APPLICATIONS OF SATELLITE REMOTE SENSING TO DEVELOP FOREST INVENTORY FOR STRATEGIC-LEVEL PLANNING

by

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ABSTRACT

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Key Words: Indian Remote Sensing (IRS), Landsat 7 enhanced thematic mapper, image merge, principle component substitution, forest unit, Forest Resource Inventory (FRI), image segmentation, accuracy assessment, user's accuracy, producer's accuracy, omission error, commission error.

Forest inventory is the fundamental base information for most decision-making processes in today's forest management planning. Recently in Ontario, with increasing industrial involvement, new environmental and multiple use issues, and rapidly developing technology, the requirement and opportunity for investigation into new inventory methods has increased. The method developed in this thesis focuses on the inventory requirements for large scale, strategic-level forest management for the boreal forest region. With recent improvement in satellite sensors and computer tools, the process of acquiring the imagery and analyzing the information has become significantly cheaper and faster. A multi-source approach is used in this project to improve upon current forest classification attempts using satellite imagery. By merging the superior multispectral properties of Landsat 7 ETM+ (30 m multispectral) with the spatially detailed IRS-1D panchromatic (5 m) imagery, an attempt is made to derive a species-level classification scheme. Image data merging techniques are explored and the utilization of image segmentation procedures is evaluated. Principle component substitution is used to integrate the imagery, and a nearest neighbour algorithm is used in an object-based classification system. Area-based accuracy assessment is used to test the success of the methods with reference derived from interpreted aerial photography. Accuracy assessments show satisfactory agreement between the thematic product and reference data, with overall accuracies reaching 72%. Pure species groups such as black spruce, jack pine and trembling aspen exhibited producer's accuracies of 90%, 83%, and 87%, respectively, with user's accuracies as high as 73%, 75%, and 61% respectively.

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INTRODUCTION

Forest inventory is the fundamental information base for decision-making in today's forest management planning process. However, forest planning and the maintenance of Forest Resource Inventory (FRI) in Ontario are becoming costly. Inventory requirements are changing to meet the needs of evolving forest practices in the province, and therefore new inventory methods should be investigated.

A forest inventory must contain the essential data required to provide the information needed for forest resource decision-making on all management planning levels. For decades, forest managers have relied on FRI as the principle base for decision-making in all levels of management. This inventory has been the most cost-effective and appropriate descriptor of Ontario's forests for many decades. Recently, with increasing industrial involvement, new environmental and multiple use issues, and rapidly developing technology, the requirement for new inventory development methods has grown stronger (Leckie and Gillis 1995).

Approximately 38% of Ontario's land base is managed by industry (Leckie and Gillis 1995), in the form of Sustainable Forest Licences (SFLs). These SFLs can occupy millions of hectares of land, managed as a single unit. An important element of controlling such large areas is regular updates of change in the forest. With the recent appointment of these SFL areas, the onus has been placed on the licensee to cooperate with government agencies to gather information facilitating inventory update. Until recently, this joint effort by the government and industry has met the needs of inventory requirements. However, like many forest operations in Ontario, the role of forest companies in FRI development has been evolving (Gillis and Leckie 1996), and will continue to do so. Keeping business sense in mind, industrial partners will likely begin to take advantage of new methods for collecting information required for inventory update, including the provision of funds for new research initiatives. Investigated methods should not only be more cost-effective, but also meet the demands of environmental issues and both timber and non-timber related management objectives and concerns. At present, forest companies currently pay for stand level details in FRI that are not used for strategic planning purposes. These stand level details are often not accurate enough for operational planning. If cost savings could be accrued from more efficient FRI systems, it might be possible to invest in more detailed inventories to support operational planning.

As a result, the forest industry's growing role in the assembly of forest inventory in Ontario, and society's demands for more holistic management of the forest, has increased pressure to reduce cost and increase efficiency in development methods. Areas such as parks and reserves are important elements in the large-scale strategies of forest management, but many parks have outdated inventory and some have never been inventoried. Inventory is inadequate in these areas due the high costs associated with inventory development. The assembly of inexpensive methods must occur to facilitate planning in Ontario's parks and reserves. In addition, the idea of landscape management of a large-scale ecological process such as fire or large ranging feature species requires forest inventory that can be applied to both protected and licensed areas.

More efficient methods should allow more frequent update of inventory, facilitating better large-scale strategic planning of the forest on a regional and sub-regional scale. Higher precision of the inventory is also becoming more important as Global Positioning Systems (GPS) play a more integral role in the operational aspects of forest management. The development of new technologies with regards to geographic information systems, image analysis and remote sensing has increased the possible pathways through which inventories might be created.

With recent improvement in satellite sensors and computer compilation, analysis and application tools, the process of acquiring the imagery and analyzing the information has become significantly faster and cheaper. Many current sensors provide adequate data on several dates throughout the leaf-on period of the year. Semi-automated computer procedures allow classification to occur within weeks of the data acquisition date. The turnover time for forest inventory development using satellite data should theoretically be a fraction of this. Semi-automated processes also decrease the level of subjectivity apparent in many manually interpreted photo-based inventories. Guidance from the user is provided for computer applications, but most of the decisions are made in an unbiased systematic fashion by software. In addition to objectivity, semi-automated procedures can be recorded and reproduced. If need be, processes can be slightly altered to meet a desired criteria and re-applied for new results.

Using digital processes to develop forest inventory will increase the precision of the map output. Conventional map-making involves various transfer stages (photo – paper map – digitized coverage), that digital imagery does not require. Once imagery is rectified and classified, areas become digital polygons immediately, reducing positional error resulting from the transfer stages of traditional FRI methods. This increased precision allows for better integration of GPS to manage, operate and monitor forested landscapes.

The approach of this project is to combine the best qualities of two satellite imagery datasets in order to determine if improvements upon current satellite-based forest classification attempts are possible. The first type, Landsat 7 ETM+ data, is utilized to gain the spectral leverage required to answer questions about the landscape. Landsat 7 possesses multi-spectral capabilities that outweigh any of its competitors at a fraction of the cost. However, the 30-metre spatial resolution of Landsat limits its spatial capability in terms of practical use in forestry application. What is needed to improve the effectiveness of this type of multi-spectral data is higher spatial resolution that may be used with the newest knowledge classifiers available. This project will investigate the benefits of the Indian Remote Sensing (IRS) satellite, a 5m resolution dataset covering a much greater area per scene (4900 km^2) than most high resolution sensors available today. The intent is that the enhanced spatial resolution of IRS integrated with the Landsat multi-spectral data may provide better information about the forest canopy, not available from each of the datasets alone. The abundance of sensors available for use, at a reasonable cost/km^2, has resulted in the ease of providing multi-source classification methods enabling datasets from different sensors to complement one another (Czaplewski 1999).

The combination of Landsat and IRS may be the solution to providing a rapid, detailed inventory turnover for large license areas. Furthermore, assessment of this dataset may give an initial indication of the potential of new sensor data (0.65-4m) presently on the market, however currently too expensive for wide area use.

The major goal of this work is to provide a new method for creating large scale (e.g. SFLs) forest management-level inventory that has:

- increased spatial accuracy as well as adequate level of information and reliability for strategic planning purposes;

- a higher cost-efficiency than current forest inventory requirements; and,

- a considerably shorter turnover than traditional methods of current inventory development in Ontario.

Two supporting objectives are to:

-Test the benefits and limitations of the IRS-1D Panchromatic sensor data as a complementary data set to Landsat 7 Thematic Mapper data; and,

-Test a new classification concept - image object segmentation to stratify the forest into forest units with similar levels of accuracy presently achieved through FRI-based methods.

LITERATURE REVIEW

FOREST INVENTORY

New government initiatives, shifting social values and increased use of forest inventories have forced a re-evaluation of the current forest inventory practices. More accurate, reliable, and timely inventories are required to accommodate public expectations, interest and involvement in land and resource management decisions, timber supply reviews, and new forest practices legislation (Gillis and Leckie 1996). This shift in social values increases the number of users of the forest inventory such as tourism outfitters, biologists and private landowners. These users have very little involvement in the creation of inventory, but depend on its range, reliability and accuracy.

Leckie and Gillis (1995) place forest inventories into three categories: extensive reconnaissance-level inventories; operational-level inventories; and, forest management-level inventories. Extensive reconnaissance-level inventories provide the manager with general strategic level information, whereas the operational-level inventories provide the user with location specific estimates required for harvest planning on commercially forested land. The current Ontario FRI was originally designed with the intent to assist primarily with timber supply characteristics of forest cover for commercial operational-level inventories (Treitz and Howarth 2000). Forest management-level inventories, on the other hand, contain information useful in terms of long-term planning and decision making for all types of forest use. The current cycle for management-level inventory update in Ontario takes place in 20-year interval (Gillis and Leckie 1993). The entire inventory procedure for an average sized management unit in the province takes approximately three years to complete (Gillis and Leckie 1993).

Presently, 9x9 inch (23cm x 23cm) aerial photography and human interpretation combined with targeted reconnaissance fieldwork help to create the current forest inventory for managed forests in Ontario (Gillis and Leckie 1996). Since the development of FRI in Ontario in 1946, aerial photography has been the most affordable method of remote sensing available to the government.

In Ontario, a scale of 1:20,000 is photographed using black and white, stereo, aerial photography and interpreted into stand-level segments, or polygons, with the help of field data collected by ground crews as truth information. This level of inventory contains details about the current state of the forest such as tree species, age, height, stocking and site class at the stand level (Gillis and Leckie 1993). In Ontario information is compiled into homogeneous groups, or forest units, for planning purposes. Forest units are aggregations of forest stands, which normally have similar species composition, develop in a similar manner (both naturally and in response to silvicultural treatments) and are managed under the same silvicultural system (OMNR 1996). Although space borne remote sensing media has not achieved the detail and detection capabilities of finely delineated forest stand structure distinguished by aerial photography, it is hypothesized that certain media and methods may allow detection of forest unit (i.e. Jack Pine Pure, Black Spruce Lowland, Mixed Hardwood, etc.) and seral stage (immature, mature, over mature) delineation.

Expectations of satellite data in the development of forest inventory were high in the 1970's. However, limited properties of available sensors lead to disappointing results. These shortcomings caused hesitation into the use of new sensors that have emerged in the last 20 years. In recent years, the cost of space borne imagery has decreased significantly, and technological advancements have enabled sensors to collect imagery with extraordinary resolution. These new capabilities for higher resolution are now becoming the focus of many researchers interested in attaining information about forested landscapes. As technological advances further improve these tools, their capabilities must be constantly tested to determine how they will fit in the development of forest inventory now and in the future (Pitt *et al.* 1997). In addition, the decreasing cost of the imagery is making research into high resolution satellite data more plausible and attractive for industrial partners.

HISTORIC REVIEW OF SATELLITE REMOTE SENSING

Differences between space-borne sensors occur primarily in their spectral and spatial properties. Multispectral sensors collect various types of reflectance of the earth's surface in the form of image bands. These bands are used individually or integrated together to delineate different features of the landscape. Spatial detail of an image is often referred to as its resolution, or area scanned on the ground by the sensor, and then contained in a single pixel of the image. A pixel of an image possesses a digital number or brightness value associated with the reflectance properties of the area in which it represents on the ground. Pixel properties vary in size, depending on the resolution capabilities of a sensor, and brightness, depending on the multi-spectral characteristics of the sensor.

The first challenge with current remote sensing tools is acquiring large areas of multispectral data, with an acceptable level of spatial detail for detecting the differences in forest structure. The next challenge lies in the repeatability of the classification system developed in order to reproduce consistent, continuous landscape assessments to facilitate large areas (Franklin *et al.* 2002b), such as northern Ontario. With a classification system in place in one region of the province, other regions may follow suit, with limited field verification.

A few issues currently exist with regard to forest mapping at regional levels using satellite remotely sensed data. Martin *et al.* (1998), King *et al.* (1999) and Franklin *et al.* (2001) have explored the benefits of high resolution multispectral and hyperspectral data for forest mapping using various types of sensors. Hyperspectral imaging, which can also be referred to as imaging spectrometry, differs from conventional remote sensing in that it covers many narrowly defined spectral channels, where as, conventional remote sensing looks at several broadly defined spectral regions (Jenson 1996). Each of these studies succeeded in semi-automated delineation of forest structure at the species and age-class level; yet, cost of imagery has limited these studies to achieving their successes allowing only small subsets of data. The decreasing cost of medium resolution satellite imagery (e.g. Landsat 7, SPOT 4) has stimulated many research projects involving large scale forest classification in the past 10 years. Many of these studies have taken advantage of multi-source image approaches, either in a multi-temporal context using same sensor data from different dates (Bauer *et al.* 1994; Schriever and Congalton 1995; Mickelson *et al.* 1998), or in a multi-sensor circumstance capitalizing on the benefits from different sensors and their respective resolutions and spectral ranges (Schistad Solberg *et al.* 1994 and Vrabel 1996). Both pathways have had individual successes in enhancing the effectiveness of Landsat TM in terms of forest landscape classification. In current literature, medium resolution (10 to 30m) satellite data has not been the choice tool for ageclass determination in forest stand structure. Successful studies in determining significant results when developing and monitoring age of forests have used high resolution data to make accurate conclusions (Shugart et al 2000). In light of these discoveries, one may conclude that 5m resolution data may be challenged when asked to disclose age information within forest stands.

Multispectral Remote Sensing

Landsat data have proven to be a valuable source of satellite data for many classification studies in the last 30 years, primarily due to its large array of spectral properties, and vast coverage area for a fraction of the cost compared to other sensors (Karteris 1990; Scott *et al.* 1996; Homer *et al.*1997 and Pax-Lenny *et al.* 2001). The Landsat TM provides images approximately 180x180 km at a very affordable cost (\$0.05/km^2, Canadian Dollars (CAD)), and although Landsat TM data is superior to any sensor currently on the market as far as multispectral imagery is concerned, this superiority is accompanied by a disadvantage. The resolution of 30m limits the data to identifying and mapping only a few broad categories of forest cover on its own (Jakubauskas 1997 and Czaplewski 1999). In a forest understory research project, Ghitter *et al.* (1995) suggest that improvements in the use of TM data may be derived from image texture analysis, due to the patchy nature of the regeneration and variable species mixture in the overstory. The relatively coarse resolution of these data is prone to pixel noise, or spectral response of two or more classes in one pixel.

In Ontario, an attempt to classify at a large scale was recently made in the Ontario Land Cover Database (OLCD). Landsat 5 Thematic Mapper (TM), a multispectral, medium (approx 30 metre) resolution sensor, allowed the OLCD to avoid traditional turnover and cost issues related to aerial photography based inventory. While the results of the classification provided a consistent thematic landscape cover of the entire province, the data permitted only broad-level classification of the forested landscape. This should be expected as literature illustrates that even the relatively coarse resolution (30 m) of the Landsat 7 sensor has had little success classifying to levels beyond Anderson level II (conifer and deciduous) in single date imagery studies (Wolter *et al.* 1995). The Landsat 7 satellite also possesses a 15m resolution panchromatic band which has been merged with the 30m spectral resolution in recent studies (Liu 2000). Recent trends (Mickelson *et al.* 1998) focusing on the use of Landsat's spectral imagery from different dates throughout the snow free time of year have incorporated a multi-temporal component into their method of classifying hardwoods in northern Massachusetts to accuracies as high as 79%. The combination of six reflective bands each from spring, summer, and fall Landsat

TM images to create an 18-band composite allowed for genus level forest classification. The study was able to delineate a total of 33 forests types, 20 of these dominant and the remainder sub-classes representing differing understory components within the 20 dominant classes.

Schriever and Congalton (1995) found that advances in spatial and spectral properties of satellite data (the progression from Landsat 1,2,3 MSS to Landsat 4,5 TM) allowed them to analyze the same scene from three separate dates (spring, summer, and fall) to explore whether leaf phenology assisted in the classification of northeastern hardwoods. Through the use of different combinations of bands from each image and experimenting with multiple types of classification systems, the study determined that seasonal variability assisted in the 74% overall accuracy result. A common denominator among these studies is the fact that they all used study areas consisting largely of hardwood species, to enhance the effect of phenological processes on different dates of satellite imagery. Although effective in hardwood dominated forests, the northern boreal forest is dominated by conifer species small windows of visible phenological reaction to the change of season are difficult to capture with satellite visits, and may not be suited for this type of image analysis.

Hyperspectral Data

Martin *et al.* (1998) demonstrated species separation with accuracies of 75% for 11 forest class types, including pure and mixed stand of deciduous and conifer species. The data used in this study were collected by an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor, and analyzed at the hyperspectral level. Hyperspectral sensors also have a high cost/km^2 associated with their data collection, thus making them useful for small sample areas, and not very practical for large continuous coverage.

High Resolution Data

The most significant advance in multispectral sensor resolution initiated with the IKONOS-2 satellite project which was launched in the summer of 2000. This sensor collects four multispectral bands at a 4m resolution, along with a single band of panchromatic 1m data. Panchromatic capability is present on many sensors available today, often at a higher resolution than the spectral scanning capability of the satellite. The panchromatic band of data is created by a sensor scanning a wide section of the colour spectrum from approximately 500 nanometres (nm) to 750 nm (varies with each sensor), resulting in an image with higher resolution. The image is a single band, allowing it more spatial detail, without compromising storage space on board the sensor. Data from IKONOS are currently priced at $18.00 to $27.00/$km^2$ (CAD), often too expensive for large area use. Regardless, research trends show that as image texture increases in forest conditions, more detailed information may be extracted from the data. Franklin *et al.* (2001) used the panchromatic data successfully to separate age classes within Douglas Fir (*Pseudotsuga menziesii* (Mirb.) Franco) using various texture measures.

Using a pixel-based classifier and small subsets of Russian MK-4 multispectral satellite photography in eastern Ontario, King *et al.* (1999) achieved an overall accuracy as high as 48% with some forest classes between 50% and

75% in user's and producer's accuracy. The resolution of this data was approximately 7.5 m in resolution. The modest overall accuracies were attributed to lack of classification and accuracy methods sensitive to the spatial variance of such high resolution data.

The IRS project serves as an important national goal in India, in terms of providing continuous, operational services for the management of the natural resources of that country (Chandrasekhar *et al.* 1996). For the purpose of this study only IRS-1C/1D will be discussed in detail. These sensors were launched in 1995 and 1997 respectively, and each satellite possesses three different types of sensors. Chandrasekhar *et al.* (1996) describe the first as a multispectral Linear Imaging Self-Scanner (LISS-III) in visible and near-IR spectral bands with a spatial resolution of 23 m. The second is a Wide-Field sensor in visible and near-IR bands, with a spatial resolution of 188 m and a swath width of approximately 800 km. The third sensor, most applicable to this study is a 5.8 m 6-bit panchromatic sensor with across track stereo viewing capability, and a swath width of 70 km. The cost of this data is approximately \$1.00/km^2. This panchromatic data is of interest for this study as an enhancement tool to Landsat spectral data. Each panchromatic sensor has a 48-day revisit capability, providing 24-day revisit coverage as the two sensors are staggered evenly in orbit.

