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An evaluation of remotely sensed wetland mapping

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AN EVALUATION OF REMOTELY SENSED WETLAND MAPPING

by

Michael J. Gluck ©

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ABSTRACT

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Landscape management is based on the maintenance of natural ecosystems and recognizes the importance of maintaining the habitat diversity of all ecosystem types. Acquiring information about the size, distribution and location of wetlands is the first step towards evaluating their habitat value in a landscape perspective. An explicit review about the strengths and limitations of any landcover database is critical prior to input into the decision making process. Techniques were developed for characterizing wetland habitat components in a landscape context utilizing remote sensing and geographic information system technologies. A hierarchy of remotely sensed data ranging from 1:5000 colour infrared aerial photography to LANDSAT Thematic Mapper satellite data was employed to compare detail of information available at each scale of data. These techniques included evaluation of ground-based wetland classification systems, air photo interpretation, investigation of approaches to image classification, and development of accuracy assessment techniques. The developed techniques were applied to a Northwestern Ontario landscape to produce a thematic layer of wetland habitat information. The effectiveness of these techniques was evaluated by assessing the accuracy of each remote sensing scale for mapping the broad scale wetland habitat at the physiognomic group level. 1:5,000 and 1:10,000 scale colour infrared aerial photography provided the best thematic accuracy at 94 percent, whereas 1:20,000 scale allowed wetland mapping at 84 percent accuracy. Satellite based mapping using Landsat Thematic Mapper integrated with digital Forest Resource Inventory map data allowed wetlands to be mapped with 72 percent accuracy. Combining physiognomically similar wetland classes increased satellite based mapping accuracy to 81 percent.

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"Wetlands are not conventional wild areas. They do not cater to established classical concepts of vista, horizon, and landscape. They force you inward, both upon yourself and upon the nonhuman world. They do not give you grand views; they humble you rather than reinforce your delusions of grandeur."

P.A. Fritzell

SPACE ISN'T THAT REMOTE
IT'S ONLY AN HOUR AWAY --
IF WE COULD DRIVE OUR CARS STRAIGHT UPWARD

Thomas Huxley

INTRODUCTION

Landscape management is based on the maintenance of natural ecosystems and recognizes the importance of maintaining the habitat diversity of all ecosystem types (Booth *et al.* 1993). Ecologically derived information characterizing landscape structure is required to develop comprehensive data bases for all ecosystem resources to implement management of our forests as landscapes (Thompson and Welsh 1993). The information required for decision-making must include the descriptions of the pattern, size and thematic character of landscape features.

Wetlands are important ecosystems in the landscape, maintaining water quality, wildlife habitat, and forming a base for economic activities. Wetland habitat comprises approximately 20% of the land surface in the boreal forest (Zoltai *et al.* 1988). Wetlands play an important role in the functioning of natural processes through important contributions to primary production, detrital food pathways, and water, carbon, and nitrogen cycles (Mitsch and Gosselink 1986). Acquiring information about the size, distribution and location of wetlands is the first step towards evaluating their habitat value in a landscape perspective.

Innovative approaches to meeting the demand for wetland habitat information have been offered through the advancement of remote sensing and geographic information systems (GIS) in recent years. Remote sensing offers excellent opportunities to obtain cost-effective data at large and synoptic scales (Roughgarden *et al.* 1991). GIS allows this information to be manipulated with other thematic layers to improve the quality of information received by the database user. Determining the effectiveness of these technologies in supplying information for wetland habitat management requires rigorous assessment of spatial, thematic, and temporal accuracy. An explicit review about the strengths and limitations of any landcover database is critical prior to input into the decision making processes.

Satellite-image based mapping of wetlands has been accomplished with varied effectiveness across North America. The literature describes many issues pertaining to creating wetland habitat maps. The two main approaches to image analysis are known as unsupervised and supervised image classification (Lillesand and Kiefer 1987). Unsupervised classification uses algorithms to locate naturally occurring spectral-based classes in the data which then must be interpreted to determine their informational utility. On the other hand, supervised classification delineates information classes in the data based on spectral thresholds imposed by interpretation of the data by the map producer.

One of the fundamental issues in producing a wetland habitat map deals with separating wetlands from the terrestrial component of the landscape. Tomlins and Boyd (1988) evaluated both supervised and unsupervised approaches to image classification using multi-temporal LANDSAT Thematic Mapper (TM) data to map estuarine, palustrine, and riverine wetlands in British Columbia. Unsupervised classification of the data produced twelve spectral classes that they qualitatively assessed as insufficient for describing more than very broad landcover classes. A supervised classification of palustrine wetlands was only able to identify one wetland class, open fen, with six percent accuracy. Confusion of this wetland with open meadows and recent cut-overs combined with relative small size severely reduced detection accuracy.

Detecting and accurately characterizing small sized wetlands is another factor in wetland mapping. Jacobson *et al.* (1987) used unsupervised classification of LANDSAT TM data to map prairie wetlands. Wetlands less than two acres in size could not be detected because of limited spatial resolution of the data. However, mapping accuracy increased with wetland size - less than one percent commission error and 30 percent omission error occurred for wetlands between two and five acres in size. Visual examination of colour composite images allowed detection of small wetlands omitted by the image classification alone.

The selection and use of wetland habitat classes has an impact on the effectiveness of wetland mapping. Bobbette and Jeglum (1990) used supervised classification of LANDSAT multi-spectral scanner (MSS) imagery in Northeastern Ontario to discriminate between six wetland classes from the Ontario Wetland Classification System (Jeglum *et al.* 1974). Overall wetland class accuracy ranged from 26.7 percent for cedar swamps to 67.3 percent for treed fens. Many of the errors occurred between physiognomically similar wetland and terrestrial landcover features. Werth and Lillesand (1979) used supervised classification of LANDSAT MSS data to identify broad landcover classes with limited success for the single emergent wetland class. Overall wetland mapping accuracy was 35 percent but was expected to improve through the delineation of wetland boundaries using aerial photography. Unfortunately, manual delineation of these boundaries was too labour intensive to be cost effective.

Jensen *et al.* (1991) obtained high correlation between mapping accuracies of multi-date SPOT (Système Propatoire d'Observation de la Terre) satellite data, 1:40,000 aerial photography and ground measurements for the inventory inland wetlands. In coastal marshes, Gross *et al.* (1987) was able to accurately measure biomass of large area, single species wetlands using a supervised classification of multi-date LANDSAT TM data. Jensen *et al.* (1986) used supervised classification of Daedalus airborne MSS (three metre resolution) data to effectively map riverine wetlands in South Carolina. Late summer LANDSAT TM data for the same area was of limited use because of plant die-off making wetland discrimination difficult. In the same study, LANDSAT MSS data was found suitable for broad scale mapping of landcover features.

In Northwestern Ontario, satellite based mapping has not been carried out as an independent effort although some full landscape mapping projects have incorporated wetlands. Darby (1990) used supervised classification of LANDSAT MSS data to detect open wetlands with 72 percent omission and 83 percent commission accuracy in mapping white-tailed deer habitat. Wetlands were mapped in northwestern Ontario as part of the Spatial Forest Database (Ontario Ministry of Natural Resources 1992). Using LANDSAT TM data, 71 percent of wetlands detected by supervised classification agreed with ground reference data. LANDSAT MSS imagery has been used to visually identify areas of shoreline-based emergent aquatic vegetation with 75 percent accuracy (Hoffman and Darby 1986).

Wetland mapping efforts have successfully merged remotely sensed data with cartographic data in GIS to assist image classification (e.g., Hellyer *et al.* 1990). Oslin (1988) combined colour infrared (CIR) air-photos rasterized to 15 metre spatial resolution with LANDSAT TM data resampled to the same ground resolution in order to allow delineation of wetland boundaries and increase mapping accuracy. Hall *et al.* (1988) digitized interpreted 1:12,000 scale CIR aerial photography for input into a GIS to create a wetland database for a 500,000 ha management unit.

Although accurately detailed information at six metre resolution was provided, the utility of this approach decreases as the size of management unit increases.

Clearly, several issues pertaining to the effectiveness of wetland mapping emerge from the literature that need more study. These include the importance of explicit accuracy assessment, alternative approaches to image classification, discrimination of wetlands from physiognomically similar terrestrial landcover features, detection of small sized wetlands, selection of wetland mapping classes, alternative types of remotely sensed data, and integration of remotely sensed data with other spatial thematic data.

The objectives of this thesis in addressing these issues were:

1. To develop techniques for characterizing wetland habitat components in a landscape context using remote sensing and GIS technologies.
2. To apply these techniques to a Northwestern Ontario landscape and produce a thematic layer of wetland habitat information.
3. To evaluate the accuracy of these techniques in modelling the broad-scale habitat structure of boreal wetlands.

STUDY AREA

The study area was an 8,000 square kilometre landscape located 75 kilometres north-east of Fort Frances, Ontario (Figure 1). As a research area, it includes portions of the Manitou, Seine, and Wabigoon Forest Management Agreements. Recent disturbances such as clear-cutting, forest fire, and road building occurred in the study area along with a large tract of older disturbance conifer forest. The study area is located within the Low Boreal wetland region of Canada (National Wetlands Working Group 1986), the Quetico section of the Boreal forest region (Rowe 1972) and the Lake of the Woods Plains ecoregion of Ontario (Wickware and Rubec 1989).

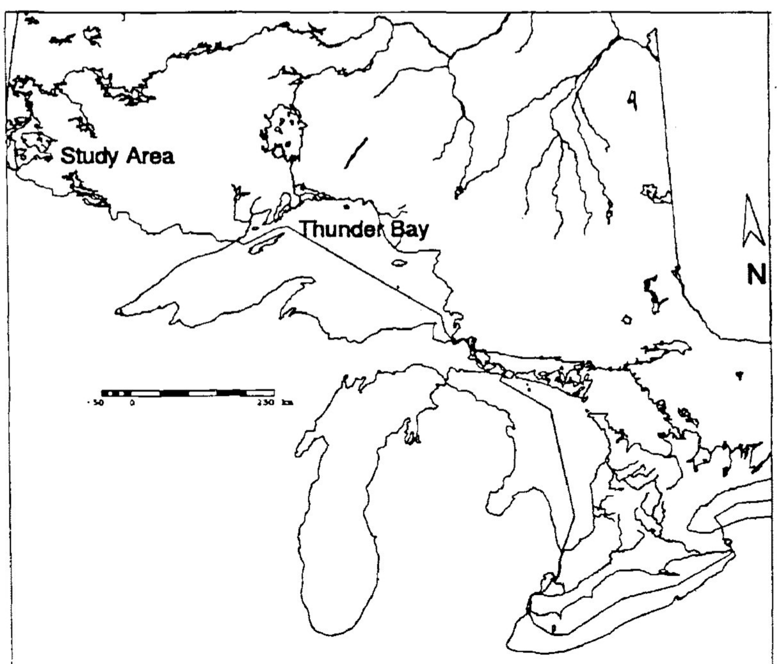


Figure 1. Location of study area.

METHODS

DEVELOPMENT OF WETLAND MAPPING TECHNIQUES

Relationships between the resolution of information provided by remotely sensed data and the ground-based classification were investigated as part of developing techniques for characterizing wetland habitat. This exercise included evaluating the utility of wetland classification systems for remote sensing applications, interpreting ground reference information, using image classification to obtain wetland habitat information from satellite data, and integrating remote sensing and GIS technologies to improve the transfer of this information.

Selection of a Wetland Mapping Classification System

Three wetland classification systems, the Canadian Wetland Classification System (CWCS) (National Wetlands Working Group 1986), the Ontario Wetland Classification System (OWCS) (Jeglum *et al.* 1974), and the Ontario Peatland Inventory Wetland Classification System (Riley 1992), were compared on the basis of each system to operate at a variety of scales within a hierarchy of spatial resolution to determine their utility for remote sensing applications. The classes of these systems had to be resolvable at different scales using spectral reflectance characteristics to be suitable for remote sensing-based wetland mapping. The Canadian Wetland classification System is an ecologically based system which provides users with a common basis of classification which can be modified to meet the needs of specific disciplines (Zoltai *et al.* 1988). The system is divided into three hierarchical levels: class, form, and type. Wetland classes are recognized on the basis of surface morphology, surface pattern, water type, and morphology of underlying mineral soil. Finally, wetland types are classified according to vegetation physiognomy (National Wetlands Working Group 1986). By placing surface morphology at the second hierarchical level, the system describes wetlands as basins or communities. Surface morphology requires identification of the landscape context of the wetland. This is a difficult task to be accomplished using image classification since it involves decisions based on non-spectral data. Describing wetland basins using the CWCS requires evaluation of landscape position, something more suited to human interpretation than computer assisted image classification.

The OWCS is a five-level hierarchical system based on formation, sub-formation, physiognomic group, dominance type, and site type (Jeglum *et al.* 1974). Since physiognomic group is addressed early in the hierarchy of this system, it is better suited to describing wetland habitat components then the CWCS. Incorporating satellite-based wetland mapping with a physiognomic-group based system increases the efficiency of classification at high levels.

Riley (1992) used The Ontario Peatland Inventory (OPI) wetland classification as a physiognomic-based hierarchical system adapted from Jeglum *et al.* (1974) and the CWCS. This system is used by the Northern Ontario Wetland Evaluation System (Ontario Ministry of Natural Resources 1993). Its objective is to operate at different scales of spatial resolution while maintaining a common denominator of wetland class (Riley, pers. comm. 1994). This system is well suited to the coarse scale of satellite-based mapping because of its adaptability to operate at various spatial scales.

These three systems were qualitatively evaluated in the field to judge how well each met the following criteria: 1) the ability to characterize wetlands at a variety of remotely sensed scales; 2) the suitability and ease of application in the study area; and 3) if the information needed for the classification could be collected independent from surrounding landscape.

