UNIVERSITY OF ALBERTA

QUANTIFYING, MAPPING, AND CHARACTERIZING TOP KILL CAUSED BY JACK PINE BUDWORM (*Choristoneura pinus pinus* Freeman) DEFOLIATION

BY

© RONALD JACK HALL

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY.

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Abstract

Top kill damage on jack pine (*Pinus banksiana* Lamb.) resulting from severe jack pine budworm (*Choristoneura pinus pinus* Freeman) defoliation impairs future growth, and causes impacts that are generally unknown. This study describes and evaluates procedures for quantifying and mapping top kill, and reports on associations between spatial patterns of top kill and stand attributes.

A method to estimate the volumes of tree top kill was developed using large-scale photo measurements and a jack pine taper model. Photo measures of the length of top kill were highly correlated with their actual lengths, and volume estimates compared favorably to ground measurements. If combined with forest sampling procedures, the use of techniques developed in this study could aid in assessing the impact of top kill on timber supply at the stand and forest level.

A system to classify severity of top kill was developed and used with 1:5000 color infrared aerial photographs to map the study area. This map was used to evaluate satellite data for mapping top kill, and assess spatial associations of top kill with stand characteristics.

Spectral differences that may be attributed to top kill using multidate, LANDSAT Thematic Mapper data were small, and classification mainly mapped the spatial extent of jack pine since discrimination among damage severity levels of top kill were poor. The influence of spectral reflectance from understory and ground vegetation partially explains this result, since mature jack pine stands tend to be relatively open.

Two novel methods of integrating spatial data from a Geographic Information System with digital image data were explored. One method used map polygons of top kill

as "training" data to explore spectral separabilities. The second method used a contingency table between top kill and spectral classes from an unsupervised classification, and this greatly aided the process of describing and labelling spectral classes.

Although the general characteristics of vulnerable stands to budworm damage have been reported, their empirical limits have not been identified. A spatial approach towards defining these relationships using digital map data, resulted in physiographic and stand characteristics that, in part, more specifically define vulnerable stands than had previously been reported.

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Chapter 1

Introduction

Jack pine budworm (*Choristoneura pinus pinus* Freeman) is among the important insect pests in Canada (MacLean 1990), and is a major defoliator of jack pine (*Pinus banksiana* Lamb.) forests in Ontario, Manitoba, Saskatchewan, and the adjacent United States Great Lakes States (Moody 1989; Mallett and Volney 1990). Budworm defoliation may be extensive, and persist in an area for many years (Volney 1988). Examples of the extent of defoliated areas reported include 3.7 million ha in Ontario in 1985 (Kondo and Taylor 1986), 2.0 million ha in Manitoba in 1985, and 176 000 ha in Saskatchewan in 1986 (Brandt and Amirault 1994). In addition, a trend towards increasing areal size of jack pine budworm outbreaks has been reported for the Prairie Provinces (Volney 1988). With defoliated areas of these magnitudes, efforts to incorporate protection strategies into forest management, by producing less susceptible forests and/or measuring the effects on forest resource production goals, are necessary (Alfaro 1988).

Damage from severe defoliation on jack pine includes growth reduction (Kulman et al., 1963), top kill (i.e., dead tree tops) (Prebble 1975), and tree mortality (Howse 1984). Surviving trees usually produce lower yields than healthy trees (Alfaro 1988; Moody and Amirault 1992), particularly if height growth has been permanently impaired by top kill (Alfaro 1991). Although significant reductions in radial growth and average volume increments have been reported after severe defoliation (Kulman et al. 1963; Cerezke 1986; Gross 1992), relatively less is known about the characteristics and impacts associated with top kill. Trees with top kill, however, have experienced considerably more defoliation than those with surviving tree tops (Gross 1992). In a recent study, Gross (1992) suggested the actual volume in a dead top is insignificant, and that loss of growth potential is of greater concern. In a previous study, however, Cerezke (1986), reported outbreaks lasting two to five years with severe defoliation often results in extensive top kill. The unknown parameter that influences these conclusions is the degree and duration of defoliation that a given stand may have sustained, and perhaps the bigger impact is the loss of future growth. Regardless, if growth reductions and top kill are combined, these types of losses have an impact that is generally unknown (Volney 1988). Thus, an improved understanding of the impacts resulting from jack pine budworm outbreaks, is essential to reduce uncertainties about future timber supply (MacLean 1990). To address this need, research to quantify the effects of forest pests at the stand level is required (MacLean 1990).

Damage assessment to address the effects of budworm defoliation associated with top kill, may be viewed from three perspectives. These perspectives are: measurement of top kill to quantify its volume, the mapping of severity of top kill at the stand level, and the association between physiographic and stand characteristics with top kill to enable the identification of potentially vulnerable stands. The objective of this thesis was to address these three aspects of top kill for an area in Saskatchewan, Canada, where a jack pine budworm outbreak was reported to have occurred (Moody and Cerezke 1986). The thesis objective was achieved by answering three research questions: 1) To what extent can a method based on large-scale photo measurements and a jack pine taper model be used to estimate the volume of tree top kill?; 2) To what extent can multidate LANDSAT TM data be used to classify and map the severity of top kill?; and 3) Are selected physiographic and stand characteristics associated with top kill? The characteristics selected include soil texture, drainage, site quality, stand origin, stand height, and crown closure.

Three studies were undertaken with each directed towards one of the research questions. To determine the impact of top kill requires quantifying its volume on individual trees. Field measurements of the lengths of top kill, however, are tedious, time consuming and difficult. An alternate method based on photo mensuration using large-scale aerial photographs was evaluated, and its limitations were determined.

To address both the second and third questions, a map outlining severity levels of top kill was required. A classification system was devised for mapping top kill, and interpretation of top kill for the study area was completed on 1:5000 color infrared aerial photographs. The map of top kill was used to analyze the spectral responses using LANDSAT TM data from three dates. This map was also overlaid with selected site quality and stand attributes to determine spatial associations. These associations were then analyzed to make inferences on characteristics of vulnerable stands.

This thesis is written in a manuscript format with each Chapter describing a separate but integrated part of the research. Relevant literature and background for the research questions is summarized as part of each Chapter. Chapter 2 provides a review of the jack pine budworm life history, followed by stand and environmental influences on budworm populations. A brief discussion on the impact of severe defoliation and survey methods to assess defoliation concludes the chapter. Chapter 3 presents a description of the study area including physiography, climate, soils, vegetation and site quality. Chapter 4 addresses the first research question by evaluating the use of large-scale aerial photographs and a jack pine taper model for estimating volumes of tree top kill. Chapter 5 addresses the second research question by evaluating a satellite remote sensing approach based on multidate LANDSAT TM data for mapping top kill. Some issues in remote sensing - Geographic Information System integration and change detection are also identified. Chapter 6 addresses the third question by determining spatial associations between site quality and stand attributes with top-kill severity to ascertain characteristics of vulnerable stands. The background material in Chapter 2 is used to help make these inferences. Chapter 7 synthesizes the results of the three studies and includes recommendations for additional research. The reader should note that the description of the study area (ie., Chapters 4, 5, and 6), and the mapping of top kill sections (ie., Chapters 5 and 6), are repeated to maintain consistency for the manuscript format.

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Chapter 2

A Review of Jack Pine Budworm Life History, Factors Influencing Insect Populations and Damage Impact

2.1 Introduction

This chapter presents a review of the jack pine budworm (*Choristoneura pinus pinus* Freeman) (Plate 2-1) life history, and of forest stand characteristics and environmental factors that influence insect populations. A review of host-pest interactions and impacts of defoliation on forest stands and trees, provides a perspective on the influence of jack pine budworm defoliation on the forest ecosystem. An overview of aerial survey classifications for defoliation severity and their limitations, provides the background for subsequent chapters that study the relationships between spatial patterns of jack pine top kill and stand characteristics.

2.2 Jack pine budworm life history

The life history of the jack pine budworm (Figure 2-1) is similar to the spruce budworm (*Choristoneura fumiferana* Clem. and *Choristoneura occidentalis* Freeman) (Prebble 1975). In both cases, moulting occurs once in the late summer and newly emerged larvae overwinter as second instars (Nealis 1987), but the two budworms differ by their preference for host tree species. Jack pine (*Pinus banksiana* Lamb.) is the principal host for jack pine budworm but scots pine (*Pinus resinosa* Ait.), eastern white pine (*Pinus strobus* L.), red pine (*Pinus sylvestris* L.), lodgepole pine (*Pinus contorta*

Dougl.), white spruce (*Picea glauca* (Mœnch) Voss), black spruce (*Picea mariana* (Mill.) B.S.P.), and tamarack (*Larix laricina* (Du Roi) K. Koch.) have also been attacked (Ives and Wong 1988), especially when near susceptible jack pine stands (De Boo and Hildahl 1968). Jack pine budworm overwinters as a second-instar larva within a silken shelter (hibernaculum) (Kulman et al. 1963) in protected locations under bark scales, between needles, or in old staminate flower buds (De Boo and Hildahl 1968). Larval emergence begins in late May soon after male cones open and new, young needles emerge (Clancy et al. 1980). The budworm larvae migrate to the tops of trees and outer crown due to their preference for male flower clusters and young foliage (Howse 1984). Defoliation spreads from the top of the tree downwards (Moody 1986). Budworm larvae establish suitable feeding sites and feed for six or more weeks while progressing through 7 instars (Cerezke 1978; Nealis 1987). The larvae are mature by mid July depending on weather conditions.

The jack pine budworm is considered a wasteful feeder (Prebble 1975) since needles are cut at the base with only the basal portion being eaten (Kulman et al. 1963). The rest of the needle is entangled in a mass of silk and frass that forms a feeding shelter along the axis of the shoots (Prebble 1975). As this material desiccates, it changes to a distinctive reddish brown color (Plate 2-2) (Martineau 1984), which is a visual indicator of defoliation severity used during aerial surveys (Moody 1986). Forest Insect and Disease Survey rangers with Forestry Canada use the intensity of red-color of the needles to rate stands as severely, moderately, lightly or not defoliated (Volney 1988).

The mature larvae pupate within the feeding shelters (Prebble 1975) and emerge as adult moths in about a week, during late July or early August (Howse 1984). After mating, they deposit eggs on needles in clusters of about 40 (Howse 1984) that hatch 10 to 14 days later (De Boo and Hildahl 1968). The first-instar larvae do not feed but instead migrate to protective locations such as crevices within the bark (Martineau 1984). The larvae then spin hibernacula and molt to over-winter as second-instar larvae (De Boo and Hildahl 1968).

The jack pine budworm is a mobile defoliator and during the adult moth stage, may disperse over long distances with the assistance of air currents (De Boo and Hildahl 1968). Emerging larvae in the spring also may disperse on silken strands (Prebble 1975). There may be mortality losses during dispersal because of exposure to adverse environments, the difficulty in finding suitable hosts, and predation by spiders and insects. (Foltz et al. 1972). The weather during larval and adult dispersal also influences population fluctuations, and either favors outbreaks or contributes to their collapse (Foltz et al. 1972). The structure of the forest stand and weather conditions during an infestation therefore play important roles in budworm population dynamics.

2.3 Influence of stand characteristics on jack pine budworm populations

A stand is a contiguous group of trees sufficiently uniform in species composition, structure (e.g., density and levels within a stand such as single-storied, multistoried), and age class (Alfaro 1988). A stand is also considered a dynamic entity (Alfaro 1991) that continually changes in composition and structure within the process of ecological succession (Kimmins 1987). Insects affect the speed of succession by either reducing growth rates or killing trees, and therefore alter species mixtures and size distributions (Alfaro 1988). Some understanding of insect responses to stand characteristics provides an indication of stand susceptibilities. Three characteristics of stands are important in influencing budworm populations: age, density and structure. Jack pine become established as extensive, pure, even-aged stands (Morris and Parker 1992), typically originating after forest fires (Rudolph and Laidly 1990), and are susceptible to insect defoliation when old enough to start flowering. Although previous studies have reported that jack pine budworm dynamics are influenced by the frequency and amount of staminate flowers (Hodson and Zehngraff 1946; Batzer and Jennings 1980), this assumption has been questioned (Nealis 1990). It is not clear whether the association between jack pine budworm and staminate flowers favors survival of jack pine budworm (Nealis 1990), and there are no reported nutritional or phenological advantages to feeding on staminate flowers (Lejeune 1950). The association between outbreaks and staminate flowers is most significant for the early feeding stages of the budworm, since older larvae are often established in the vegetative shoots, and this may be beneficial to budworm survival when population densities are low (Nealis 1990).

Based on a study to correlate fire history with budworm outbreaks for the Prairie provinces of Canada, a trend was demonstrated towards increasing outbreak size once jack pine stands reach abundant flower production (Volney 1988). In addition, as forest fire control measures are improved, a larger portion of jack pine stands will move into susceptible age-classes (Volney 1988). Stands are susceptible to outbreaks when flower production is abundant, and this is increased when responding to stress such as fire.

Sparse open stands with large-crowned trees, and dense, overstocked stands with trees of poor vigor are most susceptible to defoliation outbreaks (Dixon and Benjamin 1962; Kulman et al. 1963). Stand density also influences larval dispersal and the survival rate of small larvae (Batzer and Jennings 1980). That is, higher density stands of suppressed, male cone producing trees support larger larval populations because of available food, and lower density stands encourage dispersal losses (Batzer and Jennings 1980). This is similar for spruce budworm defoliation since dense stands are generally considered more susceptible than open stands (Wulf and Cates 1987). Defoliation may be greater in open stands, however, due to open stands being warmer and drier relative to denser stands (Wulf and Cates 1987). Open stands therefore support larger insect populations despite the higher probability of dispersal losses. The influence of stand density on insect populations depends in part, on weather and environmental site conditions.

In terms of stand structure, jack pine budworm prefers a single host tree species that occurs in even-aged and single storied stands. Jack pine budworm's host base is narrow relative to the spruce budworm for example, which can also attack trees in single and multistoried stands (Martineau 1984).

The relationship between areal extent of pure, susceptible host stands and incidence of jack pine budworm attack is unknown. In a study of spruce budworm defoliation, van Raalte (1972) suggested host stands of less than 40 ha are not susceptible to insect attack, and this may be attributable to the amount of food available to sustain an insect population. If this is applicable to jack pine budworm, then there may be a minimum stand size required before susceptibility to attack becomes a management concern. Jack pine stands that are less than 65 ha, with shapes that minimize the amount of edge have been recommended (Weber 1986). Jack pine trees along the edge of cuts often respond with crops of male flowers, and budworms tend to concentrate along these stand edges. Stand shapes that are circles, squares, and broad ovals may therefore be preferred (Weber 1986), although this may be operationally difficult to achieve. This suggests a management and ecological alternative to create smaller stands of certain shapes, and to incorporate species diversity instead of allowing large, pure jack pine stands to become established. Because jack pine often occurs on sites that are unsuitable for other tree species (Kabzems et al. 1986; Rudolph and Laidly 1990), incorporating species diversity may be difficult to achieve.

2.4 Environmental influences on jack pine budworm populations

The environment has an important influence on the abundance, activity and distribution of insects, both directly and through the host plants (Wellington 1954). Hot weather from May through July (i.e., during larval development) followed by warm weather from August through October provides favorable conditions for jack pine budworm (Ives 1981). These weather conditions contribute to outbreaks, whereas unfavorable weather such as high humidities and below-normal temperatures, contribute to population collapse (Foltz et al. 1972; Batzer and Jennings 1980). Although the association between weather parameters and the production of staminate flower crops is somewhat tenuous (Volney 1988), earlier research efforts suggest that certain weather patterns cause vegetation stress, flowering response, and predisposition to outbreaks (Hodson and Zehngraff 1946; Batzer and Jennings 1980; Ives 1981). Warm and dry weather patterns for example, result in moisture stress and encourage staminate flower production (Riemenschneider 1985) prior to outbreaks. Fire scorching also results in tree stress, and flower production (Furniss and Carolin 1977). The dependence of budworm survival on flower production was suggested by the association between a 4-year sequence of fire followed by flowering and budworm outbreaks (Volney 1988).

Moisture stress reduces tree vigor and growth rate, and increases suspectibility to insect attack (Furniss and Carolin 1977). MacAloney (1944) observed that moisture deficient sites or low rainfall, combined with severe drought, resulted in mortality of live roots, and decline in tree vigor. Since jack pine may not recuperate after it has begun to stagnate (MacAloney 1944), this decline contributes to the physiological weakening of the host tree (Kozlowski et al. 1991). The cause-and-effect relations are complex and attributable to many possible host-pest interactions involving stand structure, weather and insect.

Few papers describe the effects of physiographic site characteristics on jack pine budworm populations. Though jack pine occurs on a wide variety of sites, it often predominates on sandy, well-drained sites that have relatively poor moisture holding capacities and low site productivity (Rudolph and Laidly 1990; Sims et al. 1990). Stands growing on these locations are more likely to experience moisture stress and low tree vigor. This suggests site productivity and soil type are factors that may influence stand susceptibility and predisposition to insect attack (Clancey et al. 1980), and a higher freqency of outbreaks have been associated with drier sites (Volney and McCullough 1994).

Another factor that influences jack pine budworm populations is their natural-enemy complex that includes parasites, predators and pathogens. Foltz et al. (1972) suggested neither parasites nor predators respond proportionately to budworm populations. Bird predation is also not a major mortality factor during insect outbreaks since jack pine stands do not support large bird populations (Ives 1981). Parasites and predators have limited roles in jack pine budworm dynamics, and are dependent on alternative hosts for survival during other parts of the year (Foltz et al. 1972; Ives 1981). In a Wisconsin study, forty-six parasites were identified, and those parasites that affected the egg, overwintering larvae, and pupal stages had the greatest influence on budworm populations (Dixon and Benjamin 1963). Foltz et al. (1972) reported factors such as predation by spiders and failure to spin hibernacula, affect egg-to-second-instar age survival and cause fluctuations in budworm populations. Natural enemies of the jack pine budworm contribute to population fluctuations, and help to control populations at endemic levels, but their effects appear to be minimal during outbreaks.

2.5 Tree response to defoliation

A complete understanding of stand and tree responses to insect defoliation is difficult due to the complex interrelations between varying compositions of stands and environmental and site characteristics that lead to variable defoliation intensities. Severe defoliation does, however, modify the forest ecosystem by disrupting the rate of normal successional processes and nutrient cycling (Kimmins 1987). A recognition of these processes that underlie forest-insect relationships is considered essential to sound forest and pest management (Stoszek 1988). An ecological approach to forest protection has been suggested, whereby ecosystem stability is increased by enhancing the physiological status of trees to establish resistance (Vasechko 1983). Implementing appropriate forest and silvicultural practises and encouraging a species diversity in coexistence with natural pest enemies are approaches toward achieving a healthy physiological status (Vasechko 1983). The premise is that in healthy organisms, all processes proceed normally, and a deviation from the optimum results in physiological weakening and reduced ability to resist pests.

The main tree physiological effects of defoliation include reduced changes in tree vigor, a decrease in host resistance to other mortality agents, and a reduction in photosynthetic capacity (Kulman 1971; Coulson and Witter 1984; Moody and Amirault 1992). Host tree physiologic responses to defoliation also influence food quantity and quality for future insect generations, and contribute to the collapse of an infestation. The quantity of suitable foliage is often considered a density-dependent factor since the size of an insect population is in part limited by the kind and quality of food the insects can use (Knight and Heikkenen 1980). Repeated severe defoliation inhibits male flower and new foliage production, which, when combined with terminal shoot and bud damage, constitute the important contributing factors to population declines (Prebble 1975; Cerezke 1978; Howse 1984).

A host-insect interaction often resulting from severe defoliation is the physiological weakening and predisposition of the host to attack by secondary insects and pathogens. The host tree is therefore more susceptible to other mortality agents due to stress imposed by defoliation (DeBoo and Hildahl 1968). *Armillaria* spp. root rot (Mallett and Volney 1990) and several species of flatheaded wood borers *Chrysobothris* spp., have been associated with jack pine following defoliation (Howse 1984). Mallett and Volney (1988) attempted to ascertain whether infection by root pathogens determine the extent to which trees are damaged following budworm defoliation, or conversely, whether repeated defoliation predisposed trees to root pathogen attack. Two scenarios were presented:

1) *Armillaria* root rot may have been in the soil prior to defoliation and could have imposed sufficient stress for the tree to produce a male flower crop. If there were sufficient flowers for a budworm population to build, then budworms are attracted to trees with root rot. These trees would have insufficient starch reserves to recover from defoliation, and the fungus could consequently spread up from the root and kill the tree.
2) The stress imposed by the defoliation may have weakened the tree and predisposed it to attack by the root pathogen.

Although both scenarios can be rationalized, a full understanding of the mechanisms, factors and interactions that explain why trees die is not complete (Waring 1987; Mallett and Volney 1990). Much of the literature, however, has suggested the influence of secondary host infection on tree mortality (Kulman 1971; Knight and Heikkenen 1980; Moody and Amariault 1992).

2.6 Impact of jack pine budworm defoliation

Pest impact is often considered as any change brought about in the forest by an insect population (Coulson and Witter 1984). Reduced growth is a common impact of repeated defoliation (Myers 1988). Significant annual volume growth losses of up to 61% (Kulman 1971), 91% (Cerezke 1986), and 75% (Gross 1992) have been reported. Reduced yields are a result of top kill and reduced vigor caused by reductions in root absorption, transpiration and photosynthesis (Moody and Amirault 1992). Growth reductions have been correlated with the quantity of foliage loss. For example, trees with light defoliation exhibit greater growth rates than trees more severely defoliated (Kulman 1971). Although the effects of severe defoliation on the reduction in jack pine yield are not generally known (Volney 1988), an overestimation of future timber supply will likely result without adjustments to the growing stock that experiences defoliation (Maclean 1990).

In addition to reduced growth, impacts include morphological changes from a reduction in foliage, tree mortality, branch mortality, top kill (Plate 2-3) and crown deformity. Howse (1986) reported severe jack pine budworm defoliation repeated for two or more consecutive years may result in tree mortality, but top kill, and decreases in radial increment, are more frequent. Kulman et al. (1963) reported mortality figures from 29 to 44% for trees that were almost completely defoliated. Brandt and McDowell (1968) and Gross (1992) reported mortality was greater for intermediate and suppressed trees than for dominant trees. Tree mortality was not attributed to defoliation alone and other causal factors such as secondary agents were suggested. Since defoliation typically spreads from the top of the tree downwards, top kill occurs frequently (Cerezke 1978) and these trees become permanently impaired in merchantable height growth (Alfaro 1991).

2.7 Aerial survey to assess jack pine budworm defoliation

Aerial surveys are used to determine the extent and severity of defoliation over a forest region (Volney 1992). Such surveys generally involve sketch mapping, which entails the transfer of infestation boundaries as seen from an aircraft onto maps (Moody 1982). This process is facilitated if terrain features and landmarks viewed from an aircraft can be easily related to the geographic features on the map (Jano 1982). Aerial surveys are quick and timely (Harris and Dawson 1979), and are useful for planning more detailed damage appraisal surveys, planning egg mass surveys, planning salvage operations, and assessing insect spread rates (Moody 1982). The Forest Insect Disease Survey (FIDS) of the Canadian Forest Service has been undertaking these surveys for many years (Cerezke and Gates 1992; Moody 1992) and the long-term record this data represents is invaluable (Volney 1988). The accuracies of these aerial surveys are difficult to assess, however, and are impaired by a lack of time to record details, which often result in overestimates through inclusion of unaffected areas (Harris and Dawson 1979). Although there are many factors such as timing of surveys, weather conditions, and topography that influence survey accuracy (Kettela 1982), accuracy is largely dependent on the knowledge, skill, and experience of survey personnel (Waters et al. 1958; Twardus 1985). Though this problem can be mitigated by observer training (Sippell 1983; Innes 1988), a characteristic of the information gathered from these surveys is that it is subjective (Volney 1992). There also has been no standardized infestation severity classification system as evidenced by the variety of schemes found in several previous surveys for jack pine budworm and spruce budworm defoliation (Table 2-1). Comparisons among surveys are therefore difficult, and relationships between sketch maps and stand characteristics have not been reported in the literature. Since forest inventory maps for commercial forest zones are generally available, computing the relations between mapped stand attributes and maps of insect damage may be useful to explore.

2.8 Summary

This review chapter consisted of: the jack pine budworm life history; stand and environmental factors that influence population dynamics; and impacts from severe defoliation. Top kill is one impact associated with severe defoliation that has not been extensively studied. Quantifying the volume of top kill on individual trees will help to determine the magnitude of volume loss and its contribution to defoliation impact, and is the subject of Chapter 4. A standardardized system for classifying and mapping the severity of jack pine budworm defoliation is not available, nor has one been reported for top kill. A need therefore arose to devise such a system for top kill, and this is reported in Chapter 5 and Appendix 1. The map of top kill resulting from this system was required before evaluations of satellite data (ie. Chapter 5) and determinations of spatial association measures (ie. Chapter 6) were undertaken as outlined in Chapter 1.

Table 2-1. Survey classification systems used for jack pine budworm and spruce budworm defoliation.

Reference	Class 1	Class 2	Class 3	Class 4	Class 5	Survey
			Jack pine budworm			
Benjamin (1956) cited in Dixon (1985)	none to light	medium (defol. evident)	heavy (crowns red-brown)	severe (top kill and mortality)		aerial
Kulman et al. (1963)	New Growth: very light 0 - 25 %	light 26 - 75 %	medium 76 - 100 %	heavy 100 %	heavy 100 %	field
	Old Needles: 0 %	0 %	0 - 25 %	26 - 75 %	100 %	
Moody (1986)	light tree slightly red	moderate redness clearly evident	severe entire crown red			aerial
Gross (1992)	light 1 - 25 %	moderate 26 - 75 %	high > 75 %			field
			Spruce budworm			
Ashley et al. (1976)	light < 20 %	light < 20 %	heavy 51 - 80 %	severe > 80 %	dead 100 %	air photo
Mag and Witter (1979) cited in McCarthy et al. (1983)	no defoliation 0 - 25 %	light - moderate 21 - 50 %	heavy, no top kill 51 % +	severe 51 % + & top kill		aerial
Twardus (1985)	none 0 - 10 %	light 20 - 40 %	moderate - heavy 50 - 100 %	severe w/top kill & mortality 50 - 100 %		field
Ostaff and Maclean (1989)	0 - 10 %	11 - 30 %	31 - 60 %	61 - 99 %	100 %	air photo

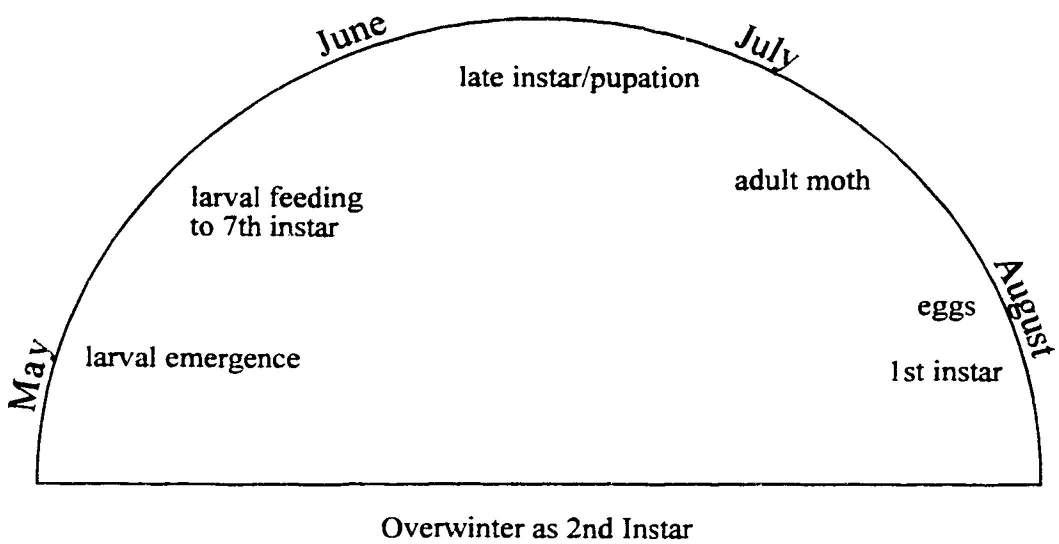

Figure 2-1. Life history of the jack pine budworm.

Plate 2-1. Mature jack pine budworm larva. Reprinted with permission from Canadian Forestry Service (Ives and Wong 1988).

Plate 2-2 Reddish brown needles caused by larval feeding. Reprinted with permission from Canadian Forestry Service (Ives and Wong 1988).

