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MONITORING AND MAPPING EASTERN ONTARIO'S
1998 FOREST ICE STORM DAMAGE

by

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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 – Between January 4 – 9, 1998, a severe ice storm struck northeastern North America. Ice loading and high winds contributed to forest damage in Eastern Ontario, a region whose economy and identity depends on an intact forest resource for maple syrup production and other activities. This thesis was a component of a larger study by the Ontario Ministry of Natural Resources (OMNR) to address the needs of the maple syrup industry resulting from the ice storm, including temporal monitoring of forest response to damage to assess forest treatment effects, and mapping local to regional scale forest damage for economic impact assessment and compensation. This work is divided into two parts to address each of these needs separately. Part I uses field measured optical instrument-based Leaf Area Index (LAI) as a damage indicator for local monitoring, while Part II applies pre and post-storm Landsat satellite imagery and environmental data, and interpolation of plot-based damage estimates to produce two separate forest damage maps. LAI and post storm LAI change were determined to be suitable damage indicators, being significantly related to initial visual damage estimates while changing through time to reflect LAI recovery in the majority of plots that were measured. Neural network modeling with Landsat and environmental data was 69.3% accurate in classifying low-to-moderate and high damage with 50% crown loss as the threshold between these two classes. Interpolation produced slightly higher mapping accuracies, but lower Kappa statistics due to a reduced number of plots used for validation. These maps were compared with aerial sketch and freezing precipitation maps produced by the OMNR and Environment Canada, respectively. Overall, there was little agreement among maps due to the patchy nature of forest damage and differences among assessment scales.

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CH 1. INTRODUCTION

Between January 4 and 9, 1998 a severe ice storm deposited freezing rain across eastern Canada and the northeastern United States from the Muskoka region in Central Ontario to Kitchener in Southern Ontario and east to New Brunswick, including northern New York and New England States (Milton and Bourque, 1999). In many parts of the affected areas, it was the worst weather disaster in recorded history. While ice storms are one of the few regional scale natural disturbances responsible for tree mortality in northern temperate forests, the storm's large spatial extent, long duration and high rain and wind intensity set it apart from all previously recorded ice storms to have hit the region. In the most severely affected areas, which included much of Eastern Ontario and Western Quebec, freezing precipitation was between 40 and 100mm (Figure 1.1).

Figure 1.1. Freezing precipitation (mm) from the January 4-9, 1998 ice storm over Eastern Ontario/Western Quebec

Ice accumulation resulted in broken trees (Figure 1.2) and downed power lines, which contributed to further adverse impacts due to long-term power outages across large areas. Power failures persisted as trees broke from ice loading, taking down residential power lines and leading to heat and water shortages. These shortages resulted in significant losses of livestock for farmers who could not provide sufficient drinking water to herds of cattle and pigs. Additional complications arose due to restricted mobility from road closures and communication failures, which made it difficult or impossible to provide immediate assistance where it was needed most.

Figure 1.2. Broken trees near Ottawa in the spring following the 1998 ice storm

Ice storms are one of the few recurring regional scale natural phenomena in eastern temperate forests that are responsible for damaging trees. They generally occur with high frequency (every 20-100 years) in the eastern United States and the region from eastern Ontario to the Atlantic Provinces of Canada. However, a storm of the magnitude and

spatial extent of the 1998 ice storm is estimated to occur very infrequently with a return period of at least 500 years (Smith, 1998). Forest response and adaptation to such damage has not been rigorously studied over the long-term (Stabb, 1998).

Following the 1998 ice storm, the Ontario Ministry of Natural Resources (OMNR) embarked on a project designed to examine the potential to aid the recovery of sugar maple bushes managed for syrup production. A 'maple experiment' was designed, consisting of fertilizer and lime treatments over a range of sugar maple site and damage classes (Lautenschlager and Nielsen, 1999). In addition, in some unmanaged stands, herbicide treatments were applied. Response to treatments was evaluated from 1999 to 2001 in relation to damage. Specific components examined (Lautenschlager and Nielsen, 1999) included: 1. sap and root starch amounts and composition; 2. soils and foliar nutrition; 3. crown condition (Lautenschlager and Winters, 2001); 4. ground and understory vegetation composition and cover (Lautenschlager et al., in prep.); and 5. understory and overstory leaf area index (LAI) and LAI change (Olthof et al., 2001; Olthof et al., 2003).

1.1 Economic impacts of the 1998 ice storm on the forest industry in Eastern Ontario

The forest industry, which includes woodlots and plantations for lumber and maple bushes for syrup production, was adversely affected by the ice storm. Woodlots and plantations were severely damaged across the ice storm region, leading to estimated

economic losses of between \$21.2 and \$32.5 million for red pine plantations and approximately \$22 million for white cedar in Eastern Ontario (Heigh et al., 2003). Immediate losses were also experienced by the maple syrup industry, as approximately 12.5% of maple syrup taps were lost during the storm (Irland, 1998). Losses were compounded by mechanical damage to plastic tubing from broken branches and cleanup efforts and by limited accessibility to sugar bushes. As a consequence, overall syrup production in the spring of 1998 was significantly reduced (Chapeskie, 2000). Long-term economic losses for the Ontario maple syrup industry were expected to be between \$4.7 and \$7.1 million, depending on the time required for full recovery to pre-storm maple syrup production levels (Kidon et al., 2001).

Regional economic impacts were determined using the best information available immediately following the ice storm. Knowledge of the overall area affected by damage, the severity of damage and the expected time for full recovery were all key inputs into economic models. In Ontario, compensation was provided under the Canada-Ontario agreement for the Ice Storm Economic Recovery Assistance Program to assist individual producers for cleanup and long-term losses during the period of forest recovery. Considerable uncertainty existed in the spatial and temporal inputs to economic models, leading to wide ranging estimates of the overall economic impacts of the storm. The extent and severity of regional damage in Eastern Ontario was determined through visual assessment in an aerial survey at specific locations along transects spaced 5 km apart (Scarr et al., 2003) (Figure 1.3) and was difficult to validate. Additionally, the time required for full recovery was not known due to the unprecedented nature of the event

damage assessment of individual sugar bushes; 2. establishment of a baseline of damage from which recovery could be monitored; and 3. more exact measurement of ice storm damage for regional estimation of economic and ecological effects.

In addition to a lack of reliable information on the spatial distribution of ice storm damage, there was also a lack of reliable information in the literature on forest response to varying degrees of damage. Initial expert opinions ranged from expected widespread mortality to full recovery within a few years. The economic models used within the Canada-Ontario Assistance Program assigned a recovery period based on the amount of damage sustained. These models assumed light damage (<25% crown loss) would require a period of five years to fully recovery, moderate (26-50% crown loss), 10 years and severe (51%+ crown loss), 15 years (Kidon et al., 2001). More exact information on the time required for full recovery was needed to refine regional economic models and especially compensation for individual producers. Lessons learned and information gathered on the 1998 ice storm event will be used to assist in providing equitable compensation for future disturbance events.

The Ontario Ministry of Natural Resources (OMNR) addressed both spatial and temporal information needs as best as possible given time and resource constraints. More accurate and precise damage assessment methods are required to improve initial estimates and to provide better information for future disturbance events. The overall goal of this thesis is to develop methods for spatial and temporal measurement of forest structural damage that better our understanding of the processes and patterns of ice storm damage and recovery.

From a practical perspective, the methods were also intended to address the OMNR's present and future information needs by providing both a methodology for assessing impacts as well as information on immediate and longer-term effects that can be expected from severe disturbance events such as ice storms.

1.2 Forest ice storm damage information needs at various spatial and temporal scales

Following the 1998 ice storm, damage information was required at three spatial scales and two temporal scales (Table 1.1): local, landscape and regional spatial scales, and short -to-medium (within weeks until the end of the growing season following the event) and medium-to-longer-term (in subsequent years) temporal scales. Spatial scales typically include specification of resolution or grain and spatial extent or coverage. Local scale refers to the individual trees and forest canopy within a given stand that is representative of a patch. In this thesis, local scale field analysis was conducted within 148 individual maple plots, each occupying 2500 m² – or 0.25 ha and containing an estimated 80-160 trees. This scale is practical to sample the forest canopy for initial damage assessment and monitoring, and for calibrating models applied to landscape and regional scales.

Table 1.1. Definition of spatial and temporal scales of ice storm damage analysis			
Spatial		Temporal	
<i>Local</i>	Single damage assessment plot	<i>Short - medium</i>	Initial damage assessment following the event
<i>Landscape</i>	Single sugar bush	<i>Medium - long</i>	Subsequent assessments
<i>Regional</i>	Eastern Ontario		

Landscape scale refers to forest patches arranged in a landscape of spatial extent intermediate between local and regional scales. The spatial extent may be defined based on the limits of forest, watershed, habitat, or other characteristics. Landscape scale was to be assessed using airborne imagery to evaluate damage to individual sugar bushes occupying several hectares to several square kilometers, however these data were of poor quality (see Chapter 4 - Data). Regional scale refers to the mosaic of landscapes present over a large area. In this thesis, regional scale analysis included mapping of forest damage across Eastern Ontario using two different methods and 30 m grid spacing, corresponding to the spatial resolution of the Landsat TM sensor. Damage mapping was performed by interpolating between 2000 temporary sample plots (TSPs) visually assessed for damage, and separately using maple plots mentioned above and pre / post ice storm Landsat TM and environmental data. Details on the methods of plot sampling are given in Chapter 4.

In addition to the areal extent of the sampling unit, the distance between sample field plots is also relevant to the scale at which damage can be effectively mapped. In the case of maple plots, distance between neighbouring plots is both lower and higher than in the case of the TSPs. Details on the spatial distribution of plot sampling are included in Chapter 5. Maple plots are adjacent within blocks as replicates in a randomized design; however, the average distance between blocks is greater than for TSPs. The effect of clumping or spatial proximity on maple plot damage modeling accuracy is investigated in Chapter 7. Both modeling with Landsat and interpolation with a dispersed set of points

are calibrated (i.e. tied to physical ground measurements) using similar plot data acquired over a similar plot area.

Generation of a damage surface from point-based damage estimates is different in the case of TSPs and maple plots, as interpolation using TSPs only has discrete point data with no data between sample locations, while damage models derived from image and environmental data can be applied between sample locations using the data in each grid cell. Thus, differences among scales affect the application of each method for local, landscape and regional assessment. Regional interpolation is not useful for local to landscape-level assessment, because it does not capture the fine spatial variation in damage at that scale. Landsat TM scale reflectance captures local to landscape variation and thus may be useful for assessment at all scales considered.

Immediate and medium-term temporal scales are potentially useful for appraisal of damage resulting directly from the event itself and are the temporal scales at which the OMNR has focused most of its efforts. Medium-to long-term assessment is potentially useful for monitoring, which is performed at the local scale using instrument-based measurements of damage in Chapter 6. It is expected that repeat assessment done over the long-term will provide the best damage estimates, as multiple measurements will minimize bias and temporal trajectories of forest change may be exploited and related to damage. Burns (1999) stated that three to five years may be required to be able to ascertain the real levels of damage suffered from the 1998 event.

