIMENTAL INDEX IS CALCULATED.
   10 BI1=(FLOAT(ISAMB7(J))/FLOAT(ISBVL(J))) * 50
C  **  ROUNDING OFF STEP.
   20 IBI1(J)=IFIX(BI1+.5)
C  **  SUMMATION OF INDEX VALUES.
      TOTAL=TOTAL+IBI1(J)
C  **  SUBSCENE PIXEL INCREMENT.
      N=N+1
      CALL INTB1 (IBI1(J),BIN)
C  **  LOGICAL 1-BYTE ASSIGNMENT.
      BI1VAL(J)=BIN
    2 CONTINUE
      CALL RANKA1 (IBI1,WIDTH,T,G)
C  **  INDEX VALUES ARE WRITTEN TO DISK.
      WRITE (13,1000) (BI1VAL(J),J=1,WIDTH)
C  **  THE 'INCR'TH VALUE FOR BOTH ISAMB7 AND ISBVL ARE WRITTEN TO
C  **  DISK FOR USE WITH THE PLOTALL SCATTERPLOT PROGRAM.
      DO 3 K=1,WIDTH,INCR
      WRITE (11,1001) ISAMB7(K),ISBVL(K)
    3 CONTINUE
    1 CONTINUE
C  **  AVERAGE EXPERIMENTAL INDEX VALUE IS CALCULATED.
      MEAN=FLOAT(TOTAL)/FLOAT(N)
C  **  SMALLEST AND LARGEST INDEX VALUE, SUBSCENE AREA IN PIXELS,
C  **  MEAN INDEX VALUE, AND BI1OMASS INDEX SUM ARE WRITTEN TO
C  **  UNIT 6.
      PRINT *,T,G,N,MEAN,TOTAL
      STOP
 1000 FORMAT (120A1)
 1001 FORMAT (I3,1X,I3)
      END
C                    --------------------
C                   ***SUBROUTINE B1INT***
C                 ------------------------------
```

```
C******THIS SUBROUTINE CONVERTS BINARY VALUES INTO THEIR INTEGER FORM
C   ***THROUGH AN OVERLAYING PROCESS.
C                 ------------------------------
C                             VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *B1INT        :  PROGRAM SUBROUTINE.
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUES INTEGER FORM.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE B1INT(BIN,INT)
      INTEGER INT
      LOGICAL * 1 BIN,H(4)
      EQUIVALENCE (H(1),KK)
      KK=0
      H(4)=BIN
      INT=KK
      RETURN
      END
C                   -------------------
C                  ***SUBROUTINE INTB1***
C                 ------------------------------
C******THIS SUBROUTINE CONVERTS INTEGER VALUES INTO THEIR BINARY FORM
C   ***THROUGH AN OVERLAYING PROCESS.  BINARY IS A MUCH MORE
C   ***EFFICIENT MEANS FOR STORING LARGE AMOUNTS OF SPATIAL
C    **INFORMATION.
C                 ------------------------------
C                             VARIABLES
C                 ------------------------------
C     *BIN          :  INDIVIDUAL VALUE'S BINARY FORM.  (1-BYTE
C                      STORAGE ALLOCATION.)
C     *H(1)         :  FIRST STORAGE POSITION OF OVERLAY ARRAY H.
C     *H(4)         :  FINAL STORAGE POSITION OF OVERLAY ARRAY H.  (1-
C                      BYTE STORAGE ALLOCATION.)
C     *INT          :  INDIVIDUAL VALUE'S INTEGER FORM.
C     *INTB1        :  PROGRAM SUBROUTINE.
C     *KK           :  OVERLAY VARIABLE WHICH CORRESPONDS TO H(1).
C                      ALSO A CONSTANT ORIGINALLY ASSIGNED TO 0.
C     ------------------------------------------------------------
      SUBROUTINE INTB1(INT,BIN)
      INTEGER INT,KK
      LOGICAL * 1 BIN,H(4)
```

```
      EQUIVALENCE (H(1),KK)
      KK=0
      KK=INT
      BIN=H(4)
      RETURN
      END
C                    --------------------
C                  ***SUBROUTINE RANKA1***
C                 ---------------------------------
C******SUBROUTINE RANKA1 ACCEPTS ARRAY VALUES ONE STRIP AT A TIME.
C *****FROM THIS STRIP OF INTEGER VALUES, THE LARGEST (G) AND
C  ****SMALLEST (T) ARE DETERMINED.  VALUES G AND T ARE RETURNED
C   ***TO THE MAIN PROGRAM EACH TIME THE SUBROUTINE HAS PROCESSED
C    **ONE STRIP.  G AND T WILL THEN BE RETURNED TO THE SUBROUTINE
C     *AS THE LARGEST AND SMALLEST VALUES WHEN THE NEXT STRIP IS
C     *TO BE PROCESSED.
C                 ---------------------------------
C                              VARIABLES
C                            ----------------------
C     *G           :  LARGEST RATIO VALUE.
C     *ISAMPL      :  ARRAY CONTAINING RATIO VALUES IN INTEGER
C                     FORMAT.  INTRODUCED ONE STRIP AT A TIME.
C     *RANK        :  STORAGE ARRAY UPON WHICH MANIPULATION IS DONE TO
C                     DETERMINE LARGEST AND SMALLEST RATIO VALUES.
C     *RANKA1      :  PROGRAM SUBROUTINE.
C     *T           :  SMALLEST RATIO VALUE.
C     *WIDTH       :  WIDTH (IN PIXELS) OF DATA STRIP.
C                     ----------------------
      SUBROUTINE RANKA1 (IBI1,WIDTH,T,G)
      DIMENSION IBI1(120),RANK(120)
      INTEGER G,IBI1,RANK,T,WIDTH
      DO 3 J=1,WIDTH
      RANK(J)=IBI1(J)
    3 CONTINUE
      DO 4 L=1,WIDTH
      IF (G .GE. RANK(L)) GO TO 24
      IF (G .LT. T) T=G
      G=RANK(L)
      GO TO 4
   24 IF (RANK(L) .GE. T) GO TO 4
      T=RANK(L)
    4 CONTINUE
      RETURN
      END
```

APPENDIX U

