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**Application of Remote Sensing in Detecting and Monitoring Forest
Regeneration Process in a Disturbed Environment**

By

Ning Wang

**A thesis submitted to the Faculty of Graduate Studies and
Research in partial fulfillment of the requirements for the
degree of**

Master of Arts

Department of Geography

Carleton University

Ottawa, Ontario

April, 1994

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**Application of Remote Sensing in Detecting and Monitoring Forest
Regeneration Process in a Disturbed Environment**

submitted by Ning Wang, B. Sc.

in partial fulfillment of the requirements for the degree of Master of Arts in
Geography

Thesis Supervisor

Chair, Department of Geography

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April, 1994

Field photo of *Kalmia* (on the right side)

Abstract

The successful regeneration of areas deforested by natural or human-caused disturbances can be facilitated by monitoring regrowth patterns with remote sensing. One factor influencing the species mix and succession is the presence of undesirable, naturally occurring competitive species on the site. In particular, the allelopathic properties of certain herbaceous species is recognized as a potentially significant threat to reforestation and natural site reclamation in boreal forest regions and northern Great Lakes-St. Lawrence forests regions. *Kalmia angustifolia*, for example, can inhibit regrowth of desirable tree species by depleting soil nitrogen levels in the vicinity. The impact can be sufficiently severe to warrant site inspection and ground intervention. Previous work by Gillespie et al. (1992) demonstrated that *Kalmia* could be detected by airborne scanner.

This thesis reports on a demonstration of potential for the operational use of Landsat TM in the detection of *Kalmia*. The Sudbury Basin was chosen as the study site as the landscape of this area has a long history of natural and human-caused disturbance with reclamation efforts ranging from intensive site preparation to natural regeneration. The *Kalmia* study is part of a long term effort in this area to assess the potential of satellite imagery for a wide range of geobotanical investigations. A multi-date approach to methodology testing was adopted in view of the fact that the ability to differentiate trees and ericaceous plants varied greatly with season.

Identification of *Kalmia* proved challenging as its spectral signature was found to be very similar to those of deciduous trees and shrubs. Visual interpretation of *Kalmia* required a two step process of PCA to differentiate between trees and shrubs, and Infrared Index analysis to highlight within shrub species variation. A complex supervised classification of a combination of bands, ratios and principal components which each individually highlight vegetation, offers considerable promise. *Kalmia* could be identified with both techniques when representing over 40% of a shrub community.

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Chapter One INTRODUCTION

With an ever increasing human population, and the quest for improved quality of life, there has never been such a big demand for natural resources, and people have never valued resources, especially nonrenewable and scarce resources, more than now. The conflicts between conservation and extraction (destruction) exist almost everywhere, and they are particularly obvious in the context of forest resources. No matter where we are in the world, we are facing a changing landscape. Forests are vulnerable to the actions of humans and nature. They can be easily destroyed by industrialization, urbanization, fire, logging, etc. The impact of forest damage to our environment is tremendous, and it is always much easier to destroy a forest than to re-establish it. Immediate detection of forest degradation, discovery of the cause of the decline, and searching for the proper site treatment are the key elements of environmental protection and restoration.

Among the various forest damage detection methods, remote sensing has the advantage of being fast, economic, and spatially comprehensive. In fact, ever since the beginning of the civilian practice of remote sensing technology, one of its most successful application areas has been forestry. The frequent earth coverage of commercial satellite images along with their improving spatial and spectral resolution has made operational monitoring of vegetation growth conditions possible. However, as the spatial and spectral

contrast among vegetation targets is not always significant, current detailed studies rely on airborne remote sensing, in which the receiving spectrum is tailored and the spatial resolution is controlled by the height of the airplane. The cost of airborne remote sensing is high and it is hard to keep it at an operational level. The use of satellite remote sensing to achieve and even exceed what can be done with airborne remote sensing has always been a challenge in the research of remote sensing.

This thesis reports the author's research in understanding and detecting the forest regeneration process using satellite remote sensing techniques on a disturbed environment -- Sudbury area of Ontario.

1.1 Background Information of the Study Area: Sudbury, Ontario

During a century of lumbering, forest fires, geological exploration, urbanization, and airborne pollution, the landscape of Sudbury has been greatly modified to such an extent that at its worst, it was referred to as resembling the surface of the Moon.

"Had nothing happened in this area, the vegetation communities that would be expected to dominate the terrain given the natural soils, climate and geographical location, belong to the Laurentian Upland section of the Great Lakes-St. Lawrence division of the North American hemlock white-pine northern hardwood forest. Prior to the exploitation of this forest by man, it

was dominated by Eastern White Pine (Pinus strobus), Eastern Hemlock (Tsuga canadensis), Sugar Maple (Acer saccharum) and Yellow Birch (Betula lutea). At the same time, because Sudbury is located in close proximity to the Boreal Forest Formation (Rowe 1959), there are inclusions of some boreal tree species and the variety of deciduous species naturally reduced near this northern extremity" (Pitblado, 1984 p.18).

With the increasing awareness of environmental degradation, great efforts have been made by governments and mining companies to restore the forest. Now the disturbed forest in Sudbury is regenerating, and the majority of the above forest species are coming back.

The regeneration, however, has not been successful everywhere. Except those areas which are very close to the sources of pollution, most disturbed places are the result of fire and clear cuts [see Fig. 1.1 Fire Risk Map of Canada]. Generally, in cases like this, nature will take care of the situation: not long after the forest has been cleared, natural regeneration occurs when seeds are brought in by wind and animals, the burned layer of the soil supplying nutrients to the young shrubs and trees. There are even fire loving tree species, such as jack pine, whose growth can be actually stimulated by fire (intense heat causes the cones to open so that the seeds can reach the soil and germinate). A few years later, when the height of the trees exceeds the height of shrubs and the tree canopies block the sun light, the growth of the trees starts to accelerate and the growth of shrubs slows down. These shrubs will eventually become the understory of a new forest.

Fig. 1.1.

Risk of Forest Fire

Source: Atlas Of Canada, Reader's Digest Association, 1981.

The above ideal situation is not happening everywhere in Sudbury. Instead, decades after fire and clearcuts, large areas of scrub with stunted and scattered coniferous trees are commonly observed. Even jack pine exhibits growth check symptom in those areas. In a heavy mining environment like Sudbury, where, large areas of vegetation had been completely destroyed by smelting emissions, there is a tendency to relate any problems of vegetation growth to air pollution. But both field investigations and literature study show that air pollution in our study area is a minor factor, as indicated in an Ontario/Canada report (1982 p.187), that *"with respect to vegetation damage, the data have indicated that in the years prior to 1972, acute and chronic vegetation injury occurred within an elliptical area which has its outermost limit at a distance of 70 KM northeast of Sudbury, vegetation injury since 1972 has been reduced to the extent that current injury occurs infrequently, being confined to relatively small isolated areas and affecting only those plant species which are most sensitive to SO₂ (Trembling Aspen, White Birch and White Pine)."* Our study area is located outside of the area of air pollution [see Fig. 1.2].

If air pollution is not the primary cause of the unsuccessful regeneration, than what is it? Millik (1987, 1991), Titus et al. (1988), and Read (1984) indicate that an ericaceous¹ shrub called *Kalmia angustifolia* L. was responsible for the growth check of some softwood trees especially black spruce. Recent field evidence from Newfoundland confirms this assumption (Gillespie, et al. 1992). Further research into the biology of *Kalmia* revealed a

1. Ericaceous - A family of plants, made up of heaths and various related plants, being predominately shrubs.

FIG. 12CAPREOL STUDY AREA LOCATION MAP

controversy concerning the effect of this shrub on forests (Mallik 1987, Benoit, et al. 1968, Gimingham 1972, Harborne, et al. 1973). During field investigation in the Sudbury Basin in June 1992, the research team had remarked on the apparent "suspension" of the regeneration process in certain quite large sites, it was this observation which caused the team to search for possible explanations, to discover the work on *Kalmia* and to verify the allelopathic¹ effects of *Kalmia* in the sites in question.

1.2 *Kalmia* and Remote Sensing

Detection of *Kalmia* can be done with high resolution airborne CASI (Compact Airborne Spectrographic Imager) images which have a spatial resolution of 2.5m (Gillespie, et al. 1992). For regional detection, this can be prohibitively time consuming and expensive, and it would be even more expensive for monitoring purpose. Satellite TM image offers continuous large area coverage of same area on the earth every 16 days. Use of such data could make the detection and monitoring cost-effective. The challenge of substituting spaceborne images for airborne ones comes from the former's much coarser 30mx30m spatial resolution and the "small and clumpy" appearance of *Kalmia*. In the study area of Sudbury, we have not found any large, pure stands of *Kalmia*. Instead, there is always a mixture of other shrubs and trees with *Kalmia*. This means every 30x30 square meter pixel of a TM image which covers an area containing *Kalmia* will provide mixed

1. Allelopathic - The inhibition of one species of plant by chemicals produced by another plant.

information, and when there is little *Kalmia* in a pixel area, differentiating it from pixels without any *Kalmia* would be difficult.

Although difficult, there are two potential reasons that satellite images could be used to detect *Kalmia*. First, the unique semi-deciduous habit of *Kalmia* enables the shrub to have a distinctive field appearance (and hopefully reflectance) among other cover types -- *'new leaves are formed in July, and retained throughout the winter with abscission occurring only after the next new set of leaves is fully formed the following summer, as a result, Kalmia varies in color from lush green in July to rustic orange-brown after mid-September'* (Gillespie et al. 1992 p.130). Second, even though TM image has a relatively coarse spatial resolution (30mx30m), it offers excellent spectral resolution. It was the author's hypothesis that after careful study of the spectral properties of different cover types, it might be possible to identify and exploit spectral differences through the development of an image processing methodology to enhance the subtle contrast between different cover types, therefore to finally map the area.

1.3 Thesis Structure

This thesis is presented in six chapters. Chapter One contains general information about the study area and the remote sensing study described in this thesis; Chapter Two reviews certain aspects of the biological and ecological literature in which the principal causes limiting forest growth in the

study area are examined; Chapter Three of this thesis provides a critical review of the state-of-the-art geomatics techniques used in forest studies. Several of the current image processing and detecting techniques are introduced and evaluated. This chapter lays a foundation for selecting, combining, and customizing appropriate image analysis techniques for the detection of *Kalmia*.

The strategic detection plan which is introduced in Chapter Four is based on these fundamental studies. It is followed by the description and justification of a step-by-step research procedure (multispectral image processing and analysis) that has been applied to the study area.

Chapter Five, Change Detection -- *Kalmia* Field Monitoring, introduces Multitemporal Image Processing and Analysis. In this chapter, various change detection and data calibration methods are described, applied, and compared, and the best method for *Kalmia* invaded field detection is selected.

The final chapter, Chapter Six, provides a summary and discussion of the research. It also offers recommendations for further research. To "complete" the study, some information about land management relating to *Kalmia* is introduced. It is recognized that the spread of *Kalmia* can only be stopped by proper land treatment, and only after effective suppression of *Kalmia* will forests, especially softwood forests, return to normal composition and growth.

Chapter Two

Ecology of the Environment and Allelopathic Nature of *Kalmia angustifolia*

Sudbury lies near the southern edge of the Canadian Shield, in a forest zone transitional between the boreal (coniferous) forest to the north and the deciduous (hardwood) forest to the south. This mixed forest zone belongs to the Great Lakes -St. Lawrence Forest Region. The forest in the study area of Sudbury has more characteristics of the boreal forest than of the deciduous forest because of its geographic location and the climate of the area.

Mainly grown on podzol, the boreal vegetation community is a spruce-fir forest with a shrub (mostly ericaceous) understory. Although the forests are found on wet boggy environments, fire happens periodically. After burning or cutting, natural regeneration takes place. While successful natural regeneration is common in many places, there are also cases of unsuccessful regeneration. The forest in the Sudbury region contains examples of both conditions.

In the study area of Sudbury, decades after a fire, large areas of Heathland with stunted and scattered coniferous trees are common. Investigating the reasons leading to this phenomenon can help us in designing a strategic program to detect and monitor the problem areas using current

geomatic techniques. It also lays the foundation for searching of the effective *Kalmia* land management methods.

This Chapter reports the author's research into possible reasons for the unsuccessful regeneration of conifer forests in Sudbury area. The research includes both reviews of the biological and ecological literature and analysis of the evidences from field investigations.

