WETLAND MAPPING FROM DIGITIZED AERIAL PHOTOGRAPHY

by

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INTRODUCTION

Increasing recognition of wetland values is leading to wetlands protection legislation in some states [1,2]. Such legislation will create the need for fast, efficient and credible assessment of wetland vegetation communities, both to delineate their boundaries and to assess their quality. The large expanses and inaccessibility of many wetlands, in addition to their uneven and unstable terrain, make ground inventory and assessment difficult, time consuming, expensive and often inaccurate. Consequently there has been an increased use of remote sensing techniques, particularly the analysis of color and color infrared photographs, to inventory and monitor wetlands.

Aerial photography provides rapid collection of a large amount of data as well as providing a unique overview of an area. The interpretation of large scale imagery (1:10000 to 1:40000) has been an integral part of many land-related studies; e.g. soil mapping [3,4,5], land-cover and land-use classification [6,7], forest management [8,9], geology [10,11], and geography [12]. Interpretation of large scale imagery usually employs manual photo interpretation techniques with or without visual enhancements. The basis of manual photo interpretation is commonly qualitative ocular estimation of land cover [13,14,15,16].

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Although most applications of remote sensing for land-cover mapping involve this type of analysis, there are cases where the use of smaller scale imagery and/or quantitative results are desired [17]. In these cases, computer-assisted interpretation of imagery should be considered. During the past decade, great strides have been made in the applications of computer technology to assist in the interpretation of multispectral data. Most of the research involving digital processing of multispectral data for identification of land cover has been applied to electro-optical scanning systems (Landsat or airborne scanners). Some authors have investigated the use of computer-assisted interpretion of digitized aerial imagery [18,19,20,21], and have documented some of the benefits and problems associated with this technique. One of the crucial components in the analysis technique is the knowledge of the relationship between light striking the film and the resultant film density. Many investigators have reported techniques to determine this relationship [22,23,24]. Largely oriented toward quality control of film processing, these techniques are also applicable to analysis of remote sensing imagery. Some investigators have applied calibration techniques to photographic imagery exposed for remote sensing purposes [25,26,27]. This paper deals with computer-assisted interpretation of wetland vegetation using properly calibrated digitized aerial photographic imagery.

Many of the problems associated with computer-assisted interpretation of photographic imagery involve improper calibration of the data before interpretation. This is particularly important if multi-emulsion (color or color infrared) film is used [25]. The data that should be used in the interpretation process are a spectral characterization of the reflected light from each land cover type. The steps necessary to generate a proper spectral characterization are documented elsewhere [25] and include a transformation between measured film density and exposure as well as a correction for radiometric lens fall-off [28,29]. After the data derived from the photographic imagery have been calibrated, a number of possible computer classification schemes can be used to interpret the data. This study has used a supervised classification scheme along with a number of generalization procedures to map wetland vegetation in the Sheboygan Marsh.

MANUAL PHOTO INTERPRETATION

The test site selected for this study is the Sheboygan Marsh, located in the Kettle Moraine country in the northwest corner of Sheboygan County, Wisconsin. The location of Sheboygan Marsh is shown on the wetland map of Wisconsin (Figure 1). Figure 2 is a black and white copy of a portion of the aerial image used in the study and shows Sheboygan Marsh.

Sheboygan Marsh occupies a depression in a glaciated area. The general direction of ice movement in the glacial till area which surrounds the marsh was northeast to southwest and many drumlins are found to the southwest of the marsh. Sheboygan Marsh covers an area of approximately 4856 hectares (12000 acres). The marsh bottom consists of three meters of peat underlain by marl and clay. About 405 hectares (1000 acres) is semi-open water with an average depth of 1 meter which supports large algae and macrophyte populations. The remainder of the marsh contains a variety of wetland vegetation including sedges, grasses, shrubs and trees.

The photography for this project was acquired on 31 July 1974 by NASA (Mission 279) using an RB-57 aircraft flying approximately 18288 m (60000 ft) above the terrain. The photography was acquired with a Wild RC-8 mapping camera equipped with a 152.4 mm (6 in) lens yielding an original photo scale of 1:120000. Kodak Aerochrome Infrared Film Type 2443 (color infrared) was used. The imagery interpreted was the original film, not a copy.

A portion of one stereopair at a scale of 1:120000 was interpreted using a zoom stereoscope and light table by an experienced photo interpreter with extensive training and experience in botany and wetlands ecology. The major vegetation associations usually interpreted on aerial imagery are natural groupings of species indicative of a given environmental condition and occurring in areas of sufficient size to give a unique tone and texture on the film. In the photo interpretation of Sheboygan Marsh, delineations of vegetation classes according to the textural and tonal characteristics described below were readily achieved. The principal difficulty in the interpretation is converting the visual categories into accurate species categories, which initially can only be done by specific correlation between imagery and field verification. The lines in the center of Figure 2 indicate the area mapped by the photo interpreter. Figure 3 is the resulting vegetation map of this area using the classification system described below. The study site in Figure 3 is approximately 1506 meters north-south by 1680 meters east-west (4941 feet by 5512 feet).

Vegetation Classes at Sheboygan Marsh

Twelve vegetation-water classes were identified on the aerial imagery and by fieldwork in the area. The descriptions below include a summary of the appearance of each vegetation class on the original color infrared transparency used for interpretation.

1. Water: Areas of open water produce a medium to dark tone on the image. The dark color and uniform smooth texture of the water are in distinct contrast to the lighter tones of the surrounding vegetation.

2. Deep Water Emergents: Exist in water depths of 20 to 70 cm or more and consist predominantly of cattail(Typha latifolia and T. angustifolia), bur-reed (Sparganium eurycarpum) and sometimes giant reed grass (Phragmites communis). These species exist in bodies of open water and appear to have a fuzzy texture and dark pink tone.