In the past, IRS-1C panchromatic images have been used in forest mapping applications overseas in Europe and Asia (Roy *et al.* 1996; Rao *et al.* 1996; Krishna Prasad *et al.* 1998 and Saraf 1999) as well as in Canada (Savopol and Armenakis 1998 and Armenakis and Savopol 1998). In North America, IRS panchromatic has been used extensively as an image backdrop tool, but little as an accompanying texture in classification processes. The province of Alberta has used this type of imagery to create an image mosaic of the entire province, and is currently using the data to assist with update of roads, oil exploration, and agriculture developments. The state of New Mexico has recently used the data for the same purpose.

Several forest product companies in northwestern Ontario have used the imagery to map forest depletion (e.g. harvest areas, natural disturbances). Data vendors currently offer a 5m orthorectified colour product, using IRS panchromatic data in combination with Landsat 7 spectral data. Cheng and Toutin (1998) discuss some of the advantages of IRS-1C, including its large scale of coverage, while still maintaining a relatively fine resolution. They also briefly discuss positive results for mapping and classification methods using IRS-1C in Germany and Switzerland.

Recently, Hoffman *et al.* (2001) experimented with the IRS-1C panchromatic sensor in a study that compared the effectiveness of its qualities against those of IKONOS-2. LISS-III bands were merged and re-sampled to 5 m with the panchromatic band, and then tested against the IKONOS-2 data. Although the study concluded that IKONOS-2 performed slightly better in certain circumstances, it also pointed out the effectiveness of IRS-1C, especially when detecting land cover or land use change. Certain features of the landscape did cause problems for classification of the IRS-1C data merge, possibly due to the lack of spectral information in the LISS-III data.

Multi-Source Remote Sensing

The goal of multi-source remote sensing is to collect an accompanying sample of imagery with additional information (higher resolution or a new spectral band), and improve the capabilities of the classification system (Czaplewski 1999). In order to gain full multi-source coverage of an area, the auxiliary data must be carefully selected. Also, the method of integration of multi-source data should be selected depending on the properties of data, to avoid image artifacts and error associate with atmospheric or sensor angle differences (Pohl and Van Genderen 1998).

Many scientists have attempted to gain better results by simply accompanying the high resolution data with larger scale medium resolution. A current study by Mizon (2003) uses IKONOS-2 4m multispectral subsets (5 subsets x 100 km^2) within the extent of a Landsat 7 coverage. Attempts were made to classify each subset into forest units, and then incorporate these thematic results as training areas within the Landsat data.

In a study using 2.5m resolution multispectral Compact Airborne Spectrographic Imager (CASI) data, Franklin *et al.* (1994) worked on separating pure and mixedwood stands of different densities and heights. Various combinations of the CASI and Landsat TM data yielded accuracies above 90% in the Sub-alpine Forest Region west of Calgary, Alberta. Recently, incorporating spectral and textural data from 8m resolution airborne multispectral video images, Franklin *et al.* (2000) have achieved 65% accuracies in species level classification in both Alberta and New Brunswick.

In the past, a cheaper multi-source classification system included data from Landsat TM and SPOT-PAN, a single panchromatic channel collecting a resolution of 10m (Chavez *et al.* 1991; Shettigara 1992; Pellemans *et al.* 1993). Munechika *et al.* (1993) improved the accuracy of a general Landsat TM classification by six percent while testing new merging methods for fusing the panchromatic SPOT band to the Landsat TM data set. More recently, Salajanu and Olson (2001) attained an accuracy of 60% for a 19-class species level classification by integrating SPOT-PAN with Landsat 7. The classifier used was a supervised maximum likelihood decision rule, based on individual pixel values.

Shaban and Dikshit (2002) completed an urban classification study using multispectral (20m resolution) and panchromatic (10 m resolution) data from SPOT 4 as merged data. The study experimented with various merging algorithms such as the Price algorithm and high pass filters of various windows sizes, along with the effects of simply including the high resolution textural band with the spectral data. The study concluded that the addition of the SPOT 4 panchromatic band to spectral bands of lower resolution significantly increases the classification accuracy compared to a classification using only original spectral bands. It also concluded that both of the merged datasets possessed inter-class variance problems, enhanced by the heterogeneous patterns of urban landscape, consequently confusing the per-pixel classifier. This inter-class variation is not uncommon in high resolution imagery covering forested landscape, and must be resolved in order to take advantage of new satellite image products.

Image Texture

Image texture is defined in many different ways, depending on the data and goals of the research project. Franklin *et al.* (2000) provide a definition that is most applicable to this study when they state "...texture information represents the spatial variation in image tone (i.e. digital grey values) that is the result of the arrangement of forest vegetation and other objects in a digital image." Individual pixels carry these digital grey values, and with increased texture in imagery the importance of quantifying the surface patterns created by pixel groupings has increased, in order to avoid confusion among classifiers traditionally caused by high spatial variance (Blaschke and Stroble 2001). Smith and Fuller (2001) briefly address the difficulties of successfully classifying high resolution imagery with traditional per pixel classifiers. Some studies have used smoothing filters to eliminate this high spatial variance in order to improve classification results (Cushnie 1987). On the other hand, image texture information has been extracted using filter algorithms of various window sizes (Kushwaha *et al.* 1994; Ryherd and Woodcock 1996 and Kiema 2002), as well as Grey Level Co-occurrence Matrices (GCLM). Filter methods measure the pixel and its neighbourhood to assess the variance of the pixel grouping and then use the variance as a value for the single pixel. GCLMs use second order probabilities to identify periodicity and structure within object texture through a variety of texture matrices (Marceau *et al.* 1990; Kushwaha *et al.* 1994; Franklin *et al.* 2001).

Narasimha Rao *et al.* (2002) have reported success in a general landscape analysis (plantation, shrub, sparse forest, dense forest) using the IRS-1D panchromatic sensor to identify patterns in second order texture measure computed by GCLM. The resulting image, produced by filters or the GCLM method, containing more generalized textural information, can be used as an accompanying data layer in a classification. Although utilization of texture has been successful in most cases, the previous examples represent only initial attempts to increase the benefits of high resolution data.

For instance, classifiers that assign classes to pixels based on not only their immediate neighbours, but also proximity to relevant objects in the image, are called contextual classifiers. Recently, (Debeir *et al.* 2002) demonstrated the improvement to accuracies by introducing context into their classification system. The study proved that contextual classification had limitations when tested window sizes were inadequate for varying sizes of homogeneous spectral zones, causing misclassification along the edges of these regions. The study also concluded that the introduction of textural and contextual might have contributed to some image artefacts, leading to problems with the final classification. (Stuckens *et al.* 2000) also confirmed the benefits of using contextual classifiers when they improved the accuracy of their classification by 5.8%.

The traditional methods of using textural information to create new auxiliary layer containing surface pattern information has intiated the importance of shape recognition in new classifiers (Green 2000). Intelligent classifiers, with human-like decision recognition capabilities are beginning to revolutionize the way finely textured data is used in classification systems. The term "segmentation" has been used to describe this sort of shape delineation. Segmentation can also be defined as the grouping of pixels forming areas with common criteria of homogeneity (Willhauck 2000).

Image Segmentation

Nel *et al.* (1994) pointed out the weaknesses of texture when used in the traditional pixel based supervised classification methods. Incorporation of texture into the classification did not improve differentiation between old growth and younger stands. This indicates that traditional classifier may not be taking advantage of the additional information contained in higher resolution imagery.

Traditional pixel based classification methods, which use only the spectral information from each pixel to allocate it to a certain class, subdivide the landscape into an arbitrary grid system inadequately related to the actual landscape structure (Smith and Fuller 2001). The resulting classification of higher resolution data takes on a "salt and pepper" appearance. By grouping these pixels into more meaningful relationships, image segmentation attempts to eliminate pixel noise problems. Once pixel groupings occur the user is left with meaningful polygons that may be integrated into GIS inventory for creation or update purposes.

Object orientated segmentation has been applied successfully in many agriculture and urban studies (Blaschke and Hay 2001, Schiewe *et al.* 2001), where object shapes and boundaries are more concrete and relatively simple to classify. In data where object shapes and boundaries are not as obvious, a key to correctly applying image segmentation is choice of scale. The extraction of meaningful image objects needs to take into account at what scale the problem may best be analyzed (Baatz and Schape 2000). A difficulty of using image segmentation for forested land cover is deciding what scale is appropriate for each problem. For example, inconsistency in stand size and composition make it difficult to assess the quality of the segmentation results for a forested image. For this reason, visual inspection is still a reliable practice in high resolution image classification (de Kok *et al.* 1999). Also, the level of operator understanding as well as prior knowledge of the properties and potential of segmentation can assist in deciding whether its use is warranted (Stuckens *et al.* 2000).

IMAGE MERGING

With the increasing availability of satellite data, fusion of digital image data has become a helpful tool for evaluation of remotely sensed imagery. As each sensor is designed with specific strengths, data from multiple sensors may compliment one another when fused correctly. Finding the method that suits each combination of sensors and the particular images being used can be challenging. Pohl and Genderen (1998) advise the user to ask the following questions before choosing the data and the method of fusion:

1) What is the objective/application of the user?
2) Which types of data are most useful for meeting these needs?

3) Which is the best "technique" of fusing these data types for that particular application?
4) What are the necessary pre-processing steps involved?

Also highlighted, are the three levels in which a fusion may take place from small scale to large scale: the pixel, the feature, and, the decision level. The pixel level fusion simply incorporates the measured physical parameter of pixels from each image, while the feature level uses previously extracted objects corresponding to characteristics in each dataset, otherwise referred to as segments. Similar objects from multiple sources are assigned to each other and then fused for further assessment using statistical techniques such as Artificial Neural Networks (ANN) or Grey Level Co-occurrence Matrices (Paola and Schowengerdt 1997). Decision level fusion uses value added data where the images are processed individually for information extraction. The information is then combined applying decision rules to reinforce common interpretation and resolve differences (Shen 1990). In Shen's study, fusion at the pixel level was used to derive more meaningful objects from a combination of the pixel data using both images. Fusing pixels before extracting features from each dataset avoided potential boundary discrepancies when fusion took place. Pixel fusion will be described in more detail than the other two levels.

When attempting a pixel level fusion of two or more images, image acquisition plays a significant role success of the fusion. Changes in the area between the acquisition dates of the imagery may influence success of the fusion product (Pohl 1996). Quality of the fused product will increase as the interval between image dates grows closer. Also, geometric accuracy should be high in order to avoid image artefacts and misinterpretation in pixel based fusion results (Pohl and van Genderen 1998). Pixels registered to each other should refer to the same object on the ground. Another pre-processing step important to the final results of the fusion is radiometric correction or normalization. Sensor-specific differences as well as atmospheric variations between dates may cause problems with fusion results (Pohl 1996). To properly monitor the effects of spatial enhancements including filters and edge enhancements on the properties of each image, these procedures should take place before the image merging process (Pohl 1996).

The idea of merging multi-sensor data has been implemented by researchers for a number of years (Dougay *et al.* 1987; Essadiki 1987; Harris *et al.* 1990 and Ehlers 1991). Merging has been used in the past with two objectives in mind. The first, for an end product that is more visually interpretable (Van Der Meer 1997), and the second, for semi-automated classification procedure enhancements (Munechika *et al.* 1993). Most merging methods use similar concepts when integrating data; however, some are more appropriate for each of the previously mentioned objectives. Multispectral images are composed of two main elements, spectral and spatial components (Munechika *et al.* 1993). When attempting to create a product that is visually more effective, the user has little concern for subtle spectral alterations to the original dataset, as long as what the interpreter's eye detects makes sense. However, when attempting to achieve the second objective, often performed statistically in a computer process, these subtle spectral alterations may cause spectrally separable targets in the original data to become inseparable (Chavez *et al.* 1991). When testing various fusion methods, trends show that with the increase of spatial resolution, a relationship exists in terms of the effect on colour saturation, or spectral properties of the image (Tu *et al.*, 2001). The goal of the fusion is to increase the spatial resolution of the dataset, while limiting the distortion of the original spectral characteristics of the data (Shettigara 1992).

A review of the merging techniques used by other researchers is required to determine which method is best suited for the data used and objectives stated in this report. More recent methods include: Intensity Hue Saturation (IHS); Principle Component Substitution (PCS); Wavelet transforms; and, Brovey transforms.

The Intensity Hue Saturation merging method uses a colour transform, whereby the Red-Green-Blue colour space of the spectral image to be enhanced is transformed mathematically into the Intensity-Hue-Saturation colour space. The band of interest is the intensity layer, which by definition represents the spatial variation, or high frequency data, from the image (Pohl 1999). These high frequency data contain many of the same properties as the panchromatic data, however, at a much lower resolution. The panchromatic image is then substituted for the intensity layer and the colour space is then transformed back to the original RGB colour space. The result is a new image, with high resolution intensity properties (Carper *et al.* 1990). A drawback of using this method is noted, as the colour space transformation allows only three multispectral bands to be included in the process. This omits potential information stored in the remaining three bands not included in the transformation. The process may be repeated on the other three bands, but all six bands will never interact simultaneously in the transformation to develop the intensity layer.

The PCS method is similar to the IHS merging technique, in that a transformation and substitution of bands also takes place. However, rather than being limited to a three channel transformation, all available bands may be included in a principle component transformation of the multispectral image. The first principle component (PC1) of the transformed image is said to account for large amounts of variation in the data (Ricotta and Avena 1999). This variation can be described as similar to the intensity information produced by an IHS transformation, and furthermore, comparable characteristics to the associated panchromatic data (Chavez *et al.* 1991). In fact, it has been documented that the PC1 layer is often better correlated to the panchromatic data than is the intensity image in many previous studies and for this reason is generally more successful at minimizing the spectral distortion common to merging methods (Chavez *et al.* 1991). A substitution of the PC1 layer by the panchromatic data takes place, and the inverse principle component transformation is created. Like the IHS merge, the new data preserves the spectral characteristics of the original data with the spatial properties found in the panchromatic data. The PCS method has been criticized in the past for an uneven mixture of the TM bands in the first principle component, thought by Zhou *et al.* (1998), to lead to variations in spectral and spatial quality in some bands. However, others have praised this method for achieving better results than the IHS merging technique, as well as other methods tested (Chavez *et al.*, 1991; Tu *et al.* 2001).

Another commonly applied merging technique involves layer ratios and multipliers to gain a sharper image appearance. Brovey transforms have been used in previous studies (Van Der Meer 1997) and although the results are impressive visually when compared to other methods, Brovey Transform tends to have difficulty maintaining image properties. It was originally developed to visually increase contrast in the low and high ends of an image's histogram (Van Der Meer 1997), allowing for more appealing visual image characteristics.

There have been many models created by researchers over the years that use the concept of differentiating high frequency image properties from low frequency image properties (Zhou *et al.* 1998, Sanjeevi *et al.* 2001). Wavelet merging techniques are based on the principle of removing the low frequency data from the high resolution data and using only the high frequency data in the merging process. It is thought that the low frequency data contained in the high resolution data is the cause of radiometric distortion. There are two types of similar wavelet methods, additive and substitution. Both involve the subtraction of the panchromatic layer from a smoothed version of itself to obtain only the high frequency data, also thought of as texture or heterogeneous data. The substitution method replaces the high frequency details of multi-spectral images with the panchromatic image. The resulting data are then re-combined with the residual low frequency of the multispectral image, also thought of as colour saturation or homogeneous data. Additive methods add the high frequencies of the panchromatic image to the high frequencies of the multi-spectral image.

In contrast to other merging techniques, the level of detail in wavelet transforms is adjustable rather than fixed, as it is controlled by the level of high frequency data extracted from the high resolution data in both substitution and addition methods. The additive method appears faster, more efficient, and unlike the substitution method, next to no decomposition of the multi-spectral data occurs. However, there is a cost associated with wavelet transformations. The total preservation of radiometric properties in each of these cases reduces the level of spatial enhancement of the final product. When performing an image merge, the challenge is to find an acceptable limit to radiometric distortion of the image, while concurrently finding a balance between radiometric loss and spatial gain.

At present, researchers have documented few quantitative methods to evaluate the performance of various image fusion techniques; most evaluation is based on visual inspection. Correlation has been used by a few to justify best relationships between data sets (Carper *et al.* 1990; Pohl and Van Genderen 1998; Tu *et al.* 2001 and Teming *et al.* 2001). Once a successful evaluation of each method is accomplished, the data may hold new information, useful to a classifier.

ACCURACY ASSESSMENT

The final but very essential aspect of any landscape classification involves the evaluation of the resulting thematic layer product by assessing the information assigned within each pixel or polygon as well as the spatial accuracy of mapped elements. Both quantitative and qualitative methods have been used to evaluate map integrity. Traditional quantitative methods usually involve point-based error matrix calculations and have been widely utilized to evaluate the accuracy of thematic maps created by satellite imagery on a pixel-by-pixel basis (Foody 2002). Qualitative methods to validate work have historically consisted of general visual inspection of mapping results (Congalton 1994). For the purpose of this study an attempt to quantitatively assess the error has been attempted.

The method of classification is an important consideration when deciding an appropriate quantitative accuracy assessment strategy. Congalton and Green (1999) point out that evaluation using polygon-based sample units is acceptable and may be more suited to users more interested in polygon detail. For the purposes of this study, a polygon-based error assessment may be required due to the nature of the segment object-based classification methods.

The reference data may be collected from the ground, and although expensive, gives the users a “true” indication of landscape information. A less costly means of collecting this reference data may include interpretation of aerial photographs, depending on the required level of detail by the user (Congalton and Green 1999). Franklin *et al.* (2002a) found that comparison of ground areas from satellite-derived classification to identical areas on orthophotographs by means of visual interpretation gave a more representative estimation of map quality. The report added that per-pixel map accuracy compilations did not always provide an understanding of the spatial distribution of map error.

METHODS

STUDY AREA

The study area is located within the Caribou Forest, under licence to Bowater Pulp and Paper Canada Inc., in the northwestern portion of the province of Ontario (Figure 1) and was selected for a number of reasons. First, the Caribou Forest possesses a relatively low intensity of forest management activity compared to other forest licenses in northwestern Ontario. This is important in terms of data acquisition, especially when using imagery from two or more dates, as differences in ground properties between images will increase error in the integration process.

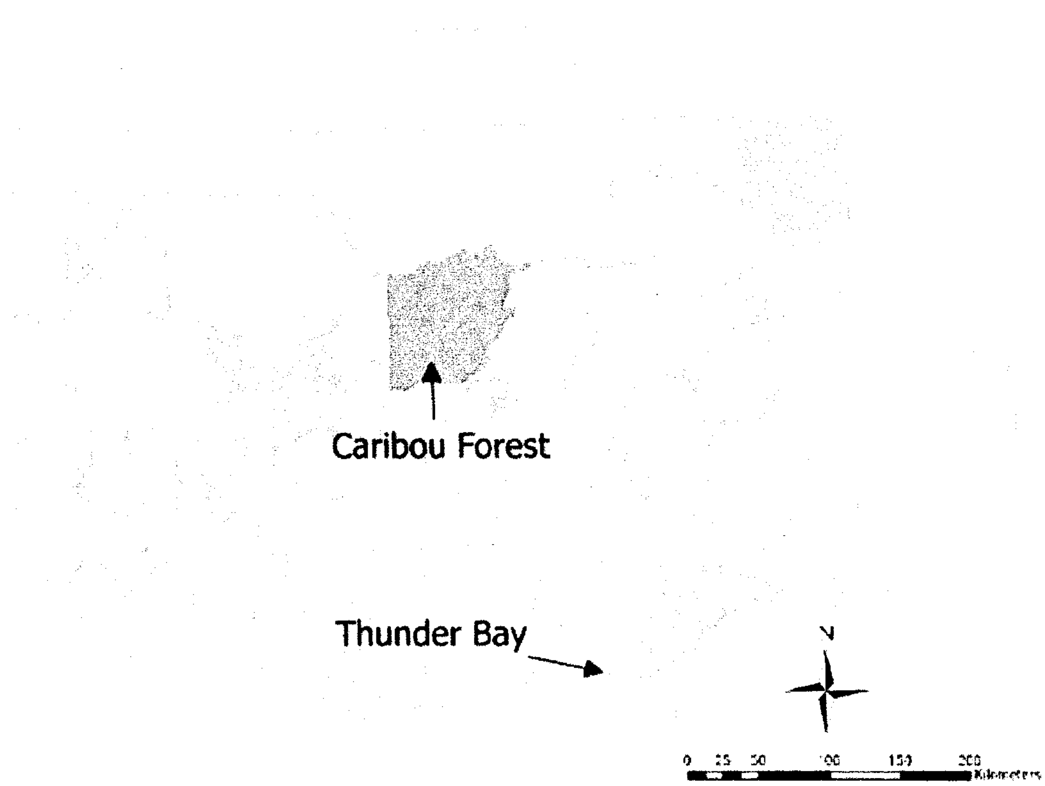


Figure 1. The Caribou Forest licence.