2.1 The Origin of the Forest

Many forest sites in the study area developed on raised bogs and are routinely threatened by burning and cutting. Knowing how the forest is formed may help us to understand why certain shrubs can possibly prevent healthy regeneration of forest.

In his book *The Forest in North America*, Vankat (1979) described how a forest develops from a bog. This process can be portrayed as:

Peat moss (*sphagnum* spp.) is the starter of the raised bog. The plant is cushionlike and contains lots of dead cells which are filled up with water. As the plants grow upward, the lower ends die off and are converted into peat.

Gradually, the individual cushions merge together to cover the entire area. When a bog is drained, peat moss ceases to grow, and the area is then rapidly converted into a shrubland (Vankat 1979). Although the types of shrubs vary, they have one thing in common, that is that they all require very few nutrients from the soil, otherwise they could not survive in the acidic, nutrient poor environment of a raised bog.

Among the various shrubs, insectivorous flora play an important role in the introduction of tree species to the bog. They obtain their primary nutrients from insects rather than from the soil. Sundew, for an example, can fix nitrogen from flies. When these plants die, their leaves and branches will add nutrients to the soil. Tree species will come only when the nutrient level is appropriate for them to survive.

The evidence in the Mer Bleu area of Ottawa supports this model. The author has found, during field investigations, that cattails, sundews, alders, deciduous and a few coniferous trees are now growing together on the boggy areas. Insects in this area are plentiful. An ongoing ecological study of this area by the Carleton University Biology Department indicates that the nutrient level and PH value in the soil have continuously increased. Small deciduous and conifers trees also have been found in the area. This phenomenon in Mer Bleu is obviously an indication of the beginning of the last stage of Vankat's model.

Along with insectivorous flora, ericaceous shrubs are also commonly found in cool temperate raised bogs. According to de Montigny (de Montigny et al. 1990), ericaceous plants are one of the most ecologically successful plants in the Northern Hemisphere. Their ecological restriction on plant nutrients in the soil is very low. They are associated with heathland conditions where conifer regeneration is often slow and chlorotic, or even excluded.

In contrast to the insectivorous flora, heath shrubs make no nutrient contribution to the site at all. They even hinder the nutrient uptake by other plants (Titus et al. 1988, Walter et al. 1985, Read 1984). Furthermore, Walter (1985) indicated that low soil temperature and lack or excess of water (a common condition in many northern bogs) leads to nitrogen deficiency which will cause xeromorphism¹ of all plants. Xeromorphism in turn will increase the possibility of bush or forest fire. Thus, the existence of heath shrubs in a raised bog has a potentially negative impact on the evolution of the area to a forest.

When the area is finally forested, fire often occurs. From laboratory observation, Mallik (1990) found that the growth of an ericaceous plant called *Kalmia angustifolia* L., which is common in many Canadian conifers forests and boggy areas, has been stimulated by fire. It is, therefore, ready to compete with other plants for light and nutrients soon after the disturbances. This observation may explain why the regeneration of trees is not successful when

1. Xeromorphism - plants become drought-resistant or drought-tolerant by structurally adapt for growth with limited water supply

preexisting forests have been burned or harvested. If such an area has been left untouched, it may become an open scrub field with sparse and stunted trees and with all plants including ericaceous plants themselves exhibiting symptoms of checked growth (Titus et al. 1988, Mallik 1987, 1991).

In the Mer Bleu area of Ottawa, where the forestation process has been successful, no *Kalmia* was found. At similar sites in the Sudbury study areas where regeneration has not been successful, *Kalmia* is plentiful. *Kalmia* is commonly seen as an understory in black spruce forest stands, or as a component of scrub fields where the original forests had been repeatedly burned or cut. It can also be found in the vegetated bogs.

Field evidence in the Sudbury Basin indicate that the sequence and the scale of Vankat's model is too simple to describe the natural world. The natural regeneration process in the raised bogs in the Sudbury site seems to be slower and less certain than may be implied by the Vankat's model.

In conclusion, it is the deciduous shrubs that have played an important role in the evolution of these forests. The presence or absence of nitrogen fixers (insectivorous) or nitrogen absorbers (certain ericaceous plants) influences the rate and the trend of the forest development. On the bases of field observations in Ottawa and Sudbury and the evidence reported in the literature, and considering the complexity of the natural world, the author suggests that climate, temperature, topography, and soil parent material have

combined effects in the introduction of different types of flora. When certain ericaceous plants are involved, the forest regeneration is likely to be retarded. Thus, a more general model of northern forest evolution is proposed as below:

2.2 The Allelopathic Nature of *Kalmia angustifolia*

The evidence of allelopathy of some ericaceous plants was first observed between *Calluna vulgaris* L. Hull. and sitka spruce in Scotland by Muller in 1897 (de Montigny et al, 1990). In Canada, this effect is strongly evident between *Kalmia angustifolia* and black spruce (Mallik 1990; Read 1984). Both group have found that the aqueous solution extracted from litter and soil of *Calluna* (U.K.) and *Kalmia* (Canada) inhibited the primary development of the roots of the conifers trees. Further study showed that *Kalmia* competes not only with trees but also with other shrubs. For example, the strongest competitor of blueberry (*Vaccinium angustifolium*) is *Kalmia* (Hall et al. 1973).

In the search for a better understanding of nutrient competition, many scientists have studied the chemical content of the Ericaceae. Harborne and Williams (1973) found that simple phenols were abundant in the Ericaceae. de Montigny (1990) believes that the phenolic compounds are implicated in the allelopathy of ericaceous plants. Read (1984) concluded that the toxicity of heath land soil results from the ability of *Calluna* (or *Kalmia*) to modify the soil environment in its favor. Controversy still exists, however, among scientists regarding the specific allelopathic mechanism of the Ericaceae.

One possible mechanism of the allelopathic behavior of ericaceous plant is that the ericoid mycorrhizae of ericaceous plants produce exoenzymes which cleave off smaller phenolic molecules from the complex organic media they grow on, and the fungi readily obtain a carbohydrate and nutrient source while increasing the availability of simple phenolics in the root environment of competitors (de Montigny et al. 1990).

Glass and Dunlop (1974) proposed a mechanism of organic acids acting as alleochemicals, specifically that phenolic acids partition the aqueous medium and lipid components of the cells according to their lipid solubilities. The membrane then becomes permeable to both anions and cations. This leads to the depolarization of the membrane potential. The subsequent dysfunction of the plasma membrane causes the failure of cells to maintain proper mineral nutrition.

Although it is still unclear which mechanism is correct, it is certain that ericaceous plants are the major cause of poor nutrient levels in the soil. Enough evidence has been found to assure us the allelopathic nature of ericaceous plants. Generally the stronger the allelopathy, the more acid the soil will be. It has also been shown that heath plants influence soil texture (de Montigny 1990). The end result is decreasing productivity of the forests.

(based on de Montigny 1990, McKeugue 1968, Benoit 1968)

Field observations in Sudbury also suggest that the dense branches and thick litter of heath (*Kalmia* and blueberry) physically intercepted and held many tree seeds and kept them away from the soil. The germination of seeds is then prohibited. Even for those tree seeds that eventually reach the soil surface, the allelopathic nature of *Kalmia* litter hinders their chance of survival.

Chapter Three

Remote Sensing Techniques in Forest Studies

The forest ecosystems of the world are being subjected to an increasing variety and intensity of stresses: nutrient depletion, loss of organic matter, compaction and erosion of soils, air pollution and acid rain effects, loss of species diversity, increased biotic disturbances (insects and diseases), and climatic change. The result is deforestation. The deforestation in many cases is a gradual process (except for those caused by drastic events like fire and floods, etc.). It always takes times for vegetation to show measurable stress. There is an urgent need for early detection of this deforestation process, because many of these processes are reversible if proper treatment is applied on time.

Beginning in 1972 when the first Earth Resources Technology Satellite (later renamed Landsat-1) was launched, satellite remote sensing has established its use in the assessment and monitoring of forest resources. Its capability to provide real-time data with synoptic and repetitive coverage gives significant opportunities compared with traditional methods. One of the most successful practice of forest monitoring uses AVHRR images for real-time global vegetation information.

For a quantitative approach to species identification and determination of percentage of surface coverage, although the spatial resolution of satellite images has increased significantly from 80M of MSS to 10M of SPOT image, computer image processing and enhancement techniques are available to facilitate image analysis and classification. The classical photo interpretation of Landsat images also plays a very important role in operational forest study.

This Chapter provide a critical overview of documented applications of various remote sensing image processing and enhancement techniques in forest studies. Owing to the data availability for this thesis, the emphasis is placed on TM imagery.

3.1 Contrast Stretch Enhancement

The sensitivity range of Landsat TM and MSS detectors was designed to record a wide range of terrain brightness from black basalt plateaus to white sea ice under a wide range of lighting conditions. Few satellite images exhibit a brightness range that utilizes the full sensitivity range of the detectors (Sabins 1986, Ahern 1989). In order to produce optimal satellite images for study, contrast stretching original data to the full range of the display medium is the common image enhancement approach.

In many remote sensing applications, linear contrast stretch and histogram equalization stretch are commonly reported. These enhancements,

unless specific stretching range is specified, can increase the overall contrast of images. They provide contrast among different levels of radiance regardless of the usefulness to the user. Therefore, they are best suited for preliminary study of a new site.

Based on the fact that bare soil, dry grass land and gravel pits cause a long tail on the histogram of TM bands, and because they are not very important to forest study, some target specific stretching techniques are applied. Ahern (1989) suggested that a square root stretch is the best stretching method for forest studies, because it has the ability to increase the contrast of low radiance (vegetation) values and compressing the contrast of high radiance values (bare soil etc.).

The formula used for the square root enhancement is:

$$DN' = 255 \times \left(\frac{DN - DN_{min}}{DN_{max} - DN_{min}} \right)^{0.5}$$

(adapted from Ahern, 1991)

This formula ensures that the output values of the enhancement are spread over the range of 0-255, the full range that can be represented by a commonly used computer (8-bit unsigned integer). When $DN = DN_{min}$, the result $DN' = 0$, and when $DN = DN_{max}$, $DN' = 255$, and when $DN_{max} > DN > DN_{min}$, the output DN' is a square root function. [see Figure 3.1]

Fig. 3.1. Square root Function

When examining Fig. 3.1, one can see that it highly compresses the high end of DN values. Water bodies are often features of a forested landscape and they occupy the low end of the histogram. Since square root stretch provides high contrast among low input values, the radiance difference in water bodies also benefits from the stretching. To shift the emphasis from water bodies to vegetation, one approach is to select the stretching range that does not contain or contains little water information; another is to use a different contrast stretch method - squared enhancement.

Contrary to square root enhancement, squared enhancement has the ability to compress the low end of input values and stretch medium to high input values. The formula used for the square enhancement is:

$$DN' = 255 \times \left(\frac{DN - DN_{min}}{DN_{max} - DN_{min}} \right)^2$$

(adapted from Ahern, 1991)

This formula also distributes the output values of the enhancement over the range of 0 - 255. When the input DN is low (water bodies), the output DN' will be even lower, and when the input is relatively high, the output will be much higher. The calculation procedure gives the highest contrast to medium to high input values as compared to other contrast stretch techniques (linear, square root, histogram, etc.). [see Figure 3.2]

Fig. 3.2. Squared Function

The shortcoming of a squared enhancement is that it highlights the difference between the high DN values. For example, when the image contains bright clouds, a stretching range should be selected to exclude the effect of clouds.

It is clear that the squared enhancement and the square root enhancement can complement one another in that one's strength is the other's shortcoming. The user should choose the proper method according to the focus of the study. In the case of the Sudbury area, because bare soil and

unhealthy shrubs (high DN values) are characteristic of the regeneration sites, squared enhancement is used. (see Chapter 4)

3.2 Simple False Color Composites of Satellite Images

Human eyes can differentiate many more colors than grey tones. For this reason, three colors, Red, Green, and Blue (RGB), are assigned to three image bands and the result, depending on the input, is usually a Simple False Color Composite (SFCC). While any three bands can produce a false color composite, the most informative SFCC is derived from assigning RGB to the three least correlated bands.