```
C       PROGRAM -- DROPPWR (JSZ/1981)
C
C       PURPOSE :  TO CREATE A NEW MAPFILE OF LANDSAT DATA BY DROPPING
C                  OUT SPECIFIC PIXEL VALUES.
C
C       INPUTS  :
C               UNIT 05 - CARDS
C                 CARD1 - COL.1 THRU 80 - TITLE
C                 CARD2 - COL.1 THRU 8 - NEW MAP IDENTIFICATION
C               UNIT 08 - FROM PROGRAM DEFINE -- MAP NUMBERS TO
C                         BE INCLUDED FOR PROCESSING.
C               UNIT 09 - EXISTING MAPFILE REPRESENTING CELLS TO DROP
C                         (VALUE OF 0 = NO DROP; ALL OTHERS DROP OUT)
C               UNIT 10 - EXISTING LANDSAT MAPFILE.
C       OUTPUTS:
C               UNIT 06 - PRINTER
C               UNIT 10 - NEW DROP OUT MAPFILE.
C
C
C       VARIABLE NAMES:
C
C       ADJUST - MAPFILE OFFSET ADJUSTMENT
C       IDA - DAY
C       IMO - MONTH
C       IYR - YEAR
C       LAST - LAST MAP NUMBER
C       LX - LENGTH OF X AXIS
C       LY - LENGTH OF Y AXIS
C       MAP - MAP NUMBER
C       MAPW - NUMBER OF MAPS WRITTEN
C       MAXX - LARGEST MAP NUMBER TO BE PROCESSED
C       MAXY - SMALLEST MAP NUMBER TO BE PROCESSED
C       MINX - REFERENCE MAP_X COORDINATE
C       MINY - REFERENCE MAP_Y COORDINATE
C       MOD - NEW MAPFILE ACRONYM
C       NMR - NUMBER OF MAPS PER ROW IN MAPFILE
C       NAME1 - MAP IDENTIFICATION LABEL FOR DIGITIZED FILE
C       NAME2 - MAP IDENTIFICATION LABEL FOR LANDSAT FILE
C       NMAPS - MAP PROCESSED
C       NPTS - MAP REPRESENTING DROPOUT CASES
C       PTS1 - 30X30 MAP FOR DIGITIZED DATA
C       PTS2 - 30X30 MAP FOR LANDSAT DATA
C       TITLE - TITLE
C
```

```
C
      INTEGER NMAPS/0/,NAME1(30),NAME2(30),LAST/0/,MAPW/0/,MOD(2),
     &LX/30/,LY/30/,TITLE(20)
      REAL PTS1(30,30),PTS2(30,30),NPTS(30,30)
      CALL DATE (IMO,IDA,IYR)
      WRITE (6,600) IMO,IDA,IYR
  600 FORMAT ('1',25X,'PROGRAM - DROPCELL',20X,A2,'/',A2,'/',A2)
      READ (5,502) TITLE
  502 FORMAT (20A4)
      WRITE (6,603) TITLE
  603 FORMAT ('0',20A4)
      READ (5,500) MOD
  500 FORMAT (2A4)
C  **  READ DEFINE FILE
      READ (8,801) NMR,MINY,MINX,MAXY,MAXX,ADJUST
  801 FORMAT (A4)
C  **  READ MAP NUMBER
    3 READ (8,801,END=99) MAP
      IF (MAP .GT. LAST) GO TO 91
      WRITE (6,694) MAP
  694 FORMAT ('-*** ERROR *** -- ATTEMPT TO READ MAP',I5,'WHICH HAS
     &ALREADY BEEN PROCESSED OR PASSED.')
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      STOP 8
   91 NMAPS=NMAPS+1
      LAST=MAP
C  **  READ COMPLETE 30X30 MAP FOR CELLS TO BE EXCLUDED (DIGITIZED
C  **  CELLS = PTS1) FROM CLUSTERED IMAGE (PTS2).

      READ (10,901) PTS2,NAME2
  901 FORMAT (31(30A4))
      DO 5 I=1,LY
      DO 6 J=1,LX
C  **  CHECK TO SEE IF CELL IS TO BE EXCLUDED.
      IF (PTS1(I,J) .EQ. 0.0) GO TO 10
C  **  IF CELL IS TO BE EXCLUDED ASSIGN -9999. TO OUTPUT DATA SET
C  **  PIXEL.
      NPTS(I,J)=-9999.
      GO TO 6
C  **  IF CELL IS NOT BE EXCLUDED ASSIGN CLUSTER CATEGORY VALUE TO
C  **  OUTPUT DATA SET PIXEL.
   10 NPTS(I,J)=PTS2(I,J)
    6 CONTINUE
    5 CONTINUE
```