The second reason for selection pertains to the recent focus by the provincial government to garner wood supply from more northerly areas and to manage parks with regard to biophysical characteristics. It was selected to relate the results to many more future large-scale inventory projects expected to take place in areas in the Northern Boreal region of Ontario with similar landscape characteristics. The "Northern Boreal Initiative" (NBI) involves a vast area of land north of existing forest licenses in Ontario for forest management. The area covered by NBI is one of the world's last great intact forests and is part of a 6,500 kilometre arc of frontier (large, ecologically intact and largely undisturbed by industrial activities) forest from Newfoundland to Alaska. Located north of approximately 51 degrees latitude, this area is approximately 37 million hectares is size (Wildlands League 2002). Forest inventory for this area has not yet been developed, and is an ideal subject for satellite remote sensing, primarily due to its lack of access. Developing the area north of the 50^{th} parallel has become a factor in the province's future plans for wood allocation. Classification of this forest will allow for better understanding of the challenges associated with attaining satellite imagery based inventories further to the north. A crucial step in the NBI will be the creation of inventories for areas of the far north, generating the need for exploration into new inventory methods designed for these areas.

Further, new initiatives to develop management strategies in the province's parks have instigated the need for updated forest inventories for these parks. As the Caribou Forest is adjacent to Wabakimi Provincial Park, results from this study would apply to possible inventory development designs in this and potentially other park reserves in the province.

The fourth reason for conducting the study in the Caribou Forest relates to the abundance of existing ground control data stemming from initiatives taken on by the licensee.

Figure 2 shows the Caribou Forest limit and lakes exclusively with the study area boundary included. The study area encompasses approximately 174,792 hectares of the total 547,460 hectares of forested land within the licence. The composition of the Caribou, based on the current forest management plan, is dominated heavily by conifer species. Black spruce (*Picea mariana* (Mill) BSP.) is the primary conifer species, and accounts for approximately 75% of the total forest composition. Jack pine (*Pinus banksiana* Lamb.) is the second most significant conifer.

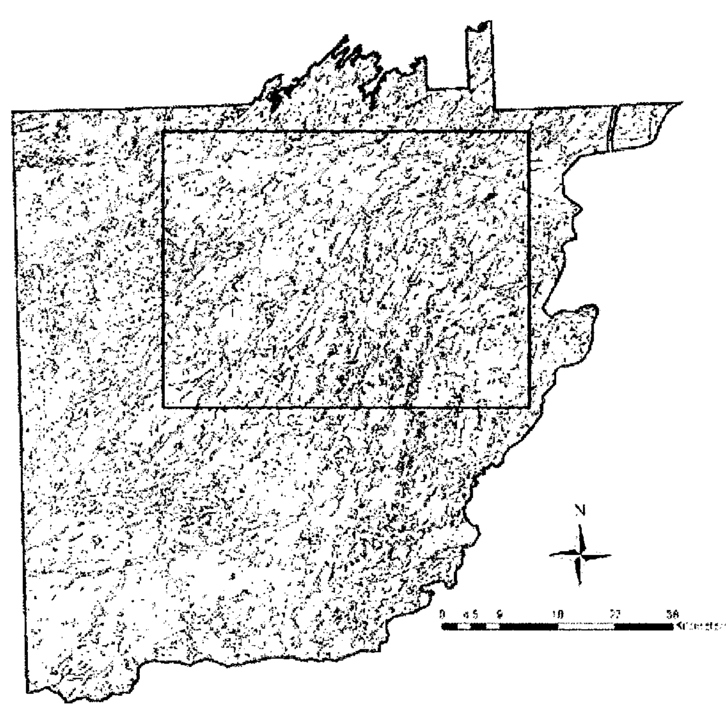


Figure 2. The study area contained within the Caribou Forest.

White birch (*Betula papyrifera* Marsh.), balsam poplar (*Populus balsamifera* L.) and trembling aspen (*Populus tremuloides* Michx.) make up all hardwood stands. Table 1 provides information for the species found in this forest at the working group level.

Table 1. Caribou forest working groups by area.

Working Group (Wg)	Hectares (Ha)	%
Black Spruce	413888	75.60%
Jack Pine	84385	15.41%
Poplar	39293	7.18%
Birch	6942	1.27%
Cedar	1453	0.27%
Balsam Fir	1090	0.20%
Larch	373	0.07%
White Spruce	37	0.01%
Total	**547,460**	**100%**

SOFTWARE TOOLS

A number of software tools are used in the data preparation and analysis stages of this project. Software packages by Environmental Systems Research Institute (ESRI) - ArcGIS and Arcview were used to manage vector database information. Erdas Imagine 8.5 was used for pre-processing and accuracy assessment stages of the process. Segmentation and classification of the imagery was performed using Ecognition 2.0. General data compilation and analysis was performed using SPSS 9.0 and Microsoft Access 2002.

FOREST CLASS DESCRIPTIONS

The forest cover was grouped into classes referred to as forest units. These forest units were derived based on FRI characteristics created to group areas that can be managed using similar silviculture prescriptions. Forest unit agglomerations were made using species composition as a primary indicator, as well as ecosite classification, to distinguish between forest units. Table 2 provides information of the forest units present in this forest as well as the FRI parameters used to assign these designations.

Table 2. Common[1] forest units and corresponding FRI parameters in the Caribou forest.

Forest Unit	Code	Main Working Group	FRI Parameters
Spruce Lowland	SPL	Spruce	Ecosite in (34, 35, 36) or Ecosite = 37 and Sb >= 7
Spruce Upland	SPU	Spruce	Wg = Sb or Sw, and Sb+Sw >= 70% and Po+Bw <= 20%
Jack Pine	PJ1	Jack Pine	Pj >= 60% and Po <= 20%
Poplar	PO1	Poplar	Po >= 70%
Mixed Conifer 1	MC1	Mixed	Conifer 50%>=, and Po<= 20% and Po+Bw <= 30%
Mixed Confier 2	MC2	Mixed	Conifer >= 60%, or Conifer >= 50% and working group is conifer sp.
Mixed Hardwood	MH1	Mixed	Po+Bw+OH >= 50%

[1]Balsam Fir, Other Conifer, Red/White Pine forest units represent a small fraction of the forest and were removed from the analysis.

The groups used for the classification (Table 3) begin as broad level forest distinctions, historically detected by Landsat data alone, and are then broken down into finer classes based on forest units. Stand age was not considered in the classification hierarchy as initial trials determined this element was confusing the classifier and producing negative results. Focus was placed on attaining meaningful forest unit level delineation.

Table 3. Classification structure targeted by methodology.

Broad Level	Forest Unit Level	Species Level
Conifer	SPL	Sb
	SPU	Sb, Sw
Conifer Mixedwood	PJ1	Pj
	MC1	Mixed
Deciduous	PO1	Po
Deciduous Mixedwood	MH1	Mixed

DATA PREPARATION

Image Acquisition

Landsat 7 data and IRS panchromatic data were used for this study. The Landsat data, acquired on July 5th, 2001, possesses 6 multi-spectral bands of information and scanned at a ground resolution of 30 m. Full coverage of the study area was available with no cloud or haze interference. The IRS panchromatic image, acquired on June 7th, 2001, possesses a single band of data scanned at a resolution of 5.8 m, and then re-sampled to 5 m pixels at the processing stage. The image was archived with Space Imaging (the vendor), with a 10% cloud cover categorization. Upon further observation of the scene, it was determined that haze in the south west corner of the image accounted for most of the 10%. This region was then excluded from the study area to minimize error in processing steps to follow. Cloud cover remaining after finalized boundaries consisted of three local "popcorn" formations, predicted as being easily isolated and removed from the data. Landsat Multispectral Scanner (MSS) as well as Landsat 5 TM were used to extract historic disturbance information from the forest, dated as far back as 28 years. Sensor specifications for all Landsat sensors used and the IRS-1D sensor can be found in Table 4.

Table 4. Image specifications of data used in thematic map production.

Sensor	Band Number	Spectral Range (microns)	Pixel Resolution (m)	Study Area Coverage	Date Aquired
	2	.525 to .605	30	Full	Jul-01
	3	.63 to .690	30	Full	Jul-01
Landsat 7 TM	4	.75 to .90	30	Full	Jul-01
	5	1.55 to 1.75	30	Full	Jul-01
	7	2.09 to 2.35	30	Full	Jul-01
Indian Remote Sensing Project IRS-1D	1	.500 to .750	5.8	Full	Jun-01
		Green to Middle IR	30	Full	Jul-95
Landsat 5 TM	2,3,4,5	Green to Middle IR	30	Full	Aug-91
		Blue to Middle IR	30	Full	Oct-85
		Green to Near IR	79	Full	Aug-84
Landsat MSS		Green to Near IR	79	Full	Jun-83
		Green to Near IR	79	Full	Aug-74

Image Rectification

All current database coverages for the Caribou Forest were provided by the provincial government (Ontario Base Map Series), and used in the rectification process. The images are georeferenced to a UTM (m) coordinate system (Zone 15 North) using the NAD 83 datum. Georeferencing of all Landsat data and IRS data were performed using provincial drainage vector data as a geographic reference. Both images were rectified with RMS errors of less than a pixel, conforming to standards used in image analysis literature (Jenson 1996).

IMAGE MERGING

Trial Design

In order to select an appropriate merging method for this dataset, a trial was performed on two subsets of the study area. These areas were selected to represent all of the characteristics of the entire image to observe how different features in the image reacted to different merging methods. Figure 3 illustrates the location of the subsets.

Figure 3. Subset areas for merging method analysis

Subset study area 1 contains a forest cover consistent with the rest of the study area, while subset study area 2 possesses some similar forest cover with the addition of some cutover coverage. This type of disturbed area occurs in other parts of the study area, and appears to contrast general spectral properties of the forested areas. It was felt that this contrast in spectral properties should be a part of one of the subsets to determine its response to the merging methods.

Brovey transforms, Wavelet transforms, IHS, and PCS are four of the most widely utilized methods when fusing satellite imagery. These four systems were tested using the selected subsets. Figures 4 and 5 outline the steps taken to determine the most effective merging technique for this study.

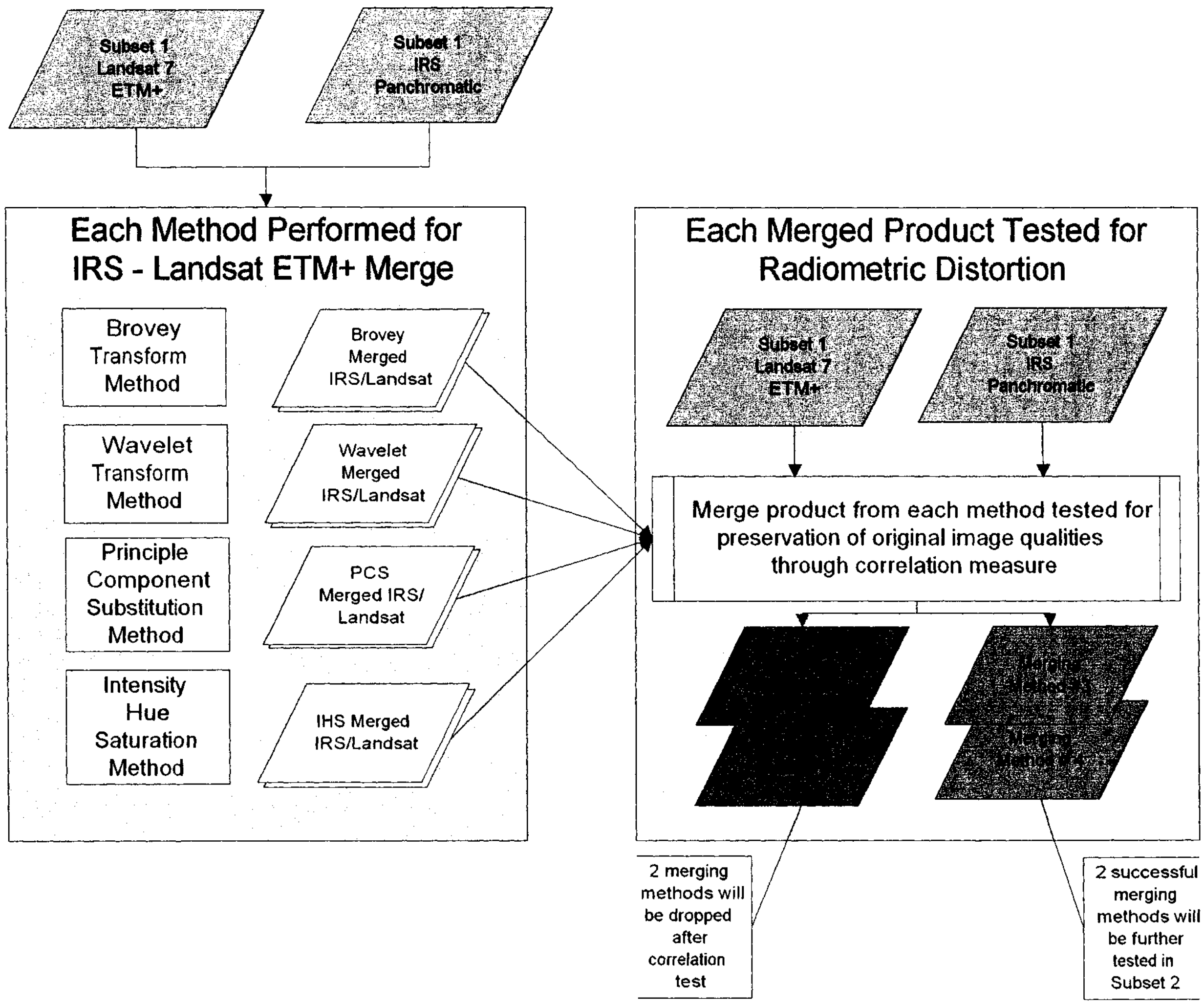


Figure 4. Steps for merging trial using 4 methods and subset 1.

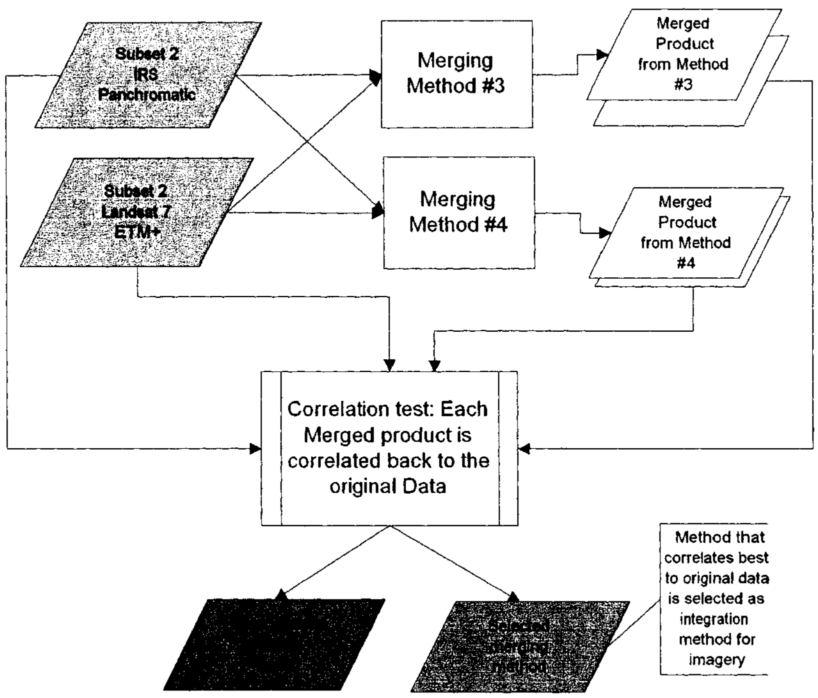


Figure 5. Steps for merging trial using 2 methods and subset 2.

<u>Brovey Transform</u>

This resolution merge is found as a default in many image analysis software packages, and uses simple ratio and multiplicative techniques to achieve a resolution merge. The algorithm used in the model is as follows:

$$[DNR/(DNR+DNG+DNB)] \times DNirs\text{-}pan = DNR\text{-}new;$$

$$[DNG/(DNR+DNG+DNB)] \times DNirs\text{-}pan = DNG\text{-}new;$$

$$[DNB/(DNR+DNG+DNB)] \times DNirs\text{-}pan = DNB\text{-}new;$$

where;

R,G,B = red, green, and blue bands of the image;

DN = Digital Number (brightness value of pixel);

and irs-pan = Panchromatic image

The Brovey transform is used primarily for producing RGB images with a higher degree of contrast, and also for producing visually appealing images. No literature was found supporting its use for computer assisted image analysis in forested landscapes. Consequently, mediocre results were expected from this method using this dataset. Testing was performed using this merging method to observe how the data used in this study would react in the transform.

Wavelet Transforms

For this trial, an additive wavelet transform seemed more suited to the data being used in the fusion process. Substitution methods resulted in little change to the Landsat image in attempts to integrate the panchromatic data. It was thought that the substitution method might be better suited to lower ratios of spatial difference between the products to be fused. In order to monitor the effects of altering the filter size in the substitution transform, two different filters were used in two separate substitution attempts. The first filter uses a window of 5 pixels, and the second filter uses a window of 15 pixels. The smoothed images were then subtracted from the original panchromatic data. The result of this subtraction, containing the high frequency data, was added to the bands of the low resolution multispectral data, combining the high frequency data from both sets of imagery. The expected result was a sharper, more detailed multispectral image.

Intensity-Hue-Saturation

A colour transform was applied to the low resolution Landsat data, and its properties were converted from RGB colour space to IHS colour space. Before the panchromatic image was substituted for the intensity layer, a normalization procedure was applied to ensure that specific image properties (e.g.

atmospheric) did not interfere with the merge. The transformation was then reversed with the substituted data, and the result was a spatially enhanced, multispectral image. Testing this method involved several different combinations of bands transformed into IHS space, to determine if any combination of three bands might be superior.