Colour Infrared Aerial Photo Based Wetland Mapping

Ground reference information consisting of field data and aerial photography was interpreted and used for the development and evaluation of techniques for characterizing wetland habitat. Approximately 300 wetland basins were visited throughout the growing season. Sketch maps were drawn at each basin which were used in conjunction with aerial photography to estimate percent cover for each physiognomic group in the basin. Dominant cover species information was also collected from visual inspection where seasonably possible. Basin locations were recorded using air photo number and for some basins a Global Positioning System was used to record geographic position. Wetlands were visited at the beginning of the field season to develop air photo interpretation skills and characterize the appearance of wetland habitat on CIR photography. The accuracy of these skills was assessed by interpreting twenty wetland basins prior to field visits and quantitatively comparing the interpreted information to that collected later in the field.

Satellite Based Wetland Mapping

The original satellite data consisted of four channels, representing the green, red, and near and middle infrared spectral reflectance bands. Individual bands were evaluated visually to determine inclusion or removal from the data set based on their utility for wetland mapping. Many of the cut-overs had pools of standing water on them and lakes had ice on them when the spring image was recorded. Unsupervised classification of all eight channels resulted in confusion between wetlands and "wet cutovers" and the creation of 10 spectral classes representing ice. Subsequently, the red, green, and near infrared bands of the spring image were dropped from the data set to reduce the confusion of wetlands with cutovers and to reduce the number of spectral classes representing ice on lakes. The remaining multi-temporal data-set was subjected to principal component analysis to investigate the structure and patterns within the data and to compact the spectral component of the data while maintaining as much of the spectral information as possible (PRINCE program; ERDAS 1991).

The first three of the five principal components were classified using an iterative self-organizing data analysis technique (Tou and Gonzalez 1974). This was accomplished using the ISODATA algorithm (ERDAS 1991) to locate 250 clusters in three dimensional principal component space. The clustering process begins with a specified number of arbitrary cluster means, processing repetitively, such that these arbitrary means will shift to the means of the clusters of the data. Once the arbitrary means are selected in the first iteration, subsequent iterations calculate new means based on the spectral locations in the last cluster. The process of shifting means is repeated until there is little change between iterations (Swain 1973). The main advantage of this multi-pass approach is its iterative nature, which does not favour the top of the image data as do single pass clustering algorithms.

The statistical data that define the final clusters are called signatures. The signature for each cluster expresses the number of bands, the mean, maximum and minimum data values for each band, and the covariance matrix for each sample or cluster. A maximum likelihood classification algorithm was used to assign individual pixels in the resulting image to clusters based on these signature files (MAXCLAS program; ERDAS 1991). Maximum likelihood decision rules are based on the probability that a pixel belongs to a certain class. This is a parametric procedure and the basic equation relies heavily on the assumption that these probabilities are equal for all classes, and that the input bands have normal distributions (ERDAS 1991).

Post classification statistics based on the reflectance values of the raw LANDSAT TM data were generated for each spectral class using the modules RAWFUNCS and CLSMEANS (Ducks Unlimited 1991) in the ELAS image analysis package (Beverley and Penton 1989). The functions module calculated frequency counts and histograms on the multi-temporal data set. The class means module related the 250 class single channel image to the multi-temporal data set and calculated the maximum, minimum, mean, and standard deviation of each LANDSAT TM band for each spectral class.

Spectral profiles were created by plotting the mean spectral reflectance for each class on the Y axis over the LANDSAT band on the X axis (Figure 2). The same mean spectral reflectance values were used to determine the colour to display each spectral class using the program CLSCOLR (Ducks Unlimited 1991). The class colour module uses the frequency counts and class means statistics to build colour tables which can simulate three-channel display of the raw data.

Colour tables are built by selecting which levels of the three screen colours, blue, green and red, to display each spectral class. Display contrast is enhanced by transforming the class values either by linear range division or by histogram equalization. Using linear range division, the class values are expanded uniformly to the full range of the display device. The drawback to linear enhancement is that infrequently occurring values are assigned to as many levels as frequently occurring values. An alternative to this enhancement is histogram equalization which assigns class values to levels on the basis of their frequency occurrence. With histogram equalization frequently occurring values are given a greater proportion of the levels in the resulting colour table.

The TRAIN and DISPlay modules of ELAS were developed by Ducks Unlimited to assign spectral classes to wetland classes. These modules provide an environment in which displaying and editing of classified satellite imagery, especially where the number of classes is very high, is made as easy and flexible as possible. The modules allow the emergent

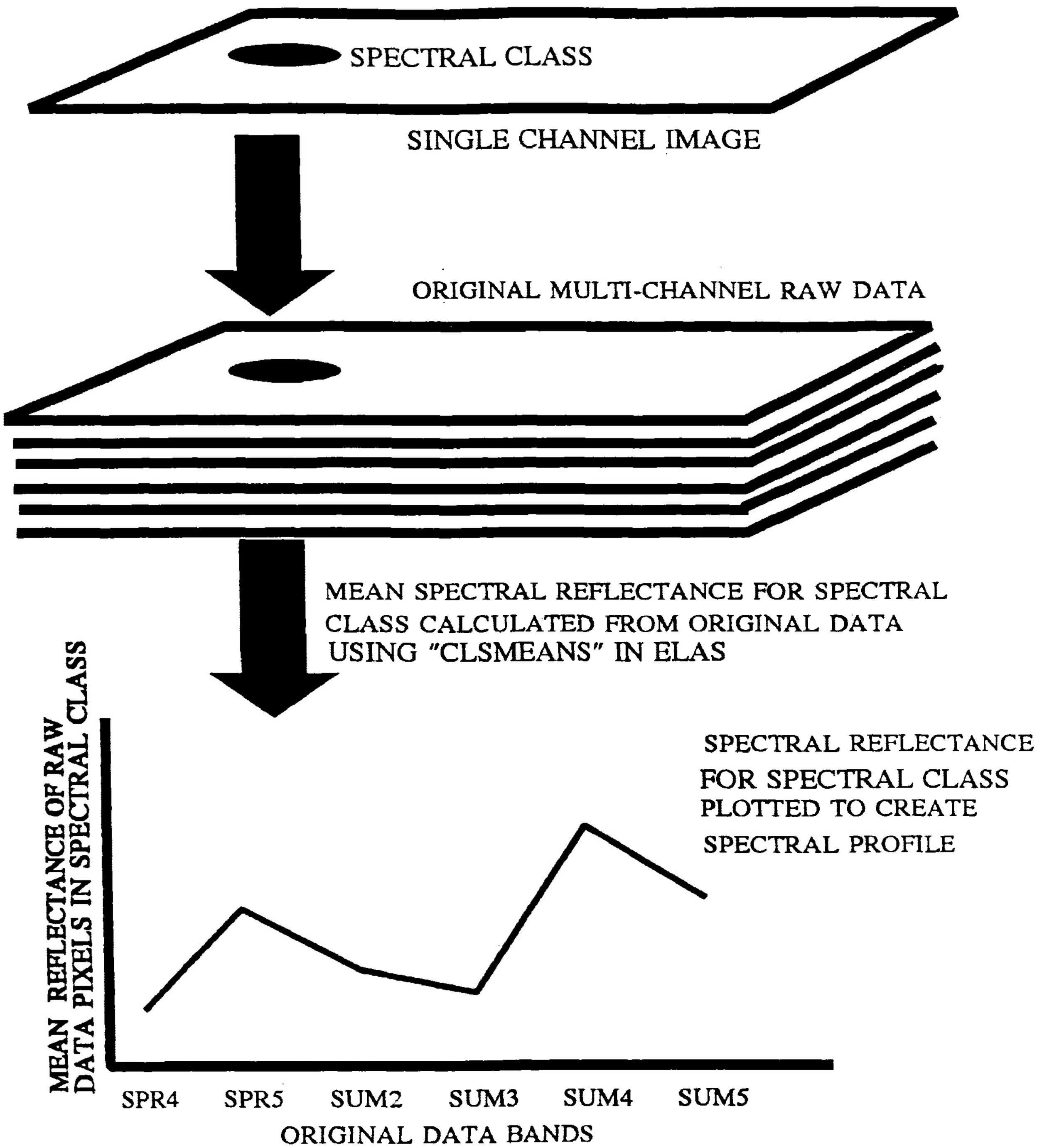


Figure 2. Schematic description of creating spectral profiles from raw multi-channel data using ELAS image analysis software. Statistics based on the raw data values of the pixels assigned to the spectral class are calculated using CLSMEANS. The mean reflection value of a spectral class can be plotted for each channel of the original data (SPR4 = spring band four, SUM2= summer band two etc.)

spatial patterns of the spectral classes in the classified data to assist in creating a wetland habitat model along with facilitating quick reference to the information provided by spectral profiles and colour tables. The spectral classes with the strongest association to the wetlands were identified using the DISPlay and TRAIN modules. Once these strongly associated classes were identified they were used as guides to assist in assigning all spectral classes to wetland classes. The process of identifying, grouping, and assigning spectral classes to wetland habitat classes was repeated until all 250 spectral classes had been assigned to a landcover class.

Forest Resource Inventory (FRI) stand maps are based on the interpretation of 1:15,840 scale black and white aerial photography and provide, along with other information, the location, forest stand, and wetland boundaries. Within a GIS environment digital FRI map data was integrated with the classified satellite imagery to separate wetland and terrestrial components of the landscape. The wetland polygons in the FRI were used to stratify the wetland basins from the landscape. An image consisting of only lakes and wetlands was created by multiplying the satellite image by a mask derived from digital FRI consisting of all lakes and wetlands having a value of one and the rest of the landscape a value of zero. Spectral classes were assigned to wetland classes only within the boundaries defined by the FRI polygons.

APPLICATION OF WETLAND MAPPING TECHNIQUES

A thematic layer of wetland habitat information was produced to apply the techniques of characterizing wetland habitat to a Northwestern Ontario landscape. A 220,000 ha portion of the study area covering eight FRI maps was used as an application area for the above methodology. The resulting wetland habitat map was superimposed onto the full landscape image to allow interpretation of wetlands in a landscape context.

EVALUATION OF WETLAND MAPPING EFFECTIVENESS

The level of accuracy achieved by the wetland habitat map was compared to CIR air-photo interpretation in terms of thematic accuracy to evaluate the accuracy of the techniques used to create the map. For the wetlands map, the same interpreted aerial photography that was used to assess air-photo interpretation was used as ground reference to assess the map accuracy. Areas that were used to develop the wetland map were not used to assess the accuracy of the map.

Mapping accuracy can be expressed in terms of omission and commission accuracy (Story and Congalton 1986). Omission accuracy estimates the proportion of observed features that are predicted by a map, whereas commission accuracy looks at the reverse by estimating the proportion of predicted features that are actually observed. A third measure, overall accuracy, expresses the agreement between predicted and observed features as a percentage of total observations.

The ability of the wetland map to delineate wetland basins was not assessed because the wetland basin polygons were delineated using the FRI map polygons. What was assessed, however, was how accurately the map represented the habitat components or wetland classes that fell within a basin. Omission and commission accuracy were obtained by comparing observed ground reference to the classified wetland map.

Two approaches to accuracy assessment were investigated -- one at a basin level, the other at a pixel level. At the basin level, a large number of basins were assessed by comparing visual measurements of the observed proportion of physiognomic group cover in each basin to the classified wetland map. The pixel level approach assessed a fewer number of basins but compared specific pixels in a ground reference layer to pixels in the wetland map.

In the basin level approach a ground reference layer containing the observed habitat composition information was created in tabular form for each wetland basin. This was accomplished using air-photo interpretation and area calculation calibrated by a dot grid to estimate percent cover of each wetland class present in the basin. For each wetland class the number of dots falling on top of the class was divided by the number of dots falling within the boundary of the wetland then multiplied by 100 to express as a percent area of the basin.

An area-based predicted habitat composition layer was created using SPANS GIS (Intera Tydac 1993) to measure the percent area of each wetland habitat class occurring in each basin. The predicted habitat composition was then compared to the observed composition to determine the accuracy of the wetland map in characterizing basins. For each wetland class, mapping error was determined from the following formula:

ERROR = observed percent area - predicted percent area (1)

where, if ERROR is positive then omission error, if negative then commission error.

The pixel level approach assessed map accuracy using digitally scanned aerial photography as a ground reference layer. Air photos were rasterized to 256 shades of grey and registered to the UTM grid of the classified satellite image using IDRISI GIS (Eastman 1993) to satisfy a root-mean-square (RMS) error of less than 15 metres. RMS or root mean square measures the overall size of the regression error. Wetland habitat features interpreted from the hard copy CIR photos were delineated using on-screen digitizing of polygon features to create an observed habitat layer. With on-screen digitizing, the image is displayed on the computer screen and a computer pointing device (i.e. mouse) is used to create a polygon. An interactive zoom feature of IDRISI allowed for accurate digitizing of basin boundaries. All of the wetland basins occurring on each photo were used in the assessment. Pixels falling along edges of wetland basins were not used in the accuracy assessment. This ground reference layer was cross-tabulated with the classified wetlands map from which omission and commission accuracy determined for each class using the following formulae:

$$\text{omission accuracy} = \frac{\text{area of agreement between observed and predicted layers}}{\text{area of observed layer (column total)}} \times 100 \quad (2)$$

$$\text{commission accuracy} = \frac{\text{area of agreement between observed and predicted layers}}{\text{area of predicted layer (row total)}} \times 100 \quad (3)$$

$$\text{overall accuracy} = \frac{\sum(\text{agreement between observed and predicted layers})}{\text{area of all observations}} \times 100 \quad (4)$$

RESULTS

DEVELOPMENT OF WETLAND MAPPING TECHNIQUES

Selection of a Wetland Mapping Classification System

Wetland units at the physiognomic group levels of the OWC and OPI systems were adapted as wetland habitat mapping units (Table 1). Both of these systems were suitable for classifying wetlands at a variety of remotely sensed scales. Wetlands were classified into habitat mapping units on the basis of dominant cover species estimated from field observation and aerial photography. The bog and fen classes of these systems were merged into single fen classes due to the scarcity of true bogs in the study area. For this reason both the graminoid and low shrub fen classes also include weak fen and rich bog classes. The OWCS distinguished fens on the basis of graminoid or shrub ground cover. However, because graminoid treed fens where rare in the study area, the OPI method of separating treed fens on the basis of tree density was employed. The CWCS required a landscape position to classify a wetland which made it unsuitable for this study.