Local scale medium-to long-term assessment was performed using LAI as an indicator of forest productivity and damage. Reasons for using LAI instead of damage for this level of assessment include the lack of repeatability or reliability in tracking damage based on visual estimation through time. LAI is also an indicator of site productivity by integrating leaf area of all vertical layers in the canopy, whereas visual damage assessment focuses on the overstory only. Specific shortcomings of the use of visual damage estimation for monitoring purposes are discussed in Chapter 3. Landscape to regional scale assessment could have also been performed using LAI for consistency with the local scale, however, there were three main reasons why this approach was not pursued. The first reason is that LAI mapping with Landsat data has been researched and performed frequently (e.g. Chen and Cihlar, 1996; Franklin et al., 1997; Fernandes et al., 2001). Second, damage and LAI were not expected to produce an identical response in Landsat imagery, mainly due to mutual shadowing and physiological change caused by damage, as discussed in Chapter 5. Finally, the OMNR needed local to landscape damage information for reasons already stated, and because damage is a simpler concept to understand and communicate to stakeholders. Because of these apparent differences between local and landscape to regional scales, this thesis is separated into two major parts addressing different but complementary research questions: Part I: to assess local forest response to damage; and Part II: to map damage regionally.

1.3 Research Objectives

This thesis evaluates three methods of damage appraisal; each designed to meet certain medium-to long-term local to regional information needs outlined above. Each method is evaluated with respect to: 1. the accuracy with which damage is estimated relative to a reference measure; and 2. where methods have been determined to be accurate enough to provide useful damage information, the precision (or repeatability) of damage estimation.

The three methods are:

1. Plot-based assessment using optical field measures of canopy structure, such as LAI and clumping – to provide local, medium-to long-term information;
2. Assessment using satellite and available environmental geospatial data - to provide landscape to regional, medium-to long-term information, and
3. Assessment from interpolation of a large number of spatially extensive field-based visual estimates of damage to provide regional medium-term information.

1.4 Thesis Structure

Chapters are as follows; those that are published are referenced.

1. Introduction: provides background on the 1998 ice storm event and information needs that arose.

2. Status of the modern maple syrup industry: examines the evolution and current state of the maple syrup industry within a changing economic and demographic rural environment.

PART I : MONITORING FOREST RESPONSE TO DAMAGE

3. Theory, methods and field measurement of forest damage: discusses various field-based methods to measure damage directly and indirectly.

4. Leaf Area Index (LAI) for local, medium-to long-term damage assessment: from Olthof et al., (2001), and Olthof et al., (2003): evaluates overstory and understory LAI and LAI change as indicators of damage for forest condition assessment and monitoring.

PART II : REGIONAL DAMAGE MAPPING

5. Satellite remote sensing of forest damage: examines the effects of structural and physiological symptoms of damage on above-canopy reflectance.

6. Mapping deciduous forest ice storm damage using Landsat and environmental data: from Olthof et al. (2004): examines damage mapping error associated with reference data selection due to the effects of random sampling and spatial autocorrelation. A damage map is produced using the best classifier and assessed with the most representative validation data obtained from these analyses.

7. Forest damage mapping using interpolation of Temporary Sample Point (TSP) damage estimates: compares interpolation mapping methods and rigorously assesses damage map produced.

8. Comparative evaluation of damage mapping results: compares maps produced from

Chapters 7 and 8, discusses innovative aspects of thesis, limitations and recommendations.

9. Conclusions

10. References

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Olthof I., D.J. King and R.A. Lautenschlager (2004). Mapping deciduous forest ice storm damage using Landsat and environmental data. *Remote Sensing of Environment*, 89: 484-496.

CH 2. STATUS OF THE MODERN MAPLE SYRUP INDUSTRY

2.1 Introduction

This research was conducted within the context of OMNR information needs for improved response and management of sugar maple to reduce adverse impacts of future ice storm events. The research formed one component of the Canada-Ontario Ice Storm Economic Recovery Assistance Program and was therefore of importance to the maple syrup industry. To lay a foundation for the development of the research, this chapter presents a discussion of some key aspects of the human-environment interactions that describe the development of the industry and its current condition.

First, the biogeography of sugar maple (*acer saccharum*) will be discussed, since it determines the area and extent of maple syrup production. Second, the historical, cultural and economic significance of the maple syrup industry are presented within the context of a historically changing rural landscape in Canada. Third, background biotic and abiotic sugar maple stressors, determined from research on widespread sugar maple decline observed through the 1980s and early 1990s, are discussed as potential threats to maple tree health, generally measured using transparency and chlorosis as indicators of crown condition. Fourth, factors that affect susceptibility of trees to ice storm damage are presented to help better understand the nature and distribution of damage across a landscape or region. Finally, in order to link sugar maple damage to potential losses in

sap production and revenues, factors that affect maple syrup production, including damage, are discussed.

2.2 Biogeography of sugar maple

The sugar maple is a dominant late successional species in northeastern hardwood forests, making up about 20-25% of volume in northeastern United States (USDA, 1999) and southeastern Canada (Robitaille, 1986) forests. Sugar maple occurs throughout the East except for the southern Piedmont and Coastal Plain. In Canada, its range extends from the southern tip of Lake Erie to northwest of Lake Superior, and as far northeast as the Gaspé Peninsula on the Atlantic coast of Quebec and east to Nova Scotia. The southern range limit is Arkansas and Georgia in the United States (Young, 1993).

Sugar maple is a very shade tolerant species, allowing it to dominate many sites. Generally, they reach the upper canopy through a series of suppressed growth periods during high canopy closure, with intermittent release periods when gaps form following disturbance (Houle and Payette, 1991). Sugar maples occur naturally in large populations, and naturally sustain population regeneration. They typically achieve reproductive maturity between 30 and 60 years of age in forest conditions and may live to 250-300 years, with certain individuals reaching up to 400 years (Loehle, 1988). Sugar maple is self-compatible, however seed from self-flowered trees tend to be quite poor. Wind is the primary means of pollination, though insects also contribute (Young, 1993). Seeds are auto rotating and wind dispersed (Houle and Payette, 1991).

Sugar maple occurs naturally in hardwood forests in association with yellow birch (*betula alleghaniensis*), American beech (*fagus grandifolia*), American basswood (*tilia americana*), white ash (*fraxinus americana*), red maple (*acer rubrum*), red oak (*quercus rubra*), black cherry (*prunus serotina*), balsam fir (*abies balsamea*) and a few other hardwood and softwood species. Because of its range, harvesting is naturally viable for both extraction of the wood resource, and clearing of forested land for alternative land use. Timberlands have been devastated by improper cutting, management practices and biotic and abiotic stressors to a point where in 1986, production of quality wood in northeastern hardwood forests was estimated to have dropped to less than 50% of its maximum potential (Robitaille, 1986).

2.3 Significance of maple syrup production and industry

2.3.1. Economic significance of maple syrup production

Quebec is the largest sugar maple producing region in the world, accounting for 74% of production in Canada in 1998, and consistently between 60-70% of world production. Other significant producing regions include Ontario, Nova Scotia, New Brunswick, which together accounted for 8% of global production in 1998, and the northeastern States in the U.S., which accounted for 18% (Quebec statistics bureau and USDA Agricultural statistics). In Quebec alone, the sugar maple industry is represented by more than 10,000 producers who produced more than 18 million litres of maple syrup in 1998.

In 1991, the sugar maple industry in Canada generated more than \$70.8 million in annual farm revenues, mainly in areas where agriculture plays a marginal role (Lachance et al., 1995). The industry therefore helps to stabilize rural economies by helping support rural populations and their forestry activities (Robitaille, 1986). In Eastern Ontario, the industry is made up of roughly 2,000 official producers who generate approximately \$11 million annually in revenues (Kidon et al., 2001). The real economic significance of maple syrup production is difficult to quantify, since revenues only include official producers who are registered with the government and who declare income from syrup production. Unofficial producers likely far outnumber official producers but operate on a smaller scale. Economic benefits from maple syrup are also difficult to precisely quantify because of other economic benefits derived from syrup production, such as tourism, as discussed below.

2.3.2. Social and cultural significance

Sugar maple is one of the most prized tree species in North America. It is valued commercially for its timber, which is used for furniture, flooring, paneling, veneer and plywood (Hosie, 1990) and for its sap that is boiled to produce maple syrup and maple sugar. Its spectacular fall colouration attracts tourists to remote rural communities where it can be appreciated. Natives used the sugar maple before colonialists settled in eastern North America. As a tree that helped shape both native and colonial cultures, the sugar maple is prized for much more than just its commercial value and has become a national symbol of Canada.

The sugar maple leaf first became a Canadian national symbol more than 300 years ago when settlers observed natives making maple sugar. One of the earliest recorded descriptions of their method of extracting maple syrup was published in the 'Philosophical Transactions of the Royal Society', London, England in 1684 (Hosie, 1990). Exactly 150 years later, the first St. Jean Baptiste society made the maple leaf its symbol. By 1848, the Toronto literary annual 'The Maple Leaf' had referred to the maple leaf as Canada's national emblem. Between 1876 and 1901, the maple leaf appeared on all Canadian coins and remains on the penny today, virtually unchanged since 1937. Canada's new flag was proclaimed in 1965, ensuring that the maple leaf will remain as this nation's most enduring symbol (Heritage Canada, 1995).

The cultural significance of the sugar maple is due in large part to the role that maple sugar played during settlement. Maple sugar was a valued commodity because it provided calories and nutrition after the winter when other food sources were often scarce. The energy from maple sugar enabled arduous and necessary work to be done, as land needed to be cleared of trees and rocks before fields could be planted. Maple sugar also kept reasonably well and was easy to store, allowing its benefits to be reaped throughout the year.

'Sugaring', or the activity of sap collection and transformation into sugar also helped shape Canadian culture. Entire families partook because it was an extremely labour intensive endeavor. Though often difficult, the changing weather lifted spirits and helped

to make sugaring more bearable. The rewards were enjoyed immediately, as maple products of all kinds were shared during long days, and sometimes nights spent in the bush finishing the day's work.

The sugar maple is also significant to many states in the North Eastern United States. Vermont, perhaps more than any other region in North America, markets itself as a maple syrup producing region. Pure Vermont Maple Syrup is a widely recognized name brand, appearing on all maple syrup produced in the state. The purity of Vermont maple syrup is enhanced by the image that Vermont portrays through its tourism marketing as 'The Green Mountain State': a region that is still largely untouched by modern human influences. This image of Vermont attracts millions of tourists each year, who come for activities such as the three-day maple festival held in Franklin County each April.

