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Integration of New Technologies for Deer Yard Assessment

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ABSTRACT

The purpose of this project was to bring together several new technologies designed to improve the information needed to implement a decision support system (DSS) for deer yards. The DSS will be used to: (1) predict the consequences of timber management activities on the supply of deer habitat and the subsequent population responses, and (2) identify the most profitable locations for yard management activities such as browse plot creation and emergency feeding. This study focused on the combined role that satellite remote sensing technologies, large scale sampling photos, and geographic information systems (GIS) can play in supplying needed deer yard habitat information.

The several data sources were brought together on a GIS platform according to an optimized design. Several habitat supply models were developed and tested in a cost/accuracy effectiveness analysis framework. Two existing models were also tested in the same framework and compared with the new models. The resulting models located and quantified suitable conifer cover for browsing and thermal protection in winter. The models were applied to the 500-km Loring Deer Yard located 50 km southwest of North Bay, Ontario. Three levels of cover and accessible area were mapped and summarized for three coniferous species groups considered to be of optimal, suitable, or marginal deer yard habitat potential.

RÉSUMÉ

Ce projet avait pour objectif de combiner plusieurs techniques nouvelles afin d'améliorer l'information nécessaire pour appliquer un système d'aide à la décision (SAD) à la gestion des ravages de cerfs. Le SAD doit servir: (1) à prévoir les répercussions des activités d'aménagement forestier sur les ressources en habitat des cerfs et, subséquemment, leurs populations; (2) à reconnaître les lieux les plus propices pour certaines activités de gestion des ravages, comme la création d'espaces de broutage et le nourrissage d'urgence. Cette étude a été axée sur le rôle que peuvent jouer les techniques de télédétection satellitaire, les photographies d'échantillonnage à grande échelle et les systèmes d'information géographique (SIG) dans l'obtention des données requises sur l'habitat des cerfs.

Les données de plusieurs sources ont été intégrées dans un environnement de SIG suivant un plan optimisé. Plusieurs modèles pour les ressources en habitat ont été construits et testés dans un cadre d'analyse de l'efficacité tenant compte du rapport coût/exactitude. Deux modèles existants ont également été testés dans les mêmes conditions et comparés aux nouveaux modèles. Les modèles mis au point permettent de localiser et de quantifier la végétation de conifère pouvant procurer aux cerfs nourriture et protection contre le froid en hiver. Ils ont été appliqués au ravage de Loring, d'une superficie de 500km^2, situé à 50km au sud-ouest de North Bay (Ontario).

Trois niveaux de végétation et de terrain accessible ont été cartographiés et résumés pour trois groupes de conifères considérés comme offrant aux cerfs un habitat potentiel optimal, suffisant ou marginal.

TABLE OF CONTENTS

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TABLE OF CONTENTS (concl.)

INTEGRATION OF NEW TECHNOLOGIES FOR DEER YARD ASSESSMENT

INTRODUCTION

The joint, long-term management of a deer yard in conjunction with timber production poses many of the problems common to developing and implementing a general, integrated management strategy. The planning procedure requires models to evaluate long term timber capacity, deer habitat suitability and supply, and a process to balance and reconcile conflicts that arise when multiple demands are placed on a shared resource base. The models must be able to predict the effects of proposed timber and deer yard management practices on long-term supply and sustainability. Considerable information is needed to drive the planning models. This project focuses on the collection of such information—characterization of suitable deer yard habitat and food supply needed to sustain a healthy deer population—within the context of timber management and other developmental activities.

New technologies, such as satellite image data processing, the use of low-altitude sampling aerial photos, geographic information systems and associated database systems, and supply projection models, are rapidly evolving and converging to process information in support of the planning process. The data gathering systems attempt to take advantage of the synergistic relationship known to exist in combining satellite image data, map data, aerial photos, and field data. Careful design and optimization can yield better information, greater reliability, and lower costs.

The deer yard habitat assessment process offers an excellent opportunity to investigate the advantages of these advances for several reasons: namely, (1) quantitative information is clearly needed for assessment, monitoring, modeling, and resource management planning purposes, (2) currently available information is lacking or unsatisfactory, (3) new methods have been found to provide better information, and (4) optimized, multistage designs may reduce the cost or increase the reliability of supplied information.

More specifically, the objective of the project was to bring together several new technologies to improve the information needed to implement a decision support system (DSS) for deer yards that integrates dynamic habitat supply and population simulation models. The DSS will be used to: (1) predict the consequences of timber management activities on the supply of deer habitat and the subsequent population responses, and (2) identify the most profitable locations for yard management activities such as browse plot creation and emergency feeding. The key habitat requirements of deer have been established as thermal cover in winter and access to browse. Coniferous forest cover, especially by that of some preferred species, and nearby openings for browsing are used to express the habitat needs (Voigt 1992).

This study focused on the combined role that satellite remote sensing technologies, large-scale sampling photos (LSP), geographic information systems, linked databases, and global positioning systems (GPS) can play in supplying deer yard habitat information.

THE DEER YARD MANAGEMENT PROBLEM

The white-tailed deer (*Odocoileus virginianus*) is a featured species by policy throughout Ontario (Bellhouse 1993). The Ontario Ministry of Natural Resources (OMNR) has recently developed a population simulation model (Broadfoot and Voigt 1992) that is used by biologists to define harvest levels to meet public demand and maintain deer at densities consistent with the carrying capacity of the habitat (i.e., the number of deer a habitat can support on a sustained basis). Winter carrying capacity, a critical driver of the population simulation, is currently assessed by measuring browse supply in the field. This process is expensive and provides only a snapshot of browse supply at a specific time. Models that provide inexpensive estimates of browse supply across a yard, and which can be projected through time and account for changes in habitat conditions related to forest succession and human activities (e.g., timber harvest), are needed. One such model, developed and described by Broadfoot et al. (1994), estimates browse supply using the OMNR's Forest Resource Inventory (FRI) attribute data and associated biomass estimates.

Carrying capacity is a function of the biomass of browse per hectare and its related accessibility to deer. Accessibility is primarily governed by snow sinking depth. The amount and dispersion of conifer cover provides thermal protection and intercepts snow, which, in turn, facilitates access to browse along the borders of stands and escape from predators. Users currently depend on FRI maps for their deer yard habitat data. The information, however, has been found unsatisfactory in several important respects: (1) the methodology was not designed for stand-level assessment and thus may be inaccurate for this purpose, (2) the FRI does not characterize the quantity of conifer cover in the understorey, (3) the FRI provides no direct measure of browse data or the dispersion or spatial distribution of conifer cover within the stand, and (4) the FRI data can be 10 to 15 years out-of-date.

The model mentioned above and described by Broadfoot et al. (1994) is currently used to estimate carrying capacity, but, because of its reliance on the FRI, has some shortcomings. First, the model is nonspatial, which means the user must rely on FRI stand-level averages; a breakdown of conifer clusters or spaces within the FRI polygon is lacking. In order to apply the model, the user is forced to make some general assumptions about browse accessibility based on percent conifer cover, and about the distribution of the conifer cover in the stand. The current model has assumed uniform, random, and clustered distributions that yield widely divergent results. Second, the conifer species and their proportions may be inaccurate or missing. This makes it difficult to evaluate the quality of the cover and the amount of browse.

A project, completed in 1991 for the Central Region Science and Technology by Dendron Resource Surveys Inc., evaluated the role of large scale aerial photos, photo interpretation of conifer cover, and mapping in a GIS environment to produce information on deer yard conifer cover, browse, and accessible areas (Dendron Resource Surveys Inc. 1991). The methodology provided excellent deer yard information, particularly through its ability to detect conifer cover beneath the main canopy and to characterize the spatial distribution of the cover within the stand (Fig. 1). However, in the limited test, the method was found to be expensive. The cost advantages of larger projects and the use of a sampling approach that focuses on the most promising stands were not explored in the 1991 investigation. The least expensive current alternative would be to reinterpret existing FRI photos according to species composition and crown cover density criteria most relevant to deer yards. Alternatively, existing data in the FRI database may be used to estimate crown cover density, as was recently investigated in a related project (Dendron Resource Surveys Inc. 1995). Although an improvement over existing FRI data, the approach will still not provide all the information required, especially in relation to the spatial distribution of conifer cover and understorey vegetation. Satellite data, shown to be effective in detecting conifer cover, may provide both the needed update and some spatial distribution data.

General coverage photo interpretation and satellite data options alone are not viable because of data limitations. Similarly, the large scale photo option, if applied to large areas, may not be feasible because of its high cost. However, an optimized, multistage sampling design that used combined coverage by existing FRI data and updates from Landsat TM or SPOT, and targeted the most promising portions of deer yards for large-scale photo sampling, can be expected to supply the required data and to relieve cost problems currently associated with the large-scale photos. Field subsampling, using aids such as GPS, can be used to check the LSP work and to supplement data on browse supply and carrying capacity.

APPROACH

The following discussion outlines the methodology used in the project. The study area, detailed procedures used, and results are described under subsequent headings.

The data collection and analysis work was organized around two main stages: namely, (1) the mapping of conifer cover, including the species composition and the area of the yard accessible by deer, and (2) the quantification of browse supply. The accessible area is defined by the conifer cover and a surrounding border or buffer for browsing. The two stages are later combined to provide an overall picture of browse supply.

Mapping Conifer Cover

A GIS loaded with existing FRI map data provided a polygon (stand) framework for data—spectral image data classification supported by aerial photo and field data were the primary inputs; the GIS and associated databases provided the platform for merging the data and subsequent analysis. By using terrain corrected and geographically referenced satellite information, the FRI data and image data were merged. Both sources, supporting one another, and local knowledge of the deer yard were used to identify areas of promising deer habitat and to set priorities for more concentrated sampling.

Selected sites were photographed with LSP at a scale of 1:5 000. The temporary lack of digital FRI coverage for part of the area skewed the selection process to some extent. The LSP samples were used to interpret and quantify features or indices related to such characteristics as winter cover, accessible area, and potential food supply. Analyzed stand information from the sampling photos was then used: (1) to calibrate data derived from FRI and to "train" and "test" the satellite image data classifiers according to deer cover criteria, and (2) to quantify key deer yard characteristics. Available field data not collected specifically for this project were used to provide more detailed information on the quality and quantity of cover and food supply. GPS positioning data were used to link the field observations into the geographic base.