```
      MAPW=MAPW+1
C  **  ASSIGN NEW MAPFILE ACRONYM
      NAME2(7)=MOD(1)
      NAME2(8)=MOD(2)
C  **  WRITE EXCLUDED POWER MAP TO DISK
      WRITE (11,901) NPTS,NAME2
C  **  WRITE EXCLUDED POWER MAP NUMBER TO PAPER
      WRITE (6,601) NMAPS
  601 FORMAT (' ',I6)
      GO TO 3
   99 WRITE (6,602)
  602 FORMAT (' -NORMAL TERMINATION-'/'- ',16('_')/' |END OF PROCESS|
     &'/' +',16(' '))
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      STOP
      END
```

APPENDIX V

```
C          PROGRAM -- AGPWR2 (JSZ/1981)
C
C          PURPOSE: TO AGGREGATE 2 DIFFERENT POWER MAPFILES INTO A
C                   SINGLE MAPFILE SO THAT ALL NON-ZERO MAPFILE
C                   VALUES HOLD A COMMON VALUE (-9999.) WITHIN THE
C                   AGGREGATE OR COMPOSITE MAPFILE.
C
C          INPUTS:
C                   UNIT 05 - CARDS
C                    CARD1 - COL.1 THRU 80 - TITLE
C                    CARD2 - COL.2 THRU 8 - NEW COMPOSITE MAP ID
C                   UNIT 08 - FROM PROGRAM DEFINE -- MAP NUMBERS TO BE
C                             INCLUDED FOR PROCESSING
C                   UNIT 09 - FIRST COMPONENT MAPFILE
C                             (VALUE OF 0 = SKIP; ALL OTHERS
C                             AGGREGATE)
C                   UNIT 10 - SECOND COMPONENT MAPFILE
C                             (VALUE OF 0 = SKIP; ALL OTHERS
C                             AGGREGATE)
C          OUTPUTS:
C                   UNIT 06 - PRINTER
C                   UNIT 11 - NEW COMPOSITE MAPFILE
C
C
C          VARIABLE NAMES:
C
C          ADJUST - MAPFILE OFFSET ADJUSTMENT
C          IDA - DAY
C          IMO - MONTH
C          IYR - YEAR
C          LAST - LAST MAP NUMBER
C          LX - LENGTH OF X AXIS
C          LY - LENGTH OF Y AXIS
C          MAP - MAP NUMBER
C          MAPW - NUMBER OF MAPS WRITTEN
C          MAXX - LARGEST MAP NUMBER TO BE PROCESSED
C          MAXY - SMALLEST MAP NUMBER TO BE PROCESSED
C          MINX - REFERENCE MAP X COORDINATE
C          MINY - REFERENCE MAP Y COORDINATE
C          MOD - NEW COMPOSITE MAPFILE ACRONYM
C          N - COUNTER
C          NMR - NUMBER OF MAPS PER ROW IN MAPFILE
C          NAME1 - MAP IDENTIFICATION LABEL FOR FIRST COMPONENT FILE
C          NAME2 - MAP IDENTIFICATION LABEL FOR SECOND COMPONENT FILE
```

```
C         NMAPS - MAP PROCESSED
C         NPTS - MAP REPRESENTING COMPOSITE FILE
C         PTS1 - 30X30 MAP FOR FIRST COMPONENT FILE
C         PTS2 - 30X30 MAP FOR SECOND COMPONENT FILE
C         TITLE - TITLE
C
      INTEGER NMAPS/0/,NAME1(30),NAME2(30),LAST/0/,MAPW/0/,
     &MOD(2),LX/30/,LY/30/,TITLE(20)
      REAL PTS1(30,30),PTS2(30,30),NPTS(30,30)
      CALL DATE (IMO,IDA,IYR)
      WRITE (6,600) IMO,IDA,IYR
  600 FORMAT ('1',25X,'PROGRAM - AGPWR2',20X,A2,'/',A2,'/',A2)
      READ (5,502) TITLE
  502 FORMAT (20A4)
      WRITE (6,603) TITLE
  603 FORMAT ('0',20A4)
      READ (5,500) MOD
  500 FORMAT (2A4)
C  **  READ DEFINE FILE
      READ (8,801) NMR,MINY,MINX,MAXY,MAXX,ADJUST
  801 FORMAT (A4)
C  **  READ MAP NUMBER
    3 READ (8,801,END=99) MAP
      IF (MAP .GT. LAST) GO TO 91
      WRITE (6,694) MAP
  694 FORMAT ('-*** ERROR *** -- ATTEMPT TO READ MAP', I5, 'WHICH HAS
     &ALREADY BEEN PROCESSED OR PASSED.')
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      REWIND 12
      STOP 8
   91 NMAPS=NMAPS+1
      LAST=MAP
C  **  READ BOTH 30X30 MAPS (2) HOLDING LOCATIONS OF CELLS TO BE
C  **  EXCLUDED.
      READ (9,901) PTS1,NAME1
      READ (10,901) PTS2,NAME2
  901 FORMAT (31(30A4))
      DO 5 I=1,LY
      DO 6 J=1,LX
C  **  CHECK TO SEE IF ONE OF THE THREE DATA SETS HAS A SPECIFIC
C  **  CELL'S LOCATION MARKED SO TO BE EXCLUDED.
      IF (PTS1(I,J).EQ.0.0.AND.PTS2(I,J).EQ.0.0.)GO TO 30
C  **  IF SO, ASSIGN -9999 TO THE OUTPUT CELL.
      NPTS(I,J)=-9999.
```