The significance of maple syrup production to the identity of a large region spanning across the Canada-US border defies its small economic importance as maple syrup income accounted for only 1% of Canadian farm revenues in 1998 (Statistics Canada, 2000). However, in certain isolated rural areas where traditional employment sectors have declined, maple syrup production and related tourism may continue to be economically significant in the absence of alternative means of subsistence.

2.4 Historical changes to Canadian rural economies and demographics

Changes in rural Eastern Canada during the last half century have helped shape the modern maple syrup industry. Since 1941, farm population has decreased by 60% in Quebec, 44% in Ontario and 83% in New Brunswick while the population of Canada tripled during the same period (Statistics Canada, 2000). While the total rural population remained relatively constant at about 5 million people from 1941 to 1971 (by 1991, only 33 percent of Canada's population lived in predominantly rural regions), the main employment sectors in rural regions changed. In 1941, 59% of the rural population lived on operational farms, decreasing to just 18% in 1976. Other significant sectors for rural economies have also changed. The forestry sector directly employed 1 in 45 people in the work force in 1941, and only 1 in 116 in 1971. The other major employer in rural areas, mining, employed 1 in 45 in 1945, decreasing to 1 in 62 thirty years later (Statistics Canada, 2000).

This shift in employment in rural areas from the traditional sectors of agriculture, mining and forestry towards other, more diverse sectors is evident from these statistics. By 1991, only 11 percent of the rural workforce in Canada was working in agriculture, forestry or fishing. While employment in traditional sectors decreased in the last 50 years, overall employment was increasing. In the 1980s, rural employment growth averaged 1.3% per year. Employment growth in rural areas was below that of urban areas, though employment growth in certain rural regions exceeded urban employment growth. These

regions of high employment growth tended to be located close to metropolitan areas (Statistics Canada, 2000).

The transformation of rural areas resulting from the decline of many traditional resource sectors has produced a need for diversification of rural economies. At the same time, rural areas have become much more accessible to tourists, while the need for outdoor recreation of urban populations living in denser quarters has increased. Combined, these changes have resulted in a flood of tourists from urban centres into rural areas and the emergence of new economic opportunities for rural inhabitants.

With the emergence of rural tourism, many maple syrup producers have reverted their operations to the traditional sugaring methods practiced nearly one hundred years ago to cater to the tourist experience. Rural tourists want to see and experience the setting that is portrayed on virtually all maple products sold. This setting includes buckets, horse-drawn sleighs and wood burning stoves used for traditional methods of sap collection and transformation. Correspondence between this rustic image of rural lifestyle and the reality that the tourist sees is necessary for the producer to succeed in selling both the experience and associated maple products. The aesthetic qualities of the rural setting are therefore paramount to its success in attracting tourists. This contrasts with modern industrial maple syrup production, which uses stainless steel fixtures and plastic tubing. Industrial production is not attractive to most tourists, however, most traditional sugarhouse operations must rely on sap or syrup from industrial processing (Hinrichs, 1995).

The diversification in the maple syrup industry from a focus on syrup production to one that encompasses both production and tourism has led to changes in sugar bush management and operations. Large sugar shacks have been built to accommodate tourists who often arrive by the busload from nearby cities. Tourists are treated to an excursion by horse drawn sleigh into the maple bush to see for themselves what traditional tapping looks like. Sap is boiled over a wood fire for the tourist to see and to experience toffee made by pouring hot syrup on the snow. Traditional meals of beans, bacon, pancakes and syrup are served. In these types of operations and where excursions are made in the sugar bush, management must focus on its aesthetic qualities. The successful operator must manage the sugar bush to maximize its productive capacity wherever tourists are not taken.

While the industry has undergone significant change in the last 140 years, much of the character of maple syrup production has remained due to the enduring aspects that make it unique. In an industry that is very sensitive to the natural environment, biophysical changes may have adverse impacts on the industry as a whole. Many of these changes are linked to natural disturbance, the effects of which may be exacerbated by human activity.

2.5 Sugar maple decline

Sugar maple decline was widely observed through much of eastern North America in the 1980s and early 1990s. Maple decline had been observed on a number of separate occasions in Ontario between 1947 and 1985, and had been attributed to a number of

biotic and abiotic causes (McIlveen et al., 1986). The most recent occurrence of maple dieback was thought to be much more intensive and widespread than previous observations, and it was suspected that for the first time, airborne pollutants from human activity contributed significantly (Lachance et al., 1995).

There are a variety of symptoms that characterize sugar maple decline, including leaf discolouration (chlorosis) and deterioration of the crown. Dieback of an individual crown usually begins with the outermost and uppermost buds and twigs, and progresses inward and downward. The leaves of a declining tree may be small and chlorotic, and may appear clumped. Growth of the tree sometimes slows before external symptoms are visible (Houston, 1998).

The most recent and widespread observation of sugar maple decline in the early 1980s led to a number of collaborative efforts to study its causes and effects. The North American Sugar Maple Project was one such effort, and included members from the Canadian Forest Service, Natural Resources Canada and the United States Department of Agriculture and Forest Service. The project monitored changes in crown condition (transparency and chlorosis) of sugar maple between 1988 and 1993 across most of its natural range at 233 sites in eastern North America. The Canadian Forest Service published results on the condition of sugar maple in the 62 sites in Canada in 1995 (Lachance et al., 1995).

According to this published report, there was an improvement nationally in sugar maple crown condition between 1988 and 1993 (Lachance et al., 1995). While none of the changes in crown condition in any region were significant, improvements in maple condition in Quebec and some of Ontario were noted in particular. Transparency decreased in these regions, most of which were severely affected by drought in the early 1990s.

No significant relation between pollution and crown condition was noticed, though a slight trend of higher levels of crown transparency was observed in areas of highest deposition, especially for nitrates. Other stress agents, including drought, insect defoliation and soil properties had a greater effect on crown condition, and may have influenced maple health synergistically with pollution. Dieback was slightly higher in stands managed for sap collection, though not significantly. Increased dieback in productive stands was attributed to frequent incursions into these sugar bushes causing increased soil compaction and tree wounding from thinning and tapping (Lachance et al., 1995). This study identified the two major sources of sugar maple stress that may contribute to decline: 1. biotic stressors, including insect defoliators, fungi and other pathogens; and 2. abiotic stressors, which include climatic and human disturbances.

2.5.1. Biotic stresses

There are more than 150 insect defoliators that feed on sugar maple, about 12 of which have the ability to cause significant and widespread damage. At any location across its

natural range, at least one of these 12 defoliators has the potential to affect sugar maple health. Many of these insects follow natural cycles of population increases, causing major adverse effects on forest condition locally, followed by population decreases. Outbreaks of forest tent caterpillar, for example, seem to occur about every seven years on average, and can last 2 to 3 years if extreme (Houston, 1998).

2.5.2. Abiotic stresses

2.5.2.1. Pollution

Human activities have introduced pollutants into the environment that are suspected to have contributed to sugar maple decline in North America in the 1980s and early 1990s. Acid rain and ozone are two major pollutants that have been identified as potential contributors to maple decline. Controlled experiments have been conducted to study the effects of these pollutants on maple seedling form and vigour.

In a study simulating the effects of acid rain deposition on maple seedlings, Dixon et al., (1995) found no significant treatment differences in seedling height, seedling diameter, foliar pigments, or photosynthetic rates. Similar results were obtained by Lawrence and David, (1996), who found that ozone and simulated acid precipitation caused few and minor effects on sugar maple trees over a three-year period. In the latter study, the authors pointed out that although they did not observe adverse effects of pollutants over the course of the experiment, sugar maple might respond adversely to exposure over a

significant part of its life. Other researchers have attempted to observe natural forest dieback as a function of atmospheric pollutants, only to find that decline is often too variable to attribute to airborne pollution alone (McIlveen, 1992).

2.5.2.2. Climate

Though sugar maple can tolerate a wide range of climatic conditions (Hosie, 1990), it can suffer from drought, soil freezing and frost. Maple decline in Quebec and eastern Ontario was largely attributed to drought in the late 1980s and early 1990s (Lachance et al., 1995). Similarly, soil moisture shortages and attacks by secondary organisms were partly responsible for dieback in northern New York State in the 1950s (Houston, 1998). Acute stress from a severe climatic event is more likely to begin decline rather than background levels of stress from pollution or other subtle stressors (Auclair et al., 1996).

Climatic factors contributing to maple decline were once thought to be unaffected by human activity. However, evidence is suggesting that extreme climatic events like the 1998 ice storm are becoming more frequent and may be attributable to climate change induced by global warming.

As winters become warmer due to climate change, temperatures close to the freezing level are likely to occur more frequently during winter months in southern Canada. Furthermore, results from climate models generally agree that the flow of moisture

into southern Canada, and the resulting precipitation, will increase in winter seasons. These factors suggest that the frequency of ice storms could increase as climate warms. The effect on the intensity of such storms is still unknown (Environment Canada, 1998).

2.6 Factors that affect tree susceptibility to ice storm damage

The overall impacts of a natural disturbance such as an ice storm are related to the severity of the event, while tree resistance to ice loading and mechanical breakage also controls local impacts. There are a number of factors that affect a tree's susceptibility to ice storm damage, including tree and landscape characteristics. Damage is usually patchy, due primarily to numerous geographic and climatic factors that affect the distribution of precipitation and trees across the landscape. Elevation differences, proximity to water bodies, inclination and aspect of slope, composition of the ground surface and direction and velocity of wind are factors that have been identified as contributors to the spatial heterogeneity of ice storm damage (Van Dyke, 1999). Climatic and geographic factors also affect tree susceptibility to damage by influencing the species and form of trees that grow on a particular site.

Tree form includes factors such as crown size, branch angle and structure. Tree form is dependent upon species, age and site. Trees on northern and eastern slopes, where microclimate is colder, are generally more prone to damage. Trees on steeper slopes are

also more susceptible due to their asymmetrical crowns caused by topography and surrounding trees. Trees that grow in the open or along edges tend to be more prone to breakage, due to their uneven crown form, exposure to wind and other climatic stresses (Van Dyke, 1999).

Proulx and Greene (2001) found that tree position within a woodlot did not affect the magnitude of damage sustained based on a qualitative damage index, but did affect the type of damage sustained. They noted that trees along forest edges tended to bend in an outward direction from the forest, while those trees in the forest tended to break. They speculated that the bending of trees in an outward direction was attributed to their asymmetrical crown structure, and the fact that they bent rather than broke to their age. The authors also showed that the magnitude of ice accumulation was the primary determinant of tree damage and that tree size was the primary determinant of damage type.

Tree species affects tree form and susceptibility to damage as well. Crown exposure, branching structure and branch size all affect the amount of ice accumulation on an individual crown. Compact crowns tend to accumulate less ice than broad crowns, making conifers generally less susceptible to damage than deciduous trees. Early successional species are more prone to damage than climax species due to their excurrent form (trunk that extends to the top of the crown) that changes to decurrent form (branching with acute angles) as they mature. The horizontal and opposing branching structure of excurrent forms tend to load more heavily with ice.