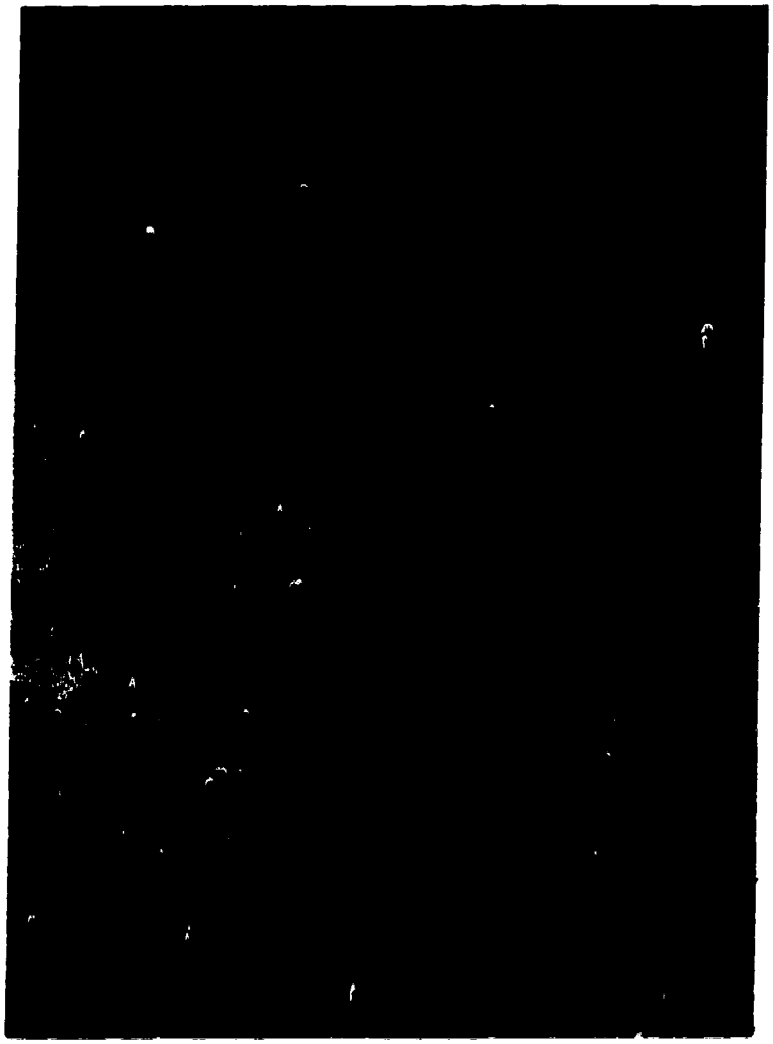

Plate 2-3. A stand of jack pine showing trees with top kill.

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Chapter 3

Description of Study Area

3.1 Introduction

The study area encompasses the Torch River Provincial Forest of Saskatchewan (Figure 3-1), and was selected because moderate to severe defoliation was reported for this area between 1985-1987 (Moody and Cerezke 1986; Cerezke and Emond 1989). The purpose of this chapter is to describe the location, physiography, climate, soils and drainage, forests and vegetation of the chosen study area.

3.2 Location and physiography

Torch River Provincial Forest is located within Universal Transverse Mercator (UTM) Zone 13, and is bounded by 550,000 mE and 5,920,000 mN on the southwest to 570,000 mE and 5,940,000 mN on the northeast. It is referenced on the southeast corner of National Topographic System (NTS) 1:50,000 map sheet 73H/9. The study area occupies approximately 4,000 ha in Townships 52 and 53, Ranges 14 and 15 west of the 2nd meridian (Anderson and Ellis 1976), and is included in the Carrot River Lowland physiographic section of the Manitoba-Saskatchewan Lowlands (Kabzems et al. 1986). The Carrot River Lowland is a gently to roughly undulating plain composed primarily of sandy fluvial-lacustrine sediments (Anderson and Ellis 1976). Based on interpretation of the 73H/9 NTS map sheet, the study area lies at elevations ranging from 330 to 380 m above sea level.

3.3 Climate and recent weather trends

The climate of the study area is described as cold, sub-humid continental (Richards and Fung 1969), characterized by relatively cool, short summers, long cold winters, and low annual precipitation. The closest meteorological station to the study area for which temperature and precipitation records have been collected is at Nipawin, Saskatchewan[1]. Published figures based on 30-year averages are available for Nipawin (Atmospheric Environment Service 1982), and these were compared with figures for the years corresponding to the most recent jack pine budworm outbreak (Figure 3-2). The average annual temperature for the study area is 0.8° C (standard deviation 0.9° C). The average May to September growing season temperatures from 1975 to 1990 were below the Canadian Climate Normal based on a 30-year average (Atmospheric Environment Service 1982) of 14.5° C (Figure 3-2). From 1985 to 1988, there was a trend toward increasing average annual growing season temperatures that coincidentally occurred during the most recent jack pine budworm outbreak.

The total annual precipitation for the area based on the Canadian Climate Normal for a 30-year average is 40.4 cm (standard deviation 9.3 cm) (Atmospheric Environment Service 1982). From 1975 to 1990, annual precipitation generally exceeded this value, including the years 1984, 1985, and 1987 during the most recent jack pine budworm outbreak (Figure 3-3). In 1986, however, the largest areal extent of defoliation (Cerezke and Emond 1989) corresponded with a drier year, and this was also the second driest year between 1975 and 1990 (Figure 3-3).

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[1] Personal Communications. Atmospheric Environment Service, Winnipeg, Manitoba. March 1993.

3.4 Soils and drainage

Soils of the study area are a result of glaciation and related lacustrine and fluvial processes (Anderson and Ellis 1976), with surficial deposits that are predominately fluvial-lacustrine in origin and overlay silty glaciolacustrine materials. Fluvial implies sediments consisting of gravel and sand that were deposited by flowing water such as streams and rivers (Agriculture Canada, 1976; Agriculture Canada Expert Committee on Soil Survey 1987). Lacustrine implies sediments consisting of stratified fine sand, silt, and clay deposited in lake water and later exposed either by lowering of the water level or by uplifting of the land (Agriculture Canada, 1976; Agriculture Canada Expert Committee on Soil Survey 1987). Fluvial-lacustrine sands consist predominately of coarse-textured quartz and feldspar minerals, and weakly to noncalcareous (i.e., little or no presence of calcium carbonate) materials (Anderson and Ellis 1976). These sediments were deposited under alternating or overlapping glaciolacustrine and glaciofluvial conditions.

The study area has been mapped at a scale of 1: 126,720 to three soil associations. The dominant association includes rapidly to well drained Eluviated Eutric Brunisols and Orthic Regosols of the Pine Association (PN-2, Anderson and Ellis 1976; red polygons, Figure 3-4). Orthic Regosols have weakly developed horizonation and may have a thin LFH, Ah and C horizon sequence with no significant B horizon development. Eluviated Eutric Brunisols have sufficient development to include a B horizon (e.g., Bm), an eluvial horizon (i.e., Ae) from which mostly clay material has been removed, and a horizon sequence such as LFH, Ae, Bm or Btj, and C (Agriculture Canada Expert Committee on Soil Survey 1987). Although the more acidic Dystric Brunisols also occur in soils of the

Pine Association, they were not identified because of the small map scale and difficulty in separation from less acid and more prevalent Eutric Brunisols (Anderson and Ellis 1976). These soils therefore range from moderately acidic to strongly acidic, are of low fertility, and low moisture holding capacity. Along the Torch River valley are Regosolic, Brunisolic, and Luvisolic soils of the Hillwash Association (HW, Anderson and Ellis 1976; green polygons, Figure 3-4). Hillwash encompasses areas of several parent materials on steep, eroded valley slopes along the Torch River (Anderson and Ellis 1976) that could not be separated cartographically at this map scale. A small area in the northeast end of the Torch River Forest consists of well-drained Orthic Gray Luvisols of the Garrick Association developed from medium to moderately fine-textured, moderately to strongly calcareous resorted glacial till (GA2, Anderson and Ellis 1976; yellow polygon, Figure 3-4). Resorted glacial till contains greater amounts of silt and clay, and therefore has greater moisture holding capacities than soils of the Pine Association as evidenced by the relatively slower drainage and finer textures within the study area (Figures 3-4, 3-5).

The area is drained by the Torch and White Fox rivers, which subsequently drains into the Saskatchewan river system. These rivers are post-glacial in origin and tend to meander.

3.5 Forest and vegetation

Forests of the study area fall within the Mixedwood Section (B.18a) of the Boreal Forest Region described by Rowe (1972), and the Mixedwood Section of the Southern Boreal Ecoregion described by Harris et al. (1983). Much of the rapidly to well drained areas (Figure 3-4) are described as the *Pinus-Cladonia/Arctostaphylos* Ecosystem that consists mostly of jack pine and understory lichens (reindeer lichen) (*Cladonia* spp.) and bearberry (*Arctostaphylos uva-ursi* (L.) Spreng.) (Kabzems et al. 1986). The density of the tree canopy and the dryness of the site determine the understory species. A very rapidly drained site will have an open canopy with lichens whereas a rapidly drained site will have a denser canopy with lichens and bearberry for ground vegetation (Kabzems et al. 1986). Jack pine grows on a variety of sites ranging from very rapidly drained to imperfectly drained, but dominates in the very rapidly drained areas where other tree species cannot grow (Kabzems et al. 1986; Rudolph and Laidly 1990). This is readily apparent when the soil drainage map (Figure 3-4) is compared to the primary species map for jack pine distribution (Figure 3-6). Forest stands of trembling aspen (*Populus tremuloides* Michx.), white spruce (*Picea glauca* (Moench) Voss), and black spruce (*Picea mariana* (Mill.) B.S.P.) also occur along the Torch River floodplain and on some rapidly drained and well-drained sites (Figures 3-5 and 3-6).

Jack pine sites are relatively dry since rapidly well drained and well drained areas on coarse textured Brunisols have little water holding capacity. The dry ecoclimate on these sites result in frequent forest fires, with deep and multiple fire scars indicative of short fire frequencies (Kabzems et al. 1986). This was verified by observing fire scars on jack pine bark during field visits to the study area. Fire also removes organic matter (Kimmins 1987), and this explains in part, the occurrence of charcoal (Anderson and Ellis 1976) and the thin LFH layer in soils of the study area.

3.6 Site classification

A site quality map was produced for the area (Allan 1993) (Figure 3-7). This map was produced by interpreting landform and vegetative patterns on 1:5000 color infrared aerial photographs. Twenty-nine field plots were located throughout the study area based on available resources, and soil profiles, vegetative descriptions, plot location, drainage, and general physiography (i.e., slope gradient and aspect, topographic position, relief shape and landform) were recorded onto field sheets. Soils were described according to the Canadian System of Soil Classification (Agriculture Canada Expert Committee on Soil Survey 1987). Vegetation data were subsequently analyzed using the Cornell Ecology Program TWINSPAN, to classify the vegetation into communities as a basis for classifying site quality. The jack pine/*Cladonia* and jack pine/*Arctostaphlos/Cladonia* communities correspond to the *Pinus-Cladonia/Arctostaphylos* ecosystem described by Kabzems et al. (1986) for example, and typify poor sites. The jack pine/bog cranberry/moss vegetation community is closely related to the *Pinus-Vaccinium-vitis-idaea/Pleurozium* ecosystem described by Kabzems et al. (1986), and represents a medium site since it supports a greater diversity of understory vegetation.

3.7 Summary

The study area is located near the town of Nipawin, Saskatchewan. Its landscape is the result of glaciation and related lacustrine and fluvial processes. Soils of the TRPF are relatively homogeneous with much of the forest consisting of Eluviated Eutric Brunisols and Orthic Regosols of the Pine Association. These soils are relatively poor to moderate in site quality due to its coarse texture and rapid drainage and mainly support jack pine stands.

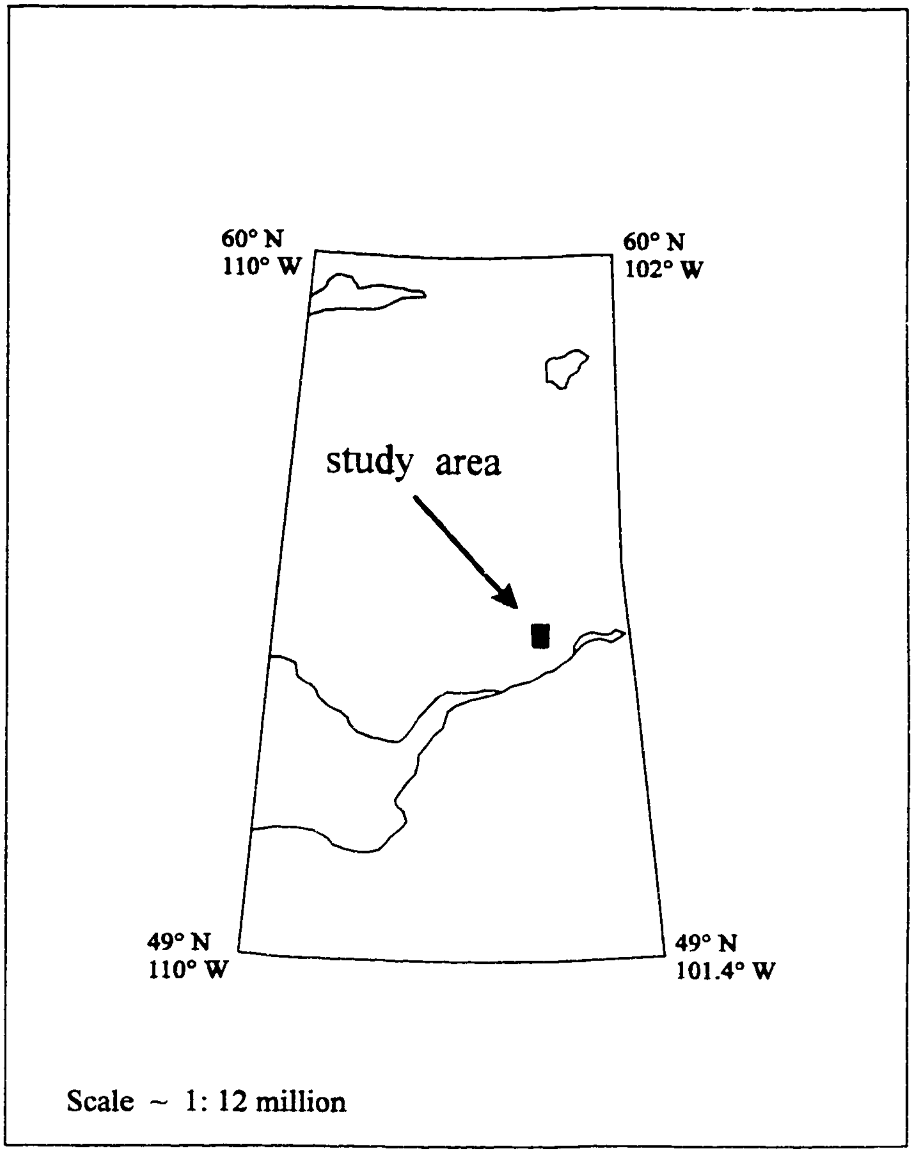

Figure 3-1. Sketch map of Saskatchewan depicting location of study area.

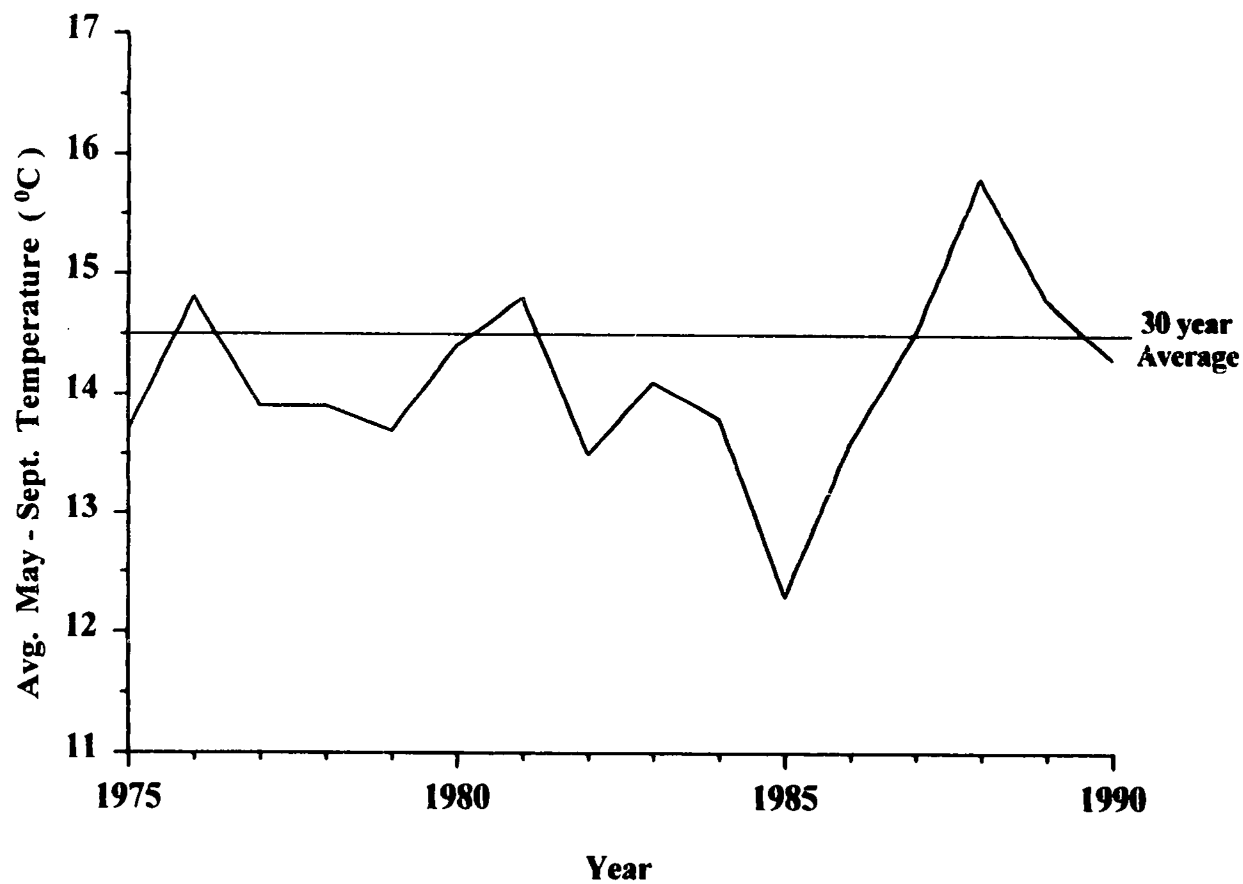

Figure 3-2. Average May-September temperatures (^{0}C) for Nipawin, Saskatchewan from 1975 to 1990.

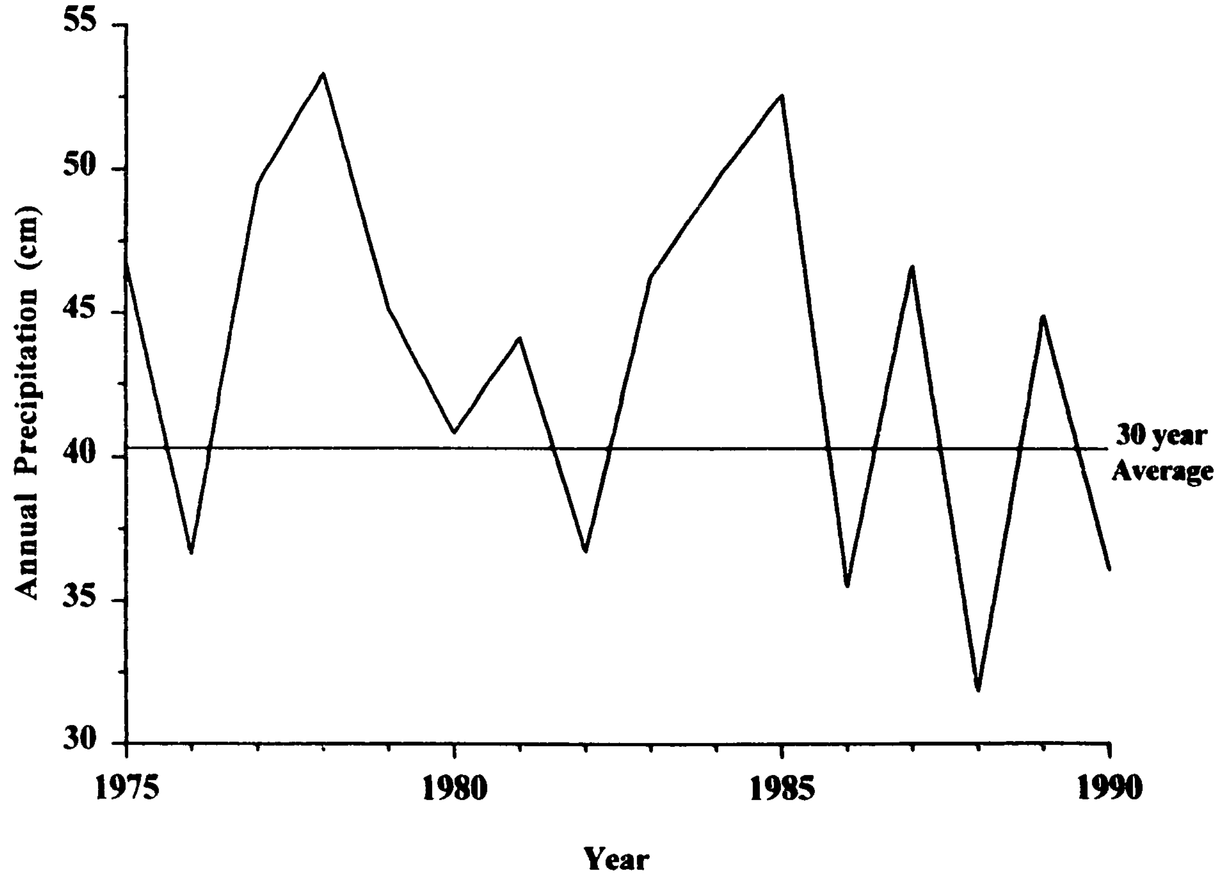

Figure 3-3. Total annual precipitation (cm) for Nipawin, Saskatchewan from 1975 to 1990.

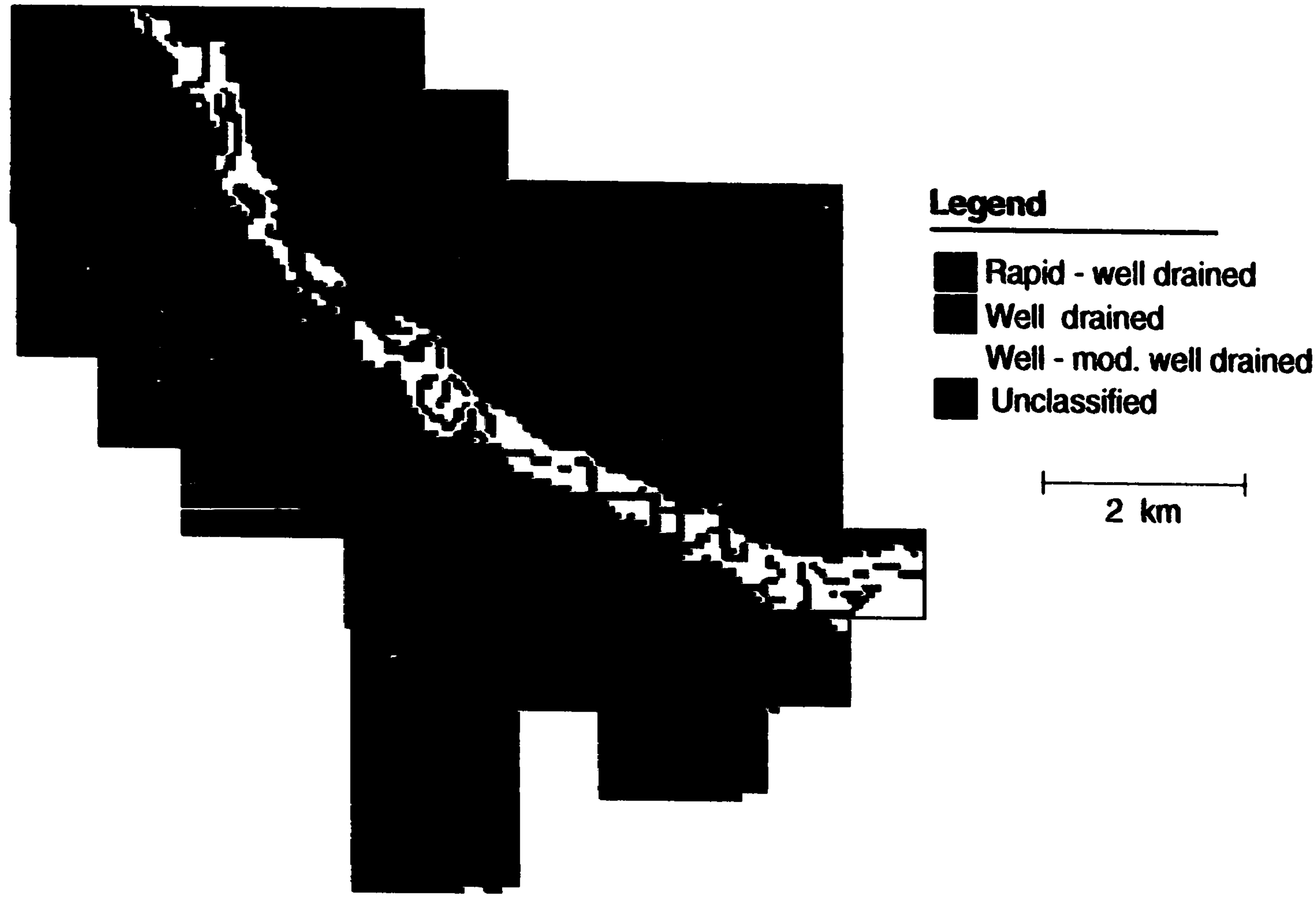

Figure 3-4. Drainage map of the Torch River Provincial Forest.

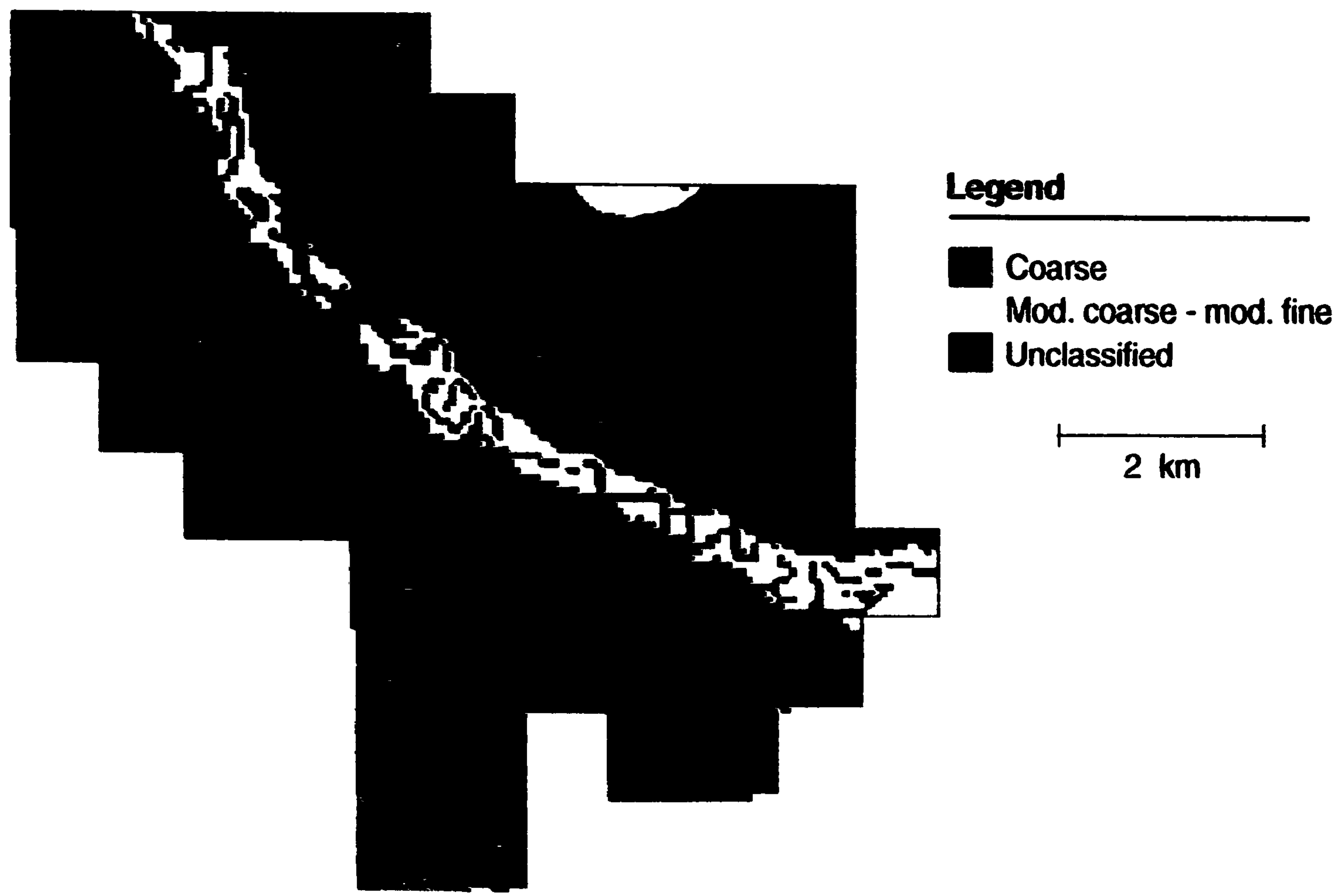

Figure 3-5. Soil texture map of the Torch River Provincial Forest.

Figure 3-6. Primary species map of the Torch River Provincial Forest.