Quantifying Browse Supply

For important FRI working groups and site classes, models have been developed that relate stand age and overstory density to the biomass of browse per hectare (Broadfoot et al. 1994). These models were developed

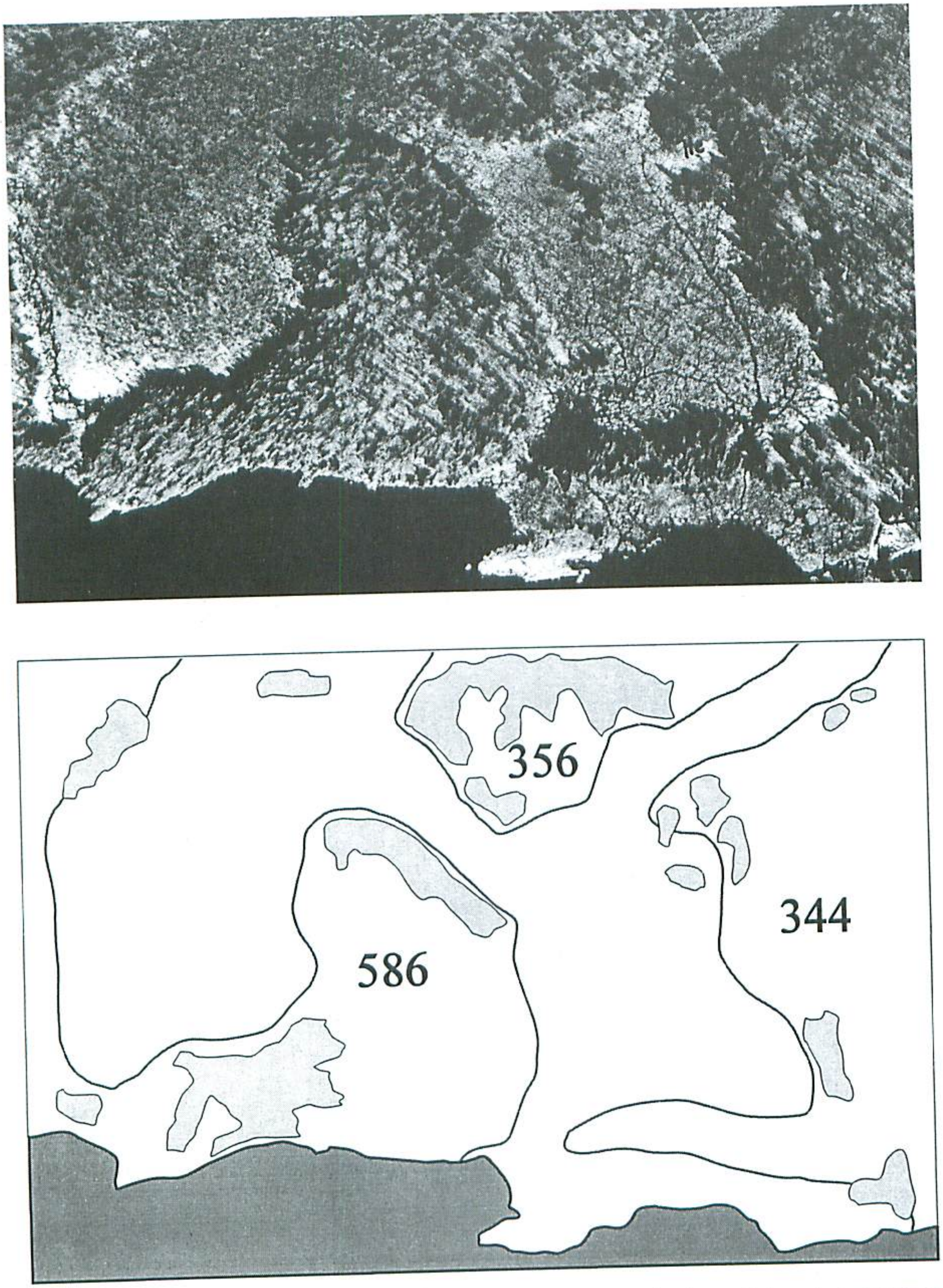

Figure 1. Enlarged portion of an FRI stand map showing the location of conifer clusters (below, shaded) mapped from interpreted 1:5 000 aerial photos (above).

from browse survey databases that currently exist in the region, and supplemented with available field data (not collected specifically for this study) using standard browse survey procedures developed by the OMNR. The GIS provided the platform for analysis, mapping, and linkage of supply information to supply analysis and simulation models.

METHODOLOGY

The methodology and procedures were developed and tested within the above framework. The procedures are outlined as follows:

Definition of Key Conifer Cover Characteristics

The relative value of conifer cover is a function of species composition of tree cluster polygons. The predominance of certain species or species combinations is important in that they provide different degrees of thermal protection. Table 1 indicates the relative importance of the cover and degree of snow interception. A predominant species or species group is one where the crown cover of the species or group exceeds that of any other conifer species in the cluster. To provide adequate cover, a cluster of conifer crowns was required to be at least 50 m^2 in area.

Table 1. Conifer species cover priorities.

Species or species groups	Priority
Hemlock or cedar	Optimal cover
White spruce, balsam fir, or white pine	Suitable cover
Red pine, jack pine, or black spruce	Marginal cover

Combined with the thermal cover, suitable deer habitat should also have openings. According to Voigt (1992) and Broadfoot et al. (1994), sites accessible to deer should be represented by the area of the conifer cover plus a 30-m buffer around the cluster. Biologists refer to the conifer cover as the **effective area**, the buffer as the **browse area,** and the combination as the **accessible area**. The remainder is called the **inaccessible area**. These are illustrated in Figure 2.

Study Area

The study area chosen for this project surrounds the Loring Deer Yard. The area in Figure 3 is 700 km^2 in size and located approximately 50 km southwest of North Bay, Ontario. The deer yard itself is 525 km^2 (Broadfoot et al. 1994). The area was excellent for the study because of its stature as a managed deer yard, its large size, and the wide range of forest cover conditions represented. Since timber management is also taking place on the deer yard, it offers a good proving ground for integrated resource management for wildlife and timber production. The study should contribute information needed for other deer habitat management studies, particularly those developing habitat supply models and/or assessing carrying capacity.

Multistage Design

The following data sources were drawn on for this project:

- Ontario base maps of the target area at a scale of 1:20 000;
- FRI digital maps of stand polygons and the associated polygon attribute database;
- Landsat Thematic Mapper (TM) satellite coverage of the area;
- SPOT multispectral coverage of part of the area;
- large scale (1:5 000) photo samples;
- field survey data; and
- data on browse supply relationships (Broadfoot et al. 1994).

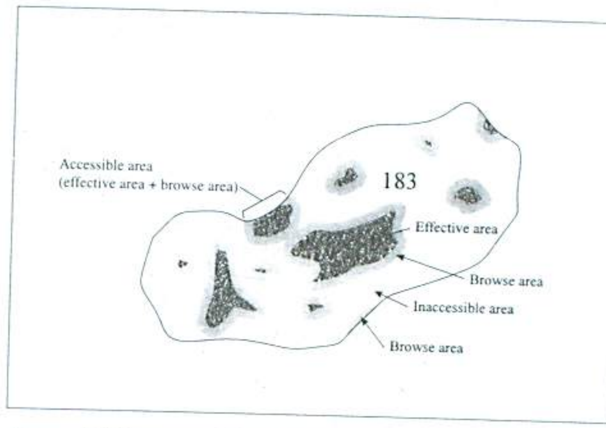

Figure 2. Diagram of FRI Polygon 183 showing the effective, browse, accessible, and inaccessible areas.

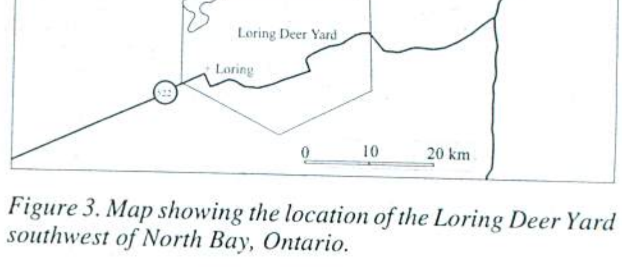

Figure 3. Map showing the location of the Loring Deer Yard southwest of North Bay, Ontario.

A multistage design for the collection of resource information is one that takes advantage of existing data, sources of general information (such as provided by satellite image data or small scale, general coverage aerial photos), and detailed data sampled at specific sites (such as by large-scale sampling photos or field survey). The design attempts to combine the relatively inexpensive generic information with specific and expensive sampled data. A good design takes advantage of the strong points of both sources in some form of optimized structure. The generic information is normally used to focus the sampling on the most important conditions and thereby limit or avoid unnecessary coverage of the least important features. More formal optimization is usually based on meeting given information requirements and reliability levels for the least cost.

An important component of the design in this project was to have a common platform for combining, processing, analyzing, and producing the required information. A GIS and linked database served this role. The foundation was the Ontario base maps in digital format at a scale of 1:20 000. The FRI forest stand polygons were registered to this base, as were the Landsat TM and SPOT image data sets, maps of conifer clusters produced from the LSP, and some field data tied in by GPS coordinates.

The design employed the following steps in approximately chronological order:

1. Obtain OBM and FRI digital map coverage of the target area.
2. Obtain LSP coverage of stands selected to focus on sites with significant cover and browse potential. The specifications and procedures for acquiring and using the LSP are described later.
3. Order cloud-free Landsat TM scenes of the target area and SPOT coverage of a portion of the area. Recent, suitable TM coverage was available; SPOT data was not available but a "programming" request was issued to obtain the coverage in early 1995. The satellite data specifications and the training and testing of the image data classifier are described in a later section.
4. Use the satellite data to update the FRI maps to account for any changes since the FRI photo interpretation and to provide supplementary information on the dispersion of conifer cover within the FRI polygon.
5. Use the LSP data to provide detailed information on effective cover, browse areas, and accessible areas summarized for FRI polygons where LSP coverage allows.
6. Enter the field to check the accuracy of the LSP photo interpretation.
7. Use the LSP data to test the accuracy of the FRI derived species groups, to train and test the satellite image data classifier, and to develop predictive models for estimating accessible area from FRI attribute data and the satellite image data classifier.
8. Use the accessible area prediction model to map and make estimates of suitable habitat and browse quantities.

Forest Resource Inventory Data

The Loring Deer Yard was rephotographed in 1992 at a scale of 1:20 000 by the OMNR's Forest Resource Inventory (FRI). The photo interpretation to FRI standards had been completed in time for this project, but stand mapping in digital format was available for just four of the ten map sheets. Accordingly, the LSP coverage and the training and testing of the Landsat TM and SPOT classifiers had to be confined to the available maps, thus limiting the scope to some extent. However, the remaining six maps were delivered near the end of this project in time for the final extrapolation of results.

The FRI stand polygons were mapped digitally on the OBM base. The linked database, which describes the polygons, included the FRI working group, species composition, age, average stand height, stocking, and site class.

Large-Scale Photo Sampling

Objective

The primary role of the large-scale photos was to provide more precise information on the species composition, size of trees, understory, and spatial distribution of the conifer cover within FRI polygons. The delineation of the clusters, together with their species composition and size, was used to map and characterize the effective area. A buffer, bordering the effective cover, was used to determine browse and accessible areas. The amount and dispersion of conifer cover, key features of deer habitat, were not well expressed in the FRI database.

Procedure

The multistage design described earlier was used as the general framework for the following tasks:

1. *Stand selection*: Ideally, the FRI map data, field data, and local knowledge of the deer yard would be used to target the FRI stands having the greatest deer habitat suitability potential. Normally, stands with the greatest potential would be candidates for LSP sampling and stands with low potential would be sampled lightly or avoided. This concentrates the

relatively costly LSP effort where it is most needed. Unfortunately, in this project, a FRI map production problem precluded the targeted selection of candidate stands. Instead, the problem constrained the LSP coverage to the two shaded areas in Figure 4. These were completely covered by 1:5 000 LSP to include as wide a set of stand conditions as possible.

