Computer-Aided Classification of Forest Cover Types

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ABSTRACT / The US National Park Service must map forest cover types over extensive areas in order to fulfill its goal of maintaining or reconstructing presettlement vegetation within national parks and monuments. Furthermore, such cover type maps must be updated on a regular basis to document vegetation changes. Computer-aided classification of small scale aerial photography is a promising technique for generating forest cover type maps efficiently and inexpensively. In this study, seven cover types were classified with an overall accuracy of 62 percent from a reproduction of a 1:120,000 color infrared transparency of a conifer-hardwood forest. The results were encouraging, given the degraded quality of the photograph and the fact that features were not centered, as well as the lack of information on lens vignetting characteristics to make corrections. Suggestions are made for resolving these problems in future research and applications. In addition, it is hypothesized that the overall accuracy is artificially low because the computer-aided classification more accurately portrayed the intermixing of cover types than the hand-drawn maps to which it was compared.

A primary goal of national park management in the United States is to maintain, or where necessary recreate, "biotic associations within each park ... as nearly as possible in the condition that prevailed when the area was first visited by the white man" (Leopold and others 1963). This goal was the recommendation of the Secretary of the Interior's Advisory Board on Wildlife Management. It was incorporated into the administrative policies of the National Park Service on 10 July 1964 (US National Park Service 1968). This study addresses one of the many scientific problems that are encountered in maintaining or reconstructing the structure and composition of presettlement forests, namely, developing an efficient procedure for accurately mapping forest cover types over extensive areas.

Vegetation Mapping

Hand-drawn maps

The first step in vegetation reconstruction is to describe and map existing vegetation. To obtain the necessary descriptive information, the vegetation is first stratified into relatively homogeneous cover types. These cover types serve as the basis for sampling vegetation characteristics.

KEY WORDS: Forest cover types, Small scale aerial photography, Vegetation reconstruction, Computer-aided classification, Computer-aided mapping.

Traditionally, stratification has been accomplished through ocular interpretation of stereo pairs of aerial photographs. The resultant vegetation maps generally consist of broadly delineated areas of relatively uniform vegetation cover. However, since photographic interpretation and hand mapping of cover types is labor-intensive and, therefore, expensive, the cost of high resolution cover type maps can be prohibitive, particularly when such maps must be updated on a regular basis. Finally, because the ability of the human eye to delineate subtle differences in tonal rendition is limited, the computer processing of non-photographic data for classifying and mapping vegetation is being investigated.

Computer Classified Maps

Computer-aided classification of vegetation from remotely sensed data has a relatively short history. Most of the work done in this field has dealt with multispectral scanner data such as are produced by the Landsat satellite. In a 1974 Laboratory for Applications of Remote Sensing (LARS) study (Hoffer 1976), for instance, five cover types were differentiated from Landsat imagery of southwestern Colorado. The types were coniferous forest, deciduous forest, grassland, water, and barren. The classification achieved 91 percent agreement with aerial photo-interpretation and field checks. In a subsequent, more intensive test over a smaller forested area, 77 percent accuracy was achieved in differentiating pine, spruce-fir, oak, aspen, grassland, water, and barren areas (Hoffer and Fleming 1978).

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Bryant and others (1978) achieved 59 percent agreement between a Landsat data classification of northern Maine and ocular photo-interpretation of the same area. The types classified were softwood, mixed-wood, and hardwood. Hoffer and others (1979) found that the overall performance of Landsat classifications of forest cover types can be increased by as much as 15 percent by using topographic data in addition to spectral data.

Kessell and Cattelino (1978) tested the adequacy of Landsat imagery as a data base for high resolution (1 to 100 ha) site inventories. Several problems with Landsat data were encountered. Although a single picture element of Landsat imagery is approximately 57 by 79 m, more than one picture element was required for the accurate interpretation of features. The investigators also discovered a 10 degree rotation in Landsat imagery printouts; this could cause the naive user to make great errors in transferring information from the images to maps. Furthermore, they noted poor agreement between Landsat imagery over forested lands and reliable ocular interpretation of 1:100,000 false color infrared aerial photographic coverage of the same area. Finally, features in the Landsat imagery were displaced as a result of image distortion. They concluded that the results of their tests were "not encouraging for site-specific use of the Landsat imagery data base" (Kessell and Cattelino 1978).

Mead and Meyer (1977) reached a similar conclusion regarding the use of Landsat digital data for classification of forest types and land use classes in Minnesota. Using state-of-the-art classification techniques they were unable to produce a classification of Landsat data of high enough accuracy to be of use to forest managers.

Less work has been done in the field of computer-aided classification of vegetation from small scale aerial photography. Akca (1971) discussed the potential for mapping forest types through microdensitometric analysis of black and white imagery. Hoffer (1971) described the use of automatic data processing (ADP) in quantitative classification of aerial photography. Multiband and multiemulsion imagery at a scale of 1:120,000 covering agricultural crops and trees was analyzed. Using these two types of imagery, corn, soybeans, pasture, and trees were classified with an overall correctness of over 90 percent (Hoffer 1971).