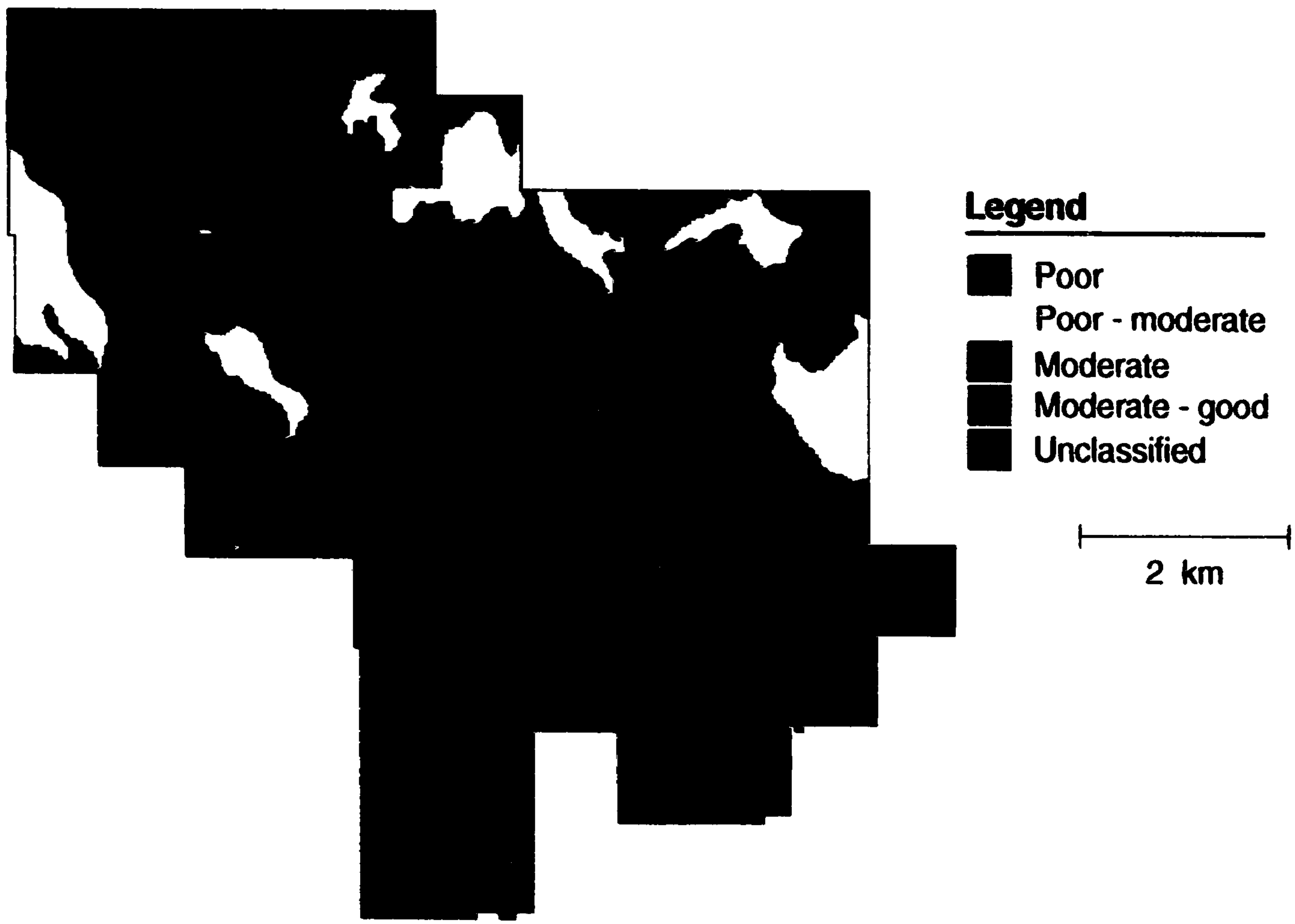

Figure 3-7. Site quality map of the Torch River Provincial Forest.

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Chapter 4

Estimating Top-Kill Volumes with Large-Scale Photos on Trees Defoliated by the Jack Pine Budworm[2]

4.1 Introduction

Jack pine budworm (*Choristoneura pinus pinus* Freeman) is a major pest of jack pine (*Pinus banksiana* Lamb.) forests in Ontario, Manitoba, Saskatchewan, and the adjacent United States Great Lakes States (Moody 1989). Damage from severe defoliation on jack pine includes growth reduction (Kulman et al., 1963), top kill (i.e., dead tree tops) (Prebble 1975), and tree mortality (Howse 1984). Surviving trees usually produce lower yields than healthy trees (Alfarao 1988; Moody and Amirault 1992), particularly if height growth has been permanently impaired by top kill (Alfarao 1991). Although the jack pine budworm is considered among the major insect pests in Canada (MacLean 1990), its effects on reduction in yield are not generally known (Volney 1988). Overestimation of future timber supply can therefore result from failure to allow for catastrophic mortality or continual reductions in growth, caused by biotic agents such as insect defoliation (MacLean 1990).

Damage impacts have seldom been quantified except in very general terms (Howse 1986). Reports of insect damage have largely been areal estimates of defoliation extent and severities based on aerial surveys and egg mass counts (Cerezke 1986; Moody 1989).

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[2] A version of this chapter has been published in the Canadian Journal of Forest Research: Hall, R.J., Titus, S.J., and Volney, W.J.A. 1993. Estimating top-kill volumes with large-scale photos on trees defoliated by the jack pine budworm. Can. J. For. Res. 23: 1337-1346.

Aerial surveys are widely used to assess and monitor the status of insect defoliators (MacLean 1990), and are quick and timely for monitoring current conditions (Harris and Dawson 1979). They are usually used to stratify the landscape but this is only the first step in obtaining volume estimates for input to timber supply calculations and harvest scheduling.

Previous studies oriented towards quantifying defoliation impacts have largely been research efforts to acquire fundamental information on its effects (Dixon and Benjamin 1962; Kulman et al. 1963; Rose 1974; Nyrop et al. 1983; Cerezke 1986; Volney 1988). Although these studies are important in their contribution, they have not focused on quantifying volumes of top kill on individual trees. The projection of top-kill volumes to the stand and forest level is a prerequisite to estimating potential defoliation impact on the jack pine timber supply. In addition, since jack pine usually does not fully recover from major stress, (MacAloney 1944), time may be a factor affecting the quality and quantity of future harvests. A trend towards increasing jack pine budworm outbreak size has recently been demonstrated (Volney 1988), and this suggests the need for estimates of volume losses (Little 1984) may also be increasing.

Measurements of length and the diameter of the main stem above the highest point of live crown to the tree top are required to estimate top-kill volume. Field measurements of both are tedious, time consuming and difficult. Large-scale photo (LSP) mensuration is a tool that may reduce the need for field evaluation of top kill. It is not known, however, whether large-scale aerial photo measurements are an accurate alternative to field measurements. The conventional photo approach to estimating individual tree volumes is to use an equation based on measured tree height and crown area (Spencer and Hall 1988). The applicability of LSP for estimating the volume of top kill is questionable, however, due to the difficulty in measuring crown area at the point between dead and live crown on the tree.

An alternative method for estimating the volume of tree top kill is to use large-scale photo measurements and a taper function. Taper functions are often used to estimate total tree volume as well as the volume for any portion of the main stem (Munro and Demaerschalk 1974; Avery and Burkhart 1983; Kozak 1988). Any suitable tree taper function can be used to estimate top-kill volume if top-kill length, tree height, and diameter are known. Height has long been measured photogrammetrically on LSP (Spencer and Hall 1988), and diameter has been predicted from LSP measurements of height and crown area (Aldred and Lowe 1978; Hall et al. 1989). If top-kill length measured on photos is strongly related to actual top-kill length, then tree height, top-kill length, and predicted diameter can be used with a taper function to estimate top-kill volume.

Estimates of top-kill volume in a stand can be estimated from sample plots measured on photos if all trees with top kill are visible on the photos. Trees with small amounts of top kill, however, may be missed during measurement on the photos. Since jack pine has a characteristic conical crown (Hosie 1973) with small diameter tree tops, missed trees will have a small influence on current volumes. This influence or bias can be estimated and adjusted by using ratio estimation procedures. The magnitude of this proportion was determined in this study.

The study objective was to determine to what extent can a method based on large-scale photo measurements and a jack pine taper model be used to estimate the volume of tree top kill? To achieve the study objective, the following 4 questions were addressed: 1) Are the lengths of top kill measured from large-scale photographs related to actual lengths of top kill?; 2) What is the relationship between tree diameter outside bark at breast height and photo measures of tree height and crown area for the study area?; 3) Are the volumes of top kill estimated using photo measurements and a taper model, related to their actual volumes?; and 4) What proportion of trees with top kill were missed on the large-scale photos and what proportion of volume of top kill did this represent?

4.2 Materials and methods

The study area encompasses the Torch River Provincial Forest of Saskatchewan, and is in the mixed wood section (B.18a) of the Boreal Forest Region of Canada, where jack pine predominates on sandy areas (Rowe 1972). It is located within the Universal Transverse Mercator (UTM) Zone 13 and is bounded by 550,000 mE and 5,920,000 mN on the southwest to 570,000 mE and 5,940,000 mN on the northeast. Moderate to severe defoliation was reported for the Torch River Provincial Forest between 1985-1987 (Moody and Cerezke 1986; Cerezke and Emond 1989).

4.2.1 Data collection

The Northern Forestry Centre computer-controlled, dual-Vinten, 70mm aerial camera system with radar altimeter was used to acquire the large-scale sampling photos

(Chapter 5 Plate 5-1) at an average scale of 1:900 with a 70% nominal overlap, on July 31, 1988 (Hall 1984; Spencer and Hall, 1988), the summer following the collapse of defoliation. Panchromatic (black & white) photos were acquired with Kodak Double-X 2405 film over nine random flight lines distributed throughout the Torch River Provincial Forest, and selected photos were printed onto transparency film. Three of the nine flight lines were also flown with normal color Kodak 2448 diapositive film as a subsample to permit a comparison between panchromatic and color films. This was logistically difficult due to the large scale of the photos, and the small areal coverage of each photo (~ 51 m x 51 m). The color photos were therefore treated as an independent sample. Photo scale control was facilitated by the placement of strategically located targets along flight lines, and by employing a radar calibration procedure (Hall 1984). All stereopairs were interpreted from film diapositives. The higher spatial resolution of a film compared to a paper medium, and the use of a high contrast duplicating film product facilitated the interpretability of dead tree tops. This has operational implications since visible top kill can be subtle, and is therefore more easily discerned on diapositive photos than on paper prints.

A random selection of twenty-seven large-scale photo plots (1 photo plot = 1 stereopair of which a plot ~ 270 m^2 is established) based on available resources was made from the acquired panchromatic (19 photo plots) and color photos (8 photo plots) to create the double sample (i.e., plot trees measured on both the photo and in the field). Although the original intent was to survey the entire Torch River Provincial Forest, only the double sample data were used in this study. Of the 378 sample trees over the 27 plots, 213 trees exhibited top kill. For each sample plot, two trees exhibiting top kill were randomly selected for stem analysis to achieve an approximate uniform distribution of the number of trees per plot. For plots having a single tree with top kill, an additional tree was chosen from another plot. This resulted in 55 trees being selected for stem analysis. These trees were cut into one metre sections, and measurement followed procedures described by the Forestry Division of the Saskatchewan Department of Natural Resources (Lindenas 1985). All section volumes were computed using Smalian's formula (Clutter et al. 1983).

Photo tree measurements of total height, crown area, and live height were obtained using a Zeiss Stereocord analytical plotter (Aldred and Lowe 1978; Spencer and Hall 1988). The length of top kill was computed as the difference between total and live height. Following standard photo-mensurational procedures, an independent data set from a previous project was first used to develop a simple linear regression calibration equation to account for possible combined photo interpreter measurement and instrumentation bias.

4.2.2 Relation between photo and actual lengths of top kill

Fitting separate linear models should adequately describe the individual relations between panchromatic and color photo measurements of top kill with their actual values. Inferences would not be possible, however, on whether panchromatic and color measurements were statistically different in their predictions of actual top kill. Indicator (or dummy) variable regression (Neter et al. 1990) based on the combined data set would provide these inferences if the data were equally varied. A preliminary F-test[3] of the error

[3] This and all subsequent statistical tests were performed at the 95% probability level.

variances from fitting the panchromatic and color photo regressions of top kill separately, showed them to be approximately equal (F = 1.13; F-table = 2.25). An indicator variable model was therefore appropriate to test whether panchromatic and color photo measures of top kill were related to their actual values (Neter et al. 1990):

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i1} X_{i2} + \varepsilon_i$$

where:

Y_i = Actual length of top kill (m)

X_{i1} = Photo-measured length of top kill (m)

X_{i2} = 0 if Color photo

= 1 if Panchromatic photo

ε_i = random error;

i = 1 to n, number of samples

Tests and inferences for comparing the regression functions for panchromatic and color photo top kill are equivalent to tests of significance of the indicator variable regression coefficients. Thus, if $\beta_2 = 0$ then β_0 is the common intercept, otherwise β_0 is the intercept for color and $\beta_0 + \beta_2$ is the intercept for panchromatic. If $\beta_3 = 0$, then β_1 is the common slope, otherwise β_1 is the slope for color and $\beta_1 + \beta_3$ is the slope for panchromatic. Beyond the tests on the regression coefficients, the indicator variable model was evaluated by examining the adjusted R^2 (Verbyla 1986) and standard error of estimate. Plots of the standardized residuals and normal probability were also employed to ensure appropriateness of the linear regression model.

4.2.3 Relation between DBH and photo-measured tree height and crown area

Previous studies to develop linear model forms of DBH as a function of tree height and/or crown area have been utilized either directly or through simple transformations such as their squares or square roots (Spencer and Hall 1988; Hall et al. 1989). Ten linear model forms were fitted using multiple linear regression techniques for the photo-ground double sample data set (Table 4-1). These models were based on the literature (Hall et al. 1989), and on the strengths of their simple correlations with DBH. The models in Table 4-1 are all intrinsically linear in model form. Although logarithmic models have also been employed in DBH estimation (Hall et al. 1989), the relatively small data set and the objective of developing a procedure for quantifying volumes of top kill did not warrant consideration of more complex models. However, once the procedures have been developed, more complex model forms could be substituted if warranted.

A random selection of 100 trees constituting one-third of the double sample was removed to create an independent data set for testing the selected model form. One or both of the following hypotheses were evaluated depending on whether tree height or crown area was in the tested model (Table 4-1):

1. Photo-measured tree height does not contribute to the prediction of tree DBH.
2. Photo-measured crown area does not contribute to the prediction of tree DBH.

These hypotheses were evaluated by the significance of their respective regression coefficients in the linear models tested. Beyond comparing statistical measures (adjusted

R^2, standard error of estimate, significance of predictor variables, standardized residual and normal probability plots) to assess model performance, the objective was to select the simplest model in terms of model form and number of predictor variables.

From the selected regression model, the test data set was used to compute average bias (i.e., the arithmetic difference between actual and predicted values) and its standard error to test the prediction abilities of the fitted model.

4.2.4 Estimating the volumes of top kill

Using a taper model, volumes of top kill may be computed as either the difference between total and live volume, or directly as the volume of the top kill portion (Figure 4-1; see variable definitions below). The latter approach was taken in this study. Hilt's taper model (Hilt 1980) as fitted to jack pine data (Bella and Somogyi 1992) was used to estimate volume:

$$
\begin{aligned}
V = {} & DBH^2 * (HT - 1.3) * k * (a * 0.4 * Y_1 + b * 0.4 * Y_1 * HT - b * 0.25 * Y_2 * HT \\
& + [(c * 0.4 * Y_1) * DBH * HT] - [(c * 0.25 * Y_2) * DBH * HT + \\
& [(d * 0.4 * Y_1) * DBH] - [d * (1/31) * Y_3 * DBH] + \\
& [(e * 0.4 * Y_1) * DBH * HT] - [e * (1/31) * Y_3 * DBH * HT]);
\end{aligned}
$$

where:

DBH = estimated tree diameter at 1.3 m from the ground (cm)

HT = photo tree height (m)

$Y_1 = X_U^{5/2} - X_L^{5/2}$;

$Y_2 = X_U^{4} - X_L^{4}$;

$Y_3 = X_U^{31} - X_L^{31}$;

X_U = upper integral limit; relative length from tip to lower limit of top kill

= predicted length of top kill / (HT - 1.3)

X_L = 0; lower integral limit and represents tip of the tree in this study

$k = \pi/4/10000 = 0.00007854$; constant for metric units

a = 1.062772, b = 0.032379, c = - 0.001028

d = 0.000231, e = - 0.00006015

The variables needed for estimating volumes of top kill using Hilt's taper model included tree DBH and photo measures of total tree height and top kill. Tree DBH was estimated from the fitted regression model (equation [2] below; Table 4-1). This approach can be conceptualized as estimating volumes from a set of three equations:

[1] Actual top kill = f_1 [photo top kill]

[2] DBH = f_2 [HT, CA]

[3] volume of top kill = f_3 [V^*]

where: HT = photo tree height (m)

CA = photo crown area (m^2)

DBH = estimated tree diameter at 1.3 m from the ground (cm)

$V^* = f_h$ [Predicted DBH, HT, Predicted top kill], Hilt's taper model

The model forms and respective parameters for equations [1] and [2] were based on results of the first two parts of this study. Hilt's volume estimates were first computed and then related to actual volumes using ordinary least squares (OLS) regression in equation [3].

Alternative parameter fitting approaches were also explored to determine if greater statistical efficiency could be obtained by solving for the parameters simultaneously. Since the dependent variables in equations [1] and [2] are used as independent variables in the taper model to compute volumes in equation [3], they exhibit a sequential relationship to [3], and are considered a recursive system of equations (Borders 1989). If the errors between equations [1] and [2] are correlated, then it is appropriate to estimate equation parameters jointly using seemingly unrelated regression (SUR) (Judge et al. 1988). SUR was used for equations [1] and [2] but efficiency gains were not obtained and significant correlation did not exist between respective error terms based on the Lagrange Multiplier statistic (Breusch and Pagan 1980). Equations [1] and [2] if treated as a block, are similar to a simple recursive system in which econometricians suggest statistically, can be consistently estimated by OLS (i.e., large sample equivalent of minimum mean square error) (Fomby et al. 1984). The OLS method yields parameter estimates that are the best linear unbiased estimates for linear equations if the error terms within an equation are independent, equally varied (homoscedastic), and the error terms between equations are not correlated (Kennedy 1985; LeMay 1988). OLS was therefore considered the most appropriate fitting technique for the set of equations presented.

4.2.5 Proportion of trees missed

The appropriateness of the study assumption that top kill only occurs if it was visible on the aerial photos, and missed trees would be small in magnitude required testing. To determine the proportion of trees with top kill that were missed on the LSP, a ratio was computed of missed trees to total trees with top kill. The volumes of these trees were then computed with Hilt's taper model. These volumes were then summed to calculate the proportion of volume for missed trees relative to all trees with top kill.

4.3 Results and discussion

4.3.1 Relation between photo and actual lengths of top kill

On average, panchromatic and color photo measurements of top kill were smaller in comparison to actual lengths measured during stem analysis (Table 4-2). Those from color film also had smaller average deviations. Photo measurements of top kill may have been underestimated because lengths of top kill are usually small, and discerning the boundary between live and dead crown is difficult. This discrimination was more obvious on the color photos but on average, the accuracy of measurememts from either film were similar (Table 4-2). Photo-measured lengths were also highly correlated with actual values (Panchromatic r = 0.75; Color r = 0.88), and these associations appeared linear (note the scatter of data in Figure 4-2). This suggested simple linear models would be reasonable to describe the relationship between photo and actual lengths of top kill.

Based on tests of the regression coefficients, there were no differences between panchromatic and color photo top kill in their relations with actual values (Table 4-3). This result was reasonable considering the relatively high standard deviations of top-kill deviations relative to their means (Table 4-3; Panchromatic 0.88m, Color 0.76m). A larger sample size is therefore necessary to ascertain differences between film types. The final model based on data for this study was photo-measured top kill as a predictor of actual lengths, with an adjusted R^2 of 0.62 and a standard error of estimate of 0.83 m (Table 4-3). Further evaluation of this model showed the standardized residuals to be equally varied and normally distributed (Figure 4-3a, 4-3b). The correlation coefficient between the standardized residuals and normal scores was 0.997, and this exceeded the critical value for the test of normality. Large-scale photo measurements of top kill are related to their actual lengths, and are adequately described with a linear equation.

4.3.2 Relation between DBH and photo-measured tree height and crown area

A comparison of the means and standard deviations for the regression and test data sets showed they were reasonable subsets of the full data set (Table 4-4). The regression data set was used to fit the DBH models, and the test data set was used to compute average bias and its variability for the selected DBH model. Correlation coefficients between the independent variables (Table 4-1) and DBH were all statistically significant, but $\mathrm{HT}\sqrt{\mathrm{CA}}$ was most strongly associated with DBH (Table 4-5). The parameters for the 10 regression models listed in Table 4-1 were therefore estimated. All 10 models were statistically significant ($P \leq 0.0001$), but variations in model performance were largely attributable to correlation among the predictor variables (Table 4-5), as evident by the large P-values for some regression coefficients (Table 4-6). There was only marginal improvement in predictive performance with more than 2 independent variables in the models. Models with photo measures of tree height and crown area were better predictors of DBH than models using either alone. This was expected since tree height and crown area were not highly correlated (r = 0.12), while crown area was more highly correlated with DBH (r = 0.59) (Table 4-5). Model 6 was selected for predicting DBH as it was the simplest model form with a high adjusted R^2, and all independent variables were statistically significant. In addition, the standardized residuals for model 6 appeared equally varied (Figure 4-4a), and were normally distributed (Figure 4-4b). The correlation coefficient between the standardized residuals and normal scores was 0.989, and this exceeded the critical value for the test of normality (Neter et al. 1990). There were no apparent departures from regression assumptions. Both tree height and crown area were concluded to contribute to the prediction of DBH for jack pine.

Based on the test data set, the average DBH from the field was 18.76 cm and the average predicted DBH using photo measured tree height and crown area was 19.24 cm. The average bias between predicted and actual DBH was 0.47 cm. Therefore on average, the regression function with photo measurements overestimated the actual DBH by approximately 0.5 cm and its standard error was 0.23 cm. For the data from the Torch River Provincial Forest, model 6 was considered a reasonable predictor of tree DBH.

4.3.3 Estimating the volumes of top kill

The high correlation of 0.93 between taper estimates and actual volumes of top kill suggested a linear model may be adequate. The intercept for this model was not significantly different from zero, however (P = 0.98), and a regression without an intercept was fit instead. The resulting model was a proportional adjustment between

Hilt's estimated volumes and actual volumes:

Predicted top-kill volume = 1.216 * Hilt's taper volume

Adjusted $R^2 = 0.90$ Standard error of estimate = 0.0023 m^3

A comparison of the taper-adjusted volumes with actual volumes of top kill suggest they are reasonable estimates given Hilt's taper model employed in this study (Table 4-7). An examination of the plot of standardized residuals showed them to be random and approximately equally varied with no bias evident.

4.3.4 Proportion of trees missed

Of the 19 photo plots on panchromatic film, 140 trees were surveyed with top kill in the field. Of the 140 trees, 126 were similarly interpreted from the LSP and 14 were not interpreted and therefore missed. By proportion, 10% of the trees with top kill were missed during interpretation on the LSP. In terms of its volume, the total volume for the 126 trees with top kill was 0.328 m^3, and for the 14 missed trees was 0.003 m^3. The proportion of trees with top kill not measured on the LSP was 0.9% by volume. Interestingly, there were only 2 missed trees with top kill of 73 over the 8 photo plots with color film. By proportion, this represented 2.7% or approximately 3% of all trees with top kill interpreted on the color film. Though measurement results from either film in this study were reported similar, this observation and results in Table 4-3 suggest color aerial film is preferable due to the increased visual discrimination of tree top kill.

Skilled interpreters can usually detect and measure parallax differences of 0.03 to 0.05 mm (Moffitt 1967; Avery 1977). If this is accepted as the minimum measurement unit for a scale of 1:900, then a length of 0.4 m long constitutes the limit of measurement precision. Top kill less than 0.4 m are therefore difficult to consistently measure.

4.4 Conclusions

A 3-step method was developed to estimate the volumes of top kill based on large-scale photo measurements. This method may also be suitable for other insect pests whose damage includes top kill and is based on 1) the measurement of top-kill length and tree height, 2) the estimation of DBH, and 3) a ratio adjustment to volume estimates obtained from a taper model. A comparison between panchromatic and color aerial photo measures was undertaken because top kill was perceived easier to measure on color film. Even though there were no statistical differences, it is preferable from a photo interpreter's perspective to use color film because of the greater image contrast between dead and live crown. Photo measurements were consistently conservative, however, and were adjusted to predict the actual lengths of top kill with a linear equation. DBH was estimated from a linear model based on photo tree height and square root of crown area. Based on tests with an independent data set, the linear model with photo measurements was a reasonable predictor of tree DBH with an average bias of 0.5 cm and a standard error of 0.2 cm.

The input of photo tree height, length of top kill, and predicted DBH into Hilt's taper model resulted in volumes of top kill which were on average, equivalent to actual volumes. The advantage of this method is that it is not contingent on a particular taper model form. Any taper function in volume terms can be used. Since taper models are often computed for specific species over relatively large areas, the relation between predicted volumes from the taper model to its actual volumes should be computed with a sample over the study area. This will determine if an adjustment to taper volumes is needed to reflect local conditions.

Although 10% of the trees with top kill were not visible on the panchromatic photos, this represented only 0.9% of total top-kill volume. This level of omission was considered acceptable; however, if required, an adjustment could be made to more accurately estimate defoliation impact on tree volumes. Color film, however, is preferred to panchromatic film since visible top kill on trees can be subtle, and are more easily interpreted and measured on color photos. By integrating this method with forest sampling procedures, volume estimates of top kill can be projected to the stand or forest level to obtain an estimate of defoliation impact on jack pine timber supply, or for studying stand changes following defoliation.

Table 4-1. Multiple linear models for DBH estimation using photo tree height and/or crown area.

Equation	Regression model form
1	$DBH = \beta_0 + \beta_1 HT$[a] $+ \varepsilon$
2	$DBH = \beta_0 + \beta_1 CA$[b] $+ \varepsilon$
3	$DBH = \beta_0 + \beta_1 \sqrt{CA} + \varepsilon$
4	$DBH = \beta_0 + \beta_1 HT \sqrt{CA} + \varepsilon$
5	$DBH = \beta_0 + \beta_1 HT + \beta_2 HT^2 + \varepsilon$
6	$DBH = \beta_0 + \beta_1 HT + \beta_2 \sqrt{CA} + \varepsilon$
7	$DBH = \beta_0 + \beta_1 HT + \beta_2 HT \sqrt{CA} + \varepsilon$
8	$DBH = \beta_0 + \beta_1 HT + \beta_2 HT \sqrt{CA} + \beta_3 \sqrt{CA} + \varepsilon$
9	$DBH = \beta_0 + \beta_1 HT + \beta_2 HT^2 + \beta_3 \sqrt{CA} + \beta_4 CA + \beta_5 HT \sqrt{CA}$
10	$DBH = \beta_0 + \beta_1 HT + \beta_2 \sqrt{CA} + \beta_3 CA + \varepsilon$

[a] HT = photo tree height

[b] CA = photo crown area

Table 4-2. Descriptive statistics for top-kill length (m).

Source	N	Statistics			
		Mean	Standard deviation	Standard error of the mean	Min, Max
Actual (felled)	55	2.25	1.35	0.18	0, 6.5
Panchromatic photo	39	1.72	1.24	0.20	0, 5.6
Color photo	16	1.79	1.38	0.34	0, 4.8
Deviations:					
Panchromatic - Actual	39	- 0.60	0.88	0.14	- 2.1, 1.5
Color - Actual	16	- 0.29	0.76	0.19	- 2.1, 0.7

Table 4-3. Indicator variable regression analysis results for top-kill length.

Run #	Statistic[a]	Model: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \varepsilon$ Parameter values β_0	β_1	β_2	β_3	Fit Statistics[b]
1. β_3 is not significant, remove and fit model without interaction term	$\hat{\beta}$	0.262	1.016	0.758	-0.258	Adj R^2= 0.63
	t	0.76	6.61	1.84	-1.38	SEE= 0.82 m
	P	0.449	0.000	0.071	0.174	
2. β_2 is not significant, remove and fit as simple linear model	$\hat{\beta}$	0.574	0.842	0.301		Adj R^2= 0.62
	t	2.20	9.50	1.23		SEE= 0.83 m
	P	0.032	0.000	0.226		
3. Final model	$\hat{\beta}$	0.793	0.839			Adj R^2= 0.62
	t	4.15	9.42			SEE= 0.83 m
	P	0.000	0.000			

[a] $\hat{\beta}$, estimated regression coefficient; t, t-value; P, P-value

[b] Adj R^2, adjusted R^2; SEE, standard error of estimate

Table 4-4. Means and standard deviations for DBH regression data sets.

Data set	Variable	Mean	Standard deviation
Full	Standing DBH (cm)	18.9	5.3
(N = 378)	Photo tree height (m)	13.9	3.0
	Photo crown area (m^2)	7.8	5.8
Regression	Standing DBH (cm)	18.8	5.3
(N = 278)	Photo tree height (m)	13.8	2.9
	Photo crown area (m^2)	7.7	5.6
Test	Standing DBH (cm)	19.0	5.3
(N = 100)	Photo tree height (m)	14.3	3.0
	Photo crown area (m^2)	8.2	6.4

Table 4-5. Pearson correlation matrix and probability of significance if $P \geq 0.05$

	DBH	CA	HT	HT^2	CA^2	$\sqrt{CA}$	HT CA	HT $\sqrt{CA}$
DBH	1.0	0.59	0.61	0.59	0.45	0.64	0.69	0.81
CA		1.0	0.12 0.05	0.11 0.08	0.93	0.97	0.95	0.83
HT			1.0	0.99	0.07 0.22	0.16	0.36	0.61
HT^2				1.0	0.06 0.22	0.14	0.35	0.60
CA^2					1.0	0.82	0.90	0.71
$\sqrt{CA}$						1.0	0.92	0.86
HT CA							1.0	0.94

Note: Refer to Table 1 for variable definitions.