Because of the simplicity of the transformation, the resulting composite is comparatively easy to interpret and the technique is widely used. For forestry study with TM images, Ahern (1989) summarized the major SFCC enhancements. [see Table 3.1]

Table 3.1 Major Forestry Study SFCC Enhancements

BLUE	GREEN	RED	GENERAL APPEARANCE	PARTICULAR CHARACTERISTICS
TM2	TM3	TM4	Color infrared photo	. good portrayal of roads, water bodies, deciduous/conifer differences
TM2	TM4	TM3	natural color	. good portrayal of roads . poorer deciduous/conifer contrast than 2,3,4

BLUE	GREEN	RED	GENERAL APPEARANCE	PARTICULAR CHARACTERISTICS
TM3	TM4	TM5	natural color	<ul style="list-style-type: none"> . good overall portrayal of vegetation type and condition . sensitive to vegetation damage . poorer road definition than 2,3,4
TM3	TM5	TM4	similar to color infrared photo, but more orange	<ul style="list-style-type: none"> . good portrayal of vegetation type and condition . roads more visible than with 3,4,5
TM3	TM4	TM7	natural color	<ul style="list-style-type: none"> . clearest definition of burned areas . revegetation of cutovers visible earlier than with 3,4,5 . very sensitive to vegetation damage
TM1	TM2	TM3	natural color	<ul style="list-style-type: none"> . very high contrast between vegetation and bare areas . very little vegetation information

(Ahern, 1989)

3.3 Multispectral Image Processing and Complex Color Composites

The data from the seven TM bands are correlated in various degrees with one another and each contains unique spectral information about the targets. The disadvantage of SFCC is that it can only take three single bands as RGB input at one time, so that subtle differences between many cover types may not be readily recognizable. To extract and enhance the target oriented spectral information and to compress the less relevant spectral information, some multispectral image processing of the original data set is required.

Using various Vegetation Indices (VIs), many researchers have attempted to reveal the identities or growth conditions of the vegetation by enhancing the subtle spectral contrast between two bands through ratioing and other mathematical calculations. Table 3.2 is a list of various vegetation indices commonly used in forestry studies.

Table 3.2 Various Vegetation Indices (Cohen 1991)

Normalized Difference Vegetation Index:

$$\text{NDVI} = (\text{TM4} - \text{TM3}) / (\text{TM4} + \text{TM3})$$

$$\text{Nir-R Ratio} = \text{TM4} / \text{TM3}$$

$$\text{Infrared Index: II} = (\text{TM4} - \text{TM5}) / (\text{TM4} + \text{TM5})$$

$$\text{Moisture Stress: MSI} = \text{TM5} / \text{TM4}$$

Leaf Water Content Index:

$$\text{LWCI} = -\lg[1 - (\text{TM4} - \text{TM5})] / -\lg[1 - \text{TM4ft} - \text{TM5ft}]$$

$$\text{Mid IR Ratio} = \text{TM5} / \text{TM7}$$

Monitoring moisture stress in plants is a major field of VI applications. Cihlar et al. (1990) examined the possibility of using the Normalized Difference Vegetation Index (NDVI) to estimate an ecological variable - root layer actual evaporation (AE). The cumulative NDVI obtained from the AVHRR was found to be highly correlated with cumulative

AE with a delay of 15 days. It was also found that when plants have water stress, AE cannot be accurately derived from the NDVI.

Cohen (1991) compared the results of VIs and the single band of TM in measuring leaf water stress. His study showed that almost all VIs (except LWCI and Mid-IR Ratio) were better correlated with leaf water potential (a measure of free energy status) than any single band, where LWCI was more correlated with relative leaf water content (a measure of the volume of water in leaf).

B.N. Rock, et al. (1989) found that the Moisture Stress Index (MSI) was better than NDVI for detecting insect defoliation in sugar maple and fir-wave of dead balsam fir stands.

These findings are typical of VI related studies, that is, the response of VIs to changes of stress as a function of the kind of measurement used and the type of vegetation studied. The studies also showed that there were confidence limits for all VIs in predicting water potential (Cohen 1991). This implies that the selection of the proper VI for a specific problem is very important: VIs may be good at qualitatively detecting forest damage (because of their high correlation with stress) but not at quantitatively assessing the impact.

The spectral contrast between two TM bands can sometime become very important in determining the nature and the status of vegetation. The reason for using various Vegetation Indices is that the calculation process usually improves the contrast thus enabling us to "see" what is originally "invisible" in the raw individual band data. Pair-wise principal component analysis is a different approach which has also been used to achieve the same goal of spectral contrast enhancement.

In the application of pair-wise PCA, a pair of medium or low correlated bands is selected from the TM data set, and PCA is performed on them. The results of such a pair-wise PCA are two non-correlated principal components (also known as eigenvectors, which are perpendicular to each other). The first principal component shows the information which is common to both, while the second principal component shows the average pattern among the portions of the variables not related to the first principal component (Chavez, 1989).

The differences between the visual and infrared bands of the TM image can be of great importance in determining the nature and condition of plants. Sometimes the difference between infrared bands is also very interesting. These differences can be obtained from interpretation of the image of the second component of pair-wise PCA (a black and white image). Based on the covariance matrix output from the PCA, the image is not hard to interpret (see Chapter 4).

Principal Component Analysis (PCA) is well known for its ability to derive a non-correlated data set from a set of correlated data. When PCA is applied to six TM bands, the first three components contain a large percent (usually >90%) of the total variances presented in the original six bands (Richards 1984). The advantages of dimensional reduction and noise reduction (noise appears randomly in TM images, therefore it is recorded in the later component) make PCA a powerful multispectral transformation technique. It is for these reasons that the first three components are used for RGB input, and a very clear and informative false color composite can be obtained. However, there are two problems which hinder the application of standard PCA to multispectral image processing, 1) the first three PCs color composite is hard to interpret, and 2) the information of interest may be subtle and mapped into one of the unused components. (Chavez et al 1989)

Recent experience with PCA image processing has indicated the maturity of this method. Based on the fact that visual TM bands TM1, TM2, and TM3 are highly correlated as are the infrared bands TM5 and TM7, Chavez (1989) has suggested that the concept of selective principal component analysis be used on those highly correlated subsets for dimensionality reduction while minimizing the amount of information lost to unused components.

When PCA is applied to a grouped TM data set, the first component of each group contains most of the information of that group. A close to nature color composite can then be produced by displaying PC1 of TM5 and TM7 as

red, TM4 as green, and PC1 of TM1, TM2 and TM3 as blue. The composite is much easier to interpret than the standard PCA as it looks similar to a TM5, 4, 3 color composite but is much more informative. *"The components not used have mostly noise, striping and bit errors, due to the high degree of correlation of the input images"* (Chavez 1989). Table 3.3 provides a summary of PCA for dimensional and color confusion reduction along with an evaluation of each method.

Table 3.3 Dimensional and color confusion reduction

R	G	B	Source	Evaluation
PC1	PC2	PC3	---	Traditional method. Good for topographic interpretation. Not good for vegetation study
PC2	PC3	PC4	Richards 1984	Highlight changes
PC Vis 1st PC of TM1,2,3	TM4	PC Ir 1st PC of TM5,7	Chavez 1989	Easier to interpret. Dimensional reduction due to high correlation
PC Vis 50% linear + 50% histogram stretch	NDVI Linear stretch	PC Ir 50% linear + 50% histogram stretch	Bryant 1989	Similar to RGB as TM5,4,3 Less noise. Better radiometric resolution. Reduced terrain information from NDVI

3.3 Multitemporal Image Processing

The development of remote sensing technology has provided us not only with images from various types of scanners and different spectral band but also images of the same area at different times. Multitemporal images

enable us to monitor dynamic changes through time. Images from different scanners allow us to study the properties of the forest with different spectral and spatial resolutions. The challenges are how to calibrate multitemporal images, how to merge data from different scanners, how to make them compatible, and how to compare them consistently and reliably. All these are fundamentals in building up a forestry monitoring system.

Integration and calibration of remote sensing data is often required when images from different sensors are involved in the multitemporal study. In a study of merging TM and SPOT pan data, Chavez et al. (1984) suggested 1) enlarging TM data by three times in both directions, 2) smoothing the TM image with 3x3 low pass filter to eliminate the blackness, 3) applying a high-pass filter to pan data, and 4) adding the result of 3) to the lower spatial but high spectral resolution TM data set. This method has been found to be better than IHS (Intensity, Hue, and Saturation) and PCA data merging which is done by replacing intensity and the first PC with pan data and then transforming back to TM bands. For TM image, the calibration of multitemporal images is summarized in table 3.4.

After image calibration, a variety of techniques based on the comparison of multitemporal digital remote sensing data can be used for change detection. These techniques include: comparison of land cover classifications of different years, image differentiating /ratioing of the same bands from different years, vegetation index differences, and pair-wise principal components analysis on the same TM bands from different years.

Table 3.4 Methods of Multitemporal Calibration

Image Requirement	Method	Source	Comments
2 years summer and fall TM images	Contrast stretch TM 4 from two seasons, TM3 from summer put into RGB Update with new set of images with same approach	Kneppeck & Ahern 1989	-simple -surface can be easily identified except for conifer trees beneath deciduous overstory -requires both summer and fall images - ignores changes in radiometric conditions
TM images from different years PCA on each pair of TM bands (old & new)	$BV_t = \frac{BV_n - \overline{BV_n}}{Mpc} + \overline{BV_o}$ where: BV _t : new corrected band brightness; BV _n : new band brightness; BV _n : mean of BV _n ; BV _o : mean of original brightness; Mpc: slope of PC1 plotted against BV _n .	Bryant et al 1989	-linear transformation easy to understand -simple calculation but Mpc not accurate -should consider the seasonal difference of the data set , if any

Based on the nature of pair-wise PCA, the first component will provide the common information, the second component will represent the change which has occurred over the time period. It is clear that for vegetation monitoring, the precondition of all the above methods is that the images from different years must be acquired at the same time of the year and under similar atmospheric condition (see Chapter 5).

Managing forests is a dynamic process. Much information about the ground is needed for decision making. Various image transformation and processing techniques can be used to gather such information. Each has its strengths and shortcomings. A rational approach in the selection of a proper methodology would be an object-oriented one.

From the point of view of forest management, the author believes a detection plan which proceeds from the general to the specific is suitable for the Sudbury study area. The first task in solving the problem of regeneration is to focus on those areas which contain *Kalmia* or are likely to have *Kalmia* invasion potential; the next step is to map the extent of field containing *Kalmia*; and finally to monitor these areas in order to find the changes over time. The next two chapters are a report of the work done according to the above plan.

Chapter Four

Kalmia Detection by Satellite Remote Sensing -- Multispectral Image Processing and Analysis

The satellite images used for this study were Landsat 5 TM images of June 4, 1984; May 19, 1989; and September 17, 1990. Which proved not to be the best candidates for this study, but they were the only images available to the author covering the study area.

The image analysis process consists of three major parts. In Part One, image preprocessing, images were enhanced and geometrically registered. Part Two involved *Kalmia* detection in which several image processing techniques, based on the spectral properties of *Kalmia*, were selected, modified and their results analyzed. The last part, change detection, focused on multitemporal image processing analysis where several change detection techniques were tested on the field areas. The current chapter covers the first two parts while Chapter Five discusses the last part.

4.1 Geometric Registration of Satellite Images

Geometric registration of satellite images to a topographic map is commonly the first step of image processing. In this study, a DTS 1:50,000 topographic map sheet containing the study areas was used as the reference

map. To achieve the highest correction accuracy, the images of the three years were compared channel by channel. The clearest image (June 1984) was selected for the first image-to-map georeferencing.

Before commencing georeferencing, it is necessary to enhance the image to facilitate the finding of corresponding ground features on the image and on the map base. The enhancement was done on the false color composite of three TM bands: TM2, TM4, and TM7.

To produce the enhanced false color composite, TM bands 4 and 7 were linear stretched and assigned to green and red respectively; a 3 x 3 high pass filter:

$$C'_t = \sum_{i=1}^8 \frac{(C_t - A_i)}{8}$$

C_t - the current centre value under the filter

*A_i - the value of *i*th position under the filter*

(adapted from PCI Users Manual, 1991)

was applied to TM band 2 (which displayed low haze effects) to facilitate edge detection. This band was linear contrast stretched and assigned to blue. In the resulting color composite, the outlines of ground features showed up clearly thereby helping with the identification of the corresponding ground control points on image and map.