In a more recent study of vegetation in south central Indiana, LARS investigators compared digitized data from small scale photography with three channels of multispectral data as data sources for an ADP classification technique (Coggeshall and others 1974). Six cover types were classified from the scene: deciduous forest, coniferous forest, water, forage, corn, and soybeans. Classification results indicated that the overall performance of the multispectral scanner data was about 81 percent. The accuracy of the classification based on photographic data was about 48 percent. The classification of the scanned photography included much misclassification of deciduous forest. The disparity in the accuracies between the two classifications was attributed mainly to the fact that the photography utilized was second generation, and to the greater dynamic range and higher spectral resolution of the scanner system as compared with the photographic system (Coggeshall and others 1974).

Kan and others (1975) studied the effect of image resolution on the accuracy of computer-aided classifications. They classified forest types in Texas from aerial photography taken at various altitudes. They concluded that high altitude imagery resulted in better classification accuracy than low altitude imagery because the level of homogeneity perceived by the sensor increased with an increase in altitude.

Given recent technical developments in densitometry of aerial photographic products (Scarpace 1978) and the increasing sophistication of image analysis techniques, computer-aided classification of vegetation from small scale aerial photography has become a potentially valuable vegetation mapping procedure. This study shows that complex forest vegetation can be classified and mapped with a reasonable degree of accuracy from computer analysis of small scale aerial photography.

Study Area

This study is based primarily on data from Bear Island, one of the twenty-two Apostle Islands in Lake Superior. Bear Island is in the Apostle Islands National Lakeshore (Fig. 1). Because of its considerable topographic variability, Bear Island supports a large subset of the diverse plant communities of the archipelago. Thus classification and mapping results from Bear Island can also be extended to much of the lakeshore's vegetation.

Physical Features

At its extreme points, Bear Island is approximately 3.9 km from north to south and 2.6 km from east to west. Its dominating topographic feature is a glacial drumlin, which rises in the southern half of the island to an elevation of 254 m. This hill slopes down to an elevation of 190 m on the northern end of the island.

Much of the sandstone bedrock of Bear Island is

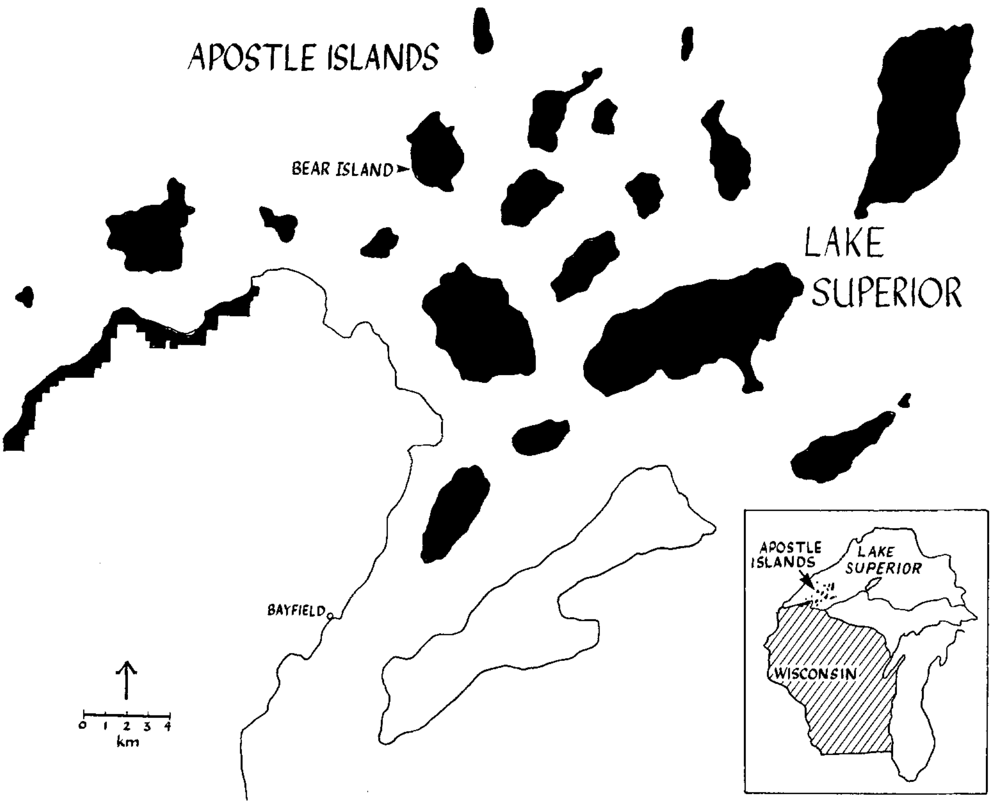

Figure 1. Location map for Bear Island. The Apostle Island National Lakeshore is shaded.

covered with glacial till deposited by the Valders ice sheet. The ice advanced from the northeast, scouring that half of the island and leaving thick deposits on the southwest side. As the ice sheet receded, the island was flooded by glacial lake waters. Lacustrine clay sediments were deposited over the till and bedrock. Subsequent wave action modified the sediments, till, and landforms. On the northern half of the island the predominant soils are poorly drained clays of lacustrine origin. In the south of the island the soils originated from water-worked glacial till. They are coarse textured and well drained (Kowalski 1976).