3. Shallow Water Emergents: Exist in 12-30 cm. of water and form a more dense cover than deep water emergents. Common species are arrowhead (Sagittaria latifolia), water plantain (Alisma plantago-aquatica), bur-reed (Sparganium eurycarpum), sweetflag (Acorus calamus), and scattered sedges (Carex rostrata and C. lacustris). They have a dark pink to pink tone depending on the Shallow Water Emergent/Water ratio.

4. Cattails: Large clones of cattail (Typha latifolia and T. angustifolia), can live in a great range of water depths (5-75 cm.) provided they can become

established on mud flats. These clones have a fuzzy texture and a very high reflectance making them appear whitish on the film.

5. Reeds: Distinctive whitish color, fuzzy textured clones of bur-reed (*Sparganium eurycarpum*).

6. Sedges and Grasses: The main species of a sedge meadow, sedges (*Carex lacustris*, *C. stricta*, *C. aquatilis*), and grasses (*Calamagrostis canadensis*, *Leerzia oryzoides*) are interspersed with forbs such as marsh milkweed (*Asclepia incarnata*), marsh fern, (*Dryopteris thelypteris*), asters (*Aster spp.*), mint (*Mentha arvensis*), and marsh cinquefoil (*Potentilla palustris*). Together these species create a fine textured, whitish-pink tone.

7. Sedges, Grasses and Forbs: Consists of a sedge and grass community with a strong component of forbs. This community grows in somewhat drier conditions than does the sedge and grass community. Common species in addition to the above listed sedges and grasses are Joe-pye weed (*Eupatorium maculatum*), boneset (*Eupatorium perfoliatum*), marsh milkweed (*Asclepias incarnata*), marsh aster (*Aster spp.*), and marsh bedstraw (*Galium tinctorium*). These species tend to form a continuous cover with little or no visible interspersion with exposed substrate and have a fine texture. They appear whitish-pink ,with pink areas within, on the film.

8. Shrubs/Forbs: A transition community between the shrub community and the sedge/grass and forbs community. Common species derived from both communities are willow (*Salix spp.*), dogwood (*Cornus stolonifera* and *C. obliqua*), and al-

der (*Alnus rugosa*), asters (*Aster spp.*), goldenrod (*Solidago spp.*), and sunflowers (*Helianthus grosseserratus*). These species have a whitish-pink and red tone of medium texture.

9. Shrubs: Common species are alder (*Alnus rugosa*), red osier dogwood (*Cornus stolonifera*), silky dogwood (*Cornus obliqua*), willows (*Salix spp.*), and buttonbush (*Cephalanthus occidentalis*). Shrubs have a medium texture and a red tone.

10. Conifers: Primarily white cedar (*Thuja occidentalis*) and tamarack (*Larix laricina*). This vegetation class displays a coarse texture and a distinctive purplish tone.

11. Hardwoods: Areas of very coarse texture. Common species are northern red oak (*Quercus borealis*), white oak (*Quercus alba*), and shag bark hickory (*Carya ovata*). They appear bright red on the film.

12. Agricultural: Areas that display patterns resulting from cultivation. Both row crops and cover crops are evident in this area.

DIGITAL INTERPRETATION OF IMAGERY

The boxed area indicated in Figure 2 and reproduced in Figure 3 in color, was scanned by an Optronics P-1700 scanning microdensitometer. The imagery was scanned through three different narrow band interference filters centered at .45, .55 and .65 micrometers. The output data were then transformed into log exposures [25] and corrected for lens fall-off [29]. The spacing between sample points on the imagery was 50 micrometers. The scanned area was approximately 253 hectares (625 acres), with each picture element (pixel) representing an area of 6.0 meters square (19.7 feet square) on the ground.

Training sets were extracted from the digital file of the imagery using the map generated from the photo interpretation (Figure 3) and computer generated character displays from the digital file as first approximations. From these training sets, statistics were generated to be used with an elliptical classifier. The classifier generated a digital file from which color-coded thematic representations of the classification could be produced. These classifications were visually checked for unclassified or misclassified areas. Training sets were added or subtracted as necessary until, after several iterations, the classification visually resembled the tonal pattern on the original aerial image. Generalized versions of the classification were also produced. Figures 4 through 6 are thematic representations of the classification and generalizations produced.

Classification

The classification procedure used for this project was a two-stage table-look-up elliptical algorithm [31]. This type of classification program uses the statistics derived from the training sets to construct a table which is a mathematical representation of the ellipses in spectral space. The program allows the interpreter to vary the size of the ellipses by entering the number of standard deviations along each of the principal axes for each class. The program determines which ellipse (if any) a pixel falls within. There are provisions in the classification program to test a subset of classes first, then, if the pixel remains unclassified, test the remaining classes. This is particularly useful for transition classes or pixels which are a mixture of a number of land covers.

In some cases, a pixel will fall into two or more ellipses. For these pixels, a maximum likelihood test is performed involving only the overlapping ellipses. This classification program can produce results similiar to a maximum likelihood classifier but with a significant cost reduction because computer time is minimized.

Generalization

Two different types of generalization or smoothing routines were investigated. The first algorithm involves checking the classes of the four or eight pixels surrounding a central pixel and changing the central pixel's classification to the class of the majority of the surrounding pixels [30]. Figure 6 is the product of such a generalization applied to the data illustrated in Figure 5. The second algorithm involves similar procedures, but changes the central pixels classification only if a threshold number of pixels of a class is contained in the surrounding pixels. A further addition allows the user to establish a set of merging priorities for each class in terms of the other classes in the classification. Figure 7 is a thematic representation of this transformation applied to the data illustrated in Figure 6. Table 1 summarizes the color key and areas classified for each vegetation type illustrated in Figures 4, 5, and 6.

DISCUSSION

The intent of this project was to investigate the use of digital interpretation of aerial photographic imagery to map the boundaries of vegetation within the wetland as well as to delineate the wetland boundary. There was little difficulty either with the manual photo interpretation or with the computer-assisted interpretation in accomplishing this latter task. This was mainly due to the very distinct differences between wetland communities and the cultivated fields that surround the marsh. Assessing the accuracy of the digital interpretation with regard to the boundaries of the individual wetland communities is more difficult.