Overall crown surface area also plays a role in ice accumulation. Trees with finer branching structure have greater surface area for accumulation per tree volume than trees with coarser branches. Older trees tend to be more prone to breakage due to increased crown size, decay, disease and less flexible branches than younger trees. Trees in the upper canopy suffer most due to exposure and crown size. Wood strength does not seem to play a significant role in a species' susceptibility to damage.

Given these factors affecting species' susceptibility to damage, sugar maples have been classified as intermediate to highly susceptible to damage from ice loading (Van Dyke, 1999; Hauer et al., 1994). Figure 2.1 shows tree characteristics that affect susceptibility to damage from ice loading.

Figure 2.1. Tree characteristics that affect susceptibility to ice storm damage: tree at left – low susceptibility, right – high susceptibility. (Hauer et al., 1994).

2.7 Factors that affect maple syrup production

2.7.1. Climate

Climate plays an important role in determining how much maple syrup a tree will produce because it governs the timing and duration of sap production. Strong sap production only occurs during the springtime when daytime high temperatures exceed the freezing mark, and nighttime lows fall below freezing (Noland, 1999). Longer-term production will be maximized if tree growth rates are high, since the number of potential taps per tree is determined by tree diameter. Higher growth rates also imply increased photosynthetic production, which governs the amount and sweetness of sap. While climate is a major determinant of sap production, it cannot be managed. However, microclimate can to some degree. Sugar maple trees on south to west facing aspects are most desirable in order to maximize photosynthetic capacity and therefore sap production (Houston et al., 1998).

2.7.2. Tree form

Both sap quantity and sap sweetness govern the overall amount of syrup that can be produced by a sugar maple stand. Generally, fast growing and vigorous trees with large crowns are most desirable for maximizing syrup production. Both the volume and sugar concentration of sap are related to crown depth, density and height. Trees with live crown ratios between 50 to 75% of their total height yield about 25% more sap than similar size

trees with live crown ratios of less than 50% (Coons, 1999). Trees that grow more than 2.5cm in diameter every 2 to 5 years will yield up to 30% more sap than those that grow the same amount every 7 to 10 years. Of trees of similar stem diameter, those with 50 percent larger crown diameters will produce twice as much sap (Coons, 1999; Houston, 1998). Trees with deeper crowns also produce more sap (Houston et al., 1998). Thus, trees with more leaf area per crown, spread over a large crown diameter and height will accumulate and store more energy reserves during the summer months. A portion of these reserves, estimated at about 10% of a tree's total reserves (Coons, 1999), provides sap the following spring. Unfortunately, crown form that favours sap production is also more susceptible to ice storm damage than a less productive and compact crown.

2.7.3. Structural damage

Any tree injury, including injury from drilling tapholes, will produce a physiological response in the tree. Resources normally used for maintenance of the tree are re-allocated to the damaged area to serve a protective function (Coons, 1999). The concept of compartmentalization allows an understanding of the response mechanisms of trees to injury.

Compartmentalization is the process of 'walling off' wounded areas to protect the tree from the spread of defects, infection and decay. These wounded areas trigger a chemical response in the tree that causes wood discolouration or stain (Smith and Shortle, 1998).

Discolouration reduces the value of wood for timber, and stained areas do not produce sap.

Defoliation due to the structural damage of crowns will affect the ability of the tree to acquire and store energy reserves. Defoliation in the summer may seriously reduce sap production the following spring. If a tree has some reserves, it will convert these to sugar as soon as the weather permits, depleting the reserves for other physiological functions (Coons, 1999).

The response of trees to mechanical damage can be understood in terms of resource allocation. The tree can store a certain amount of starch reserves depending on its crown volume or photosynthetic capacity. Energy that is not used for maintenance, growth, reproduction and repair in the growing season is stored as starch in the root mass. When the weather conditions are suitable for leaf-out the following spring, starch reserves are converted to sugar. Damage has two effects on tree physiology that can reduce sap production. First, it reduces the photosynthetic capacity of the tree, and therefore the total amount of energy available for storage. Second, energy reserves are diverted to compartmentalize the injury to reduce the risk of further damage. These two effects reduce the amount of starch reserves, and therefore, the amount and sweetness of sap.

Few studies have documented specific effects of damage on sap production and sweetness. Wargo et al. (1972) measured significantly reduced fall root starch levels caused by recent sugar maple defoliation. Kolb et al. (1992) reported reduced root total

non-structural carbohydrates (TNC) levels, sap production and sweetness the spring following insect defoliation, and continuing one year after the defoliation event for the most severely affected trees. Noland (2003), monitored root starch, sap sweetness, sap production and syrup production in sugar bushes of varying damage across Eastern Ontario in three consecutive years following the 1998 ice storm event. He found that severely damaged trees with more than 50% crown loss resulting from the ice storm generally had reduced root starch concentrations. Syrup production was also reduced in damaged trees in all three years, and most consistently in severely damaged trees with greater than 50% crown loss.

The effects of damage on syrup production may be subtle due to numerous other factors that also control syrup production. However, the effects of damage on syrup production from a sugar bush may also be considered in terms of probability of tree mortality. Below 50% crown loss, trees generally have a high to moderate chance of survival depending on tree vigour prior to the event, while trees that suffer more than 50% crown loss will have varying chances of survival from moderate to low with expected internal infection and / or growth suppression (Coons, 1999; QMNR, 2000). Fifty percent crown loss has often been used as a threshold to distinguish between trees that are expected to suffer little to no effects from damage, from trees that are expected to decline further and experience reduced syrup production levels.

2.8 Conclusions

The sugar maple is one of the most highly prized tree species in North America for its economic value, but perhaps more so for the role it played during early settlement, which has led to its significant cultural value. Several factors have been identified that threaten maple health and the industry that relies upon it. Rural changes have brought about a decrease in the Canadian rural population. This, combined with increasing industrialization of maple syrup production, has led to a decline in the number of people who practice 'sugaring'. Additional threats to the industry include sugar maple decline, which is periodic but seems to be caused by a number of natural biotic and abiotic stress factors, coupled with human pollution thought to be at least partly responsible for the most recent and widespread episode in the late 1980s and early 1990s. These factors, as well as management that selects for certain tree characteristics that maximize productive capacity, predispose sugar maples to mechanical damage caused by disturbance. Tree forms that maximize crown volume, especially from lateral branch growth, tend to produce more sap than narrow trees with small crown volumes because of their greater leaf area and productive capacity. Lateral and fine branch structures of productive trees tend to load more heavily with ice and are therefore more susceptible to breakage from ice and wind. The effects of damage on sap production are not always clear because of numerous other factors that also contribute. Several studies have documented decreased sap production levels for high levels of damage at the individual tree level. Other studies

have linked crown loss due to mechanical damage to increased probability of mortality, thereby causing decreased sap production at the stand level.

PART I : MONITORING FOREST RESPONSE TO DAMAGE

CH 3. THEORY, METHODS AND FIELD MEASUREMENT OF FOREST DAMAGE

3.1 Introduction

This chapter reviews methods to characterize forest damage in the field, and to model damage at regional scales using satellite optical remote sensing. Because forest damage resulting from a sudden disturbance event such as an ice storm produces short-term changes in forest structure, emphasis will be placed on structural indicators of damage. Reviews of methods to characterize forest structure and canopy architecture in the field already exist (Welles, 1990; Norman and Campbell, 1991; Chen et al., 1997a) and will be overviewed in this chapter with emphasis on indirect field-based optical methods.

3.2 Definitions: forest structure and structural damage

3.2.1. Forest structure

The terms forest structure, canopy structure and canopy architecture are often used interchangeably, though forest structure may include stem measurements in addition to canopy parameters. Canopy structure has been defined as the size, shape, orientation and positional distributions of various plant organs such as leaves, stems, branches, flowers

and fruits (Norman and Campbell, 1991). Alteration of forest structure by disturbance that causes plant tissues to be removed is referred to as structural damage. A full quantitative survey of structural parameters in a forest by direct measurement is impossible, and therefore they are often described qualitatively. Where a more rigorous and quantitative description of forest structure is required, statistics are used to explain the quantity and spatial arrangement of plant organs.

Treatment of forest structure in a quantitative manner allows the use of mathematics to infer structure from easily measurable forest characteristics such as light transmittance or basal area. Relations between measured forest characteristics and forest structure are derived through either physical (Chen and Cihlar, 1995) or statistical (allometric) models (Gower et al., 1997). Quantitative measurement of forest structure enables more precision and repeatability and facilitates scaling to an arbitrary level, from tree to stand for example, by adding individual tree measurements for the number of trees in the stand.

Environmental scientists and forest managers require spatially extensive descriptions of forest structure. Forest structure varies across space, affecting gas and energy exchanges between vegetation and the atmosphere by influencing surface radiation interception, precipitation interception, evapotranspiration, productivity and turbulent transport (Welles and Norman, 1991). Spatial information on structure is also needed by forest managers to inventory forest quantity and quality for wood production.

As forest structure describes the size, shape and position of plant organs, it is largely associated with the spatial configuration of the forest. Canopy spatial indicators derived through field measurement or remote sensing can be employed to characterize its configuration and have been shown to be useful for quantifying forest structure (Chen and Cihlar, 1995; Wulder et al., 1996; Olthof and King, 1997; Olthof and King, 2000; Cosmopoulos and King, 2004). These measures can explain structure at a variety of scales from the assemblage of leaves on a branch to the arrangement of branches on a tree and the configuration of trees within the stand. An example index employed in this research is 'clumping', which has been used to describe spatial arrangement at these scales (Chen and Cihlar, 1995; Van Gardingen et al., 1999), with higher clumping referring to more irregular and grouped structures, and lower clumping representing more even or random arrangements.

3.2.2. Forest structural damage

Forest structural damage may be defined as changes in forest structure resulting from either: 1) biotic or abiotic stress agents including insect, disease or age causing physiological stress and / or natural decline; or 2) a sudden catastrophic event such as fire or extreme weather. These changes can occur at scales from individual leaves to entire forest canopies depending on the spatial and temporal scale at which the stress or damage agent operates. For example, sudden catastrophic weather events such as wind or ice storms cause branches to break and trees to topple. In contrast, many types of insect damage cause defoliation in the short term that may lead to more extensive structural

damage due to declining forest health in the longer term. Though considerable overlap exists between damage and health, their symptoms are not identical.

Forest health generally considers stress and damage effects on forest structure and function by integrating measurement of both morphological (structural) and physiological (functional) indicators (OMNR, 1997; Sampson et al., 2000). Physiological decline or impairment is often referred to as tree (physiological) stress. Stress can be measured as changes in leaf reflectance indicating actual damage from the stress factor and the active response of the tree to the stress (Stone, 1998). Though damaged trees often exhibit leaf discoloration due to stress, the residual crown left after a tree has suffered damage may be quite vigorous due to active partitioning of the wound (Coons, 1999). Thus, a crown may be healthy from a physiological perspective in spite of structural loss suffered from a damage event. In this thesis, damage only refers to structural changes of the forest caused by a damage agent, and not physiological stress. Symptoms of physiological stress are only considered for ways in which they may complement, or confuse structural indicators of damage.