Vegetation

In 1852, Joseph Norwood conducted a geological survey of the Apostle Islands. Included in his notes was this description of the area's vegetation: "Along the lakeshore of the islands are thickets of evergreens. The surface is covered with cedar, birch, aspen, hemlock, and pine. There are patches of 'sugar tree land' and some natural meadows" (Fredrick and Rakestraw 1976). Fredrick and Rakestraw (1976) used surveyor records from 1840 to 1850 to describe the presettlement vegetation of the area. They concluded that the northern half of Bear Island and its eastern and western shores were dominated by hemlock (*Tsuga canadensis* [L.] Carr.). The remainder of the island was covered with sugar maple (*Acer saccharum* Marsh.).

Much of the original vegetation on the Apostle Islands has been replaced as a result of the logging that began in the late 1800s. At first logging was limited to white pine (*Pinus strobus* L.), which was taken for lumber. In the

1950s, however, most of the merchantable hemlock on Bear Island was cut, and high quality hardwoods were cut for veneer and furniture stock (Fredrick and Rakestraw 1976). Much evidence of logging remains on Bear Island, including tree stumps, logging roads, and the decaying log structures of a logging camp.

The results of a 1971 timber cruise of Bear Island indicated that 86 percent of the island was covered with "northern hardwoods," 7 percent with spruce (*Picea* spp.) and balsam fir (*Abies balsamea* [L.] Mill.), and 7 percent with aspen (*Populus tremuloides* Michx.) and birch (*Betula* spp.) (Fredrick and Rakestraw 1976). The area that originally supported hemlock is covered today with white cedar (*Thuja occidentalis* L.), white birch (*Betula papyrifera* Marsh.), hemlock, and "northern hardwoods" (Fredrick and Rakestraw 1976). This vegetation occurs on the poorly drained clayey soils of the northern half of the island. The white cedar forms the understory, and the overstory consists of white birch and yellow birch (*Betula lutea* Michx. F.). Also occurring on these poorly drained soils are scattered large white pine and hemlock, and dense thickets of balsam fir. A spectacular grove of large old hemlock stands near the bottom of the northeast flank of the drumlin. The well drained loamy sands of the drumlin that were formerly dominated by sugar maple still support this species (Fredrick and Rakestraw 1976). White birch also occurs with the sugar maple throughout the area. Lesser amounts of northern red oak (*Quercus borealis* Michx.), white cedar, and hemlock are also present. At the top of the drumlin is a bog containing white pine, black spruce (*Picea mariana* [Mill.] B.S.P.), and tamarack (*Larix laricina* [Du Roi] K. Koch). Below the steep southern slope of the drumlin is a sand spit on which stands large red pine (*Pinus resinosa* Ait.) and white pine, and a plantation of pole-sized white pine.

The general impression of the island is that of a complex mosaic of vegetation. Groups of tree species form small pieces of the mosaic in response to micro-site variations and disturbance history. Large, pure stands of single tree species are not found on the island.

Methods

Collection of Ground Data

The overstory vegetation on Bear Island was stratified from 1:15,840 black and white infrared vertical photographs. Nine major cover types were identified from stereo-coverage of the island on the basis of texture, pattern, shape, tone, and shadow (Zsilinszky 1966). The cover types were delineated on transparent plastic, and then a zoom transfer scope was used to superimpose and copy the types onto a USGS 1:24,000 topographic map. Stratified random sampling was used to obtain ground data for each of the nine cover types (Freese 1962). Sample plots of 405 m^2 were allocated in proportion to the area of each type. The type covering the most area was designated five sample plots, while the least extensive cover type received two sample plots. A total of 33 circular plots (shown as dots in Fig. 2) were allocated among all nine cover types. A photo-mosaic of Bear Island, showing the location of sample plots and the boundaries of the cover types, is presented in Fig. 2.

The species and diameter at 137 cm above the ground were recorded for all mature and pole-sized trees within each plot. Trees 25.4 cm or greater in diameter were classed as mature, and trees 12.7 cm to 25.4 cm in diameter were placed in the pole class. Table 1 summarizes the species composition of the combined pole and mature size classes for each type as determined by the sample. Although the cover types could be distinguished from one another using black and white infrared stereo models, they nevertheless exhibit considerable overlap in species composition.

A polar ordination (Bray and Curtis 1957) was performed on the overstory species composition data in Table 1 to determine the degree of similarity that may have existed among the cover types. The null hypothesis was that all pairs of cover types were dissimilar with regard to species composition. However, a three-axis ordination showed that cover types VI, VII, and VIII formed a group while the other types were widely separated from one another. Therefore, for the computer-aided classification of Bear Island, types VI, VII, and VIII were treated as a single cover type.