When examining the map and the image, it was easy to identify lake edges and river bends. Such features are commonly used as ground control points. The risk here is that the water bodies are not stable over time. For example, in spring flood the margin of a lake or river differs from that in winter time. Thus if the image and the map were from different seasons, the accuracy of such a geometric registration might not be reliable. Even in the same season but different years, water margins may also differ. This would have a large impact on the subsequent image-to-image geometric registration for multitemporal study.

For the above reasons, the ground control points selected for this work were stable land marks such as major road intersections and man made reservoir edges which were clear on both the image and the topographic map. Features like hydro lines, railway tracks and agricultural field boundaries were also used. Fortunately, since the area is relatively developed, such features are generally well distributed and abundant.

After the first registration, there are two options in processing the subsequent images. First, image-to-map registration, i.e., repeat the first step to register every subsequent image with the map; Second, image-to-image, i.e., use the geocorrected image as a master image for the registration of the subsequent images.

Upon first consideration, image-to-map registration would seem to be more accurate than an image-to-image registration because only one common standard (map) is introduced. An image-to-image registration approach represents a different standard (from topographic map to master image). In fact, however, this is not true. Every registration can introduce some errors and when two geocorrected images are brought together for analysis, the error in the result will be the cumulation of the individual errors. Due to the large difference between satellite image geometry and map geometry, an image-to-map registration is difficult. Also, because the approximate accuracy of a 1:50,000 map is about 50m, and the TM pixel size is 30m, errors can be easily introduced every time when a image-to-map registration is conducted. On the other hand, if the first image is carefully registered, the advantages of image-to-image registration increase when the number of images to be georeferenced increases. These advantages include both high accuracy and fast registration. The reason is that the master and the uncorrected images are usually enhanced by the same approach, so that finding the corresponding land marks on two such images is much easier and more accurate than looking for the corresponding points between an image and a map. "In practice, image-to-image is two to three times more accurate than image-to-map registration" (Forster, 1991).

Consequently, the image-to-image georeferencing approach was used for the multitemporal TM data set of the Sudbury study area. The procedure of geometric registration is illustrated in Fig. 4.1. After the best image had been carefully georeferenced to the topographic map, all the subsequent images were registered to this "master image".

Figure 4.1 Procedure of Geometric Registration

When all the images were geometrically referenced, they were ready for further analysis. Through careful consideration of the properties of the multispectral images, some site specific image processing and analysis techniques for *Kalmia* detection were developed, applied, and compared in the Sudbury research site.

4.2 Image Enhancement via Color Composite

4.2.1 Color Composite using the Squared Method of Enhancement

As mentioned in Chapter Three, conventional image enhancement methods (i.e., linear, histogram enhancement) have not proven adequate for exhibiting the differences within the vegetation community. Square root enhancement can emphasize water bodies and green vegetations. A squared

enhancement is most suitable for the study area, because it can highlight green vegetation as well as bare soil and shrub fields which are the common components of a regeneration site.

Because squaring is a very powerful stretching technique, selecting the most appropriate spectrum range is important to insure that irrelevant information is not included. The stretching range of each image is scene dependent.

The TM data obtained from June 1984 were affected by about 5% clouds. It must be eliminated from the stretching range so that its effect does not obscure useful vegetation information. The high DN values of clouds can be truncated, leaving the rest of the data untouched if the proper thresholds range is established. The shadows of the clouds have a DN value within the DN range of various water bodies and moist soils. This means that they can not be masked out by using the threshold method. However, since the shadows have the same shape as the clouds and appear on the top left of their corresponding pieces of clouds because of the illumination angle, it is quite easy to differentiate them visually from water bodies so no further efforts were made to "correct" the DN in cloud shadow areas.

The DN value range of the three TM bands chosen for color composites is listed in Table 4.1.

Table 4.1 DN Value Range of June, 1984 TM Bands 5, 4, 3 Raw Data

	TM 5	TM 4	TM 3
Min	0	9	14
Max	140	117	58
Clouds Min	113	89	55

The squared method of enhancement range for TM 5 is 0 to 113, the range for TM 4 is 9 to 89, and the range for TM 3 is 14 to 55.

Plate 1 records the image product of the enhancement. It can be compared with Plate 2, a square root enhancement. Plate 1 has more detail and contrast than Plate 2. The result of a linear stretch also provided poorer contrast than the squared enhancement.

Plate 3 is a similar color composite product with TM Bands 7, 4, 3 using the same enhancement approach. Compared with Plate 1, this composite is darker due to the strong absorption of water in TM 7 causing lower DN values and therefore a darker appearance in the resulting image.

Both Plate 1 and Plate 3 appear generally close to natural colors and thus facilitate visual interpretation of the composite (Transparency 1 can be used to assist this interpretation): the mono-culture conifer plantations, such as red pine and jack pine plantations, are presented in uniform green tone; those wet area conifers (mainly black spruce), have a dark and uneven green tone; deciduous trees, such as white birch, poplar, and maple show in bright

green; grass fields and some agricultural fields are in yellowish green; old clear cuts and burned fields, in which some containing *Kalmia*, are represented in dark red; the recent clear cuts are in pink; gravel pits and roads are in purple. Such an enhanced image is useful for overall examination of the study area. Its resemblances to real world colors makes it a good image-base-map to use in field investigations.

4.2.2 Color Composite of Principal Components Analysis (PCA)

The principal components analysis is an excellent approach for dimensional deduction of TM data, as its three major eigenvectors can be produced from more than three input bands (Bryant 1989, Chavez et al 1989). This feature can provide the interpreter with more spectral detail than the three band color composites.

The first two TM bands (the shortest wavelength bands) are generally degraded by atmospheric scattering. As TM1 usually contains a great amount of haze and provides little vegetation information, it was not used for the input of PCA. TM2 which picks up the green reflectance peak of vegetation is useful for assessing plant vigor. It should be included in the input of PCA unless there are significant scattering effects. The high degree of correlation among TM 1, 2, and 3 makes it possible to use only TM3 to represent the information from visible bands when TM 2 is contaminated.

The TM2 of June 1984 was judged to have little degradation due to atmospheric scattering, so this band along with TM3, 4, 5, 7 was used as the input for the principal components analysis. A mask of the study area which excludes clouds, was applied to the data set to eliminate the effect of clouds.

Table 4.2 lists statistical results of the PCA of TM 2, 3, 4, 5, 7. From the eigenvectors of the covariance matrix in Table 4.2, we can see that PC 1 (Principal Component one) has positive contributions from all input bands, with strong loadings from infrared bands (TM 4, 5, and 7) providing the overall brightness information. The highest loading of PC 1 comes from TM 5 which is sensitive to moisture content of the targets, since shrub fields usually contain bare soil and dry litter, they have higher reflectance values in TM 5 than healthy trees. PC 2 has the highest positive TM 4 loading which responds to biomass. Since trees canopies have very strong reflectance in TM 4, this vector very likely represents trees. PC 3 has high negative loadings from the visual band TM 3, the chlorophyll absorption of healthy green vegetation should result in a brighter appearance than that of the water stressed shrub field, but this eigenvector also has negative loadings from TM 2 and TM 4 and a positive loading from the near infrared band TM 5, the combined effect of these loadings is stronger than the result of the negative loading of TM 3. Therefore, on the image of PC 3, light areas highlight shrub fields.

The color assignment is based on the above analysis: red for PC 1, green for PC 2 and blue for PC 3 (See Plate 4). Since both PC 1 (red) and PC 3 (blue)

contained shrub information, shrub fields, in Plate 4, appear in a magenta tone (red + blue).

**Table 4.2 Principal Components Analysis of June 1984 data
V5.1 EASI/PACE**

Input channels: 2 3 4 5 6

Output Channels: 12 13 14 16 17

Eigenchannels: 1 2 3 4 5

Sampling Bitmap: 4

Sample Size: 425546

Channel	Mean	Deviation
2	30.7690	4.7644
3	27.6990	7.2118
4	66.3189	18.5307
5	74.1176	22.1627
6	28.4780	10.8654

Eigenchannels	Eigenvalue	Deviation	% Variance
1	778.1450	27.8953	75.74%
2	218.4817	14.7811	21.27%
3	25.4963	5.0494	2.48%
4	4.3215	2.0788	.42%
5	.8924	.9447	.09%

Eigenvectors of covariance matrix (arranged by rows):

	TM2	TM3	TM4	TM5	TM7
PC1	.13529210	.18060340	.49194200	.77307700	.33079150
PC2	-.07092877	-.24606960	.84034590	-.30891340	-.36443040
PC3	-.50747740	-.70649220	-.16508810	.43216900	-.17120660
PC4	.20857290	.30048460	-.13729770	.34571570	-.85313320

PC5	-.82196670	.56339180	.07554201	-.02519191	-.02488532
-----	------------	-----------	-----------	------------	------------

Eigenvectors of covariance matrix (normalized,%):

	TM2	TM3	TM4	TM5	TM7
PC1	7.0770	9.4470	25.7331	40.4391	17.3035
PC2	-3.8744	-13.4413	45.9030	-16.8740	-19.9066
PC3	-25.5987	-35.6367	-8.3275	21.7999	-8.6362
PC4	11.3035	16.2846	-7.4408	18.7359	-46.2352
PC5	-54.3997	37.2866	4.9995	-1.6673	-1.6470

When the individual bands were examined, data from TM 2 of May 1989 and September 1990 were found to contain significant striping noise. As a result, TM2 was excluded from the input of PCA enhancement.

Consequently only four bands were used for the 1989 and 1990 PCA input, i.e., TM 3, 4, 5, 7. The three vectors for the color composite were selected by examining the statistical results of the principal components analysis. Table 4.3 contains the statistical result for the May 1989 image.

**Table 4.3 Principal Components Analysis of May 1989 data
V5.1 EASI/PACE**

Input channels: 3 4 5 6

Output Channels: 12 13 15 16

Eigenchannels: 1 2 3 4

Sampling Window: 0 0 936 467

Sample Size: 425546

Channel	Mean	Deviation
3	67.9201	2.7044
4	60.5996	5.2581

5	94.6371	26.2341
7	42.0965	14.0584

Eigenchannels	Eigenvalue	Deviation	% Variance
1	899.7162	29.9953	97.71%
2	13.1905	3.6319	1.43%
3	5.4068	2.3250	.59%
4	2.5137	1.5855	.27%

Eigenvectors of covariance matrix (arranged by rows):

	TM3	TM4	TM5	TM7
PC1	.06829327	.13664660	.87375550	.46175230
PC2	.01666743	-.85505600	-.13238280	.50107480
PC3	-.46024840	-.44603600	.43863250	-.62994040
PC4	.88500270	-.22640350	.16318000	-.37267140

Eigenvectors of covariance matrix (normalized%):

	TM3	TM4	TM5	TM7
PC1	4.4333	8.8706	56.7209	29.9752
PC2	1.1073	-56.8075	-8.7951	33.2900
PC3	-23.3054	-22.5857	22.2108	-31.8980
PC4	53.7258	-13.7443	9.9062	-20.8025

As shown in the covariance matrix of Table 4.3, PC 1, representing the brightness, has heavy loadings from TM 5 and TM 7 and light loadings from TM 3 and TM 4. In the image, water should appear dark and shrubs should be brighter than green trees at this time of the year. This vector was assigned to red. PC 2 has a very strong negative loading from TM 4, so this vector is negated first and then assigned to green, representing green trees. PC 3 has a

high negative loading from TM 7. When assigned to blue, water would appear blue, and since TM 4 loading is negative and TM 5 loading is positive, the shrubs will also have a blue tone. This color assignment along with the color assignment of PC 1 causes the shrub fields to have the appearance of magenta (red + blue). Plate 5 is the color composite of the May 1989 PCA. Plate 6 is the color composite of the September 1990 PCA.

4.2.3. The Color Composite of PCA and the Vegetation Index Combination

The PCA and vegetation index combination method use PC 1 of TM 5 and TM 7 as red, NDVI as green, and PC 1 of TM 1, 2 and 3 as blue to derive a color composite. It has the advantages of the dimensional deduction of PCA and the unique vegetation information obtained from a vegetation index. The composite has the potential to be very informative because it includes all the available bands and highlights the vegetation information. The resulting images had a similar appearance as seen in Plates 4, 5, 6.

Using the various color composites of the study area, the general land cover types can be differentiated. The interpretation of these color composites can be used as a guide for field investigation. It helps in targeting the problem field to obtain related ground truth information for further research on *Kalmia* detection.