Table 4-6. DBH regression statistics.

Equation	Fitted model	Adj R^2	SEE	β's not significant at $P > 0.05$
1	$3.853 + 1.0867\ HT$	0.36	4.22	none
2	$14.51 + 0.5613\ CA$	0.34	4.28	none
3	$8.815 + 3.813\sqrt{CA}$	0.41	4.06	none
4	$8.675 + 0.2774\ HT\sqrt{CA}$	0.65	3.14	none
5	$-0.5575 + 1.742\ HT - 0.02323\ HT^2$	0.36	4.22	$P(\beta_2) = 0.25$
6	$-2.656 + 0.9261\ HT + 3.323\sqrt{CA}$	0.67	3.04	none
7	$5.666 + 0.3179\ HT + 0.2399\ HT\sqrt{CA}$	0.67	3.05	none
8	$0.6188 + 0.68076\ HT + 0.09622\ HT\sqrt{CA} + 2.02206\sqrt{CA}$	0.67	3.04	$P(\beta_2)$ = 0.[illegible]1 $P(\beta_3) = 0.06$
9	$-0.9864 + 0.6384\ HT - 0.007737\ HT^2 + 3.461\sqrt{CA}$ $- 0.4381\ CA + 0.1868\ HT\sqrt{CA}$	0.68	3.00	$P(\beta_1) = 0.14$ $P(\beta_2) = 0.59$
10	$5.08907 + 0.3346\ HT\sqrt{CA} + 2.185\sqrt{CA}$ $- 0.5516\ CA$	0.67	3.02	none

Note: Refer to Table 1 for equation number and β coefficient references. Adj R^2, adjusted R^2; SEE, standard error of estimate

Table 4-7. Descriptive statistics for actual and top-kill volume estimates.

Variable (m^3)	Mean	Standard deviation	Standard error
Actual volume	0.003999	0.006453	0.000895
OLS volume	0.003993	0.006025	0.000835

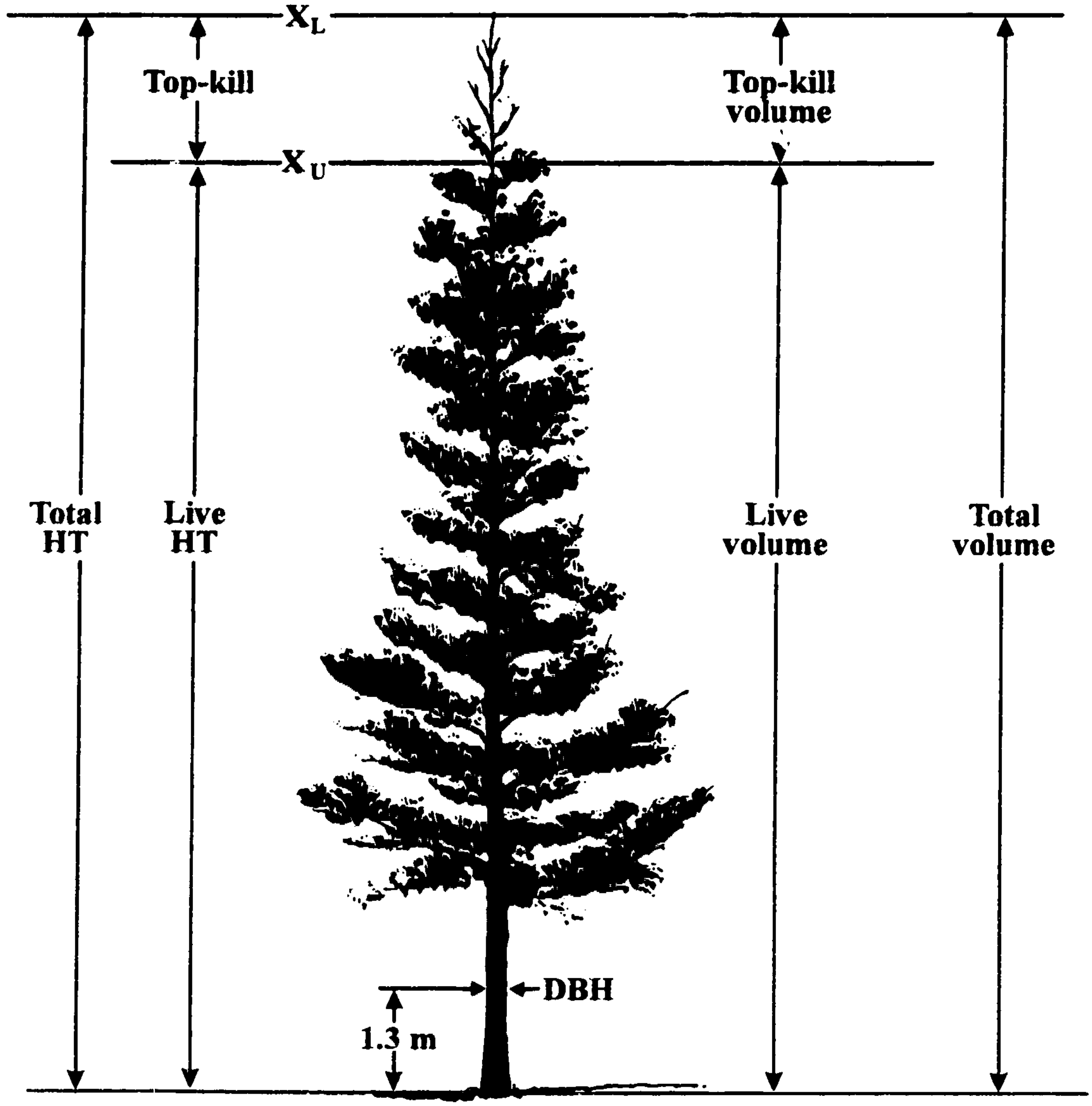

Figure 4-1. Schematic of a tree profile depicting top kill.

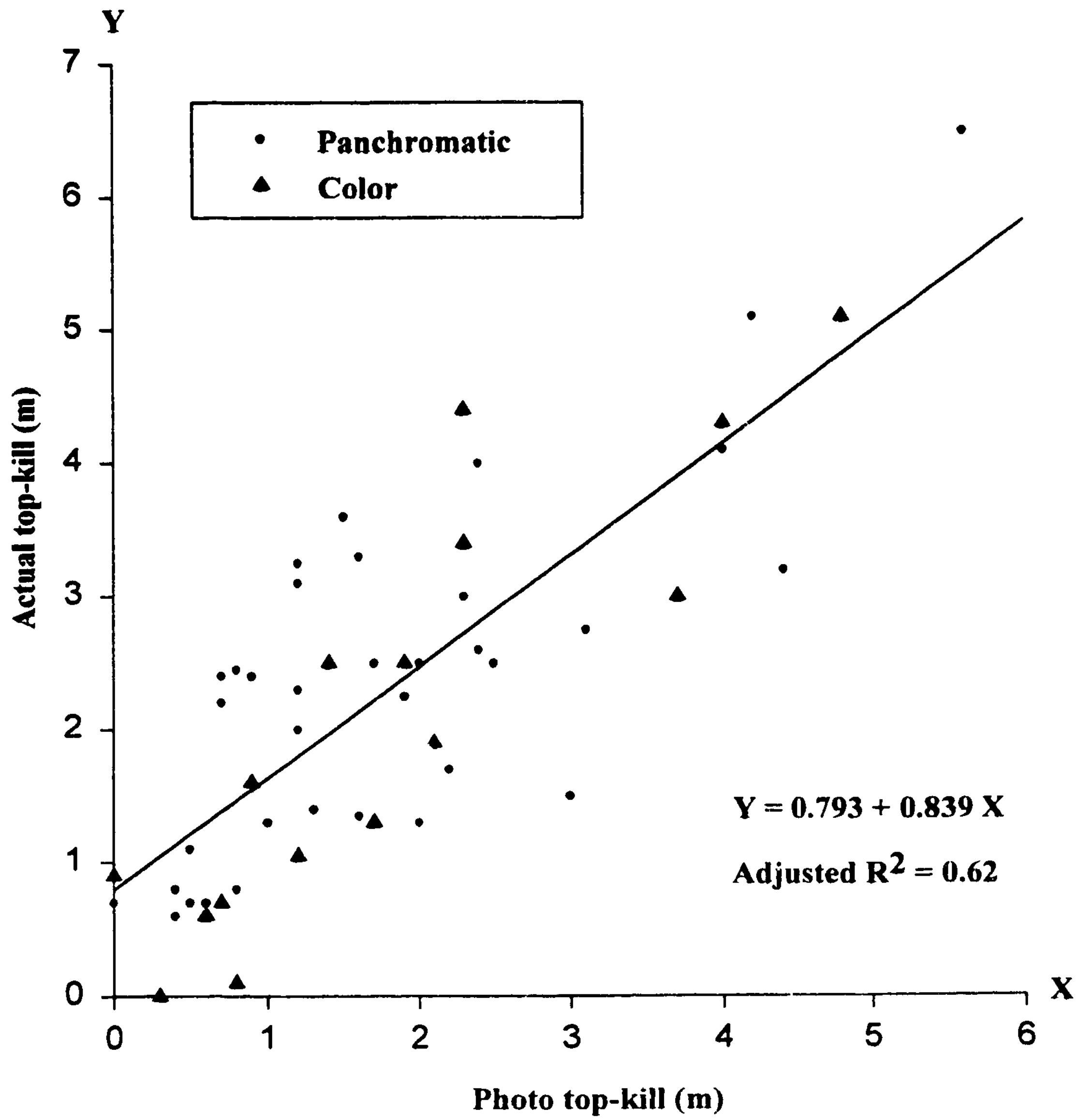

Figure 4-2. Scatterplot of felled and photo measured top kill.

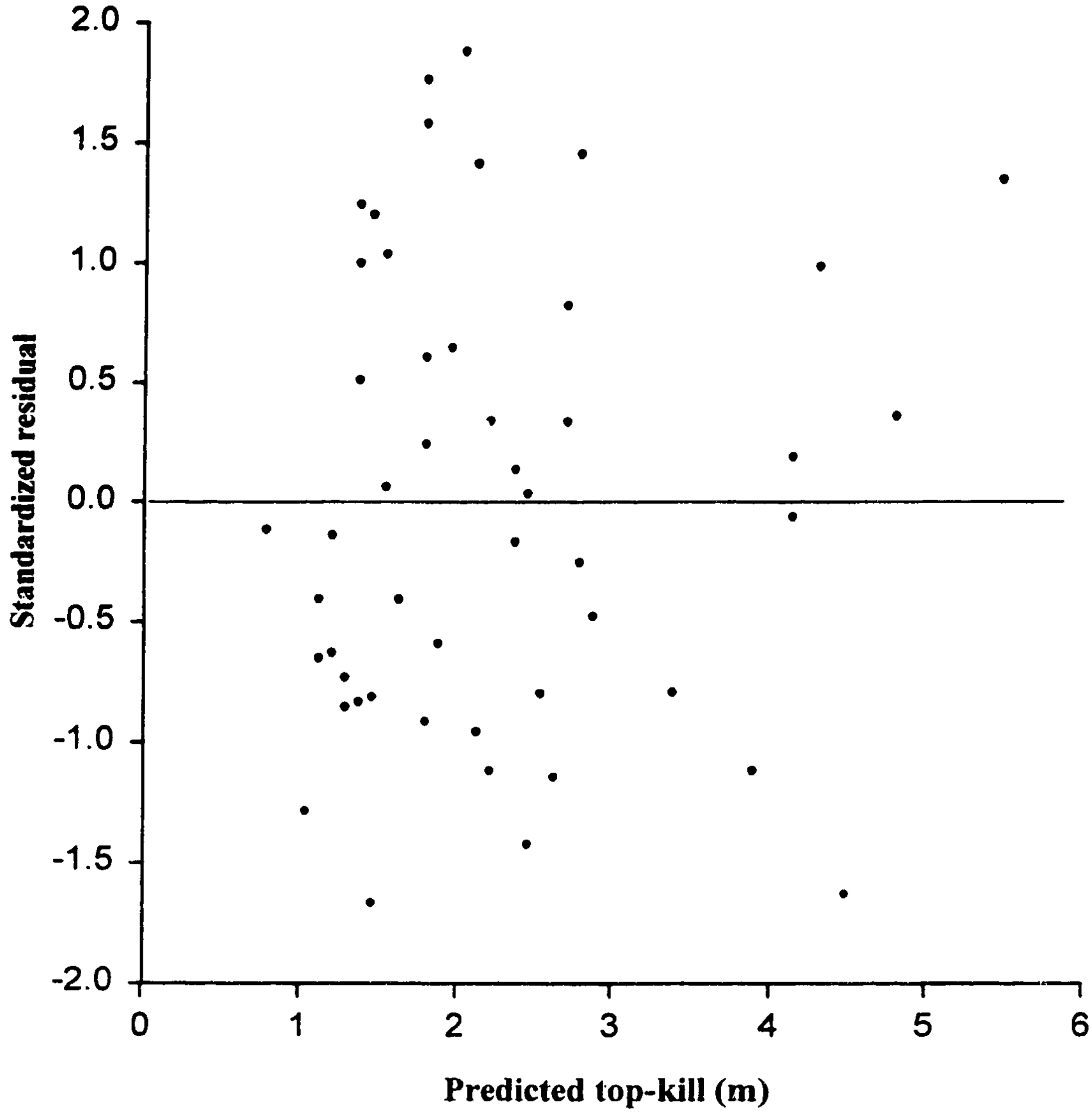

Figure 4-3a. Standardized residual plot for photo top-kill regression model.

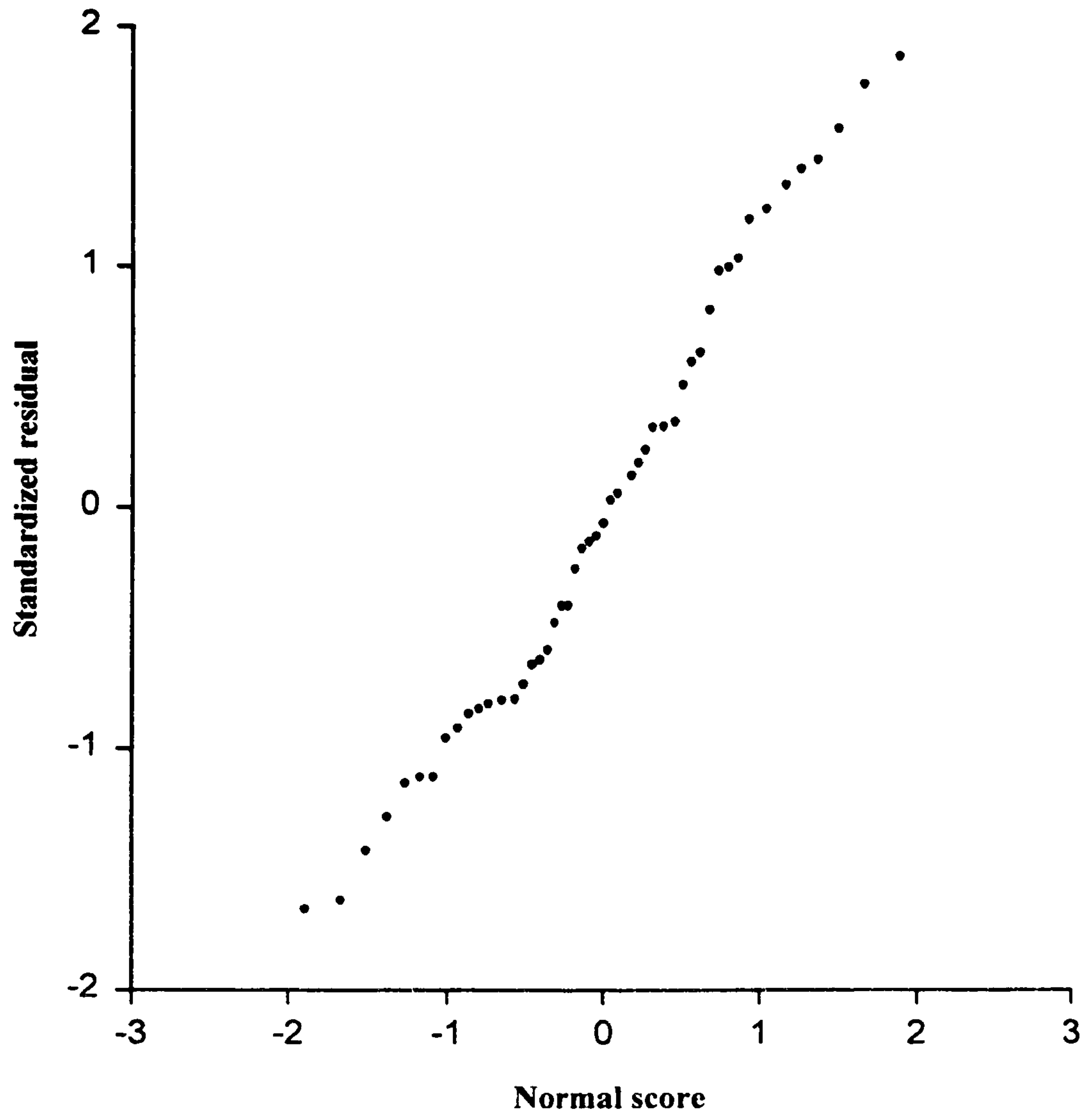

Figure 4-3b. Normal probability plot for photo top-kill regression model.

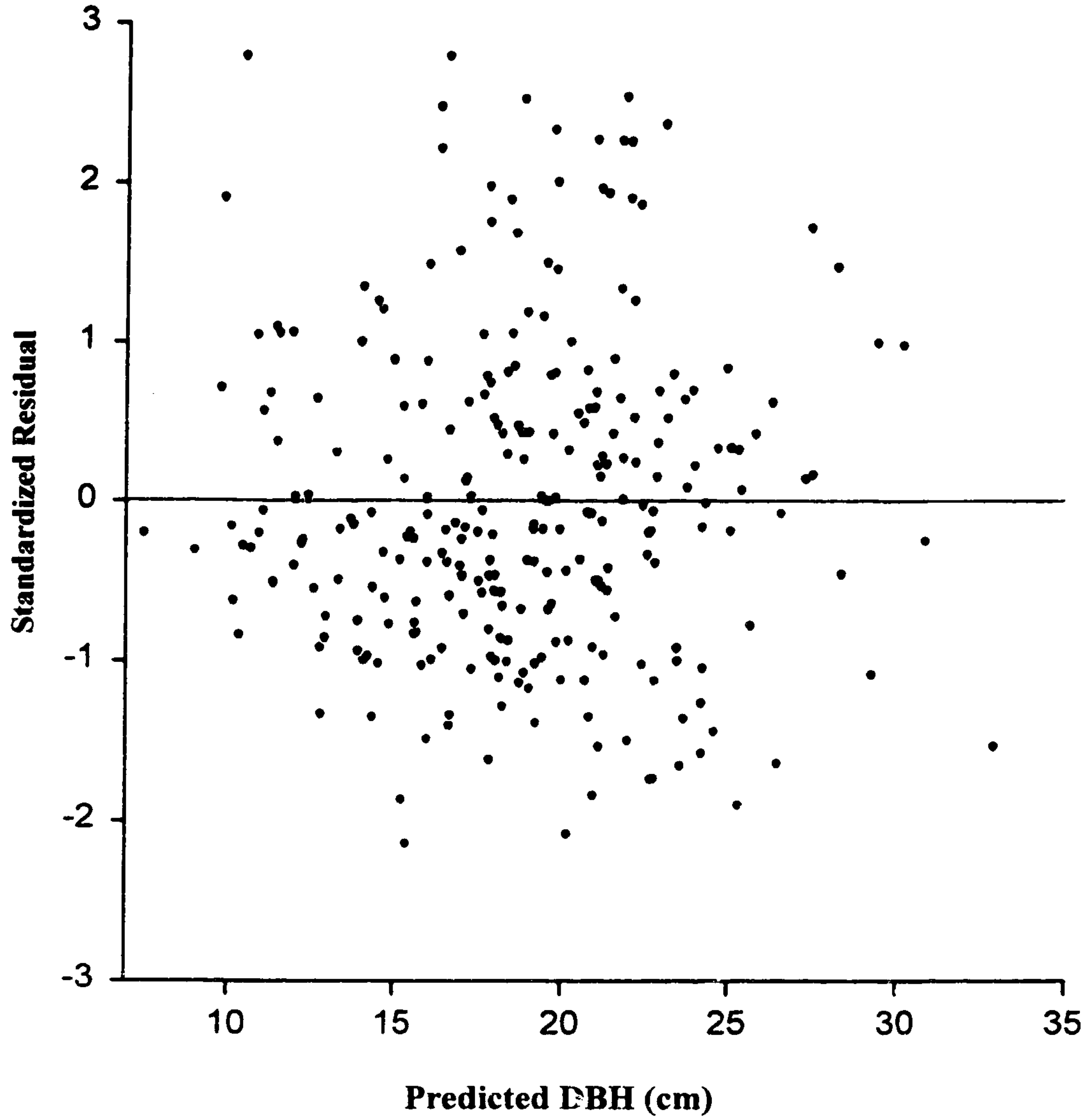

Figure 4-4a. Standardized residual plot for DBH regression model.

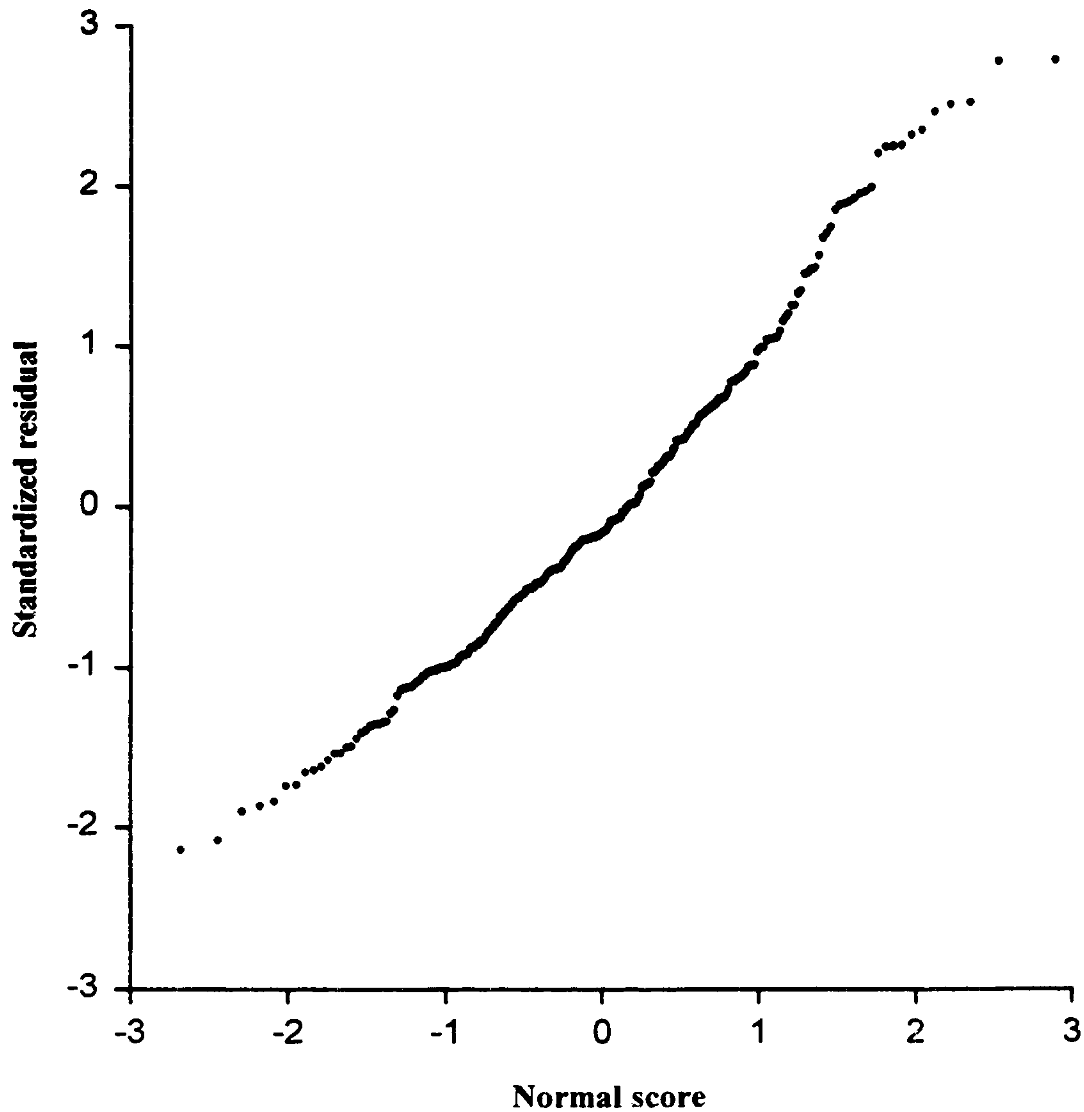

Figure 4-4b. Normal probability plot for DBH regression model.

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Chapter 5

Evaluation of LANDSAT Thematic Mapper Data for Mapping Top kill caused by Severe Jack Pine Budworm Defoliation

5.1 Introduction

In Canada, although remote sensing research has been conducted on detecting and mapping defoliation from forest insects such as the eastern spruce budworm [*Choristoneura fumiferana* (Clem.)] (Ahern et al. 1986; Leckie and Ostaff 1988; Leckie et al. 1989; Beaubien and Pilon 1990; Franklin and Raske 1994), forest tent caterpillar (*Malacosoma disstria* Hubner) (Hall et al. 1983; 1984), eastern hemlock looper [*Lambdina fiscellaria* (Guen.)] (Franklin 1989; Luther et al. 1991), and blackheaded budworm [*Acleris variana* (Fern.)] (Luther et al. 1991), there has been relatively little work directed towards the jack pine budworm (*Choristoneura pinus pinus* Freeman) (Dixon 1987 in Manitoba; Hopkins et al. 1988 in the Lake States, USA). Jack pine budworm is a major defoliator of jack pine (*Pinus banksiana* Lamb.) forests in Ontario, Manitoba, Saskatchewan, and the adjacent United States Great Lakes States (Moody 1989). Damage from severe defoliation on jack pine includes top kill (i.e., dead tree tops) (Prebble 1975), and tree mortality (Howse 1984). The jack pine budworm is considered among the major insect pests in Canada (MacLean 1990), and methods to detect and map its spatial distribution are needed for programs directed at monitoring and assessing its damage impact.

Jack pine budworm overwinters as a second-instar larva and emerges in late May soon after male cones open and new, young needles emerge (Clancy et al. 1980). The budworm larvae migrate to the tops and outer crown of trees due to their preference for male flower clusters and young foliage (Howse 1984). Defoliation spreads from the top of the tree downwards (Moody 1986). Only the basal portion of the needle is eaten while the rest becomes entangled in a mass of silk and larval excrement that changes to a distinctive reddish brown color as this material desiccates (Kulman et al. 1963; Martineau 1984). The red discoloration is a visible indicator of defoliation severity used during aerial surveys (Moody 1986), with stands being rated as severely, moderately, lightly, or not defoliated (Volney 1988).

The basis for using digital LANDSAT Thematic Mapper (TM) data to detect defoliation damage lies in observing changes to spectral reflectance of forest canopies between two points in time (Ahern and Leckie 1987). The red discoloration is likely the stage at which the greatest spectral change occurs relative to the normal pattern, and this explains the timing selected for most studies of defoliation damage (Leckie and Ostaff 1988; Ahern et al. 1991; Franklin and Raske 1994). The timing for the mapping of defoliation is therefore critical because peak coloration occurs during a short period from late June to early July (Howse 1984). Wind and rain removes the red needles resulting in exposed branches and top kill if severe defoliation was sustained (Plate 5-1). The short period, during which the red discoloration is visible on trees, results in a very narrow window for acquiring cloud-free satellite images, and has been a major limitation to the usefulness of satellite data for this application (Leckie 1986).

Defoliation imposes changes to the morphological and physiological characteristics of trees that are interrelated. Foliage loss and top kill reduces the photosynthetic capacity of the tree, and this will reduce growth, tree vigor, and may predispose the tree to attack by other destructive agents (Kulman et al. 1963; Howse 1984; Mallett and Volney 1990; Gross 1992; Moody and Amirault 1992). These combined morphological and physiological changes, can result in changes to spectral reflectance characteristics relative to the normal pattern (Murtha 1982). The question is whether or not these changes in reflectance characteristics are large enough to be detected with image data acquired from a satellite platform, such as the LANDSAT TM. Data from this satellite provide a wide range of spectral information that might be used as an indicator of damaged forests (Koch et al. 1986). If these spectral changes can be detected after the red needle coloration stage has passed, then there is a potentially larger window for acquisition of cloud-free satellite data. A larger time window also enhances the potential use of these data for routine damage assessment of jack pine budworm defoliation.

The study objective was to determine the extent to which multidate LANDSAT TM digital data could be used to classify and map the severity of top kill over jack pine stands. This objective was met by answering the following questions: 1) What are the spectral characteristics of top kill?; 2) Is severity of top kill spectrally separable?; and 3) Are spectral classes resulting from an unsupervised image classification related to severity of top kill?