Image Classification

The image used for computer classification was a reproduction of 1:120,000 color infrared RB57 9 × 9 inch (23 × 23 cm) transparency. The copy was highly degraded, and none of the islands shown were centered in the image. Vignetting characteristics for the lens used were unavailable; so proper corrections for lens falloff could not be made. The steps involved in computer classification of the image are outlined in Fig. 3. All computer programs shown in the flow chart were developed by the University of Wisconsin Environmental Remote Sensing Center of the Institute for Environmental Studies.

The transparency and its corresponding film wedge

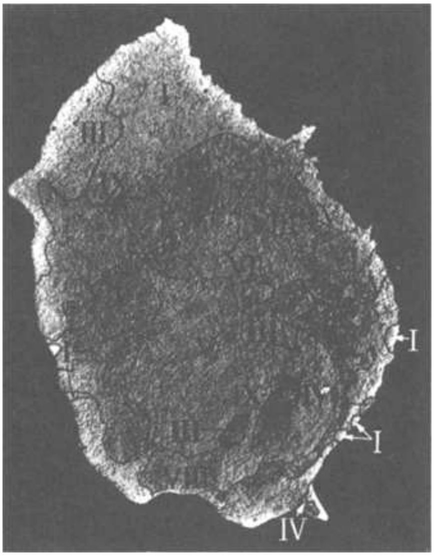

Figure 2. Aerial photo-mosaic of Bear Island, showing location of sample plots (dots) and hand-drawn forest cover type boundaries. Unlabeled areas are not forested. Original scale of 1:15,840.

were densitometrically scanned on an Optronics P-1700 scanning microdensitometer at 50 μm intervals. In this instrument, a narrow band of wavelengths of light penetrates a 50 × 50 μm area on the transparency. This area is known as a picture element, or pixel. Given the scale of the scanned image, each pixel represents an area on the ground of 6 × 6 m. The density of the film at each pixel is recorded according to the following relationship:

$$\text{Density} = \log\,[P_0(\lambda)/P(\lambda)]$$

where $P_0(\lambda)$ is the amount of light of wavelength (λ) in ergs/sq cm incident on the film and $P(\lambda)$ is the fraction of $P_0(\lambda)$ that passes through the film. The film then moves 50 micrometers and a new measurement is recorded. The image was scanned three times. Each time the light was restricted by a 10 nanometer narrow band pass filter centered on 450, 550, or 650 nanometers, respectively. In this manner, values were recorded for the green, red, and infrared-sensitive emulsion layers of the film.

The density measured by the microdensitometer at a particular pixel is the integral density of the transparency at that pixel over a specific wavelength range. Integral density is the sum of the densities of the film layers and is derived from the following expression:

$$D(\lambda) = D_b(\lambda) + D_y(\lambda) + D_m(\lambda) + D_c(\lambda)$$

where $D(\lambda)$ is the integral density of the film, $D_b(\lambda)$ is the density of the base material, and $D_y(\lambda)$, $D_m(\lambda)$, and $D_c(\lambda)$ are the analytical densities of the yellow, magenta, and cyan layers of the film, respectively (Scarpace 1978). The integral spectral density of the film at a particular pixel is related to the exposure at that pixel.

Table 1. Species composition of the nine forest cover types on Bear Island

Species	Forest cover type								
	I	II	III	IV	V	VI	VII	VIII	IX
Thuja occidentalis	25*	26	45	0	5	23	59	38	0
Betula papyrifera	50	2	12	0	43	18	35	29	5
Abies balsamea	18	11	6	0	2	18	2	22	0
Acer saccharum	1	0	1	5	28	18	0	2	0
Betula alleghaniensis	0	15	34	0	9	18	1	7	3
Tsuga canadensis	0	24	2	0	0	3	0	0	0
Acer rubrum	1	20	0	20	2	0	2	0	0
Pinus strobus	2	0	0	40	0	0	1	0	41
Pinus resinosa	0	0	0	35	2	0	0	0	0
Quercus borealis	1	0	0	0	9	0	0	2	0
Prunus spp.	0	2	0	0	0	2	0	0	0
Larix laricina	2	0	0	0	0	0	0	0	24
Picea mariana	0	0	0	0	0	0	0	0	27
Total	100	100	100	100	100	100	100	100	100

*The entries in the table are the percent species composition in the combined pole and mature size classes.