Table 1. Wetland classes selected as habitat components for wetland mapping (adapted from Riley 1992 and Jeglum *et al.* 1974).

WETLAND CLASS	CHARACTERISTIC FEATURES	DOMINANT COVER SPECIES
open water	water depth > 2 m	not included
shoreline	water depth < 2 m	not included
deep marsh	Submergent, floating, and emergent vegetation with 25% to 75% canopy closure, mud substrate, minerotrophic.	*Nuphar variegatum, Nympae spp., Polygonum natans*
shallow marsh	Submergent and emergent vegetation with 75% to 100% canopy closure, mud substrate, minerotrophic.	*Sparganium eurycarpum, Scirpus acutus, Eleocharis acicularus*
meadow marsh	Emergent graminoid closed canopy, on mud substrate, minerotrophic conditions, seasonal flooding.	*Calamagrostis canadensis, Scirpus cyperinus, Carex rostrata*
graminoid fen	Emergent sedge-rich closed canopy, on decomposing peat substrate (often floating mat), poor minerotrophic, periodically flooded.	*Carex lasiocarpa, C. limosa, C. aquatilus*
low shrub fen	Low shrubs (less than 150 cm tall), some sedges, on decomposing peat substrate (often floating mat), poor minerotrophic, periodically flooded.	*Myrica gale, Chamaedaphne calyculata Carex lasiocarpa*
low density treed fen	Conifer tree species, taller than 150 cm, 10% to 15% canopy closure, on a sphagnum dominated peat substrate, ombotrophic, ericaceous shrub ground cover.	*Picea mariana, Larix laricina, Chamaedaphnae calyculata*
moderate density treed fen	Conifer tree species, taller than 150 cm, 15% to 25% canopy closure, on a sphagnum dominated peat substrate, ombotrophic, ericaceous shrub ground cover.	*Picea mariana, Larix laricina, Chamaedaphnae calyculata*
thicket swamp	Tall shrub species greater than 150 cm, with 25% or greater canopy cover, on a mud substrate, minerotrophic, graminoid or herbaceous ground cover.	*Alnus rugosa, Salix spp., Cornus stolonifera*
conifer swamp	Conifer tree species greater than 200 cm tall, greater than 25% canopy closure, on organic substrate	*Picea mariana, Thuja occidentalis, Larix laricina*

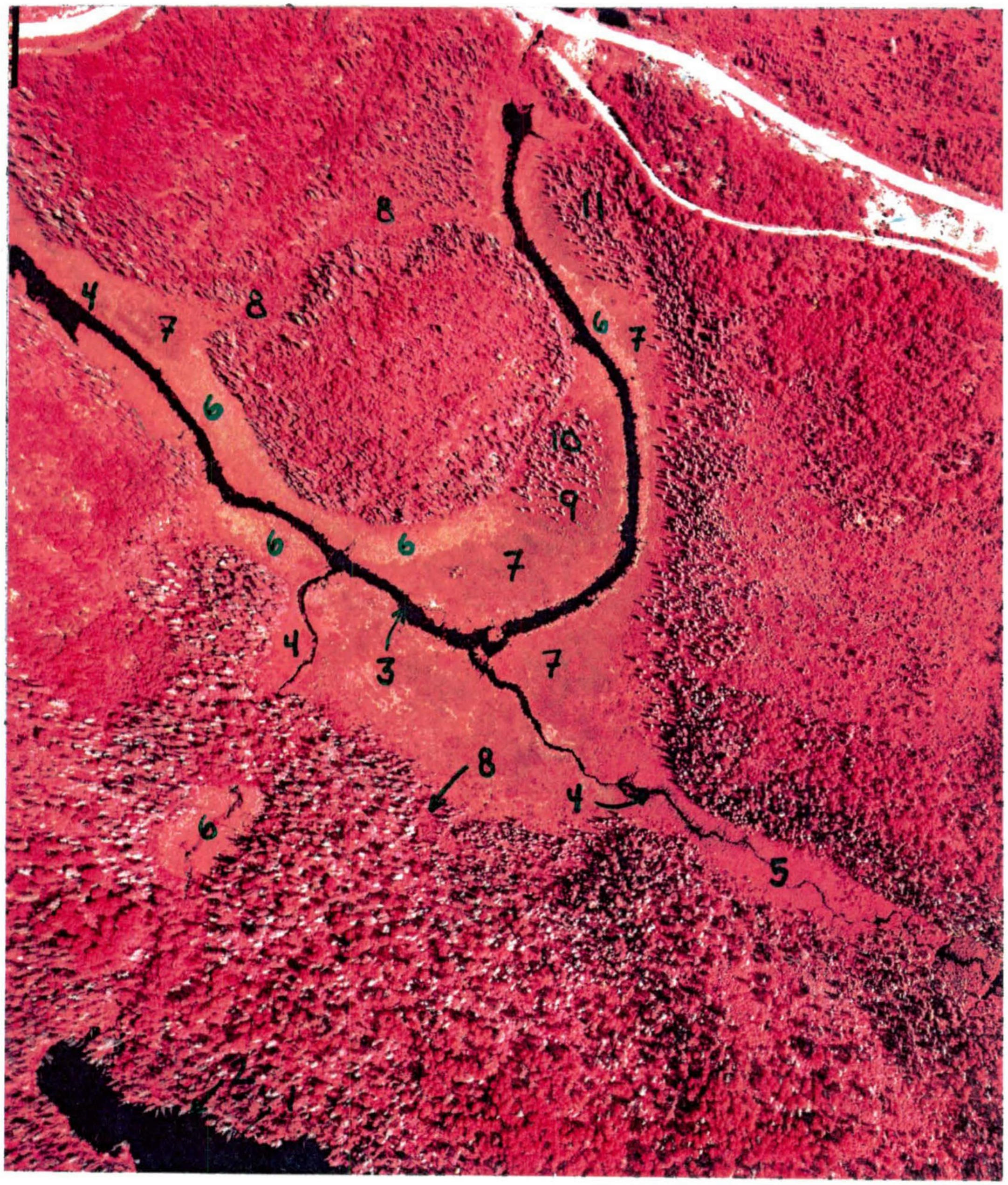
Colour Infrared Aerial Photography Based Wetland Mapping

Wetlands occurring within the transect of the CIR aerial photography were interpreted and the appearance of wetland habitat classes characterized. Each mapping class is described below in terms of the colour and texture of its appearance. The utility of different scales of CIR aerial photography for wetland mapping was evaluated based on these descriptions. Figure 3 is a 1:5,000 scale CIR aerial photograph of a wetland basin with habitat mapping classes identified. Habitat class boundaries were not drawn to show natural boundaries

Deep marshes with water depths greater than 15 cm and thin canopied emergent, submergent, and/or floating macrophytes growing in mud substrate appear dark red to red-black in colour. A mottled texture corresponds to the interspersion of water and thin canopied plants in the marsh. Spectral response is dominated by the absorption of green, red, and near infrared energies by the water with reflectance occurring in areas of shallow or turbid water, or areas with macrophytes present. Many floating broad leaved emergents such as *Nuphar* often appear in clumps of fuzzy dark patches along reddish black shoreline.

Shallow marshes with water depths of less than 15 cm and emergent aquatic macrophytes with closed canopies appear dark red to light orange in colour depending on water depth.

Figure 3. A 1:5,000 scale CIR aerial photograph of a wetland basin with habitat mapping classes identified. Habitat class boundaries were not drawn so that natural boundaries could be shown.



LEGEND

1 = open water
2 = shoreline
3 = deep marsh
4 = shallow marsh
5 = meadow marsh
6 = graminoid fen
7 = low shrub fen
8 = thicket swamp
9 = low density treed fen
10 = moderate density treed fen
11 = conifer swamp

Texture varies from medium to smooth depending on species present. For example, a shallow *Carex* marsh with a dense canopy growing on a mud substrate will have a smooth textured light orange-red colour that becomes more red as water depth increases.

Meadow marshes generally have dense graminoid vegetation with little surface water. Soil moisture and dominant species are factors affecting spectral reflectance. A *Calamagrostis* meadow appears red-pink to light red in colour with a fine to medium texture representative of lush growth with even density growing on drier soils. A *Scirpus* meadow, which has denser growth and a clumped appearance, generally grows on wetter soils and appears light-red in colour with a coarser texture (not unlike the texture of shrubs).

Graminoid fens are distinguished from meadow marshes on aerial photography based mainly on landscape position. Both share a red-pink to light red colour with a fine to medium texture representative of lush growth with even density. Meadow marshes are often adjacent to other marshes whereas fens are not. Fens generally grow on poorer soils than do meadow marshes and the intensity of colour is slightly reduced as a result. Poor fens are easily identified by their unique orange-yellow colours which are caused by the reduced emission of green energy by the chlorophyll-poor vegetation, the absorption of near infrared into the moist peat mats, and the increased reflection in the red portion of the spectrum. Although rare in the study area, open bogs often appear orange, yellow, and red in the visible portion of the spectrum.

Low shrub fens in the study area are dominated by *Myrica* and leather leaf [*Chamaedaphne calyculata* (L.) Moench] growing on a peat substrate. Water depth varies with shrubs sometimes growing along shorelines in flooded conditions and other times interspersed with graminoid fens. Colour depends on amount of water present and varies from red to dark red. Increased density of shrub cover results in increased absorption of energy in the red, infrared and green portions of the energy spectrum. Leather leaf commonly maintains dead branches after foliage has dropped giving it a greyish appearance on CIR photography. A mottled texture and clumped appearance reflect the uneven canopy and growth pattern of the fen. *Myrica* fens often occupy a transition zone between graminoid fens and alder thickets allowing for interpretation based on recognition of neighbouring physiognomic groups.

Thicket swamps are probably best identified by taking advantage of relief contrast furnished by stereo pairs. Alder (*Alnus*) is easily visible because it often grows to a medium height in relation to shorter height marshes and fens and taller forest landcover. The pattern of alder occupying low areas of poor drainage in the landscape thus breaking up continuous forest is easily identified on aerial photography. The dense, healthy vegetation appears a deep red colour with medium texture on CIR photography.

Treed fens are identified by two features - peat-based substrate and stunted or stressed trees. Unhealthy trees (*Picea mariana* (Mill) BSP., *Larix laricina* (DuRoi) K.Koch) growing in nutrient-poor conditions often result in low chlorophyll levels indicated by foliar discolouration. In stressed conditions a plant's ability to reflect infrared is reduced causing a shift from red to pink colour on CIR photography. As a result, trees in treed fens often appear light pink to white in colour. Treed fens were easily separated into low-density and moderate density groups at all scales of photography.

Conifer swamps are interpretable by their light purple-grey colour and mottled texture. This is indicative of the small-crowned tight-canopied trees (e.g., black spruce) often with dead lower canopies common in swamp conditions. Conifer needles reflect less infrared energy then deciduous leaves because of their morphology (smaller surface area, thinner mesophyll etc.), and the dead branch layers in the lower sections of the crown absorb most incoming infrared. The combination of these factors creates a light purple-grey colour.

Satellite Based Wetland Mapping

Two LANDSAT TM images of the same area were acquired for April 20, 1991, and on August 7, 1990. The spring image was geocoded at a pixel size of 25 metres to 1:50,000 National Topographical Series map sheets to satisfy an RMS error of less than 25 metres. The summer image was then co-registered to the spring image using image to image registration. A first order transformation was used with eighty-three points to satisfy an RMS error of less than 25 metres. Any areas not covered by both images were removed.

Evaluation of LANDSAT TM bands based on a preliminary utilization of the whole spring and summer data set showed that the visible and near-infrared channels of the spring imagery did not contribute additional information useful to image classification. Subsequently these channels were omitted and a second multi-temporal data set capturing the hydrological and vegetation changes between spring and summer was created by selecting the middle infrared band of the spring image with the green, red, near and middle infrared bands of the summer image.

The first three principal components represented 99.62 percent of the variance of the spectral reflectance in the raw data (Table 2).

Table 2. Summary of principal component analysis of spring middle-infrared, summer green, red, near and middle-infrared reflection bands.

PRINCIPAL COMPONENT	VARIANCE	TOTAL VARIANCE
1	92.54%	92.54%
2	4.91%	97.45%
3	2.17%	99.62%
4	0.31%	99.93%
5	0.07%	100.00%

The first principal component (PC) corresponded to the range of spectral reflectance values resulting from the vegetative differences in landcover in the data. PC1 accounted for 92.54 percent of the variance in the input data set and could be visually interpreted to represent the difference between the low visible reflection and high infrared reflection values. The second principal component corresponded to moisture differences in the landscape. This component accounted for 4.9 percent of the variance in the data and could be visually interpreted to represent the difference between wet and dry components of the landscape. The third principal component, while accounting for only 2.7 percent of the variance in the data, was important particularly for the interpretation of wetlands. Visually comparing the values of the PC data displayed on a 250 level grey scale, PC3 separated the wetlands from the rest of the landscape very well. The fourth and fifth PCs represented only 0.4 percent of the variance in the input data set and could not be visually identified as important to the interpretation of the image. PC4 and PC5 were not used for the subsequent cluster analysis, thus reducing unwanted information from the data set.

Unsupervised classification produced a single channel, 250 class image from the first three principal components. Conceptually, the 250 spectral classes could be thought of as building blocks which were interpreted, grouped and assigned to wetland classes to create a model of wetland habitat structure. Spectral profiles and colour tables were generated from the post-classification statistics based on the reflectance values of the raw data that were generated for each spectral class.

Spectral profiles were created by plotting the post classification statistics to aid in interpreting features based on their spectral reflectance characteristics. Spectral class assignment was accomplished, in part, by linking spectral profiles to reflective characteristics based on the ecology of the wetland classes. For example a deep marsh has less vegetation cover as compared to a shallow marsh. The post classification statistics were also used to create colour tables to enhance the qualitative information for image interpretation. The appearance of a colour table is based on the combination of spectral channels and screen colours selected. For example, a colour table emulating colour-infrared photography was created by displaying the mean of the green band reflectance as blue, the red band as green and the near-infrared as red.