Structural damage predisposes trees to further injury because exposed wounds compromise the forest's ability to resist additional stress agents. Stress resistance is diminished through two mechanisms that may act synergistically. First, maintenance, growth and repair are reduced because energy must be re-allocated to compartmentalize damaged limbs (Coons, 1999). Second, additional stress agents such as insects, pathogens, stain, disease and decay may enter into the cambium through open wounds

(Houston, 1998). The degree of structural damage sustained, the level of external stress and the ability of trees to cope with stress will dictate whether a forest is in decline or recovery following a damage event.

Structural damage does not necessarily imply declining forest health, since it typically represents a natural transition from old growth to new growth. For example, fire started by a lightning strike must be recognized as a disturbance event that is necessary for renewal, and thus long-term sustainability of many ecosystems. Therefore, damage, decline or disturbance events should be considered relative to what is normal in an ecological context and history. With this view of damage, fire and other natural events only become damaging agents when their size and/or frequency increase relative to their natural disturbance cycle. Whether one wishes to consider natural disturbance as a damaging event depends on one's perspective. For example, if the primary concern is wood production, then one may consider a naturally declining over-mature forest to be damaged. Where the user must consider a broader set of forest values, then natural disturbance should be excluded as a damaging agent. Thus, damage is a value-laden term whose definition depends on its use.

Increased disturbance size or frequency beyond a natural and established ecological cycle implies that an external stress factor is adversely affecting forest health through changes to the growth conditions of the forest. The external stress factor may be pollution or site modification and is often anthropogenic in origin. As an example of pollution, contamination from mining may cause forest health to decline because of altered soil and

site characteristics that become unsuitable for forest growth (Olthof and King, 2000). Site modification encompasses everything that produces changes to the environmental growth conditions of the forest, including pollution, forest fragmentation and climate change. The level and duration of external stress dictates a site's characteristics and the level of vegetative growth (productivity), if any, that it can support. Thus, decline may be temporary as site characteristics change and a new, less productive equilibrium is reached between a site's potential to support growth and actual productivity.

3.2.3. Damage as pre/post disturbance change

Forest damage will result in structure and growth that deviates from that of a healthy stand. Monitoring temporal changes in forest structure provides a useful diagnostic tool for assessing departures from the expected development of an undamaged stand (OMNR, 1997). In order to measure the difference between expected (undisturbed) and measured forest structural development related to the amount of damage sustained, an estimate of pre-disturbance forest structure - such as crown volume - is required. This approach uses pre-post disturbance change to quantify damage as the difference between intact, undisturbed structure and structure altered by the event. Alternatively, damage may be reliably measured without reference to a pre-disturbance condition provided that structure is relatively homogeneous throughout the assessment area before disturbance, and that the damaged area is smaller than the total area so that there is some undamaged forest for comparison. Such measurements may include the number of broken branches (Pellikka et

al., 2000; Lautenschlager and Winters, 2001) or the volume of downed woody debris (Battaglia et al., 1999; King et al., 2004).

3.3 Measuring forest damage using field-based techniques

Damage occurs at a range of scales from individual leaves to entire forest canopies (Mageau et al., 1995). Damage assessment may be conducted at any scale between these extremes, and is dependent on the areal extent of the disturbance event and the information needs that arise.

Damage severity depends on the scale at which it is assessed. Within individual crowns, assessment may be performed at the branch level to determine what part of the crown needs to be pruned to save a tree from further decline. At the stand level, trees may be assessed individually in order to determine which ones should be thinned from the stand based on the amount of damage suffered. Extreme damage may require harvest or salvage of nearly all trees in the stand. At each of these scales, the factors that control damage differ, and so does the spatial pattern of damage.

Damage is controlled by factors listed in Chapter 1. Briefly, at the individual tree level, factors such as tree species and form, age, disease and decay, and position within the stand have all been identified as contributing factors to damage (Hauer et al. 1994; Van Dyke, 1999; Proulx and Greene, 2001). Thus, damage may vary from tree to tree within the stand, depending on the distribution of these susceptibility factors. When damage is

assessed at the stand level and compared among stands, variation within the stand is removed and generally, changes in damage across the landscape decrease due to an increased sample size or area. Therefore, with increasing area of damage assessment, damage generally becomes more homogeneous across the landscape. At these smaller scales, damage is controlled more by climatic and environmental factors such as wind, freezing precipitation and topography (Van Dyke, 1999). Due to different factors controlling the severity and distribution of damage at different scales, damage assessed at a fine scale may not be directly comparable to a coarse-scale assessment.

3.3.1. Direct methods

3.3.1.1. Visual estimation of percent crown loss

Visual estimation of defoliation or crown loss is widely used as an initial quantitative measure of structural damage (Franklin et al., 1995; Vogelmann and Rock, 1989; Lambert et al., 1995; Vogelmann, 1990; Ekstrand, 1994; Radeloff et al., 1999; Lautenschlager and Nielsen, 1999). It is measured as the amount of crown lost to disturbance relative to an estimated (or imagined) pre-disturbance crown volume. Such measurements provide reliable damage assessment immediately following a disturbance event, however, they become problematic when monitoring the response to damage over a longer period because they rely on an estimated pre-disturbance crown volume. Where significant crown loss has occurred, the crown perimeter may be projected and broken branch wounds may be seen directly from the ground to approximate pre-disturbance

volume shortly after the event. However, as new growth occurs or the crown begins to die back, pre-disturbance crown volume becomes increasingly difficult to estimate precisely. Wounds may become obscured by new growth and stain so that they become difficult to see from the ground.

3.3.1.2. Destructive sampling

Destructive sampling usually involves felling a set of trees representative of the structure of the stand. Sampling is usually done in a hierarchical fashion, both from the top down (small to larger scale) (Norman and Campbell, 1991) to select representative trees and then from the bottom up (large to smaller scale) (Gower et al., 1997) to sample individual trees. Destructive sampling can be used to directly measure structural parameters or to develop and validate allometric relationships between structural parameters.

Representative sampling is essential to the development of predictive relationships that link measurements between scales. Once representative trees have been selected, direct measurement may be performed by sampling in a hierarchical fashion and iteratively scaling measurements from leaf to shoot, shoot to branch and branch to tree using biomass - structure relations to link measurements between scales. No single sampling method may be appropriate for all tree types; instead, familiarity with the tree and all of its components is required to design a sampling scheme that adequately represents its structure. There are nearly as many sampling methods as there are structural scaling studies (Norman and Campbell, 1991), however, one study by Gower et al. (1997)

provides a detailed examination of the principles of hierarchical sampling and subsequent scaling from leaf to tree.

3.3.3. Indirect instrument-based measurements

A number of field instruments exist that measure light transmittance through the forest canopy to indirectly estimate forest structure. The main structural indicators of canopy damage that are easily obtained with these instruments are leaf area index (LAI), clumping, and leaf angle distribution. LAI has been defined as half the total leaf area per unit ground surface area (Chen and Black, 1992). In this thesis, LAI and LAI change are considered as indicators of damage visually estimated shortly after the event as percent crown loss. LAI decreases immediately following a damage event due to uprooting and breakage of leaves, branches and stems. In this thesis and in Olthof et al. (2001; 2003), strong relations are reported of LAI and post-event LAI change with sugar maple crown loss caused by ice storm damage.

Clumping, which is a second structural damage indicator defined in Section 3.2.1, has been shown to increase with increasing structural damage in at least one study (Olthof et al., 2001 and in this thesis) due to the irregular configuration of the residual canopy following an ice storm damage event. Airborne image texture as a surrogate measure for canopy spatial configuration or clumping has been significantly related to spruce budworm defoliation (Franklin et al., 1995) and structural damage caused by acid minesite conditions (Olthof and King, 2000; Cosmopoulos and King, 2004).

A third indicator of damage is leaf angle distribution, which must be measured or assumed in order to obtain reliable field-based optical estimates of LAI from the canopy gap fraction obtained at a single zenith angle. Though primarily a physiological symptom, leaves have been shown to ‘droop’ as a response to stress agents (Milton et al., 1989). This response may preclude the application of assumed leaf angle distributions obtained in non-damaged forests for LAI measurement in damaged forests. Both LAI and clumping may be obtained from the forest gap fraction and gap size distribution as described in the following sections.

3.3.4. Optical gap fraction inversion

Forest canopies are formed from a three-dimensional structure consisting of tree biomass and empty space in between. These empty spaces are referred to as gaps. Whether a gap exists or not above a point in three-dimensional space in the forest depends on the height of that point. Most gap measurement is done at less than 2m from the ground, and thus if a point at this height is directly illuminated by the sun, then a gap exists directly above that point in the canopy in the sun’s direction. Gap fraction has been related to animal habitat, microclimate (Parker, 2003), among other environmental variables and is measured to derive other structural parameters such as LAI using physical models. The complementary measure of gap fraction is fractional crown cover, since the sum of the two equals unity.

The equations used to calculate LAI from gap fraction data were originally developed for inclined point quadrat sampling. This method of sampling consists of inserting a probe from the ground up through the canopy at a known zenith and azimuth angle and counting the number of leaves the probe contacts, with the number of zero contacts relative to the number of samples being the gap fraction. The procedure is repeated several times to obtain gap fraction data across a range of zenith and azimuth angles. It was first developed in New Zealand in 1933 by Levy and Madden, and later refined by Warren and Wilson (1960) (cited in Norman and Campbell, 1991). The same leaf interception concepts can be applied to sunlight penetrating the canopy and either being intercepted by leaves or passing through gaps. Optical instruments have been developed that measure the total amount of penetrating sunlight within a specific view angle, or the size and location of sunflecks and shadows beneath the canopy. Both can be used to calculate the gap fraction and from that determine LAI.

Models are used to invert point quadrat gap fraction data to obtain foliage density and leaf angle distribution. Both of these parameters are required to calculate LAI in canopies with leaves distributed randomly through space. Models developed for point quadrat sampling apply the same mathematics as those commonly used to invert optical gap fraction data using commercially available instrumentation. The LAI 2000 Plant Canopy Analyzer and TRAC optical instrument are two such devices. Both can obtain optical gap fraction data at multiple view angles and are described in Section 3.5.

3.3.4.1 Foliage density

Regardless of how gap fraction data are obtained, each method applies the Poisson distribution to gap fraction data to obtain foliage surface area density in m^2 per m^3 canopy volume from the point of LAI measurement to the top of crowns (Norman and Campbell, 1991). The Poisson distribution is used to generate the necessary information about the third dimension, i.e., leaf density from two-dimensional sunfleck or gap fraction projected on a flat surface or sensor. The Poisson distribution is the theoretical probability of the number of successes, or occurrences of any given category of event, in an arbitrary interval of time or space, where there is a small but consistent probability of independent occurrences at each moment in the interval (Olson, 1987). For forest canopies, the distribution is the basic binomial situation with two categories of outcome (foliage or gap). The distribution is random since it assumes that each sample is independent of any other sample.