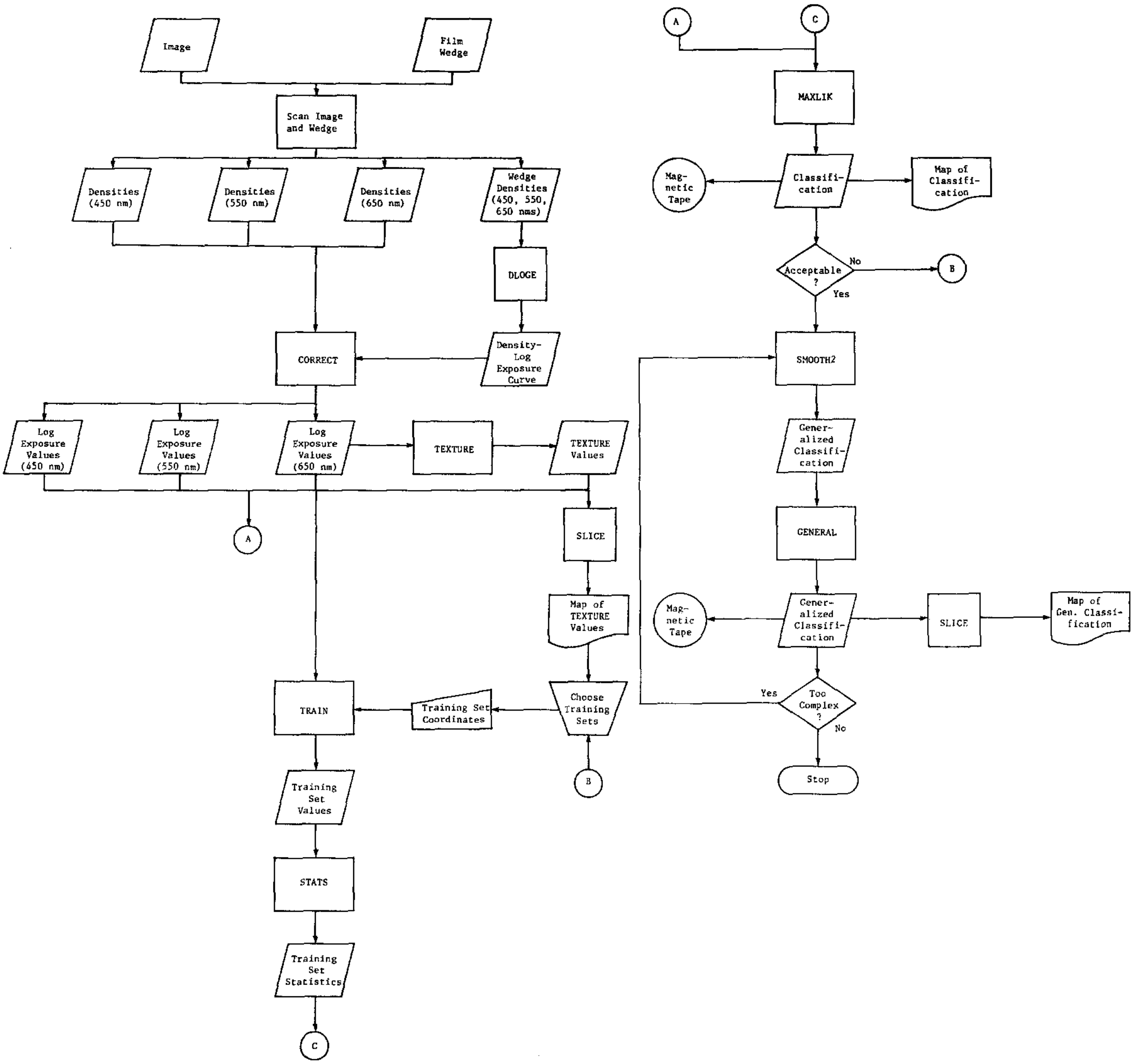

Figure 3. Flow chart of the image classification process.

The relationship between film density and exposure is determined through the use of a film wedge specific to the film under analysis. The film wedge consists of a series of exposed rectangles on the film, which constitute a gradient of densities. Prior to film processing, light of known intensity is projected through a series of glass panels of known densities. This series of panels is a step wedge. Prior to processing, the light is projected through the step wedge and onto an unexposed segment of the film. The resulting film wedge establishes the relationship between film density and exposure. Program DLOGE takes the density values obtained by scanning the film wedge and, using exposure values from the step wedge, derives the curve of film density plotted against the log of exposure. Program CORRECT takes this film characteristic curve and the density values obtained by scanning the image, and converts each density value to a number that is proportional to the relative log of exposure. At this point, program SLICE can be used to produce digital maps of these relative exposure values from any of the bands in which the image was scanned.

The exposure values from the infrared-sensitive layer were transformed by program TEXTURE to create transformed data. Program TEXTURE calculates the standard deviation of a 9 pixel neighborhood and records it in the central pixel. Then it moves to the next pixel to compute and record the standard deviation of its immediate neighbors. This calculation is an indication of the relative brightness values of neighboring pixels. Areas with sharply contrasting bright and dull components characteristically have high texture values. These values have been found useful in distinguishing different features in computer classifications of imagery. Values generated by program TEXTURE were treated as an additional band of spectral data. Finally, all the data were averaged into 36 × 36 m pixels for the analysis.

A central assumption made in mapping features from film exposure values is that the amount of energy reflected by a feature in each of the sensed wavelengths is unique. The combination of exposure values from a feature is called its spectral signature. To obtain an approximation of the spectral signatures of the cover types on Bear Island, several computer programs were employed.