A visual comparison of Figures 3 through 6, indicates that the classification is quite good. In order to quantify the accuracy of the classification, a photo interpretation sampling scheme was devised [32]. For this investigation two hundred and fifty pixels were randomly chosen within the study area. Each of these two hundred and fifty pixels was "marked" with a symbol and number in each channel of the digitized imagery. The symbol currently being used is a square with tick marks on each side. The three channels of the digitized imagery were then made into a simulated color infrared image by producing black and white color separations on the Optronics densitometer and projecting these on a color additive viewer. The marked pixels were then interpreted and compared with the results of the computer classification and generalized files. The procedure was repeated a second time with another set of randomly chosen points. Figure 8 is one of the color separations showing the marked pixels.

Tables 2 through 4 are comparisons between the photo interpretation of the marked imagery and the computer classifications/generalizations. Along the top of each table are the class numbers for the marked image interpretation. Along the left side of each table are the class numbers for the computer classification of the same pixels. Class 0 represents an unclassified pixel. The values in Tables 2, 3, and 4 represent how each of the interpreted marked pixels was classified by the computer program. For example, from Table 2, one can deduce that 20 marked pixels were interpreted as class 6 by both the manual and computer techniques. Also, 5 marked pixels that were interpreted as class 9 by the manual interpretation were classified as class 8 by the computer interpretation. Along the bottom of each table are the number of pixels interpreted for each class by the manual method. Along the right side of each table are the number of pixels interpreted for each class by the computer technique. The diagonal of the matrix represents exactly how many pixels were classified the same by both the computer and photo interpreter. Ideally we would want a diagonal matrix. There are some differences between the computer classification and the manual photo interpretation (Figure 3). Much of this difference is due to the "resolution" differences between the techniques. The digital analysis techniques are able to map the vegetation communities in much greater detail than what was possible for the photo interpreter. One limitation in the manual interpretation was the width of lines drawn by the pen. The width of the line for a "00" pen at a scale of 1:120000 corresponds to 24 meters (79 feet) on the ground, 4 pixels in the digital file. The objective of this paper is to test the feasibility of high resolution wetland mapping from small scale imagery by both digital and manual interpretation methods. Consequently even though the manual photo interpretation could have been performed on an enlarged image of the marsh (with the associated degradation due to the photographic copy process) we felt that the scales of the interpreted imagery should remain identical for purposes of comparison.

Several walking and boating tours were taken in Sheboygan Marsh to familiarize the interpreters with the vegetation types and later to verify the vegetation assignments made by the digital interpretation. Much of the verification was accomplished in the winter months which greatly aided the ground survey due to the frozen ground and water. The dominant species were easily recognizable and no gross misclassifications were noted.

Examining Tables 2 through 4, it is evident that the digital classification is a reasonable approximation of a wetland community map. Since field verification of the results on a pixel-by-pixel basis was not practical, we are using the manual photo interpretation of the reconstituted marked imagery viewed on the additive viewer as the basis for an assessment of the accuracy of the classification. The classification itself (Figure 5) is approximately 83% correct. That is, 83% of the pixels classified were classified as the same class by the computer interpretation and by the manual photo interpretation of the marked pixels, assuming the manual photo interpretation of the marked pixels to be correct. The first generalized version (Figure 6) approaches 90% correct while the second generalized result (Figure 7) is about 87% correct.

A closer examination of these tables indicates that the percentages quoted above are a lower bound on an accuracy assessment. Almost all of the misclassifications are associated with adjacent classes in the interpretation (i.e., between Shrubs/Forbs and Shrubs). During photo interpretation of the marked images the areas adjacent to the marked pixels were also considered before class assignment. It is most likely that the computer classification is correct on a pixel-by-pixel basis. Therefore, we would estimate that the first generalized transformation (Figure 6) is actually 95 to 98% correct.

In order to estimate the accuracy of the hand-drawn map produced by manual photo interpretation (Figure 3), an overlay with randomly chosen points was constructed. These points corresponded to the same pixel locations in the digital file used to construct Tables 2-4. The land-cover type at each point was compared with the pixel-by-pixel photo interpretation done on the color additive viewer of the corresponding point and a confusion matrix was then constructed (Table 5). As can be seen, the generalization produced by the manual interpretation (Figure 3) shows less agreement with the pixel-by-pixel interpretation than with the computer assisted interpretation. The point interpretation of the manual photo interpretation was only 56% and 60% accurate. There is little doubt that if every pixel were photo interpreted individually a very good interpretation would result. However, the time involved in such an interpretation would be prohibitive. It is interesting to note that the generalized interpretation depicted in Figure 7 appears to be a close approximation to the manual interpretation, but it is much more accurate.

The poor agreement between the manual photo interpretation and the interpretation of the marked imagery (our standard) might be expected since the manual interpretation was attempted on imagery with a scale of 1:120000. Even with 30 times magnification (which was available to the interpreter on the zoom stereoscope), interpretation of every 50 to 100 micrometers on the film is a very difficult task. The human interpreter tended to gloss over the small details on the imagery. The computer assisted interpretation was consistent in the treatment of detail throughout the imagery. There is little doubt that manual interpretation of imagery at a scale of 1:12000 would have resulted in closer approximation of the wetland community boundaries, however each image would only cover 1/100 of the area of a 1:120000 image.

The costs for digital classification are always an important consideration. Usually the costs for computer-assisted interpretation are higher than the corresponding manual interpretation. One of the reasons that this is generally the case is that cost comparisons are made for interpretations of imagery at the same scale. It has been our experience that for imagery of the same scale manual interpretation is less expensive than computer-assisted interpretation. Computer assisted interpretation becomes a cost effective tool when applied to small scale imagery. The computer costs for producing the classifications and generalizations presented in this paper were less than $200. The expenditure of time was about 15 hours. These costs are for the use of University of Wisconsin Univac 1100/82 by University projects, approximately one half the commercial rates. The total wetland area of 4856 hectares (12000 acres) could be classified at a comparable rate by using signature extension. These costs seem resonable, especially if one keeps in mind that the interpretation would have a ground resolution of 6.0 meters (19.7 ft.). The imagery for this study was provided by NASA at no cost to the authors. The USGS's HAP (High Altitude Photography) program is currently acquiring high altitude photographic imagery across the U.S. and, like NASA, will make it available to the public for a nominal cost.