Principle Component Substitution

Using the PCS method, the data contained in the original Landsat bands were transformed using a principle component transformation. The IRS panchromatic was then normalized to the first principle component (PC1), and then substituted in place of PC1. As indicated by past research, the properties of the first component are more often highly correlated to the properties of the panchromatic data. If true, the PCS method may cause less image property distortion than the IHS method. The data was then transformed to its original state using an inverse principle component transformation, resulting in a new spatially enhanced Landsat image.

Image Normalization

When using satellite data from different dates it is important to consider atmospheric differences between the datasets. When using data from two or more different sensors, variation between sensor properties may cause inaccuracies during data processing. Normalization of the data is used to minimize this effect by eliminating inconsistencies in pixel values. In order to proceed with the last two methods in this trial, normalization of the panchromatic data must precede the substitution stage. In the case of the IHS merging system, the panchromatic image had to be normalized with the intensity layer before it could be substituted, and for the PCS method, the first component had to be matched. A random sample of the pixel values was taken of the IRS image and the images to be substituted from each method. A regression curve was generated and applied to the high resolution panchromatic data in each case.

Image Evaluation

An evaluation of each merging method for the two subsets consisted of a general visual inspection, as well as a correlation assessment of each band from the enhanced product against the original band of Landsat data. Determination of the appropriate sample size to collect from each image was necessary, as the correlation coefficient resulting from a Pearson Correlation would be influenced differently with varying sample sizes, [Mackereth (pers. comm., 10 April, 2002)]. The formula used in the test measures the strength of the linear relationship between two random variables. The equation is as follows:

$$r = \frac{SS_{xy}}{\sqrt{SS_{xx} SS_{yy}}}$$

Where

SS_{xy} = the sum of products of distances of x and y measurements from their means;

SS_{xx} = the sum of squares of the distances between x measurements and their means;

SS_{yy} = the sum of squares of the distances between y measurements and their means.

As the sample size increased the denominator term also increased, as degrees of freedom (df) increased, and the Pearson Correlation Co-efficient (r) decreased if all else was constant. However, it is unlikely that the numerator term would remain constant as sample size increased so it was not immediately clear how the r term was influenced. Therefore, the significance level of correlation with a sample of 10 pixels was not really comparable to that of a sample of 1,000 pixels. Since the sample size was constant for the various bands all correlations and associated significance tests should be comparable. However, if the sample size was too small the predictions of r may not be accurate. In order to test that sample sizes from the images were not influencing the resulting r value, verification that the sample was giving a stable estimate of standard deviation was required [Mackereth (pers. comm., 10 April, 2002)]. As sample size increased the estimate of mean and variance should fluctuate about the true population value and eventually stabilize. A collection of sample sizes for three of the six bands from the merged data were collected and plotted to determine the point of standard deviation stability.

Once the appropriate sample size was determined the results of each merging trial could now be evaluated. The correlation coefficient is an indicator of how well the product of the merge maintained its spectral properties. None of the products were expected to perfectly correlate to the original image, as changes in texture have occurred. However, it was assumed that the product with the highest average (from multiple bands) correlation coefficient indicated that the image was suitable for further analysis.

CLASSIFICATION METHOD

Image Segmentation

The goal of image segmentation is to extract from the image, areas with consistent image properties. Segmentation attempts to simplify the heterogeneity of finely resolved imagery that has historically caused classification error. In simple delineation situations, this may lead to areas of homogeneous characteristics being separated from areas with heterogeneous characteristics. In the case of forest structure, differences in image properties may be less obvious than this and require separation of two heterogeneous areas based on a small difference in spectral and spatial properties. The end result of segmentation is a set of image objects to be further processed as whole units, rather than the traditional pixel by pixel classification. The segmentation algorithm allows the user to control object spectral properties and shape by adjusting parameters in combination with a scale parameter that controls the average size of image objects. Figure 6 outlines the segmentation process.

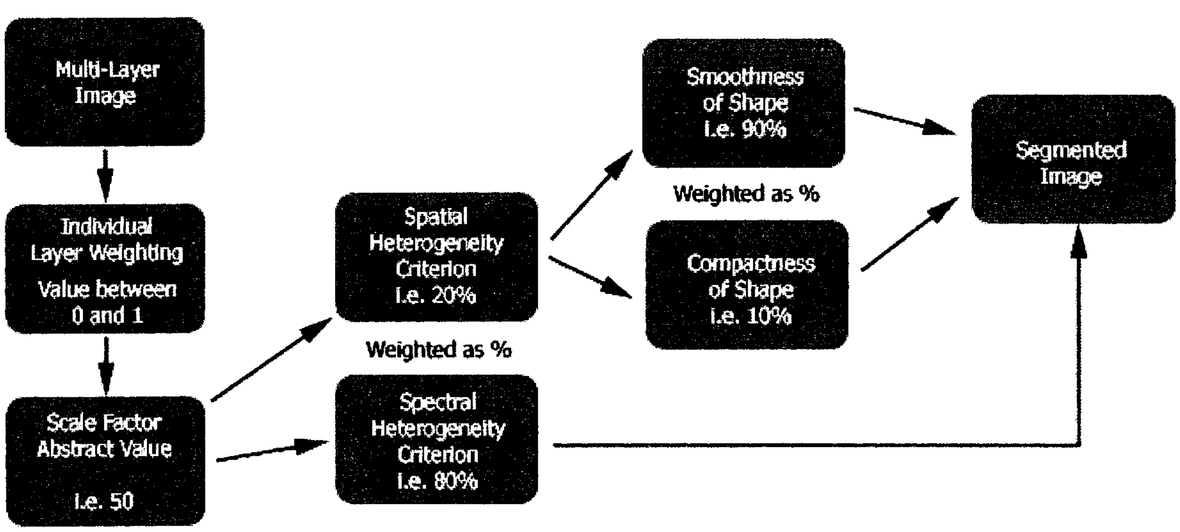


Figure 6. Segmentation parameters and process.

The procedure of image segmentation can be described as a region merging technique, whereby objects begin at the pixel level and are merged with one another based on a set of decision criteria (Baatz and Schape 2000). The merging decision, or fusion value, is based on the previously mentioned local criteria or parameters, describing the similarity of adjacent image objects. In many cases the exclusive minimization of spectral heterogeneity leads to branched segments or to image objects with fractally shaped borderlines. By mixing the spectral heterogeneity with a criterion for spatial heterogeneity, the shape of each image object may be controlled. The spatial heterogeneity may be further defined by its smoothness (creates long, diverse, irregularly shaped objects) or compactness (creates systematic, consistently shaped objects). Balancing these spatial parameters allows for flexibility in shape properties. In addition, the scale parameter sets the measure for the maximum change in heterogeneity that may occur when merging to image objects.

Stratification of the imagery into these objects was based on a trial and error system and satisfaction of the segments was based on the user's interpretation of what appropriate level will suit the classification. The segmentation is repeatable. Therefore the user may grow accustomed to the parameters and how each one affects the segmentation of the data in question. Although time consuming, the satisfactory image objects are the basis of the remaining classification procedures, and will assist in dealing with image texture appropriately. Care was taken to ensure proper segmentation of the layers.

At first glance of the newly merged data, the human eye delineates features on the image that appear to be different, especially features such as wetlands, roads, or disturbance patterns. Differences in forest structure were also apparent in many cases, often when hardwood and softwood components varied within the stand. The aim of the segmentation was to imitate these human perceptions using the segmentation algorithm (Baatz and Schape 2000). Using the green, red and near infrared bands evenly weighted, along with a Normalized Difference Vegetation Index (NDVI) and certain band ratios, the segmentation was performed altering one parameter at a time, until user satisfaction was achieved. Allowing the algorithm to make decisions on boundary placements, but not letting it change the perception of what the user visualizes as important. The user should maintain control in terms of what should and should not be delineated.

It is important to note that the selected scale factor ultimately decides how large a segment can be, and therefore a larger forest stand that is not necessarily different may be split by the segmentation. Large, homogeneous areas on the image that exceed the limitations of the scale parameter, are split into image objects, by the segmentation process, that meet the requirements of the scale parameter selected. Possessing similar statistical properties, these image objects will be classified together and later rejoined as one unit. For this reason, choice of scale in the case of this data was always set smaller, in order to ensure that smaller groups of different forest types were not combined.

It is also crucial to understand that the algorithm does not segment an image object based on the knowledge of a previously non-neighbouring segmented object. Image objects are selected for separation depending only on the difference in spatial properties of the object or objects neighbouring the object in question. Figure 7 displays an example of the segmentation used for this classification.

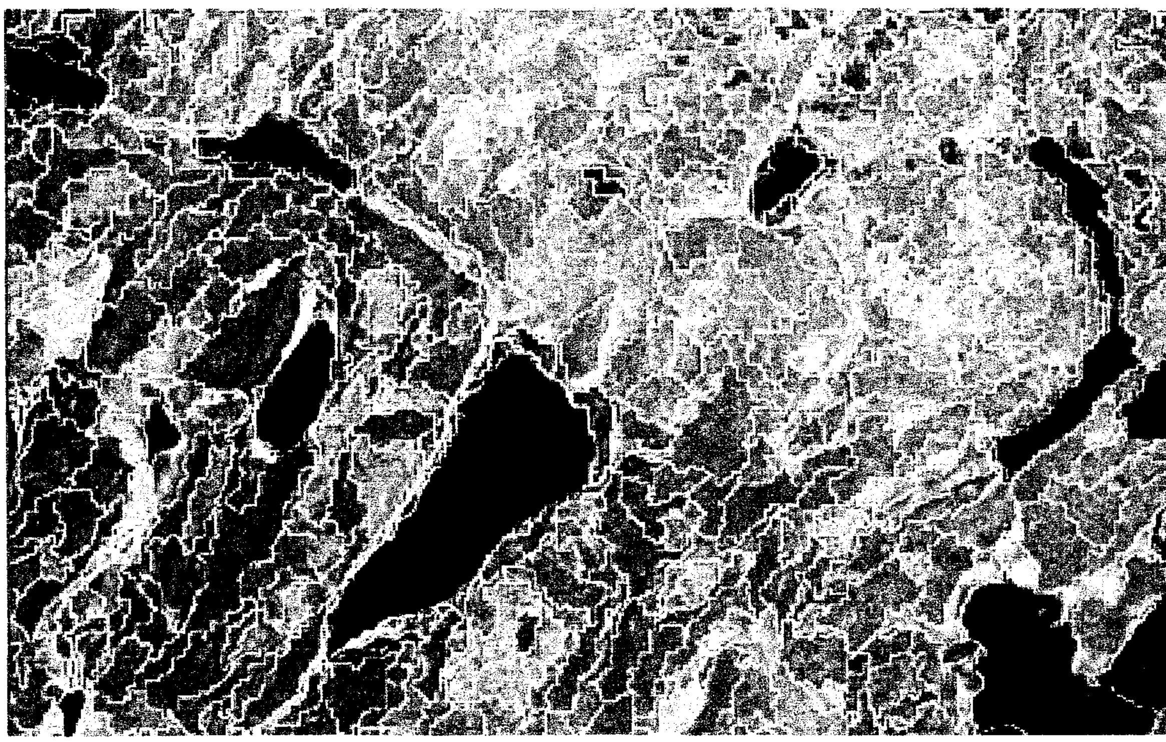


Figure 7. Subset of image objects, yellow polygons resulting from analysis of Landsat data merged with IRS panchromatic data. Image displayed using near IR, middle IR, and red ordered as RGB.

Ground Truth Data

The data used to train this classifier consists of existing field point clusters overlain across the image in a two-kilometre grid system. Field plot data was collected in 1996 by Bowater Pulp and Paper Canada Inc. Each cluster contains four sample points spread 200m apart from one another. Each sample point

($2m^2$/ha BAF prisms) recorded various stand structure variables such as basal area, height, age, and species composition. This field point data was used by a photo interpreter to develop a polygon layer possessing the current FRI interpreted polygons, generalized into the operational forest units currently used in the Caribou Forest for management purposes. Training sites were selected from these datasets based on an agreement of image object dimensions to the polygon layer, and then reaffirmed using the data from field plots to ensure correct representation of the forest class (Figure 8). Verification of these truth areas were also reaffirmed using field visits during the training process to ensure that classes were being accurately represented on the image.

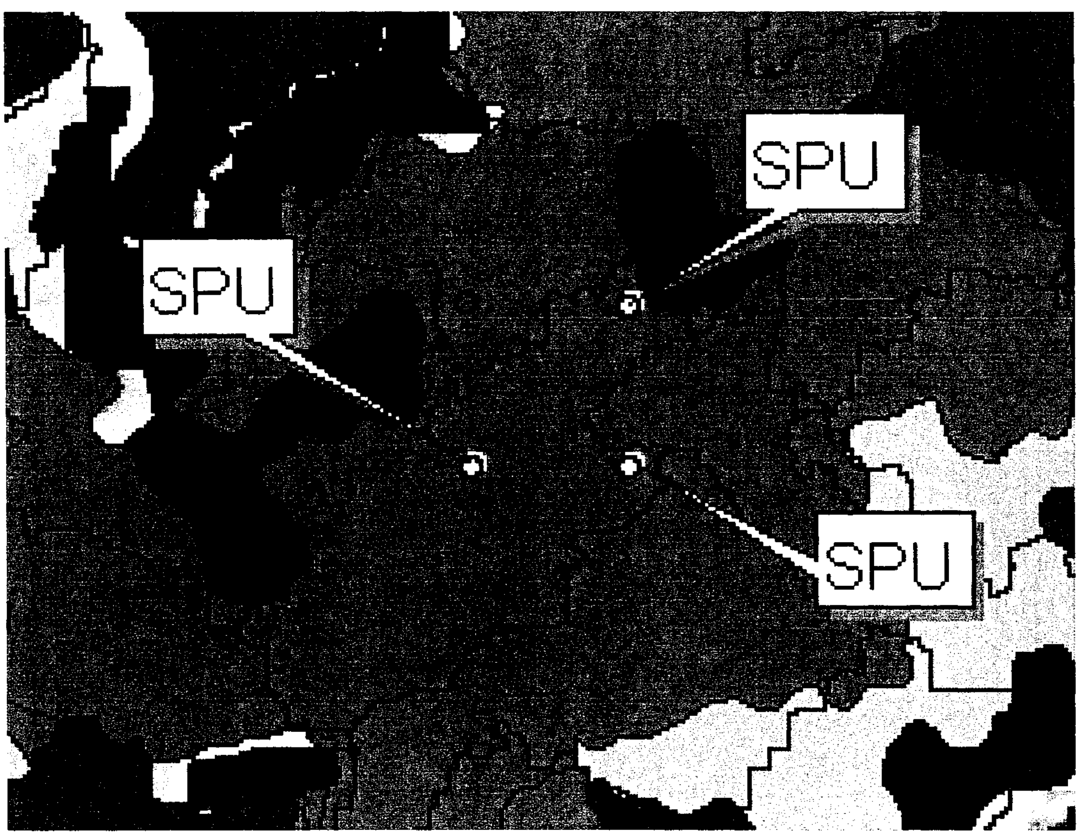


Figure 8. Forest unit grid (bright green = SPU), field data points, and image objects (red polygons) overlaid in training stage.

Image Classification

In order to produce statistically valid results from the classifier, it is important to meet certain requirements when training the classifier. In order to successfully train the classifier, careful attention to consistency when selecting sample areas, as well as sampling from a diverse representation of each class is necessary. The classifier used in this study is a supervised nearest neighbour algorithm, with the ability manipulate membership functions depending on the dimensions of the data.

Using the truth data described in the previous section as well as general knowledge of obvious image features, image objects were selected and assigned to their respective forest unit classes. The image objects selected as samples contribute more diverse information to the classifier than simply pixel brightness used in single pixel classifiers. The relationship of pixels contained within an image object creates measured properties in terms of colour, shape, and spatial information relating to each image object. When introducing samples to each class, it was important to ensure that representative samples were being used, as one unrepresentative sample may throw the balance of the classifier off very easily. The use of image objects allows for an iterative cycle of adding and removing sample objects as the user sees fit. When a class was poorly represented in the feature space, more samples were added to strengthen the classification. Likewise, an unrepresentative sample was removed if the sample was felt to be confusing the classifier.

The selected samples create multi-dimensional feature spaces of known classes. The classifier then placed remaining image objects into these known classes using membership functions. Membership functions are a simple form of translating an arbitrary feature range into a uniform range between 0 and 1, where 0 represents no membership to a class, and 1 represents full membership to a class. The use of membership functions are most effective in situations where a class may be separated from other classes by just a few features or perhaps only one feature. For instance, removing a water class or clouded areas initially by implementing cut-off ranges of image object means using just the infrared channels in the data, is a common example of manipulating the membership functions of the classifier. When dealing with more complex feature space (e.g. spruce and pine classes), user designated membership functions may lead to large overlap regions in the feature space, and therefore these classes may only be separated using the nearest neighbour algorithm.

Once a typical representation of each class is established, the nearest neighbour algorithm looks for the closest sample object in the feature space for each unclassified image object. The classifier measures distance of image object to sample object using the equation:

$$d = \sqrt{\sum_{f} \left[\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right]^2}$$

where;

d = distance between sample objects;

$v_f^{(s)}$ = Feature value of sample object for feature f;

$v_f^{(o)}$ = Feature value of image object for feature f; and,

σ_f = Standard deviation of the feature values for feature f.

Once the distance in feature space is determined for an image object it used with a Gaussian function, where the function slope value controls the assignment of the image object. The function slope uses the distance of the object to the sample, weighted by the standard deviation of all samples in the class. The result of this equation assigns the image object with a value between 0 and 1, referred to hereafter in as the membership value of an object. This function slope can be adjusted to allow for more stringent or more lenient group memberships. The algorithm will give the image object a membership value for each of the classes and report the best membership (closest to value 1) to a class as well as how the image object fit into the remaining classes. This feature of the algorithm allows the user to take advantage of the fuzzy logic classification theory.

Fuzzy logic is a classification term that encompasses the mathematical approach to quantifying uncertain statements (Foody 1999). Rather than assigning either 1 (full membership) or 0 (no membership), the algorithm instead calculates the degree of membership (value between 0 and 1) of the image object to any possible classified group. Due to its abstract nature and frequently argued applicability (Runesson 2001), it is used in this classification as a guide to indicate where confusion between classes may be occurring.

Image layers used in the classifier extended beyond just the spatially enhanced Landsat data layers. A NDVI was created and added, as well as some commonly used ratios including the near infrared band divided by each of the green (4/2) and red (4/3) channels of the Landsat sensor. These ratios and transformations have been known to increase separability between vegetation classes in other studies (Jensen 1996), and may add to the dimensions of the feature space.

Accuracy Assessment

Problems assessing area-based classifications with point-based accuracy reference data have lead to poor accuracy results in past studies (Boudewyn *et al.* 2000). Therefore, an area-based reference set was used to assess the quality of the IRS/Landsat 7 classification. Medium scale, black and white photography (1:20,000) taken in 1997, was used primarily for the assessment stage of the process. The photographs were interpreted to a forest unit level using the predetermined boundaries created in the image segmentation stage of the system, to ensure consistent evaluation of species composition in similar areas. Transparencies containing image objects were overlaid on the photographs and areas within the boundaries of each object were interpreted and given a species composition. A subset of the study area (Figure 9) was selected for photo interpretation, providing a continuous and diverse measurement of ground properties on approximately 20% of the land cover in a centralized region of the Caribou forest.