2. *Photo acquisition*: The LSP were acquired on subcontract according to the photo specifications in Table 2.

The two shaded blocks in Figure 4, about 210 km^2, were successfully photographed on 3 and 4 May 1994. A total of 870 photos covered the two blocks.

3. *Base map preparation*: Base maps at a scale of 1:5 000 were prepared of the project area. These used available enlarged Ontario base map coverage at 1:20 000. The base maps were needed to tie the tree cluster polygons delineated on the 1:5 000 photos to the FRI digital maps and satellite data.

4. *Photo interpretation*: The conifer tree clusters were interpreted, delineated, and coded on the 1:5 000 photos according to the classification criteria in Table 3. For all conifer species except hemlock (*Tsuga canadensis* [L.] Carr.), the cluster height must be taller than 10 m to be considered effective cover. Hemlocks between 5 m and 10 m are also considered effective cover and thus appear as an additional category in Table 3.

The proportion of each species in the cluster was coded to the nearest 10 percent based on crown cover density expressed as a single digit accompanying each species code. Thus a cluster may be described as He5 he1 Sw4, the proportions adding up to 10. If only one species was present, the proportion was deleted.

5. *Field check*: The 1:5 000 photo interpretation work was checked in the field to assess the accuracy of the classification. Browse conditions and quantities, deer

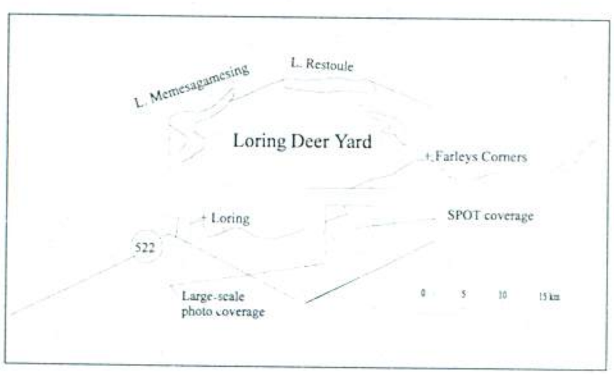

Figure 4. Map of the Loring Deer Yard showing where the Landsat TM and SPOT classifier were trained and tested.

occurrence, and carrying capacity data were available from related studies but were not collected specifically for this project.

6. *Map preparation*: The delineations and codes were transferred to the base maps using geographic features common to both the photos and map. Where such features were lacking, some additional control points were added. The polygons were digitized in a GIS at a scale of 1:5 000 and the codes were entered into an associated database. An algorithm added buffers to the tree cluster polygons. The mapped clusters were then merged to the FRI polygons for analysis purposes, and to provide the training and test data for the satellite image data processing task and accessible area estimation model.

Test results

Figure 2 illustrates how the conifer cluster delineations on the 1:5 000 photos were used to classify the effective area and the browse area generated from the addition of the 30-m buffer. It also shows the resulting accessible and inaccessible areas.

Figure 2 further illustrates how the tree clusters are linked to an FRI polygon and used to summarize its cover categories. As shown, the linkage includes the extension of clusters from adjacent FRI polygons, either a portion of effective area or browse area. The analysis summarized all FRI polygons in the project area that were covered by the 1:5 000 photos.

Table 2. Photo specifications.

Camera format:	Cartographic camera: 230 mm by 230 mm format
Photo scale:	Nominal 1:5 000
Lens focal length:	Nominal 150 mm
Film type:	Black and white panchromatic
Overlap (forward):	60 percent to 65 percent
Minimum sidelap:	20 percent
Season:	April 15 to May 10, preemergent hardwood flush and with little or no snow on the ground

Table 3. Tree cluster classification criteria.

Cluster description	Code
Hemlock clusters 5 m to 10 m height	he
Hemlock clusters >10 m	He
Other conifers >10 m	Standard FRI species codes

The tree clusters produced from the 1:5 000 photos were thoroughly checked in the field. The location of the main story tree clusters and their species coding were found to be virtually without error. However, although the incidence of conifer under cover was low, where it did occur the interpreter had difficulty recognizing it under stands with a conifer overstory. The deciduous stands did not pose such a problem.

The cost of using the 1:5 000 photos to produce the tree cluster information (effective area, browse area, and accessible area), including the cost of obtaining new photo coverage, photo interpretation, mapping, and GIS analysis to generate the deer cover information, is summarized in Table 4. The total area covered by the photos was approximately 210 km^2. Because of the much larger area involved than in previous trials, and the attendant economies of scale, the per hectare cost was nearly one-tenth that reported on the initial development work on the methodology (Dendron Resource Surveys Inc. 1991).

Satellite Image Data Classification

Objective

For the purposes of deer yard habitat assessment, satellite data may contribute in two primary ways: namely, (1) the detection and mapping of conifer cover, and (2) the classification of the conifer cover by species or species groups. Satellite data offer the advantage of timeliness—the ability to account for changes in the cover since the FRI data were acquired—and the important potential, in the present context, to map the distribution of conifer cover **within** the FRI stand polygon. The latter offers the chance of not only determining effective area but also, once registered to the cartographic base, the application of buffers to the margins of the polygons to quantify browse and accessible area—the latter being the chief attribute of interest.

Table 4. Summary of costs required to acquire, interpret, and map the conifer clusters from the 1:5 000 photos.

Task	Total cost ($)	Cost/hectare ($)
Photo acquisition	13,000	0.62
Base mapping	1,856	0.09
Photo interpretation	10,827	0.51
Photo-to-map transfer	7,976	0.38
Coding/checking	6,692	0.32
Digitizing	12,431	0.59
Database entry	7,925	0.38
Cover and browse area analysis	581	0.03
Map production	963	0.04
Total	62,251	2.96

The use of satellite data to classify conifer cover has been investigated in similar applications (Lillesand and Kiefer 1979, Richards 1986). These studies suggest generally that the separation of the conifer cover from other signatures is feasible. However, the discrimination of conifer species differences has proven more elusive, especially where species mixtures are common.

The goal of this satellite data study was to establish how well the two objectives can be met for deer habitat assessment purposes.

Procedure

1. *Acquisition of satellite image data*: Landsat 5 Thematic Mapper data were obtained for two dates: 14 February 1993 and 28 August 1993. In both cases, cloud-free, precision-corrected, three-band subscenes were ordered. Each subscene covered most of the deer yard. A SPOT panchromatic and multispectral mini-scene (6.5 km by 6.5 km), map oriented and precision corrected, was obtained for a central portion of the deer yard (Fig. 4) on 25 March 1995.
2. *Registration to map base*: These scenes were loaded onto a PCI Enterprises Inc. image data classification system and registered to the digital cartographic base. The registration error was not expected to exceed two pixels (each pixel measured 30 m by 30 m in the case of TM, 20 m by 20 m in the case of SPOT multispectral data, and 10 m by 10 m for the SPOT panchromatic channel).
3. *Satellite image data classifier*: Large-scale photos (LSP), described in the preceding section, provided the conifer cover data needed to train and test the image data classifier. The cluster maps were imported into the OBM base to which the satellite data was registered. Thus, the LSP cluster data were directly connected to the satellite pixel data for training and testing purposes.
4. *Training and testing*: The image data classifier was "trained" to detect and separate conifer cover from hardwood forest cover and other background features (clearings, water, other vegetation, cutover, burns, roads, etc.). The training established the link between the multispectral and multidate TM or SPOT signatures and conifer cover. The classifier was also trained to detect conifer species. The 1:5 000 photo-interpreted and mapped tree clusters provided the basic data for this. One-half of the data set was used for training and one-half was reserved for testing the finished classifier. The training and test clusters were separated at random. Because the registration

of the image data to the base could have an error of a pixel or two, only conifer signatures (groups of conifer pixels) larger than 1 ha where selected. This provided more leeway to eliminate borderline pixels.

The image data classification training and test procedures are described in detail in Appendix A. The steps are summarized as follows:

- Check the registration of the pixel data to the cartographic base. Cartographic features such as lakes, rivers, and roads were used to assess the registration.
- Using the training data set, train the classifier (maximum likelihood classifier—Appendix B) to separate conifer cover from the deciduous cover and other features.
- Using the same classifier algorithm, train the classifier to discriminate conifer categories, starting with individual species and proceeding to the three categories in Table 1.
- Finally, subject the trained classifier to a trial against the test data set aside to evaluate the conifer cover detection and the ability to discriminate the conifer species and species groups.

5. *Classifier assessment*: A simple method for assessing the effectiveness of an image data classifier involved the use of a correlation matrix. The matrix arranged the interpreted classes as column headings and actual classes, as obtained from the LSP as row headings. The pixel classifications were sorted by what the classifier and test data indicated and placed in corresponding cells opposite the matching headings. The matrix was used to evaluate the overall accuracy of the classifier, and to indicate among which classes the errors or confusion were occurring. This test framework allowed both the conifer cover detection and species discrimination objectives to be evaluated.

Test results

The Landsat Thematic Mapper (TM) scenes covered most of the deer yard; the SPOT data covered only a 6.5-km by 6.5-km block as shown in Figure 4. The results of the TM test on the full LSP data set, represented by the shaded area in Figure 4, are presented first, followed by a comparison of the TM and SPOT classifiers on the 6.5-km block. The best TM multispectral/multidate classifier found in the first test was used in the comparison.

All classifications were performed with the Maximum Likelihood Classifier (Appendix B), the recommended classifier for forest stand classification. The February and August 1993 TM images were tested separately and in combination. The accuracy performance of the classifier was assessed in terms of the percentage of pixels classified as conifer compared to that indicated by the test data. These originated from the interpreted and mapped 1:5 000 photos.

A preliminary assessment can be made from the data used to "train" the classifier—what is most often reported in classifier investigations. However, a much more realistic accuracy assessment can be made from the independent test data set. Both results are presented in this report.

TM conifer cover classification

A fundamental question is how well the satellite image data classifier can separate conifer cover from other objects (e.g., deciduous stands, brush and open areas, water). The results are presented in Table 5. The overall rating is the proportion of pixels falling in conifer cover that were correctly classified as such by the classifier.

The results indicate that the classifier is a reliable means of discriminating conifer cover from the background of other forest cover, vegetation, openings, and water. The classifier should also be an effective means of identifying and updating conifer stands after disturbances, and for detecting conifer cover that may have been missed during the FRI photo interpretation. The test data results, which were of lower accuracy than the training data accuracy rating, provide a more realistic assessment of the classifier performance because the test data set emulates a new population of conifer clusters. The February image was more reliable than either the August or the combined image. The superiority of the February image is no surprise, but the low performance of the combined image is. The explanation relates to strictness with which the classifier places doubtful classes into the null class (the one without conifer cover). The combined image data was attempted because multi-date classification has been found to improve the discrimination of conifer and hardwood stands in some cases. The test of the ability of the classifier to detect conifer cover is explained in more detail in Appendix B.

Figure 5 compares the LSP (above) and TM (below) classifications of conifer cover on a portion of an FRI map. The delineated LSP conifer clusters (shaded) comprise the effective area. The crosshatched counterpart below are conifer cover detected by the TM classifier. Note the rendition of individual TM pixels close to FRI Polygon

Table 5. Conifer cover classification accuracy (percent).