Evaluating the profiles of spectral classes assigned to the same wetland class showed that the slope, rather than the intercept of the spectral profiles characterized their association. Multiple channel image analysis commonly uses image ratioing to utilize the differences between spectral bands. To emulate image ratioing in a single channel image, Wards minimum distance cluster analysis (Ward 1963) was applied to the slopes of the spectral profiles to locate secondary clusters in the spectral class data set (proc cluster; SAS 1988). This analysis organized the spectral classes into 40 large classes based on both the band intercept and image ratio based values. Although these large classes could not be directly associated with wetland classes, they were used to associate spectral classes with one another and aid in spectral class assignment. A second single channel image with 40 classes was created from these 40 classes and colour tables generated for it. The 40 class image served two purposes. First, it identified groups of spectral classes from the 250 class image that could be evaluated with the aid of colour tables and ground reference to determine if they represented similar landcover types. Second, with a colour table that had the same combination of spectral channels and screen colours, the image could be made to look similar to the 250 class image. By reducing the number of spectral classes to 40 additional classes representing wetland classes could be overlaid onto the image since the ELAS software being used was limited to 256 classes.

Spectral classes were assigned to wetland information classes using ground reference data, spectral profiles and colour tables described above. These techniques were used to interpret, organize, and assign spectral classes to wetland classes to create a wetland habitat model. Wetland classes were characterized in terms of spectral reflectance expressed by the profiles derived from the post classification statistics.

Open water is characterized spectrally in the April imagery by moderate near infrared reflection in spring caused by ice with relatively no reflection in the other bands (Figure 4). Shoreline classes are characterized by a relatively low and flat spectral profile resulting from the absorption of energy by water.

Deep marsh is characterized by relatively low reflection levels across the spectral profile (Figure 4). A slight rise in summer near infrared reflection can be related to the emergence of aquatic macrophytes. Reflection values, especially in the infrared bands, varies according to density of macrophyte cover and water depth.

Shallow marsh is characterized along with deep marsh as having relatively low reflection across the spectral profile (Figure 4). Again, reflection values vary according to density of plant cover and water depth. Shallow marsh has slightly higher values in spring middle infrared reflection resulting from lower water levels absorbing less energy and more dead vegetation, from the previous season, reflecting greater amounts of

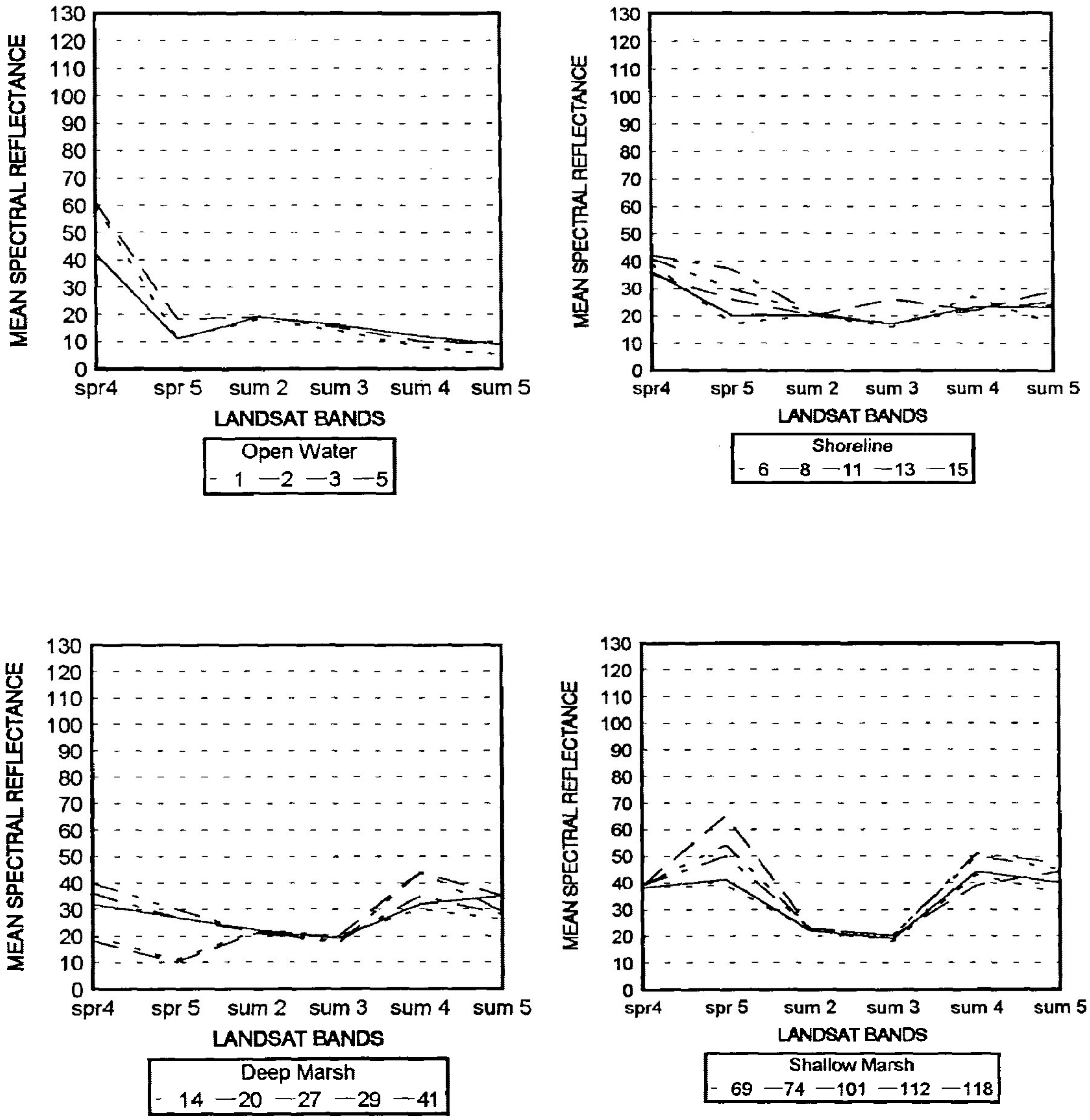


Figure 4. Spectral profiles plotted for spectral classes associated with wetland classes. SPR4=spring Thematic Mapper (TM) band 4, SUM5=summer TM band 5 etc.

energy.

Meadow marsh was easily distinguished from the other marshes by high infrared reflection values (Figure 5). Near infrared increases from spring to summer as a result of increased graminoid growth. Middle infrared reflection is very high in the spring due to fallen dead graminoid cover from previous season (based on field observation) but decreases slightly over the growing season as new vegetation takes over the canopy.

Graminoid fen is difficult to distinguish from meadow marsh especially in drier fens (Figure 5). More commonly, graminoid fens follow the same seasonal pattern of infrared reflection as does meadow marsh, but with slightly lower middle infrared values in the spring and summer due to a wetter growing environment (Figure 5). Fen graminoids (especially in poorer fens) generally have less leaf surface area than meadow species. This results in slightly lower reflectance values in summer near infrared reflection values for fens than meadows.

Low shrub fens are dominated by shrub cover that reflects less green and infrared energy than do graminoids (Figure 5). The spectral profile of low shrub fens show a moderate increase in near infrared reflection resulting from leafing out of shrubs such as *Myrica*. These fens have stable moderate middle infrared reflection values resulting from a more constant growing environment than graminoid fens.

The spectral profiles of thicket swamps are characterized by two

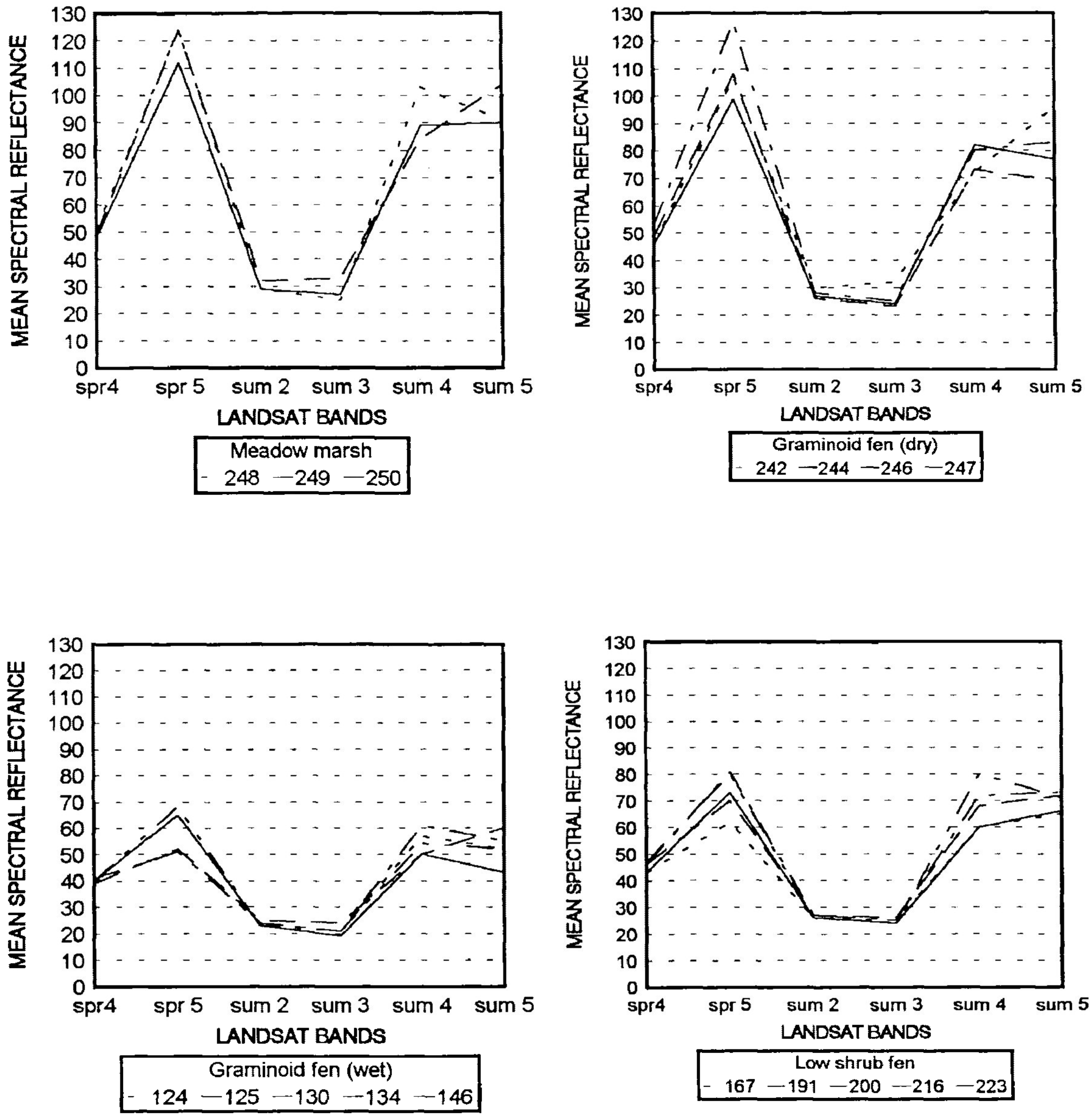


Figure 5. Spectral profiles plotted for spectral classes associated with wetland classes. SPR4=spring thematic mapper (TM) band 4, SUM5=summer TM band 5 etc.

moderately high peaks in the spring middle infrared and summer near infrared reflection (Figure 6). These peaks represent the increase of reflected near infrared energy resulting from leafing-out of alder from spring to summer and the decrease in middle infrared reflected by dead leaf litter.

The spectral profiles of low density and moderate density treed fens are unique from other wetland classes but similar to one-another (Figure 6). Both fens show a moderate increase from spring to summer in near infrared reflection. The increase in near infrared caused by emerging understorey vegetation is greater in low density than moderate density treed fens. Both fens show almost no change in middle infrared reflection resulting from similar moisture environments from spring to summer.

The spectral profile of conifer swamps is very similar to deep marsh, although the two share almost no physical similarities (Figure 6). The relatively low profile is due to the strong absorption of all energy by the conifers growing in a wet environment. The slight increase in near infrared reflection indicates new growth on the trees, whereas the stable middle infrared values express the moist growing environment of the swamp.