5.2 Materials and methods

The study area encompasses the approximate 47 km^2 area of the Torch River

Provincial Forest in Saskatchewan. This area is in the Mixedwood section (B.18a) of the Boreal Forest Region of Canada, where jack pine predominates on sandy areas (Rowe 1972). It is located within the Universal Transverse Mercator (UTM) Zone 13 and is bounded by 550,000 mE and 5,920,000 mN on the southwest to 570,000 mE and 5,940,000 mN on the northeast, on a gently undulating plain at elevations ranging from 330 to 380 m above sea level. Soils are relatively homogeneous with much of the area consisting of Eluviated Eutric Brunisols and Orthic Regosols of the Pine Association (Anderson and Ellis 1976). These soils are poor to moderate in site quality due to their coarse texture and rapid drainage, and mainly support jack pine stands (Kabzems et al. 1986; Rudolph and Laidly 1990). Moderate to severe defoliation was reported for the study area between 1984 and 1987 (Moody and Cerezke 1986; Cerezke and Emond 1989), and various levels of top-kill damage were observed following defoliation.

5.2.1 LANDSAT data acquisition

LANDSAT-5 Thematic Mapper (TM) digital data were acquired for three dates corresponding to before, during and after the collapse of insect defoliation (July 20, 1984, August 11, 1986, August 30, 1987, respectively). The data were ordered with corrections for systematic errors in both along-line and along-track directions (Murphy and Fisher 1985), and were radiometrically corrected (i.e., CAL-2, linear) for normalization of the sensor (Ahern et al. 1987). Although all seven bands of the LANDSAT TM image data were acquired, the thermal infrared was not used in this study due to its low spatial resolution (Stenback and Congalton 1990) and lack of contrast in forested areas (Hopkins et al. 1988).

The July 20, 1984 image was assumed to represent the "before" outbreak period, and the August 11, 1986 image represented the "during" defoliation period. Similar to the difficulties in acquiring images encountered by Leckie (1986), cloud-free data during active larval feeding, from June to early July, were not available from 1985 and 1986. The August 30, 1987 image represented the "collapse" of defoliation period. With only these image data available for less than the optimum time, this study focused on a study of top kill for both the 1986 and 1987 images. All digital image processing was undertaken on a PCI EASI/PACE[4] image processing system. A more detailed outline of the methods is included in Appendix 1.

5.2.2 Atmospheric correction, geometric correction, image registration

Atmospheric effects in remote sensing images are primarily due to atmospheric attenuation of radiation from the ground surface, and to scattering of solar radiation (Moik 1980). Atmospheric correction becomes important when temporal data are to be compared since the atmosphere will be different on different image dates (Mather 1987). Previous studies also suggest that removal of atmospheric effects result in remote sensing data that are better related to ground cover characteristics, thus improving image classification accuracies and detection of spectral changes (Kaufman and Sendra 1988; Kawata et al. 1988; Fraser et al. 1992). The image data were corrected for the atmosphere using the reflectance method developed by Ahern and Sirois (1989).

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[4] The mention of trade names is for information only and does not imply endorsement.

A subset of each LANDSAT image encompassing the study area was geometrically corrected to achieve two-date image registration, and facilitate integration with vector data comprising the light, moderate and severe top kill from the SPANS Geographic Information System (GIS). The spectral differences between images attributable to top kill were assumed to be subtle, and there were concerns that image preprocessing could alter these differences. Thus, resampling was undertaken using a nearest neighbour pixel resampling algorithm (Shlien 1979) as radiometric values do not change when the pixel size is kept relatively constant (Derenyi and Saleh 1989; Duggin and Robinove 1990).

Twelve ground control points were identified on both the image and on 1:12,500 UTM-based forest cover maps, available from the Saskatchewan Forestry Branch. The UTM coordinates for the control points on the map were digitized in a Geographic Information System to minimize the likelihood of manual measurement errors. Two image databases were created, one for the 1984-1986 image data, and one for the 1984-1987 image data. Image-to image registration was not possible due to an artifact in the EASI/PACE system employed when correcting images smaller than the 1024 pixel by 1024 line display size. Separate geometric corrections were therefore undertaken on each image. To achieve accurate spatial registration of two images for digital change detection, rectification from image to map should be within ¼ to ½ a pixel (Jensen 1986), and this was achieved for this study (Appendix 2). The final image database size was 800 pixels by 800 lines with a 25 m resampled pixel size that corresponded to the 20 km by 20 km map extent on the SPANS GIS database.

5.2.3 Mapping top kill

Color infrared aerial photographs at 1:5000 were acquired during the summer of 1988, one year following the reported collapse of a jack pine budworm infestation (Cerezke and Emond 1989). Since there has been no standard infestation severity classification system reported in the literature (Chapter 2 Table 2-1), a classification system specifically for mapping top kill was devised (Table 5-1). The classification system was based on discrete levels that appeared separable, given that field survey data and 1:900 scale 70-mm, large-scale aerial photographs (Plate 5-1) were available from a previous study (Hall et al., 1993). Both the occurrence and apparent length of top kill on individual trees were considered during interpretation, based on rules assigned to the classification system (Table 5-1). The placement of polygon lines and assignment of attribute labels (Table 5-1) were based on the collective and cooperative interpretation between two photo interpreters. Top kill in jack pine stands ranged from none along the valley of the Torch River to moderate and severe within the provincial forest (Figure 5-1). Since spectral differences between these classes may be too small to discriminate with LANDSAT TM data, several sets of aggregated damage severity classes of top kill were produced to determine if spectral separabilities would change with a smaller number of more broadly defined classes (Table 5-2).

5.2.4 Image analysis procedures

The image analysis procedures were conducted on both the 1984-86 and 1984-87 data sets. In addition to the six reflective TM image bands from each date, the normalized difference vegetation index (NDVI) was also computed. The NDVI is among those vegetation indices frequently reported for forest damage applications (Nelson 1983; Chamignon and Manière 1990; Clerke and Dull 1990; Volgelmann 1990; Ardö 1992). It is computed as the difference between near infrared (NIR) and red (R) spectral bands normalized by their summation (Townshend and Justice 1989), and calculated by (NIR - R)/(NIR + R). The NDVI calculation results in single values that indicate the relative amount of living, green vegetation over a ground resolution cell that is represented on an image by a pixel. Differences in NDVI values between two dates have been used to show change in the vegetative canopy (Singh 1989; Abednego and Collet 1992; Mouat et al. 1993).

Analyses employing the full set of image bands from each date may be inefficient due to high correlation among adjacent bands. Some studies have also concluded that one image band from each of the reflective regions (ie., red, near infrared, mid-infrared), represent most of the spectral information for vegetation inherent in TM data (Horler and Ahern 1986; Beaubien and Pilon 1990; Moore and Bauer 1990). An image band subset was therefore selected from each date in which a visible and two reflected infrared bands were used with the NDVI band. In total, four LANDSAT TM band data sets were assembled for analysis (Table 5-3).

The differences between respective bands from 1984 to 1986, and from 1984 to 1987 were computed. Of the many image channel transformations employed in change detection studies (Nelson 1983), the differencing transformation is the most widely used because of its simplicity (Singh 1989). Classification accuracies have also been reported equal to those obtained from more sophisticated approaches (Nelson 1983). Band difference images have been used to monitor gypsy moth (*Lymantria dispar* L.) defoliation (Williams and Stauffer 1978), and forest decline associated with mortality (Vogelmann 1988). If top kill could be detected with image band differences, then more sophisticated approaches such as principle component analyses (Eklundh and Singh 1993; Gong 1993) and forest defoliation models (Brockhaus et al. 1993) could be explored to determine if alternative methods would be more appropriate for damage assessment.

To determine the spectral characteristics of top kill, the boundary and polygons of top kill as mapped for the Torch River Provincial Forest was imported from the SPANS GIS. General trends were first determined on changes in average LANDSAT TM band values between 1984, 1986 and 1987. These values were compared to average LANDSAT TM band values for nil, light, moderate and severe top kill. Changes in band values attributable to top kill could then be observed for the 1986 and 1987 images.

To determine if mapped top-kill classes were spectrally separable, Bhattacharyya Distance (B-distance) was used as a measure of statistical separability between pairs of probability distributions (Mather 1987; Richards 1993). A comparison of calculated B-distance values is one means of discriminating between a set of classes based on a given set of features (spectral bands) (Leckie and Ostaff 1988; Joria et al. 1991). B-distance is asymptotically 2.0 with the value 0 indicating complete overlap between signatures of two classes, and 2.0 indicating complete separation (PCI Inc. 1993; Richards 1993). Average B-distance values were compared for the six top-kill class sets (Table 5-2) with four Band sets (Table 5-3). If separabilities were high, statistics of the top-kill classes could be used as training areas for supervised maximum likelihood classifications in similar areas. In this study, the B-distance was used only to determine which of the six top-kill classification systems and four Band sets were most separable. The Band sets resulting in the highest separabilities were used in a subsequent image classification.

An unsupervised classification approach was also completed to determine if spectral classes were related to severity of top kill. This was followed by the creation of contingency tables to evaluate associations between the spectral classes and top-kill class set 1 (nil, light, moderate, severe, unclassified) (Table 5-1). A preliminary evaluation was undertaken of the different methods of unsupervised classification available on the PCI EASI/PACE system. These included the K-Means (Tou and Gonzalez 1974), ISODATA (Tou and Gonzalez 1974, Richards 1993), and non-parametric clustering (Narendra and Goldberg 1977) routines. The ISODATA algorithm was selected because the spectral classes produced most resembled land cover types in the study area. This algorithm generates a user specified number of clusters in one pass through the image data, and then iteratively goes through the image to modify cluster characteristics until results converge with stable cluster characteristics (McGwire 1992). A total of 4 unsupervised classifications were conducted for the 1984-86 and 1984-87 data sets (ie., Band data set 1 or 3 [Table 5-3] and its associated subset). Input parameters necessary to drive the ISODATA classification included: a minimum (3) and maximum (10) number of clusters to be generated; starting clusters located diagonally along the n-dimensional histogram; a maximum number of iterations (99) to allow convergence; a minimum number of pixels in a cluster (5); and a cluster standard deviation (3) (PCI Inc. 1993).

Unsupervised classification is generally considered a two-step process consisting of spectral class generation followed by assignment of information labels (Jensen 1986, Richards 1993). A one-to-one relationship between spectral classes and information classes, however, doesn't usually exist (Hoffer 1986). Instead, several spectral classes may relate to a single land cover class, or a spectral class may relate to several land cover classes (Hoffer 1986). Spectral classes that corresponded to a top-kill class with 10% or more of the pixels were merged and assessed using measures based on average accuracy (ie., sum of major diagonal divided by total of table in percent accuracies), and Kappa Coefficient of Agreement (Hudson and Ramm 1987; Congalton 1991). The 10% threshold appeared to be a reasonable breakpoint when contingency tables were created between the spectral classes and top-kill map.

5.3 Results and discussion

5.3.1 Spectral characteristics of top kill

The differences in spectral response patterns of top kill on LANDSAT TM data before the outbreak (1984), were expected to be only slightly different from those during (1986) and after (1987). Although an affected tree has less foliage and is physiologically weak, its appearance is still predominately green (Plate 5-1; Chapter 2 Plate 2-3). For each top-kill severity class, their respective average band values and standard deviations were considered reasonable descriptors of their frequency distribution since they were relatively unimodal. Comparisons of average TM band values over the study area for the three years, exhibit a small reduction in values across all bands (Table 5-4). NDVI values, however, increase in each year from 1984 (Table 5-4). This increase may be attributable to effects of reflectance from ground vegetation since much of the area consists of jack pine in relatively open stands. Vegetation indices such as NDVI are based on the principle that as the presence and amount of healthy green vegetation increases, the reflectance of near infrared radiation increases, and the absorption of red radiation increases (Rutstein 1992). The interpretation of NDVI, however, may only apply to high canopy closure conditions. Under open stands, the effect of ground vegetation and soil can mask the effect of tree foliage (Guyot et al. 1989). In the study area, ground vegetation consisted primarily of bearberry (*Arctostaphylos uva-ursi* (L.) Spreng.), reindeer lichen (*Cladonia* spp.), and spreading dogbane (*Apocynum androsaemifolium* L.). Bearberry was most extensive and along with dogbane, is red in color and due to high reflection in the near infrared on 1.5000 color infrared aerial photographs. Reindeer lichen is yellowish white in the field, and appears greyish white on color infrared aerial photos. This may explain the result of higher NDVI (Table 5-4) values for open canopies, and is supported by results of previous studies (Spanner et al. 1990; Rutstein 1992). The trend of increasing NDVI by damage class from 1984 to 1987 (Figure 5-2 and Appendix 3) was consistent with those reported for the study area (Table 5-4).

Changes in spectral characteristics were also evaluated for each severity class. Greater changes were observed over the two-year period from 1984 to 1986, than from 1986 to 1987 (Figure 5-2 and Appendix 3). LANDSAT TM band values following budworm attack and top kill, are decreasing and consistent with the trend reported for the entire study area (Table 5-4). The largest difference occurred in TM Band 5 from 1986 to 1987 for the light, moderate and severe top-kill severity class (Figure 5-2). TM band 5 is in the mid-infrared region that is sensitive in part, to leaf moisture content, and as leaf moisture content decreases, reflectance will increase (Hoffer 1978). This observation was not explained by the weather during the 1984 to 1986 outbreak since, relative to 30-year averages (Chapter 3 Figures 3-2, 3-3), 1986 was below average for both temperature and moisture. The trend may instead be attributable to reduced foliage and loss of needle moisture content because of reduced photosynthetic capacity and physiologic activity caused by the stress of defoliation (Joria et al. 1991). Other possible explanations for the small decreasing trends include the shadow effect from using August images in 1986 and 1987 relative to the July 1984 image, and the residual errors associated with the atmospheric correction process.

5.3.2 Spectral separability of top-kill classes

Spectral separabilities using B-Distance were expected to be low because spectral reflectance differences among classes of top kill for all TM bands from 1984 to 1987 were small. Discrimination among top-kill categories was higher with all TM bands than with band differences (Table 5-5). B-distance values using band subsets (Band set 2 and 4, Table 5-3) were smaller but similar in pattern across top-kill classification systems 1 to 6. Caution is warranted in interpreting this observation since, as the number of image bands increases, separability increases (Kim and Landgrebe 1990). Although Band set 1 was selected for image classification, Band set 2 was also used to test the effect of using the smaller number of selected bands on classification accuracy. Separabilities using band differences were small and likely attributed to the small spectral reflectance differences observed in each TM band over the 3 dates (Figure 5-2).

B-distance values were smaller for the 1984-87 data set than for the 1984-86 data set (Table 5-5). This was unexpected since jack pine typically does not recover from major stress, but will instead continue to degrade (MacAloney 1944). Spectral differences were therefore expected to be larger for the 1984-87 data set than for the 1984-86 data set. A possible explanation is that the effect of ground vegetation is increasing, and this is masking more of the effects of the overstory. This is supported by the trend to increasing rather than decreasing NDVI values (Table 5-4, Figure 5-2).

In comparing B-distances for each of the 6 top-kill severity classification systems (Table 5-2) over the 4 Band sets, top-kill class set 6 had the highest values (Table 5-5). The highest average separability obtained was 1.45 with Band set 1 (14 image bands) and top-kill class set 6 (nil, light-severe top kill, unclassified). This implies that discrimination is poor among top-kill categories. The separabilities obtained are considered very poor to poor (PCI Inc. 1993), and insufficient to justify use of these data in a supervised maximum likelihood classification.

5.3.3 Spectral classes and top-kill severity

Unsupervised classification methods usually result in spectral classes that must be assigned information labels to describe their content (Richards 1993). It has been difficult to assign these labels, and to determine the extent to which spectral classes correlate to land cover classes of interest as portrayed on a map (Robinove 1981). An advantage of the remote sensing - GIS integration approach in this study is the use of a contingency table to link an image classification result to the map of top kill. The ISODATA unsupervised classification is an iterative process that based on the input parameters specified, resulted in nine spectral classes (Table 5-6). Band sets 1 (14 channel) and 2 (8 channel) for the 1984-86, and 1984-87 data sets (Table 5-3) each had 3 spectral classes that contained approximately ⅓ of their pixels in each of the light, moderate, and severe top-kill categories (Table 5-6 a,b,c,d). For example, spectral class 5 of Table 5-6a consisted of approximately ⅓ of the light top-kill class pixels, and the same proportions of pixels in the moderate and severe top-kill classes. This pattern of 3 spectral classes is consistent for the 1984-86 and 1984-87 data sets.

Absence of top kill corresponded to spectral classes located mainly in the Torch River valley, an area of trembling aspen (*Populus tremuloides* Michx.), jack pine, black spruce (*Picea mariana* (Mill.) B.S.P.) and white spruce (*Picea glauca* (Moench) Voss) as defined by the primary species map (Figure 3-6). Areas unrelated to top kill that was labelled "Unclassified" was more variable because it included water, forest regeneration in a previously burned area, and exposed areas with ground vegetation consisting of bearberry, reindeer lichen and dogbane as determined from the color infrared aerial photographs and ground information of the study area.

From the contingency table of the merged top-kill classes verses merged spectral classes (Table 5-7), average classification accuracies ranged from 70.5 percent to 73.2 percent, and Kappa classification accuracies ranged from 50.9 percent to 58.7 percent (Table 5-8). The Kappa accuracies were lower due to the omissions and commissions that occurred, particularly in the "nil" and "unclassified" classes and their variable composition.

Presenting the contingency tables in terms of pixel numbers similar to most papers (Karteris 1990; Joria et al. 1991; Fiorella and Ripple 1993) can result in a biased representation when there are unequal cell sizes. The large number of pixels in the light-severe top-kill class relative to nil and unclassified classes (Table 5-6) results in a weighting that can give an inflated estimate of accuracy (Schowengerdt 1983). Its presentation in terms of percentages relative to the reference map (top-kill map set 1: nil, light, moderate, severe top kill, unclassified) provides a more representative measure of accuracy for the purposes of this project. This is often labelled the "producer's accuracy" because the producer of the classification is interested in how well a certain area can be classified (Congalton 1991). The accuracy figures in Table 5-8 are only moderately high, and are based on just three categories: nil, light-severe top kill, and unclassified. Classification accuracies between the 14 channel (Band set 1) and 8 channel (Band set 2) data sets were similar (Table 5-8). Interestingly, classification accuracy with the 1984-87 image data is slightly greater for the 8 channel data set than with the 14 channel data set.

5.4 Conclusions

The reflectance spectra of stands are a combination of reflectance spectra of trees, soil and ground vegetation (Guyot et al. 1989). Stand reflectance depends on the relative amounts of these components within a ground resolution cell. A factor contributing to difficulties in classification of medium and high damage sites is the influence of understory and ground vegetation (Guyot et al. 1989). This was likely the most significant factor that influenced the results obtained with this study. Bearberry and reindeer lichen in open stands are highly reflective in the near infrared and visible portions of the spectrum, respectively, and this may have masked the spectral response from trees with top kill. Although changes in spectral response patterns from 1984 to 1987 were evident and may be attributable to defoliation, they were small compared with changes typically observed by red trees as a symptom of strain (Murtha 1993) by a forest pest (Leckie and Ostaff 1988; Franklin 1989; Ahern et al. 1991; Franklin and Raske 1994). This may also explain the trend of increasing NDVI values from 1984 to 1987.

Beyond evaluating the spectral separabilities among nil, light, moderate and severe top kill, 5 additional classification systems were created that comprised a smaller number of more broadly defined classes. Based on comparisons with 4 spectral band data sets, spectral separabilities among classes of top kill were low. The separabilities were highest when light, moderate, and severe levels of top kill were grouped. A spectral basis for classification of top kill could not be identified with the band combinations and aggregations of mapped top-kill severity classes evaluated.

Spectral classes resulting from an ISODATA unsupervised classification were associated with nil, light, moderate and severe top-kill classes in a contingency table. The integration of remote sensing and GIS technologies when appropriate, offers a useful approach towards characterizing and labelling spectral classes by allowing the use of contingency tables to associate initial spectral classes with mapped classes. Although the unsupervised classifications did result in spectral classes that were associated with top kill, it did so with only one class because of poor discrimination among severity classes. These results agree with those from the spectral separability analysis. An average classification accuracy of 70% was achieved when spectral and top-kill severity classes were aggregated to a 3-class system (nil, light-to-severe top kill, unclassified). This result confirms that severity of top kill was not separable with the LANDSAT TM data available for this study. The differences in classification performance between the 14 and 8 band data sets for the 1984-86 and 1984-87 images were small. This result confirms previous studies (Horler and Ahern 1986; Beaubien and Pilon 1990) that suggest most of the spectral information for vegetation, can be obtained from an image band in the red, near infrared, and mid-infrared regions. Thus, these results define the extent by which multidate LANDSAT TM data can be used to classify and map patterns of top kill caused by budworm defoliation.

Although accuracy results were relatively low given the LANDSAT TM spatial resolution and the timing of image data available, a consideration is whether or not there is a spectral basis for classes to be mapped. A fundamental assumption in image analysis is that the radiance properties of an image represent properties of ground attributes, and that spectral classes bear some relation to specific ground cover classes (Duggin and Robinove 1990). Although the map of top kill produced with 1:5000 scale aerial photographs may have adequately represented the spatial distribution of patterns of top kill at that scale, it may have been inappropriate for comparison with satellite data. This is because conceptually, the system to interpret photos and map top kill may not be equivalent to their spectral responses recorded on the image.

Because top kill occurs predominately in stands of jack pine, and the spectral changes attributed to top kill were small, the classified image mainly mapped the occurrence of this species. This result suggests change detection is better suited when spectral changes are large since, as spectral changes become more subtle, the ability to detect changes will become more difficult. Image data of greater spatial resolution, or better timed to coincide with maximum spectral changes when the foliage is red, is therefore, more appropriate for mapping damage caused by severe defoliation.

Table 5-1. Top-kill map classification system used with 1:5000 color infrared aerial photographs.

Severity rating	Class limits	Description
Nil	0 %	Interpreted forest stand, no visible top-kill
Light	1 - 25 %	Up to 25% of a forest stand by number of trees or scattered trees with small amounts of visible top-kill
Moderate	26 - 50 %	From 26 to 50% of a forest stand by number of trees, or scattered trees comprising at least ¼ of the stand with visible top-kill at least 60 cm in length
Severe	51 - 100 %	At least 50% of a forest stand by number of trees and exhibiting significant amounts of top-kill that likely exceeds 1 m in length
Unclassified	not applicable	Regenerating areas or areas not supporting forest stands

Table 5-2. Sets of top-kill map classes to compare with the 1984-86 and 1984-87 LANDSAT 2-date image band data sets.

Top-kill class set	Description of top-kill classes		
1	1. nil	3. moderate	5. unclassified
	2. light	4. severe	
2	1. nil	3. severe	
	2. light-moderate	4. unclassified	
3	1. nil-light	2. moderate-severe	3. unclassified
4	1. nil-moderate	2. severe	
5	1. nil	3. moderate-severe	
	2. light	4. unclassified	
6	1. nil	2. light-severe	3. unclassified

Table 5-3. LANDSAT TM Band sets used to compute spectral separabilities.

	Data set	
	1984-86	1984-87
Band set 1	LANDSAT TM 1, 2, 3, 4, 5, 7, NDVI for 1984 and 1986 images	LANDSAT TM 1, 2, 3, 4, 5, 7, NDVI for 1984 and 1987 images
Band set 2	LANDSAT TM 3, 4, 5, NDVI for 1984 and 1986 images	LANDSAT TM 3, 4, 5, NDVI for 1984 and 1987 images
Band set 3	Band differences: 1984 - 1986 for image bands defined in Band set 1	Band differences: 1984 - 1987 for image bands defined in Band set 1
Band set 4	Band differences: 1984 - 1986 for image bands defined in Band set 2	Band differences: 1984 - 1987 for image bands defined in Band set 2

Table 5-4. Average LANDSAT TM digital numbers over the Torch River Provincial Forest for 1984, 1986, and 1987.

	LANDSAT TM digital numbers					
	1984		1986		1987	
LANDSAT TM band	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
1 450 - 520 ηm	24.4	8.7	24.3	8.8	22.2	7.8
2 520 - 600 ηm	40.8	12.6	36.4	10.5	34.9	8.7
3 630 - 690 ηm	48.6	21.0	38.4	13.9	34.7	13.0
4 760 - 900 ηm	84.0	17.9	79.7	16.9	78.7	14.0
5 1550 - 1750 ηm	78.1	20.6	77.6	19.5	71.0	20.0
7 2080 - 2350 ηm	47.2	20.0	43.9	17.1	40.4	15.8
NDVI	168.9	27.7	178.1	23.4	181.8	21.0

Table 5-5. Comparison of average spectral separabilities (B-distance) by top-kill classification systems.

		B-distance	
		1984-86	1984-87
Band set 1[a]:			
Top-kill class set[b]:	1	1.20	0.85
	2	1.36	0.96
	3	1.19	0.55
	4	1.34	0.68
	5	1.27	0.88
	6	1.45	0.96
Band set 2:			
Top-kill class set:	1	1.06	0.74
	2	1.21	0.83
	3	0.99	0.44
	4	1.18	0.55
	5	1.09	0.77
	6	1.23	0.82
Band set 3:			
Top-kill class set:	1	0.64	0.39
	2	0.74	0.45
	3	0.64	0.18
	4	0.73	0.27
	5	0.68	0.39
	6	0.77	0.43
Band set 4:			
Top-kill class set:	1	0.57	0.35
	2	0.65	0.40
	3	0.56	0.16
	4	0.64	0.24
	5	0.60	0.40
	6	0.67	0.38

[a] LANDSAT TM band sets defined in Table 5-6.
[b] Top-kill class sets defined in Table 5-2.

Table 5-6. Contingency tables with spectral classes from ISODATA classifications to determine associations with nil, light, moderate, and severe top kill. (Note: Table values in bold correspond to merged spectral classes.)

a) 1984-86 Band set 1, 14 channel classification

		Percent of pixels classified into top-kill class									
Top-kill class	# pixels	1	2	3	4	5	6	7	8	9	Classes to merge
1 Nil	4870	1.0	13.0	**35.9**	**41.7**	2.0	0.5	5.5	0.3	0.2	3, 4
2 Light	28896	0	**14.5**	7.0	2.1	**38.7**	**33.5**	3.8	0.4	0	2, 5, 6
3 Moderate	8761	0	**33.1**	7.5	1.0	**29.9**	**22.7**	5.3	0.5	0	2, 5, 6
4 Severe	12534	0	**23.8**	5.4	0.3	**34.1**	**32.6**	3.7	0.2	0	2, 5, 6
5 Unclassified	15413	**3.5**	9.9	8.6	14.6	6.7	5.4	**25.8**	**20.2**	**5.2**	1, 7, 8, 9

b) 1984-86 Band set 2, 8 channel classification

		Percent of pixels classified into top-kill class									
Top-kill class	# pixels	1	2	3	4	5	6	7	8	9	Classes to merge
1 Nil	4870	**22.8**	**28.5**	7.6	**32.1**	2.1	0.6	5.0	1.0	0.2	1, 2, 4
2 Light	28896	7.4	0.6	**15.6**	3.8	**35.8**	**32.3**	2.8	1.6	0.1	3, 5, 6
3 Moderate	8761	10.7	0.2	**35.7**	2.8	**22.9**	**21.0**	4.9	1.7	0.1	3, 5, 6
4 Severe	12534	8.5	0.1	**28.8**	1.4	**25.7**	**30.8**	3.7	1.0	0	3, 5, 6
5 Unclassified	15413	7.4	6.2	9.8	12.1	7.1	7.6	**18.4**	**21.3**	**10.2**	7, 8, 9

Table 5-6 continued.

c) 1984-87 Band set 1, 14 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class									
		1	2	3	4	5	6	7	8	9	Classes to merge
1 Nil	4870	25.5	**61.9**	2.5	5.4	0.5	3.4	0.4	0.3	0	2
2 Light	28896	**16.7**	4.6	**41.1**	3.5	**31.1**	2.8	0.1	0.1	0	1, 3, 5
3 Moderate	8761	**35.2**	3.6	**28.7**	5.8	**22.7**	3.7	0.2	0	0	1, 3, 5
4 Severe	12534	**25.7**	1.6	**31.6**	6.3	**32.3**	2.4	0.1	0	0	1, 3, 5
5 Unclassified	15413	12.2	13.2	7.7	**16.7**	5.9	**23.5**	**15.0**	**4.1**	**1.7**	4, 6, 7, 8, 9

d) 1984-87 Band set 2, 8 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class									
		1	2	3	4	5	6	7	8	9	Classes to merge
1 Nil	4870	25.5	**62.4**	0.6	2.3	5.6	0.5	2.3	0.6	0.1	2
2 Light	28896	**15.7**	4.7	0	**38.2**	3.5	**35.4**	2.3	0.2	0	1, 4, 6
3 Moderate	8761	**33.4**	3.6	0	**30.7**	6.0	**23.1**	3.0	0.1	0	1, 4, 6
4 Severe	12534	**24.6**	1.5	0	**32.7**	5.9	**33.1**	2.1	0.1	0	1, 4, 6
5 Unclassified	15413	11.6	14.7	**3.7**	5.4	**18.2**	6.0	**23.7**	**14.0**	**2.7**	3, 5, 7, 8, 9

Table 5-7. Contingency tables with merged top-kill classes.

a) 1984-86 Band set 1, 14 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class		
		1	2	3
1 Nil	4870	77.5	15.4	7.1
2 Light-Severe top-kill	50191	8.1	87.4	4.4
3 Unclassified	15413	23.2	22.1	54.7

b) 1984-86 Band set 2, 8 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class		
		1	2	3
1 Nil	4870	83.4	10.3	6.3
2 Light-Severe top-kill	50191	11.7	83.3	5.0
3 Unclassified	15413	25.7	24.4	49.9

c) 1984-87 Band set 1, 14 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class		
		1	2	3
1 Nil	4870	61.9	28.5	9.6
2 Light-Severe top-kill	50191	3.7	88.7	7.6
3 Unclassified	15413	13.2	25.8	60.9

d) 1984-87 Band set 2, 8 channel classification

Top-kill class	# pixels	Percent of pixels classified into top-kill class		
		1	2	3
1 Nil	4870	62.4	28.3	9.2
2 Light-Severe top-kill	50191	3.7	89.2	7.1
3 Unclassified	15413	14.7	23.0	62.3

Table 5-8. Classification accuracies in percent for merged classes in 1984-86 and 1984-87.