```
      GO TO 6
C  **  IF NOT, ASSIGN 0.0 TO THE OUTPUT CELL.
   30 NPTS(I,J)=0.0
    6 CONTINUE
    5 CONTINUE
      MAPW=MAPW+1
C  **  ASSIGN NEW MAPFILE ACRONYM
      NAME2(7)=MOD(1)
      NAME2(8)=MOD(2)
C  **  WRITE MERGED EXCLUSION POWER MAP TO DISK.
      WRITE (11,901) NPTS,NAME3
C  **  WRITE POWER MAP NUMBER TO PAPER.
      WRITE (6,601) NMAPS
  601 FORMAT (' ',I6)
      GO TO 3
   99 WRITE (6,602)
  602 FORMAT ('-NORMAL TERMINATION -'/'- ',16('_')/
     & | END OF PROCESS | '/'+ ',16('_'))
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      STOP
      END
```

APPENDIX W

```
C          PROGRAM -- AGPWR3 (JSZ/1981)
C
C          PURPOSE: TO AGGREGATE 3 DIFFERENT POWER MAPFILES INTO A
C                   SINGLE MAPFILE SO THAT ALL NON-ZERO MAPFILE
C                   VALUES HOLD A COMMON VALUE (-9999.) WITHIN THE
C                   AGGREGATE OR COMPOSITE MAPFILE.
C
C          INPUTS:
C                   UNIT 05 - CARDS
C                    CARD1 - COL.1 THRU 80 - TITLE
C                    CARD2 - COL.2 THRU 8 - NEW COMPOSITE MAP ID
C                   UNIT 08 - FROM PROGRAM DEFINE -- MAP NUMBERS TO BE
C                             INCLUDED FOR PROCESSING
C                   UNIT 09 - FIRST COMPONENT MAPFILE
C                             (VALUE OF 0 = SKIP; ALL OTHERS
C                             AGGREGATE)
C                   UNIT 10 - SECOND COMPONENT MAPFILE
C                             (VALUE OF 0 = SKIP; ALL OTHERS
C                             AGGREGATE)
C                   UNIT 11 - THIRD COMPONENT MAPFILE
C                             (VALUE OF 0 = SKIP; ALL OTHERS
C                             AGGREGATE)
C          OUTPUTS:
C                   UNIT 06 - PRINTER
C                   UNIT 12 - NEW COMPOSITE MAPFILE
C
C
C          VARIABLE NAMES:
C
C          ADJUST - MAPFILE OFFSET ADJUSTMENT
C          IDA - DAY
C          IMO - MONTH
C          IYR - YEAR
C          LAST - LAST MAP NUMBER
C          LX - LENGTH OF X AXIS
C          LY - LENGTH OF Y AXIS
C          MAP - MAP NUMBER
C          MAPW - NUMBER OF MAPS WRITTEN
C          MAXX - LARGEST MAP NUMBER TO BE PROCESSED
C          MAXY - SMALLEST MAP NUMBER TO BE PROCESSED
C          MINX - REFERENCE MAP_X COORDINATE
C          MINY - REFERENCE MAP_Y COORDINATE
C          MOD - NEW COMPOSITE MAPFILE ACRONYM
C          N - COUNTER
```

```
C         NMR - NUMBER OF MAPS PER ROW IN MAPFILE
C         NAME1 - MAP IDENTIFICATION LABEL FOR FIRST COMPONENT FILE
C         NAME2 - MAP IDENTIFICATION LABEL FOR SECOND COMPONENT FILE
C         NAME3 - MAP IDENTIFICATION LABEL FOR THIRD COMPONENT FILE
C         NMAPS - MAP PROCESSED
C         NPTS - MAP REPRESENTING COMPOSITE FILE
C         PTS1 - 30X30 MAP FOR FIRST COMPONENT FILE
C         PTS2 - 30X30 MAP FOR SECOND COMPONENT FILE
C         PTS3 - 30X30 MAP FOR THIRD COMPONENT FILE
C         TITLE - TITLE
C
      INTEGER NMAPS/0/,NAME1(30),NAME2(30),NAME3(30),LAST/0/,MAPW/0/,
     &MOD(2),LX/30/,LY/30/,TITLE(20)
      REAL PTS1(30,30),PTS2(30,30),PTS3(30,30),NPTS(30,30)
      CALL DATE (IMO,IDA,IYR)
      WRITE (6,600) IMO,IDA,IYR
  600 FORMAT ('1',25X,'PROGRAM - AGPWR3',20X,A2,'/',A2,'/',A2)
      READ (5,502) TITLE
  502 FORMAT (20A4)
      WRITE (6,603) TITLE
  603 FORMAT ('0',20A4)
      READ (5,500) MOD
  500 FORMAT (2A4)
C  **  READ DEFINE FILE
      READ (8,801) NMR,MINY,MINX,MAXY,MAXX,ADJUST
  801 FORMAT (A4)
C  **  READ MAP NUMBER
    3 READ (8,801,END=99) MAP
      IF (MAP .GT. LAST) GO TO 91
      WRITE (6,694) MAP
  694 FORMAT ('-*** ERROR *** -- ATTEMPT TO READ MAP', I5, 'WHICH HAS
     &ALREADY BEEN PROCESSED OR PASSED.')
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      REWIND 12
      STOP 8
   91 NMAPS=NMAPS+1
      LAST=MAP
C  **  READ ALL 30X30 MAPS (3) HOLDING LOCATIONS OF CELLS TO BE
C  **  EXCLUDED.
      READ (9,901) PTS1,NAME1
      READ (10,901) PTS2,NAME2
      READ (11,901) PTS3,NAME3
  901 FORMAT (31(30A4))
      DO 5 I=1,LY
```