Integration of remote sensing and GIS allowed assignment of spectral classes to wetland habitat classes without omission and commission error to non-wetland features. Some spectral classes occurred

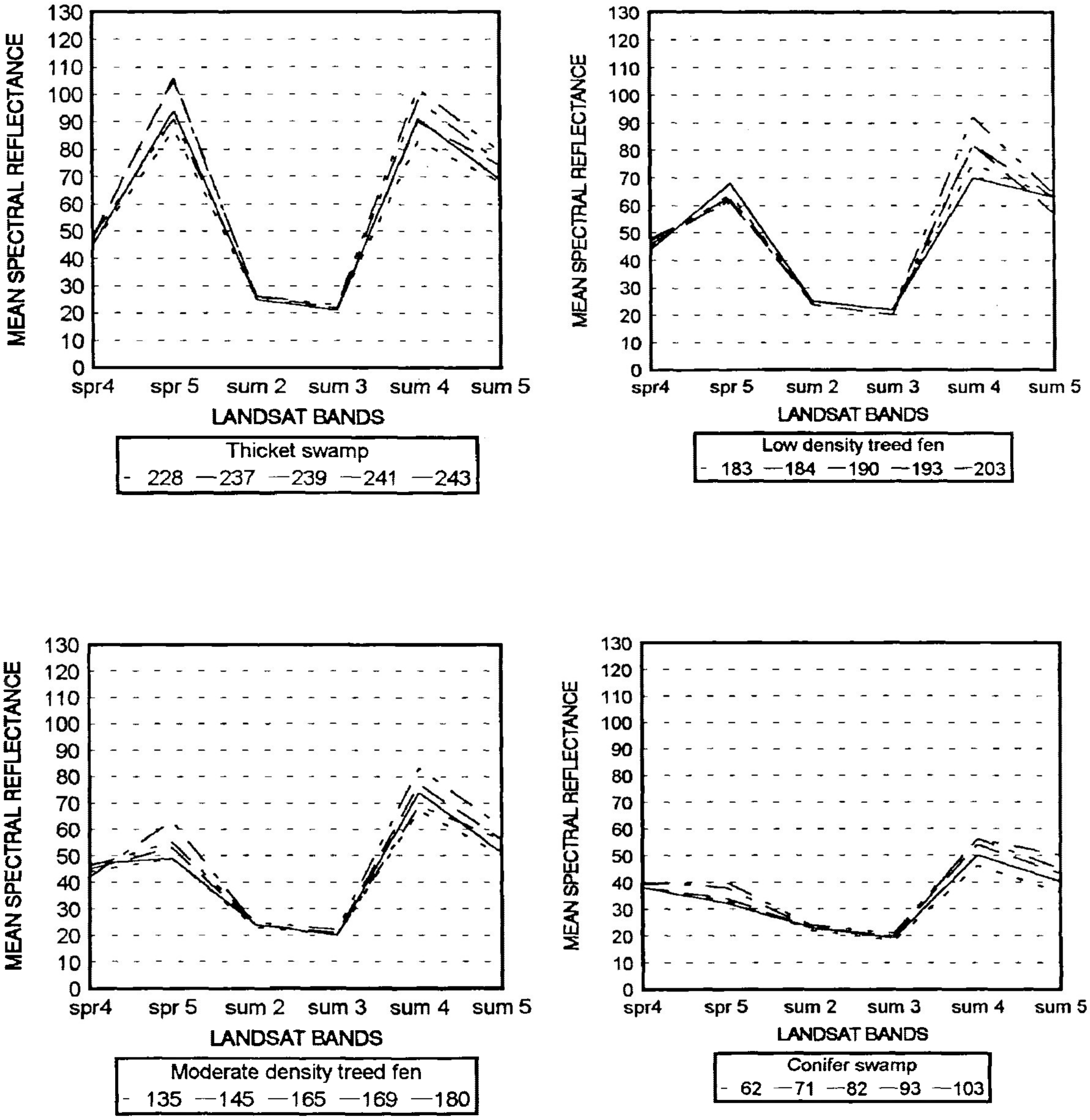


Figure 6. Spectral profiles plotted for spectral classes associated with wetland classes. SPR4=spring Thematic Mapper (TM) band 4, SUM5= summer TM band 5 etc.

both in wetland basins and in terrestrial landcover features. Spectral confusion between terrestrial and wetland features was resolved by incorporating digital FRI map data with the classified satellite data (Figure 7). FRI maps were registered to the single channel image with a first order RMS of less than 15 metres. Registration error was more pronounced along north-south oriented lakeshores and wetland boundaries.

APPLICATION OF WETLAND MAPPING TECHNIQUES

The techniques for characterizing wetland habitat structure were applied to a 2,200 square kilometre portion of the study area. Once the spectral classes were assigned to wetland classes, the wetland classes were superimposed onto the 40 class image to create the classified wetland habitat map. The classified wetland map is shown at two scales -- 1:250,000 or the management unit scale (Figure 8) and at 1:40,000 (Figure 9) to provide a better picture of the detail available.

Figure 7. Technique for integrating Forest Resource Inventory (FRI) and satellite data using SPANS Geographic Information System. From top to bottom: 1) Highlighted spectral class 248 illustrates spectral confusion between young cutovers and meadow marshes that cannot be resolved by the clustering algorithm. 2) Digital FRI is used to separate wetlands from the rest of the landscape using polygon boundaries. 3) The result is a single channel image with 250 spectral classes that can be assigned to wetland habitat classes.

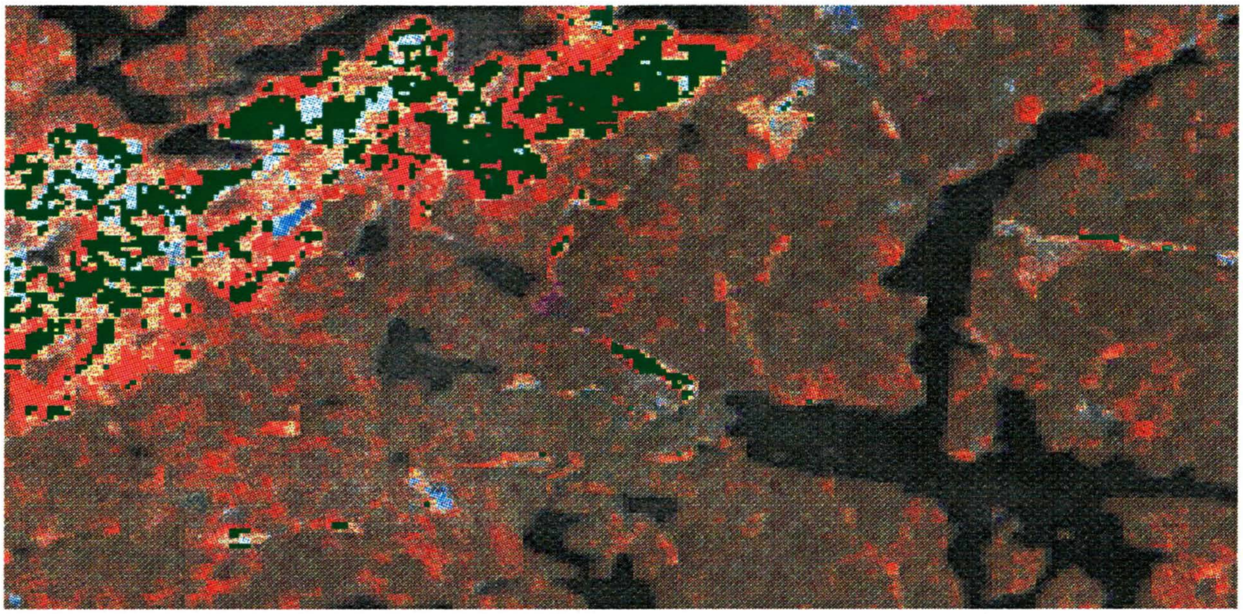
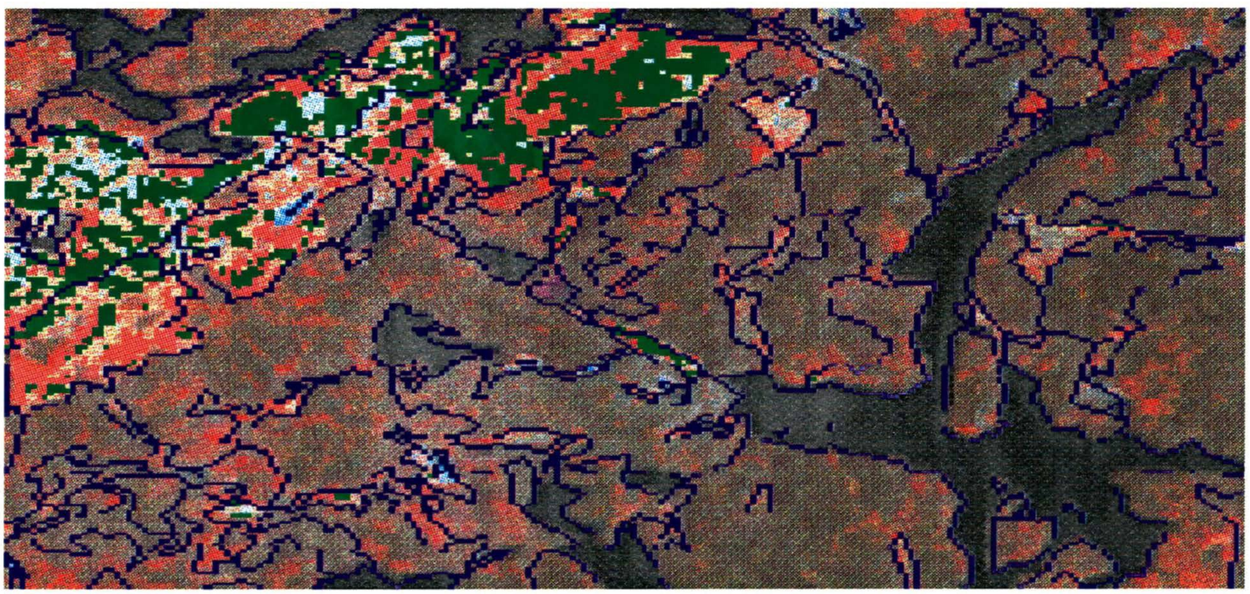
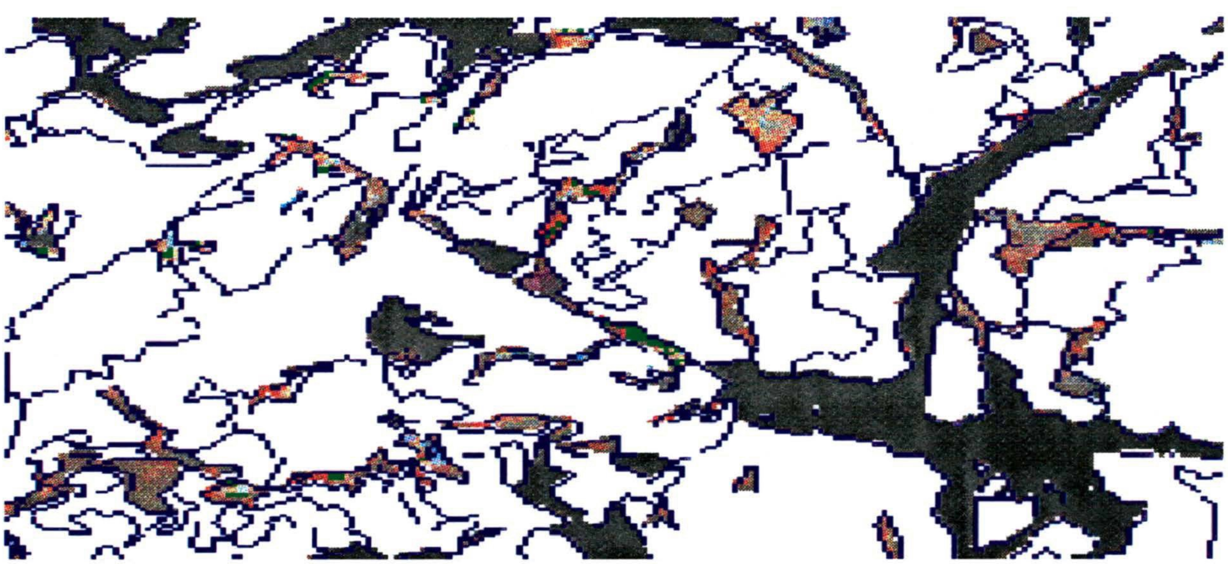




Figure 8. LANDSAT TM-based wetland habitat map for entire area of application. Legend key shows wetland habitat classes. Wetland habitat map is superimposed onto 40 class image that is displayed using a colour table that can be used to interpret the landscape as follows: dark maroon colours are dense conifer forest, lighter browns are conifer mixedwood forest, light oranges are deciduous and deciduous mixedwood forest, light yellows and blues are recently disturbed (within last 20 years) forest cover.