The photo interpreter selected to interpret image object polygons was provided by Bowater Pulp and Paper Canada Inc., and possessed over 30 years

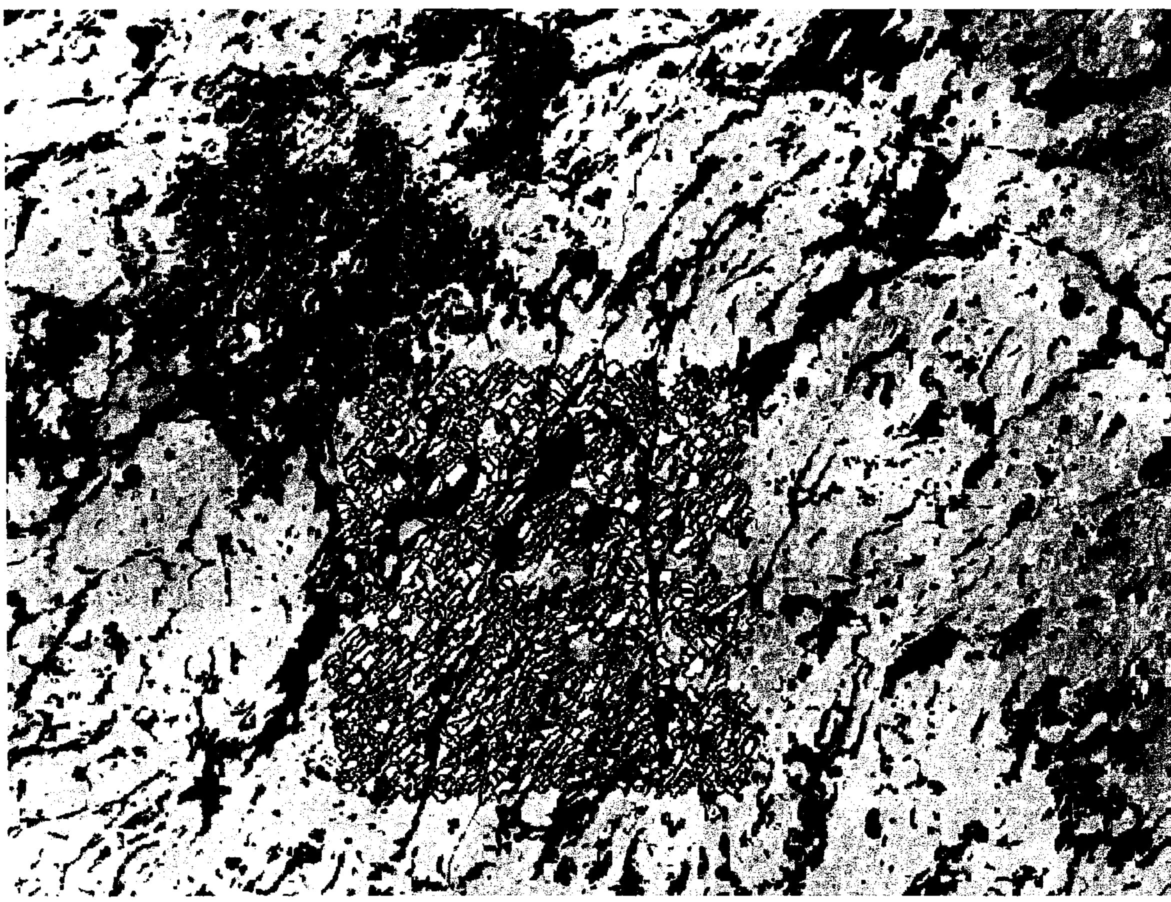


Figure 9. Extent of photo interpreted area (yellow polygons)

of experience interpreting photography in the boreal forest, particularly in Bowater's forest licenses. The interpreter also took part in the field check work during the photo inventory of the Caribou Forest license in the 1970's.

Collecting appropriate reference data for use in an error matrix reinforces the integrity of the evaluation of the thematic product. Criteria such as the data's sample size as well as sample stratification can affect the results of an accuracy assessment. Congalton and Green (1999) suggest a minimum sample size of 50 reference areas or points for most classifications to provide a good balance between statistical validity and practicality. In this study, sample size was achieved for all classes with exception of the pure trembling aspen class due to lack of this cover type in the study area. For the purpose of this study, it was practical to collect more than 50 area samples for all other classes.

Proper sample stratification is often compromised when trying to save time and money in the sampling procedures. Ideally, the photo interpreter should sample random segmented polygons from the entire study area overlain on photography, however, this was not possible due to budget constraints of the study. Instead, the sample was taken randomly from the continuously interpreted area (20% of study area), and used in the error matrices. All areas used in the error matrices are selected randomly within classes.

Accuracy assessments in remote sensing research traditionally use three primary measures to assess the degree of success for a classifier: a user's accuracy, a producer's accuracy, and an overall accuracy. Producer's accuracy is a ratio designed to indicate the proportion of each class being correctly classified on the map as indicated by the reference data. User's accuracy extracts a ratio of per class of agreement of the thematic product to what might actually exist on the ground. Overall accuracy is simply the sum of correctly classified sample units divided by the total reference points, and is thought to take both producer's and user's accuracy into account. An error matrix is used to tabulate these measures, and displays errors of omission and commission from each class. Omission errors indicate when a reference area was incorrectly excluded from its correct class. Errors of commission indicate reference areas incorrectly assigned to a particular class that actually belong in other classes.

A Kappa statistic was also calculated for every matrix as a fourth measure of the thematic product. Calculating the Kappa statistic incorporates the user's, producer's and overall accuracy totals, and is used widely by the remote sensing community. It is a statistic used to measure the agreement, beyond chance, between two maps (e.g. output map of a classification and ground-truthed map). Correctly assigned areas may have been assigned by chance and not based on the classification decision rule. The Kappa value indicates how accurate the classification output is after this chance, or random, portion has been removed (Congalton and Green 1999). A formal equation for Kappa is represented by:

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ij} - \sum_{i=1}^{r}(x_i * x_j)}{N^2 - \sum^{r}(x_i * x_j)}$$

where; r = the number of rows in the error matrix;

x_{ij} = the number of observations in row *i* and column *j*, on the major diagonal;

x_i = total number of observations in row *i*;

x_j = total number of observations in column *j*;

and, N = the total number of observations included in the matrix.

To obtain comparison, the remaining field point data (not used in training stage) will be used in a secondary assessment to determine whether the point-based accuracy assessment is adequate for this study.

All of the components described this far combine to form the primary method for developing a strategic forest inventory. Figure 10 shows how the components fit together. In addition to the primary method, an alternative method was also tested.

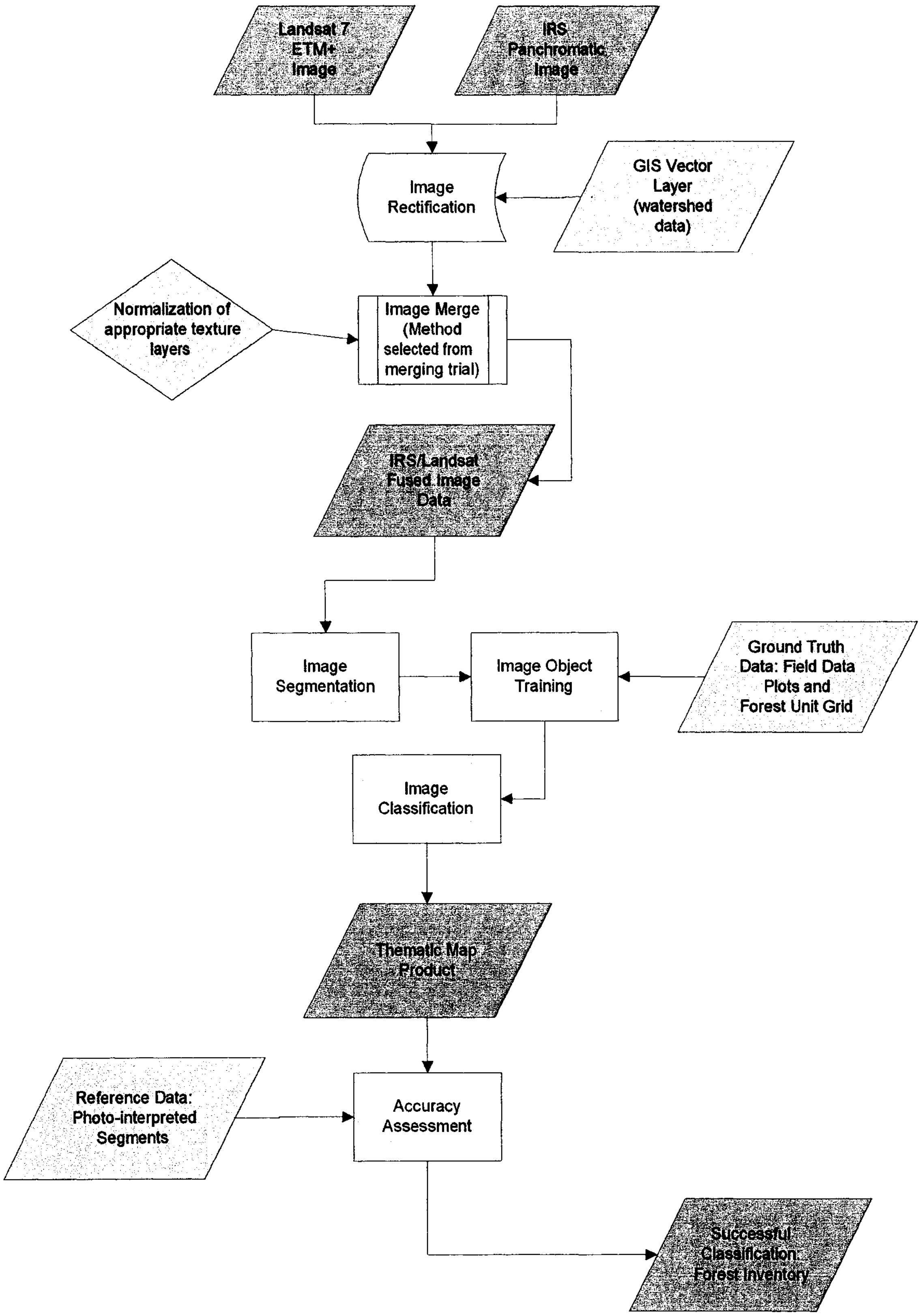


Figure 10. Primary method used in the study of classifying imagery into forest inventory.

ALTERNATIVE METHOD

The reference (photo interpreted) might also act as an effective tool for training the classifier. Its ability to train the classifier was examined, as an alternative to the existing field points and forest unit grid used in the primary method. If successful, it could be included in the process of training an area that has limited field point data or inventory coverage. For both the primary and alternative method, the original (and less expensive) Landsat data was used as a control to help gauge the level of improvement achieved from merging.

Table 5. Summary of alternative classification attempts and respective satellite data, ground truth, and reference methods.

Classification Method	Satellite Data	Ground Truth	Reference
Primary Method	Merged IRS/Landsat	2 km Stratified Field Plots (Field Crew Collected) & Forest Unit Grid	Photo Interpreted Segments
Primary Method Control	Landsat	2 km Stratified Field Plots (Field Crew Collected) & Forest Unit Grid	Aspatial Comparison
Alternative Method	Merged IRS/Landsat	Photo Interpreted Segments	Aspatial Comparison
Alternative Method Contro	Landsat	Photo Interpreted Segments	Aspatial Comparison

The results of classifications performed using alternative methods were measured aspatially with the merged classification result and each other. Area based spatial assessment was only performed on the merged data due to budget constraints. These alternative method results will be compared to the IRS/Landsat result using non-site specific area assessment, based on class area totals within the study area.

COST COMPARISON

A cost analysis was performed to illustrate a comparison between traditional FRI methods and the procedures used in this thesis. Costs for each stage of conventional FRI methods were attained from local contractors based on 1:20,000 scale, black and white photography, for an average sized SFL in northwestern Ontario. Cost for satellite inventory methods were derived based on the estimated time required to complete a project. Accuracy assessment stages of the primary method were not included in the cost, as practical applications of satellite-derived inventory usually assume accuracy based on previous research into the methods.

RESULTS

IMAGE FUSION - PRIMARY METHOD

Correlation Sample Size

A variety of pixel sample sizes were tested in order to verify at what point the sample was giving a stable estimate of standard deviation. Brightness values from three bands from the Landsat image were used to graph the results. Figures 11-13 show the results of the plotted standard deviation results from samples taken in 1% pixel sample divisions. Sample pixels were selected randomly excluding any points that occurred in water. Sample sizes of up to 20% of the total population were tested. In all three cases the standard deviation appeared to stabilize at a sample size of 10%. Throughout the rest of the procedure a sample of at least 10% of any image was used to statistically evaluate all merging techniques.

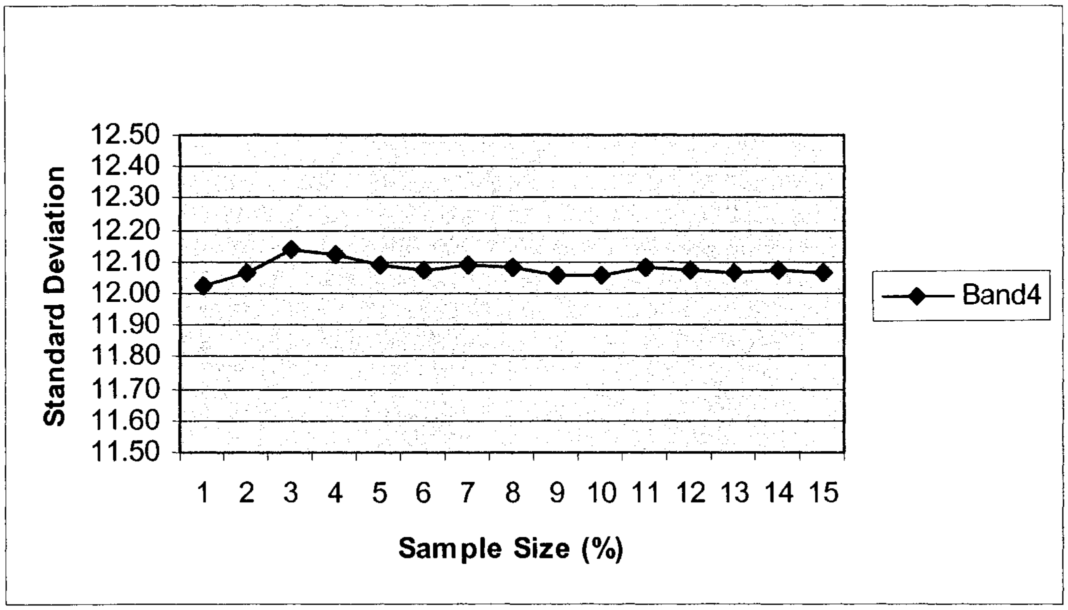


Figure 11. Fluctuation of standard deviation for varying sample sizes of Band 4.

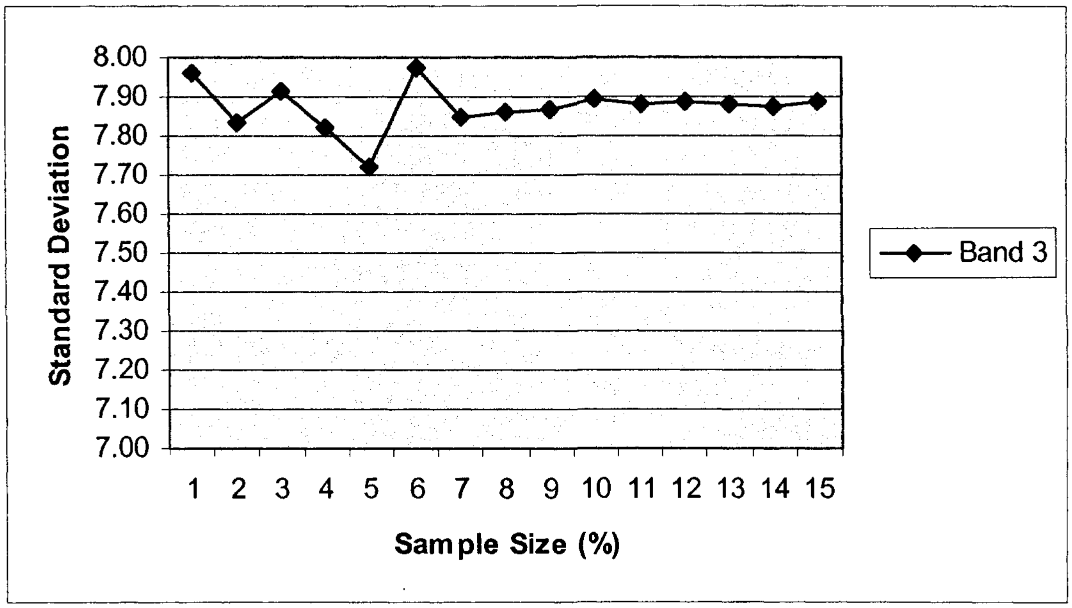


Figure 12. Fluctuation of standard deviation for varying sample sizes of Band 3.

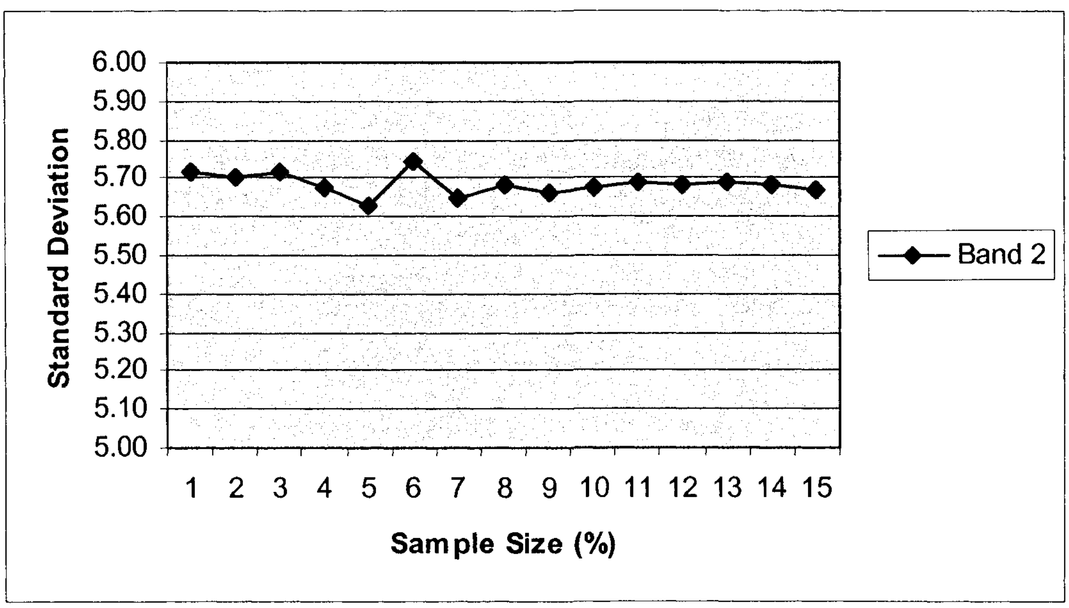


Figure 13. Fluctuation of standard deviation for varying sample sizes of Band 2.

Normalization

Normalization procedures took place in all of the merging procedures. However, the presentation of results for each normalization attempt is not necessary to compare successes and failures of each merging technique. For the PCS merge of the full study area, all results of the merging process are presented in full.