The Poisson probability function relates the mean number of occurrences (n_1) per unit space λ to the probability of occurrence in a unit space:

$$(1a) P_{Poisson}(n_1) = \frac{\lambda^{n_1} e^{-\lambda}}{n_1!}$$

Relating gap fraction, or the probability of solar beam transmittance per unit space $P(\theta)$ to foliage density u , equation 1a becomes:

$$(1b) P(\theta) = \exp[-G(\theta)uS(\theta)]$$

where $G(\theta)$ is the projected element width area on a plane perpendicular to θ and $S(\theta)$ is the path length through the canopy at angle θ . The product of foliage density times path length gives LAI, i.e.

$$(2) LAI = u S(\theta)$$

The assumptions that must be met in order for the Poisson distribution to be valid for analyzing gap fraction data are (Nilson (1971), from Van Gardingen, 1999):

1. The stand consists of a very large number of statistically independent layers i.e. leaves are randomly distributed in space.
2. The probability of observing more than one leaf per layer is small compared with the probability of observing one leaf (per layer), i.e. leaves seldom overlap within a layer.
3. The probability of observing a contact within a layer is equal to the mean number of contacts per layer i.e. probability = frequency / total.

3.3.4.2 Leaf Angle Distribution

A second critical parameter for measurement of LAI is the leaf angle distribution in both vertical and horizontal directions (zenith and azimuth). Azimuthal symmetry is often

assumed and valid for real canopies (Kucharik et al., 1998), but separate leaf orientations can be calculated where azimuthal asymmetry is known to occur (Lang et al., 1985). Leaf angle distribution is often described as the mean fraction of foliage surface projected perpendicular to the direction of measurement. A spherical foliage orientation distribution is often assumed, because it represents many real canopy types well and its projected foliage surface remains constant ($G(\theta) = 0.5$) with angle θ (Kucharik et al., 1998).

Other numerical approximations used to describe leaf orientation include the single-parameter ellipsoidal model (Welles, 1990) and the two-parameter beta distribution (Kucharik et al., 1998). The single-parameter model is the ratio of the horizontal and vertical radii of the ellipse describing the relative frequency of leaf orientations in the zenith direction. A spherical leaf distribution has a ratio of 1, indicating that the leaf angle is distributed uniformly in the zenith direction. The two-parameter model describes the mean and variance of the leaf inclination angle distribution. A second two-parameter distribution may be used to describe the azimuthal orientation if the assumption of randomness in azimuth is not valid.

Leaf angle distribution is obtained using equation 1b. Measurements of sunlit fraction and path length over a range of angles will give an average foliage density u and projection coefficient $G(\theta)$. A spherical leaf angle distribution is often assumed for LAI calculation of tree canopies when multiple zenith angle gap fraction measurements are not taken (Zhang et al., 1999).

3.3.4.3 Effects of non-randomness on LAI measurement

The assumption of random foliage distribution in space (assumption 1) is met only in specific types of vegetation. Light attenuation in vegetation canopies is dependent upon and also influences the spatial configuration of leaves. This effect is most easily seen comparing overstory and understory vegetation distributions in space. Understory tends to grow more abundantly where overstory is absent and vice versa. The dependence of canopy architecture on light attenuation makes the assumption of independence, and thus randomness, invalid for many real canopies.

Lang et al. (1985) tested the effects of different plant architectures on optical measures of LAI and leaf angle measurements obtained from direct measurement. Sunflower and sorghum crops were chosen to study these effects. An important difference between the two plants is that sunflower is heliotropic (turning toward the sun), while sorghum is not. Heliotropism results in the angular distribution of sunflower leaves changing with time of day, leading to a non-uniform leaf distribution with azimuth angle. Thus, sorghum, with its uniform leaf distribution was expected to meet the assumption of spatial randomness, while sunflower was not.

Lang et al. (1985) obtained good correspondence between optical and direct measures of LAI for sorghum, due to its uniform distribution of leaves with azimuth angle and random spatial distribution. LAI was underestimated in sunflower due to gaps between

plants and non-uniform distribution of leaves in azimuth. The authors also concluded that detailed leaf angle distribution cannot be reliably obtained from optical measures, even for ideal distributions of vegetation, but that mean leaf angle can be obtained with some degree of accuracy.

Underestimations of indirect LAI measurements have also been reported consistently in forests with non-random distributions of vegetation (Planchais and Pontailleur, 1997; Kucharik et al., 1998; Herbert and Fownes, 1997; Chen and Black, 1992; Chason et al., 1991). By comparing conventional hemispherical photographic analysis and direct methods of LAI estimation, Van Gardingen et al. (1999) found that the optical method underestimated LAI by as much as 50% compared to direct method estimates in mixed and deciduous woodlands.

Planchais and Pontailleur (1997) used the LiCor LAI 2000 and hemispheric photographs to derive LAI estimates from multiple angle gap fraction data in young beech stands. The two optical methods gave similar gap fraction and LAI estimates, but were consistently 25% lower than estimates obtained through allometric relations between basal area and LAI. Kucharik et al. (1998) determined that LAI values were 45% and 17% too low in aspen and balsam poplar stands, respectively, due to the effects of non-randomness on LiCor estimates of LAI. Herbert and Fownes (1997), obtained similar results for broad-leaf tropical hardwoods, with optical methods underestimating LAI by a factor of 2.44. Under coniferous canopies, Chen and Black (1992) found that non-randomness reduces indirect estimates of LAI by approximately 35% in Douglas fir, while Gower and

Norman (1991) obtained similar underestimates (35-40%) under a variety of coniferous tree types. This consistent under estimation of LAI due to spatial non-randomness has led to identification of the quantity measured using such methods as 'effective LAI' (L_e) (Chen and Cihlar, 1995).

3.3.4.4 Measures of canopy non-randomness

As a consequence of the above research findings, recent attempts have been made to quantify deviations from randomness in foliage or gap elements. A number of techniques have been devised to account for the effect of non-randomness, or foliage clumping on effective LAI estimates. The most reliable estimate of foliage clumping is obtained through both direct and indirect estimates of LAI, with the clumping factor equal to the ratio of indirect to direct measurement (L_e / LAI) (Kucharik et al., 1998). This clumping factor (Ω) can then be used to convert effective LAI, measured by most commercial instruments such as the LAI-2000 (Chen and Cihlar, 1995) that assume a random canopy distribution, to real LAI for the non-random case using equation 3.

$$(3) \quad L_e = \Omega LAI$$

Gower and Norman (1991) corrected indirect estimates by multiplying by the ratio of the projected needle area to shoot silhouette area for four different conifer species and obtained good agreement with direct sampling estimates of LAI. Lang and Yuequin (1986) devised a method to improve LAI estimates in clumped canopies by taking the

logarithm of the gap fraction over a certain distance and using the log-average to derive structural information. The basis for this approach is the assumption that vegetation tends towards randomness over the averaging distance so that the Poisson distribution is valid. Lang and Yuequin (1986) developed this procedure for techniques using gap fraction information in the direction of the sun from measured sunflecks. Van Gardingen (1999) later modified this technique for use with hemispherical photography.

Chen and Cihlar (1995) developed a unique method to account for clumping in non-random canopies. They used the gap size distribution to identify gaps that appear at probabilities in excess of a random gap distribution. The largest gaps are iteratively removed and the residual gap size distribution is checked until the gap size distribution approximates randomness. The clumping factor is then calculated as the ratio of the natural logarithms of the measured gap size to the theoretical gap size with a random distribution (equation 3). Thus, the clumping factor ranges from 0 for a non-random distribution (extreme case: stacked foliage) to 1 for a perfectly random distribution where the measured gap fraction resembles a Poisson distribution without removal of any large gaps. The clumping factor is then used to convert projected (effective) LAI to LAI using equation 3.

3.4 Instrumentation

Instruments that use the gap fraction inversion method include hemispherical sensors such as the Licor LAI 2000 and hemispherical canopy imaging using either analogue

photographs (Pearcy, 1991; Van Gardingen et al., 1998; Comeau et al., 1998; Chen et al., 1997a) or hemispherical digital imaging (Leblanc et al., 2002). Alternatively, line transect instruments such as the TRAC (Chen and Cihlar, 1995) can be used as in this thesis. The LAI 2000 is perhaps the most widely known commercial instrument for indirect LAI estimation. Other instruments that use a different inversion technique to obtain LAI from the amount of Photosynthetically Active Radiation (PAR) sensed in the range of 400-700nm will not be reviewed. These instruments include the LI-191 line quantum sensor from LiCor Inc. (Lincoln, NE) and the Decagon Devices (Pullman, WA) AccuPAR (Welles and Cohen, 1996).

3.4.1. TRAC instrument

The TRAC instrument measures sunflecks on the forest floor resulting from direct transmission of light through the canopy in the direction of the sun. It takes continuous light readings while the sensor is moved along transects so profiles of radiance are obtained beneath the canopy. These profiles are then analyzed to obtain gap fraction and gap size distribution information. Because the instrument acquires data along profiles in the direction of the solar zenith, repeat measurements over a range of solar zenith angles are required to obtain leaf angle distribution.

The TRAC consists of a Li-Cor quantum sensor affixed to a wand housing a data storage unit. Photon flux density measurements in micromoles per metre squared per second ($\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$) are acquired continuously at a rate of 32 per second and distance stamps

are inserted to reference the data to ground distance. Ground distance is marked at constant intervals in the forest prior to measurement, usually by placing flags every 10m along transects. Transects are set perpendicular to the direction of sun azimuth during measurement and it is recommended that the solar zenith angle be between 30 and 60 degrees during measurement (Chen et al., 2000).

The theory behind treatment of TRAC data and level of processing accounts for clumping and penumbra effects in calculating LAI, and therefore should be considered an improvement over other instruments. For accurate gap delineation, the TRAC uses rate of change in photon flux density along the measurement profile to account for gaps with fuzzy edges caused by the penumbra effect. Gap size distribution is analyzed to obtain an estimate of canopy clumping (see above) (Chen and Cihlar, 1995).

The advantages to the use of instruments such as the TRAC over other optical instruments such as the Licor LAI 2000 lie in the relative quickness with which measurements can be made if leaf angle distribution is assumed. The advantage of using the theory applied to the TRAC specifically is in its ability to account for clumping of forest canopies. This may be especially important when measuring LAI in a damaged forest, since gaps left by broken branches and stems often result in a clumped canopy. In Olthof et al. (2001), TRAC data are used to show that the degree of forest damage sustained in sugar maple plots from the ice storm was significantly related to clumping. Another advantage of the TRAC is that it does not require an above-canopy reference reading, while the Licor LAI 2000 does.