CONCLUSIONS

We believe that computer-assisted interpretation of small scale aerial imagery is a cost effective and accurate method of mapping complex vegetation patterns if high resolution information is desired. This type of technique is well suited for problems such as monitoring changes in species composition due to environmental factors. This type of technique is a feasible method of monitoring and mapping large areas of wetlands. This type of interpretation also has the added advantage of being in a computer-compatible form, which can be transformed into any geo-reference system of interest.

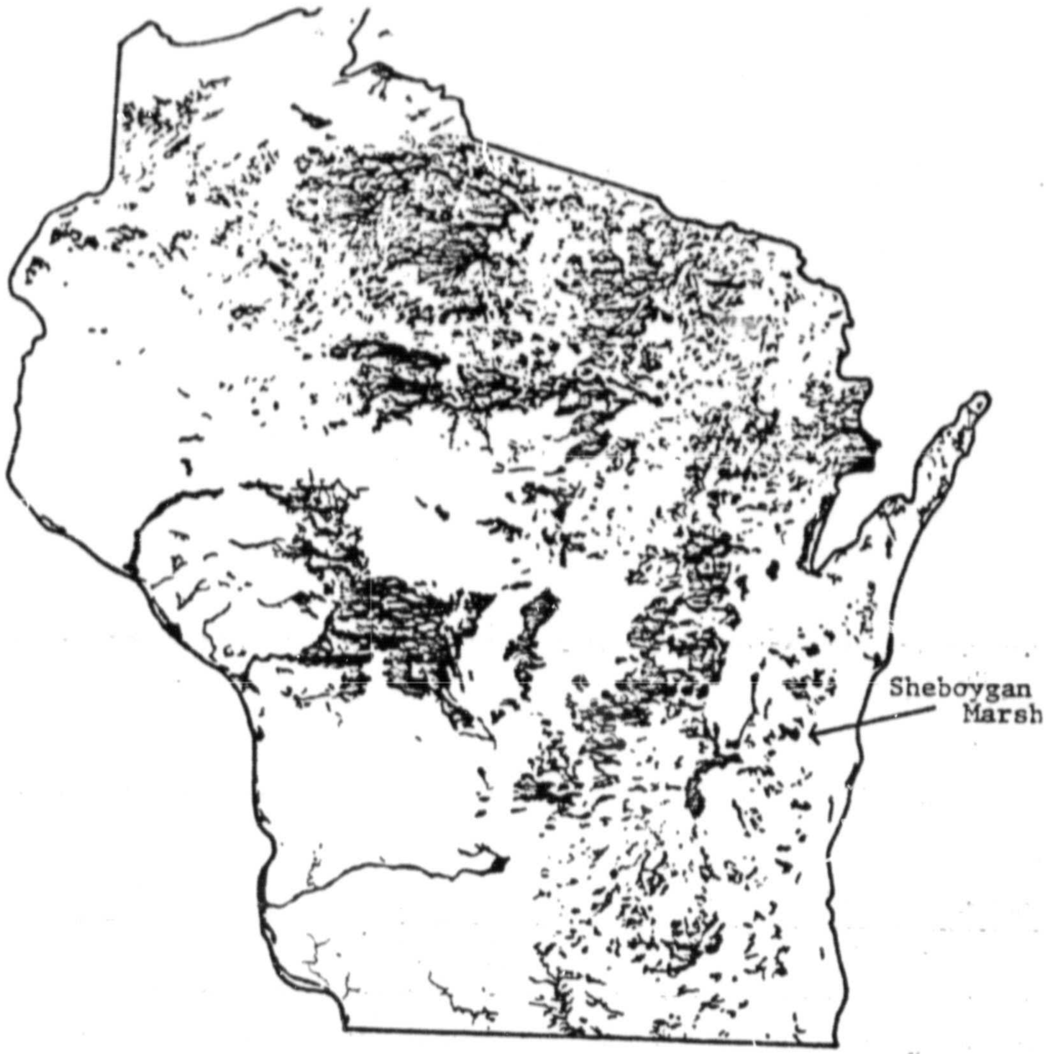
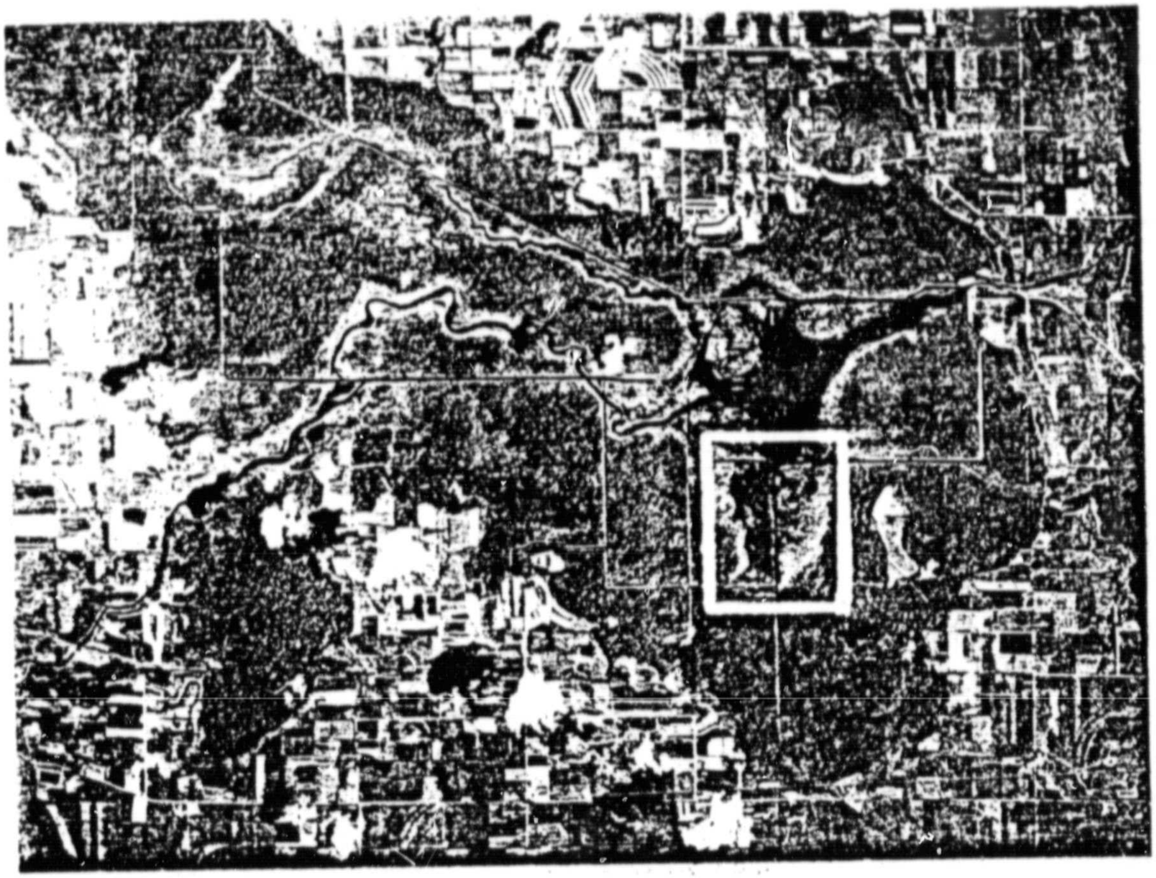