4.3 Kalmia Detection

4.3.1 Special Image Processing Techniques for Kalmia Detection

The spectral properties of *Kalmia* are very similar to those of deciduous trees and deciduous shrubs. Although pure *Kalmia* stands have a distinctive spectral signature compared to other cover types, this signature forms part of a continuum between pure alder stands and areas of deciduous shrubs (Gillespie et al. 1993). In the test area of Sudbury, pure stands of *Kalmia* were not found, but mixtures of *Kalmia* and other shrubs in open fields and the growth of *Kalmia* with other shrubs as the understory of forested land is readily apparent.

Depending on the site characteristics of the study area and the nature of the data set, *Kalmia* detection must address two issues: 1) distinction of deciduous shrubs from deciduous trees, and 2) identification of shrub fields which have been invaded by *Kalmia*.

4.3.1.1 Distinguishing Deciduous Trees from Deciduous Shrubs

Visual separation of deciduous trees and deciduous shrubs can be achieved from the various color composites described in the last section.

However, in this section, a more direct method is presented using pair-wise PCA.

As introduced in last Chapter, when two bands are used as input for a PCA, the first eigenvector is the average of the two input bands, containing the information that is common to both input bands. It can be referred to as the brightness image. The second eigenvector which is the difference between the two input bands conveys the unique information of the two input bands. Table 4.4 gives the TM bands' means and standard deviations extracted from known sites of treed areas and shrub fields.

Table 4.4 June 1984 Band Means and Standard Deviations for Deciduous Trees and Shrubs

		TM1	TM2	TM3	TM4	TM5	TM7
D. Tree	Mean	69.04	29.82	22.80	89.77	73.71	22.78
	SD	1.62	1.67	1.56	7.36	7.80	2.92
	Mean/SD	49.62	17.86	14.62	12.20	9.75	7.80
D. shrubs	Mean	81.70	32.51	34.59	46.97	103.50	48.35
	SD	4.45	2.88	3.94	3.99	8.41	4.79
	Mean/SD	18.36	11.29	8.78	11.77	12.31	10.10

From this table, it can be seen that the differences in Mean/SD ratio between deciduous trees and shrubs exist in both the visual bands, TM 1, 2, 3, and the infrared bands, TM 4, 5, 7. The high TM 1 mean values in both

deciduous treed areas and shrub fields are the evidences of atmospheric scattering. Therefore, TM 1 should not be used in further vegetation study unless the scattering effects are reduced through data processing.

With the application of three sampling masks (created based on field investigation), deciduous trees, *Kalmia* dominated sites, and blueberry dominated sites, scatter plots for every possible band pair combinations have been generated. These plots were examined visually to choose the best band pairs to be used for the pair-wise PCA. Plate 7 contains four sample scatter plots.

From Plate 7, it can be seen that the scatter plots of the *Kalmia* dominated field and the blueberry dominated field have a strong overlap which means that they cannot be effectively separated by this combination. To illustrate the selection process more clearly, the masks of these two types of shrub fields were combined by using the logical operation "OR" to get a generic mask of "shrubs fields".

Plates 8 and 9 are the scatter plots of the best band pairs for the three different years (1984, 1989, 1990). What they have in common is that the data clusters of trees and shrubs follow the same trend. This trend, as illustrated, is the direction of the first principal component of the two input bands which contain the information from both trees and shrubs. The second principal component is the vector perpendicular to the first principal component. Since the scatter plots of shrubs always appear on top of the scatter plots of trees, and

because high values of the second principal component represent shrub fields, shrub fields will have a bright appearance.

From Plate 7, 8, 9, we can see that the second principal component of TM band pairs TM 4 and TM 5 has the ability to highlight the shrub fields as distinct from the deciduous tree fields. As the quality of these two bands is usually reliable (less affected by atmospheric haze), they are recommended for the separation of deciduous trees and shrubs. The TM 2 and TM 7 pair is good only when TM 2 is free of haze and striping noise. Caution should be taken when using them.

The statistics of the two eigenvectors are provided in Table 4.5. From this table, we can see that PC 2 of TM 4 and TM 5 has a negative loading from TM 4, and a positive loading from TM 5. Since healthy green vegetation causes high reflectance in the TM4 band and relatively low reflectance in the TM 5 band, we can predict that on the black and white image of PC 2 of TM 4 and 5, healthy trees will have a dark appearance and the healthier the vegetation, the darker the appearance, i.e., plant health is inversely proportional to brightness. In early June of 1984, the time of image acquisition, new leaves and dry leaves coexist on the blueberry and *Kalmia* branches, resulting in weak reflectance in the TM 4 band and strong reflectance in the TM 5. Thus, based on the table, shrub fields should have a bright appearance on the image. The results shown on Plates 8 and 9 confirmed these predictions.

Table 4.5 Selective Principal Component Analysis June 84 Data V5.1 EASI/PACE

Input Channels: 4 5
 Output Channels: 8
 Eigenchannels : 2
 Sampling Bitmap: 4
 Sample size : 425546

Channel	Mean	Deviation
4	66.3189	18.5307
5	74.1176	22.1627

Covariance matrix for input channels:

	4	5
4	343.386	
5	237.193	491.185

Eigenchannel	Eigenvalue	Deviation	%Variance
1	665.7244	25.8016	79.77%
2	168.8468	12.9941	20.23%

Eigenvectors of covariance matrix (arranged by rows):

-.59268170 -.80543670
 -.80543670 .59268170

Scaling Information:

Eigen	Output	-----Unscaled-----	Deviation	Midpoint	Scale
Channl	Channl	Min	Max	Range	Factor
2	8	-70.387	51.279	all	127.000
					1.000

Plate 10 is the black and white image of PC 2 of the June 1984 TM Bands 4 and 5. On this image the shrub fields are highlighted as bright areas. Roads and hydro lines are also highlighted and can be easily differentiated from shrub fields by their linear appearance on the image. The built up areas and wet lands appear in different shades of grey.

Dark shading is usually superior to bright shading for highlighting areas of interest. To show the difference, the PCA of another June 1984 pair of TM bands which provide contrast between shrubs and trees (TM 2 and TM 7) was calculated, and the PC 2 was negated and linear stretched, the result being that on Plate 11, the dark areas are the shrub fields which possibly contain *Kalmia*.

Plates 12 and 13 display the extent of fields of shrub in the spring of 1989 and the fall of 1990. When comparing these two with Plates 10 and 11, many areas where vegetation cover had changed can be pinpointed. These images can be used for general examination of shrub fields and studies of vegetation change. They also provide the target areas for the identification of shrub fields which have been invaded by *Kalmia*.

4.3.1.2 Separation of *Kalmia* Dominated Fields and Blueberry Dominated Fields

The next step of detection - distinguishing fields containing *Kalmia* from fields without *Kalmia*, is difficult because the general spectral differences between fields containing different shrub are not significant. This

is especially so when *Kalmia* content is low ($\leq 20\%$), because the difference between blueberry and *Kalmia* fields and blueberry and sweet fern fields is particularly small. When there is more *Kalmia* (40%), the contrast becomes sufficiently great that differentiation of vegetation communities in the infrared bands becomes possible.

Table 4.6 provides the statistics for the three shrub land cover types which have similar spectral properties in Sudbury. The data was extracted from the training sites.

Table 4.6 Means and Standard Deviations of TM Bands on Three Different Shrub Cover Types, June 1984 Data

		TM1	TM2	TM3	TM4	TM5	TM7
Bb+Sf	Mean	81.69	32.34	34.95	45.91	105.51	49.02
	SD	3.86	2.70	3.61	4.10	4.38	3.27
	Mean/SD	21.16	11.98	9.68	11.20	24.09	14.99
Bb+K	Mean	82.40	32.86	34.82	46.88	105.09	50.05
(80%+20%)	SD	4.44	2.79	3.84	2.82	8.88	3.58
	Mean/SD	18.56	11.06	9.07	16.62	11.83	13.98
K (40%)	Mean	79.50	31.72	32.68	50.73	91.69	40.58
	SD	5.47	3.47	4.67	4.64	7.34	5.01
	Mean/SD	14.55	9.14	7.00	10.93	12.49	8.10

Since the contrasts between fields containing different kinds of shrubs are not significant, *Kalmia* mapping is challenging. From the training site data provided in table 4.6, it can be seen that when *Kalmia* content is less than 40%,

it will cause a signature on the image similar to that of the fields without *Kalmia*. *Kalmia*'s sparse growth pattern was well observed during field work, mixture of species over small areas is quite common. Thus, TM bands cannot be used to detect these *Kalmia*.

In Table 4.6 the greatest difference between fields containing *Kalmia* (40%+) and those without *Kalmia* (no *Kalmia* or *Kalmia* < 20%) exist in TM 5. Also there are some differences in TM 3, 4, and 7. In both TM 3 and 5, the reflectance from a field with *Kalmia* is lower than that of a *Kalmia* free shrub field, but in TM 4, the reflectance from fields containing 40% or more *Kalmia* is lower. What this indicates is that the application of a vegetation index to separate these shrubs is possible.

Fig. 4.2 is the plot of the mean values of the three TM bands under the masks of known sites. This figure proved to be of assistance in selecting a proper vegetation index for *Kalmia* field detection.

Figure 4.2 Relationship between *Kalmia* Dominant and Blueberry Dominant Fields

If a Normalized Difference Vegetation Index (NDVI):

$$(TM4 - TM3) / (TM4 + TM3)$$

is used, *Kalmia* dominated areas will have a higher value, and blueberry dominated areas will have a lower value. If the Infrared Index is used:

$$(TM5 - TM4) / (TM5 + TM4),$$

Kalmia dominated areas will have a lower value than blueberry fields. Since the contrast between TM 3 and TM 4 is smaller than that between TM 4 and TM 5, an Infrared Index was used for *Kalmia* detection.

From the formula for the Infrared Index (II), it can be seen that II will have a value between 0 and 1, i.e., $0 \leq II \leq 1$. In order to utilize the full range of grey levels that can be represented by the computer (0 - 255), the II value was multiplied by 255. This makes the distribution of Modified II (MII) fall into the range of 0 - 255.

$$MII = 255 \times II = \frac{255 \times (TM5 - TM4)}{TM5 + TM4}$$

The next step is to display the image of MII on the monitor, examine the image, and obtain the MII range of different cover types. This has been done by checking the histogram of MII under the masks of areas dominated by *Kalmia*, by blueberry and *Kalmia*, and by blueberry and sweet fern. See Fig.4.3.

In Fig.4.3, the histograms of the two blueberry dominated fields (blueberry and *Kalmia* and blueberry and sweet fern) have similar MII distributions. This again confirms that TM bands are not able to detect a *Kalmia* invasion when the *Kalmia* content of the shrub field is small. On the other hand, the shape of the histogram for *Kalmia* dominated fields is quite different from that of the blueberry dominated field, and the range of MII distribution is also different. These features make the final separation of *Kalmia* dominated fields from blueberry dominated fields possible.

Fig. 4.3 HIS Histogramming Database Image June 84 data VS.1 EASI/PACE

C:\SUD84PIX\geosud84.pix [S 35PIC 936P 467L] 06-NOV-92

16 [8U] RTR SMOD:NONE (255*C5-255*C4+)/(C5+C4+) 31-AUG-93

Number of pixels plotted: 507 Cell width: 1

Mean: 73.673 Median: 74 Standard Deviation: 12.433

16 [8U] RTR SMOD:NONE (255*C5-255*C4+)/(C5+C4+) 31-AUG-93

Number of pixels plotted: 1097 Cell width: 1

Mean: 97.117 Median: 102 Standard Deviation: 13.899

HIS Histogramming Database Image V5.1 EASI/PACE 10:43 14-SEP-93
 C:\SUD84PIX\geosud84.pix (S 35PIC 936P 467L) 06-NOV-92
 16 [8U] RTR SHOD:NONE (255*C5-255*C4+)/(C5+C4+) 31-AUG-93

Number of pixels plotted: 1105 Cell width: 2
 Mean: 100.405 Median: 103 Standard Deviation: 11.509

16 [8U] RTR SHOD:NONE (255*C5-255*C4+)/(C5+C4+) 31-AUG-93

Under D.trees Sites

The separation of the shrub fields as described above has been accomplished by thresholding MII values. Following examination of the MII distribution of different cover types, it was found that the convergence of the required classes is good. Thus, if the training site median is used as the center of class extraction, one standard deviation from the median as the thresholding range, then this range ought to have a very good inclusion of the frequently occurring MII values in the specific class. MII values outside this range occur less frequently. Those values could result from inaccurate training site selection and inclusion. Even if they are from the right class, a large thresholding range could cause class confusion.