LANDSAT dataset[a]	Year of dataset	Average accuracy	Kappa
Band set 1: 14 channels	1984-86	73.2	56.5
Band set 2: 8 channels	1984-86	72.2	50.9
Band set 1: 14 channels	1984-87	70.5	56.9
Band set 2: 8 channels	1984-87	71.3	58.7

[a] Refer to Table 5-6 for definition of datasets.

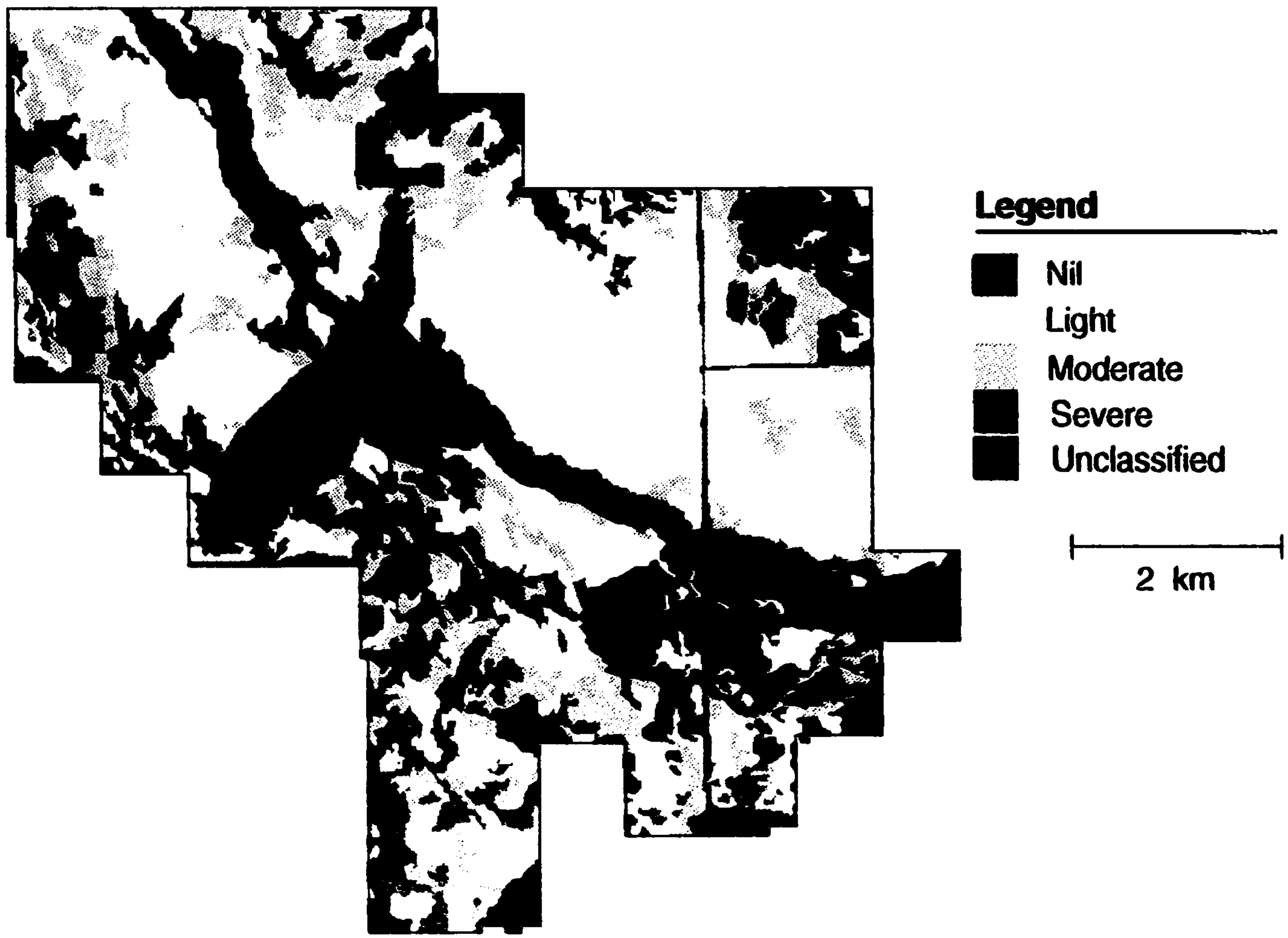


Figure 5-1. Top-kill map of the Torch River Provincial Forest from interpretation of 1:5000 color infrared aerial photographs.

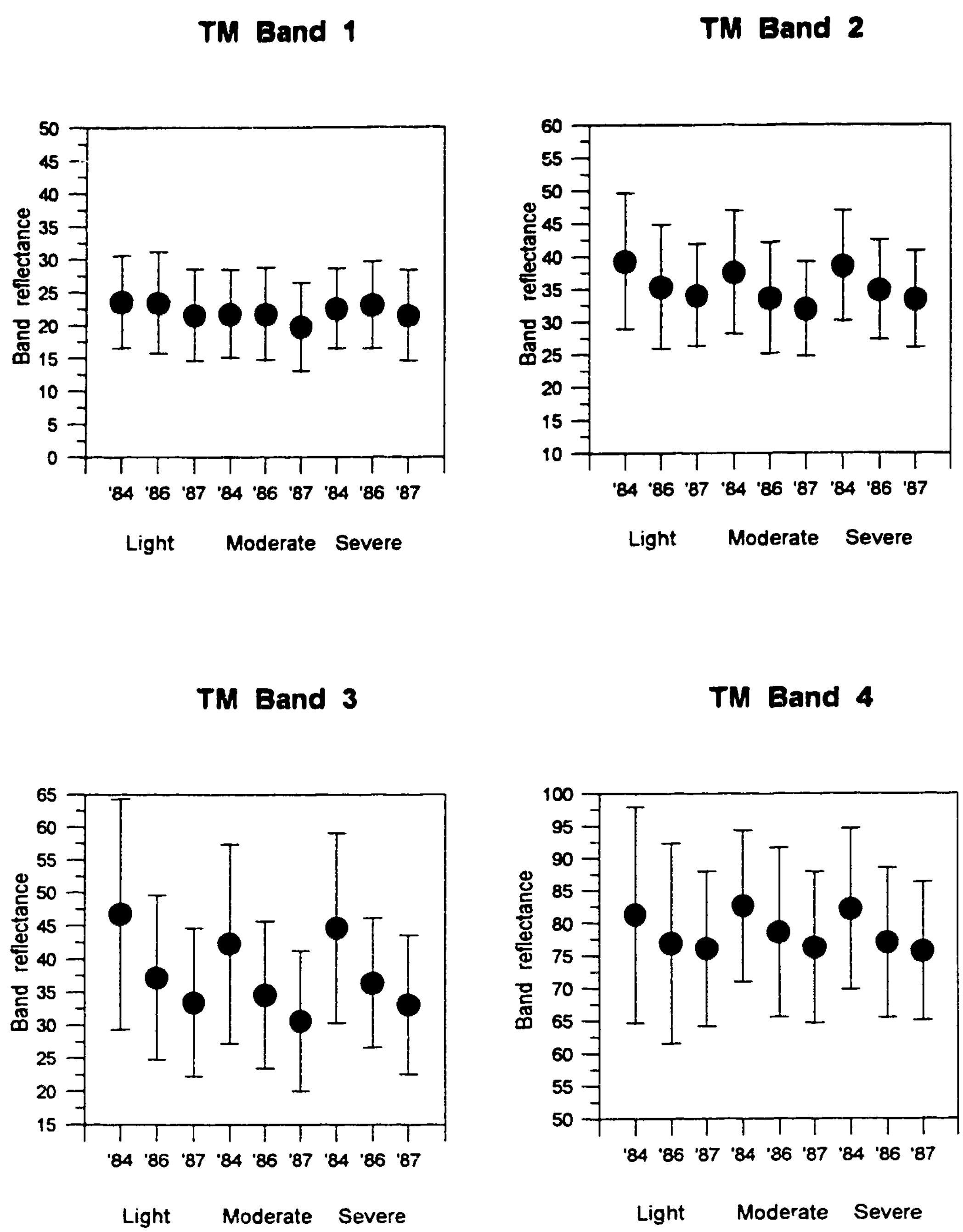
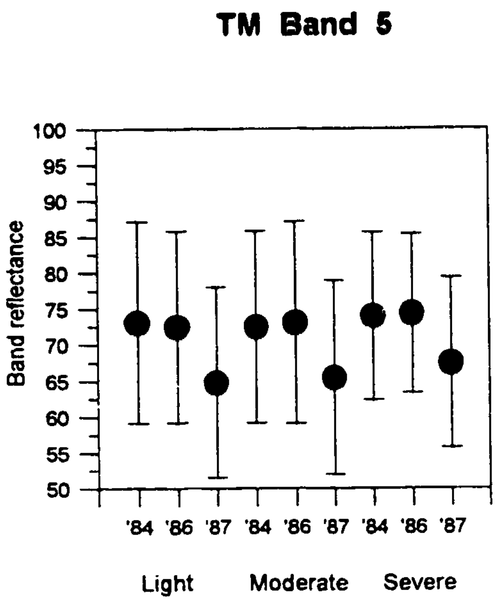
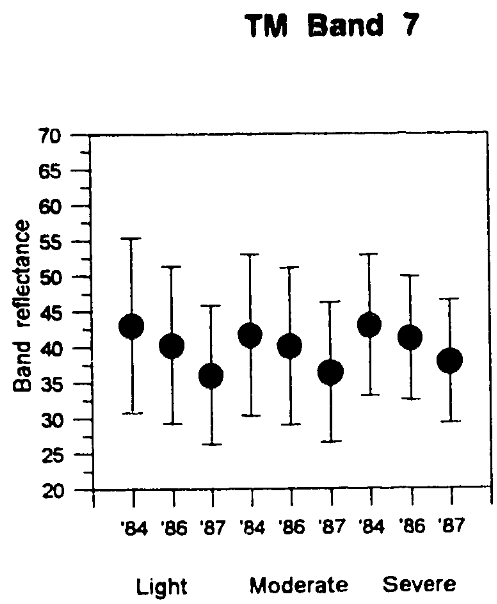


Figure 5-2. Mean spectral band reflectance for light, moderate and severe top-kill areas in 1984, 1986, and 1987. (Error bars are ± 1 standard deviation)





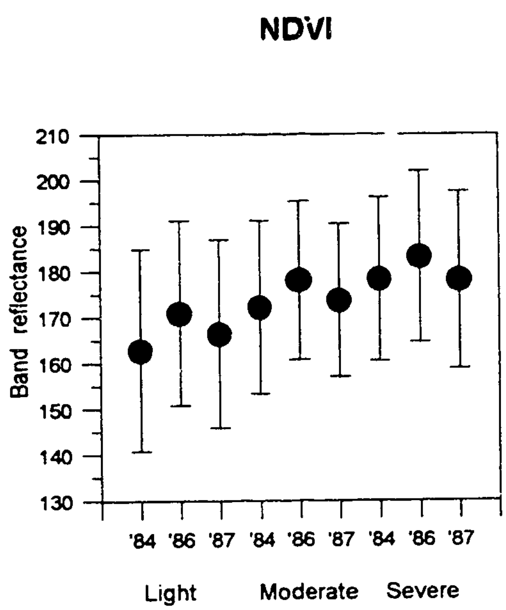


Figure 5-2. continued.

Figure 5-3a. ISODATA unsupervised classification of top-kill areas, 1984-86, 14 channels.

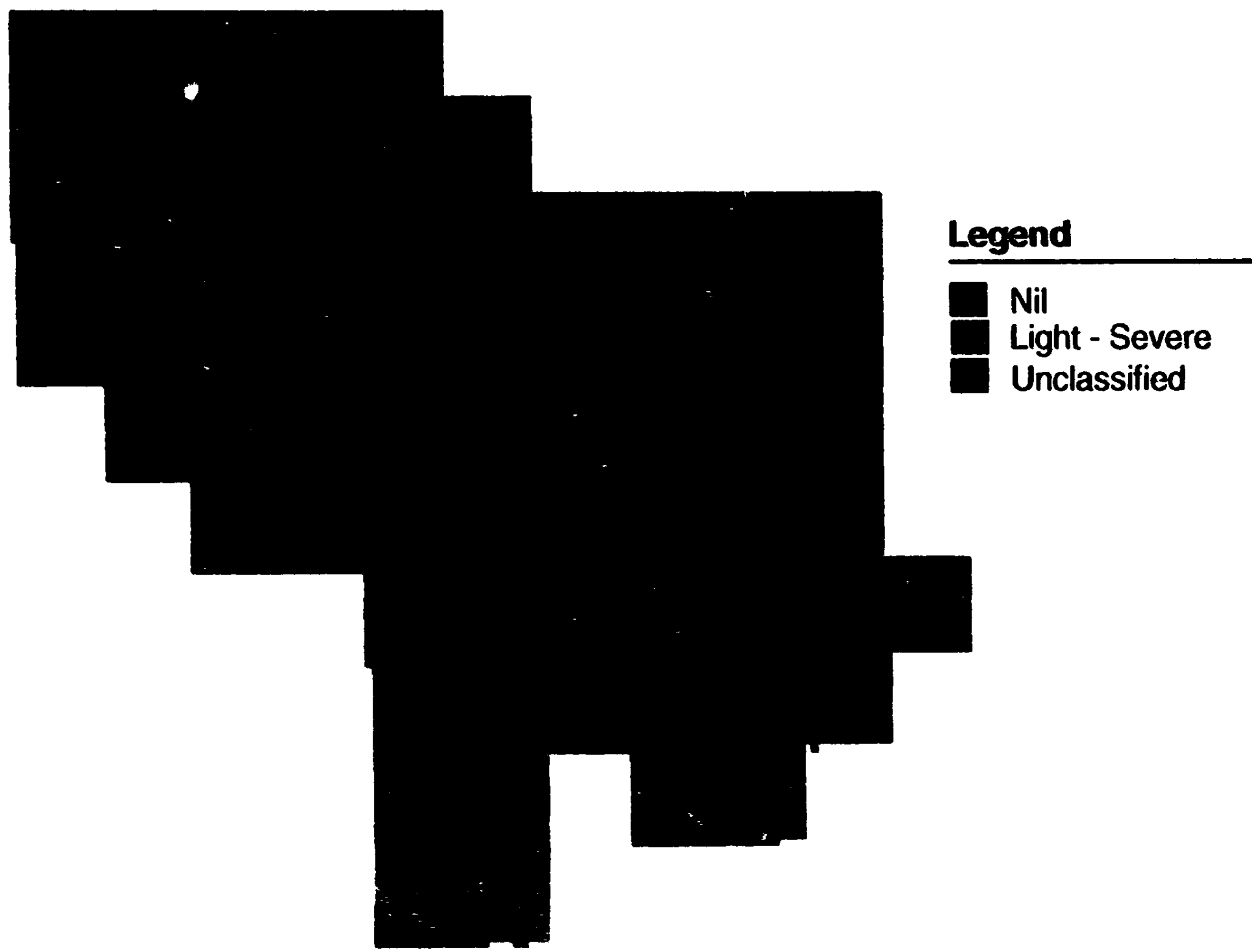


Figure 5-3b. ISODATA unsupervised classification of top-kill areas. 1984-86. 8 channels.

Figure 5-3c. ISODATA unsupervised classification of top-kill areas, 1984-87, 14 channels.

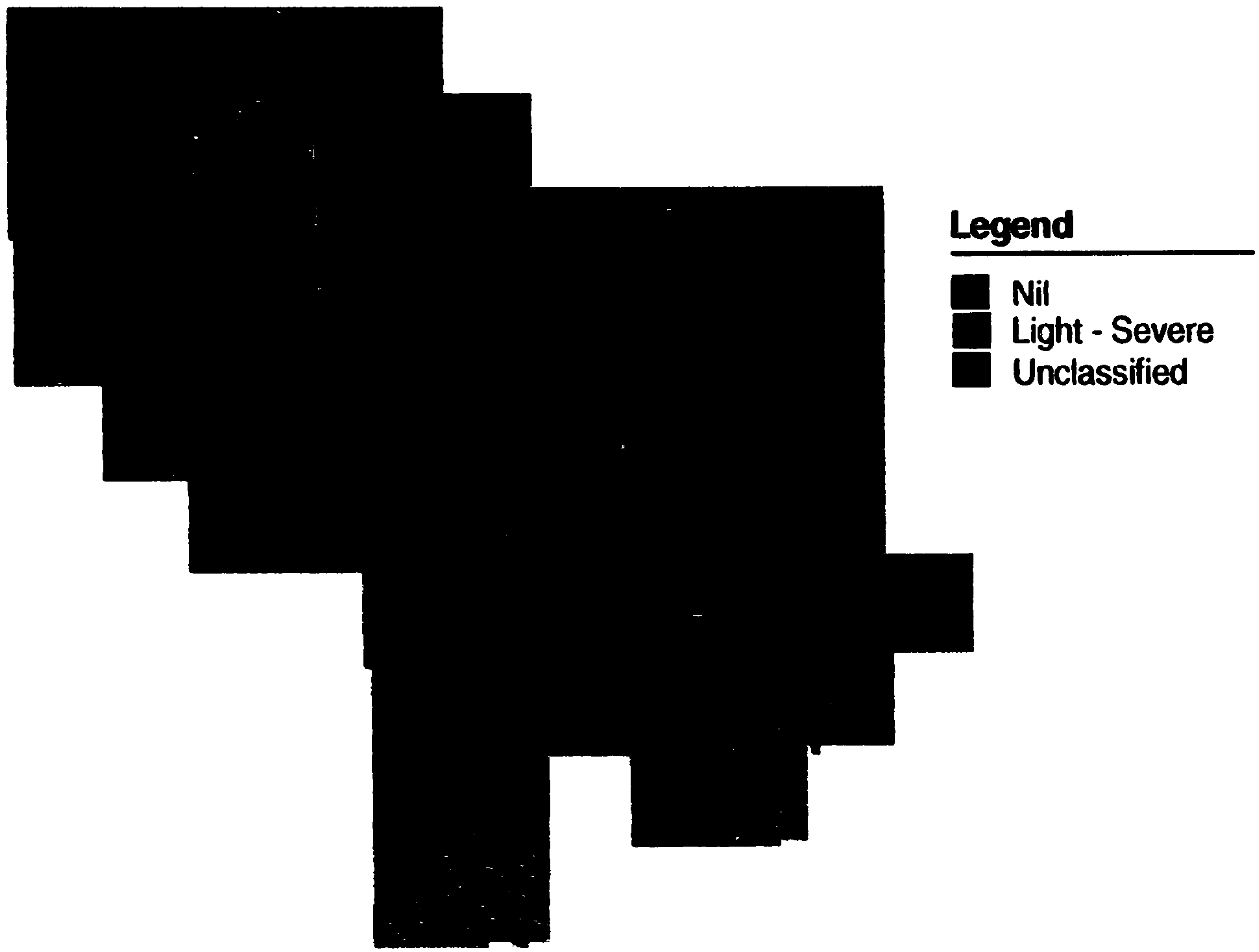


Figure 5-3d. ISODATA unsupervised classification of top-kill areas, 1984-87, 8 channels.

Plate 5-1. 70-mm large-scale photo stereopair depicting jack pine trees with top kill.

Note: annotations on the photographs indicate:

1: jack pine with top kill

2: healthy jack pine

3: reindeer lichen

5.5 References

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Chapter 6

Characterizing Vulnerability of Stands to Damage from Jack Pine Budworm Defoliation

6.1 Introduction

Jack pine budworm (*Choristoneura pinus pinus* Freeman) is among the important insect pests in Canada (MacLean 1990), and is a major defoliator of jack pine (*Pinus banksiana* Lamb.) forests in Ontario, Manitoba, Saskatchewan, and the adjacent United States Great Lakes States (Moody 1989; Mallett and Volney 1990). Budworm defoliation may be extensive, and persist in an area for many years (Volney 1988). Severe defoliation reduces tree growth and vigor, and may cause top kill (i.e., dead tree tops), mortality, and predispose trees for attack by other destructive agents (Kulman et al. 1963; Howse 1984; Mallett and Volney 1990; Gross 1992; Moody and Amirault 1992; Volney 1994). Significant reductions in radial growth and average volume increments have been reported (Kulman et al. 1963; Cerezke 1986; Gross 1992), and these types of losses could have significant impacts on jack pine timber supply (Volney 1988) in their respective regions. An approach to minimize such losses is to schedule harvests based on information about stand vulnerability and projected yield reductions (Maclean 1990). Such information has considerable potential as a management tool when integrated into a forest management system that combines harvest scheduling, vulnerability rating, and protection planning (Erdle et al. 1984; Erdle 1989).

Vulnerability is the likelihood of damage to a stand once budworm attack occurs

(Witter 1985), and vulnerability ratings have been based on stand characteristics (MacLean 1985). Stands vary in their species composition, age structure, site, etc., and these factors influence the degree of growth losses and tree mortality caused by budworm defoliation (MacLean 1985). Thus, fundamental to the development of vulnerability ratings, is the determination of relationships between damage severity and stand characteristics. Previous studies have suggested growth losses and mortality are greatest for stands that are growing on poor sites, are open-grown with large-crowned trees, over-mature, of poor vigor, and/or are suppressed (Dixon and Benjamin 1962; Kulman et al. 1963; Cerezke 1978). Although variations in budworm population densities have been related to differences in stand attributes (Clancy et al. 1980), their empirical limits have not been available.

A source of stand structure information is forest inventory maps that often describe cover types by a nominal (eg., species composition) and ordinal (eg., age, height, crown closure, site quality) forest classification system (Gillis and Leckie 1993). If a map of damage severity is produced and compared to the forest inventory map, then spatial associations between damage severity class and stand attributes can be tested based on contingency table analyses. If strong associations are found, the location of those stands most susceptible to jack pine budworm damage can be identified.

Surveys to map budworm defoliation are often undertaken when the desiccation of accumulated feeding debris and frass imparts a reddish color, since this color is used for defoliation assessment (Volney 1988). For the jack pine budworm, this occurs during a relatively short period from late June to early July (Howse 1984). If damage surveys follow the collapse of an outbreak, then the extent of top kill indicates severity of defoliation in the area. A map of top kill may still be appropriate for comparison with a forest inventory map since trees with top kill may be indicative of stands vulnerable to damage (Volney 1994).

The objective of this study was to answer the question: Are selected physiographic and stand characteristics associated with top kill? The characteristics selected include soil texture, drainage, site quality, stand origin, stand height, and crown closure.

6.2 Materials and methods

The study area encompasses the approximate 47 km^2 of the Torch River Provincial Forest in Saskatchewan. This area is in the Mixedwood section (B.18a) of the Boreal Forest Region of Canada, where jack pine predominates on sandy areas (Rowe 1972). It is located within the Universal Transverse Mercator (UTM) Zone 13 and is bounded by 550,000 mE and 5,920,000 mN on the southwest to 570,000 mE and 5,940,000 mN on the northeast, on a gently undulating plain at elevations ranging from 330 to 380 m above sea level. Soils are relatively homogeneous with much of the area consisting of Eluviated Eutric Brunisols and Orthic Regosols of the Pine Association (Anderson and Ellis 1976). These soils are poor to moderate in site quality due to their coarse texture and rapid drainage, and mainly support jack pine stands (Kabzems et al. 1986; Rudolph and Laidly 1990). Moderate to severe defoliation was reported for the study area between 1984 and 1987 (Moody and Cerezke 1986; Cerezke and Emond 1989), and various levels of top kill damage were observed following defoliation.

6.2.1 Mapping top kill

Color infrared aerial photographs at 1:5000 were acquired during the summer of 1988, one year following the reported collapse of a jack pine budworm infestation (Cerezke and Emond 1989). Since there has been no standard infestation severity classification system reported in the literature (Table 2-1), a classification system was devised specifically for mapping top kill (Chapter 5 Table 5-1). The classification system was based on discrete levels that appeared separable, given that field survey data and 1:900 scale 70-mm large-scale aerial photographs (Chapter 5 Plate 5-1) were available from a previous study (Hall et al. 1993). Both the occurrence and apparent length of top kill on individual trees were considered during interpretation, based on rules assigned to the classification system (Chapter 5 Table 5-1). Top kill in jack pine stands ranged from nil along the Torch River to moderate and severe within the provincial forest (Chapter 5 Figure 5-1).

6.2.2 Forest inventory map database

A series of four contiguous, 1: 12,500 scale forest inventory maps were obtained for the study area. The inventory maps were originally acquired from the Forestry Branch of Saskatchewan Parks and Renewable Resources as ESRI Arc/Info[5] coverages. Soil texture, drainage, primary species, stand origin, stand height, and crown closure (Table 6-1) were recoded from map code (Gillis and Leckie 1993) to an ordinal rank (map class #) to prepare the data for calculations of associations. These maps were imported to the

[5] The mention of trade names is for information only and does not imply endorsement.

SPANS Geographic Information System, and joined together to form a single map of forest cover polygons that represents the entire study area. In a Geographic Information System data layer, a polygon is represented by a unique numeric identifier that links the graphic information to the attribute database (Burrough 1986). The forest cover polygons were subsequently reclassified to produce a separate map for each attribute (Chapter 3 Figures 3-4, 3-5, 3-6 and Figures 6-1, 6-2, 6-3) based on its ordinal map class number (Table 6-1). The initial soil texture and drainage attributes were derived from the soil survey (Anderson and Ellis 1976), and revised by the Forestry Branch during photo interpretation and ground surveys, when the forest cover map was being produced.

A site quality map was also produced by interpreting landform and vegetative patterns on 1:5000 color infrared aerial photographs. Following the photo interpretation, twenty-nine field plots were established, and soil profiles, vegetative descriptions, plot location, drainage, and general physiography (i.e., slope gradient and aspect, topgraphic position, relief shape and landform) were recorded. Vegetation data were analyzed using the Cornell Ecology Program TWINSPAN, to classify the vegetation into communities as a basis for classifying site quality. A map of four levels of site quality ranging from poor to moderate - good was produced (Table 6-1 and Chapter 3, Figure 3-7).

6.2.3 Measures of association

Measures of association, or degree of dependence can be evaluated with a contingency table, which is a two-way cross tabulation of two variables (Conover 1980; Clark and Hosking 1986). Although the X^2 statistic can be computed from the contingency table to test for dependence between two variables, it does not provide a measure of its magnitude (Clark and Hosking 1986). Of the several procedures that do provide measures for the strength of the relation, Cramer's V was used because calculated coefficients range from 0 to 1, and it corrects for deficiencies observed with similar measures such as the Contingency Coefficient (Bishop et al. 1975; Reynolds 1977). In addition, Foody (1994) rationalized it was the preferred means of assessing associations when analyzing ordinal level data. Cramer's V is calculated by (Clark and Hosking 1986):

$$V = \left[\frac{X^2}{N \min[r-1, c-1]}\right]^{1/2}$$

where: V = Cramer's V coefficient

X^2 = calculated chi square from contingency table

N = overall sample size

r = number of rows

c = number of columns

When interpreting Cramer's V, its value is not directly comparable to the more familiar Pearson's product-moment correlation coefficient, or, to Spearman's rank correlation coefficient (Siegel 1956; Reynolds 1977). As such, a small value may seem to suggest poor association, but there is no standard for judging its magnitude.

Cramer's V was calculated between the top-kill classes and each of soil texture, drainage, site quality, stand origin, stand height and crown closure classes. A test of the significance of association was computed at the 95% probability level. Although one can test the significance and determine confidence intervals for the sampling distribution of

Cramer's V by calculating its asymptotic variance (Bishop et al. 1975), the distribution is mathematically complex (Siegel 1956; Reynolds 1977). Since the properties of Cramer's V is asymptotic, its significance can be computed from the X^2 statistic as an approximate test of significance when sample size is "sufficiently" large (Reynolds 1977; Clark and Hosking 1986). The sampling units for the contingency table was based on the number of cells between corresponding regions (eg., rapid drainage and severe top kill) from a grid as produced from the SPANS Geographic Information System. A concern with this approach is the possible influence of spatial autocorrelation with map data that is not sampled randomly (Dale et al. 1991). This is attributed to observed and expected frequencies that may not be compared in a standard X^2 test when the observed counts are not independent (Cliff and Ord 1981, p. 195). Too many apparently significant results can occur if spatial autocorrelation exists in the data (Dale et al. 1991). Due to the logistical difficulties in procuring large random samples, the influence of spatial autocorrelation was avoided by adopting a conservative approach that represent the data as a summation of cells in square kilometer units (Appendix 4). An illustration of how conservative this approach is for crown closure as an example, is presented in Appendix 5.