Data set	February	August	February/August
Training	95.1	97.8	84.6
Test	84.9	72.7	33.6

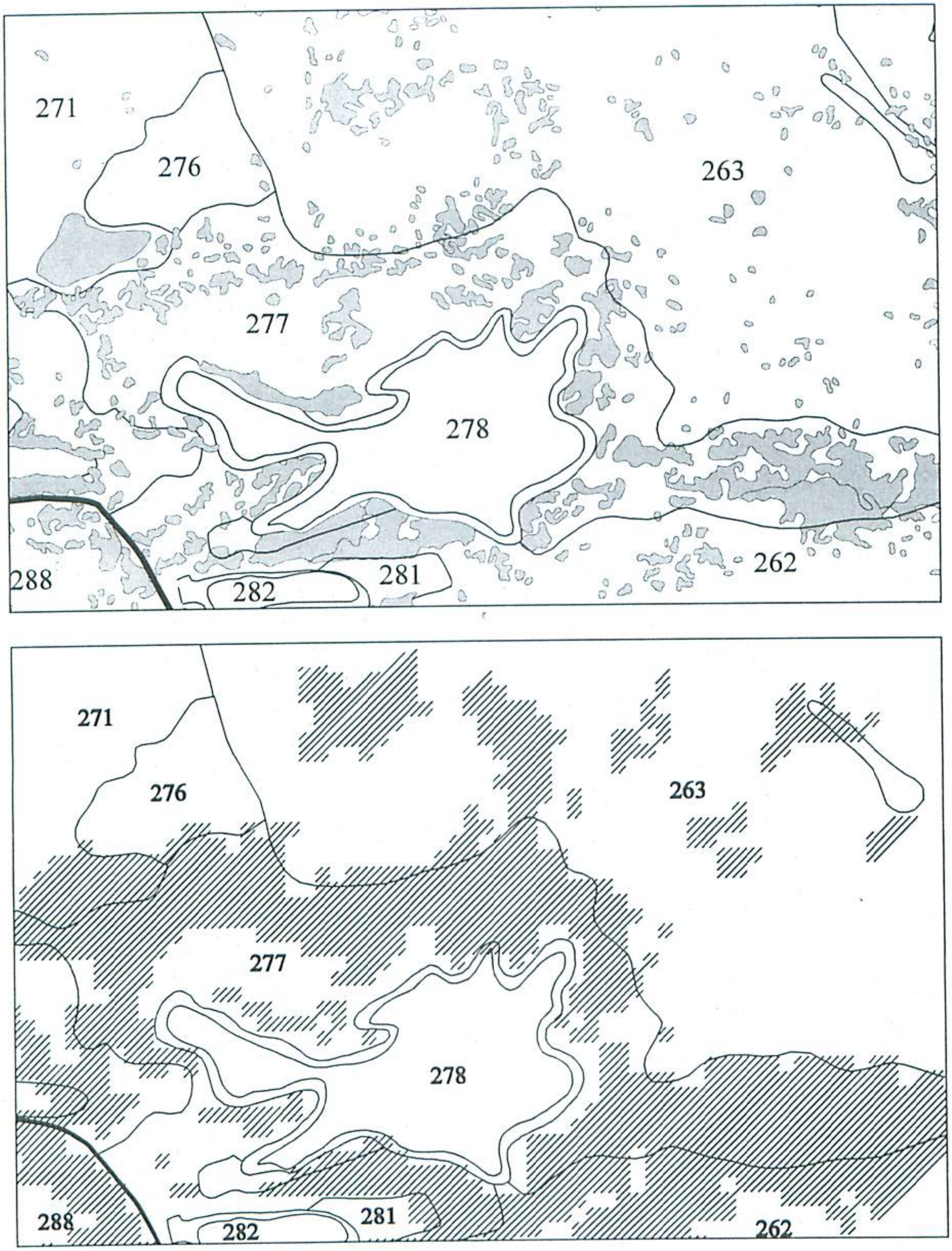

Figure 5. A portion of an FRI map showing stand polygons (numbered) and conifer clusters mapped from LSP (above), and the same area classified from TM date (below).

Identifier 263. Comparison of the two maps, particularly along the FRI polygon boundaries, illustrates how the TM classifier detects the conifer cover and is able to represent the distribution of effective area. The missed areas generally relate to small LSP clusters, dispersion, and admixtures with hardwoods. Since the TM classifier has been adjusted to be quite sensitive to the presence of conifer cover, it may overestimate the actual area of such cover by picking up small conifer clusters or shadows from hardwood stands that have a similar tonal value. Some evidence of this can be seen in FRI Polygon 271. However, such a systematic error can be detected by the LSP counterpart and adjusted. The 30-m browse area buffers are applied by the GIS. The direct TM estimate of accessible area within the polygon is the sum of their effective and browse areas.

TM species discrimination

The next objective was to test how well conifer species or species aggregations can be separated. The results, presented in Table 6, express the overall accuracy of the discrimination on an individual species basis. As can be seen in Appendix B, white pine (*Pinus strobus* L.), red pine (*Pinus resinosa* Ait.), and black spruce (*Picea mariana* [Mill.] B.S.P.) were discriminated more accurately than the other conifer species (hemlock, cedar [*Thuja occidentalish.*], white spruce [*Picea glauca* (Moench) Voss], and balsam fir [*Abies balsamea* (L.) Mill.]). Unfortunately, the latter happened to be the key cover species. Nevertheless, the classification accuracy is too low to be of much practical value. The accuracy ratings of the training data set, although included in Table 6, are higher and less realistic than those of the test counterpart because the test data emulates application of the classifier to a new population.

The third step was to test how well the most separable conifer species could be discriminated. The most separable species (hemlock/cedar, pines, and spruces) are similar to the minimal groupings in Table 1. The results of the test are presented in Table 7.

The "other" column in Table 7 pertains to other conifer species, hardwoods, and non-forested categories. The percentages along the highlighted diagonal indicate the accuracies with which key individual species are correctly classified. If all the pixels were correctly identified, the percentages along the diagonal would equal 100. The overall accuracy of 46 percent was better than by chance alone (33 percent), but it was not considered adequate for the deer yard application.

The cost of acquiring and registering the image data to the geographic base, training and implementing the TM classifier, applying the 30-m browse buffer to the conifer cover in the GIS, and database work to append the resulting data to the FRI database is summarized in Table 8. The costs are based on the actual time taken for an experienced operator to carry out the tasks on an image data classification system (charged on an hourly rate). To better simulate the cost of operational implementation of the TM classifier, the time required to develop the methodology was excluded.

SPOT conifer cover classification

The following is a comparison of the SPOT classifier compared to the best TM classifier on the 6.5-km by 6.5-km block in Figure 4. On the 6.5-km block, both the TM and SPOT classifiers were tested in their ability to detect the presence of conifer cover as mapped from the LSP. The results of the comparison are presented in Table 9.

The TM and SPOT columns, which pertain to the LSP classification, diverged slightly because the differing pixel sizes affect how the classes are counted. The TM classifier correctly detected 85.2 percent of the conifer cover mapped from the LSP; SPOT was no different at 85.6 percent. The TM result is similar to the accuracy found in the earlier test over the much larger area. Looking at the overall classification accuracy of the conifer cover and "other" category, the TM and SPOT classifiers were slightly more that 90 percent accurate. Also, the confusion between the conifer and the "other" category tend to compensate, resulting in estimates of conifer cover within 5 percent of each other. The two overall accuracy assessments, however, mean much less than the

Table 6. Overall species classification accuracy (percent).

Data set	February	August	February/August
Training	61.3	58.6	74.6
Test	21.9	26.1	15.2

Table 7. Overall conifer species classification accuracy (percent) of the three most separable species.

Test standard	Pixels	Percent classified: Hemlock	Red pine	Black spruce	Other
Hemlock	3138	46.1	0.6	7.0	46.3
Red pine	158	5.1	36.5	1.3	57.1
Black spruce	723	13.3	0.1	47.2	39.4

Overall accuracy = 45.9 percent.

Table 8. Summary of costs of using Landsat TM image data to map conifer cover over the project area.

Task	Cost ($)	Cost/ha ($)
Acquisition of a Landsat TM image data of the project area	3,520	0.07
Registration of the image data to the base map	1,145	0.02
Training and testing of the image data classifier	1,145	0.02
Implementation of the classifier including time on the PCI system	1,550	0.03
Application of browse buffers in the GIS environment	435	0.01
Summarization and addition of data to the FRI database	470	0.01
Map production	450	0.01
Total cost	9,020	0.17

Table 9. Conifer classification by TM and SPOT in hectares.

	TM classifier			SPOT classifier		
LSP classes	Conifer	Other	LSP total	Conifer	Other	LSP total
Conifer	113.0	19.6	132.6	115.8	19.5	135.3
Other	25.7	330.6	356.3	27.6	326.0	353.6
Total	138.7	350.2	488.9	143.4	345.5	488.9

conifer detection accuracy because, in the deer yard assessment context, positional accuracy is of primary importance. Thus, the 85 percent detection accuracy is the best measure of accuracy performance. The eventual effectiveness is assessed later when the results of the classification are linked to the cartographic base, the buffers are added, and the accessible area is determined. The SPOT classifier was not better than the TM classifier in discriminating individual conifer species.

The overall cost of SPOT image data, registration, training, GIS application of buffers, and summarization is about the same as for the TM. However, since the TM image covered the whole target area (500 km^2) and the SPOT image covered only 42 km^2, the per hectare cost of SPOT is much higher. This could be reduced by ordering a larger SPOT scene, but the acquisition cost is still higher than the TM on a per hectare basis.

Assessment of Deer Yard Suitability

In this project the suitability of the forest for deer habitat depended on locating conifer cover, identifying the species comprising the cover, and determining the accessible area associated with the cover. The ability of the mapped FRI stand polygons and associated attribute data to detect conifer cover and the species composition is assessed in one test. An accessibility estimation model, which draws on the relationships between FRI attribute data, satellite data, and LSP derived accessibility, is assessed in a second test. Since accessibility data were not directly available in the FRI data set, the purpose of the model was to use FRI data and/or satellite data to estimate accessible area. Finally, the effectiveness of the model is compared with methods based on LSP and satellite data alone, and with two models previously developed by Broadfoot et al. (1994). The comparison was confined to the two shaded areas in Figure 4.

Usefulness of FRI species data

The existing FRI data sets contain information on the predominant species (called the working group) and codes for up to ten species together with a 1-digit number expressing the proportion of each species present in the stand. The species data originates from photo interpretation of FRI black and white photos of the deer yard. Some of the stand descriptions may have been confirmed from sample plot data or field checking.

To determine the reliability of the species information in relation to the deer yard suitability question, a test was carried out to compare the species proportions with those derived from the LSP clusters. The test included only FRI stands that were covered by LSP photos.

To simplify the species comparison, the FRI species proportions were aggregated into the three species groups: namely, (1) cedar and hemlock, (2) white spruce, balsam fir, and white pine, and (3) red pine, jack pine (*Pinus banksiana* Lamb.), and black spruce. Likewise, the LSP species codes were aggregated into the three species groups. Although most conifer species can be accurately distinguished on the 1:5 000 photos, one species pair cannot: white spruce and black spruce. However, other information such as soil type, site, and drainage conditions can help make the separation. So also can the FRI stand codes, which were used in these investigations.