In the actual process of class extraction, standard deviation was not used strictly to limit the range of thresholding, rather, it was used as a reference. The thresholding range was finally decided by checking the histogram of MII values for different classes. For a *Kalmia* dominated field, the thresholding ranges were 69 - 75 and 77 - 88. The resulting bitmaps have been combined together by using the logical operation "OR". For blueberry dominated fields, the thresholding range was 90 - 112. From this separation, it was determined that *Kalmia* dominated fields occupy an area of 16.7 square kilometers, and blueberry dominated fields have an area of 7.4 square kilometers in the 312.0 square kilometer study area.

In order to provide more contrast between deciduous trees and shrubs, The NDVI value of the study area was calculated (although the Infrared Index image is able to separate deciduous trees and shrubs, it can not separate

deciduous trees from water bodies). For the same data representation reason, the formula used was:

$$NNDVI = 255 \times NDVI = \frac{255 \times (TM4 - TM3)}{TM4 + TM3}$$

The NNDVI image had also been thresholds with the range of NNDVI of deciduous trees. The area covered by deciduous trees is 63.1 Square Km. The resulting bitmap of deciduous trees along with the *Kalmia* and blueberry dominated fields is shown in Plate 14. The areas that are grass, crop, and bog shrubs that do not contain *Kalmia* were successfully excluded.

The accuracy of this classification is derived from the formula:

$$Accuracy = \frac{(Pr - Pw)}{Pt} \times 100$$

where:

Pr = # of pixels correctly classified in the checking site

Pw = # of pixels misclassified in the checking site

Pt = total pixels of the checking site

This formula takes commission and omission errors in the classification into consideration. Table 4.7 is the accuracy report.

**Table 4.7 Accuracy Report of Thresholding Classification,
June 1984 Data**

<i>Kalmia</i> Dominated Field ($\geq 40\%$)	65.1%
---	-------

Blueberry Dominated Field	68.6%
Deciduous Trees	70.6%

When examining the MII histograms of May 1989 and September 1990 under the masks of the above three land cover types, it can be seen that the class confusion exists not only for fields dominated by different kinds of shrubs, but also for fields having a mix of shrubs and deciduous trees. See Fig. 4.4 for the histograms of the May 1989 MII. Because of the large overlaps in the values of the histograms of different land cover types, it was very difficult to decide on the range of thresholding, and its reliability. It is for this reason that the MII method was not applied to the 1989 and 1990 data set.

4.3.2 Unsupervised Classification

Unsupervised classification was carried out in parallel to the above mentioned detecting methods. It provided a different perspective, as this approach is based only on the numerical distribution of the data set and is subject to the least human intervention except for choice in class aggregation and separation after classification (if necessary). This method can take all the appropriate TM bands as input. The resulting classes do not necessarily, however, correspond with meaningful ground features or cover types.

Plate 15 is the unsupervised classification of June 1984 data with TM bands 1, 2, 3, 4, 5, and 7 as input bands and using the K - means (minimum distance) clustering method. The post-classification processing includes class

Fig.4.4 **Histogramming Database Image May 89 Data****VS.1 EASI/PAGE****C:\SUD89PIX\geosud89.pix****[8 37PIC****936P****467L] 22-FEB-92****8 [8U] RTR****SMOD:NONE (255*C5-255*C4+)/(C5+C4+)****13-SEP-93** **Number of pixels plotted: 428 Cell width: 1****Mean: 71.643 Median: 72 Standard Deviation: 6.953****1****Under B.berry and Kalmia Sites (80 20)** **Number of pixels plotted: 1097 Cell width: 1****Mean: 82.298 Median: 84 Standard Deviation: 6.735****1**

Under B.berry and S.fern Sites

Number of pixels plotted: 1032 Cell width: 1
Mean: 81.344 Median: 82 Standard Deviation: 4.189

Under D.trees Sites

Number of pixels plotted: 823 Cell width: 2
Mean: 80.691 Median: 82 Standard Deviation: 11.465

aggregation and 3x3 mode filtering for the purpose of reducing the influence of linear features like roads and hydro lines.

This investigation found that unsupervised classification cannot distinguish between the blueberry dominated shrub fields with or without *Kalmia*. There is a general agreement between this classification and the MII thresholding result. A significant difference is that the area that has been classified as "*Kalmia* dominated field" located in the southern part of the study area is not identified by the MII method. Further field work is required in this area to verify this.

4.3.3 Supervised Classification

Fig. 4.5 is a study area ground truth map of the interested cover types. It was produced using data from field investigation in June 1992. This field work has emphasized on investigating vegetation composition in the study area. General vegetation cover information is also available from the records of previous years' (1989,1991) field work in geological and geobotanical studies from CCRS. This information is not detailed enough to be the ground truth data for classification, but rather served as general reference.

The training sites for each class were selected from Fig. 4.5. Generally, the number of the training sites is half or slightly more than half the number of total known sites. When choosing the training sites, the spatial distribution and site diversification were balanced to attempt to include all possible site

Fig 45 STUDY AREA GROUND TRUTH MAP FROM FIELD INVESTIGATION

conditions. The rest of the known sites were used for classification accuracy checking.

The supervised classification was carried out using a variety of bands and band combinations and is discussed below. It may appear that the larger the number of bands that are used for the classification, the more accurate the result will be. This is not necessarily true. Generally, when each of the input bands conveys unique and useful information, four or five input bands can lead to an optimal classification result. However, if many correlated bands are used as input, the information content of an important band can be masked by the input from other bands. In such case, the accuracy of the classification would be lower (Thomas et al., 1987).

In the TM data set, the three visual bands always have a very high correlation, and so do the infrared bands. Principal component analysis can decorrelate the input bands and achieve dimensional reduction without losing important information. Since the first eigenvector usually contains more than 90% of the variance of the highly correlated input data set, when it is used instead of all the correlated bands as input for supervised classification, there will be fewer input channels, the computing time will be reduced, and, more importantly, the chances of class confusion will be less.

For the data set of June 1984, the input channels of supervised classification were selected from the best bands and band combinations

available. More specifically, six channels were used for the input of best channel selection: TM 4, TM 5, NDVI, Infrared Index (MII), PC 1 of TM 1, 2, 3, and PC 1 of TM 5, 7.

The selection procedure was first to create signatures of the interested classes using the training site information, then use the program called "Multispectral Channel Selection" which is provided in PCI to choose the four best channels from these six channels for supervised classification. The report of this selection is provided in Table 4.8. From this report, the best channels for the June 1984 data classification were: TM 4, TM 5, MII, and PC 1 of TM 5, 7. Based on the above result, a maximum likelihood classification was finally carried out on the four best channels, and Plate 16 was the result of this classification.

In Plate 16, in order to avoid redundancy with unsupervised classification, not all pixels were classified. Only those of selected cover types were extracted. The rest of the image remained unclassified. The Maximum Likelihood Report of Supervised Classification is given in Table 4.9. The accuracy of the classification was evaluated by encoding the bitmaps of known sites into a channel (subarea channel) and comparing this channel with the classified image. As indicated in Table 4.9, a very high accuracy has been achieved. It should be noted that, this accuracy is calculated differently from that for the classification of MII method. The formula:

$$\text{Accuracy} = (Pr / Pt) \times 100\%$$

Pr = # of pixels correctly classified in the checking site

Table 4.8 Multispectral Channel Selection Report June 84

Initial Channels: 4, 5, 7, 8, 16, 17
 (TM4 TM5 NDVI PC1(5&7) II PC1(1,2&3) Respectively)

Initial Criterion Value : 2507.0660

Final Criterion Value : 2420.0730

The Number of New Nodes : 2

Level : 1, 2

Nodes Expanded : 1, 1

Nodes Rejected : 4, 1

 Optimal Channels: 4, 5, 8, 16 (TM4 TM5 II PC1 (5&7))

Initial Divergence Table

	29	30	53	94
+	-----			
30	17.418			
53	2.615	21.226		
94	9774.127	5831.130	8474.358	
95	258.533	131.121	477.601	82.527

Final Divergence Table

	29	30	53	94
+	-----			
30	16.155			
53	2.104	19.341		
94	9375.879	5545.907	8408.534	
95	224.306	119.255	421.019	68.230

Table 4.9 MLR Maximum Likelihood Report June 84 Data

V5.1 EASI/PACE

Subarea Reports using theme channel 6 and subarea channel 8:

6 [8U] PMO 3 * 3 Mode filter MASK: 7DBIC: 5 07-SEP-93
 8 [8U] MAP Encoded bitmap: 8, 9, 19, 12 08-SEP-93

Totalization Report for Subarea code: 0

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
2 Sb	10	38349	34.51	9.09	9.01
3 mkalm	50	19406	17.47	4.60	4.56
18 bbdomi	100	7821	7.04	1.85	1.84
6 decidtr	200	90857	81.77	21.53	21.35
Null	0	265531	238.98	62.93	62.40
		-----	-----	-----	-----
Subarea totals		421964	379.77	100.00	99.16

Totalization Report for Subarea code: 10

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
2 Sb	10	279	.25	94.90	.07
3 mkalm	50	0	.00	.00	.00
18 bbdomi	100	0	.00	.00	.00
6 decidtr	200	2	.00	.68	.00
Null	0	13	.01	4.42	.00
		-----	-----	-----	-----
Subarea totals		294	.26	100.00	.07

Totalization Report for Subarea code: 50

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
2 Sb	10	0	.00	.00	.00
3 mkalm	50	187	.17	91.22	.04
18 bbdomi	100	15	.01	7.32	.00
6 decidtr	200	0	.00	.00	.00
Null	0	3	.00	1.46	.00
		-----	-----	-----	-----
Subarea totals		205	.18	100.00	.05

Totalization Report for Subarea code: 100

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
2 Sb	10	0	.00	.00	.00
3 mkalm	50	59	.05	2.68	.01
18 bbdomi	100	2024	1.82	91.92	.48
6 decidtr	200	0	.00	.00	.00
Null	0	119	.11	5.40	.03
		-----	-----	-----	-----

Subarea totals 2202 1.98 100.00 .52

Totalization Report for Subarea code: 200

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
2 Sb	10	8	.01	.91	.00
3 mkalm	50	0	.00	.00	.00
18 bbdomi	100	0	.00	.00	.00
6 decidtr	200	867	.78	98.41	.20
Null	0	6	.01	.68	.00
Subarea totals		881	.79	100.00	.21

MLR Maximum Likelihood Report

V5.1 EASI/PACE 11:07 08-SEP-93

6 [8U] FMO 3 * 3 Mode filter MASK: 7DBIC: 5 07-SEP-93

Totalization Report for theme channel: 6

Seg Name	Code	Pixels	Sq. Kilometers	%Image
2 Sb	10	38636	34.77	9.08
3 mkalm	50	19652	17.69	4.62
18 bbdomi	100	9860	8.87	2.32
6 decidtr	200	91726	82.55	21.55
Null	0	265672	239.10	62.43
Image total		425546	382.99	100.00

1

MLR Maximum Likelihood Report

V5.1 EASI/PACE 11:07 08-SEP-93

Areas		Percent Pixels Classified by Code					
Code	Name	Pixels	0	10	50	100	200
10	Sb	294	4.4	94.9	.0	.0	.7
50	mkalm	205	1.5	.0	91.2	7.3	.0
100	bbdomi	2202	5.4	.0	2.7	91.9	.0
200	decidtr	881	.7	.9	.0	.0	98.4

Average accuracy = 94.11%

Overall accuracy = 93.72%

Kappa Coefficient = .89168 Standard Deviation = .00685

Confidence Level :

99% .89168 +/- .01768

95% .89168 +/- .01343

90% .89168 +/- .01127

Pt = total pixels of the checking site

does not take into consideration the omission and commission errors involved in the classification, thus this high accuracy is biased and not comparable with the previous one.

A comparison of Plates 14, 15 and 16 shows a relatively high agreement among them. It is noticeable that the supervised classification has included more area into the class of *Kalmia* dominated field, this could explain the "high accuracy" of the output report. However, since these three methods are independent from each other, although some further field check is required to fully document and verify the results of each of the detection techniques, a certain degree of confidence in the application of these methods to *Kalmia* detection is assured.