A character map of the infrared-sensitive band values was produced by program SLICE. Polygons encompassing large areas within each of the cover types were delineated, and the coordinates of their apices determined. These polygons enclosed the 15 training sets used in the final classification. Program TRAIN uses the apices to locate the polygons in the four bands and extracts the encompassed values. The values from the polygonal training sets for Types VI, VII, and VIII were combined into one training set for class VI-VII-VIII because of the similarity in the species composition of the three cover types. Program STATS calculates descriptive statistics for each of the training sets. The statistics from a training set describe a class (Fig. 4).

The program used to classify the data utilizes a maximum likelihood classifier with a threshold. Program MAXLIK checks each pixel in the scanned scene individually and calculates the exact probability of that pixel occurring in each of the classes. It then assigns each pixel to the class in which it has the maximum probability of occurring. Pixels whose values exceed four standard deviations from the means of all classes are designated as unclassified. Program MAXLIK stores the classification in a computer file and outputs a line printer character map of the classification.

It was decided that the degree of complexity represented by this map was too high for the purposes of this study. Therefore, SMOOTH2 was used to generalize the map. Generalization routines such as SMOOTH2 check neighborhoods of pixels and retain or change the characters present according to the desired level of complexity. The purpose of using such a routine is to reduce the level of detail of the map by changing very small clusters of characters (from one to ten pixels) to the class of the majority of their neighbors. The actual classification remains unchanged, but the map products, such as character maps and film products, can be generalized to the level of detail desired. Each generalization of the original classification may represent a loss of information, but result in a gain in comprehensibility.

Results

The results of the study were reasonably good, given the poor quality of the image scanned and the complexity of the vegetation mosaic on Bear Island. A black and white version of the generalized classification map of the island is shown in Fig. 5. In Fig. 5, the seven classes are represented by shades of gray and unclassified areas are white. Fig. 5 was produced using the photo-write mode of the microdensitometer.

Pixels in Fig. 5 are more concentrated within given geographic areas when the classes they represent contain species that are not abundant in other classes. For example, class 5 pixels are concentrated in a roughly circular region in the south of the island. This class, which is distinguished from other classes by its sugar maple component, occurs on the well drained soils of the drumlin. Class 5 decreases in occurrence with distance from the drumlin. Near the middle of this circular region of class 5 pixels, on top of the drumlin, is a small bog community dominated by tamarack and black spruce, with small white pine dominated vegetation types located on two sides.

The area of each of the seven classes is shown in Table 2. These areas were computed by program CCOUNT,

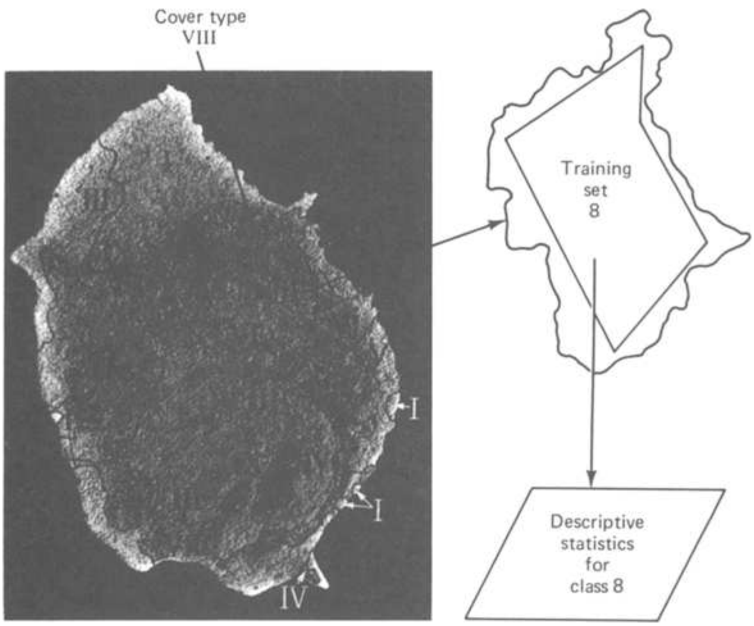

Figure 4. Procedure for generating computer-aided classification from hand-drawn cover type map: (1) polygonal training sets are manually located within cover types; (2) descriptive statistics are calculated for the values comprising each training set. Values from training set 8 subsequently combined with the values from training sets 6 and 7 to create one training set for class 6-7-8.

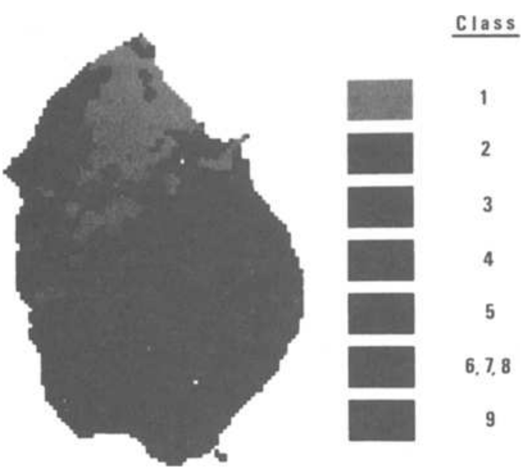

Figure 5. Generalized computer-aided classification of Bear Island. Classes are shown in shades of gray. Unclassified areas are white. The smallest visible squares are picture elements that represent a ground area of 36 × 36 m.

which counts the pixels of a class and multiplies the sum by the area represented by each pixel. In this classification a pixel represents 36 × 36 m on the ground. Class 5 covers the greatest area of the island (261.9 ha). The class with the least areal extent (8.4 ha) is class 9.