Figure 1. Wetland Map of Wisconsin, approximate scale 1:4,200,000



Fi ure 2. Black and white copy of a portion of the aerial imagery used in this study. The scale of the original was 1:120,000. The lines indicate the area mapped by both conventional and computer-assisted interpretation.

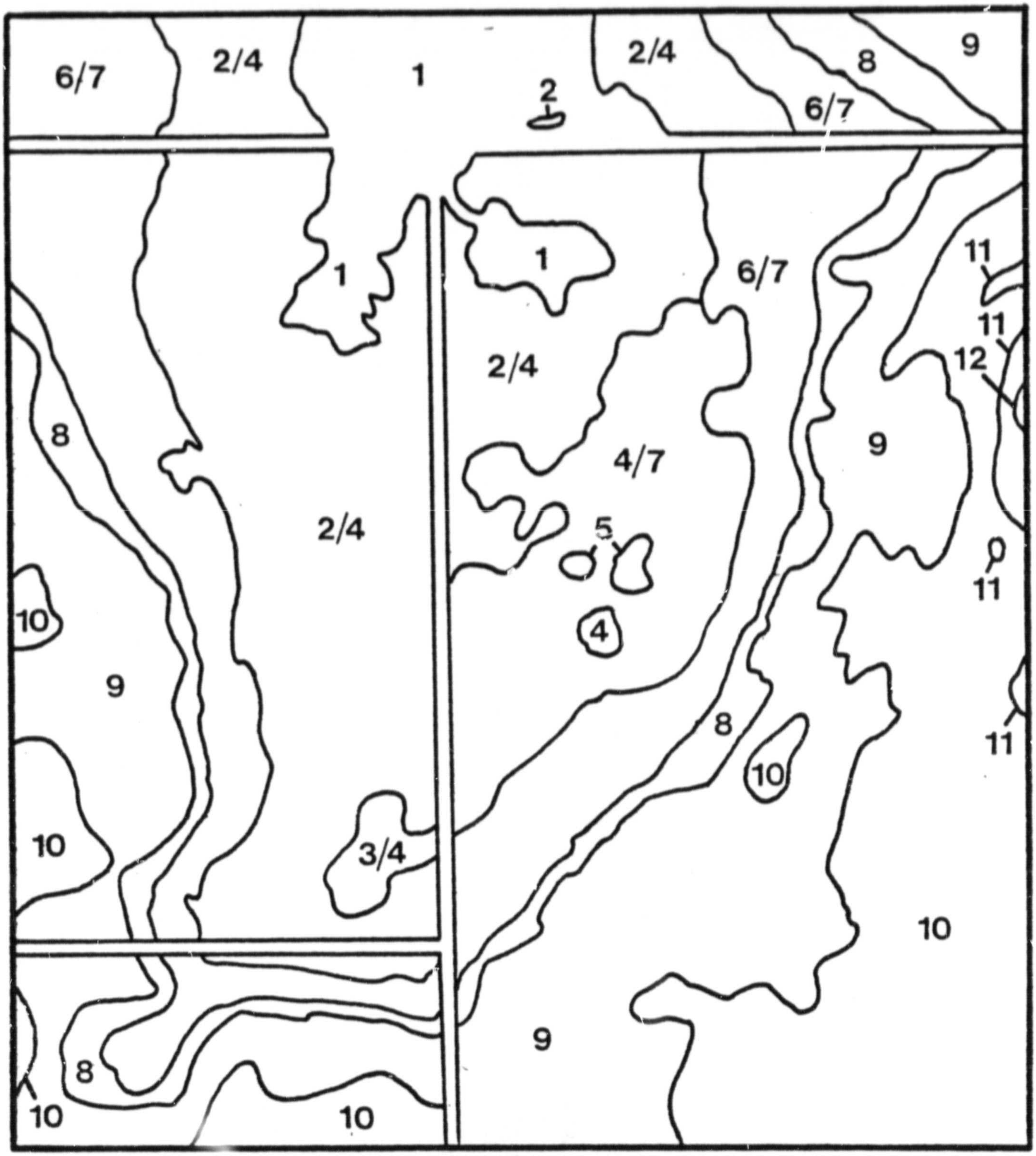


Figure 3. The vegetation classes as mapped by conventional photo interpretation of the area indicated in Figure 2. See Table 1. for key.