Preliminary Image Fusion – Subset Study Area 1

The first trial including all of the merging methods and was intended to determine weaker methods for this data set. Table 6 provides a description of the correlation to the original Landsat band results in more detail. The variable being compared in the correlation is pixel brightness. Due to the limitations of IHS and Brovey methods using band combinations possessing only three bands, the green, red and near infrared bands were used for comparison.

Table 6. Correlation of brightness values of merge product bands with original Landsat bands in subset 1.

Fusion Method	Band 4 (r)	Band 3 (r)	Band 2 (r)	Average (r)
"IHS"	0.91	0.71	0.63	0.75
"PCS"	0.88	0.95	0.90	0.91
Brovey	0.79	0.62	0.71	0.71
Wavelet 15x15	0.99	0.95	0.93	0.95
Wavelet 5x5	1.00	0.97	0.97	0.98

Both wavelet methods along with principle component substitution have the highest correlated with the bands of the original image. However, upon visual inspection, it was noted that wavelet transforms had little effect on the image in terms of textural enhancement. Table 7 displays the relationship of the texture product from each method, correlated back to the original IRS panchromatic image.

Table 7. Correlation of brightness values of merged product textural features with original IRS panchromatic band.

Fusion Method	IRSPAN (r)
"IHS"	0.97
"PCS"	0.96
Brovey	0.93
Wavelet 15x15	0.72
Wavelet 5x5	0.69

PCS and IHS continued to hold the textural integrity of the IRS panchromatic data, as well as the Brovey transform at 0.93. Wavelet transform subsets found in figures 12 and 13 degraded the texture of the high resolution data, resulting in better radiometric preservation, however adding little new information to the image. Figure 14 exhibit the results of the Brovey transform, which correlated well texturally, but was unsuccessful at maintaining the spectral integrity of the original image in all bands as expected. Although not obviously apparent in the small samples of subset 1 (Figures 14-19), in-depth visual inspection of the images agreed with statistical analysis, confirming Brovey and Wavelet transforms as unsuited for this data. Although the IHS method compared texturally in the correlation tests quite well, it possessed an average radiometric correlation of only 0.75, with the near infrared band respectively high, but the red and green somewhat lower. Further testing with IHS method on this subset, using a different band combination of the two middle infrared channels, and the near infrared (band 7, band 5, and band 4), showed improved correlations (r

Figure 14. Original Landsat bands 4,3,2.

Figure 15. Wavelet 5x5; Bands 4,3,2.

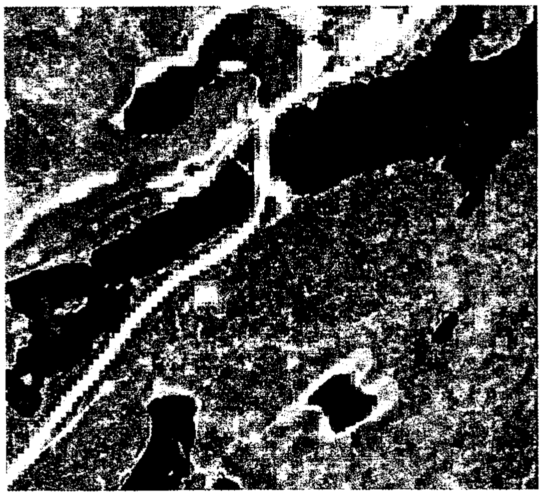


Figure 16. Wavelet 15x15; Bands 4,3,2.

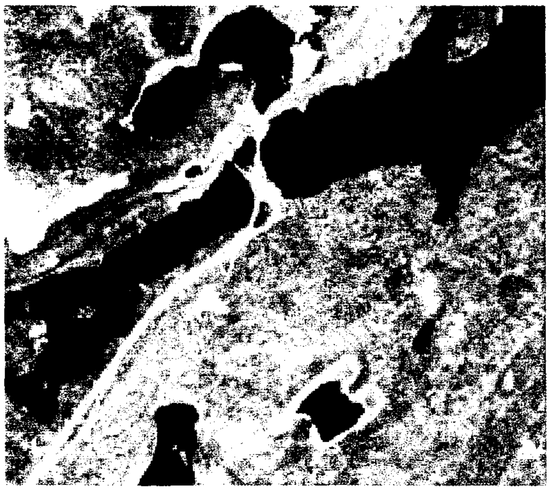


Figure 17. Brovey; Bands 4,3,2.

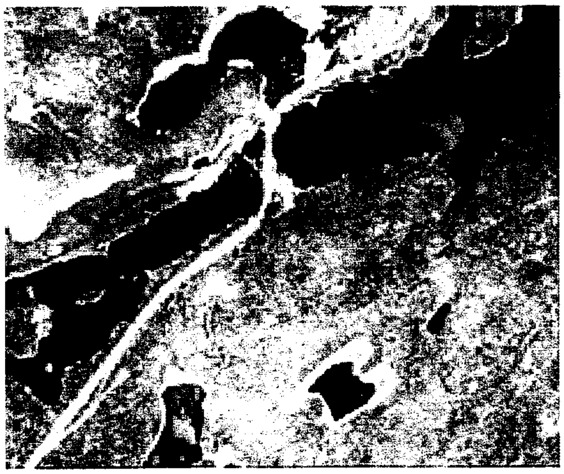


Figure 18. IHS merge; 4,3,2.

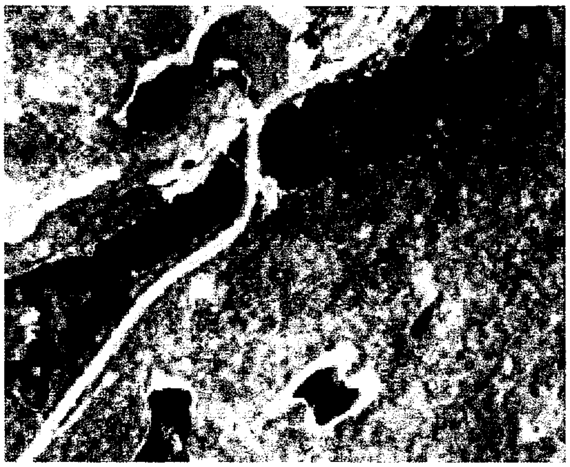


Figure 19. PCS merge; Bands 4,3,2.

value) of 0.77, 0.82, and 0.81 respectively, for an average of 0.80. The PCS method correlated well in all respects.

Preliminary Image Fusion – Subset Study Area 2

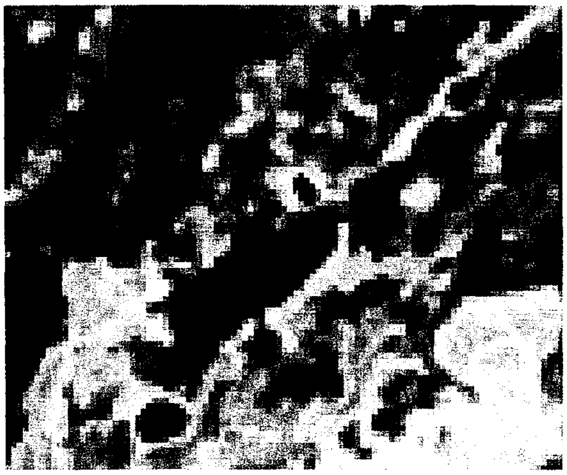
The second subset was used to test IHS and PCS merging method further. All available three-band combinations using the IHS method were used and compared to the PCS method. Results of the correlations are displayed in Table 8. Once again, the PCS product correlations (average 0.89) were consistently superior to those of IHS products.

Table 8. PCS and HIS brightness values (various band combinations) correlations to original Landsat bands.

Fusion Method	Band 2 (r)	Band 3 (r)	Band 4 (r)	Band 5 (r)	Band 7 (r)	Average (r)
PCS	0.87	0.91	0.88	0.84	0.93	0.89
IHS432	0.60	0.89	0.89			0.79
IHS532	0.45	0.72		0.86		0.68
IHS542	0.61		0.87	0.91		0.79
IHS543		0.80	0.86	0.89		0.85
IHS754			0.84	0.85	0.86	0.85

The highest correlations for IHS occur with the combination of bands 5, 4 and 3 as well as bands 7, 5 and 4, at and average of 0.85. The green and red bands continued to compare lower values in the correlation. Figures 20-22 display a small portion of the subset study area 2 with the merge products as well as the original Landsat bands middle infrared (5) as red display, near infrared (4) as green display, and red (3) as blue display.

The PCS method consistently ranked high (r^2 = 0.88-0.95) in most band comparisons to the original data. The IHS method is limited to a three-band combination, and the variation in these combinations caused changes in band correlations. Because it is difficult to identify what effects different band combinations have on the quality of the merge, error caused in the classification by the merging method may be more difficult to isolate and control. For both of these reasons, PCS method was selected as the appropriate merging method for this dataset, and was used exclusively to merge data for the entire study area.



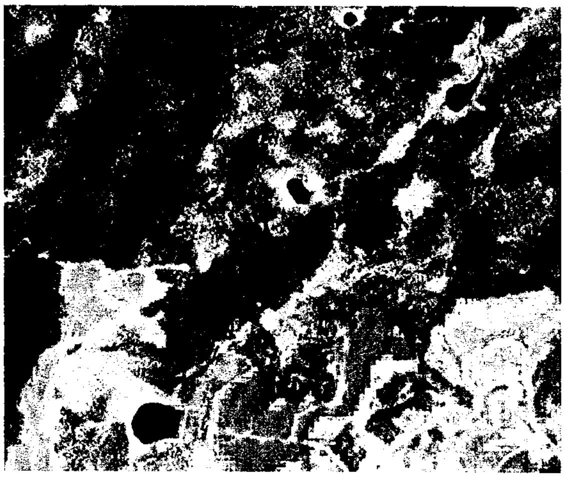


Figure 20. Original Landsat bands 5,4,3. Figure 21. IHS merge; bands 5,4,3.

Figure 22. PCS merge; bands 5,4,3.

Secondary Image Fusion – Full Study Area

In order to normalize the IRS panchromatic image to the first component (PC1) of the transformed Landsat data, a quadratic (second order) equation was developed using regression techniques. A random sample of pixels (10% of pixel population) coinciding from both images was collected from non-water locations, and regressed to develop the quadratic curve found in Figure 23.

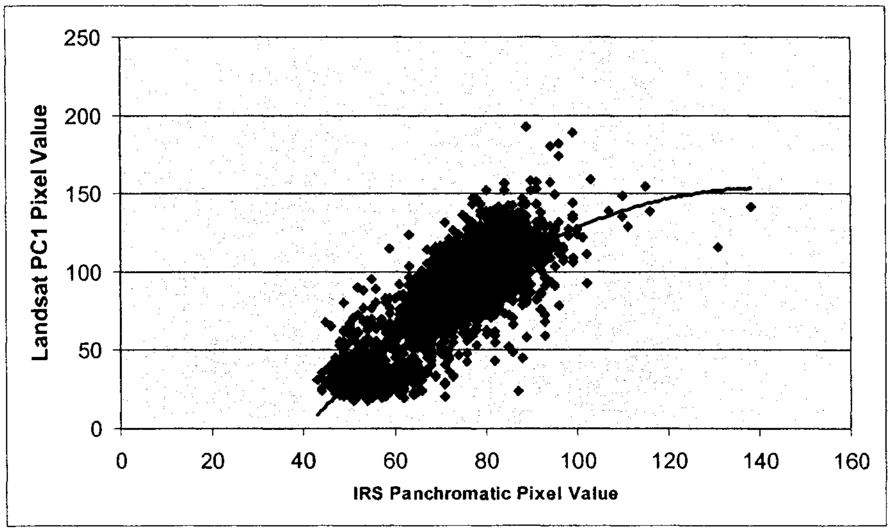


Figure 23. Quadratic curve regressed from pixels of IRS and Landsat PC1.

The resulting formula to be applied to the IRS image generated by the curve is as follows:

$$\mathbf{y = (-0.0151)x^2 + (4.2436)\,x - 145.46}$$

where;

y = normalized IRS pixel; and,

x = original IRS pixel.

The r^2 value for the curve, indicating the regression model's prediction capacity is equal to 0.73.

Found below in figures 24-26 are the histograms of the first principle component as well as the pre-normalized IRS image, followed by the normalized IRS panchromatic data. In each of the graphs, the x-axis represents the brightness level. The y-axis represent the total number of pixels in each category.

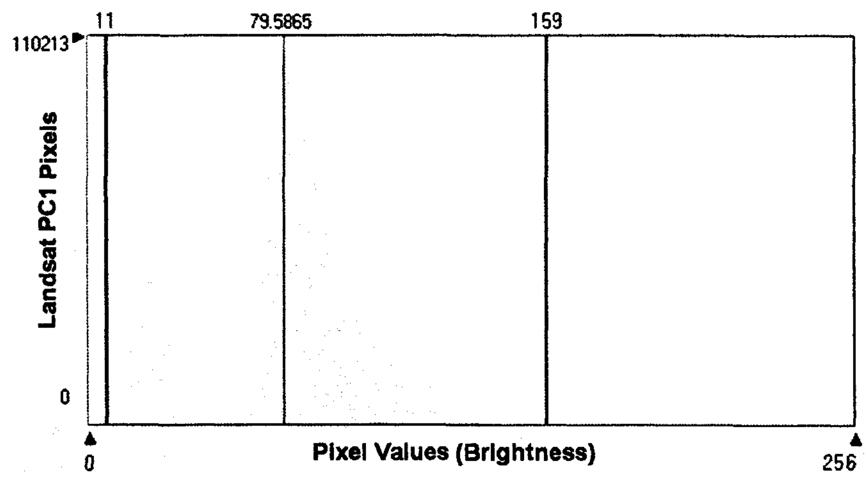


Figure 24. Histogram of original Landsat PC1 band

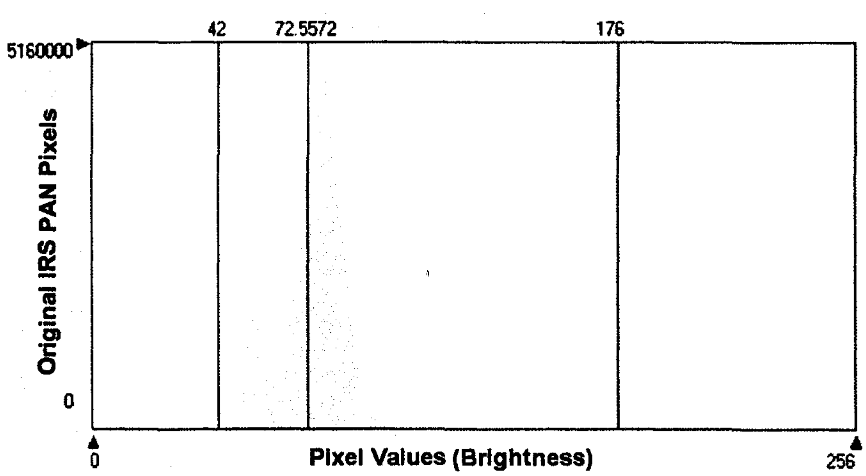


Figure 25. Histogram of original IRS PAN band.

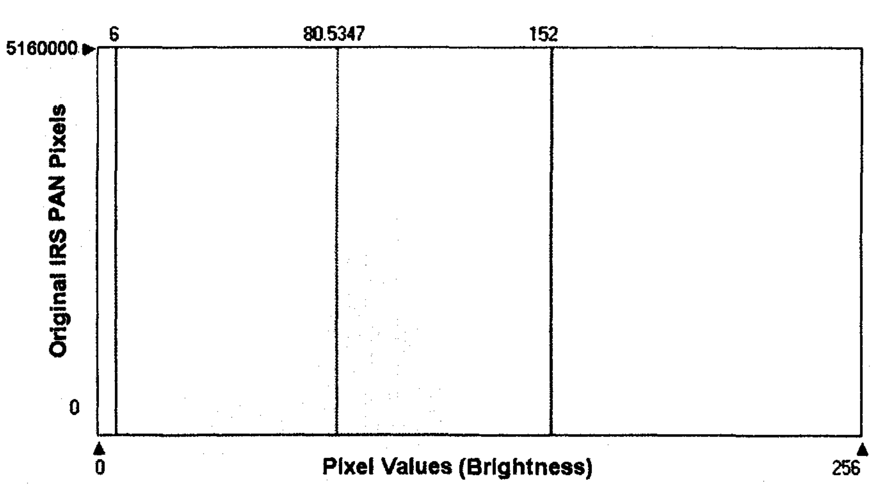


Figure 26. Histogram of normalized IRS PAN data.

The PC1 band from the Landsat image possessed a mean pixel value of 79.58 as well as a standard deviation of 28.07. The original IRS contained values of 72.56 and 10.86 respectively before applying the quadratic equation. The normalized image resulting was a closer match to the PC1 band with a mean pixel value of 80.53 and a standard deviation of 23. Visual inspection of both images indicated satisfactory balance in preparation for substitution.

Correlation Test

Once the merge was completed, the test of correlation took place to determine the success of maintaining as many of the original spectral properties as possible from the Landsat data. Correlation tests similar to those in the first trials were carried out. The correlation results for brightness values of bands two, three, four, five, and seven possessed correlation coefficients of 0.81, 0.85, 0.91, 0.86 and 0.90 respectively for an average of 0.87.

CLASSIFICATION RESULTS

Segmentation Parameters

After many executions of the segmentation procedure, a set of parameters was selected for final segmentation forest units. A multi-layer image consisting of Landsat/IRS merged bands 2-7, NDVI and ratios (Band 4/Band 2, Band 4/Band 3) were weighted all with values of 1. A scale factor of 50 was selected to represent the most ideal size cut-off for segments. Spectral and spatial heterogeneity were weighted as 80% and 20% respectively, and finally smoothness and compactness of shape were ideal at 90% and 10%. These settings produced the most realistic delineation of forest units to the user's satisfaction.

Segmentation Analysis

Most of the evaluations to assess the results of the image segmentation were visual. However, one measure to confirm the segmentation's suitability beyond visual inspection was to compare the average segmented object size to the average FRI polygon size. The average image object polygon was 23.4 ha, compared to the average polygon size of 21.5 ha in the current FRI coverage.

An example of visual inspection of the image segmentation stage is displayed in Figure 27. Two stands meeting the minimum requirement for operational scale were identified by the segmentation algorithm and separated appropriately. Field plots confirm that these areas were indeed hardwood dominated stands, and different than neighbouring mixed-wood stands.

As well as interpreting the composition within the segmented boundaries, the interpreter was also asked to evaluate the effectiveness of the boundary placement derived from the image segmentation. Instructions were given to highlight the boundaries where problems may exist with the segmentation. No significant problems with the segmentation were identified by the interpreter through visual inspection of the stratification.