```
      DO 6 J=1,LX
C  **  CHECK TO SEE IF ONE OF THE THREE DATA SETS HAS A SPECIFIC
C  **  CELL'S LOCATION MARKED SO TO BE EXCLUDED.
      IF (PTS1(I,J).EQ.0.0.AND.PTS2(I,J).EQ.0.0.AND.PTS3(I,J).EQ.0.0)
     &GO TO 40
C  **  IF SO, ASSIGN -9999 TO THE OUTPUT CELL.
      NPTS(I,J)=-9999.
      GO TO 6
C  **  IF NOT, ASSIGN 0.0 TO THE OUTPUT CELL.
   40 NPTS(I,J)=0.0
    6 CONTINUE
    5 CONTINUE
      MAPW=MAPW+1
C  **  ASSIGN NEW MAPFILE ACRONYM
      NAME2(7)=MOD(1)
      NAME2(8)=MOD(2)
C  **  WRITE MERGED EXCLUSION POWER MAP TO DISK.
      WRITE (12,901) NPTS,NAME3
C  **  WRITE POWER MAP NUMBER TO PAPER.
      WRITE (6,601) NMAPS,NAME3
  601 FORMAT ('0',I6,4X,8A4)
      GO TO 3
   99 WRITE (6,602)
  602 FORMAT ('-NORMAL TERMINATION -'/'- ',16('_')/'
     & | END OF PROCESS |'/'+ ',16('_'))
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      REWIND 12
      STOP
      END
```

APPENDIX X

```
C   PROGRAM - CONDITN (JSZ/1981)
C
C   PURPOSE:  THIS PROGRAM USES A DECISION-TREE SCHEME TO RECLASSIFY
C             OR FOREGO CLASSIFICATION OF LANDSAT AGRICULTURE OR
C             FOREST LAND USE/COVER CLUSTERS AS BASED ON
C             CONDITIONAL ENVIRONMENTAL FACTORS.
C
C   INPUTS:
C             UNIT 05 - CARDS
C              CARD1 - COL.1 THRU 80 - TITLE
C              CARD2 - COL.1 THRU 8 - NEW MAP ID LABEL
C              CARD3 - COL.1 THRU 80 - TOTAL NUMBER OF FOREST
C                      LAND USE/COVER CLUSTERS
C              CARD4 - COL.1 THRU 80 - FOREST LAND USE/COVER CLUSTER
C                      VALUES
C              CARD5 - COL.1 THRU 80 - TOTAL NUMBER OF AGRICULTURE
C                      LAND USE/COVER CLUSTERS
C              CARD6 - COL.1 THRU 80 - AGRICULTURE LAND USE/COVER
C                      CLUSTER VALUES
C              CARD7 - COL.1 THRU 80 - TOTAL NUMBER OF CLUSTERS
C             UNIT 08 - 13 DISK INPUT
C              UNIT 8 - FROM PROGRAM DEFINE -- MAP PARAMETERS
C                       INCLUDED FOR PROCESSING
C              UNIT 9 - EXCLUSION DATA SET
C              UNIT 10 - STUDY AREA ELEVATIONS
C              UNIT 11 - STUDY AREA SLOPES
C              UNIT 12 - STUDY AREA ASPECTS
C              UNIT 13 - STUDY AREA DISTANCES FROM WATER
C   OUTPUTS:
C             UNIT 6 - PRINTER
C             UNIT 14 - CONDITIONALLY CLASSIFIED DATA SET
C
C
C   VARIABLES:
C
C      ACLUNO - TOTAL NUMBER OF CLUSTERS WHICH REPRESENT AGRICULTURE
C               LAND USE COVER TYPES
C      ACLUVL - NUMERIC VALUES (ARRAY) WHICH REPRESENT INDIVIDUAL
C               AGRICULTURE CLUSTERS
C      ADJUST - MAPFILE OFFSET ADJUSTMENT
C      AGCOND - CONDITIONAL AGRICULTURE LAND USE/COVER SUBROUTINE
C      ANAME - MAP ID LABEL FOR ASPECT FILE
C      ASPECT - 30X30 MAP OF ASPECTS
C      ELEV - 30X30 MAP OF ELEVATIONS
```