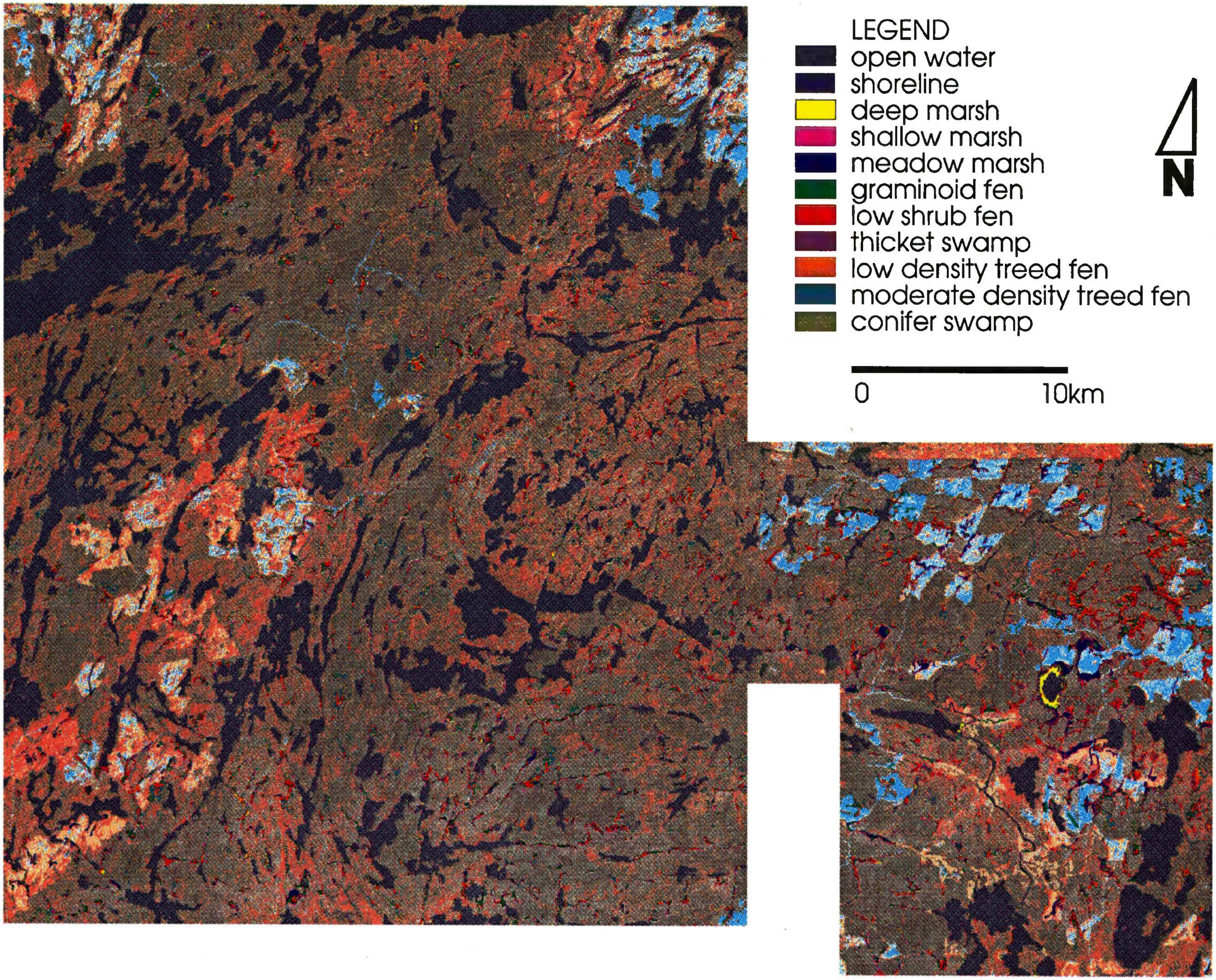
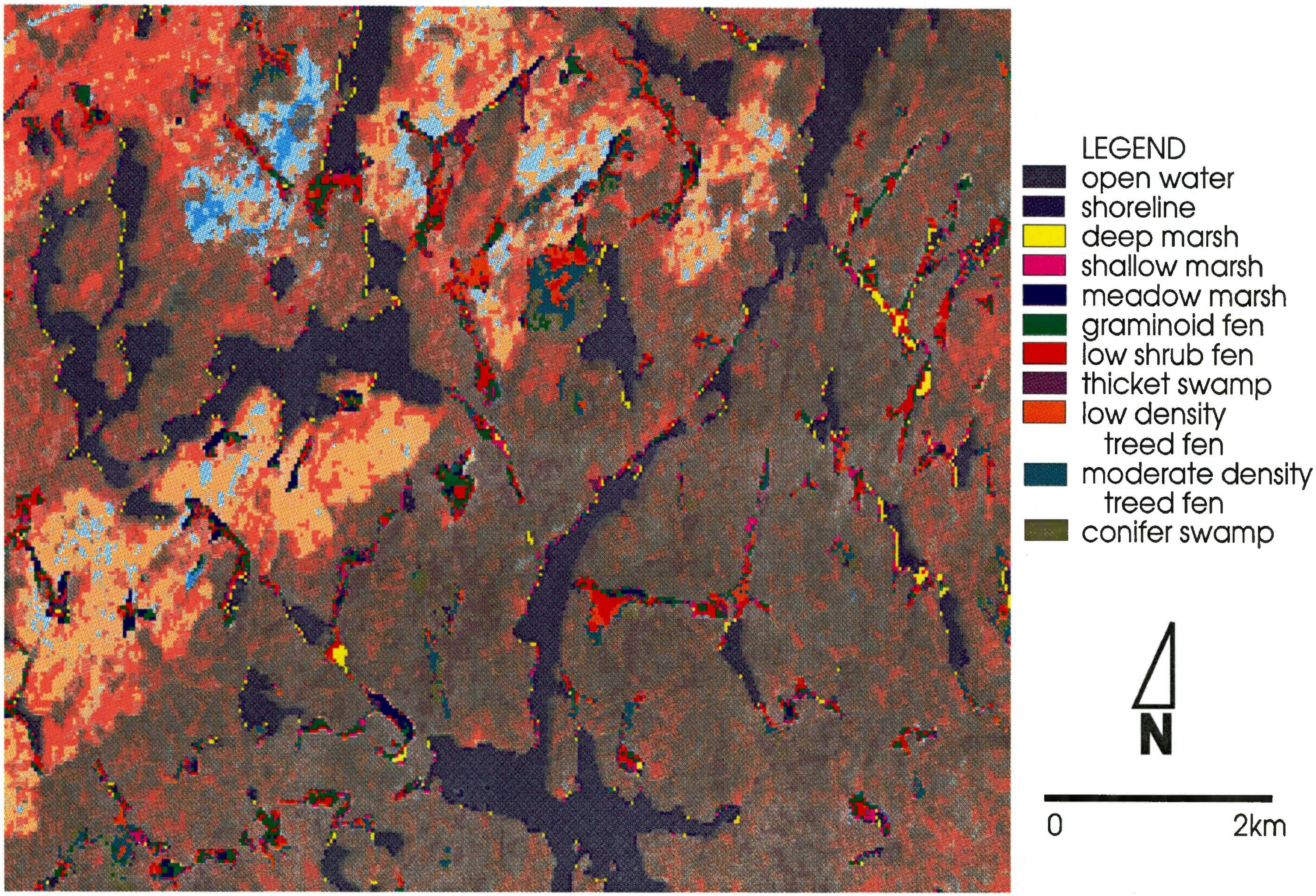

LEGEND
open water
shoreline
deep marsh
shallow marsh
meadow marsh
graminoid fen
low shrub fen
thicket swamp
low density treed fen
moderate density treed fen
conifer swamp
N
0
10km

Figure 9. Enlarged detail of LANDSAT TM-based wetland habitat map. Legend key shows wetland habitat classes. Wetland habitat map is superimposed onto 40 class image that is displayed using a colour table that can be used to interpret the landscape as follows: dark maroon colours are dense conifer forest, lighter browns are conifer mixedwood forest, light oranges are deciduous and deciduous mixedwood forest, light yellows and blues are recently disturbed (within last 20 years) forest cover.


LEGEND
open water
shoreline
deep marsh
shallow marsh
meadow marsh
graminoid fen
low shrub fen
thicket swamp
low density treed fen
moderate density treed fen
conifer swamp
N
0
2km

EVALUATION OF WETLAND MAPPING TECHNIQUES

Colour Infrared Aerial Photography Based Wetland Mapping

A total of 20 wetland basins were visually interpreted from air photos and then visited in the field to provide a measure of the accuracy of wetland habitat class interpretation. Not all wetlands occurred in all three scales of the photography, thus results are not equally distributed for all scales. Overall accuracy (percent correct) of interpreted wetland polygons was 82, 94 and 94 percent for 1:20,000, 1:10,000 and 1:5,000 respectively (Table 3).

Satellite Based Wetland Mapping

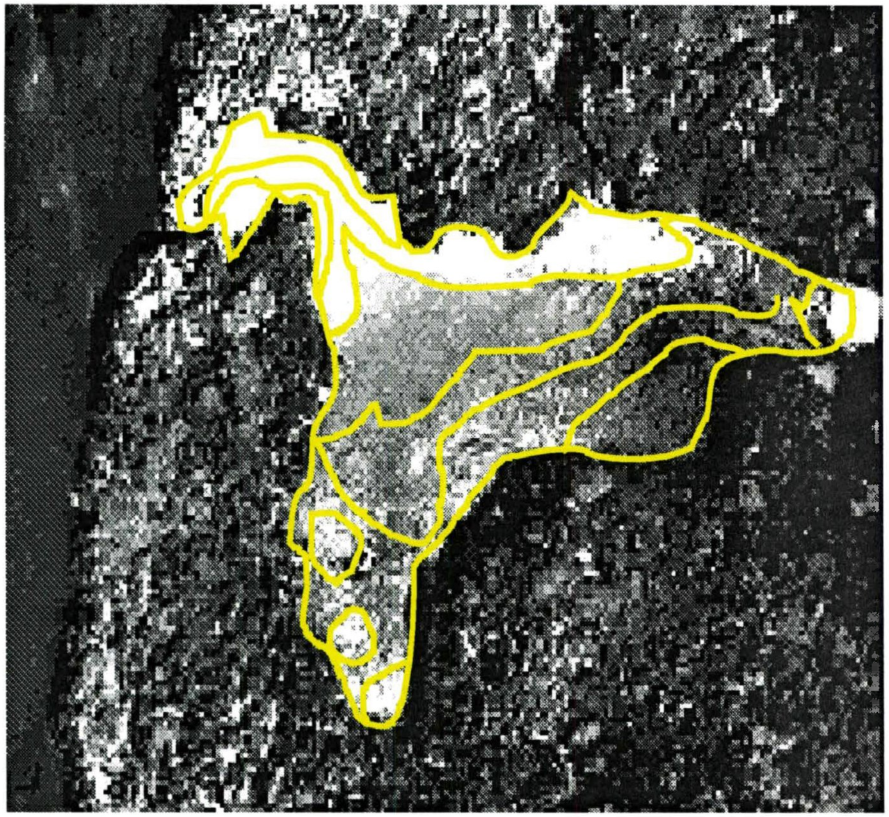
For the basin approach to accuracy assessment 40 wetland basins containing over 150 wetland classes were interpreted using ground reference data. Omission and commission errors for all wetland classes present in each basin were calculated (Figure 10). Mean percent error over all basins for each wetland class ranged from two to ten percent. The percentage values were transformed using an arcsine transformation (Zar 1984) to calculate overall means for accuracy (Table 4). These error values provide an estimate of the mean percent area of a wetland basin, by

Table 3. Summary of omission and commission accuracy for CIR air photo interpretation of 20 wetland basins. Overall accuracy (percent correct) was 82, 94, and 94 percent for 1:20 000, 1:10 000 and 1:5000 respectively. Sample sizes for each scale indicated in parentheses.

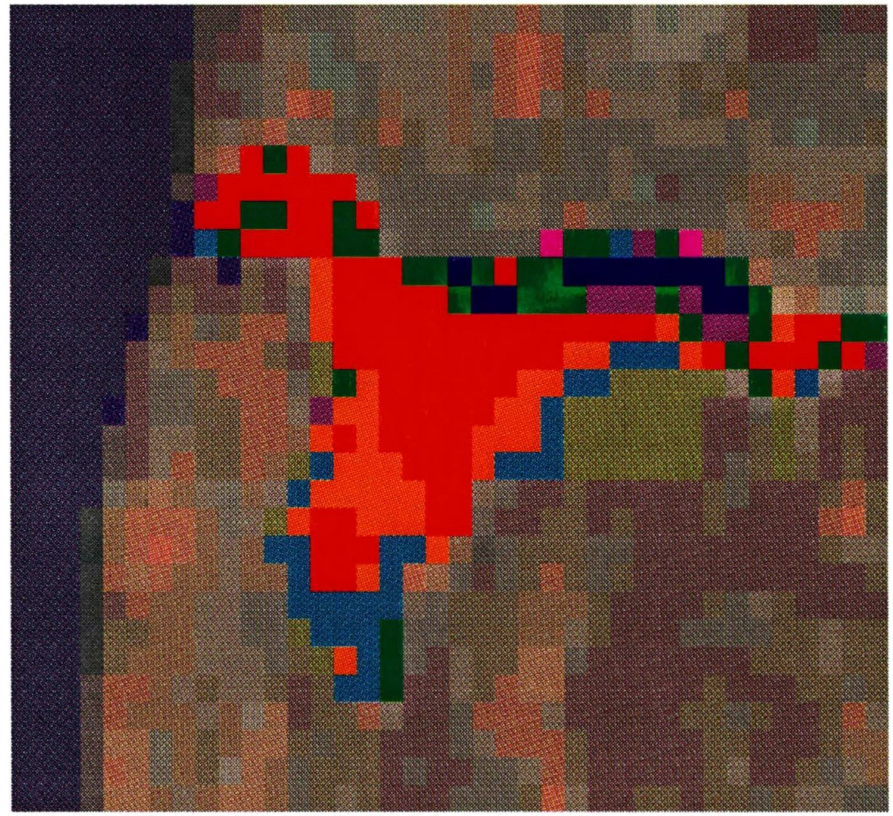
SCALE ACCURACY	deep marsh	shallow marsh	meadow marsh	graminoid fen	low shrub fen	thicket swamp	low density treed fen	moderate density treed fen	conifer swamp
1:20000	(12)	(9)	(8)	(14)	(15)	(15)	(6)	(4)	(6)
omission	100	75	86	75	64	92	60	100	100
commission	100	86	66	75	86	75	75	75	100
1:10000	(13)	(10)	(8)	(15)	(15)	(13)	(9)	(2)	(7)
omission	100	90	85	100	85	100	100	100	100
commission	100	100	75	91	92	100	90	100	100
1:5000	(12)	(8)	(10)	(15)	(17)	(10)	(9)	(5)	(7)
omission	100	75	100	100	88	100	100	100	100
commission	100	100	75	89	93	100	90	100	100

Figure 10. Example of the basin level approach to accuracy assessment for a single wetland basin. Percent area of each wetland class occurring in the basin is estimated using a dot grid to create an observed habitat layer. SPANS geographic information system is used to calculate percent area for each wetland class in the classified map to create a predicted habitat layer. Differences are expressed as omission and commission error.

RASTERIZED AERIAL PHOTOGRAPH



SATELLITE BASED WETLAND HABITAT MAP



WETLAND CLASS	OBSERVED % AREA	PREDICTED % AREA	OMISSION ACCURACY	COMMISSION ACCURACY
meadow marsh	10	5	95	--
graminoid fen	5	15	--	90
low shrub fen	20	25	--	95
thicket swamp	10	5	95	--
low density treed fen	15	15	100	100
moderate density treed fen	20	15	95	--
conifer swamp	20	20	100	100
total			85	85

Table 4. Omission and commission errors expressed as mean percent area of wetland basins. Error values based only on wetland basins with wetland class identified by interpretation of ground reference or classified model respectively (SD = standard deviation).

WETLAND CLASS	MEAN PERCENT OMISSION ERROR (SD)	MEAN PERCENT COMMISSION ERROR (SD)
OPEN WATER	0.0 (n/a)	3.4 (8.9)
SHORELINE	2.5 (6.4)	4.8 (7.6)
DEEP MARSH	5.7 (4.2)	5.6 (11.5)
SHALLOW MARSH	4.7 (9.4)	5.5 (9.2)
MEADOW MARSH	5.8 (10.7)	0.0 (n/a)
GRAMINOID FEN	9.4 (10.6)	4.7 (4.8)
LOW SHRUB FEN	8.3 (12.1)	4.8 (16.3)
THICKET SWAMP	7.0 (7.2)	4.3 (6.7)
MEDIUM DENSITY TREED FEN	3.7 (6.3)	5.2 (6.9)
LOW DENSITY TREED FEN	5.4 (7.6)	4.7 (6.4)
CONIFER SWAMP	14.1 (16.6)	6.0 (8.6)

wetland class, that was incorrectly mapped. Omission and commission error estimates were calculated only for those wetland classes identified by the interpreter or the classified model respectively. For example, no estimate of omission was calculated for a wetland class if it was not present in the basin. The highest omission error, 14 percent, occurred with conifer swamps. The largest commission error, 6 percent also occurred with conifer swamps.