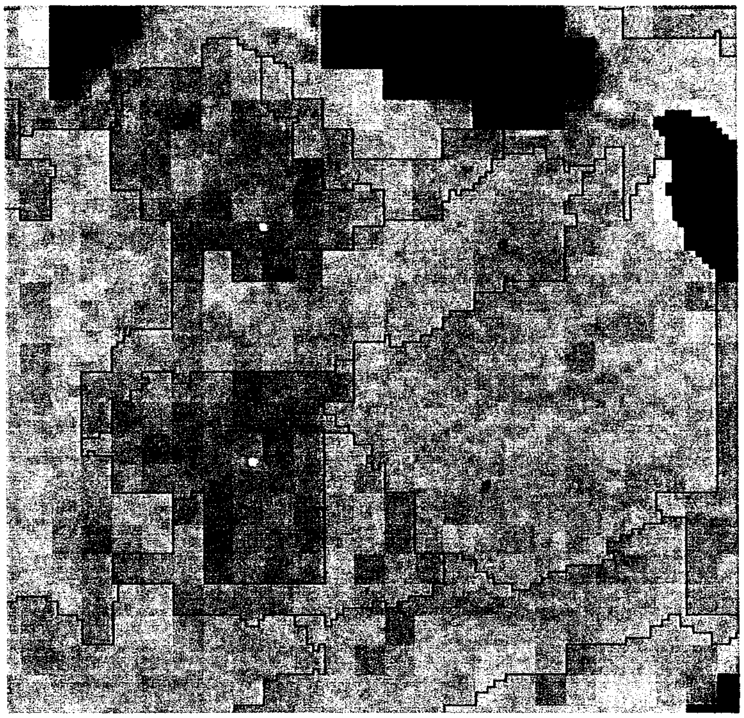


Figure 27. Example of segmentation results; yellow field plots indicate one forest type, while green indicate another; blue lined polygons represent image segmentation.

Classification of Image Objects

Once training of each class was completed, using ground truth data, a statistical description of each class is developed by the classifier. During final classification of the image objects, the description of each class is compared to each object, assigning a membership value to the object for each class (varying between 0 and 1). The object is then integrated into the class with highest assignment of membership. A default minimum membership to each group was set to 0.5 to monitor those objects that had little agreement with any of the classes.

Non-Spatial Assessment

The thematic map product resulting from the classification of the merged data showed great potential in terms of forest unit distribution. It should be noted, that initial results were based on the classifications performed with the field plot and forest unit grid data as a training set. A non-spatial comparison of the two classifications, merged IRS/Landsat and raw Landsat satellite data, to original forest unit coverage (determined by the FRI) had good agreement in terms of proportional area in relation to the FRI (Table 9). In all classes the IRS/Landsat data showed better agreement with FRI than the Landsat data alone. Proportions of mature forest cover in the broad classes indicate a slight shift towards the mixed conifer class, as well as a decrease in the pure hardwood class when comparing the merged data against FRI. It is possible that the classifier was unable to distinguish between a stand with 70% spruce composition and a stand with slightly less spruce (i.e. 60% spruce, 40% other conifer). This increase in conifer mixed-wood is much more pronounced in the classification made by the Landsat data alone.

Table 9. Non-spatial comparison of broad forest cover categories.

Broad Forest Cover	**FRI**		**IRS/Landsat**		**Landsat Raw**	
	Ha	%	Ha	%	Ha	%
Conifer	130833	74.85%	126090	72.14%	104910	60.02%
Mixed Conifer	32696	18.71%	40579	23.22%	59744	34.18%
Hardwood	3981	2.28%	1733	0.99%	1398	0.80%
Mixed Hardwood	7282	4.17%	6390	3.66%	8740	5.00%
Totals	174792	100.00%	174792	100.00%	174792	100.00%

A similar pattern of improved classification using the merged data was found for forest unit level classifications with the exception of jack pine. Both classifications show proportionally more jack pine area compared to the FRI data source. Spruce lowland area decreased substantially when using the raw Landsat data, most likely associated with the increase in mixed conifer composition.

Table 10. Non-spatial comparison of forest unit level classification.

Forest Unit	**FRI**		**IRS/Landsat (Primary Method)**		**Landsat Raw (Alternative Method #2)**	
Cover	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
SPU	65813	37.65%	60159	34.42%	56773	32.48%
SPL	44394	25.40%	39970	22.87%	25519	14.60%
PJ1	19989	11.44%	25456	14.56%	22083	12.63%
OC1	637	0.36%	504	0.29%	542	0.31%
PO1	3981	2.28%	1733	0.99%	1398	0.80%
MC1	32696	18.71%	40579	23.22%	60810	34.79%
MH1	7282	4.17%	6390	3.66%	8740	5.00%
Totals	174792	100.00%	174792	100.00%	174792	100.00%

Spatial Accuracy

Area-Based Assessment

An area-based assessment of image objects was performed to calculate the spatial integrity of the classification using IRS/Landsat merged data. Interpretation of the image objects using medium scale (1:20,000), black and white photographs allowed for a more consistent evaluation of spatial relationships between ground area composition and image object allocation, compared to evaluation using non-spatial assessments. The construction of a new matrix (Table 11) contains promising results, using the area based reference system. Units used in the matrix represent number of polygons counted. Low sample references to hardwood based forest stands were attributed to a limited presence of hardwoods in study area.

Table 11. Spatial error matrix using photo interpreted reference.

		Reference (Photo Interpretation)							
		SPU	SPL	MC1	PJ1	PO1	MH1	Row Total	User's
IRS/Landsat Class	SPU	**135**	12	40	29	1	4	221	61.09%
	SPL	98	**101**	25	25	2	0	251	40.24%
	MC1	37	10	**67**	29	5	6	154	43.51%
	PJ1	16	1	38	**181**	0	3	239	75.73%
	PO1	2	0	3	0	**17**	6	28	60.71%
	MH1	0	4	5	2	6	**52**	69	75.36%
Column Total		288	128	178	266	31	71	**962**	
Producer's		46.88%	78.91%	37.64%	68.05%	54.84%	73.24%		**Overall = 58%**

Using the area-based accuracy assessment an overall accuracy of 58% resulted. Calculation of the Kappa statistic revealed $K_{hat} = 0.46$. The Kappa statistic indicates that, beyond chance, the classification agrees with the photo interpreted reference 46% of the time. Classes contributing to this decrease in overall accuracy were most likely the spruce classes as well as the mixed forest classes, confirming the observations made in the non-spatial comparisons. Positives were observed as lowland spruce classes approach 80% in the producer's column, as well as pine just under 70% and mixed hardwood at 73%.

To explore the possibility that the classifier was able to allocate spruce correctly, the matrix was reconstructed grouping the spruce upland and spruce lowland classes. Table 12 presents the result of this restructuring. By combining the spruce classes together, overall accuracy of the matrix increased 10% to 68%, with $K_{hat} = 0.55$. Spruce combined into one class was differentiated correctly 83% of the time. Upon further exploration of the stands classified incorrectly, it was noted that many of the omission errors were attributed to stands with less than 80% pure species composition. The matrix was again restructured, omitting stands with mixed species tendencies in Table 13, to evaluate the classifier's ability to distinguish stands approaching pure conditions.

Table 12. Spatial error matrix using photo interpreted reference and spruce classes combined.

		Reference (Photo Interpreted)						
		SB	MC1	PJ1	PO1	MH1	Row Total	User's
IRS/Landsat Class	SB	**346**	65	54	3	4	472	73.31%
	MC1	47	**67**	29	5	6	154	43.51%
	PJ1	17	38	**181**	0	3	239	75.73%
	PO1	2	3	0	**17**	6	28	60.71%
	MH1	4	5	2	6	**52**	69	75.36%
Column Total		416	178	266	31	71	**962**	
Producer's		83.17%	37.64%	68.05%	54.84%	73.24%		**Overall = 68%**

Table 13. Spatial error matrix using photo interpreted reference where pure stands exhibit working groups greater than 80%.

		Reference (Photo Interpreted)							
		SPU	SPL	MC1	PJ1	PO1	MH1	Row Total	User's
IRS/Landsat Class	SPU	**65**	11	40	2	0	4	122	53.28%
	SPL	35	**91**	25	6	0	0	157	57.96%
	MC1	5	9	**67**	6	0	6	93	72.04%
	PJ1	5	1	38	**69**	0	3	116	59.48%
	PO1	1	0	3	0	**14**	6	24	58.33%
	MH1	0	2	5	0	2	**52**	61	85.25%
Column Total		111	114	178	83	16	71	**573**	
Producer's		58.56%	79.82%	37.64%	83.13%	87.50%	73.24%		**Overall = 62%**

Overall accuracy for this matrix totalled 62% (K_{hat} = 0.54). Decreases in user's accuracy for these classes appeared to be predominantly attributed to commission of stands to both mixed forest classes. Confusion in upland spruce stands can be explained by high commission error (approximately 30%) to the lowland spruce class. However, this misclassification did not seem to work both ways. Other notable improvements were made in the pine and trembling aspen classes of 83% and 87% respectively. This matrix was restructured (Table 14) to include spruce classes together, for a measure of the classifications ability to allocate spruce in general.

Table 14. Spatial error matrix using photo interpreted reference where pure stands exhibit working groups greater than 80%, and spruce classes combined.

		Reference (Photo Interpreted)						
		SB	MC1	PJ1	PO1	MH1	Row Total	User's
IRS/Landsat Class	SB	**202**	65	8	0	4	279	72.40%
	MC1	14	**67**	6	0	6	93	72.04%
	PJ1	6	38	**69**	0	3	116	59.48%
	PO1	1	3	0	**14**	6	24	58.33%
	MH1	0	5	0	2	**52**	59	88.14%
Column Total		223	178	83	16	71	**571**	
Producer's		90.58%	37.64%	83.13%	87.50%	73.24%		**Overall = 72%**

The overall accuracy for this matrix was 72% (K_{hat} = 0.72), and demonstrated the ability of the classifier to separate forest stands approaching pure conditions to a very acceptable level of accuracy. As expected, both mixed wood classes tend to absorb the majority of commission errors from these stands.

Point-Based Assessment

Initially, the remaining field plot data (points not used in training stage) were hypothesized to be adequate to construct this error matrix. However, results of this matrix were not reflective of the successes presented in the aspatial evaluation or the photo-based spatial accuracy assessment.

Table 15 shows poor correspondence between the classification and the reference derived from these remaining field plots. An imbalance in reference points (i.e. hardwood vs. conifer classes) was caused by a general lack of hardwood cover in the study area.

Table 15. Spatial error matrix evaluating IRS/Landsat integrated data using field plot reference data.

		Reference (Field Plots)							
		SPU	SPL	MC1	PJ1	PO1	MH1	Row Total	User's
IRS/Landsat Class	SPU	**78**	24	69	40	1	4	216	36.11%
	SPL	45	**63**	54	42	4	0	208	30.29%
	MC1	47	36	**105**	24	10	6	228	46.05%
	PJ1	24	1	59	**57**	0	7	148	38.51%
	PO1	2	0	10	0	**10**	10	32	31.25%
	MH1	0	4	10	2	6	**40**	62	64.52%
Column Total		196	128	307	165	31	67	**894**	
Producer's		39.80%	49.22%	34.20%	34.55%	32.26%	59.70%		**Overall = 42%**

Calculating user's and producer's accuracy, as well as an overall percentage of 42% for this matrix indicated poor classification results. A Kappa statistic of 0.23 reaffirms the poor agreement within the error matrix. However, upon visual inspection of the classification, results displayed by this table did not represent visual quality of the thematic product.

Upon closer evaluation of reference data, inconsistencies were observed in terms of scale, as well as point location (i.e. distance from boundaries). This indicates a point-based accuracy assessment was not the most appropriate means to evaluate a classification system based on image objects.

Alternative Classification Method

Most forests in Ontario do not have a grid of point data to train a classifier. In many areas, photo interpretation might be used on portions of the forest to train a classifier. A non-site specific assessment was performed to test a classification using the photo-interpreted area as a training set to the classifier, as an alternative to using field point data for training. The alternative method uses the IRS/Landsat merged data, and with training data from photo-interpreted data. A control test, using only Landsat data, was also performed for this method. The results are compared in Table 16 to the original classification, and also summarized in bar graph format in Figure 25. Attempts to classify the Landsat data in its raw form were also made, first, using the field plot and forest unit grid data as training, and second, using the photo interpreted data to train.

Table 16. Non-site specific assessment of alternative classification method.

Image Data	Class	Training Method Field Point Data/Grid Total Area (%)	Training Method Photo Interpreted Based Total Area (%)
IRS/Landsat	SPU	34.4%	39.30%
	SPL	22.9%	17.68%
	PJ1	14.6%	18.38%
	PO1	1.0%	1.03%
	MC1	23.2%	19.73%
	MH1	3.7%	3.88%
Landsat (Control)	SPU	32.5%	36.2%
	SPL	14.6%	12.5%
	PJ1	12.6%	14.1%
	PO1	0.8%	1.6%
	MC1	34.8%	31.1%
	MH1	5.0%	4.5%

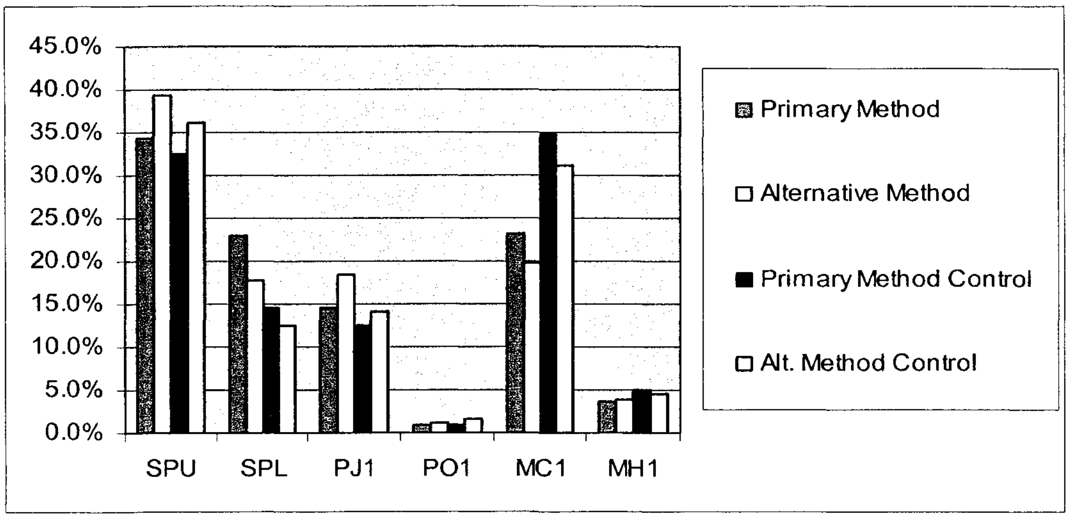


Figure 28. Graphical presentation of non-site specific assessment for alternative method.

Using the photo-interpreted reference data as a training set produces similar results when compared to classifications trained with the primary method. The classification derived from the merged product showed a decrease of nearly 3.5% in the mixed conifer class using the photo interpretation training, as well as an approximate 4% increase in overall jack pine composition. An increase of 5% was observed in upland spruce classes, accompanied by a decrease of 5% in the lowland spruce class. Comparison of each training method used in conjunction with the Landsat data exclusively indicated little variation between results. Most notable fluctuation occurred in the upland spruce class, as the photo trained classification increases this composition a total of 4.3%.

While training methods provided relatively small fluctuations between classes, this was not the case when comparisons were made between image data sets. Large increases of approximately 10% were present in mixed conifer classes for both training methods using the Landsat data alone. Mixed hardwood classes also increased in both cases. Pure spruce and pine classes decline in all cases, most likely shifting into the mixed conifer category. Observations were made for these spruce and pine classes to determine if incorrectly allocated stands were indeed shifting into mixed-wood stands. A total of 30 randomly selected stands from spruce upland, spruce lowland, and jack pine were visited on the thematic map produced from a Landsat image classification. The stands were then compared to the original forest unit grid. The comparison can only be made generally, as stand boundary discrepancies occur between the stands in almost every case, however, Table 17 gives a good indication that the shift of some pure stand area into mixed-conifer area is occurring.

Table 17. Illustration of misclassifications using Landsat control classification.

		FRI Stand						
	Stand Type	SPU	SPL	MC1	PJ1	PO1	MH1	Total
	SPU	17	2	8	2	0	1	30
Landsat (Control)	SPL	7	11	9	2	0	1	30
	PJ1	7	3	4	14	0	2	30

COST COMPARISON

The cost of this procedure is a fraction of traditional FRI methods, with cost reduction for image acquisition costs, and elimination of much of the GIS data loading stage. Table 18 summarizes costs associated with each method.

Table 18. Cost comparison different inventory development methods.

Item	Study IRS/Landsat (CAD)	Conventional FRI Producing FU Map (CAD)	Conventional FRI (CAD)
Image/Photo Acquisition	$0.03/ha	$0.14/ha	$0.07/ha
Ground Truth	$0.14/ha	$0.14/ha	$0.21/ha
Image Analysis/Software/Photo Interpretation	$0.03/ha	$0.05/ha	$0.22/ha
GIS Data Load	$0.00/ha	$0.10/ha	$0.15/ha
Totals	$0.20/ha	$0.43/ha	$0.65/ha

The FRI delivers much more information about forest stands, such as species composition, age, height and stocking. However, only the forest unit and age class levels of detail are used for strategic planning. Table 18 also demonstrates the hypothetical cost of achieving forest unit level classification using traditional FRI methods and materials. The cost savings report at this stage could allow the forest unit map to form the basis for stratified random samples to determine other values of interest, such as stocking, volume or age of the forest. Once areas have been selected for operation, more detailed inventory would target those areas to better guide forest operations in terms of forecasting wildlife habitat quality, timber availability or forest renewal needs. Costs are reported based on past forest inventory project proposals and contracted cost research.

DISCUSSION

The classification system implemented in this thesis shows the benefits of multi-source, space-borne approach when considering the assembly of reliable and cost-effective forest inventory. Using the various strengths of different sensors in an integrated fashion can improve capabilities of inventory development for strategic level planning at decreased costs and with shorter production periods than traditional methods.

PRE-CLASSIFICATION

Image Acquisition

The acquisition process of Landsat 7 data was very reliable, with many occurrences of leaf-on, cloud-free images per season. With a 16-day revisit cycle, an abundance of data was available. The same cannot be said for the IRS-1C and IRS-1D panchromatic sensor, particularly in northwestern Ontario. Although the revisit cycle is speculated to be every 48 days for each sensor (2 images every 48 days), many of these re-visits to northwestern Ontario by each sensor produced no results without apparent reason. No image was produced from the visit in June 2003, speculated to be due to transmission errors during down-linking phase, but no confirmation that this actually caused the problem. Another random problem, exclusive to the IRS-1D sensor, occurred specifically with the left array of the sensor. On more than one occasion, an image was compromised by a loss of data collection on the left third of the image. The vendor, Space Imaging Inc., suggests that this was a problem with the sensor itself and not the downlink process. When considering IRS for a project, ensuring an image is available is highly recommended.

Since the initiation of this project, a new SPOT sensor has entered the market offering panchromatic products similar to the properties of IRS-1C and IRS-1D. The SPOT 5 sensor is equipped with two panchromatic sensors, the first scanning at 5m resolution with 8-bit spectral detail, and the second scanning at 2.5m resolution at an equivalent bit rating. Scene sizes for both types of SPOT 5 products are comparable to IRS at 60 x 60 km. The 5 m data is more expensive than IRS at approximately \$2.21/km^2 (CAD), and the 2.5 m data is double the cost at approximately \$4.42/km^2 (CAD). Substituting this data for the IRS imagery used in this thesis would have increased costs slightly but would still remain significantly less expensive than conventional FRI. Either of these sensors could be utilized to achieve the same goals while producing forest inventories in the future.