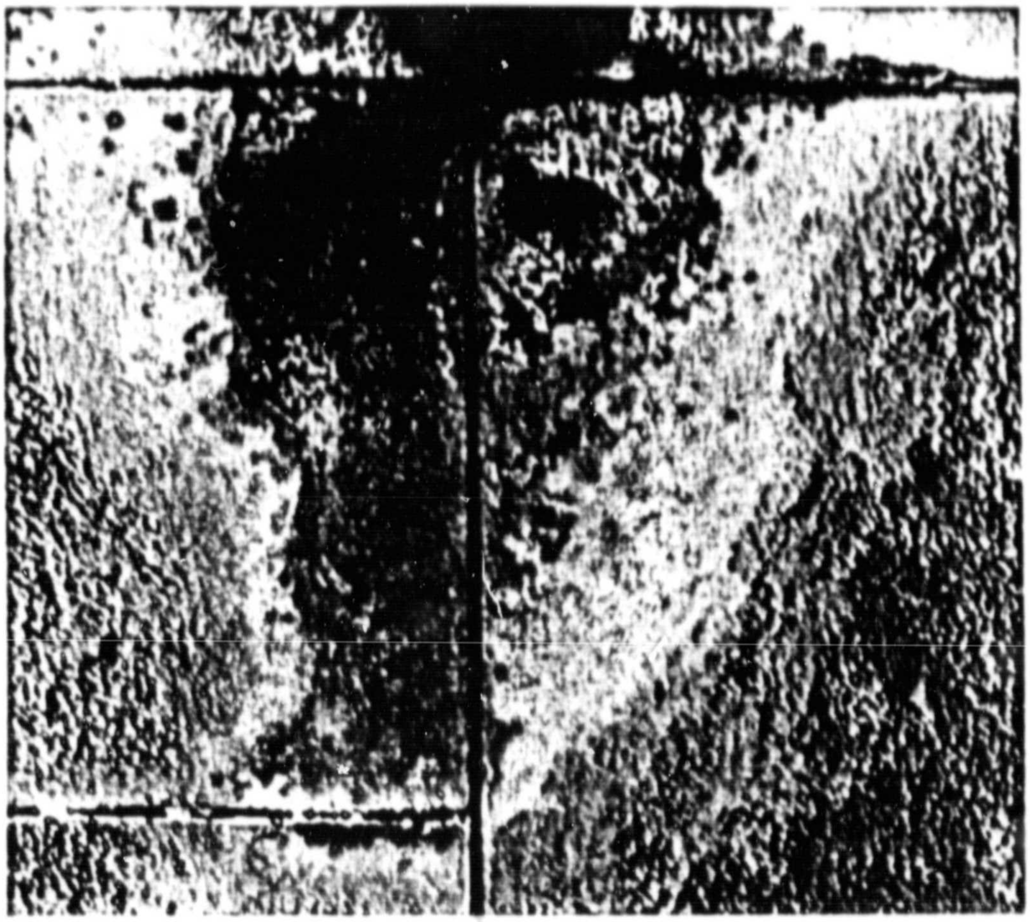


Figure 4. Enlargement of the portion of the color infrared transparency that was used for manual and computer-assisted interpretation.

Figure 5. Thematic representation of the classified image.

See Table 1. for key.

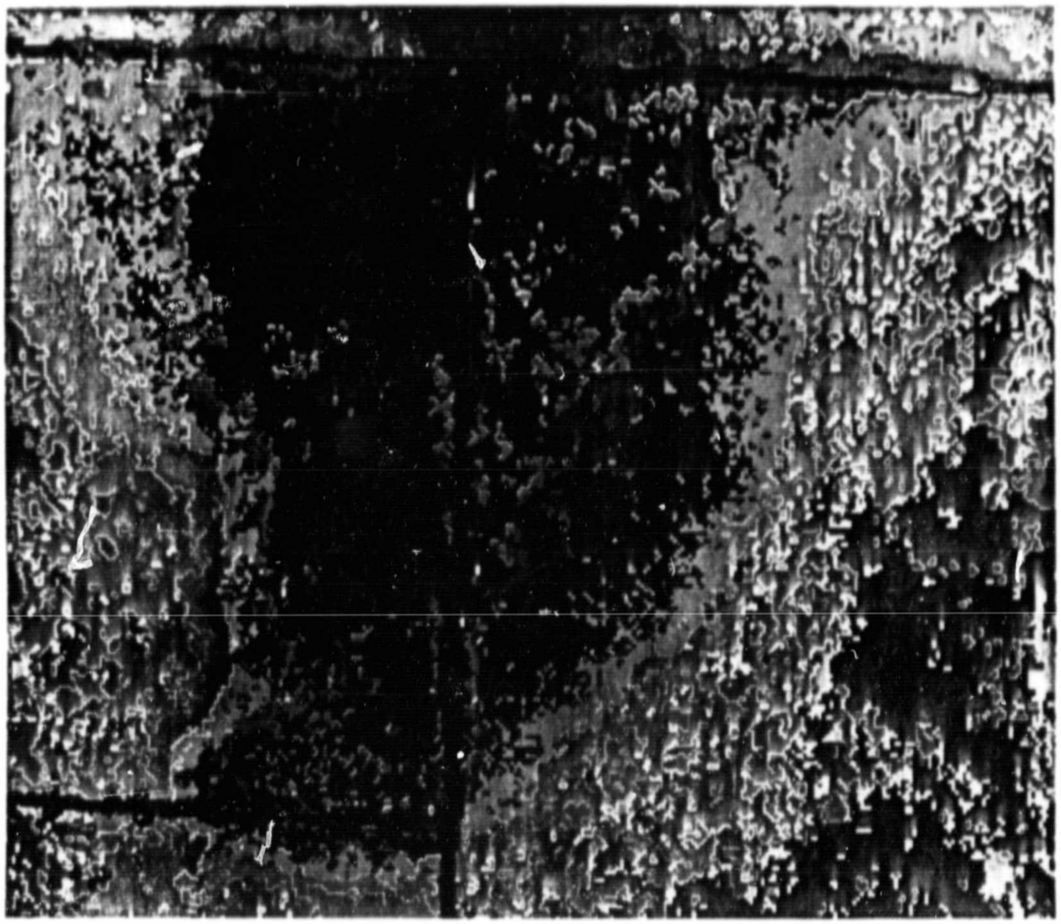


Figure 6. Thematic representation of the nearest-neighbor generalization of the classified scene. See Table 1. for color key.