Disadvantages include the need for repeat measurements over a range of solar zenith angles to obtain the leaf angle distribution. Although a permanent record of the radiance profile allows visualization of the canopy and offers the possibility to monitor the profile through time, it is not as useful a visualization tool as hemispherical photography. This is compounded by the variability in LAI measurement over a range of solar zenith angles, making it necessary to acquire multi-temporal repeat measurements at the same time of day to allow meaningful comparison. In this thesis and in Olthof et al. (2001), it was found that greater measurement variability existed between repeats acquired on the same day at different times than between repeats acquired on different days, but at a similar time of day.

Finally, plot setup for the TRAC can be time consuming and difficult since measurement transects must be aligned perpendicular to the solar azimuth during measurement. Because the TRAC needs clear sky conditions, plot setup requires some degree of certainty about what sky conditions will be like when measurements are to be made. If plots are located far apart, an east west transect alignment is best since this gives the largest measurement window possible of 20 degrees on both sides of solar noon (from approximately 11am to 1pm summertime in E. Ontario). Measurements taken outside of this window may require a correction to the projected element width, which varies as the cosine of the solar azimuth (Chen et al., 2000).

Due to the limitations of both the TRAC and the LAI-2000, measurements from both instruments have been combined to derive better LAI estimates. Multi-angle measurements acquired simultaneously with the LAI-2000 have been used to obtain leaf angle distribution and effective LAI. The TRAC is then used to obtain clumping, which enables the conversion of effective LAI to LAI using equation 3 (Chen and Cihlar, 1995; Chen et al., 1997a).

3.5 Summary and conclusions

Forest damage produces changes in the size, shape and orientation of plant organs, whose description is collectively referred to as forest structure. Damage can result from a catastrophic event or gradual decline, depending on the intensity and duration of the damage or stress agent. Because disturbance cycles produce damage and are necessary for ecosystem renewal, a damage event must be considered within an ecological and historical context. Damage event frequency and intensity that depart from an established disturbance cycle indicate the presence of an external stress agent acting on the forest. The level of stress exerted on the forest and its ability to cope will dictate whether a forest is in decline or recovery following a damage event.

Forest damage is most often estimated visually by making reference to a pre-disturbance condition. Damage estimates such as percent crown loss are based on an estimated pre-disturbance crown volume. This type of measurement can be quite reliable for estimating damage shortly after a disturbance event, but may be problematic for monitoring the

response to damage. This is because as new growth or further damage occurs in the growing seasons following the disturbance event, pre-disturbance crown volume becomes increasingly difficult to estimate reliably. Allometric relations based on purely statistical relations between parts of a tree can sometimes be used to obtain an estimate of pre-disturbance condition. The magnitude of difference between pre-disturbance structure obtained from allometric relations and measured structure after the event can be related to the severity of damage suffered by a tree.

Monitoring the response to damage requires repeatable measurements of canopy structure that can be related to initial damage estimates, such as Leaf Area Index (LAI) and foliage clumping. Conceptually, instrument-based measurements should be more repeatable than visual estimates because bias between assessors and between seasons will not exist as long as instrument calibration and use remain constant. Several direct and indirect methods exist to quantify canopy structure. Direct methods vary depending on the forest being measured, but generally rely on hierarchical sampling from the top down to select representative trees to sample, and then from the bottom up to measure individual trees.

Indirect methods rely on light transmitted through the canopy to obtain gap fraction and gap distribution measurements. These measurements are inverted using the Poisson distribution to generate foliage density, which can be converted to LAI using the average path length of the light beam transmitted through the canopy. The Poisson distribution relies on the assumption that foliage is distributed randomly through space and is often invalid for real canopies. Therefore, several authors have devised methods to account for

the effects of non-randomness, or clumping on LAI measurement. One such method was discussed, whereby a clumping index is derived from the gap size distribution obtained from transect measurements of light transmittance and applied to 'effective' LAI measurements that assume randomness.

Instruments used to obtain indirect measurements of LAI are numerous, but generally rely on either hemispherical optical sensors or line-transect sensors. The former can either be photography or light sensors that rely on above canopy readings taken in a clearing nearby to unmix the below-canopy signal to foliage and gap fractions. Gap fraction is obtained directly in hemispherical photographs using simple image processing techniques. Line sensors require transects to be set up in advance, and obtain gap fraction and distribution at a single solar zenith angle. Each instrument has its advantages and disadvantages, and should be selected based on operational and information needs and constraints.

CH. 4. LAI AS A LOCAL, MEDIUM TO LONG-TERM DAMAGE INDICATOR

4.1 Introduction

This chapter assesses the potential of leaf area index (LAI) as an indicator of canopy damage for local, medium to long-term monitoring purposes. Much of the research presented in this chapter was published in Olthof et al. (2001) and Olthof et al. (2003). Problems with the use of visual estimates of percent crown loss for damage monitoring purposes have already been addressed in Chapter 2, and can be summarized as follows:

1. Visual estimation of percent crown loss is subjective, leading to reduced accuracy and precision.
2. The precision of the measurement provided by the OMNR could not be assessed, since repeat measurements in individual plots were not performed.
3. The accuracy of measurements cannot be assessed either, because no absolute damage measurement exists. However, accuracy of individual plot measurements is not as important as consistency (precision) of plot measurements. In other words, relative differences among plot measurements are more critical than any bias that might exist in all measurements.
4. Visual estimation of percent crown loss is problematic for monitoring purposes, since it is measured relative to pre-storm crown volume, which becomes increasingly difficult to estimate reliably as time since disturbance passes.

In spite of these shortcomings, visual estimation of percent crown loss is still widely used as an initial damage measure (Irland, 1998; Boulet et al., 2000; Lautenschlager and Winters, 2001) due to its simplicity and reliability, provided that assessment is conducted shortly after disturbance. However, problems persist for longer-term monitoring purposes. Instrument-based measurement of canopy structure based on the gap fraction, which is more objective and repeatable through time, is presented as a better alternative to visual estimation for monitoring. The potential of such measurements for damage assessment has already been discussed in Chapter 2.

While a lack of repeated measurement of the visual estimates of damage in this study does not allow a quantitative assessment of precision, instrument-based precision can be determined through repeat sampling in individual plots. Canopy response to damage can then be evaluated in relation to precision to assign a level of confidence to measured between-season change. This chapter evaluates LAI and LAI change relations with the reference damage measure of percent crown loss. Total LAI and LAI change, as measured with the TRAC, are partitioned into overstory and understory contributions by incorporating ground vegetation survey data into the analyses. Partitioning in this manner allows monitoring of overstory maple trees tapped for syrup production. Other factors that may contribute to measured LAI change, such as drought, are considered as well and are also presented in Olthof et al. (2003).

Generally, this research was designed to develop methods for monitoring local canopy change in relation to both the damage sustained and the treatments applied by the

OMNR, as well as to identify potential causes for observed variations. Specific objectives of this study were to:

1. Measure total canopy LAI using optical instrumentation for the 1999, 2000 and 2001 growing seasons;
2. Determine understory LAI from line intercept vegetation data for the 1999 and 2001 growing seasons;
3. Separate understory LAI (objective 2) from total canopy LAI (objective 1) to obtain overstory LAI for 1999 and 2001;
4. Evaluate relations of annual LAI and LAI change in the plots with crown loss estimates made following the storm, and
5. Assess short-term treatment effects on LAI change.

4.2 Data

4.2.1. Study area

The study area is defined by the spatial extent of the Eastern Ontario Model Forest (EOMF) and also includes some blocks to the west (Figure 4.1). The EOMF covers 1.5 million hectares, from the Counties of Leeds and Lanark, to the Quebec border and St Lawrence River. However, it is not woodland in the usual sense, since only 34% of the region is currently forested. The rest of the land is used for other purposes such as

farming, urban development, wetland conservation, road transport, or was previously developed and is now being reforested (EOMF, 2003).

Figure 4.1. Forest cover within the Eastern Ontario Model Forest (EOMF) (OMNR)

4.2.2. *Maple plots*

4.2.2.1. Layout

The 38 maple experiment blocks are shown in Figure 4.2 (Lautenschlager and Nielsen, 1999). Each 1 hectare block is square, 100m on a side and is divided into four 50m x 50m plots consisting of one control and three fertilizer or herbicide / fertilizer treatments randomly assigned to plots and applied in the spring of 1999 (Table 4.1). Of the 38 blocks, 18 are focus blocks with microclimate stations recording soil moisture and

temperature, air temperature, relative humidity, and light (Lautenschlager and Nielsen, 1999).

Figure 4.2. Block locations and numbers in sugar bushes, across southeastern Ontario

Table 4.1. Plot treatments for sugar maple ice damage study in Eastern Ontario

Treatment	Fertilizer / herbicide application
Non-herbicide Blocks, n = 35	
A	no treatment
B	500 kg Dolomitic lime + 50 kg phosphorus + 50 kg potassium
C	50 kg phosphorus + 50 kg potassium
D	500 kg Dolomitic lime
Herbicide Blocks, n = 3	
A	no treatment
B	500 kg Dolomitic lime + 50 kg phosphorus + 50 kg potassium and herbicide (Vision®) control
C	500 kg Dolomitic lime + 50 kg phosphorus + 50 kg potassium
D	Herbicide treatment (Vision®)

4.2.2.2. Damage measurement

The OMNR provided both block and plot-based damage measures acquired independently in the fall of 1998. The first damage measure was visually estimated by experts from Agriculture Canada as percent canopy loss within blocks. The second was the percentage of crown loss on an individual tree basis estimated for six focus trees per plot, estimated to be representative of average damage in the plot. The individual tree crown loss data, averaged over the entire block (N = 24 per block) correlated well with the block-based damage estimates ($r = 0.93$, $N = 34$ blocks), indicating consistency between these two damage measures. Individual tree estimates of crown loss were unavailable for 1998 in 3 blocks (blocks 29, 41 and 44). In subsequent maple plot-based analysis, the average percent crown loss of the six focus trees was used as the primary damage measure.

4.2.2.3. Ground vegetation survey

Near-ground vegetation survey data were collected by the OMNR during the summers of 1999 (in the second growing season after the storm) and 2001 (in the fourth growing season after the storm). A line intercept method (Canfield, 1941) was used along randomly located lines in each plot.

In 1999, near-ground vegetation was surveyed along five 10-metre lines per plot. In 2001, the number of lines was increased to 20 per plot, while each line measured 5m in length. This change was made in order to better capture the species richness of near-ground vegetation in 2001, and was not considered to have produced any bias in ground vegetation cover between years. Vegetation was recorded by species and layers as well as the start-end distance in centimetres on each line. All green or mostly green vegetation less than 7m in height that crossed the line (projected vertically) was recorded. A metre stick and height pole were used to determine vegetation heights.