Table 3 compares the cover type map, produced from manual photo-interpretation, with the generalized computer classification. To produce this table, a large subset (the training set) of each cover type was analyzed. The table shows the percentage of each subset designated to each class. The Arabic numerals heading the rows represent the classes derived from training sets, while the corresponding Roman numerals on the columns represent the hand-drawn cover types from which the training sets were taken. Thus, as shown in column I, 89.1 percent of the pixels from the training sets for cover type I, were classed as class 1. The remainder of that training set's pixels more closely fit the distribution of spectral signatures of other classes and were classified accordingly.

Numbers on the diagonal from upper left to lower right in Table 3 indicate the level of agreement between classes and the cover types they represent. Were the classification to exactly mirror the cover type map, all

Table 2. Area covered by each class in the generalized classification

Class	Area (ha)
1	117.9
2	100.7
3	91.0
4	15.2
5	261.9
6-7-8	75.2
9	8.4
Total	670.3

numbers on this line would equal 100 percent. A departure from 100 percent on the diagonal is normally interpreted as an indication of the accuracy of the computer classification. However, it is suggested that it is also a measure of the complexity of the vegetation. In other words, high values on the diagonal occur for cover types whose spectral signatures overlap little with the spectral signatures of other types. This indicates that cover types that have low proportions of other types within their boundaries exhibit high values on the diagonal. Conversely, low values occur for cover types that have a high proportion of other cover types within their boundaries.

Ocular stratification is influenced by a bias towards homogeneity, which computer classification does not share. Since the maximum likelihood algorithm assigns each individual pixel to the class with the statistical description it best fits, it is hypothesized that the resultant classification more accurately demonstrates the intermixing of cover types than the hand-drawn map. Furthermore, it is hypothesized that the intermixing of cover types detected by the computer classification is, in part, responsible for the 62 percent overall correspondence found between the cover types and classes (Table 3).

The correlation between the spectral signature and species composition of cover types can be seen by comparing Tables 1 and 3. Cover type IX, for example, is composed primarily of coniferous species. The two species that dominate type IX, tamarack and spruce, are much less abundant in most of the other cover types. Thus we would expect this type to have a spectral signature that differs from that of the other types. This is shown to be the case in Table 3; 74.8 percent of the type IX training set was classified as class 9.

Table 1 shows that type IV is less distinct, in terms of species composition, than is type IX. This lack of distinctiveness is the result of the mixing of pine trees and hardwoods in type IV. Since the species composition of type IV overlaps with the other types, its spectral signature overlaps as well. Therefore, particular pixels within the area of cover type IV are more accurately described by a class other than class 4. This explains why only 29.5 percent of the type IV training set was classified as class 4; the remaining 70.5 percent of the training set more closely resembled other cover types and was so classified.

A visual comparison of the classification in Fig. 5 with the 1:15,840 black and white photo-mosaic of the island in Fig. 2 shows considerable similarity in the general vegetation patterns. The contrast between the vegetation of the drumlin on the southern half of the island and that of the poorly drained soils on the northern half is obvious. Upon close inspection of the classification, the general shape of cover type I can be seen. The shape is composed, however, not simply of class 1 pixels, but

Table 3. Distribution of classes among cover types. The matrix shows how the pixels from within each cover type's training set were classified. In each entry, the percentage of pixels in a particular cover type's training set that were classified as a particular class are shown. Overall matching cover type-class correspondence is 62%.

Class	Cover type (hand-drawn)						
(from training sets)	I	II	III	IV	V	VI-VII-VIII	IX
1	89.1	1.1	26.5	—	—	10.4	6.3
2	0.6	86.7	1.9	29.5	0.6	26.0	6.3
3	9.4	—	63.0	2.3	—	11.7	—
4	—	2.2	2.0	29.5	—	7.5	6.3
5	—	8.9	—	27.3	98.9	16.6	—
6-7-8	0.6	—	6.6	2.3	0.5	26.3	6.3
9	0.3	1.1	—	—	—	1.5	74.8
Unclassified	—	—	—	9.1	—	—	—

rather it is made up of a combination of classes. This heterogeneity is also visible in the aerial photograph. Analogously, the shapes of many of the hand-drawn cover types are discernable in the classification. In other words, the classification resembles the cover type map, but appears to improve upon it by showing how the types are intermixed. However, further research is needed to test the validity of the hypothesis that less than a 100 percent correspondence between cover types and classes is, in part, the result of this intermixing of types.