For the pixel approach, six CIR aerial photographs containing over 500 hectares of wetlands were interpreted and used to create a ground reference layer of physiognomic groups. Wetland classes for all photographs were added together to determine class omission and commission accuracy (Table 5). The overall agreement between the ground reference layer and classified wetland habitat map was 72 percent.

Wetland classes that were physiognomically similar were grouped together into broader classes to investigate the effect on map accuracy. In both the ground reference and habitat map layers open water and shoreline were grouped into water, deep and shallow marsh into marsh, meadow marsh and graminoid fen into graminoid, and low and moderate density treed fens were combined with conifer swamp into treed wetland. Low shrub fen and alder thicket were not combined with other classes. Omission and commission accuracy were calculated for these broad classes and the overall level of agreement at the broad level was 81 percent (Table 6).

Table 5. Error matrix of wetland habitat components observed from aerial photography and classified wetlands map. Percent correct expressed as omission and commission accuracy. Units represent 50 square metre areas.

		WETLANDS FROM GROUND REFERENCE LAYER										COMMISSION ACCURACY
WETLAND HABITAT MAP	ow	sl	dm	sm	mm	gf	lsf	ts	ldtf	mdtf	cs	
open water	5749	1151	84	36	165	0	5	0	0	0	1	80
shoreline	2	2149	381	128	158	33	32	19	1	67	919	55
deep marsh	0	163	2062	260	0	43	41	17	4	2	68	78
shallow marsh	0	134	366	1365	108	267	143	56	99	173	382	44
meadow marsh	0	0	0	4	2815	865	234	152	1	0	0	69
graminoid fen	0	1	191	441	769	11317	2567	499	356	183	253	68
low shrub fen	0	13	104	161	168	1732	11444	557	1132	495	324	71
alder thicket	0	24	67	81	154	448	737	3530	548	417	297	56
low density treed fen	0	3	38	16	75	226	1073	292	5423	1264	191	63
moderate density treed fen	0	24	68	57	12	149	442	110	1321	9862	2523	68
conifer swamp	0	85	223	101	5	139	169	45	210	807	18300	91
OMISSION ACCURACY	100	57	58	52	64	74	68	67	60	74	79	72

Table 6. Error matrix of broad wetland habitat components observed from aerial photography and classified wetlands map. Percent correct expressed as omission and commission accuracy. Units represent 50 square metre areas.

CLASSIFIED WETLAND HABITAT MAP	GROUND REFERENCE LAYER						COMMISSION ACCURACY
	water	marsh	graminoid	shrub	thicket	treed	
water	9051	629	356	37	19	988	82
marsh	297	4053	418	184	73	728	70
graminoid	1	636	15766	2801	651	793	76
low shrub	13	265	1900	11444	557	1951	71
thicket	24	148	602	737	3530	1262	56
treed	112	503	606	1684	447	39901	92
OMISSION ACCURACY	95	65	80	68	67	87	81

DISCUSSION

DEVELOPMENT OF WETLAND MAPPING TECHNIQUES

The first objective of this thesis was to develop techniques to characterize wetland habitat components in a landscape context using remote sensing and GIS technologies. Steps in achieving this objective included linking wetland habitat information in a hierarchy of detection scales, CIR air photo interpretation, LANDSAT TM image classification and interpretation, and the integration of non-spectral data using GIS. The first link in connecting ground based wetland classification with remotely sensed wetland habitat information was the creation of wetland class descriptions from CIR air photo interpretation. In a bottom-up approach, the characteristics defined at this scale facilitated interpretation of the same features at increasingly smaller scales.

The need for timely and accurate ground reference information is not always met by existing aerial photography. If this occurs supplementary aerial photography (SAP) is usually required. CIR photography has a distinct advantage over panchromatic film for mapping vegetation features. Flying transects of SAP reduced the amount of field data required sufficiently to justify its use in the study, especially in areas with poor access.

The main strengths of the approach to image classification are the ability to optimize the spectral resolution of the data independent of the interpreter, the ability to detect emergent spatial patterns, and the procedure of stratifying wetlands from the rest of the landscape. Often many supervised approaches to image classification are forced to omit or aggregate wetland mapping classes due to an inability to connect features interpreted using finer scale ground reference with the information in the satellite data (e.g., Werth and Lillesand 1978, Darby 1990, Ontario Ministry of Natural Resources 1992). An unsupervised approach to image classification does not assign informational value to the image until after the spectral resolution of the data has been determined. There are two advantages to this: 1) the producer does not introduce a bias into the classification until after the full resolution of the data is obtained; and 2), the clustering algorithm detects information structure in the data which indicates to the producer that spectral discrimination is possible.

Detection of ecological pattern is a noted research priority for characterizing and inventorying landscapes (e.g., Iverson *et al.* 1989, Leckie 1990, Roughgarden *et al.* 1991). Although unsupervised image classification did not explicitly classify spatial patterns in the data set, the emergent spatial patterns of the spectral classes offered the opportunity for visual discrimination of these patterns at a landscape scale. Using the

ELAS programs designed by Ducks Unlimited (Ducks Unlimited 1991, Koeln *et al.* 1986), these emergent spatial patterns became as important as the spectral information in the data for landcover interpretation. Wetland basins were often composed of discrete habitat types that were homogeneous in character and detectable at the 30 metre resolution of the TM data. Spectral classes were often directly related to wetland habitat ground reference on the basis of spatial pattern alone.

The inability to separate wetland basins from the rest of the landscape is a problem which limits the success of wetland mapping (e.g., Werth and Lillesand 1978, Tomlins and Boyd 1988, Ontario Ministry of Natural Resources 1992). Oslin's (1978) use of rasterized CIR photography to detect wetland boundaries offers increased spatial resolution, but the utility of this type of process is limited by the effort required to apply it to large geographic areas. Using the FRI wetland boundaries to delineate wetlands within the landscape offered an alternative solution to this problem. Integrating classified satellite data with a mosaic of FRI maps on a landscape scale offered an acceptable level of spatial resolution with a relatively small amount of effort.

A greater number of non-water and non-shoreline pixels occurred on the west side of the lakes relative to the east side (Figure 5). This may have been caused by registration error between the FRI maps and the satellite imagery. Attempts were made to restrict error to no more than one pixel, but it still contributed to omission and commission errors along edges of wetlands. Another possibility for these pixels may have been a systematic error caused by scanner saturation. As the TM scanner moves across the landscape, abrupt changes in landcover features will affect the measurement of pixels occurring between dramatically different features such as water and land. For these reasons, pixels along the side of wetlands were not included in the accuracy assessment. The magnitude of these errors was a factor of wetland size and shape. Wetlands with high perimeter to area ratios were more likely to be affected than those with low ratios.

APPLICATION OF WETLAND MAPPING TECHNIQUES

The developed techniques for characterizing wetland habitat were applied to a 2,200 square kilometre landscape for which digital FRI was available. Relative to other wetland mapping efforts this is a large area of application. Many applications concentrate on discriminating detailed wetland classes (i.e., genus-based) for small geographic areas (e.g., Jensen *et al.* 1986, 1991, Gross *et al.* 1987). Other applications have used medium sized study areas up to 1,000 square kilometres to interpret physiognomic-based wetland classes (e.g., Hall *et al.* 1987, Bobbette and Jeglum 1990). Most full-landcover mapping efforts are applied in Ontario, to areas greater than 1000 square kilometres and usually do not distinguish wetlands beyond open or treed (e.g. Darby 1990, Ontario Ministry of Natural Resources 1992). For this study the area of application could be expanded with the addition of the remaining digital FRI required to cover the entire 8,000 square kilometre TM scene.

Incorporating FRI or similar existing data with spectral data in a GIS is practical as one of the first steps in creating a landcover database. This source of data will continue to be made available in digital form and should be integrated with other management unit applications wherever possible (Parry 1993). Integration of digital map data is not limited to FRI, but also includes Ontario Land Inventory, Ontario Base Maps, digital elevation models and a host of other satellite based efforts.

The wetland habitat map was developed in raster format but is quite easily transformed into vector format, which is more commonly used for inventory purposes. The procedures followed in creating a predicted habitat information layer can be modified to create a table suitable for incorporation into a vector-based GIS such as ARC/INFO.

EVALUATION OF WETLAND MAPPING TECHNIQUES

The third objective of this thesis was to evaluate the accuracy of the developed techniques in providing wetland habitat information across a range of spatial scales. This evaluation can be discussed in terms of what resolution of information can be provided at what scale. Each scale of data has advantages and limitations which can be expressed as the level of accuracy possible in interpreting wetland information.

CIR aerial photography provides excellent overall accuracies at 1:5,000 and 1:10,000 scales (94 percent for each) and good (82 percent) at the 1:20,000 scale (Table 4). Aerial photography also offers the opportunity to interpret wetland basins in the context of their landscape position. This is advantageous in resolving classes that are physiognomically similar but different in terms of geographic location -- meadow marsh and graminoid fen for example.

From a management viewpoint, the larger 1:20,000 scale photography offers a larger picture of the landscape with a reduction in ability to discriminate similar wetland classes. On the other hand, 1:5,000 scale allows interpretation of wetland classes, sometimes to the genus level, along with other features of interest (e.g. moose aquatic feeding pathways). The limitations of this scale is the small geographic area covered by one photo (one-sixteenth of a 1:20,000 photo) and the increased relief displacement around the edges of the photo. Between these scales is the 1:10,000 scale which allows interpretation of almost all of the features the 1:5,000 does, but with four times the coverage area per photo and considerably less relief displacement.

Results show that classified multi-temporal LANDSAT TM imagery, when integrated with digital FRI, provides resolution of wetland habitat structure with 72 percent overall accuracy. Broader wetland classes obtained by combining physiognomically similar groups increased overall accuracy to 81 percent. An examination of the literature finds that most wetland mapping errors have been attributed to confusion between related wetland classes (e.g., Tomlins and Boyd 1988, Hellyer *et al.* 1990, Bobbette and Jeglum 1990). Wetlands succession occurs with the establishment of new plant species in response to changing environmental conditions (Van der Valk 1981). In boreal wetlands the general trend, based on macrofossil analysis of wetlands, is towards a treed state, although successional changes do not necessarily follow this fixed continuum (Figure 11) (Zoltai *et al.* 1988).

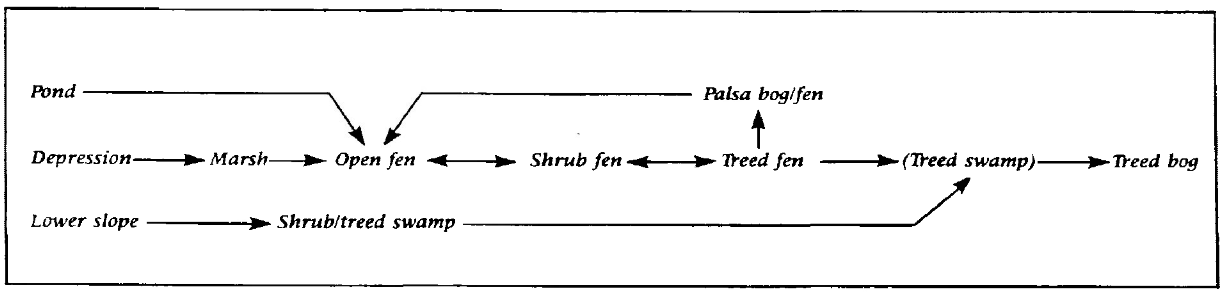


Figure 11. Diagram of wetland development trends in boreal wetland regions (from Zoltai *et al.* 1988).

Changing environmental conditions may cause a mixture of vegetation to be present in a basin. This feature of wetlands is probably the cause of mapping error between two related classes -- for example, forty-four percent of the graminoid fens omitted by the wetland map were classified as low shrub fen, the class that graminoid fen tends to move towards. If changing environmental conditions cause graminoid vegetation to be replaced by low shrubs, the shrub growth can be patchy within the wetland, thus more or less equal areas of graminoids and low shrubs may occur within a pixel measurement. The effect of this environmental gradient also affects commission error, for example 49 percent of wetlands incorrectly called graminoid fen actually were low shrub fens. The reverse of these errors can be seen in the accuracy results of low shrub fen. Forty-seven percent of the low shrub fen area omitted was called graminoid fen. Thirty-seven percent of the wetland area incorrectly called low shrub fen was graminoid fen. Other development based inaccuracies occur between deep and shallow marsh, graminoid fen and meadow marsh, and the treed fens.

Error also occurs between groups which share neither ecological nor physiognomic characteristics. For example, the spectral profile of shorelines (Figure 4) is quite similar to that of conifer swamp (Figure 6). These two groups, for different reasons, share spectral reflectance characteristics. Both tend to absorb more energy than other wetlands creating low, flat spectral profiles that result in small areas of conifer swamp being assigned to shoreline classes. For the map user, these errors are quite easily detected and adjustments can be made.

While the accuracy in CIR air photo interpretation is superior to satellite-based information in terms of its accuracy, this difference is balanced in the context of database creation. As GIS offers new opportunities to interrogate wetland habitat information with other thematic layers, the effort required to place this information into a database is an important issue (Jensen *et al.* 1991). Satellite-based wetland mapping provides output in a digital format which can be more easily incorporated into comparable databases for large geographic areas. Also, as area of application increases so does the effort required to transfer information interpreted from aerial photography to a digital database.

RECOMMENDATIONS FOR FURTHER RESEARCH AND OPERATIONAL APPLICATIONS

This work has provided an example of how wetland inventory can be evaluated at multiple scales of resolution. In the process of developing, applying and evaluating techniques for wetland mapping recommendations for possible future research and/or operational applications were generated.

The ability to successfully map wetlands in a landscape context is directly related to being able to separate them from the rest of the landscape. From an operational standpoint integrating FRI and satellite data should be feasible and would be an interesting application on a regional level. However, because wetlands occur as discrete interruptions in a landscape it may be possible to analyze the texture of remotely sensed data to aid in locating the boundaries.

Riparian zones are interfaces between terrestrial and non-terrestrial landcovers. These areas are extremely important from a wildlife management viewpoint. Because they are very narrow in shape, they are difficult to detect using remote sensing alone. Future research is required to model the interface between wetlands and forest and attempt to predict the type of riparian community.