The following steps were needed to complete the test:

- overlay the 1:5 000 LSP clusters on the FRI stand polygons;
- aggregate the area of the LSP clusters within an FRI polygon;
- summarize the aggregated area by species group;
- allocate the FRI polygon area by the species proportions and aggregate into the three species groups;
- compare the species group area totals by FRI and LSP sources; and
- make a correlation matrix to compare the frequency of occurrence of the predominant species (working group) by FRI and LSP sources.

The results of the area comparison are shown in Table 10. Overall, on a polygon area basis, the FRI attribute data produces estimates that are 33 percent higher than the 1:5 000 source. This was anticipated because the FRI data were based on the interpretation of photos at a scale of 1:20 000. As scale increases, the open areas around the canopy clusters are clearly visible on the 1:5 000 photos but tend to merge into the canopy cover and shadows at the smaller scale, thereby making the cover appear more dense. Because this tendency is fairly constant with scale, its effect can generally be detected and corrected.

The correlation matrix, which compares how the two methods assess the predominant species group, is presented in Table 11. The shaded numbers along the diagonal are the number of FRI polygons that were classified as belonging to the same groups using both FRI and LSP data sources. The latter was adopted as the "true" cases. The off-diagonal (or unshaded) entries represent the number of polygons where the data sources disagreed (were confused). Overall, on an FRI stand polygon count basis, the FRI attribute data was 9 percent low in counts of Species Group 1 and 1 percent low in Species Group 2. The third group had too few stands to make a reliable estimate. In this project, the second and third species groups could be lumped together without adverse effects.

Table 10. Comparison of how FRI and LSP classify the area (ha) of three conifer species groups on the same area.

Source	Species Group 1	Species Group 2	Species Group 3	All species
FRI	1 559.8	1 451.9	126.9	3 138.6
LSP	1 335.4	931.6	99.2	2 366.2
Difference	224.4	520.3	27.7	772.4

The overall evaluation based on the comparison of the row and column totals, however, did not reflect the degree of confusion among classes and unclassified cases. Seventeen percent of the counts were either confused or not classified as one of the conifer classes.

The results of the two tests show that the FRI data can be used as a fairly reliable means of detecting and classifying conifer cover (effective area) for deer yard purposes. However, some field or LSP data are required to "tune " the area estimates. Although the existing FRI can address the need for effective area data, it does not offer direct data on accessible area.

Accessible Area Prediction Model

The existing FRI data contain no information on the spatial distribution of conifer cover within the stand polygon, nor on the browse or accessible area associated with the cover. However, a prediction model was investigated as a means of deriving such information from other available FRI data fields, such as polygon area, polygon perimeter, conifer species proportions, stocking, stand height, age, etc. The accessible area determined accurately from the LSP was used to develop and test different models. A successful model would then be applied to all FRI polygons that have no supporting LSP data. Likewise, the satellite classification, which covered all the polygons,

Table 11. Correlation matrix comparing how the FRI and LSP identify the predominant species of FRI polygons.

LSP source	FRI source Group* 1	Group 2	Group 3	Other**	Total
Group 1	186	32	2	33	253
Group 2	28	99	2	35	164
Group 3	2	9	1	0	12
Other	17	25	1	16	59
Total	233	165	6	84	488

* Groups refer to three species groups.
** Other refers to unclassified cases.

may be used directly or indirectly in the model either alone or in combination with the FRI data. The satellite estimate of accessible area within an FRI polygon was tested as an additional variable in the prediction model.

The prediction model was posed in the following general form:

AA = b0 + b1*EA + b2*PA + b3*TM + b4*PP + b5*ST + b6*HT + b7*AG + b8*SI

where: AA is the **accessible area** (ha) from LSP;

PA is the FRI polygon area (ha);

ST is the stocking (proportion);

EA is the area of conifer cover (ha) derived from the FRI polygon area, proportion conifer, and stocking (EA = % Conifer species*ST*PA);

TM is the area (ha) of conifer cover from the TM classifier;

PP is the FRI polygon perimeter (m);

HT is the stand height (m);

AG is the stand age;

SI is the site class; and

b0, b1, ... are regression coefficients.

The above can be cast as a linear multiple regression model of the form:

Y = b0 + b1*X1 + b2*X2 + b3*X3 + ... + bN*XN

and used to estimate the model coefficients b0 to bN, which may then be used as the prediction model for the accessible area for particular FRI polygons.

Many variations of the model were tested using stepwise regression. The following variables emerged as the most effective: (1) accessible area estimated from the satellite data (TM), (2) the total area of conifer cover (EA) estimated from the FRI data, and (3) polygon area (PA). Age, stocking, and FRI polygon perimeter emerged as minor contributors in some tests of data subsets. Only the first three were consistently strong. The three models in Table 12 were found to be the most effective.

The models were run over all FRI polygons having LSP clusters. The combined TM and FRI model was the strongest, although the TM model alone has almost as much predictive power. The TM/FRI model accounts for 86 percent of the variation in accessible area, and estimates it, on average, to within ± 7.7 ha two-thirds of the time. Development of separate models by FRI dominant conifer species (working group) did not consistently improve the reliability of the model. The second model could be used successfully in cases where TM imagery is unavailable or is considered to be too expensive. The third model primarily corrects for systematic differences between direct TM measures of accessible area and actual measures based on the LSP. The three models were used for comparison.

Comparison of methods

Seven methods of determining accessible area were compared: five from this project and two from previous work by Broadfoot et al. (1994). The first method was the test standard based on LSP alone; the second was based on the direct results of the TM image data classification; the third used the LSP data and TM image data together; the fourth used LSP and FRI data together; and the fifth used a combination of LSP, TM image data, and FRI. The last method mentioned employed the equations developed earlier and presented in Table 12. The two models by Broadfoot et al. (1994) included a random conifer cover distribution assumption and a clumped distribution model derived through computer simulations. The comparison was made in terms of accuracy and cost. The accuracy is expressed as a systematic error component (shifts consistently above or below the true or standard value) and a random component that expressed variations from stand to stand. The LSP estimate of accessible area was adopted as the true value. The comparison involved only the two shaded areas in Figure 4 that have complete LSP coverage. The results of the comparison are presented in Table 13.

Table 12. Accessible area estimation models based on FRI and TM variables.

Accessible area estimation model	N*	R ** (ha)	Se***
AA = 0.3656 + 0.8167 X TM + 0.1512 X EA	432	0.86	7.74
AA = 1.3491 + 1.0731 X EA + 0.2934 X PA	432	0.72	10.70
AA = 0.4699 + 0.8575 X TM	432	0.85	7.78

* N is the number of polygon observations.

** R is multiple correlation coefficient squared.

*** Se is the standard deviation of regression residual errors.

As seen in Table 13, assessment of the accessible area directly from the TM classifier was 15 percent higher than the standard. The Broadfoot random model was 39 percent higher, and the Broadfoot clumped model was 59 percent lower. The systematic error of the other methods was 1 percent high. The TM method was high because of the sensitivity of the classifier to the presence of conifer in the pixels comprising a polygon. The effect can be seen graphically by comparing how the conifer clusters are mapped by the LSP and the TM classifier in Figure 5. The spread in the Broadfoot model probably means that the actual distribution of conifer cover is part way between a random distribution and the degree of clumping assumed in the Broadfoot simulation.

The variation in accessible area estimates from one FRI polygon to another is a more important expression of accuracy because no further control or adjustment can be made. An error of estimate of ± 7.7 ha can be interpreted to mean that a polygon 25 ha in size will, on average, be estimated to within about 30 percent two-thirds of the time. Since these are random errors, sums over a number of stands comprising a study area or a planning zone will, according to the sample size principle, reduce the variability of averages. For example, the LSP comparison area contains 438 stands with accessible area. The estimate of the average accessible area will have a variability of about $\pm 7.7/\sqrt{438}$ or 0.36 ha or 1.5 percent of the average.

The FRI digital maps and polygon data are common to, and needed for, all seven methods. Thus the cost of acquiring the OBM and FRI data were not included in the comparison. Fortunately, these data were already available and the considerable expense of acquiring the FRI spatial and attribute data set did not have to be borne by the project. However, the FRI model costs shown in Table 13 included the steps required to assemble the GIS digital base, the FRI spatial data and the associated polygon database, some LSP data to calibrate the model, and an algorithm to calculate the accessible area and append it to the FRI database. The costs of the two Broadfoot models were based on the 2 or 3 days needed for one person to set up the existing FRI database and the biomass estimation models. Because of the large systematic errors in the Broadfoot models at the scale tested, and because no means was available to calibrate or adjust them, they were dropped from further cost/effectiveness comparison.

The cost of the LSP method includes the full costs of acquiring the photos, interpreting, delineating and coding the conifer clusters, mapping, digitizing, and entering the codes into a database. These costs were summarized in Table 4. Likewise, the cost of any of the methods using the TM classifier must reflect the cost of acquiring the image data and producing the conifer classification summarized in Table 8. However, the cost of the LSP in the cases where an accessible area model is used does not need as much LSP coverage as was obtained in the project—coverage of 100 to 150 stands would be adequate to develop or calibrate the models. Thus, the cost of the LSP component was assumed to be about 30 percent of that actually needed to cover the 438 stands in this project.

Methods 3, 4, and 5 were compared in a simple cost/effectiveness framework. The framework assesses the cost required to estimate the total accessible area of the test area (shaded areas in Fig. 4) to an accuracy level equivalent to the most accurate of the three (Method 5 at ± 30.8 percent for $27,720). In order to raise Method 4 at $18,700 to the same level of accuracy, the level of effort, as derived from the sample size rule, would have to be increased by a factor of 1.9, which brings the cost up to about $35,500. To raise Method 3 to the same accuracy standard would require that its budget be raised to about $21,000. Method 3—LSP supported TM—requires the lowest budget of the three and therefore emerges as the best option. Furthermore, the TM offers additional information, such as a means of updating for recent changes or

Table 13. Comparison of seven methods of determining accessible area.

Method	Accessible area (ha)	Systematic error (%)	Standard error (ha)	Standard error (%)	Cost ($)
1. LSP (1:5 000 photos) - standard	8 381.4	0.0	0.0	0.0	62,251
2. TM classifier direct	9 646.8	+ 15.1	8.4	33.6	9,020
3. TM model (LSP calibrated)	8 477.9	+ 1.2	7.8	31.2	20,420
4. FRI model (LSP calibrated)	8 460.4	+ 0.9	10.7	42.8	18,700
5. TM/FRI model (LSP calibrated)	8 484.4	+ 1.2	7.7	30.8	27,720
6. Broadfoot - random distribution	11 634.5	+ 38.9	18.7	74.8	800
7. Broadfoot - clumped distribution	3 835.3	- 54.2	15.6	62.4	800

disturbances in the stands, and preliminary conifer cover information for deciding on the best sites for the LSP sampling. Although Method 3 comes out best, this should not imply that Method 4 could not be used, perhaps where acquisition of TM data and deployment of an image data classification system is not practical.