```
C       ENAME - MAP ID LABEL FOR ELEVATION FILE
C       FCLUNO - TOTAL NUMBER OF CLUSTERS WHICH REPRESENT FOREST LAND
C                USE/COVER TYPES
C       FCLUVL - NUMERIC VALUES (ARRAY) WHICH REPRESENT INDIVIDUAL
C                FOREST CLUSTERS
C       FOCOND - CONDITIONAL FOREST LAND USE/COVER SUBROUTINE
C       HIGHVA - GREATEST CLUSTER VALUE OR TOTAL NUMBER OF CLUSTERS
C       IDA - DAY
C       IMAGE - REPRESENTATIVE CLASSIFICATION CATEGORY FOR EACH CELL
C       IMO - MONTH
C       IYR - YEAR
C       LAST - LAST MAP NUMBER
C       LX - LENGTH OF X AXIS
C       LY - LENGTH OF Y AXIS
C       MAP - MAP NUMBER
C       MAXX - LARGEST MAP NUMBER TO BE PROCESSED
C       MAXY - SMALLEST MAP NUMBER TO BE PROCESSED
C       MINX - REFERENCE MAP_X COORDINATE
C       MINY - REFERENCE MAP_Y COORDINATE
C       MOD - NEW MAPFILE ACRONYM
C       NMR - NUMBER OF MAPS PER ROW IN MAPFILE
C       NAME - MAP ID LABEL FOR EXCLUSION FILE
C       NMAPS - MAP PROCESSED
C       NPT - CELL CLASSIFICATION/RECLASSIFICATION CATEGORY
C             ACCORDING TO A MODIFIED ANDERSON ET AL. (1976) SYSTEM
C       PTS - 30X30 MAP OF CLUSTERED DATA. THIS DATA WILL HAVE
C             ALREADY BEEN PROCESSED USING THE EXCLUSION PROCEDURE.
C       SLOPE - 30X30 MAP OF SLOPES
C       SNAME - MAP ID LABEL FOR SLOPE FILE
C       TITLE - TITLE
C       TOTAL - TOTAL NUMBER OF TRANSFERS FROM SUBROUTINE AGCOND TO
C               SUBROUTINE FOCOND
C       TRANS - 0 OR 1 VALUES INDICATING WHETHER SUBROUTINE AGCOND
C               TRANSFERRED TO SUBROUTINE FOCOND WITHIN THE COURSE
C               OF THE PROGRAMS EXECUTION
C       WDIST - 30X30 MAP OF DISTANCES FROM WATER
C       WNAME - MAP ID LABEL FOR DISTANCE FROM WATER FILE
C
        INTEGER FCLUNO,ACLUNO,HIGHVA,TITLE(20),ENAME(30),SNAME(30),
       &ANAME(30),WNAME(30),NAME(30),MOD(2),TOTAL,ADJUST
        REAL PTS(30,30),ELEV(30,30),SLOPE(30,30),ASPECT(30,30),
       &WDIST(30,30),NPTS(30,30),FCLUVL(100),ACLUVL(100),NPT,TRANS
        DATA FCLUVL/100*9999./,ACLUVL/100*9999./,NMAPS/0/,TOTAL/0/,
       &LX/30/,LY/30/
        CALL DATE (IMO,IDA,IYR)
        WRITE (6,600) IMO,IDA,IYR
  600 FORMAT ('1',25X,'PROGRAM - CONDITIONAL',17X,A2,'/',A2,'/',A2)
```

```
      READ (5,50) TITLE
   50 FORMAT (20A4)
      WRITE (6,60) TITLE
   60 FORMAT ('0',20A4)
      READ (5,51) MOD
   51 FORMAT (2A4)
C  **  READ AGRICULTURE AND FOREST LAND USE/COVER CLUSTER PARAMETERS.
      READ (5,*) FCLUNO
      PRINT *,FCLUNO
      READ (5,*) (FCLUVL(J),J=1,FCLUNO)
      WRITE (6,*) (FCLUVL(J),J=1,FCLUNO)
      READ (5,*) ACLUNO
      PRINT *,ACLUNO
      READ (5,*) (ACLUVL(J),J=1,ACLUNO)
      WRITE (6,*) (ACLUVL(J),J=1,ACLUNO)
      READ (5,*) HIGHVA
      PRINT *,HIGHVA
C  **  READ DEFINE FILE
      READ (8,801) NMR,MINY,MINX,MAXY,MAXX,ADJUST
  801 FORMAT (I4)
C  **  READ MAP NUMBER
    3 READ (8,801,END=1) MAP
      NMAPS=NMAPS+1
C  **  READ ONE COMPLETE POWER MAP FOR EACH CONDITIONAL DATA SET
      READ (9,901) PTS,NAME
      READ (10,901) ELEV,ENAME
      READ (11,901) SLOPE,SNAME
      READ (12,901) ASPECT,ANAME
      READ (13,901) WDIST,WNAME
  901 FORMAT (31(30A4))
      DO 5 I=1,LY
      DO 6 J=1,LX
C  **  CHECK TO SEE IF CELL HAD PREVIOUSLY BEEN DROPPED OUT
      IF (PTS(I,J).NE.-9999.) GO TO 9
C  **  IF DROPPED OUT, ASSIGN CELL A CLASSIFICATION CATEGORY OF
C  **  -9999.
      NPTS(I,J)=-9999.
      GO TO 6
    9 DO 7 K=1,HIGHVA
C  **  CHECK WHETHER CLUSTERS BELONG TO A FOREST OR AGRICULTURE LAND
C  **  USE/COVER
      IF (FCLUVL(K).EQ.9999.) GO TO 98
      IF (PTS(I,J).EQ.FCLUVL(K)) GO TO 99
    7 CONTINUE
   98 TRANS=0.
C  **  CALL FOR AGRICULTURE CONDITIONAL SUBROUTINE
      CALL AGCOND (ELEV(I,J),SLOPE(I,J),ASPECT(I,J),WDIST(I,J),
```