Since the distribution of observed top-kill areas was highly variable among the attributes, the values in the contingency table were normalized by transforming them to percentages (Bishop et al. 1975, p. 383). The expected values used in calculation of X^2 were based on row and column totals of the percent cell frequencies. This approach was conducted so that several contingency tables could be compared.

Minnick's Coefficient of Areal Correspondence (Minnick 1964) was employed to determine the association between the map attribute class levels and the top-kill severity classes. Minnick's procedure is a measure of areal correspondence that determines the degree to which two regions overlap. Its index is an indicator of spatial association, if one assumes that a relation exists between two spatially distributed phenomena that overlap. For example, if severe top kill is observed on stands of certain age classes, then those types of stands may be vulnerable to severe top kill. Since there is no probability distribution for Minnick's coefficients, values that generally exceeded 0.10 were considered to be indicative of meaningful associations. Minnick's Coefficient is computed using algebra of sets (Minnick 1964):

$$C_m = \frac{A \cap B}{A \cup B - (A \cap B)}$$

where: C_m = Minnick's Coefficient

A = Map A (eg., top-kill severity class)

B = Map B (eg., stand origin class)

$A \cap B$ = A intersect B; ie. the area common to A and B

$A \cup B$ = A union B; ie. the areas belonging to either A or B, or to both A and B.

Coefficients were computed for each pair of classes between top kill and individual stand attributes. For example, the 9 stand origin and 4 top-kill classes resulted in 36 Coefficients being computed (Table 6-3d).

6.3 Results and discussion

6.3.1 Tests of independence and Cramer's V measure of association

The contingency tables produced and used for calculating X^2 and Cramer's V are presented in Appendix 4. To determine if soil, site and forest cover type attributes were significantly associated with top kill, X^2 tests of independence were first undertaken. At a probability level of 0.05, soil texture, drainage and site quality were associated with top-kill severity (Table 6.2). Crown closure, stand origin and stand height classes, as represented on the forest cover map, were statistically independent of top kill. This latter result was unexpected since low density mature and overmature stands have been reported as those most susceptible to budworm damage (Dixon and Benjamin 1962). A possible explanation is that although a probability value of 0.05 is frequently used, the choice of the value is often arbitrary (Warren 1986). Also, the X^2 test of independence for this application is only considered an approximation (Siegel 1956) to the sampling distribution of Cramer's V.

Another possible explanation is that the polygons from mapping top kill may not coincide with those of the forest inventory map due to the criteria used for mapping, or, to map inaccuracies. For example, stands tend to be defined by management considerations (Bauer et al. 1994), whereas polygons of top kill were based on relatively homogeneous patterns of stands with dead tree tops. Accuracy statements for either map were also not available, and variations in accuracy across either map (Duggin and Robinove 1990) could explain why strong associations were not found.

The values of Cramer's V is interpreted as a measure of the relative strength of the relationship between pairings of individual attributes with top kill. Of these, soil texture and drainage were the attributes most highly associated with top kill (Table 6.2). Stand origin, site quality and stand height are intermediate, and crown closure was the least associated with top kill. This demonstrates that for this study, dryness of a site has a greater influence on vulnerability than other stand characteristics. This result is consistent with the observation by others that frequent outbreaks and higher budworm numbers are associated with drier sites (Volney and McCullough 1994).

Stand origin is often mentioned before crown closure as being related to stand vulnerability (Gagnon and Chabot 1990). Stand origin in this study was more highly associated with top kill than crown closure (Table 6-2). The relationship between stand height and top kill was expected to be similar to that for stand origin since older, mature stands that sustain top kill are the taller stands. Much of the study area was in the *Pinus-Cladonia/Arctostaphylos* ecosystem where pure, open, understocked (crown closure less than 45%) jack pine stands occur (Kabzems et al. 1986). Thus, crown closure classes A and B (Table 6-1) are dominant in the study area (Figure 6-3), but crown closure (4 classes) is more broadly defined than stand origin (10 classes). In addition, the system defined for mapping top kill was based strictly on proportions of trees with dead tops (Chapter 5 Table 5-1), and perhaps some consideration should have been given to stand structure as influenced by crown closure. Although this consideration may improve associations with top kill, the few, broad crown closure classes would still limit the amount of improvements, if any.

6.3.2 Characterizing vulnerable stands

Processes affecting jack pine budworm population behavior may operate at very local levels (Volney and McCullough 1994). The physiological state of trees, conditioned by site (eg. soil texture, drainage) and stand (eg. age, crown closure) characteristics, influences their vulnerability to budworm damage (Gagnon and Chabot 1990). Thus, association of these characteristics with top kill may help to identify vulnerable stands. A tabulation of Minnick's Coefficient of Areal Correspondence for each attribute provides the basis for inferences on the vulnerability of these stands (Table 6-3 a,b,c,d,e,f,g).

Coefficients for soil texture and drainage were equivalent among light, moderate and severe top kill (Table 6-3 a,b). This was expected since coarse textured soils are associated with rapid drainage, and typical of dry sites. Absence of top kill was associated with moderately-coarse texture and moderately-well drained areas that are indicative of better sites (Table 6-3 a,b). The largest coefficient of 0.57 occurred between light top kill and coarse texture or rapid drainage. This result is consistent with studies citing high risk to jack pine budworm on dry sites (Jones and Campbell 1986), and frequent outbreaks being associated with drier sites (Volney and McCullough 1994). This result is also similar for spruce budworm (*Choristoneura fumiferana* Clem.) damage (Gagnon and Chabot 1990).

Poor and moderate site quality were associated with light, moderate and severe top kill (Table 6-3c). The largest coefficient of 0.54 occurred between poor site quality and light top kill. Poor sites in the study area are nutrient poor and characterized by low tree productivity (Kabzems et al. 1986). The association between poor sites and top kill is similar to the reported tendency for frequent outbreaks to occur on nutrient-poor soils (Volney and McCullough 1994). This implies that poor site quality is a component of stand vulnerability to jack pine budworm damage.

There were differences in stand origin associations with top kill. Light top kill was associated with stands at age-class mid-points of 95, 55, and 45 years, whereas, moderate and severe top kill were associated with stands at age-class mid-points of 95 and 85 years (Table 6-3d). The association of the older stands with moderate and severe top kill appears consistent with long standing reports that mature jack pine stands are more vulnerable to severe damage than younger stands (Dixon and Benjamin 1962). Much of the jack pine in the study area is managed on an 80 year rotation (Kabzems et al. 1986), and the stands associated with moderate and severe top kill exceed this age. Since jack pine stands may begin to "disintegrate" after 60 years on the poorest sites (Rudolph and Laidly 1990), it may be desireable to reduce the occurrence of vulnerable stands by reducing rotation age (Jones and Campbell 1986; Gross 1992).

The trends exhibited for stand origin are somewhat similar to those for height, since older stands are also the taller stands. Light top kill was associated with stands in the 5, 10, and 15 m height classes (Table 6-3e). Moderate top kill was associated with taller stands of 20 m, and severe top kill was associated with stands in both the 15 and 20 m height classes (Table 6-3e). Thus, trends of more severe damage on the taller stands were observed, with a greater range of heights for "severe" than for "moderate" top kill.

Jack pine budworm populations have been associated with open-grown jack pine that occur in stands with low crown closures (Kulman et al. 1963). In the study area, light top kill occurred throughout all crown closures whereas, moderate and severe top kill was dominant in the more open stands of 10-55% crown closures (Table 6-3f). Moderate and severe top kill is associated with the more open stands, and may be more vulnerable than denser stands.

6.4 Conclusions

A stand's vulnerability may be considered as the sum of characteristics, including stand structure and environment, which predispose it to damage during an attack of a given serverity (Gagnon and Chabot 1990). A requisite to vulnerability rating systems that are based entirely on characteristics of the forest (MacLean 1985), is the understanding of relationships between these characteristics and damage severity sustained from severe defoliation. A unique spatial approach using a Geographic Information System was implemented, and the association of site quality and forest inventory maps to the map of top kill was evaluated. The only similar approach identified in the literature was that for spruce budworm vulnerability by Wickware and Sims (1990). Their approach did not attempt evaluation of associations but instead, was based on application of a vulnerability index defined by Gagnon and Chabot (1990).

A summary of stand characteristics with the highest associations with top kill may aid in identifying vulnerable stands. Stands that sustained moderate to severe top kill occupied poor-to-moderate sites that were on coarse-textured, rapidly-drained soils. These stands were of age-class mid-points ranging from 85 to 95 years, had crown closures that ranged from 10 to 55%, and were 15 to 20 m tall. These results appear to agree in general with previous studies that mention these attributes (Dixon and Benjamin 1962; Kulman et al. 1963; Cerezke 1978; Volney and McCullough 1994).

Applying these results to unaffected jack pine stands require assumptions of the relationships between site and stand attributes, and damage that may occur as a result of outbreaks (Wulf and Cates 1987). Some caution must be exercised when applying the results because jack pine budworm dynamics are far more intricate than simple associations. This is attributed to complex interactions between the environment, physiography, and stand structure on budworm population dynamics. For example, weather may influence budworm populations directly, or indirectly by host tree response that affects the food quality of jack pine needles (Clancy et al. 1980; Volney and McCullough 1994). Similar work that was conducted on spruce budworm outbreaks has suggested attempts to deduce underlying causes of stand susceptibility from observations of defoliation alone can be misleading (Campbell 1993).

The unknown accuracies of the physiographic and stand attribute maps may have influenced the strengths of associations obtained. Although such information is seldom reported (Lunetta et al. 1991), efforts are needed to procure accuracy statements of source maps so that their influence on analysis, particularly through error propagation (Walsh et al. 1987; Thapa and Bossler 1992) can be assessed.

This study confirms that vulnerability to jack pine budworm damage may be explained, in part, by soil, site quality and stand attributes. These associations may be valuable in producing hazard maps, and in helping managers to define planning options that reduce losses to future timber supply.

Table 6-1. Classification system used for Saskatchewan forest inventory maps.

Attribute	Map code	Map class #	Attribute	Map code	Map class #
Crown closure			Stand height		
10% - 30%	A	1	2.5 - 7.5 m	5	1
30% - 55%	B	2	7.5 - 12.5 m	10	2
55% - 80%	C	3	12.5 - 17.5 m	15	3
80 % +	D	4	17.5 - 22.5 m	20	4
			22.5 + m	25	5
Stand origin					
1856-1865 (125+)	86	1	Soil texture		
1866-1875 (115+)	87	2	Coarse - Mod. Coarse	CMC	1
1876-1885 (105+)	88	3	Mod. Coarse - Mod. Fine	MCMF	2
1886-1895 (95+)	89	4	Organic	O	3
1896-1905 (85+)	90	5			
1916-1925 (65+)	92	6	Drainage		
1926-1935 (55+)	93	7	Rapid-Well drained	RW	1
1936-1945 (45+)	94	8	Well-drained	W	2
1946-1955 (35+)	95	9	Well-Mod. well drained	WMW	3
1956-1965 (25+)	96	10			
			Species		
Site quality			Jack pine	jP	1
Poor	P	1	Aspen	tA	2
Poor - Moderate	P-M	2	White spruce	wS	3
Moderate	M	3	Black spruce	bS	4
Moderate - Good	M-G	4			

Table 6-2 Tests of independence and Cramer's V associations for site quality and stand characteristics with top-kill severity.

Attribute	Calculated X^2	Degrees of Freedom	Table χ^2	Cramer's V
Soil texture	36.2[a]	3	7.82	0.60
Drainage	38.3[a]	6	12.59	0.44
Site quality	18.5[a]	9	16.92	0.25
Stand origin	25.8	24	36.42	0.29
Stand height	15.5	12	21.03	0.23
Crown closure	6.29	9	16.92	0.14

[a] indicates significant association at $\alpha = 0.05$.

Table 6-3. Minnick's Coefficient of Areal Correspondence for site quality and stand characteristics with top-kill severity. (Table values in bold indicate Coefficients considered significant.)

a) Soil texture

Top kill	Coarse	Moderately - coarse
Nil	0.06	**0.44**
Light	**0.57**	0.02
Moderate	**0.16**	0.01
Severe	**0.20**	0.00

b) Drainage

Top kill	Rapid	Well	Moderate - well
Nil	0.06	0.01	**0.45**
Light	**0.57**	0.01	0.01
Moderate	**0.16**	0.00	0.01
Severe	**0.20**	0.00	0.00

c) Site quality

Top kill	Poor	Poor - Moderate	Moderate	Moderate - Good
Nil	0.01	0.02	0.11	**0.24**
Light	**0.54**	0.08	0.10	0.03
Moderate	**0.13**	0.08	**0.13**	0.03
Good	**0.19**	0.08	**0.11**	0.01

Table 6-3 continued.

d) Stand origin (median of class in years, Table 6-1)

Top kill	115	105	95	85	65	55	45	35	25
Nil	0.00	0.04	0.02	0.09	0.11	0.07	**0.13**	0.01	0.02
Light	0.00	0.00	**0.12**	0.08	0.03	**0.41**	**0.18**	0.04	0.00
Moderate	0.00	0.00	**0.11**	**0.15**	0.03	0.07	0.04	0.07	0.01
Severe	0.00	0.00	**0.13**	**0.28**	0.05	0.06	0.02	0.05	0.00

e) Stand height

Top kill	5 m	10 m	15 m	20 m	25 m
Nil	0.04	0.10	**0.13**	0.01	0.00
Light	**0.17**	**0.41**	**0.15**	0.10	0.00
Moderate	0.05	0.09	0.10	**0.16**	0.00
Severe	0.05	0.07	**0.21**	**0.20**	0.00

f) Crown closure

Top kill	10 - 30 %	30 - 55 %	55 - 80 %	> 80 %
Nil	0.03	0.07	**0.12**	0.09
Light	**0.13**	**0.24**	**0.28**	**0.17**
Moderate	**0.15**	**0.12**	0.10	0.03
Severe	**0.16**	**0.16**	**0.13**	0.02

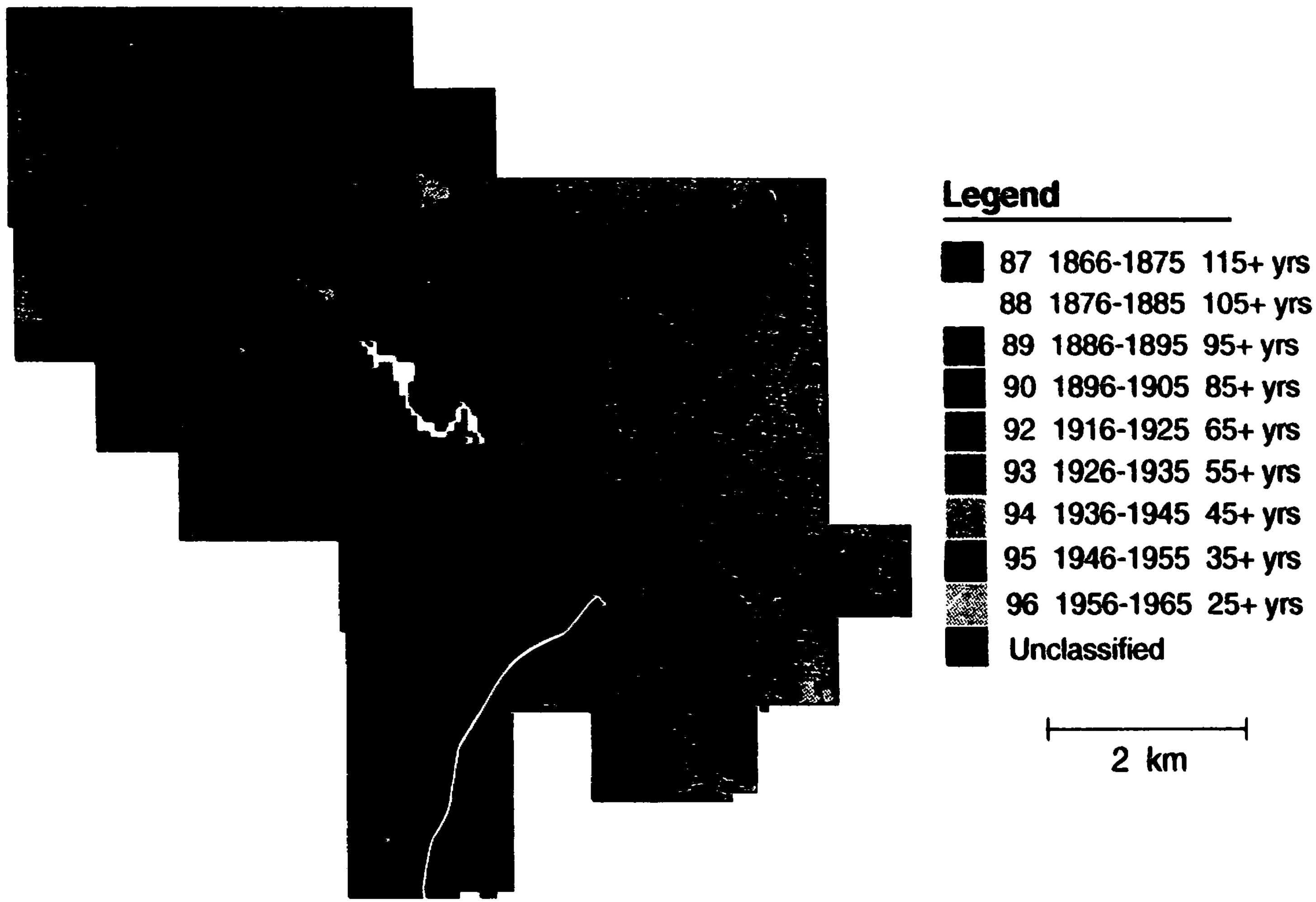

Figure 6-1. Stand origin map oi the Torch River Provincial Forest.

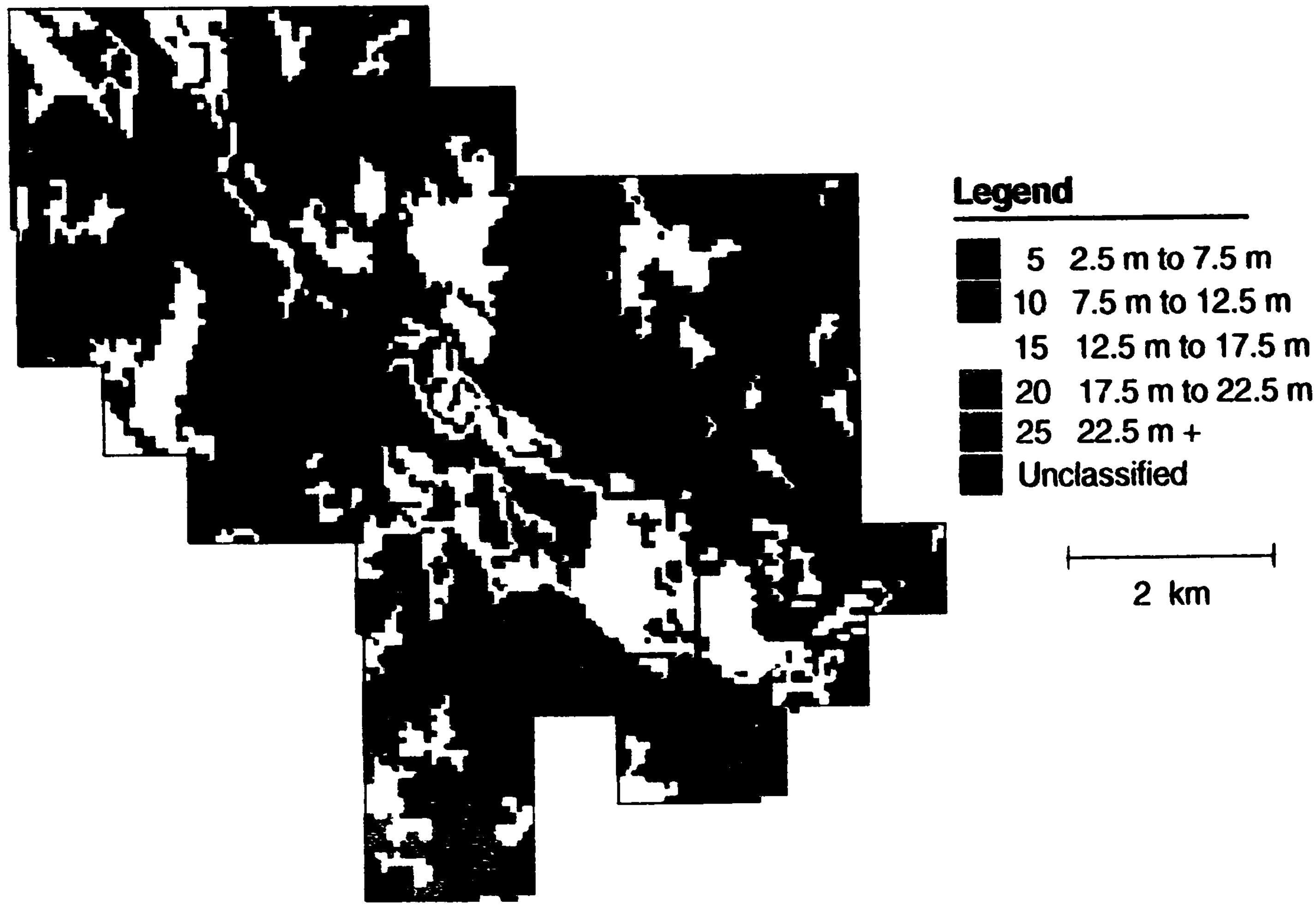

Figure 6-2. Stand height map of the Torch River Provincial Forest.

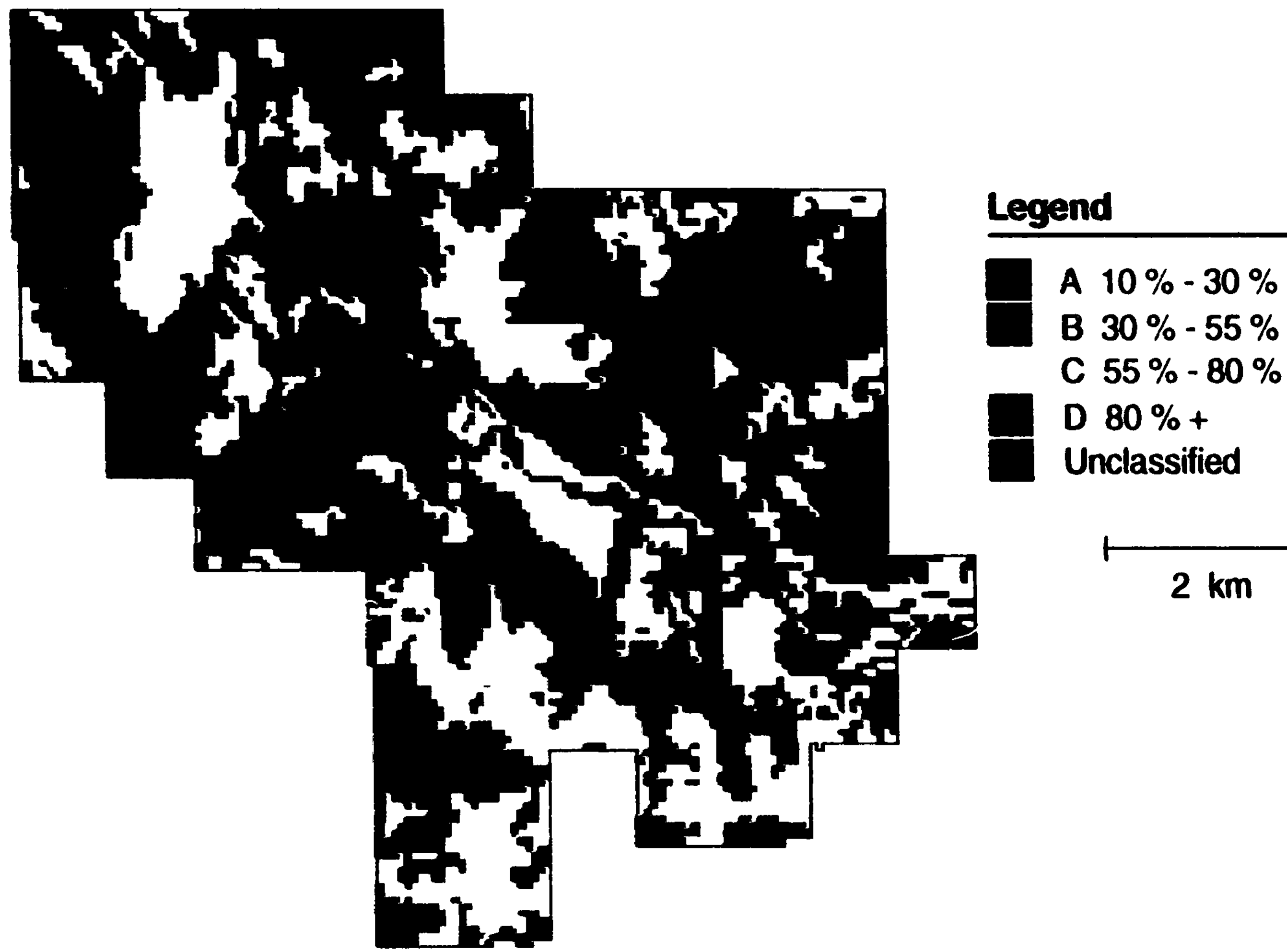

Figure 6-3. Crown closure map of the Torch River Provincial Forest.

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Chapter 7

General Discussions and Conclusions

This Ph.D. thesis describes a study of top kill on jack pine from three perspectives: 1) developing a photo-mensurational procedure for estimating the volume of tree top kill to assess impact; 2) evaluating a multidate, satellite remote sensing approach for mapping the areal extent and severity of top kill; and 3) exploring spatial associations between trees with varying degrees of top kill and stand environmental characteristics that may function as vulnerability indicators. The background for the study included a literature review of the jack pine budworm life history, and the forest stand attributes and environmental factors that influence insect populations.

Relatively little attention has previously been focused on the impact of top kill and its associations with stand characteristics. This may be attributed in part, to the difficulty of measuring top kill in the field, its perceived minor contribution to impacts on merchantable tree volumes, and its difficulty in mapping damage patterns. Nevertheless, trees with severe defoliation may sustain significant amounts of top kill that impairs future growth, and mature trees exhibit poor capabilities to recover. Thus, an approach based on measurements from large-scale photographs and a jack pine taper model, was developed to quantify top kill. Photo measurements of the lengths of top kill were highly correlated and linearly associated with their actual lengths. In addition, estimates of volume derived using taper models compared favorably with actual volumes. An advantage of using taper models that is not available with photo-derived volume models, is the ability to determine impacts in terms of merchantable volumes. The photogrammetric limitations for this method were also determined. The method of using photo measurements in a taper model represents a new contribution to photo mensuration. This approach also results in a potential application to forest inventory, and may solve a recurring problem that limits large-scale photo use for volume estimation. This problem has been the high cost of destructive tree sampling to derive volume models.

The background review confirmed that there is no standardized infestation severity classification system for mapping outbreaks. In addition, although aerial surveys are widely used to assess defoliation, they are not accurate enough to be used in relating damage such as volume and growth losses to severity of defoliation. Since this study concentrated on impacts associated with top kill, a classification scheme was devised to map top kill using relatively larg[illegible]le 1:5000 color infrared aerial photographs. This map was used to represent the actual extent of damage so that a remote sensing mapping approach using multidate, LANDSAT Thematic Mapper satellite images could be evaluated. This approach employed a remote sensing - Geographic Information System integration method (see Chapter 5, p. 91), whereby the digital map of top kill was used as training data to explore spectral separabilities.

LANDSAT Thematic Mapper images corresponding to before (1984), during (1986), and after (1987) the outbreak were obtained to create two image data sets (1984-86 and 1984-87) for assessing spectral changes that may relate to damage. Because the anticipated changes were small, an important prerequisite was image preprocessing that consisted of atmospheric and geometric corrections. The images were calibrated to reflectance units, and then geometrically corrected and resampled prior to the image analysis. The images were also acquired during a relatively narrow time frame to minimize phenological changes to jack pine trees. Spectral differences among light, moderate, and severe top kill were small. The differences were attributed in part, to effects of reflectance from ground vegetation in relatively open jack pine stands, since the reflectance spectra of stands depend on the proportion of trees and ground vegetation within a pixel. Spectral separabilities were higher for the 1984-86 data set than for the 1984-87 data set. The spectral separabilities were also smaller when simple band differences were used as image bands, relative to the LANDSAT TM bands from each date. Other possible reasons for why top-kill damage was difficult to detect include the timing and spatial resolution of LANDSAT TM data, the shadow differences between July and August images, and residual errors that may have resulted from the atmospheric correction process. Based on these results, further attempts to distinguish damage classes using other change detection algorithms such as principle component analysis and defoliation models was not warranted.

A contingency table was used to compare the nine spectral classes from the unsupervised classification with the nil, light, moderate, severe and unclassified classes on the map of top kill. Because of difficulties usually encountered in assigning information labels to spectral classes from an unsupervised classification, this approach is a potentially new means of identifying these classes. Spectral classes can be described and signatures developed for application to other similar areas. The integration of polygonal information from a Geographic Information System, can greatly assist remote sensing analyses.

Based on the image data of the study area, and the fact that top-kill damage is confined to jack pine, the classified image mainly mapped the occurrence of this species. Areas of light, moderate and severe top kill could not be discriminated. Change detection approaches using LANDSAT TM data were not appropriate for detecting top-kill severity, and is therefore more suitable when the spectral differences are larger.