Estimation of Winter Browse Supply

Winter forage biomass estimates, expressed in kg/ha, were used as the primary measure of browse supply in this project. The per hectare estimates have been found to vary with species composition of stands, development stage, site class, canopy density, and deer browsing intensity. Broadfoot et al. (1994) have developed a generalized winter forage biomass model based specifically on: (1) cover type derived from FRI working groups or their aggregations; (2) development stage derived from combinations of working group, site, and age; and (3) canopy density based on two levels of FRI stocking. A BASIC program (Appendix C), prepared for this project, implemented the model using the procedures and data in Broadfoot et al. (1994). The per hectare estimates produced from the model were applied to all FRI stands in the deer yard by calculating the biomass per hectare for the particular stand characteristics and multiplying it by the stand's accessible area. The resulting forage biomass quantities were then appended to the FRI stand database where the biomass supply could be queried and summarized, and the distribution of concentrations mapped. Likewise, planning areas could be defined in the GIS to analyze the biomass supply and spatial distribution.

RESULTS

The browse supply quantities appended to the FRI database can be summarized by map sheet, stand, species group or working group, age class, etc. or for defined blocks, zones, or planning areas within the project area. For example, Table 14 provides a breakdown of accessible area and browse supply by species or species aggregations across the full deer yard. The accessible area estimates were based on the LSP-calibrated TM/FRI model (Model 5 in Table 13). The first two species correspond to the optimal conifer cover, the next three species to suitable cover, and the next two to marginal cover. The remaining three species groups are generally not considered to provide suitable cover based on FRI criteria. However, the LSP data indicate that they may contain substantial accessible area and quantities of browse.

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this project was to investigate the role that emerging data collection technology can play in providing information for the management of white-tailed deer habitat. The key habitat requirements center on the winter thermal cover provided by coniferous trees and an adequate supply of accessible browse to sustain a healthy population. The information is needed to manage deer yards on a sustainable basis in conjunction with timber management practices, the needs of all wildlife, and other uses of the forest that influence deer habitat.

The data sources included digital Ontario base maps, Forest Resource Inventory maps and an associated polygon attribute database in GIS format, satellite image data, large scale sampling photos, and the use of a global positioning system to locate field observations. The GIS provided a common cartographic base for bringing together the several sources of data.

Table 14. Accessible area and browse supply on the deer yard by species or species groups.

Conifer cover priority	Species or species aggregations	Accessible area (ha)	Browse biomass (kg)
Optimal	Hemlock	3 171.4	16 275.7
	Cedar	226.8	8 413.7
Suitable	White spruce	448.3	10 037.1
	Balsam fir	1 831.8	12 461.0
	White pine	602.5	16 109.2
Marginal	Red pine, scots pine, and jack pine	258.1	2 902.4
	Black spruce	606.0	4 323.7
Unsuitable	Other conifer species	95.1	1 184.4
	Tolerant hardwoods	14 511.2	127 687.5
	Intolerant hardwoods	2 128.2	24 770.6
	Total	23 879.4	224 165.3

The OBM was used successfully as the cartographic foundation for the project. The FRI polygon data, which included delineated forest stands, were registered to the base. The satellite classification and LSP data were mapped on to the base. The GPS enabled field data to be precisely positioned on the map base. The satellite and LSP data were summarized to the FRI stand polygon level and appended to the attribute database.

The LSP methodology was confirmed as a very useful and reliable means of isolating conifer cover clusters and assessing their species composition. When the clusters are digitally mapped, a browse area buffer can be readily applied by the GIS and used to evaluate effective areas, browse areas, and accessible areas within the stand. The methodology is expensive, but was found to be much less so than in the initial development trials because of the larger size and attendant economies of scale.

The FRI data provided useful conifer cover species information and data that can be used to estimate effective area and accessible area. However, since the FRI provides no information on the distribution of the cover within the stand, the LSP had to be relied on to develop simple estimation models. These models established linear relationships between accessible area (obtained from the LSP), TM classifications, and FRI stand attribute data.

Landsat Thematic Mapper and SPOT multispectral and panchromatic data were tested. Both were successful in separating conifer cover from hardwood cover and other features. However, the image data were found to be ineffective in separating coniferous species. The SPOT data, although of higher resolution and much more expensive than the TM, was not much better than the TM in any of the classification tasks. The TM provided useful information on the spatial distribution of conifer cover within the FRI polygons and, when registered to the cartographic base and the browse buffer added by the GIS, could be used to estimate the effective areas, browse areas, and accessible areas. However, the estimation of these areas without supporting LSP data resulted in large systematic errors. Thus a small quantity of LSP data was needed to calibrate the estimation models to remove such errors. The TM/LSP model, nevertheless, was found to be reliable and can estimate the accessible area of an FRI stand to within about ± 7.7 ha 67 percent of the time, and with the systematic error removed. Models based only on FRI/LSP data were found to be accurate to within about ± 10.7 ha. This means that nearly twice as much LSP support is needed to achieve the same reliability in estimates. The additional cost of the extra LSP will more than cover the cost of the TM. Thus the FRI/LSP combination will provide good estimates, but not as efficiently as the TM/LSP combination. Additionally, the TM provides a means of updating changes since the FRI photos were acquired. The TM also supports the FRI data in targeting the LSP sampling.

The random and cluster models developed by Broadfoot et al. (1994) produced estimates in this project that deviated markedly from the test standard both in terms of systematic error and variability. Calibration of the randomization/clumping simulations may reduce the systematic component. However, it is unlikely that much can be done to reduce the variability.

The GIS provided an excellent platform for combining the several data sources. It also offered an effective means of presenting the cover and browse results, either as maps showing the distribution of the cover or as quantitative data summarizing accessible areas or browse supply. Database queries allow breakdowns to be made by working group, age and site classes, and defined planning areas or zones. The GIS can also be used to locate promising deer habitat for more intensive analysis or treatments, such as supplemental feeding. If stand development simulations are made based on FRI stand projections, future deer habitat suitability, browse supply, and carrying capacity can be predicted for medium and long term planning purposes.

The GPS was found to be an effective means of tying field data to the geographic base.

The following deer yard assessment methodology, based on a multistage design, is recommended:

1. Obtain available OBM and FRI digital coverage of a prospective deer yard.
2. Optionally, obtain Landsat TM coverage of the target area.
3. Use the FRI and/or TM classier to locate FRI stand polygons with a significant conifer cover. Use FRI data to classify the cover by suitability priority (optimal, suitable, or marginal).
4. Select 100 to 200 stands for LSP sampling weighted according to priority and estimated accessible area. The estimate does not need to be calibrated at this stage.
5. Obtain the LSP coverage of the selected polygons. Follow the LSP specifications in Table 2.
6 Photo interpret (delineate and code) conifer clusters on the LSP according to the criteria in Table 3. Map, digitize, and overlay the LSP clusters on the FRI polygon map; use the GIS to apply the browse buffer; summarize effective areas, browse areas, and accessible areas; and append the data to the FRI attribute database.

7. Optionally, use the LSP data to calibrate the TM classifier and apply this classifier to all polygons in the target area. Append the results to the FRI attribute database.
8. Use the available FRI, TM, and LSP data to calibrate (estimate new coefficients) for the accessible area models (Table 11).
9. Use the models to estimate the accessible area of all polygons in the target area and append the result to the FRI database.
10. Use the biomass model (Appendix C) to calculate the browse supply on each FRI polygon in the target area and append the result to the FRI attribute database.
11. Use the GIS to map the distributions of conifer cover and the location of priority polygons on the deer yard, portions thereof, or defined planning areas. Use database queries to report accessible area and browse supply summaries similar to the results in Table 14. Apply models (not implemented in this project) to assess sustainable carrying capacities.

The application of one of the models developed and calibrated in this project to other deer yards, without new LSP data, may be possible. However, systematic drifts must be expected, especially as the forest stands change in species composition, structure, and conifer cluster distribution. Re-interpretation of 1:15 840 or even 1:20 000 FRI photos to specifically address the conifer cluster delineation requirements may help to track the drift. The 1:10 000 scale photos available in some cases will provide an even better substitute, but considerable caution should be exercised in considering such alternatives to LSP.

Even a relatively small sample of 1:5 000 photos, in the hands of a skilled photo interpreter, will accurately discern the conifer components; provide the spatial distribution of conifer cover; and yield a reliable means of mapping effective area, browse area, and accessible area for browse supply appraisal purposes. When applying the methodology to a new deer yard, such data can be used either to confirm the applicability of the current models or provide the data necessary to recalibrate them to match the new forest stand conditions.

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APPENDIX A. IMAGE DATA CLASSIFICATION PROCEDURES.

METHODOLOGY

TM Registration

From the PAMAP GIS system an image of the lakes and rivers was exported and used as the master for image-to-image registration. Also from the PAMAP, an image of the TEST classes was imported as a separate image. The master image has UTM coordinates and can easily be imported back into PAMAP. Each of the two TM scenes were then each registered individually to this master image. Next, the rivers and lake channels and the TEST classes image were made into bitmaps. A visual examination of the result by flickering the bitmaps on top of the TM images showed good registration in the area common to both the PAMAP-generated images and the TM images. The registration over the rest of the image outside the TEST bitmap will be linearly similar.

Bitmap Generation

Two approaches were taken to generating the bitmap used to define a class for use in the image classification.

The first approach involved a visual collection of pixels for each class. The TEST class was used to orient on the image of stands for each class occurrence. By examining the values collected in each EDIT class bitmap, a bitmap with consistent values and a low standard deviation can be gathered.

The second approach was to use the TEST classes as the EDIT class and eliminate all pixels having values outside an observed central cluster.

Comparing these two approaches for the classes of hemlock, cedar, and white spruce, little difference was found in the derived class signatures. Therefore, the rest of the classes were continued using the second approach; this was easier and considered to be more precise. The first approach of collecting pixels tended to produce a mean centering around the average of the first few stands. This may not be representative of the actual mean.

Classification

Once the bitmaps were edited to make the EDIT classes, a signature was produced for each class. Three signatures, using the February images, the August images, and the combined August and February images, were produced for each bitmap.

The classification performed in all cases used the Maximum Likelihood procedures described in Appendix B. Rather than being forced into the most likely class, a null class was produced for nonclassified pixels. The classification image was then compared with the "truth" TEST and EDIT images, and the results displayed in a confusion (correlation) matrix.

Finally, the image was visually examined for classification fit. Here the classification image was burned into class bitmaps that were flickered over the images to visually examine the precision of the fit.

Results

Conifer Classification - August

Subarea reports using Theme Channel 7 and Subarea Channel 4:

7 [SU] MCD Conifer Classification Thrs=3

4L[8U] MCD Water and conifer TEST classes

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Water	30 440	94.4	5.6
Conifer	8 915	27.3	72.7

Average accuracy = 72.70 percent.

Overall accuracy = 72.70 percent.

Subarea reports using Theme Channel 7 and Subarea Channel 5:

7 [8U] MCD Conifer Classification Thrs=3

5L [8U] MCD Conifer EDIT class

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Conifer	3 346	2.2	97.8

Average accuracy = 97.76 percent.

Overall accuracy = 97.76 percent.

Conifer Classification - February

Subarea reports using Theme Channel 7 and Subarea Channel 5:

7 [8U] MCD Classified as conifer 14-Mar-95

5L[8U] MCD Conifer and water TEST classes 14-Mar-95

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Water	30 440	98.5	1.5
Conifer	8 915	15.1	84.9

Average accuracy = 84.92 percent.