```
     &TRANS,NPT
      GO TO 97
C  **  CALL FOR FOREST CONDITIONAL SUBROUTINE
   99 CALL FOCOND (ELEV(I,J),SLOPE(I,J),ASPECT(I,J),WDIST(I,J),
     &NPT)
C  **  ASSIGN CONDITIONALLY CLASSIFIED DATA TO POWER MAPFILE STORAGE.
   97 NPTS(I,J)=NPT
C  **  SUM TOTAL TRANSFERS
      IF (TRANS.EQ.1) TOTAL=TOTAL+1
    6 CONTINUE
    5 CONTINUE
C  **  ASSIGN CLASSIFIED FILE ACRONYM
      NAME(7)=MOD(1)
      NAME(8)=MOD(2)
C  **  WRITE COMPLETE CLASSIFIED 30X30 MAP TO DISK STORAGE
      WRITE (14,902) NPTS,NAME
  902 FORMAT (31(30A4))
      GO TO 3
    1 WRITE (6,68) TOTAL
   68 FORMAT ('0','TOTAL EQUAL TO ',I6)
      WRITE (6,69)
   69 FORMAT ('-NORMAL TERMINATION-'/
     &   '- ',16('_')/' | END OF PROCESS | '/'+ ',16('_'))
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      REWIND 12
      REWIND 13
      REWIND 14
      STOP
      END
      SUBROUTINE AGCOND (ELEV,SLOPE,ASPECT,WDIST,TRANS,IMAGE)
      REAL IMAGE,TRANS,X
      IF (ELEV.LE.2100.) GO TO 601
      IF (SLOPE.LE.3.)GO TO 602
      TRANS=1.
      CALL FOCOND (ELEV,SLOPE,ASPECT,WDIST,X)
      IMAGE=X
      GO TO 1000
  602 IMAGE=9.
      GO TO 1000
  601 IF (ELEV.GT.2010.) GO TO 401
      IF (ELEV.GT.1720) GO TO 500
      IF (WDIST.GE.1.) GO TO 501
      IMAGE=5.
      GO TO 1000
```

```
 501 IMAGE=9.
     GO TO 1000
 500 IF (SLOPE.LE..001) GO TO 502
     IMAGE=9.
     GO TO 1000
 502 IF (WDIST.GT.2.) GO TO 503
     IMAGE=9.
     GO TO 1000
 503 IMAGE=8.
     GO TO 1000
 401 IF (SLOPE.LE.3.) GO TO 301
     TRANS=1.
     CALL FOCOND(ELEV,SLOPE,ASPECT,WDIST,X)
     IMAGE=X
     GO TO 1000
 301 IF (SLOPE.GT..001) GO TO 304
     IF (WDIST.GT.2.) GO TO 302
     IMAGE=9.
     GO TO 1000
 302 IMAGE=8.
     GO TO 1000
 304 IMAGE=9.
1000 RETURN
     END
      SUBROUTINE FOCOND (ELEV,SLOPE,ASPECT,WDIST,IMAGE)
     REAL IMAGE
     IF (ASPECT.LT.261.) GO TO 200
 102 IF (WDIST.GE.1.) GO TO 101
     IMAGE=5.
     GO TO 1000
 101 IMAGE=41.
     GO TO 1000
 200 IF (ASPECT.LE.145.) GO TO 102
     IF (ASPECT.GE.196..AND.ASPECT.LE.260.) GO TO 400
     IF (WDIST.GE.1.) GO TO 301
     IMAGE=5.
     GO TO 1000
 301 IMAGE=43.
     GO TO 1000
 400 IF (SLOPE.LT.3.) GO TO 401
     IF (WDIST.GT.2.) GO TO 402
     IMAGE=43.
     GO TO 1000
```

```
 402 IMAGE=42.
     GO TO 1000
 401 IMAGE=43.
1000 RETURN
     END
```

APPENDIX Y

```
C       PROGRAM -- DROPPWR2 (JSZ/1981)
C
C       PURPOSE :  TO CREATE A NEW MAPFILE OF LANDSAT DATA BY CHANGING
C                  SPECIFIC PIXEL VALUES.
C
C       INPUTS  :
C               UNIT 05 - CARDS
C                 CARD1 - COL.1 THRU 80 - TITLE
C                 CARD2 - COL.1 THRU 8 - NEW MAP IDENTIFICATION
C                 CARD3 - COL.1 THRU 80 - VALUE ASSIGNED TO CHANGED
C                         PIXELS.
C                 CARD4 - COL.1 THRU 80 - BEGINNING AND END RANGE
C                         VALUES WHICH CORRESPOND TO AN OVERLAID
C                         IMAGE AND PIXELS OF THAT IMAGE WHICH WILL
C                         RETAIN THEIR ORIGINAL VALUES.
C
C               UNIT 08 - FROM PROGRAM DEFINE -- MAP NUMBERS TO
C                         BE INCLUDED FOR PROCESSING.
C               UNIT 09 - EXISTING MAPFILE REPRESENTING IMAGE WHERE
C                         SPECIFIC PIXEL VALUES WILL BE CHANGED.
C               UNIT 10 - EXISTING DISTANCE (DIST4) MAPFILE.
C       OUTPUTS:
C               UNIT 06 - PRINTER
C               UNIT 10 - NEW MAPFILE.
C
C
C       VARIABLE NAMES:
C
C       ADJUST - MAPFILE OFFSET ADJUSTMENT
C       ASSIGN - NEW VALUE FOR CHANGED PIXELS
C       BEGIN  - STARTING OR FIRST VALUE OF RANGE
C       END - ENDING OR LAST VALUE OF RANGE
C       IDA - DAY
C       IMO - MONTH
C       IYR - YEAR
C       LAST - LAST MAP NUMBER
C       LX - LENGTH OF X AXIS
C       LY - LENGTH OF Y AXIS
C       MAP - MAP NUMBER
C       MAPW - NUMBER OF MAPS WRITTEN
C       MAXX - LARGEST MAP NUMBER TO BE PROCESSED
C       MAXY - SMALLEST MAP NUMBER TO BE PROCESSED
C       MINX - REFERENCE MAP_X COORDINATE
C       MINY - REFERENCE MAP_Y COORDINATE
```