Although similar results were achieved by the three methods, the individual approaches differed greatly. Of the three, the vegetation index thresholding is the simplest method. It requires the least computation time but is somewhat subjective. The accuracy of this method is highly dependent on the thresholding range selected by the human analyst. The selection of the thresholding range is in turn dependent on the existing MII contrast between various targets. Therefore, this method is not only subject to human judgement and experience, but also case dependent.

The output classes of the unsupervised classification need to be carefully inspected. To obtain a meaningful classification map, class aggregation and separation are required. Without thorough knowledge of the study area, any class aggregation and separation would be risky. The classified images should only be used as references for further research. This method is computation intensive.

The conventional supervised classification is usually the most time consuming method. In this study, however, the input number of channels for classification was controlled. The optimal channels were selected and only the most significant and most easily confused cover types were extracted and examined. Such a supervised classification was fast.

When the next data set, TM images of May 17, 1989, was used, however, the contrast between TM bands for the different shrubs and deciduous trees was very low. Only TM 5 showed any difference; all the others had very similar values for *Kalmia* dominated fields, blueberry dominated fields, and even deciduous treed areas. It is not surprising that the application of the above detecting techniques to separate *Kalmia* from other deciduous shrubs and trees was not successful. The Infrared Index method, like the unsupervised classification, was unable to separate *Kalmia* from other cover types. When applying the supervised classification, the inputs for channel selection were: TM 3, TM 4, TM 5, NDVI, II, PC 1 of TM 1, 2, and 3, PC 1 of TM 5 and 7, the best channels for supervised classification obtained from the program were: TM 4, TM 5, NDVI, and II. As shown in the reports

of channel selection and Maximum Likelihood Classification on the next page, the classification accuracy decreased and the class confusion increased compared to the classification result of June 1984 image (See Plate 17, Table 4.10 and Table 4.11).

These observations are explainable in terms of seasonal differences. In June image, deciduous trees have already full grown green leaves resulting in high reflectance in the near infrared band, TM 4. In the mid May image, many tree leaves have either not come out yet or are very small. The major component is dry branches and leaves, similar to the deciduous shrub fields. They cause similar spectral signatures on the TM images. Thus for the TM images acquired during this time period, only conifer trees can be easily distinguished.

Seasonal field conditions can explain why the next set of TM images, images from fall, 1990 could not be used for *Kalmia* detection either. In the fall deciduous trees go into senescence, thus becoming very similar in spectral signature to deciduous shrubs. However, in the late fall, after all the other deciduous vegetation has shed, the semi-deciduous *Kalmia* still keep their reddish leaves. The clear contrast between *Kalmia*, coniferous, and deciduous vegetation at this time can produce ideal spectral contrasts on TM images. The late fall is also therefore, a good time for *Kalmia* detection. Recent research conducted in Newfoundland [Gillespie et al. 1992] confirms this theory. Unfortunately, no late fall imagery was available to the author to test this hypothesis in the study area.

Table 4.10 CHNSEL Multispectral Channel Selection May 89 Data V5.1 EASI/PACE

Initial Channels: 3, 4, 5, 8, 9, 11, 12

Initial Criterion Value : 3112.7770

Final Criterion Value : 3075.2960

The Number of New Nodes : 3

Level : 1, 2, 3

Nodes Expanded : 1, 1, 1

Nodes Rejected : 4, 0, 1

Optimal Channels: 4, 5, 8, 9
-----Initial Divergence Table

	59	60	61
+	-----		
60	6.301		
61	33.703	23.158	
63	6181.221	6344.500	6087.782

Final Divergence Table

	59	60	61
+	-----		
60	3.635		
61	15.049	18.673	
63	6076.422	6317.583	6020.411

Table 4.11 MLR Maximum Likelihood Report May 89 Data

V5.1 EASI/PACE

Subarea Reports using theme channel 7 and subarea channel 6:

7 [8U] FMO 3 * 3 Mode filter DBIC: 5 16-SEP-93
 6 [8U] MAP Encoded bitmap: 2, 3, 4, 5 16-SEP-93

Totalization Report for Subarea code: 0

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
10 mkalm	10	99499	89.23	22.98	22.76
11 bbdomi	100	8396	7.53	1.94	1.92
12 decidtr	200	105563	94.67	24.39	24.15
13 BSWET	250	124577	111.72	28.78	28.50
Null	0	94858	85.07	21.91	21.70
Subarea totals		432893	388.22	100.00	99.03

Totalization Report for Subarea code: 10

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
10 mkalm	10	352	.32	82.24	.08
11 bbdomi	100	63	.06	14.72	.01
12 decidtr	200	8	.01	1.87	.00
13 BSWET	250	5	.00	1.17	.00
Subarea totals		428	.38	100.00	.10

Totalization Report for Subarea code: 100

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
10 mkalm	10	145	.13	6.81	.03
11 bbdomi	100	1967	1.76	92.39	.45
12 decidtr	200	7	.01	.33	.00
13 BSWET	250	10	.01	.47	.00
Subarea totals		2129	1.91	100.00	.49

1

MLR Maximum Likelihood Report V5.1 EASI/PACE 15:57 16-SEP-93

Subarea Reports using theme channel 7 and subarea channel 6:

7 [8U] FMO 3 * 3 Mode filter DBIC: 5 16-SEP-93
 6 [8U] MAP Encoded bitmap: 2, 3, 4, 5 16-SEP-93

Totalization Report for Subarea code: 200

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
10 mkalm	10	28	.03	2.05	.01
11 bbdomi	100	39	.03	2.85	.01
12 decidtr	200	1270	1.14	92.84	.29
13 BSWET	250	31	.03	2.27	.01
Subarea totals		1368	1.23	100.00	.31

Totalization Report for Subarea code: 250

Seg Name	Code	Pixels	Sq. Kilometers	%Subarea	%Image
10 mkalm	10	8	.01	2.72	.00
11 bbdomi	100	0	.00	.00	.00
12 decidtr	200	1	.00	.34	.00
13 BSWET	250	265	.24	90.14	.06
Null	0	20	.02	6.80	.00
Subarea totals		294	.26	100.00	.07

1

MLR Maximum Likelihood Report

V5.1 EASI/PACE 15:57 16-SEP-93

5 [8U] MLC F mka bbd dec BSW

16-SEP-93

Totalization Report for theme channel: 5

Seg Name	Code	Pixels	Sq. Kilometers	%Image
10 mkalm	10	101283	90.83	23.17
11 bbdomi	100	15465	13.87	3.54
12 decidtr	200	103701	93.00	23.72
13 BSWET	250	119456	107.13	27.33
Null	0	97207	87.17	22.24
Image total		437112	392.00	100.00

1

MLR Maximum Likelihood Report

V5.1 EASI/PACE 15:57 16-SEP-93

Areas		Percent Pixels Classified by Code					
Code	Name	Pixels	0	10	100	200	250
10	mkalm	428	.5	71.3	22.2	3.5	2.6
100	bbdomi	2129	.5	12.4	85.6	.9	.7
200	decidtr	1368	1.2	5.1	4.9	86.6	2.1
250	BSWET	294	6.8	2.7	.0	.3	90.1

Average accuracy = 83.40%

Overall accuracy = 84.78%

Kappa Coefficient = .76521 Standard Deviation = .00830

Confidence Level :

99% .76521 +/- .02142

95% .76521 +/- .01627

90% .76521 +/- .01366

Among the images available (spring, early summer, and fall), the best for *Kalmia* detection is the early summer image. At this time when deciduous trees and shrubs have vigorous growth, *Kalmia* has a mixture of old and new leaves due to its semi-deciduous nature. If a shrub field contains enough *Kalmia*, the contrast between *Kalmia* and deciduous shrubs can be picked up by the TM image. Therefore, this field can be differentiated from other shrub fields.

Chapter Five

Change Detection -- *Kalmia* Field Monitoring -- Multitemporal Image Processing and Analysis

Kalmia is a very tolerant shrub, it can grow in well drained, poorly drained, nutrient rich and acidic environments. It is a very competitive shrub, its introduction will inhibit the growth of many other trees and shrubs. *Kalmia* is also a fast growing shrub, the spreading of this shrub can rapidly put many adjacent trees in danger. But perhaps the most serious effect of unchecked *Kalmia* growth is the degradation of soil.

Early detection of *Kalmia* is the most critical step of land management. Once site priorities are established the most seriously affected site can be field sampled and monitored over time through the use of multi-temporal imagery.

The basic promise in using remote sensing data for change detection is that changes in land cover lead to changes in radiance values, and changes in radiance due to land cover change must be large with respect to radiance changes caused by other factors (Ingram et al., 1981). These other factors include: 1) differences in atmospheric conditions, 2) differences in Sun angle and 3) differences in soil moisture (Jenson 1983). The impact of these factors may be partially reduced by selecting the appropriate data. For example, Landsat data required at the same season may reduce problems resulting from Sun angle differences and vegetation phenology changes. Some change

detection methods can also reduce the effects of factors other than land cover change.

The multirate TM images used for this study are from June 1984 and May 1989. Although it was intended that early June data from 1989 should be used, the May image was the nearest one in time available in the CCRS tape library of the study area. The September image acquired in 1990 is also used, together they allow seasonal differences to be compared.

5.1 Detection of Seasonal Changes by Use of the Image Regression Method

Among various change detection techniques, according to the report of Singh (1989), the image regression method has the highest accuracy. This method, accounts for differences in the mean and variance between pixel values for different dates so that adverse effects from differences in atmospheric conditions or Sun angle are reduced (Jenson 1983). It is based on the assumption that the same TM bands obtained from the same area but at different times, would still bear a linear relationship with each other. This assumption is true in most cases but has exceptions.

When this procedure was used to monitor changes in the Sudbury area, the first step was to examine the TM pairs from 1984 and 1989. Only those band pairs which showed a linear relationship were processed further. They

were differentiated for change detection, and in fact, among those noise free band pairs of 1984 and 1989 (i.e., TM3, 4, 5, 7), only the TM3 and TM4 pairs have a linear relationship.

The formula used for change detection is:

$$DN_{id} = (DN_{ie} - DN_i) / 2 + 127$$

where DN_{id} is an image of change in band i ; DN_{ie} is the expected image of band i at time 2, based on the regression line of band i at time 1 and time 2; and DN_i is the band i value at time 2. From this formula, areas with no change will have a grey tone, whereas areas with changes will have either brighter or darker tones on the DN_{id} image.

The black and white image of change in TM4 is easy to analyze rationally, but it is hard to find the boundaries of the area that has been changed. Because the change of grey tone is continuous, the threshold values for different classes are hard to determine. Two methods were tried to solve this problem. The first was histogram cluster classification of the difference image; the second was creation of a color composite of the difference image and TM 5 (see Plate 18). Both of the methods showed better results than direct thresholding of the single image of change because they are more objective.

5.2 Change Detection Using Histogram Modification Method

The next change detection method tested involved modification of the histogram of the band pair from two years. The mean and standard deviation values were used to calibrate the second image to produce a corrected image of second time. The goal is to match the histogram of the second band with that of the first band. It is obvious that this method is most suitable if the histograms of the two bands have similar shapes but different means and standard deviations. However, there will be a problem if the two bands have different shapes of histogram. When applied properly, this method would make the two set of data ready to compare. The formula for this operation is:

$$DN_{vt} = (DN_{vi} - M_{vi}) \times SD_{vo} / SD_{vi} + M_{vo}$$

where DN_{vt} is the corrected DN value; DN_{vi} , M_{vi} and SD_{vi} are the DN value, mean and standard deviation of band i for time 2; M_{vo} and SD_{vo} are the mean and standard deviation of the same band in time 1.

With this method, TM bands 3, 4, 5 from 1989 are corrected using the same bands from 1984 as references, and because the 1984 data set contains clouds, the correction is done with a mask of the study area which excludes clouds.

The difference image was created by the subtraction of TM 3, 4, 5 of 1984 from the corrected 1989 TM 3, 4, 5, using the formula:

$$DNd = (DNe - DNo) / 2 + 127$$

This formula will also assign grey (brightness = 127) to the unchanged area. The changed area will have either a darker or brighter tone in the difference image. A similar approach, as discussed in the last section, can be used to analyze the difference images.