Data Merging

Principle component substitution proved to be the most efficient means to integrate the spectral properties of the Landsat 7 system with the spatial properties of the IRS panchromatic data. In terms of image preservation, correlation evaluation showed only marginal differences between PCS and IHS merging methods with PCS performing better in all cases. When transforming the data using the IHS transformation, uncertainty arose regarding the effects of transforming only three bands at a time, and then later combining several transformations to form an enhanced, six-band composite. PCS avoided this uncertainty by transforming all six spectral bands of the Landsat scene at once, including all spatial variation in the first component. The correlation results accompanied by the transformation limitations of IHS (only three bands at a time) provided adequate reason to select PCS as the most appropriate integration method. Visual inspection of each product was also performed and agreed with all statistical evaluations.

Integrating the properties of the panchromatic data offered two types of improvement to the spectral data of Landsat. First, enhanced edges of forest stands were more clearly distinguished in the merged product. This improvement should minimize the traditional problem of mixed pixels (Foody 1999) in raw Landsat 7 data, removing some of the fuzziness commonly associated with boundary placement in terms of medium resolution satellite data delineation. Second, from a visual standpoint, new features in forest cover were now present in the merged data. In most cases this was attributed to varying density distribution from stand to stand, as well as crown dimension differences. In stands with less dense canopies, it was easily determined whether understory features were contributing to the spectral properties of the stand, rather than tree crowns. When observing these same stands using the Landsat 7 data it was unclear whether spectral properties were attributed to overstory or understory characteristics. Judging by the results of the classifier these two enhancements of the Landsat data are as detectable both statistically and visually.

Image Segmentation

Segmentation of the merged product was successful in isolating important features of the image. From an operational standpoint, the results presented many successes in terms parameter selection and its affect on delineation quality.

POST- CLASSIFICATION

Developing meaningful age data from the merged product returned negative results in pre-study trials with the data. Now ruling out this data for a source of age information, it was necessary to find other ways of age determination in order to justify the data developed by methodology used in this study. A number of sources could be used to determine broad age classes to assist with strategic management planning, depending on the type of landbase in question. For areas with no inventory such as parks or conservation reserves historic fire data can be used as a base provide strategic direction. In areas that possess current inventories, natural and man made disturbances are being documented every year, and in some ways this documentation should be considered one of the most accurate inventory methods to date. In terms of non-disturbed forest area, this data can be grown from year to year in our information systems until depletion occurs and area is placed back into zero ageclass. In light of these ideas, it was decided to carry on with a forest unit focused classification, and consider other ways to attain age information to use in conjunction with the positive species results.

Site-Specific Assessment

Area-Based Spatial Assessment

The results of the area-based error matrix performed on the classification performed using the merged data were indeed positive. All matrices presented a general confusion in the mixedwood conifer class with omission errors accumulating in other conifer based forest units when compared to photo interpreted segments. Upon further exploration, confusion was predominantly attributed to spectral overlap occurring in forest stands with species compositions with 59% of one conifer species, dominating the canopy, and therefore forcing a mixed conifer into the pure class of that species. The same can be said for forest stands with 60% to 70% pure spruce or pine compositions committing to the mixed conifer class. Perhaps this data was unable to assess these transitional stages adequately.

Within the matrices measuring success of lowland versus upland spruce classes a moderate level of accuracy (producer's SPU 58.5%, SPL 79.82% and users 53.3% and 57.96%) was achieved when stands with working groups greater than 80% were isolated in the matrix. This achievement could be an important component of a strategic management decision process in terms of the allocation of winter and summer harvest operations within the SFL. In terms of the errors, the lowland spruce class absorbed a high percentage of omission errors of upland spruce. This was expected, as much of the spectral and textural component of each class would be relatively similar. Canopy differences at this scale might not be adequate in distinguishing these types of forest as effectively as they could be distinguished from photos or field plots. It should be pointed out that many of the incorrectly allocated spruce upland stands possessed a small element of hardwood in the canopy. The inclusion of a hardwood component in these upland sites may have increased the brightness in the canopy enough to shift the classification of upland sites into spruce lowland classes. Many lowland spruce sites visited in the Caribou Forest possessed little canopy closure, and therefore, may be showing more understory in the Landsat spectral data. This understory is often composed of Alder (*Alnus rugosa* (Betulaceae)) and Labrador Tea ((*Ledum groenlandicum* (Oeder.)), which may reflect in a manner similar to the reflectance properties in hardwood crowns.

The ability of the classifier to distinguish spruce in general was reaffirmed in the second matrix (Table 13) when lowland and upland sites were combined, resulting in an 83% producer's success rate.

In the third matrix (Table 14), an attempt to determine what type of forest cover were committing to mixed classes from the omissions of pure forest unit classes. By re-sampling the reference data of only stands possessing greater than 80% of a pure species, it was confirmed that compositions less pure were contributing to most of the error in the matrix. Increases to 83% in the pine class, as well as 87% in the poplar class were apparent in forests with 20% or less mixed wood characteristics. Transitional stages from pure to mixed stand condition were obviously difficult for the classification to define.

Confusion of mixed conifer stands by the classifier was not a surprising find in terms of this classification method. The appearance of mixed-wood stands will vary from site to site in any satellite image, regardless of its spectral or spatial properties. In this study, a mixed conifer stand possessed less than 30% hardwood composition, with the remaining composition made up of any conifer species. The remaining conifer composition could not exceed 59% of any particular species. If exceeded, the stand became a pure stand of that species. In other words, 70% of this composition can be made up of any combination of two or more species. In many cases, a stand defined as mixed wood conifer, may have possessed up to 60% spruce and 40% pine, or vice versa. In terms of training the classifier, many of these stands shared the same spectral and textural properties of stands with 70% spruce and 30% pine compositions, which are classed as either upland or lowland spruce in the classification scheme.

Variation of mixed stands introduced difficulty into the training and decision rule creation of image classification (Franklin *et al.* 2001), and for this reason was attributed for much of the misclassifications in this study. Martin *et al.* (1998) encountered similar problems identifying mixed conifer classes using high resolution data, and suggest that difficulty in training site selection as the cause. More descriptions of canopy structure in field data collection may be required to accurately map these types of forests. However, this type of forest structure measurement is notoriously difficult to measure in the field (Congalton 1991). Furthermore, the interpreter's ability to assess these 10% transition areas between a pure and mixedwood condition may also lead to subjectivity in the reference data. Although the classification algorithm is based upon distinguishing species composition to within 10% of total basal area, photo interpreters may not be able to reliably distinguish this level of detail.

On the other hand, considering how similarly these mixed wood conifer stands will be managed when compared to a pure conifer stand, this weakness of the classifier would not lead to inappropriate forest management decisions.

Point-Based Spatial Assessment

Assessment of the classification using existing forest inventory plots and grids was attempted in order to remove the photo interpretation stage out of the classification procedure. Many problems with point-based accuracy assessment have been documented (Congalton and Green 1999; Boudewyn *et al.* 2000) as problematic for the evaluation of thematic products (e.g. satellite images). The results were no different in this study, as the error matrix displayed poor results in all classes.

Initially, all points derived from sample data not used in the training stage of the classification methods were included in the spatial assessment of the classification. After satisfactory results were observed, investigation into individual point placement indicated that points located along boundaries of classified stands resulted in misclassification error in many situations. An example of this incidence is observed in Figure 26. Field crews measuring forest structure in transitional areas of the forest were not necessarily incorrect. However, the location of the plot did not correspond exactly to where the classifier selected the boundary placement between two different stands. The yellow point shown in Figure 29 provides an example of this occurrence and represents forest information from the mixed hardwood class (beige colour). However, the point has fallen on the outside of this stand, and into its neighbouring stand. This neighbouring stand, classified as mixed conifer (blue polygons), may be correct, but was misclassified due to this point location. Another source of error could also have occurred during GIS data loading of the sample point locations. Field crews merely "pin-pricked" aerial photography while at the point location. This point was later transferred from photo to map with the FRI interpretation, leaving two potential sources of inaccuracy. Points falling in areas close to, or inside of stand transition may lead to misclassification, compromising accuracy of the thematic product.

Boudewyn *et al.* (2000) conclude that buffering the stands in order to exclude these points located in transitional areas had no overall positive or negative effect on classification accuracy. Results from this study reaffirm these findings. All attempts made to buffer regions of transitions to exclude these field plots were unsuccessful at improving the matrix results.

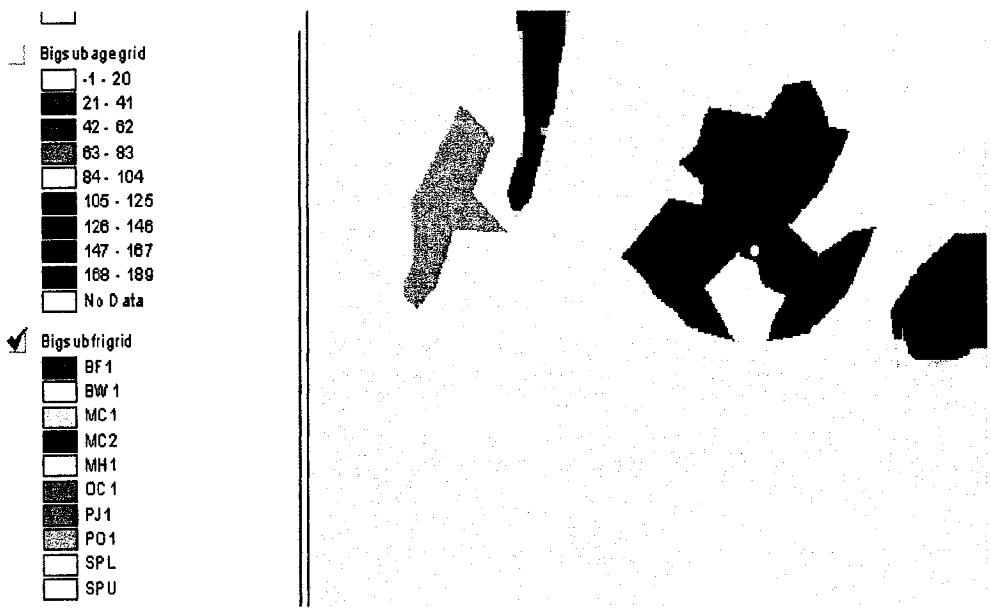


Figure 29. Example of plot location in transitional area.

Exploring the results of the buffering attempts brought forth a new discovery. Figure 30 demonstrates another problem related to point-based accuracy assessment, in that field points may have been representative of a small area within the image object (i.e. forest stand), but did not correctly represent the entire image object (blue polygon features depict image object boundaries). Although the field point located within the segment may accurately describe the forest unit within sampled trees, it is misrepresenting the broader elements of the image object. In this example, the plot was not in a location excluded by the buffering process, and consequently, remained in the assessment.

Developing an area-based assessment using the current forest unit grid was also attempted with little success. First, it should be understood that in most cases the boundaries delineated by the FRI interpreter (from which the forest unit grid was created) differed in varying degrees from the boundaries delineated by the segmentation software. These differences may cause fluctuation in species composition, leading to changes in polygon composition. For this reason, it was determined that these inconsistencies could be contributing to errors when testing accuracy of classification.

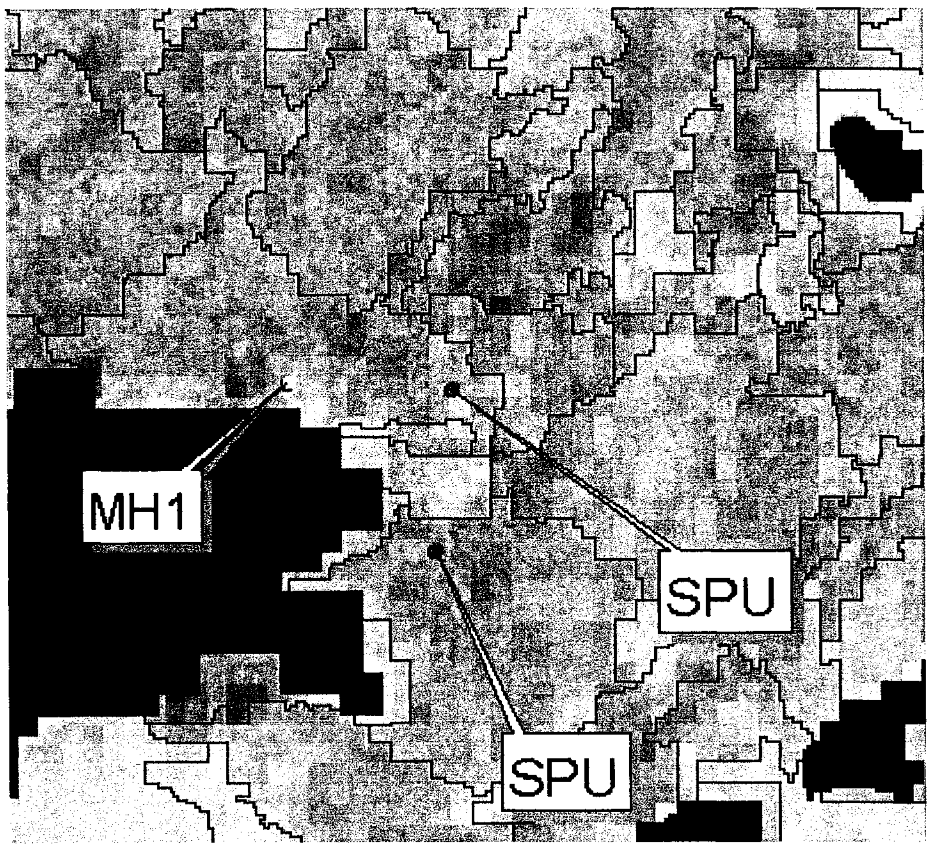


Figure 30. Field data located in small mixed hardwood area; located in upland spruce dominated image object.

These discoveries are influential in ruling out the possibility of using existing FRI data as a testing component of classifications to follow this one. New reference data creation is recommended, preferably utilizing predetermined image objects to assess the truth source.

Aerial Photography-Based Spatial Assessment

In light of issues with point-based spatial assessment of an area-based classification system, and alternative method to assessing the classification was required. Interpretation of aerial photography may be susceptible to error when attempting to determine stand age, height, understory, etc., depending on the scale of the photos and skill of the interpreter. However, delineating to the forest unit level is considerably less demanding, and can be completed accurately by an experienced interpreter. The interpreter used in this study possessed over 30 years of experience interpreting aerial photography in the boreal forest and therefore was quite confident in his ability to distinguish forest unit level interpretation. From this interpretation, a reliable truth dataset emerged, allowing direct comparison of ground properties to classification result.

Non-Site Specific Assessment

Non-site specific assessments were carried out as accompanying assessments to the site specific assessment performed with the classification. Past literature (Congalton 1991; Jensen 1996) has criticized studies that use this method exclusively to determine whether a classifier has achieved acceptable results. However, if used properly, this assessment can provide insight into the successes and failures of a classification. For example, comparing two maps, where one is deemed to be acceptable and the other is to be tested against it, can provide an indication whether the map being tested is providing some positive results. The map created by the classification of the merged data was deemed successful. This allowed other classifications performed with different data sets to be compared to this initial classification, for an indication of achievements and failures.

Important conclusions can be made from the classifier's success using merged data in conjunction with photo-interpreted training data. Mild but significant fluctuations in compositions were observed in all conifer classes, most notably, the increase in pine and spruce classes. These changes may be a result of inadequate coverage of photo-interpreted area with respect to image data extent. Photo interpretation may still be an acceptable substitution for existing FRI in the training stages of this system. However, broader coverage of the entire area may be required to select a larger, more representative set of training for the forest class signatures. This will increase the cost of obtaining the training data, but will likely be cheaper than collecting field data.

The IRS/Landsat merged data consistently performed better than the Landsat alone in classifying forest units similar to the FRI standard. When compared with merged product, observations of significantly increased mixed conifer composition were noted in each control classification. Furthermore, mixed hardwood composition also increased in both cases. From this, it can be assumed that the increased spatial detail provided by the IRS panchromatic allowed the classifier to better distinguish these stands, particularly when a single species was more dominant in a mixedwood state.

In terms of cost, the methods in this thesis should allow the forest manager the ability to spend less to gain strategic level forest inventory data for the entire area of interest. By spending less at this intial stage, forest managers now have the option to focus more detailed inventory efforts on target areas for operation. For example, stratified random field samples of forest units and forest unit seral stage combinations would generate empirical yield table and habitat structure matrices. These tables and matrices would be sufficient to forecast current and future forest conditions that are forest management planning requirements in Ontario (OMNR 1996). These tables would be statistically verifiable and the data collection cost would be less than the current, non-verifiable procedures used with conventional FRI.

CONCLUSION

The primary method developed in this thesis accomplished the main goal of providing a new process for creating large scale forest management-level inventory in five components. These components and a description of how they were addressed are discussed below.

1. Adequate level of information and reliability – Classification consisted of forest unit cover classes, including spruce upland and lowland, jack pine, mixed conifer, poplar and mixed hardwoods. This level of species cover can be used for landscape and sub-regional planning. The overall accuracy of this classification was 72%, with highlights in black spruce (overall 90%), jack pine (83%) and poplar (83%). While age was not developed directly from the data, age determination was considered from other sources.
2. Higher cost-efficiency than current forest inventory requirements – Total cost for new method was considerably lower than conventional FRI development procedures by approximately \$65.00/km^2 (Canadian Dollars). The speed and cost efficient means of classifying merged image objects to forest units offers several possibilities to enhance forest management. These savings would allow for inventory dollars to be reallocated for areas selected for operations to further refine operational decisions.
3. Shorter turnover than traditional methods – using conventional inventory methods, it takes three years to complete an FRI for an average forest

licence in northwestern Ontario. Mapping the Caribou Forest using the methods described in this work was completed in less time than the summer season in a research stage of development. Much of the time taken in this period related to learning the system, and when removing the learning curve, this process may be completed in a matter of weeks. Resulting classification is ready for implementation into a GIS database, with polygons containing the attributes of the inventory, immediately after it is deemed acceptable.

4. Semi-automated techniques reduce the level of subjectivity often prone to traditional FRI methods. Processes are repeatable, and for this reason, can be adjusted and re-applied to meet user needs.
5. The increased availability of satellite data allows for flexibility when choosing imagery suited for the targeted inventory. Sensors with different strengths can be integrated to meet the needs of many different levels of inventory.

While achieving these goals, two accompanying objectives were formed and met by this thesis. Explanation of the goals and how they were achieved are as follows:

1. Testing IRS-1D as a complementary dataset to Landsat 7 TM data – The results of the merging trial showed promising preservation of the spectral and spatial properties of each image when integrated with each other. Principle component substitution proved to integrate the data most

effectively, and lead to satisfactory delineation of the forest into forest units.

2. Testing a new classification technique, image segmentation – the segmentation portion of the process is crucial to the results of the classifier. Gained understanding of significant features for the segmentation process occurred. The concept of image segmentation undoubtedly dealt with textural features more effectively than traditional classification tools. The segmentation results were observed by a trained photo interpreter, and deemed representative to what was occurring in the corresponding aerial photography.

The methods provided in this thesis allow the forest manager to now make choices for alternate forest inventory schemes. The forest information provided by the method may assist the forestry community to progress with changes occurring in how the forest will be managed and where operations will occur in the coming years in Canada.

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