```
C       MOD - NEW MAPFILE ACRONYM
C       NMR - NUMBER OF MAPS PER ROW IN MAPFILE
C       NMAPS - MAP PROCESSED
C       NPTS - MAP REPRESENTING DROPOUT CASES
C       RDIST - 30X30 MAP FOR DISTANCE DATA
C       RNAME - MAP IDENTIFICATION LABEL FOR DISTANCE FILE
C       TITLE - TITLE
C       TNAME - MAP IDENTIFICATION LABEL FOR OVERLAID MAPFILE
C       TPTS - 30X30 MAP FOR OVERLAID DATA
C
C
      INTEGER TITLE(20),TNAME(30),RNAME(30),MOD(2),ADJUST
      REAL ASSIGN,BEGIN,END,TPTS(30,30),RDIST(30,30),NPTS(30,30)
      DATA NMAPS/0/,MAPW/0/,LX/30/,LY/30/
      CALL DATE (IMO,IDA,IYR)
      WRITE (6,600) IMO,IDA,IYR
  600 FORMAT ('1',25X,'PROGRAM - DROPCELL2',20X,A2,'/',A2,'/',A2)
      READ (5,502) TITLE
  502 FORMAT (20A4)
      WRITE (6,603) TITLE
  603 FORMAT ('0',20A4)
      READ (5,500) MOD
  500 FORMAT (2A4)
      READ (5,*) ASSIGN
      PRINT *,ASSIGN
      READ (5,*) BEGIN,END
      PRINT *,BEGIN,END
C  **  READ DEFINE FILE
      READ (8,801) NMR,MINY,MINX,MAXY,MAXX,ADJUST
  801 FORMAT (A4)
C  **  READ MAP NUMBER
    3 READ (8,801,END=99) MAP
      IF (MAP .GT. LAST) GO TO 91
      WRITE (6,694) MAP
  694 FORMAT ('-*** ERROR *** -- ATTEMPT TO READ MAP',I5,'WHICH HAS
     &ALREADY BEEN PROCESSED OR PASSED.')
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      STOP 8
   91 NMAPS=NMAPS+1
      LAST=MAP
C  **  READ COMPLETE 30X30 MAP FOR CELLS TO BE REMOVED (TRUTH
C  **  CELLS = PTS1) CORRESPONDING TO DISTANCE IMAGE (PTS2).
      READ (9,901) TPTS,TNAME1
      READ (10,901) RDIST,RNAME
```

```
  901 FORMAT (31(30A4))
      DO 5 I=1,LY
      DO 6 J=1,LX
C  **  CHECK TO SEE IF CELL IS TO BE REMOVED.
      IF (RDIST(I,J).GE.BEGIN.AND.RDIST(I,J).LE.END) GO TO 100
C  **  IF CELL IS TO BE CHANGED ASSIGN X TO OUTPUT DATA SET
C  **  PIXEL.
      NPTS(I,J)=ASSIGN
      GO TO 6
C  **  IF CELL IS NOT TO BE CHANGED ASSIGN ORIGINAL VALUE TO
C  **  OUTPUT DATA SET PIXEL.
  100 NPTS(I,J)=TPTS(I,J)
    6 CONTINUE
    5 CONTINUE
      MAPW=MAPW+1
C  **  ASSIGN NEW MAPFILE ACRONYM
      TNAME(7)=MOD(1)
      TNAME(8)=MOD(2)
C  **  WRITE CHANGED POWER MAP TO DISK
      WRITE (11,901) NPTS,TNAME
C  **  WRITE CHANGED POWER MAP NUMBER TO PAPER
      WRITE (6,602) NMAPS
  602 FORMAT (' ','MAP',I4,1X,'PROCESSED')
      GO TO 3
    1 WRITE (6,601) NMAPS
  601 FORMAT ('0',3X,I4,1X,'MAPS PROCESSED')
      WRITE (6,69)
   69 FORMAT (' -NORMAL TERMINATION-'/'- ',16('_')/' |END OF PROCESS|
     &'/' +',16(' '))
      REWIND 8
      REWIND 9
      REWIND 10
      REWIND 11
      STOP
      END
```

APPENDIX Z

GIPSY PROGRAM SEQUENCE

This sequence of GIPSY commands was used in classifying both the 4-band and 9-band Landsat images for the Montgomery County study area.

COMMAND - Brief Description

BINSIF - Converts an 8-bit binary sequential file into a GIPSY Standard Image Format (SIF) file.

COMBIN - Combines 2 images into 1 image.

PRNCP - Forms the principal components of an image.

LCOMB - Linearly combines several bands of an input image.

SBIMG - Extracts a subimage.

ARITHM - Arithmetic package for 2 images or 1 image and a constant.

XPCMP - Expands or compresses an image scale.

AVGIMG - Rectangular box filter convolution for a N by N neighborhood.

CNCFCT - Performs a central neighborhood cubic facet calculation.

EDGE - Detects edges on the output from CNCFCT.

CONCT - Labels maximally connected components of a binary image.

FILL - Performs region filling of y-labels into pixels having non-positive labels.

RELBL - Relabels the symbolic image with positive sequential labels.

SHRINK - Shrinks categories of a symbolic image (optional).

XPCMP - Expands or compresses image scale.

RELBL - Relabels the symbolic image with positive sequential labels.

PRPMBI - Computes a property file for a multi-band image.

ELIMRG - Eliminates regions.

FILL - Performs region filling of y-labels into pixels having non-positive labels.

RELBL - Relabels the symbolic image with positive sequential labels.

PRPMBI - Computes a property file for a multi-band image.

GENMST - Generates a minimum spanning tree of a complete graph.

MSTCLU - Performs clustering by minimum spanning tree.

PRPSIF - Creates a SIF with region properties.

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