Discussion

The computer-aided classification of Bear Island indicates extensive intermixing of forest cover types. Rather than consisting of large areas of uniform species composition, such as are commonly seen in hand-drawn cover type maps, the computer classification exhibits a more patchy appearance, suggesting a mosaic of relatively small, homogeneous units. The vegetation shown in the photomosaic of Bear Island also exhibits this patchy appearance. The validity of the mosaic-like nature of the classification is further supported by considerable evidence in the literature for this spatial arrangement of vegetation in the Great Lakes forest region (Cooper 1913, Maissurow 1941, Stearns 1949, Bray 1956, Heinselman 1974, and Payandeh 1974).

Since the method presented here produces maps that exhibit the mosaic pattern of forest cover types, it is uniquely suited to the vegetation reconstruction mapping needs of the National Park Service. Maps generated by this method appear to provide the accuracy, resolution, and detail required for sampling vegetation.

Several other attributes of computer-aided classifications contribute to their suitability for Park Service needs. Given high quality photographic coverage of an area of interest, vegetation mapping can be accomplished with a reasonable level of accuracy. First, exposure values for the entire area to be mapped are obtained by scanning the imagery. Next a representative subset of the area is stratified, sampled, and classified in the manner presented in this paper. Finally, the training sets used to classify the subset are used to classify the remainder of the area. The method is potentially efficient because only the areas covered by the training sets must be mapped in a labor-intensive manner involving ocular photo-interpretation and field sampling.

Computer-aided classification is also efficient because fewer photographs are taken with small scale imagery than is necessary when using the large scale (usually 1:15,840) photography required for ocular interpretation. In other words, since a large area is covered by each frame, fewer frames are required for complete coverage of the area to be mapped. Furthermore, even at a much smaller scale, color infrared imagery contains more information than does 1:15,840 black and white imagery. This additional information is utilized in computer mapping techniques.

Another attribute of computer-aided classification is that the maps can be easily updated to reflect changes in the vegetation. Current imagery is obtained and analyzed in a manner identical to that of the original mapping effort. Because of the minimal field sampling required, the cost of updating maps in this manner should be relatively low.

One of the potentially most useful characteristics of the computer classification technique is the variety of ways the results can be displayed. The classifications are stored on magnetic tape and can be reproduced instantly as line printer character maps, digital incremental plotter maps, and temporary or hard copy CRT displays. Through the use of generalization programs, the complexity of the classification can be altered to suit specific user needs. Subsets of the classified scene can be easily extracted and displayed separately to enhance interpretation of particular features. Further enhancement of individual features can also be achieved through the choice of colors used in photographic or CRT display products.

The computer-aided mapping method has potential applicability to many mapping problems other than vegetation reconstruction. Any effort requiring detailed cover type maps to serve as the basis for sampling could make use of the method. For example, the method could be used to produce base maps for land use planning, forest inventory, and wilderness resource mapping.

Suggestions for Further Research

The results reported in this paper could be improved upon through the use of optimal imagery. All classification results are dependent upon the quality of the scanned imagery. The more the imagery is tailored to the specific requirements of the computer-aided classification method, the more favorable are the results. The following suggested imagery specifications are made to aid future investigators' efforts.

The optimal imagery for computer-aided classification of forest vegetation is, in the opinion of the authors, color infrared film exposed at a scale of between 1:50,000 and 1:100,000. Color infrared film is chosen for its high information content. Choice of scale is affected by the relationship of information content to cost of data processing. The information content of imagery increases as a step function with increasing image scale. A scale of 1:80,000 seems optimal in these two regards.

For the proper densitometric corrections to be made, the imagery scanned must be accompanied by a film-specific film wedge. The step wedge densities used in creating the film wedge must also be available. In the optimal situation, white targets with known reflectance characteristics should be placed on the ground in the area to be photographed. The relationship between reflectance and film density can then be determined directly. The researcher must be aware of any camera filters used during image procurement. It should be specified that no anti-vignetting filter be utilized. Such a filter compensates for lens falloff by methodically reducing the amount of light allowed into the central portion of the lens. Anti-vignetting filters are commonly used for producing imagery for ocular interpretation. For digital classification purposes, it is preferable that lens falloff be corrected mathematically in the data. For this correction, falloff characteristics must be available for the lens used. To minimize falloff over the areas to be mapped, the photography must be planned so that the images are centered as nearly as possible over the areas of interest.

Two major factors are contributing to the increasing utility of computerized classification and mapping of vegetation. First, high speed digital computers are increasing in availability and economic efficiency. Second, image processing and analysis methods are becoming more sophisticated. For example, recent work involving densitometry on multi-emulsion imagery (Scarpace 1978) has made possible the quantitative analysis of film imagery presented here.

The tools for efficiently and economically producing accurate vegetation maps through computer-aided classification of small scale photography are available. They are well suited to many of the mapping needs of vegetation managers. With further research and testing of the methodology, computer-aided vegetation mapping will become an indispensable aid to the Park Service. The vegetation management goal of the Park Service has been clearly defined (US National Park Service 1968). The vegetation mapping methodology presented in this paper can help the Park Service to approach this goal.

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