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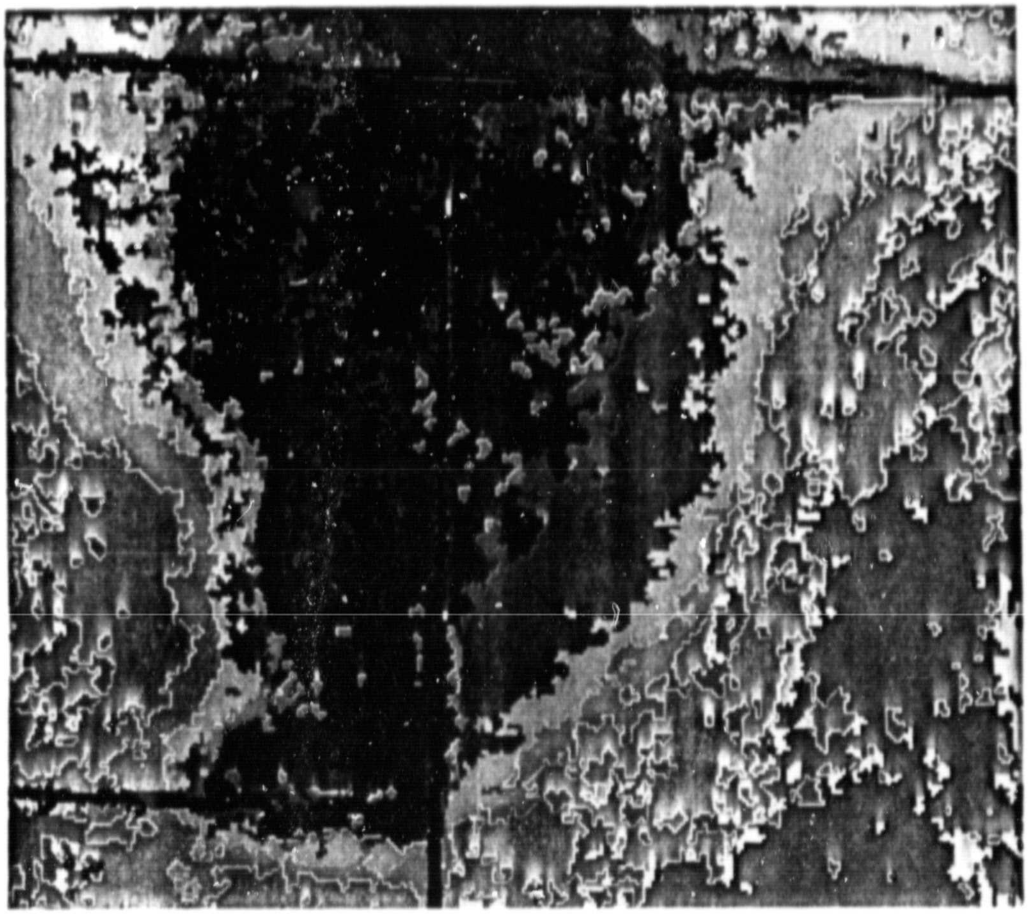

Figure 7. Thematic representation of the region generalization of the classified scene. See Table 1. for color key.