The satellite-based wetland map was developed in a raster-based format which may be beneficial for some types of GIS modelling, but is impractical for landscape inventory because of the storage space the data requires. More commonly a GIS used for inventory purposes operates on a vector structure. Theoretically, the raster map should be able to be translated into vectors and table files -- again an interesting operational application.

As timber management moves to incorporate the concepts of landscape management, the forest will be recognized as an ecosystem made up of a mosaic of landcover types. The wetland inventory techniques developed here offer "ecosystem managers" a set of practical tools to effectively protect the sustainability of wetlands in the development of the new generation forest timber management planning.

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APPENDICES

APPENDIX 1 - REMOTE SENSING BASICS

SPECTRAL REFLECTANCE OF FEATURES

Remotely sensed data can be translated into meaningful information about landcover features only by knowing how different features reflect and absorb energy. The amount of energy reflected at a particular wavelength varies according to the physical characteristics of landcover features. Interpretation of spectral data requires knowledge of how different features at reflect at different wavelengths. Individual features such as soil, vegetation, water and their interaction is important for interpreting any type landcover. One way to characterize spectral reflection along the energy spectrum is to plot a spectral curve or profile (Figure A-1).

Soil

Factors that influence amount of energy reflected by soil include moisture content, texture, surface roughness, mineral content, and organic matter content (Lillesand and Kiefer 1987). Well drained, course textured soils reflect more energy than poorly drained soils. Surface roughness and organic matter reduce reflectance by absorbing greater amounts of energy.

Vegetation

Reflection and absorption the visible portion of the electromagnetic spectrum is affected by chlorophylls, carotenes, and xanthopylls (Puritch 1981). In the spectral profile of healthy vegetation, the main absorption occurs in the red and blue bands and reflection in the green band. The colour of leaves becomes off-green as chlorophyll degenerates created by an increase in red reflectance (Rock *et al.* 1986). Although the green reflectance remains unchanged, fluctuations in vegetation condition can be monitored through the red band.

Water is the main factor influencing reflection and absorption in the near infrared portion of the spectrum. Reflection in the near-infrared region is characteristically high and controlled by refractive index discontinuities within the leaf (Knipling 1970). The more hydrated the leaf the greater the refraction of incoming radiation. Increased refraction means decreased reflection. Increased reflection in the near infrared indicates water-stressed plats because of the increased number of air-cell interfaces in dehydrated leaves.

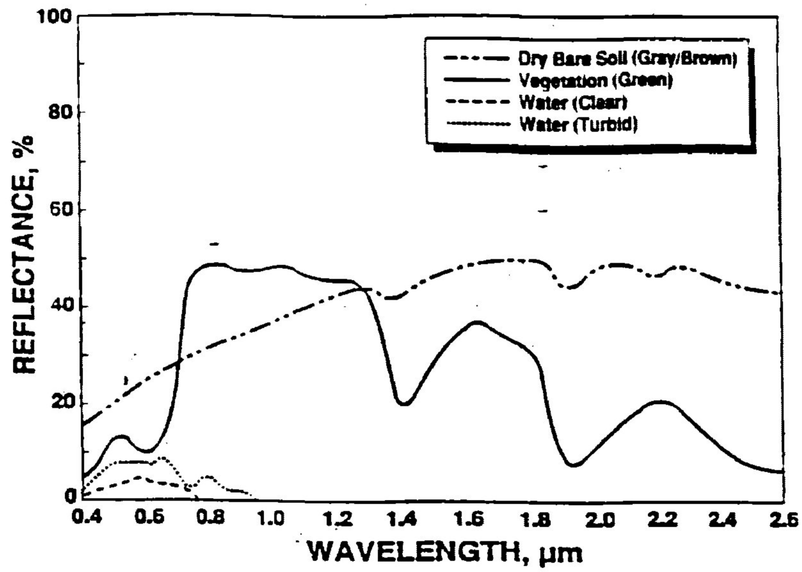

Figure A-1. Spectral profiles of bare soil, green vegetation, and clear and turbid water (from Lillesand and Kiefer 1987).

<u>Water</u>

The most distinctive feature about water is the complete absorption of near and middle infrared energy (Lillesand and Kiefer 1987). However, different conditions of water bodies can alter this characteristic in the visible and infrared spectrum. Aquatic vegetation, shoreline, and suspended solids all increase the amount of visible energy reflected. Also, the presence of ice on lakes increases the amount of infrared energy reflected or emitted.

COLOUR INFRARED AERIAL PHOTOGRAPHY

Aerial photography can be used to map almost any landcover feature. It provides flexibility in acquisition time, scale, and film used. Colour infrared (CIR) photography has a distinct advantage over panchromatic film for mapping vegetation features because of its ability to record the photographic portion of the near infrared spectrum. In this portion (0.7 to 0.9 µm), great differences in foliage conditions and varieties are expressed that are not seen in the visible spectrum. Other benefits to CIR include penetration of haze by excluding the blue portion of the spectrum and rendition of colour not found in black and white panchromatic film.

Landcover features can be described in terms of hue, chroma, texture, and pattern (Avery and Berlin 1985). Hue describes the colour of an object. For infrared film the reproduced colours are different from true colour: true green reflectance reproduces as blue, true red as green and true infrared as red. Chroma describes the strength of the colour and can be used to interpret the strength of reflection. Texture is used to express the frequency of change and arrangement of these colours using terms such as fine, medium, coarse and mottled. Pattern is the spatial arrangement of objects in relation to those around them. Using photo stereo pairs provides relief contrast as an additional aid in interpreting photography.

LANDSAT THEMATIC MAPPER

LANDSAT Thematic Mapper (TM) is a multi-spectral scanner capable of detecting radiation reflected from the surface of the earth. This radiation is focused by a mirror and lens onto detectors and the intensity of the detected radiation quantified and recorded digitally as numeric values. LANDSAT TM is an optical-mechanical scanner which forms an image by sweeping the footprint or field of view of the scanner across the surface of the earth and recording the reflectance intensity for each thirty metre ground resolution cell. LANDSAT has a repetitive, sun-synchronous orbit that passes over the same area every sixteen days. The sixteen-day orbital cycle divides the world into 233 paths running pole to pole providing global coverage where ground receiver stations exist.

LANDSAT TM is capable of recording reflected energy in 7 discrete bands of the electromagnetic spectrum (Table 2). Bands one, two and three record the blue (0.45 - 0.52 μm), green (0.52-0.60 μm), and red (0.63 - 0.69 μm) portions of the visible spectrum, four (0.76 - 0.90 μm) and five (1.55 - 1.75 μm) the near and middle infrared, band six (10.40 -12.50 μm) emitted energy and band seven (20.80 - 23.50 μm) thermal infrared energy. Different LANDSAT bands are suited to detecting features based on energy reflected by landcover. The ground resolution of LANDSAT TM is 30m in all bands except six which has 120 metre resolution.

Table 2. Description of feature characterization properties of LANDSAT TM bands (from Energy, Mines and Resources Canada 1986).

SPECTRAL BAND	DESCRIPTION OF FEATURE CHARACTERIZATION
Band 1	(0.45-0.52μm) BLUE - Maximum penetration of water, useful for bathometric mapping in shoreline. Used for distinguishing soil from vegetation and deciduous from coniferous plants.
Band 2	(0.52-0.60μm) GREEN - Matches green reflectance peak of vegetation, which is useful for assessing plant vigour.
Band 3	(0.63-0.69μm) RED - Matches a chlorophyll absorption band that is important for discriminating vegetation types.
Band 4	(0.76-0.90μm) NEAR INFRARED - Useful for determining biomass content and for mapping shorelines, crop identification emphasis soil-crop and land-water contrast.
Band 5	(1.55-1.75μm) MIDDLE INFRARED - Indicates moisture content of soil and vegetation. Penetrates thin clouds. Good contrast between vegetation types.
Band 6	(10.4-12.5μm) THERMAL INFRARED - Nighttime images are useful for thermal mapping and for estimating soil moisture.
Band 7	(2.08-2.35μm) SHORTWAVE INFRARED - Coincides with an absorption band caused by hydroxyl ions in minerals. Ratios of bands 5 and 7 are potentially useful for mapping hydrothermally altered rocks associated with mineral deposits.

LANDSAT MSS

LANDSAT MSS is a multispectral scanner capable of recording four spectral bands and viewing an 185 km wide swath with a resolution cell size of 79 by 79 metres on the ground (Iverson *et al.* 1989). It records four bands of information in the following portions of the energy spectrum:

0.5-0.6μm (band 1), 0.6-0.7μm (band 2), 0.7-0.8μm (band3) and 0.8-1.1μm (band4).

SPOT

The SPOT (Système probatoire d'observation de la terre) carries the Haute resolution visible pushbroom type scanner. It has two identical sensors that can record three bands of information in the visible spectrum at 20 metre resolution or in a single panchromatic band at 10 metre ground resolution (Iverson *et al.* 1989). The sensors can be directed up to 27 degrees to the side to allow acquisition of stereo imagery on two successive passes of the satellite. It passes over Canada, on average, every 2 days allowing for frequent acquisition.

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APPENDIX II - SAMPLE WETLAND DATA SHEET

WETLAND DATA SHEET

DATE: May 14

APPROXIMATE UTM LOCATION: 487672 E, 5428995 N

AERIAL PHOTO NUMBER: 4901 10-71

GENERAL LOCATION DESCRIPTION: just west of end of Capital Road

GPS FILE NAME(S): M0514113B

① [illegible] N5428[illegible] E 48[illegible]73 41[illegible]m

WETLAND DESCRIPTION

SIZE : 1 ha

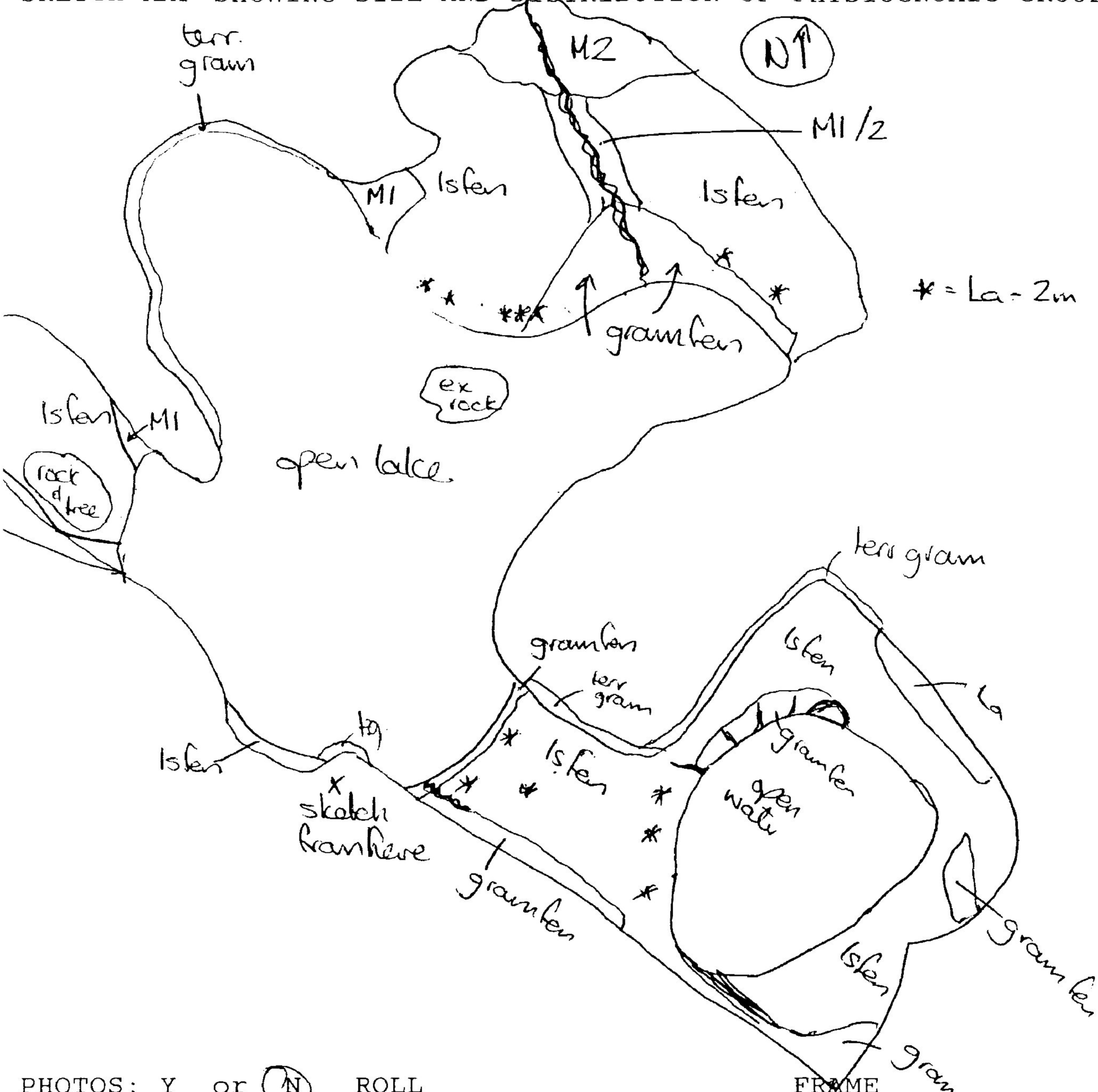
DESCRIPTION OF SURROUNDING AREA: ~~[illegible]~~ old cut-over

PHYSIOGNOMIC GROUP(S), DOMINANT SPECIES, WITH PERCENT COVER:

Sphagnum 100%
scirpus 50%
Sb <1m tall shrub many
Pj (trace) 2m tall
e.s. 50% lab tea vac
shrubby moss
alder trace

lowshrub/gram bog

SKETCH MAP SHOWING SIZE AND DISTRIBUTION OF PHYSIOGNOMIC GROUPS



PHOTOS: Y or (N) ROLL ____________ FRAME ____________

ADDITIONAL COMMENTS: strip of terr gramminoids around portion of perimeter