Overall accuracy = 84.92 percent.

Subarea reports using Theme Channel 7 and Subarea 6:

7 [6U] MCD Classified as conifer 14-Mar-95

6L[8U] MCD Conifer EDIT class 14-Mar-95

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Conifer	3 291	4.9	95.1

Average accuracy = 95.11 percent.

Overall accuracy = 95.11 percent.

Subarea reports using Theme Channel 10 and Subarea 9:

10 [6U] MCD Classified as conifer 14-Mar-95

9L[8U] MCD Conifer EDIT class 14-Mar-95

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Conifer	1 454	13.4	86.6

Average accuracy = 86.59 percent.

Overall accuracy = 86.59 percent.

Conifer Classification - February/August

Subarea reports using Theme Channel 10 and Subarea Channel 8:

10[8U] MCD Classified as conifer 14-Mar-95

8L[8U] MCD Conifer and water TEST classes 14-Mar-95

Areas		Pixels classified by code (%)	
Code name	Pixels	Null	Conifer
Water	30 440	99.9	0.1
Conifer	8 915	66.4	33.6

Average accuracy = 33.60 percent.

Overall accuracy = 33.60 percent.

Species Classification - February

Subarea reports using Classified Channel 7 and TEST Area Channel 5:

Areas		Pixels classified by code (%)							
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	3 183	35.5	15.8	10.0	7.7	12.3	7.0	4.2	7.5
15 Cedar	237	8.4	4.6	41.4	4.6	16.5	7.2	0.0	17.5
20 White spruce	384	38.5	5.7	8.9	11.2	13.0	2.9	13.3	6.5
25 Balsam fir	1 566	35.8	6.3	10.8	9.9	22.0	1.5	4.0	9.8
30 White pine	2 664	24.5	5.5	8.2	5.2	2.3	27.0	17.0	10.2
35 Red pine	158	38.6	0.0	2.5	7.6	2.5	0.0	48.1	0.6
40 Black spruce	723	8.3	10.8	23.9	6.1	21.3	5.8	1.0	22.8

Average accuracy = 26.90 percent.

Overall accuracy = 21.86 percent.

Subarea reports using Classified Channel 7 and EDIT Area Channel 6:

Areas		Pixels classified by code (%)								
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	388	0.0	52.1	15.7	5.9	17.3	3.9	0.0	5.2
15 Cedar	26	0.0	0.0	73.1	0.0	7.7	7.7	0.0	11.5
20 White spruce	38	0.0	18.4	2.6	42.1	15.8	10.5	5.3	5.3
25 Balsam fir	266	0.0	10.2	16.2	9.4	52.6	0.0	0.0	11.7
30 White pine	528	0.0	3.4	6.2	4.5	0.0	81.8	0.4	3.6
35 Red pine	29	6.9	0.0	0.0	20.7	0.0	0.0	72.4	0.0
40 Black spruce	179	0.0	14.5	29.1	3.4	11.7	7.3	0.0	34.1

Average accuracy = 58.31 percent.

Overall accuracy = 61.28 percent.

Species Classification - August

Subarea reports using Classified Channel 7 and TEST Area Channel 5:

Areas		Pixels classified by code (%)							
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	3 183	36.4	32.0	1.6	8.7	12.4	5.4	0.6	3.0
15 Cedar	237	16.0	4.6	16.0	1.7	13.1	12.2	0.8	35.4
20 White spruce	384	42.4	10.7	2.6	13.3	8.1	11.5	6.8	4.7
25 Balsam fir	1 566	34.4	15.5	4.4	7.4	16.8	10.5	1.4	9.6
30 White pine	2 664	26.7	7.7	7.5	12.9	8.8	23.8	0.4	12.2
35 Red pine	158	51.3	2.5	0.0	3.8	1.3	3.8	36.7	0.6
40 Black spruce	723	32.4	6.1	5.5	3.3	7.6	8.6	0.1	36.4

Average accuracy = 24.99 percent.

Overall accuracy = 26.07 percent.

Subarea reports using Classified Channel 7 and EDIT Area Channel 6:

Areas		Pixels classified by code (%)							
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	388	0.0	75.3	0.0	10.8	12.4	1.5	0.0	0.0
15 Cedar	26	0.0	0.0	88.5	0.0	0.0	0.0	0.0	11.5
20 White spruce	38	0.0	10.5	0.0	68.4	15.8	5.3	0.0	0.0
25 Balsam fir	266	0.4	18.8	4.9	16.2	41.0	17.7	0.0	1.1
30 White pine	528	0.9	0.9	14.8	13.3	12.3	45.8	0.0	11.9
35 Red pine	29	0.0	0.0	0.0	0.0	0.0	0.0	100	0.0
40 Black spruce	179	1.7	0.0	12.3	0.0	1.7	11.2	0.0	73.2

Average accuracy = 70.31 percent.

Overall accuracy = 58.60 percent.

Species Classification - February/August

Subarea reports using Classified Channel 7 and Subarea Channel 5:

Areas		Pixels classified by code (%)							
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	3 183	76.8	12.4	0.5	1.8	5.9	1.7	0.0	0.8
15 Cedar	237	51.1	1.3	9.3	0.4	11.4	3.4	0.0	23.2
20 White spruce	384	81.8	1.8	1.0	7.6	4.9	0.8	0.0	2.1
25 Balsam fir	1 566	75.0	3.4	0.7	2.2	14.8	0.6	0.1	3.3
30 White pine	2 664	68.6	2.0	1.4	3.0	1.6	18.1	0.0	5.3
35 Red pine	158	81.6	0.0	0.0	0.0	0.0	0.0	18.4	0.0
40 Black spruce	723	60.6	3.2	2.4	0.8	7.1	2.6	0.0	23.4

Average accuracy = 14.83 percent.

Overall accuracy = 15.21 percent.

Subarea reports using Classified Channel 7 and Subarea Channel 6:

Areas		Pixels classified by code (%)							
Code name	Pixels	0	10	15	20	25	30	35	40
10 Hemlock	388	6.7	75.5	0.0	6.2	9.8	1.8	0.0	0.0
15 Cedar	26	0.0	0.0	80.8	0.0	0.0	3.8	0.0	15.4
20 White spruce	38	7.9	5.3	0.0	68.4	13.2	5.3	0.0	0.0
25 Balsam fir	266	11.3	8.6	1.1	7.5	69.2	0.0	0.0	2.3
30 White pine	528	11.9	1.9	2.3	4.7	0.4	75.2	0.0	3.6
35 Red pine	29	17.2	0.0	0.0	0.0	0.0	0.0	82.8	0.0
40 Black spruce	179	10.6	0.0	6.7	0.0	2.8	2.2	0.0	77.7

Average accuracy = 75.64 percent.

Overall accuracy = 74.55 percent.

TM Signatures of EDIT Class

August Image

Hemlock signature

Sample size: 388 Encoding: 10

TM band	Mean	Deviation
3	20.123711	0.725212
4	81.355667	5.142034
5	54.391754	3.808717

Cedar signature

Sample size: 26 Encoding: 15

TM band	Mean	Deviation
3	18.692308	0.461538
4	64.961540	2.084388
5	43.423077	1.668096

White spruce signature

Sample size: 38 Encoding: 20

TM band	Mean	Deviation
3	20.078947	0.839222
4	74.552635	2.721236
5	47.710526	3.363174

Balsam fir signature

Sample size: 266 Encoding: 25

TM band	Mean	Deviation
3	19.278196	1.126265
4	73.827065	4.513157
5	49.533836	3.388501

White pine signature

Sample size: 528 Encoding: 30

TM band	Mean	Deviation
3	19.861742	1.233149
4	68.204544	3.940829
5	45.196968	2.852934

Red pine signature

Sample size: 29 Encoding: 35

TM band	Mean	Deviation
3	19.034483	1.033333
4	76.413795	2.684758
5	37.344826	3.632002

Black spruce signature

Sample size: 179 Encoding: 40

TM band	Mean	Deviation
3	19.273743	1.199596
4	60.921787	3.597722
5	42.111732	2.644448

February Image

Hemlock signature

Sample size: 388 Encoding: 10

TM band	Mean	Deviation
3	31.015465	3.068760
4	39.654640	2.699619
5	21.090206	1.638646

Cedar signature

Sample size: 26 Encoding: 15

TM band	Mean	Deviation
3	27.153847	1.291758
4	35.269230	2.781224
5	18.423077	2.151441

White spruce signature

Sample size: 38 Encoding: 20

TM band	Mean	Deviation
3	34.368420	3.382782
4	41.973682	2.942312
5	19.736841	2.582168

Balsam fir signature

Sample size: 266 Encoding: 25

TM band	Mean	Deviation
3	32.838345	4.068053
4	37.458645	3.017521
5	19.598497	2.217717

White pine signature

Sample size: 528 Encoding: 30

TM band	Mean	Deviation
3	27.865530	2.348215
4	41.907196	2.698363
5	19.178030	1.231888

Red pine signature

Sample size: 29 Encoding: 35

TM band	Mean	Deviation
3	34.068966	4.555641
4	46.620689	4.163998
5	16.551723	3.469932

Black spruce signature

Sample size: 179 Encoding: 40

TM band	Mean	Deviation
3	27.988827	2.545648
4	36.201118	2.596473
5	18.245810	2.271003

Observations

Assumptions

1. TEST Class is accurate in terms of species spectral radiation.
2. EDIT Class is accurate in terms of species spectral radiation.
3. TM image is linearly orthocorrected.

Conifer Classification

Classification of either the February or the August images for a single conifer class was quite successful. Table A1 presents the percent accuracy results using the two sets of bitmaps to test the classification. Surprisingly, the classification using the February/August images was not very good in terms of the TEST bitmap. This was likely because the signatures are too tightly bundled and a lot of pixels are put in the null class unnecessarily. As for the TEST class, the separation is better in February when the hardwoods are leafless.

Table A1. Classification percent accuracy results.

	August	February	Combined
EDIT	97.8	95.1	84.6
TEST	72.7	84.9	33.6

Table A2 provides the results for the TEST bitmap set. The August water class is not as separable as in the February image because the aquatic vegetation can be closer in signature to the forest than will be ice or snow. Also, the registration was quite accurate over the area of the TEST bitmap as the water class is very accurately classified. Poor registration would be manifest where the water bitmap pixels fall over land, and hence would be classified as either null or conifer. Therefore, Assumption 3 was concluded to be correct.

Table A2. Bitmap set results.

	August	February	Combined
TEST conifer	72.7	84.9	33.6
Water	94.4	98.5	99.9

Species Classification (Separation)

The above tables indicate that classification by species is not feasible; there is too much confusion between the conifers. This occurs both in the TEST and EDIT bitmap sets. Using the TEST bitmaps there was some concern with misregistration, although this is unlikely to be a primary cause. Using the EDIT classes that are carefully selected pixels, good separation would be expected if it were spectrally feasible. Visual examination of the spectral clusters or feature spaces among the images confirmed the difficulty of separating by species. As far as separating by species groups, it could have been examined further but was unlikely to provide adequate separation (i.e., better that 80 percent) in terms of the TEST bitmaps. Visual examination of the TEST bitmap data shows a wide overlap of values within species classes, and thus a weak ability to discriminate among them.