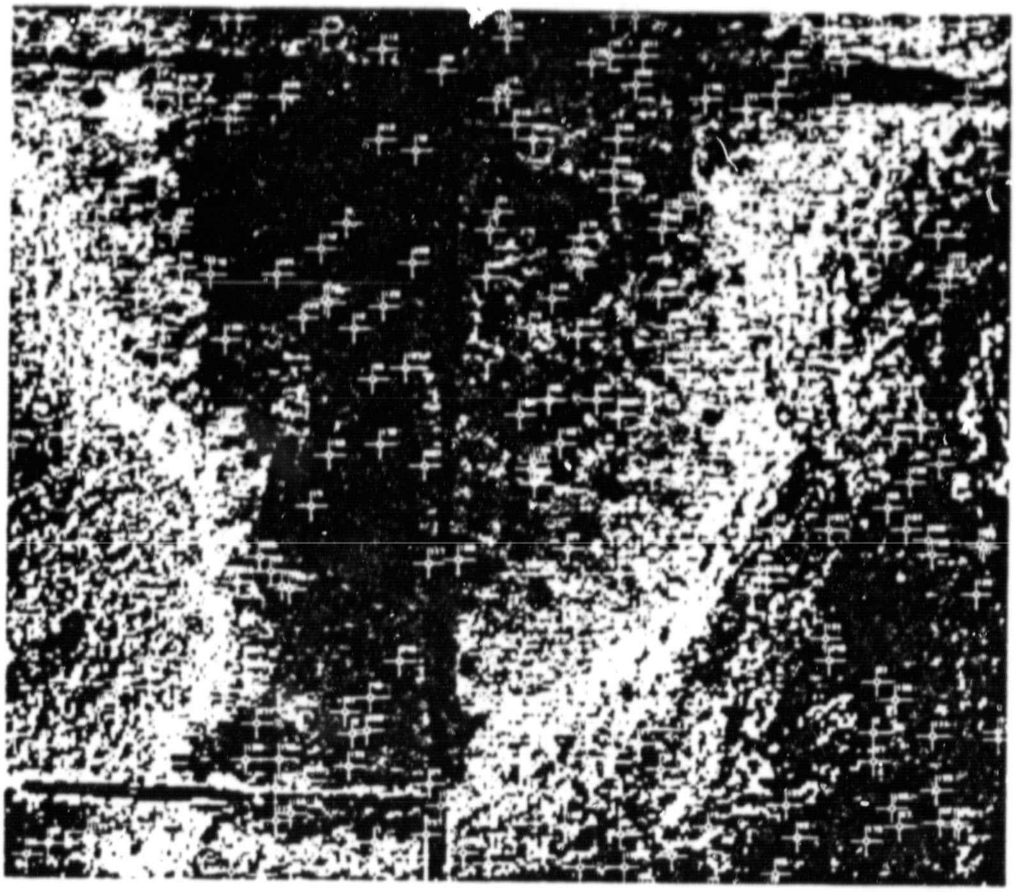

Figure 8. A portion of one of the color separations used to generate the marked imagery in the accuracy assessment part of the study.

Table 1. Colors and comparisons between the original and two generalized computer classifications (see Figures 4-6).

Class Number	Class	Color	Number of pixels for: Original	Smoothed	Generalized
0	Unclassified	Black	9504	898	578
1	Water	Blue	3670	3834	3687
2	Deep Water Emergents	Dark Green	4919	5211	5146
3	Shallow Water Emergents	Green	11381	13018	13948
4	Cattails	Dark Magenta	3861	3138	2072
5	Reeds	Dark Blue	119	112	110
6	Sedges and Grasses	Dark Red	6333	6917	6898
7	Sedges/Grasses and Forbs	Magenta	6323	6911	7125
8	Shrubs/Forbs	Dark Yellow	5076	6203	6014
9	Shrubs	Cyan	7274	10485	11883
10	Conifers	Red	8377	10347	10436
11	Hardwoods	Yellow	3369	3114	2289
12	Agricultural	Dark Cyan	74	92	94
			70280	70280	70280

Table 2. Confusion matrix comparing the manual interpretation of the marked image vs. the original computer classification of the identical pixels. The sample size was 250. See Table 1 for corresponding resource names.

MANUAL INTERPRETATION NUMBER/CLASS

COMPUTER CLASSIFICATION	0	1	2	3	4	5	6	7	8	9	10	11	12	
0:	0	2		4				2	1	9	5	1		24
1:		10	1	2										13
2:			8	2										10
3:			4	40										44
4:				3	8				1	1				13
5:						1								1
6:				3	1		20							24
7:							4	20						24
8:									16	5				21
9:					1				2	27				30
10:				1	1					3	32	1		38
11:					1							6		7
12:													1	1
TOTALS	0	12	13	55	12	1	24	22	20	45	37	2 6	1	250

THE TOTAL PER CENT CORRECT INCLUDING THE UNCLASSIFIED CATEGORY IS: 77.86

THE TOTAL PER CENT CORRECT WITHOUT THE UNCLASSIFIED CATEGORY IS: 84.35

Table 3. Confusion matrix comparing the manual interpretation of the marked image vs. the smoothed computer classification of the identical pixels. The sample size was 250. See Table 1 for corresponding resource names.

		MANUAL INTERPRETATION, NUMBER/CLASS													
		0	1	2	3	4	5	6	7	8	9	10	11	12	
COMPUTER	0:	0									1				1
	1:		12	1	2										15
	2:			8	1										9
	3:			4	47										51
	4:				3	10									13
CLASSIFICATION	5:						1								1
	6:				2	1		22							25
	7:							2	22						24
	8:									18	5				23
	9:									2	38				40
	10:										1	37	1		39
	11:					1							7		8
	12:													1	1
	TOTALS	0	12	13	55	12	1	24	22	20	45	37	8	1	250

THE TOTAL PER CENT CORRECT INCLUDING THE UNCLASSIFIED CATEGORY IS: 82.56

THE TOTAL PER CENT CORRECT WITHOUT THE UNCLASSIFIED CATEGORY IS: 89.44

Table 4. Confusion matrix comparing the manual interpretation of the marked image vs. the generalized computer classification of the identical pixels. The sample size was 250. See Table 1 for corresponding resource names.

COMPUTER CLASSIFICATION	MANUAL INTERPRETATION NUMBER/CLASS													
	0	1	2	3	4	5	6	7	8	9	10	11	12	
0:	0									1				1
1:		12	1											13
2:			9	3										12
3:			3	49	4		2							58
4:				2	6									8
5:						1								1
6:				1	1		19	4						25
7:							3	18	1					22
8:									18	3				21
9:									1	39	1			41
10:										1	36	2		39
11:					1					1		6		8
12:													1	1
TOTALS	0	12	13	55	12	1	24	22	20	45	37	8	1	250

THE TOTAL PER CENT CORRECT INCLUDING THE UNCLASSIFIED CATEGORY IS: 79.44

THE TOTAL PER CENT CORRECT WITHOUT THE UNCLASSIFIED CATEGORY IS: 86.06

Table 5. Confusion matrix comparing the manual interpretation of the marked image vs. the conventional manual photo interpretation (Figure 2). The sample size was 250. See Table 1 for corresponding resource names.

PIXEL BY PIXEL INTERPRETATION NUMBER/CLASS

MANUAL INTERPRETATION	0	1	2	3	4	5	6	7	8	9	10	11	12	
0:	0													0
1:		12												12
2:		1	12											13
3:			42	0			7	3						52
4:					6		8							14
5:			1			0								1
6:			1				13	11						25
7:			1					21						22
8:							11		2	5	1			19
9:										36	9			45
10:											38			38
11:										1	7	0		8
12:											1		0	1
TOTALS	13	57	0	6	0	39	35	2	42	56	0	0		250

THE TOTAL PER CENT CORRECT WITHOUT THE UNCLASSIFIED CATEGORY IS: 56.00

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