Although the background review outlined the characteristics of stands considered vulnerable to budworm damage, empirical estimates for these have not been available. A spatial approach was used to obtain associations whereby stand structure and site quality maps were overlaid with the map of top kill. Jack pine stands on coarse-textured, rapid-drained soils of poor site quality appear most vulnerable to budworm damage. For the study area, these stands are 85 to 95 years of age with heights of 15 to 20 m, and crown closures that range from 10 to 55% Although these attributes may help forest managers to locate high risk stands, budworm populations and resulting damage are influenced by complex interactions with the environment. The results are therefore insufficient for predicting damage in themselves, and should be combined with research that outlines other determinants of budworm population behavior. Thus, the results are a first approximation towards characterizing vulnerable stands, and contribute to efforts that define planning options to reduce risk of damage, and losses to future timber supply.

The use of Cramer's V and Minnick's Coefficient of Areal Correspondence is novel in evaluating spatial associations within forest ecosystems. Although procedures are needed for sample selection to avoid possible influences of spatial autocorrelation (see

Appendix 5), the inferences made with these measures are remarkably consistent with published studies. This may attest to the potential utility of forest inventory and site quality map data in describing the characteristics of stands vulnerable to jack pine budworm damage.

Several recommendations are presented for future work:

1. A stratified random sampling scheme is recommended if the methods developed for quantifying top kill are to be implemented. Although the procedures for and limits of measuring the lengths of top kill, and quantifying their volumes were determined, an efficient means of allocating sample plots is needed. The classification system for mapping top kill may be useful for stratifying stands. Randomly located photo plots within stratified units could then be established to quantify damage from top kill, and to determine its influence on merchantable volumes.

2. Higher resolution image data such as from the airborne MEIS (Multi-detector Electro-optical Imaging Scanner) may be required for digital detection and mapping of stands with top kill. Image data at 5, 10, and 15 m spatial resolutions should be explored to determine the feasibility of mapping stands with top kill or defoliation. The coarsest spatial resolution that still detects damaged stands would be the most cost-effective for application due to its larger areal coverage. Alternatively, the proposed constellation of Worldview Imaging Corporation's satellites, that will offer green, red and near infrared coverage at 15 m resolution

for 30- by 30-km areas[6], should be evaluated when available. In addition, research in hyperspectral imaging and analysis with high spectral resolution data will in the future, provide the tools to help define the spectral characteristics of damaged stands. Thus, as improvements in the data resolution of future remote sensing sensor systems and analysis capabilities become available, the ability to undertake pest damage studies should improve.

3. The ability to detect areas of infestation may be enhanced if satellite data acquisition is better timed to coincide with the red color stage during a budworm outbreak. Spectral differences as a result of severe defoliation should be larger than that observed for top kill. A classification system for mapping levels of defoliation severity is needed, however, and may be adapted from the system used in this study or from other investigations. In designing a classification system, consideration should be given to objects such as ground vegetation and stand density that may influence the spectral responses from defoliated stands. Ideally, future classifications systems will be compatible for both air photo interpretation and digital image analysis.

4. In addition to the future availability of high resolution digital images, research in subpixel analysis algorithms, and neural networks for image classification may help to address the difficulties encountered in analyzing mixed pixels. Investigations into these methods for potential application to damaged stands are therefore recommended.

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[6]Forrest, D. 1994. Innovation watch. GIS World 7(1): 58.

5. Fire scars were observed on many trees during field work in the study area, and the sketchy information available for previous fires suggested some areas may have been burned more than once. Since results from published research suggest tree response to stress from fire influences pest outbreaks, a detailed map of fire occurrence may help to identify stands vulnerable to budworm damage. Future studies that are similar to that undertaken for this thesis, should endeavour to include detailed fire history maps, if available.

6. Values of association between stand attributes and defoliation severity may be larger than with those obtained using top kill. Replicating this study during an insect outbreak may therefore help to better define the ability to map damage severity, and to identify the characteristics of vulnerable stands.

7. It is not known whether a spatial autocorrelation coefficient would help to explain spatial relationships between stand attributes and budworm damage. The research strategy in spatial statistics is to assume no pattern exists in a map. A hypothesis test therefore assists in determining whether observed patterns are significantly different from a random pattern, and this may be a useful approach to test specific hypotheses of spatial relationships. For example, a map overlay between a stand attribute such as stand origin and defoliation severity could be used to produce a residual map, and a test could be undertaken for significance of residual patterns.

8. To meet increasing demands for information in forest management, inventory classification systems are changing by requiring existing attributes to be mapped to a larger number of more specific classes. For example, instead of 5 or 6 m

height classes used in Alberta and Saskatchewan, the trend is to specify actual stand height. Crown closure is also being expanded from 4 relatively broad classes to 10 classes that range from 0 to 100 percent. Forest cover maps that are based on these detailed specifications may help to more specifically characterize stand vulnerability, and this will warrant future investigations.

These recommendations provide several possibilities for extensions to this study. The objectives for this study of top kill were met, and the findings should contribute to an improved understanding of its impacts and characteristics relative to what has previously been reported. These results should also help to encourage incorporation of pest management options in resource planning, and this will lead to better management of the jack pine forest resource.

Appendices

Appendix 1. Elaboration of preprocessing methods for Chapter 5.

Appendix 2. Residual mean square (RMS) errors in pixel and line directions for the three image dates.

Appendix 3. Descriptive statistics for light, moderate, and severe top-kill areas in 1984, 1986, and 1987.

Appendix 4. Contingency tables used for calculation of χ^2 and Cramer's V for soil, site quality and stand attributes with severity of top kill.

Appendix 5. Influence of spatial autocorrelation on the X^2 statistic and sampling procedures for rectification.

Appendix 1. Elaboration of preprocessing methods for Chapter 5.

Atmospheric correction, geometric correction, image registration

Atmospheric effects in remote sensing images are primarily due to atmospheric attenuation of radiation from the ground surface, and to Rayleigh and Mie (i.e., caused by water vapor and dust) scattering of solar radiation (Moik 1980). Because Rayleigh and Mie scattering and attenuation are wavelength dependent, the effects of the atmosphere are different among the spectral bands (Richards 1993). Atmospheric correction becomes important when temporal data are to be compared since the atmosphere will be different on different image dates (Mather 1987). It is also important when band ratioing is to be applied since the effects of scattering (i.e., scattering varies inversely with wavelength) results in a biased estimate of the band ratio (Mather 1987; Kaufman 1988). Radiometric corrections therefore ensure that spatial or temporal changes in green vegetation are real differences and not artifacts from atmospheric and illumination differences (Ahern et al. 1987). Previous studies also suggest that removal of atmospheric effects from remote sensing data results in remote sensing data that are better related to ground cover characteristics, thus improving image classification accuracies and detection of spectral changes (Kaufman and Sendra 1988; Kawata et al. 1988; Fraser et al. 1992).

Although there are several methods for atmospheric correction (Richards 1993; Kaufman and Sendra 1988; Chavez 1989; Richter 1990; Fraser at al. 1992), the reflectance method developed by Ahern and Sirois (1989) was applied to each image date because of computer programs that were available from the Canada Centre for Remote Sensing (CCRS). In addition, atmospheric and illumination corrections with this method are conveniently derived from the image scene content alone, and the corrected image is transformed to reflectance units on an 8-bit (0 to 255) digital number scale that is suited for subsequent digital processing. For each band, the mean scene radiance provides an estimate of average scene albedo, and the minimum value on the histogram is an estimate of path radiance (Jenson 1986; Mather 1987). The histogram minimum value of the visible bands is based on the full image or image area that also contains areas of low reflectance such as from clear water (Ahern and Sirois 1989). Together with geometrical factors derived from the latitude, longitude, date, and time, these estimates are used with a radiative transfer model (Ahern et al. 1982) to provide an estimate of total downwelling irradiance (Ahern and Sirois 1989). The algorithms for the computation of solar azimuth, solar elevation and a look-up table for the image correction have been implemented in SUNELEV (Teillet 1987) and ENHPAR (Fedosejevs 1988) respectively, on the Landsat Digital Image Analysis System (LDIAS) at CCRS. Calibrated reflectances from this method are considered good to within 10 percent of their true value, and this is the best that can be expected from combined uncertainties of the absolute sensor calibration, and the atmospheric correction methodology[7].

A subset of each LANDSAT image encompassing the study area was geometrically corrected, to facilitate two-date image registration, and subsequent integration with vector data comprising the light, moderate, and severe top-kill severity polygons from the SPANS geographic information system (GIS). The geometric rectification process included establishing ground control points between the image and a reference map that

[7] Ahern, F.J. Canada Centre for Remote Sensing. Personal communications. August 10, 1992.

are related geometrically by a least squares, first order affine transformation to correct for rotation, displacement, scaling and skew (Jensen 1986). This approach was considered reasonable since systematic distortions due to for example, earth rotation, earth curvature, mirror scan velocity, and satellite orientation (ie., altitude, attitude), were already corrected during preprocessing at the satellite receiving station[8]. The spectral differences between multidate images attributable to top kill were assumed to be subtle, and there was concern that image preprocessing procedures could alter these differences. Thus, nearest neighbour pixel resampling was undertaken to determine the pixel brightness values in the corrected image (Shlien 1979), because radiometric values do not change when the pixel size is kept relatively constant (Derenyi and Saleh 1989; Duggin and Robinove 1990). Other resampling algorithms, such as cubic convolution, can significantly alter pixel values which degrade radiometric accuracy (Ahern et al. 1987; Derenyi and Saleh 1989).

Based on the well-defined road network, 12 ground control points were identified on both the image and on 1:12 500 UTM-based forest cover maps, available from the Saskatchewan Forestry Branch. The UTM coordinates for the control points on the map were digitized in a Geographic Information System to minimize the likelihood of manual measurement errors. Two image databases were created, one for the 1984-1986 image data, and one for the 1984-1987 image data. The standard process of geometrically correcting one image as the master (eg., 1984) and performing image-to-image registration for the other dates was not possible due to an artifact in the EASI/PACE system when correcting images smaller than the 1024 by 1024 display size. Separate geometric

[8] Radarsat International. 1994. Canadian LANDSAT and SPOT products and services. Richmond, B.C.

corrections were therefore undertaken on each image while attempting to maintain residual errors within one half pixel. This error is consistent with the nominal thickness of a 1 mm plotted line which at the 1:12 500 forest cover map scale represents 12.5 m on the SPANS GIS database. For accurate spatial registration of two images to a standard map projection for digital change detection, rectification from image to map should be within ¼ to ½ a pixel (Jensen 1986), and this was achieved for this study (Appendix 2). The final image database size was 800 pixels by 800 lines with a 25 m resampled pixel size that corresponded to the 20 km by 20 km map extent on the SPANS GIS database.

Mapping top kill

Color infrared aerial photographs at 1:5000 were acquired during the summer of 1988, one year following the reported collapse of a jack pine budworm infestation (Cerezke and Emond 1989). Since there has been no standard infestation severity classification system reported in the literature (Chapter 2 Table 2-1), a classification system specifically for mapping top-kill was devised for this study (Chapter 5 Table 5-1). The classification system was based on discrete levels that appeared separable, given that field survey data and 1:900 scale 70-mm large-scale aerial photographs (Chapter 5 Plate 5-1) were available from a previous study (Hall et al., 1993). Both the occurrence and apparent length of top kill on individual trees were considered during interpretation, based on rules assigned to the classification system (Chapter 5 Table 5-1).

Visual interpretation of aerial photographs is accomplished by the detection and identification of objects of interest by employing the six basic elements (i.e., tone or color, size, shape, texture, shadow, pattern) supplemented by height, forest site and ecological association (Howard 1991). Variations in knowledge and skill of the interpreter (Hilborn 1981; Paine 1981), and in how they employ the interpretive elements, result in unavoidable differences in interpreted products. To reduce the magnitude of this subjective variation, the placement of polygon lines and assignment of attribute labels (Chapter 5 Table 5-1) were based on the collective and cooperative interpretation between two photo interpreters in this study. Top-kill damage to jack pine stands from the jack pine budworm ranged from nil along the Torch River to moderate and severe within the provincial forest (Chapter 5 Figure 5-1). Since spectral differences between these classes may be too small to discriminate with LANDSAT TM data, several sets of aggregated top-kill map classes were also produced to determine if spectral separabilities would change with a smaller number of more broadly defined classes (Chapter 5 Table 5-2).

Change detection background

The objective of change detection is to identify differences in the state of an object by observing it at different times (Singh 1989). The use of LANDSAT TM data for change detection involves the manipulations of digital numbers, recorded at two or more moments in time, over six wavelength bands, for pixels that represent prior to resampling, approximately 30 m by 30 m on the ground. Digital change detection approaches are characterized by the image channel transformation and analysis techniques used to delineate areas of significant alterations (Singh 1989).

Of the image channel transformations that have been employed in change detection studies (Nelson 1983), spectral channel differencing and vegetative index differencing were employed in this study. The calculation of a channel difference is (Singh 1989):

$$\textbf{Difference} = \textbf{Band}_1 - \textbf{Band}_2 + 128$$

A constant is added to avoid negative values. The differencing transformation is the most widely used because of its simplicity, and various authors have reported classification accuracies equal to those obtained from more sophisticated approaches (Nelson 1983). Image differencing involves subtracting the imagery of one date from that of another (Jenson 1986). The difference produces a residual image that indicates the relative change in reflectance between two dates (Singh 1989). This technique is appropriate when the objective is to quantify the amount and direction of change rather than to quantify specific cover types (Sader and Winne 1992). Although image differencing is the most widely used technique for change detection, a critical requirement is deciding where to place the threshold boundaries between change and no change pixels displayed in the histogram (Jensen 1986). Simple differences can be confusing, however, since the same magnitude can be computed from different band values between two dates unless standardized differences are employed (Coppin and Bauer 1992). Band difference images have been used to monitor gypsy moth (*Lymantria dispar* L.) defoliation (Williams and Stauffer 1978), and forest decline associated with mortality (Vogelmann 1988).

Vegetation indices are linear or ratio combinations of spectral reflectance measurements in the green or red and near infrared parts of the spectrum (Bouman 1992). The normalized difference vegetation index (NDVI) is among those vegetation indices frequently reported for forest damage applications (Nelson 1983; Chamignon and Manière

1990; Clerke and Dull 1990; Volgelmann 1990; Ardö 1992). It is computed as the difference between near infrared (NIR) and red (R) spectral bands standardized by their summation (Townshend and Justice 1989). Theoretically, the NDVI results in a new image channel whose value can range from -1 to +1. By adding 1 to the ratio to avoid negative values, and multiplying the result by 128, the value range extends from 0 to 256 to make more effective use of an 8-bit dynamic range (Dagorne et al. 1990):

$$\mathbf{NDVI} = \left[\frac{(\mathbf{NIR} - \mathbf{R})}{(\mathbf{NIR} + \mathbf{R})} + 1\right] \times 128$$

The NDVI produces single values that are interpreted to indicate the relative amount of living, green vegetation within an area on the ground represented by a pixel, with high values assumed to indicate ground areas covered by substantial proportions of healthy green vegetation (Campbell 1987). Differences in NDVI values between two dates have been used as an indicator of change in the vegetative canopy (Singh 1989; Abednego and Collet 1992).

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Appendix 2. Residual mean square (RMS) errors in the pixel and line directions for the three image dates.

Image date	Image direction (RMS as proportion of 30 m LANDSAT TM cell)	
	Pixel (easting)	Line (northing)
July 20, 1984	0.32	0.37
August 11, 1986	0.25	0.52
August 30, 1987	0.34	0.31

Appendix 3. Descriptive statistics for light, moderate, and severe top-kill areas in 1984, 1986, and 1987.

Top kill	TM Band 1		TM Band 2		TM Band 3		TM Band 4		TM Band 5		TM Band 7		NDVI	
	$\bar{X}$[1]	S[1]	$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S	$\bar{X}$	S
Light														
1984	23.6	7.0	39.3	10.4	46.8	17.5	81.3	16.6	73.1	14.0	43.1	12.3	162.8	22.0
1986	23.5	7.7	35.4	9.5	37.2	12.4	76.9	15.4	72.5	13.3	40.3	11.0	172.2	18.8
1987	21.6	7.0	34.1	7.8	33.4	11.2	76.1	11.9	64.8	13.2	36.1	9.7	178.3	17.8
Moderate														
1984	21.8	6.7	37.6	9.4	42.3	15.1	84.0	13.6	72.5	13.3	41.7	11.3	170.9	20.1
1986	21.8	7.0	33.7	8.5	34.6	11.1	78.6	13.0	73.1	14.0	40.1	11.0	177.9	17.2
1987	19.8	6.7	32.0	7.2	30.6	10.6	76.3	11.6	65.8	13.9	36.4	9.8	183.2	18.6
Severe														
1984	22.6	6.1	38.6	8.4	44.7	14.4	82.2	12.4	74.0	11.6	43.0	9.9	166.4	20.5
1986	23.1	6.6	34.9	7.6	36.4	9.8	77.0	11.5	74.4	10.9	41.2	8.7	173.7	16.6
1987	21.5	6.9	33.5	7.4	33.1	10.5	75.7	10.6	67.5	11.8	37.9	8.6	178.1	19.3

[1] $\bar{X}$ = mean band value; S = standard deviation

Appendix 4.

Contingency tables used for calculating X^2 and Cramer's V for soil, site quality and stand attributes with severity of top kill.

Tables are presented for: Soil texture, Drainage, Site quality, Stand origin, Stand height, and Crown closure.

Soil texture contingency table

Severity of top kill	Attribute	Soil texture: Coarse	Soil texture: Mod. coarse - Mod. fine	Total
Nil	Area (km^2)	1.958	1.918	3.876
	Total %	5.508	5.394	10.90
	Expected %	10.18	0.725	10.90
Light	Area (km^2)	19.28	0.362	19.64
	Total %	54.23	1.018	55.24
	Expected %	51.57	3.674	55.24
Moderate	Area (km^2)	5.166	0.068	5.233
	Total %	14.53	0.190	14.72
	Expected %	13.74	0.979	14.72
Severe	Area (km^2)	6.786	0.017	6.803
	Total %	19.09	0.047	19.13
	Expected %	17.86	1.272	19.13
	Total area (km^2)	33.19	2.364	35.55
	Total %	93.35	6.650	100.0

Drainage contingency table

		Drainage			
Severity of top kill	Attribute	Rapid	Well	Mod. well	Total
Nil	Area (km^2)	1.959	0.057	1.859	3.876
	Total %	5.511	0.161	5.230	10.90
	Expected %	10.18	0.064	0.659	10.90
Light	Area (km^2)	19.28	0.125	0.233	19.64
	Total %	54.24	0.352	0.656	55.24
	Expected %	51.58	0.325	3.340	55.24
Moderate	Area (km^2)	5.167	0.026	0.040	5.233
	Total %	14.53	0.075	0.114	14.72
	Expected %	13.74	0.086	0.890	14.72
Severe	Area (km^2)	6.786	0.00	0.016	6.802
	Total %	19.09	0.00	0.046	19.13
	Expected %	17.86	0.112	1.157	19.13
	Total area (km^2)	33.19	0.209	2.149	35.55
	Total %	93.37	0.588	6.045	100.00

Site quality contingency table

Severity of top kill	Attribute	Site quality: Poor	Poor-moderate	Moderate	Moderate-good	Total
Nil	Area (km^2)	0.345	0.098	0.702	0.642	1.787
	Total %	1.035	0.294	2.106	1.926	5.361
	Expected (%)	3.748	0.488	0.881	0.243	5.361
Light	Area (km^2)	15.00	1.590	2.301	0.610	19.50
	Total %	44.99	4.770	6.902	1.830	58.50
	Expected (%)	40.90	5.330	9.610	2.655	58.50
Moderate	Area (km^2)	3.186	0.643	1.228	0.214	5.271
	Total %	9.558	1.929	3.683	0.642	15.81
	Expected (%)	11.06	1.441	2.598	0.718	15.81
Severe	Area (km^2)	4.779	0.706	1.246	0.047	6.778
	Total %	14.33	2.119	3.738	0.140	20.33
	Expected (%)	14.22	1.852	3.340	0.923	20.33
	Total area (km^2)	23.31	3.037	5.476	1.513	33.34
	Expected (%)	69.92	9.111	16.43	4.539	100.0

Stand origin contingency table

Severity of top kill	Attribute	Stand origin									
		115 yrs	105 yrs	95 yrs	85 yrs	65 yrs	55 yrs	45 yrs	35 yrs	25 yrs	Total
Nil	Area (km^2)	0.015	0.137	0.190	0.940	0.113	0.992	1.057	0.063	0.071	3.578
	Total %	0.040	0.400	0.557	2.753	0.330	2.904	3.096	0.184	0.208	10.48
	Expected %	0.005	0.047	1.577	2.429	0.353	3.836	1.655	0.530	0.043	10.48
Light	Area (km^2)	0.001	0.016	2.610	2.005	0.492	9.199	3.695	0.837	0.017	18.87
	Total %	0.003	0.048	7.643	5.870	1.442	26.94	10.82	2.453	0.051	55.27
	Expected %	0.026	0.248	8.320	12.81	1.863	20.24	8.729	2.798	0.229	55.27
Moderate	Area (km^2)	0.000	0.000	1.016	1.725	0.206	1.155	0.401	0.409	0.053	4.966
	Total %	0.000	0.000	2.976	5.051	0.604	3.383	1.173	1.197	0.155	14.54
	Expected %	0.007	0.065	2.189	3.372	0.490	5.325	2.297	0.736	0.067	14.54
Severe	Area (km^2)	0.000	0.000	1.324	3.249	0.340	1.161	0.241	0.419	0.000	6.734
	Total %	0.000	0.000	3.878	9.514	0.995	3.398	0.705	1.228	0.000	19.72
	Expected %	0.009	0.088	2.968	4.572	0.665	7.221	3.114	0.998	0.082	19.72
	Total area (km^2)	0.016	0.153	5.141	7.919	1.151	12.51	5.394	1.729	0.141	34.15
	Total %	0.047	0.449	15.05	23.19	3.371	36.62	15.79	5.062	0.414	100.0

Stand height contingency table

Severity of top kill	Attribute	Stand height: 5 m	10 m	15 m	20 m	25 m	Total
Nil	Area (km^2)	0.323	1.677	1.461	0.101	0.015	3.577
	Total %	0.946	4.911	4.278	0.296	0.04[illegible]	10.48
	Expected %	1.474	4.345	2.838	1.814	0.005	10.48
Light	Area (km^2)	3.457	9.606	3.653	2.157	0.001	18.87
	Total %	10.12	28.13	10.70	6.316	0.003	55.26
	Expected %	7.778	22.92	14.97	11.43	0.026	55.26
Moderate	Area (km^2)	0.495	1.588	1.347	1.535	0.000	4.966
	Total %	1.450	4.651	3.944	4.496	0.000	14.54
	Expected %	2.046	6.031	3.939	2.518	0.007	14.54
Severe	Area (km^2)	0.531	1.293	2.790	2.121	0.000	6.734
	Total %	1.554	3.786	8.168	6.210	0.000	19.72
	Expected %	2.775	8.178	5.341	3.415	0.009	19.72
	Total area (km^2)	4.806	14.16	9.251	5.914	0.016	34.15
	Total %	14.07	41.47	27.09	17.32	0.047	100.0

Crown closure contingency table

Severity of top kill	Attribute	Crown closure A (10-30 %)	B (30-55 %)	C (55-80 %)	D (80% +)	Total
Nil	Area (km^2)	0.353	0.930	1.626	0.668	3.577
	Total %	1.034	2.723	4.760	1.957	10.47
	Expected %	2.108	3.220	3.686	1.461	10.47
Light	Area (km^2)	3.047	5.617	6.694	3.515	18.87
	Total %	8.922	16.45	19.60	10.29	55.27
	Expected %	11.12	16.99	19.44	7.708	55.27
Moderate	Area (km^2)	1.559	1.611	1.494	0.301	4.966
	Total %	4.566	4.718	4.374	0.882	14.54
	Expected %	2.926	4.470	5.116	2.028	14.54
Severe	Area (km^2)	1.913	2.340	2.202	0.278	6.734
	Total %	5.603	6.852	6.449	0.815	19.72
	Expected %	3.968	6.062	6.938	2.750	19.72
	Total area (km^2)	6.873	10.50	12.02	4.763	34.15
	Total %	20.12	30.74	35.18	13.95	100.0

Appendix 5. Influence of spatial autocorrelation on the X^2 statistic and sampling procedures for rectification.

A possible problem in tests of significance for contingency tables is the occurrence of spatial autocorrelation, when sampling units are from a grid instead of being randomly selected (Dale et al. 1991). Spatial autocorrelation causes statistical tests to be too liberal, and results are often more significant than are justified (Dale et al. 1991). This effect can be observed with the extremely large value of the X^2 statistic (14145.65) in the contingency table that was compiled as an example for top kill with crown closure (Appendix 5 Table 1). The size of the study area is approximately 34 km^2 with the unclassified areas removed. In the SPANS Geographic Information System, the area was gridded at quad level 12 which resulted in a 12.3 m cell size. The map scale was 1:12,500, and this cell size is commensurate with a nominal 1 mm positional error often associated with digitizing, and represents the precision a map can generally be represented under (Burrough 1987). Thus, between top kill and crown closure, there was a total of 225,000 cells. Sampling all cells resulted in spatial autocorrelation effects that highly inflated the X^2 statistic. This value was substantially larger than the overly conservative approach implemented in this study that presented the contingency table as summations of cells (Appendix 4). This approach resulted in a X^2 value of 6.29 (Chapter 6 Table 6-2) that was not statistically significant when compared to the χ^2 table va[illegible]

The extremely large X^2 value suggests that significant associations would still occur if procedures were implemented for removal of spatial autocorrelation effects by random sampling. The following methodology presents one possible set of procedures:

1) In the SPANS Geographic Information System, generate a systematic grid of points with the model procedure:

   E Samgrid Generate sample grid of points
   { Num if class(map name) > 0}

   "Num" is a suitable value that will generate a high density of points if the class value of a map exceeds zero. For example, using an area of 44.17 km^2, a value of 0.00293 will generate a grid with approximately 15,000 points. This procedure will generate a point table file with Morton number, longitude, and latitude but no attributes.

2) Also, in SPANS, run the following procedure iteratively for each map layer to append map attributes to the point table file created in 1):

   Model Points / Append Class

   Note the column number and the name of the attribute that is being appended to the table file. When this process is completed, export the database to produce an ASCII file that may be imported to a text editor.

3) Import the table file to a text editor and strip off the header and geographic reference coordinates. Check the file to ensure unclassified cells whose value is 0 are not present in the file. Save this data file for import into a database program.

4) Using a program such as Dbase IV, create a database structure that matches the columns in the ASCII data file. The labels for the fields in the database should be available from the process undertaken in 2). Import the data to create a database file. Once this is done, add another field to contain the random numbers. For example, to create a field of random numbers in Dbase IV, a short program such as the following is required:

```
use cramer.dbf
* Compute random #'s from 1 to 15000
Do while .not. eof()
   num = rand()*15000
   replace random_num with num
skip
Enddo
```

5) With the database file complete with random numbers, extract out a random sample (eg. ⅓) into a new database file (eg. Sample.dbf):

Copy to Sample.dbf fields topkill, origin, site for random_num <= 5000

In this Sample.dbf file, run successive Count commands for each pair of attribute values to derive values for building the contingency tables:

eg. Count for topkill = 1 .and. origin = 1 (repeat for all attribute values)

6) With these numbers recorded, open a spreadsheet program such as Quattro Pro and input these values. Then compute Expected values, X^2 (Huntsberger and Billingsley 1989) and Cramer's V (Clark and Hosking 1986).

These procedures were tested by creating a small systematic sample of 1251 points. Approximately 25% of these points were randomly selected using the procedure outlined in step 4) to select points between 1 and 350. A contingency table was created and both the X^2 statistic and Cramer's V was computed for the 304 resulting points (Appendix 5, Table 2). Even with this small sample, the X^2 statistic was significant (Chapter 6, Table 6-2) when compared to the χ^2 table value (Table 6-2), and the difference in Cramer's V is small (0.16 [Appendix 5, Table 2] vs. 0.14 [Table 6-2]). These results imply that significant associations would still occur with a higher intensity of random sampling.

References

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Appendix 5 Table 1. Crown closure contingency table with cell freqencies.

Severity of top kill	Attribute	Crown closure A (10-30 %)	B (30-55 %)	C (55-80 %)	D (80% +)	Total
Nil	Cell count	2327	6128	10710	4404	23569
	Expected # cells	4743	7246	8293	3287	23569
Light	Cell count	20074	37009	44105	23159	124348
	Expected # cells	25025	38228	43752	17343	124348
Moderate	Cell count	10274	10617	9842	1985	32717
	Expected # cells	6584	10058	11512	4563	32717
Severe	Cell count	12606	15417	14510	1833	44366
	Expected # cells	8929	13639	15610	6188	44366
	Total # cells	45281	69171	79167	31382	225000
						Calculated X^2 = 14145.65

Appendix 5 Table 2. Crown closure contingency table with cell freqencies based on random sample.

		Crown closure				
Severity of top kill	Attribute	A (10-30 %)	B (30-55 %)	C (55-80 %)	D (80% +)	Total
Nil	Cell count	0	3	4	3	10
	Expected # cells	2	3	4	1	10
Light	Cell count	28	54	63	33	178
	Expected # cells	37	53	63	25	178
Moderate	Cell count	10	14	19	3	46
	Expected # cells	10	14	16	6	46
Severe	Cell count	25	20	22	3	70
	Expected # cells	15	21	25	10	70
	Total # cells	63	91	108	42	304
						Calc. $X^2 = 23.8$
						Cramer's V = 0.16