Conclusions

Conifer species as a single category can be successfully discriminated from all other features, including hardwood stands, water, and other "backgound" features. The best separation is achieved using a winter image.

Further editing of the conifer class signature could be considered to see what sort of separation can be done when combining winter and summer images. However, adequate conifer cover discrimination is possible using a single image, thus avoiding the cost of an extra TM scene.

In this project species separation was not feasible using TM images. It may be possible to discriminate broad species classes, but useful separations of species groups of relevance to the deer habitat requirements were not possible.

APPENDIX B. MAXIMUM LIKELIHOOD IMAGE CLASSIFIER.

The following information on the Maximum Likelihood Classifier (MLC) was extracted from the PCI image data classification system Help feature.

MLC classifies all image data on a database file using a set of 256 (64 on MS-DOS) possible class signature segments as specified by the DBS1 parameter. Each segment stores signature data pertaining to a particular class. Class signature segments are created using CSG.

The result of the classification is a theme map directed to a specified database image channel (DBOC). A theme map encodes each class with a unique grey level. The grey-level value used to encode a class is specified when the class signature is created (VALU for CSG). If the theme map is later directed to the display, a pseudocolor table should be loaded so that each class is represented by a different color. If more than 1 output channel is specified, the 2nd, 3rd, ..., nth most likely classes will be stored in the 2nd, 3rd, ..., nth output channels, respectively. Up to 16 (4 on MS-DOS) output channels can be specified. The number of output channels cannot be more than the number of signatures. If parallelepiped classification is chosen, only one output channel can be specified.

The NULLCLAS parameter allows the user to specify whether every pixel should be classified. If this option is "YES" then a pixel is assigned to a class only if it is within the gaussian threshold specified for the class. If it is not within any threshold, it is assigned to the NULL (0) class. If the option is "NO" then the thresholds are ignored and every pixel will be assigned to the most probable class (i.e., nearest class based on Mahalanobis distance).

If the MATRIX parameter is turned on (YES) and DBSA is specified, a confusion matrix report will be generated. This report is based on the assumption that the values encoded in the DBSA channel correspond to the classification encoding values in the source channel (DBIC). Furthermore, it is expected that the areas in DBSA specify either the training areas for the signatures used to create the DBIC classification, or the testing areas where the user knows the classes already from reference data. If these conditions are not met, the confusion matrix report is not meaningful. If training areas are used, the confusion matrix gives information on how much of each original training area was actually classified as being in the class that the training was meant to represent. If many pixels in the training areas were classified in classes different than those intended, it is likely that the training areas were not appropriate. Testing areas are areas of representative, uniform land cover that are different from, and considerably more extensive than, training areas. They are often located during the training stage of supervised classification by intentionally designating more candidate training areas than are actually needed to develop the classification statistics. A subset of these may then be withheld for the postclassification accuracy assessment, again using the confusion matrix to express the results. The accuracies obtained in these areas represent at least a first approximation to classification performance throughout the scene.

An example report generated on the irvine.pix database is provided in Table B1

Table B1. Irvine.pix database report.

Code	Name	Pixels	0	10	20	30	40	50	60	70	80
10	Water1	470	0.2	96.4	0.0	2.8	0.6	0.0	0.0	0.0	0.0
20	Water2	145	2.8	0.7	89.7	6.9	0.0	0.0	0.0	0.0	0.0
30	Urban	3 829	1.5	0.0	0.0	92.9	2.7	0.0	0.5	2.4	0.0
40	Range	1 835	0.0	1.7	0.0	7.4	79.1	1.2	0.0	3.8	6.9
50	Crop1	1 536	0.0	0.0	0.0	5.7	4.7	88.4	0.0	0.0	1.2
60	Crop2	2 057	1.7	0.0	0.0	10.2	0.7	0.0	87.5	0.0	0.0
70	Crop3	350	0.0	0.0	0.0	2.0	2.6	0.0	0.0	95.4	0.0
80	Forest	1 973	0.0	0.5	0.0	1.3	1.6	0.4	0.0	0.0	96.2

In this example, of the 470 pixels in the "Water1" training area, 96.4 percent were classified as "Water1"; 0.2 percent were not classified at all (0). Looking down the matrix, "Range" (40) suffered from the worst classification confusion, with only 79.1 percent of the training area classified as "Range".

The average accuracy is the average of the accuracies for each class; the overall accuracy is a similar average with the accuracy of each class weighted by the proportion of test samples for that class in the total training or testing set. Thus, the more accurate estimates of accuracy (i.e., those from larger test samples) are weighted more heavily in the overall accuracy.

In the above example, average and overall accuracy are calculated as follows:

Average accuracy = (96.4 + 89.7 + 79.1 + 88.4 + 87.5 + 95.4 + 96.2)/8

Overall accuracy = (96.4*470 + 89.7*145 + etc. ... + 96.2*1973)/(Pixel sum)

APPENDIX C. BASIC PROGRAM USED TO IMPLEMENT THE BROWSE SUPPLY MODEL.

```
10 ' Program BIOMASS.BAS to find the biomass per ha for FRI polygons
15 B$=SPACE$(10)      ' 23/11/95
20 DIM KGPH(10,5,2)    'I indexes cover type, J development stage, K stocking
25 DIM DS(10,4,3),WG(10),AREA(10)    ' I and J as above, L indexes site index
27 CLS:LOCATE 10,10,1:INPUT "File name (fineasta) ———>",FILE$
30 OPEN FILE$ + ".mod" FOR INPUT AS #1
40 OPEN "KGPH.DAT" FOR INPUT AS #2
50 FOR I=1 TO 10:FOR J=1 TO 5:FOR K=1 TO 2: INPUT #2,KGPH(I,J,K):NEXT:NEXT:NEXT
60 CLOSE #2
70 OPEN "DEV_STG.DAT" FOR INPUT AS #2
80 FOR L=1 TO 3:FOR I=1 TO 10:FOR J=1 TO 4: INPUT #2,DS(I,J,L):NEXT:NEXT:NEXT
90 CLOSE #2
100 ' OPEN "DEER.DAT" FOR OUTPUT AS #2  'Append biomass data to file and write
101                        'out to a new file.  Not currently used.
102                        'Output currently summarized and printed
140 IF EOF(1) THEN 800
150 LINE INPUT #1,A$:INPUT #1,B$      '255 byte string A$ + rest of string
160 WG$=MID$(A$,96,2)              'FRI working group extracted
170 SITE$=MID$(A$,138,1)           'FRI site class
180 AGE=VAL(MID$(A$,128,3))          'FRI stand age
185 ACCESS=VAL(MID$(A$,189,10))        'Accessible area extracted from string
190 STOCK=VAL(MID$(A$,135,3))         'FRI stocking
195 IF STOCK <.7 THEN K=1 ELSE K=2     'Sets the stocking level to K=1 or 2
200 ' Cover type coding based on FRI working group
210 IF WG$="PO" OR WG$="33" THEN I=1:GOTO 500  'Aspen
220 IF WG$="PB" OR WG$="33" THEN I=1:GOTO 500  'Balsam poplar
230 IF WG$="BW" OR WG$="36" THEN I=1:GOTO 500  'White birch
240 IF WG$="MH" OR WG$="22" THEN I=2:GOTO 500  'Hard maple
245 IF WG$="M " OR WG$="23" THEN I=2:GOTO 500  'Maple general
250 IF WG$="OR" OR WG$="28" THEN I=2:GOTO 500  'Red oak
255 IF WG$="O " OR WG$="28" THEN I=2:GOTO 500  'Oak general
260 IF WG$="MS" OR WG$="24" THEN I=2:GOTO 500  'Soft maples
270 IF WG$="OW" OR WG$="28" THEN I=2:GOTO 500  'White oak
280 IF WG$="AW" OR WG$="20" THEN I=2:GOTO 500  'White ash
290 IF WG$="AB" OR WG$="20" THEN I=2:GOTO 500  'Black ash
295 IF WG$="A " OR WG$="20" THEN I=2:GOTO 500  'Ash general
300 IF WG$="BY" OR WG$="26" THEN I=2:GOTO 500  'Yellow birch
305 IF WG$="H " OR WG$="29" THEN I=2:GOTO 500  'Other hardwood
310 IF WG$="S " OR WG$="10" THEN I=5:GOTO 500  'Spruce general
320 IF WG$="PW" OR WG$="01" THEN I=4:GOTO 500  'White pine
```

```
330 IF WG$="PR" OR WG$="04" THEN I=7:I1=4:GOTO 510   'Red pine
340 IF WG$="PS" OR WG$="08" THEN I=7:I1=4:GOTO 510   'Scotts pine
350 IF WG$="SW" OR WG$="12" THEN I=5:GOTO 500   'White spruce
360 IF WG$="B " OR WG$="13" THEN I=3:I1=5:GOTO 510   'I1 indexes species group
370 IF WG$="SB" OR WG$="11" THEN I=6:GOTO 500   'Black spruce
380 IF WG$="PJ" OR WG$="07" THEN I=7:GOTO 500   'Jack pine
390 IF WG$="HE" OR WG$="16" THEN I=8:GOTO 500   'Hemlock
400 IF WG$="CE" OR WG$="17" THEN I=9:GOTO 500   'Cedar
410 IF WG$="L " OR WG$="18" THEN I=10:GOTO 500  'Tamarack
420 IF WG$="OC" OR WG$="19" THEN I=10:GOTO 500  'Other conifer
430 IF WG$="C " OR WG$="19" THEN I=10:GOTO 500  'Other conifer
440 IF WG$="  " THEN 140                  'Blank working group
450 PRINT "Strange code:  ";WG$:STOP
500 ' Branch on the basis of site class
501 I1=I
510 IF SITE$="X" OR SITE$="1" THEN L=1: GOTO 600
520 IF SITE$="2" THEN L=2:GOTO 600
530 IF SITE$="3" OR SITE$="4" THEN L=3:GOTO 600
540 IF SITE$=" " THEN 140
550 PRINT "Strange site code:  ";SITE$:STOP
600 IF AGE>DS(I1,4,L) THEN J=5:GOTO 700
610 IF AGE>DS(I1,3,L) THEN J=4:GOTO 700
620 IF AGE>DS(I1,2,L) THEN J=3:GOTO 700
630 IF AGE>DS(I1,1,L) THEN J=2:GOTO 700
640 J=1
700 '  Use I, J and K (cover type, development stage and stocking level
710 '  to get biomass load (kg/ha) - called KGPH
720 TOTBIO=ACCESS*KGPH(I1,J,K)
730 WG(I)=WG(I) + TOTBIO:AREA(I)=AREA(I) + ACCESS
780 GOTO 140
800 FOR I=1 TO 10
810 PRINT USING "######.#  ######.#";WG(I),AREA(I)
820 SUMBM=SUMBM + WG(I)
825 SUMAR=SUMAR + AREA(I)
830 NEXT
840 PRINT:PRINT USING "######.#  ######.#";SUMBM,SUMAR
900 ' Termination
910 CLOSE
920 PRINT "Fin"
930 END
```

Notes