5.3 Detection of Change Using A Multidate Color Composite

5.3.1 TM 5 Color Composite

Probably this is the simplest method for change detection. Adam (1990) made a color composite of the Los Angeles area with the TM band 7 from two different dates. It has been demonstrated that this method can detect changes to vegetation effectively. In dealing with the data set from Sudbury, it appears that although TM 7 has better clouds penetration ability, it contains less vegetation information than TM 5. Consequently TM 5 was used for the color composite. The TM 5 color composite provides more vegetation cover type contrast when compared with TM 7 color composite.

The color composite is created by assigning red to the later date (1989) TM 5, and green and blue to the earlier date (1984) TM 5 (see Plate 19). As a result, DN values that have the same red, green, and blue intensities for both

dates are shades of grey and will remain shades of grey. DN values that were high in the earlier date will have the color of cyan. A high TM 5 value means either the vegetation in that area is subject to moisture stress, or the moisture content in the soil of that area is low, and it is not hard to differentiate vegetation from bare soil. Vegetation under moisture stress is of most interest in this study. As indicated in Chapter Two, heath shrubs make no nutrient contribution to the site where they are grown, and they hinder the nutrient uptake by other plants. The low soil temperature, and the lack or excess of water lead to nitrogen deficiency which will cause xeromorphism of all plants. The color composite, which is sensitive to moisture content, can pick up these areas. These areas, especially those in depressions, and close to soft wood stands, are particularly dangerous to the forest for two reasons. One is the invasion of *Kalmia* into the forest; the other is the increase of fire hazard possibility in the area. Special attention and proper land treatment are required, therefore, in those areas.

The clearcut area in the western part of the study area appears pinkish red (Transparent two can be used to assist the interpretation of Plate 18 and 19). This is caused by the combination of the regeneration of jack pine and wide spacing between the young trees. This is in clear contrast to the older clearcuts which have a tone of cyan. The bright red areas in the central part of the study area represent the spread of heath shrubs. The white areas indicate that the TM 5 values are high in both time periods -- the scrub fields are subject to moisture stress. The dark red patterns are the shadow of clouds, and because shadows exist in the 1984 data set but not in the 1989 data, they can be easily differentiated from vegetation under stress.

5.3.2 Moisture Stress Index Color Composite

The TM 5 color composite method introduced above does not take changes other than land cover change between the two dates into consideration. The Moisture Stress Index Color Composite method, on the other hand, uses the ratio between TM 5 and 4, ($MSI = TM5 * 100 / TM 4$), i.e., the moisture stress index instead of the single TM 5 band, to reduce the effect of different illumination and atmospheric condition in the final color composite.

The color composite is made by assigning red to moisture stress index for 1989, and green and blue to the moisture stress index for 1984. The interpretation of this image is similar to the TM 5 color composite.

The result of this method, however, is not as good as the TM 5 color composite. The reason is the time difference of the two data sets. Since the two images are 3 weeks apart, and this is the season when new leaves come out on deciduous trees, in those deciduous treed areas which had no change in ground cover type between 1984 and 1989, the 1989 image ought to have a higher TM 5 value and lower TM 4 value than the 1984 image. As a result, on the color composite of the moisture index, areas with change along with deciduous treed areas both show up as a red tone. Had same date images been available, this method would have achieved a better result.

The pair-wise principal components analysis of the same band on two dates is another method of monitoring change. When the images are acquired from the same date of the different years under the same conditions, the second principal component will highlight the changes.

According to Brand et al. (1991), the time interval between doing forest surveys should be 5 to 7 years for natural regeneration after fire and clear cut. The satellite images acquired for monitoring forest change should be of the same season, or as close as possible.

From comparison of the above monitoring techniques, the color composite of MSI or TM5 is recommended, based on the simplicity and objectivity of the method.

Chapter Six

Conclusions and Discussion

The research for this thesis has been presented in two parts. First, an investigation and analysis of the reasons for the observed unsuccessful forest regeneration in Sudbury study area; and second, research on the application of the satellite remote sensing technologies to detect and monitor the regeneration.

In the first part of the work, an ericaceous shrub - *Kalmia angustifolia* has been found to be responsible for the growth check of coniferous trees, especially black spruce. The evidence of allelopathic behavior of *Kalmia* has been reported in the literature as well as observed in the field in Sudbury. This thesis represents the first investigation of the relationship between *Kalmia* and the unsuccessful vegetation regeneration in Sudbury area. Findings of this study indicate that the commonly accepted theory that pollution is the principal cause of growth check of trees in Sudbury may need to be reconsidered.

The second part of this thesis, a pilot study of substituting less expensive satellite remote sensing for airborne remote sensing in mapping and monitoring the study area has produced some promising results. Some site specific techniques were developed, modified, and tested; other currently

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widely used techniques were introduced and evaluated. When the *Kalmia* content exceeds 40% in the scrub field, the areas can be differentiated from other vegetation cover types with satellite TM imagery. When *Kalmia* is not dominant in the scrub field, or when *Kalmia* is the understory of the black spruce forest, it can not be detected by TM imagery.

The timing of acquiring images is very important as only early summer and late fall images have been found to be sensitive enough for *Kalmia* detection. It should be noted that optimal fall imagery was not available for this study due to budget limitation.

This thesis has demonstrated that there is significant potential for the use of satellite imagery in detecting and monitoring the presents of *Kalmia* and its negative effect on forest regeneration. This work can contribute to a cost-effective operational management model which addresses detection, monitoring and cost effective remediation.

Based on this pilot study, a five phase general operational procedure for *Kalmia* detection and monitoring using satellite TM images is presented below:

Phase One: Image Acquisition

Good quality early summer/late fall images. The suggested time interval for monitoring is 5 years.

Phase Two: Preliminary Image Processing

1. Image to image georeferencing
2. Color composite of study area (RGB input):
 - a. TM 5,4,3 squared enhancement, or
 - b. PC1 of TM5,7 NDVI, PC1TM1,2,3
3. General analysis of study area from above color composites

Phase Three: Field Investigation

1. Recognize the pattern of the appearance of *Kalmia* and its associates
2. Select training sites and outline on the composite images

Phase Four: *Kalmia* Detection

1. Extract statistical data from training sites
2. Separate shrubs from deciduous trees:
 - a. Interpretation / classification of the two color composite, or
 - b. Selective PCA of TM2,7 or TM4,5 and unsupervised classification of the second component
3. Separate Shrub Field With and Without *Kalmia*
 - a. Thresholding MII image, or
 - b. Supervised classification on selected input bands and bands combinations

Phase Five: Field Monitoring

1. Color composite of TM5 or MSI image
2. Selective PCA of same band from different years
3. Update GIS data base

Results presented in this thesis suggest that further field investigation is warranted, particularly to validate the supervised classification. This work has demonstrated the importance of selecting imagery dates according to careful examination of field conditions. The current work was carried on without having the benefit of this knowledge at the outset and the budget to acquire optimum imagery later in the study. Whenever relevant, however, suggestions have been made regarding optimum ground conditions for imagery selection.

Further research is warranted in the following contexts:

- 1) to define the actual allelopathic mechanism of *Kalmia* which account for effects on other plants. Such work could lead to the definition of more effective approaches to the management of forest regeneration on a site by site basis;
- 2) to include more visual band information into the classification process, for example, instead of using only MII, add NDVI to increase the classification accuracy; and
- 3) to replicate the approach demonstrated here in other geographic location where *Kalmia* is a concern.

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APPENDIX "A"

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TM 5.4.3. COLOUR COMPOSITE OF JUNE 84 DATA

CUSTOM SQUARE ENHANCEMENT

1:100 000 Scale

Kilometers 1 0 1 2 3 4 5 6 7

Miles 1 0 1 2 3 4 5

plate 1.

TM 5,4,3 COLOUR COMPOSITE OF JUNE 84 DATA

CUSTOM SCQA RE ROOT ENHANCEMENT

plate 2.

TM 7,4,3 COLOUR COMPOSITE OF JUNE 84 DATA

CUSTOM SQUARE ENHANCEMENT

1:100 000 Scale

plate 3.

COLOUR COMPOSITE OF FIRST THREE EIGENVECTORS FROM PCA OF JUNE 84

BANDS USED FOR PCA: TM2, 3, 4, 5, 7 PCI=RED PC2=GREEN PC3=BLUE

1:100 000 Scale

SPC1

plate 4

COLOUR COMPOSITE OF FIRST THREE EIGENVECTORS FROM PCA OF MAY 89

PCA INPUT: TM3,4,5,7 PC1-RED -PC2-GREEN PC3-BLUE HISIQ

SPCI

File 5.

PCA OF TM3, 4, 5, 7 FALL 90 DATA

PC1=RED, PC2=GREEN, PC3=BLUE

1:100,000 Scale

Plate 6.

SCATTER PLOTS OF TM BANDS PAIRS 84 DATA

GREEN=D. TREES MAGENTA=Bb. DOMINANT CYAN=K. DOMINANT Plate 7.

FALL 90 DATA

TME

TM5

JUNE 84 DATA

SCATTER PLOTS OF TM2.7 (84) AND TM4.5 (90)

SCATTER PLOT OF 89 TM4 AND TM5

TM DATA ACQUIRED MAY 17, 1989

plate 9.

EIGEN VECTOR TWO OF PCA OF TM4 AND TM5

DARK-TREES BRIGHT-SCRUB FIELD

1:100 000 Scale

plate 10.

NEGATIVE PRINT OF EIGENVECTOR TWO OF TM2, 7 JUNE 84 DATA

LINEAR ENHANCEMENT

1:100,000 Scale

Kilometers 1 2 3 4 5 6 7
Miles 1 2 3 4 5

BRIGHT TREES DARK - SCRUB FIELD MAY BE DATA

1:100,000 Scale

Plate 12.

NEGATIVE PRINT OF EIGENVECTOR TWO OF TM4.5 FALL 90 DATA

LINEAR ENHANCEMENT

1:100 000 Scale

Kilometers 1 0 1 2 3 4 5 6 7

Miles 1 0 1 2 3 4 5

plate 13

109

SPCI

BITMAPS OF SCRUB FIELDS AND DECIDUOUS TREES IN JUNE 84

CYAN=KALINIA DOMI. MAGENTA=BLUEBERRY DOMI. GREEN=DECIDUOUS TREE

1:100 000 Scale

Kilometers 0 1 2 3 4 5 6 7

Miles 0 1 2 3 4 5

UNSUPERVISED CLASSIFICATION OF 84 DATA

JUNE 84 TM1.2.3.4.5.7 AS INPUT

1:100 000 Scale

SPCI

Plate 15.

■	water bodies
■	Pr plantation
■	Pr Pj regeneration with deciduous mix
■	Bw etc
■	wet land
■	Sb with Kalmia and L. tea
□	Po and Bw well drained
■	swamp scrubs and small Sb
■	grass fields
■	kalmia dominated field with Pj and Sb
■	old burnt or cut with Bb dominant
■	new cut regeneration
■	builtup area
■	dry pit
■	wet pit
■	clouds

SUPERVISED CLASSIFICATION OF 84 DATA

INPUT: TM4 TM5 PCI OF TM5 & 7 II

1:100 000 Scale

plate 16.

SUPERVISED CLASSIFICATION OF 89 DATA

INPUT BANDS TM4 TM5 TM7 TM11

1:100,000 Scale

Plate 17.

Kalmia dominated field with Pj and Sb
old burnt or cut with Bb dominant
Deciduous trees
Sb in depression with Kalmia

Legend for plates 16 & 17

LAND COVER CHANGE DETECTION MAP

R-TMS, G-TM4 DIFFERENCE MAP, B-TM3 DIFFERENCE MAP HISTOGRAM

1:100 000 Scale

Kilometers 1 0 1 2 3 4 5 6 7

Miles 1 0 1 2 3 4 5

plate 18.

LAND COVER CHANGE DETECTION MAP

R - 89 TMS, G - 84 TMS - B: HISTORIC; UNDER CLOUD MASK

1:100 000 Scale

COLOR COMPOSITE INTERPRETATION KEY (Transparency I)

C: Coniferous Tree
 NT: New Clear-cut
 CP: Coniferous Plantation
 OT: Old Clear-cut
 D: Deciduous Tree
 P: Gravel Pit
 G: Grass Field
 S: Shrub Field

CHANGE DETECTION (Transparency II)

CL: Clouds

***: Vegetation under constant moisture stress**

O: New moisture stress area

END

31-05-95

FIN