Measured ground vegetation heights were assigned to one of three layers (0.0 – 0.5m, 0.5 – 2.0m, 2.0 – 7.0m) (Lautenschlager *et al.*, in prep.). Because the TRAC was held at 1.5m height, only the ground vegetation surveyed in the 2.0m – 7.0m layer that was ‘seen’ by the TRAC was used in this analysis.

4.2.2.4. TRAC measurement: LAI and clumping

Three 50m transects were installed in individual plots in an east-west direction for TRAC measurement. Transects were spaced 10m apart, and were always located in the northern portion of the plot to ensure that radiation incident upon the instrument was passing through the canopy in the plot (as the sun zenith was always at approximately 40° during measurement). The transects consisted of metal flags placed at ten metre intervals. An operational strategy for transect installation and measurement had to be developed because the blocks were located across Eastern Ontario and measurement had to be performed under clear sky conditions. They were typically set up in a given plot before the day of measurement when the sky was cloudy or in the early or late part of the day. This allowed measurements to be taken during a cloud free or partly cloudy period between 11 AM and 3PM (± 2 hours of solar noon) when the sun was within 20 degrees of perpendicularity to the transect. This is considered an acceptable range of solar angle variation for consistent LAI measurement (Chen, 2000). An assistant walked ahead of the operator to clear any obstructions that would have impeded a steady pace. All measurements were taken on clear days to ensure that the boundaries between sunflecks and shadows were sharp for consistent gap detection and measurement. In calculating LAI using the software provided, a mean leaf element width for sugar maple of 85mm was used (Chen, 2000.)

4.3 Methods

4.3.1. *LAI measurement*

LAI was measured using the TRAC optical instrument and sampling protocol outlined earlier in the summer of 1999 in 23 of the set of 36 maple blocks analyzed, and the remaining 13 blocks were measured in 2000. Nine of the blocks that were measured in 1999 were re-measured in 2000. In 2001, 31 blocks were measured, 20 of which were measured in 1999. Every effort was made to re-measure blocks in 2000 and 2001 at the same time of day and on the same date as in 1999. In many plots, LAI was measured more than once during a single day or measured on a few days to evaluate the TRAC instrument precision and sensitivity to solar zenith angle. Where such repeat measurements were taken, an average was calculated to represent LAI of the plot for that year. For the 20 blocks (80 plots) measured in 1999 and 2001, understory vegetation data were used to separately analyze the contributions of understory and overstory layers to total LAI and to LAI change (Table 4.2).

4.3.2. *LAI samples analyzed*

Average percent crown loss for samples of blocks in which LAI was measured in each year revealed differences among samples. To ensure that observed changes were real and not caused by a bias in the sample of blocks measured in one year, blocks with extreme crown loss were removed from a given year so that all years represented a similar degree

of initial crown loss. The sample of 20 blocks used for the 1999 – 2001 change analysis had a higher mean percent crown loss than all blocks combined ($N = 34$), while blocks measured in 2000 had a lower percent crown loss. Z-scores showed no differences between individual samples and population means beyond $z < 1.33$ ($P = 0.908$). However, the sample of 20 blocks used in the 1999 – 2001 change analysis exhibited positive bias, while the sample of 22 blocks from 2000 showed negative bias. The net effect was that the two sample means were 1.86 standard scores apart. To mitigate this problem, three blocks (5, 6, 19) from the 2000 sample that had the lowest damage and that could not be used in the 1999 - 2001 change analysis (they weren't measured in 1999) were removed. The remaining 19 blocks that were used as the 2000 LAI measurement sample had a similar distribution of damage scores to the 1999 – 2001 sample (Table 4.2).

4.3.4. Determination of ground vegetation LAI

Near-ground vegetation LAI needed to be calculated so that its contribution could be removed from the total canopy LAI above 1.5m (hereafter termed 'total LAI') as measured by the TRAC. Equation 1a was used to convert understory gap fraction of the 2.0m - 7.0m layer to effective LAI. Because near-ground vegetation distances were recorded along line (L) by species (Sp) as well as by layer, plots could have overlap (O) between different species occurring in the same layer. This overlap resulted in percent cover values exceeding 100% in cases where the overlap between species exceeded the gap fraction. Therefore, overlap between species was eliminated on a plot-by-plot basis to

obtain near-ground vegetation gap fraction estimates (Figure 4.3).

Table 4.2. Blocks in which LAI was measured and for which LAI data were analyzed				
blocks where LAI was measured				
block	% damage	1999	2000	2001
1	68	(x)		
2	69	x		x
3	41	x	x	x
5	10		(x)	(x)
6	9		(x)	(x)
7	34		x	
8	37		x	(x)
9	61	x	x	x
10	17		x	
11	60		x	(x)
12	64	x		x
13	51		x	(x)
14	70		x	(x)
15	37	x		x
16	56		x	(x)
17	21		x	(x)
19	10		(x)	(x)
20	10	(x)		
21	77	x		x
22	32		x	(x)
23	35	x		x
24	45	x		x
25	28	x		x
26	62	x		x
27	69	x		x
28	29	x		x
29	35	(x)		
30	72	x	x	x
31	6	x	x	x
32	12	x		x
39		x	x	x
40	35	x	x	x
41			x	(x)
42	64	x	x	x
43	46	x	x	x
44		x	x	x
N	33	23	22	31
Mean % damage	42	46	39	43

(x) removed from analysis - see text, Section 4.3.2.

Start and end distances of ground vegetation interception on each line were provided by the OMNR in a spreadsheet for each species occurring in each layer. The data were sorted in ascending order by line number and by start distance along the line. A set of fields consisting of Boolean operators was used to determine overlap given all possible combinations of species occurrence within the layer.

Figure 4.3. Understory vegetation gap fraction (GF) calculation from line intercept data of length L. Species 1 – 4 intercept along segments Sp₁₋₄, with overlap between species 1 and 2 at Ov₁ and between species 2 and 3 at Ov₂.

Total overlap was summed for all lines within a plot and was subsequently subtracted from the sum of distances obtained from the start and end points to obtain vertically projected cover of all species along all lines. Subtraction of cover from the summed length of all lines, divided by the summed length of all lines gave the understory gap fraction (equation 4.1).

$$GF_{\text{understory}} = \left[\sum_{i=1}^m L_i - \left(\sum_{j=1}^n Sp_j - \sum_{k=1}^o Ov_k \right) \right] / \sum_{i=1}^m L_i \quad (4.1)$$

where: GF Plot gap fraction

 L Line length for lines $i = 1$ to m in a plot

 Sp Species intercept length along line L for intercept lengths $j = 1$ to n

 O Overlap length between species for overlap lengths $k = 1$ to o

The projection coefficient varies slightly with zenith angle for an assumed spherical foliage distribution (Warren-Wilson and Reeves, 1959). Near-ground vegetation gap fraction was obtained vertically (i.e., at 0 degrees zenith), while the TRAC data were obtained at a mean zenith angle of 40 degrees. The projection coefficient, $G(\theta) = 0.5$, for the TRAC data assumed a spherical foliage distribution. For the understory vegetation, $G(\theta)$ was obtained from a graph in Welles and Norman (1991) showing changes in the projection coefficient with zenith angle for different mean leaf angles. The curve for which $G(\theta) = 0.5$ at 40 degrees zenith angle corresponded to a mean leaf angle of 45 degrees, and was projected to a zenith angle of 0 degrees (vertically) to give $G(\theta) = 0.6$ for the understory.

The clumping indices obtained from TRAC measurements of the entire canopy above 1.5m were used to convert understory effective LAI to understory LAI. Mean clumping values were 0.83 in 1999, increasing to 0.86 in 2001, which does not represent a significant increase but may indicate a trend towards an increasingly random gap size distribution since the ice storm. Typically, clumping values varied by less than 5% within a given year for a given range of solar zenith angles, producing similar variations in LAI

calculated from effective LAI using equation 2. The effects of clumping errors on understory LAI removal from total LAI should not be great since understory contributions to total LAI were low compared to overstory contributions.

4.3.5. *TRAC precision analysis*

The repeatability of TRAC measurement is mainly influenced by the sun's position, and therefore the portion of the canopy being sampled. As a result, there is a certain amount of variability in TRAC LAI measurement, which can be quantified by repeatedly sampling single plots. Twenty-nine plots were repeatedly sampled (either two or three times) within the 2000 growing season. Eighteen of the 29 plots had repeated measurements taken at different times during the same day, while the remaining 11 plots had repeated measurements taken over a span of several days.

The differences of repeat TRAC measurements ($N = 112$) formed a precision distribution that was normal (Figure 4.4). The two-tailed 95% confidence limits for the precision distribution were determined from the standard deviation ($\pm 1.96 \times \sigma$) to be ± 1.20 , and were confirmed by 104 of 112 (93%) of repeat differences within the calculated 95% confidence interval. This error represents 23% of the mean LAI measured in 2000, and is similar to the 2σ range of 28% for broadleaf stands reported in Fernandes et al. (2001). Precision errors were due to the sun's position at the time of measurement in addition to phenological leaf area changes over the course of the growing season. Analysis of variance revealed that changes in solar zenith angle caused the largest variation in

repeated differences, as within day repeated measurements exhibited greater variance than between dates (F-test, $\alpha = 0.08$).

Figure 4.4. Within and between season LAI measurement differences

The precision analysis was designed to address a certain amount of phenological variation in LAI. Leblanc and Chen (2001) showed seasonal LAI variation measured with the LAI-2000 under diffuse illumination conditions in two temperate deciduous forests. During the measurement period from June 13 to September 5, 1997, LAI varied by 1.2 and 0.9 at two sites. Therefore, less than half of the total LAI variation accounted for in

the precision analysis may be attributable to vegetation phenology.

4.3.6. *LAI change analysis*

Total LAI change was evaluated between consecutive years and for the period from 1999 to 2001. Total LAI measured with the TRAC in both 1999 and 2001 was converted to overstory LAI by subtracting understory contributions to LAI obtained from ground vegetation surveys in those years. Understory and overstory LAI change was evaluated for 20 blocks (80 plots) measured in both 1999 and 2001. LAI change was calculated by subtracting 1999 LAI from 2001 LAI ($2001_{LAI} - 1999_{LAI}$) on a plot-by-plot basis for overstory and understory layers separately. Positive change indicated an increase in between season LAI while negative change indicated a decrease in LAI in the two-year period.

The significance of the observed change was evaluated using the TRAC precision distribution of repeat differences. Only overstory change was evaluated in this manner, and did not account for precision errors in the measurement of ground vegetation. It was assumed that since ground vegetation was measured directly, there would be relatively little error in its measurement. Percentage certainty with which LAI increased or decreased, based on a one-tailed normal probability distribution of repeat differences (precision) was assigned to each plot (Figure 4.5).

Figure 4.5. Example of 1999 to 2001 LAI change ($Z_A = 0.7$ LAI increase) indicating certainty of measured LAI increase in the grey area.

4.3.7. Percent LAI change

The damage measure used in this study is a normalized measure of crown loss since it is estimated relative to a pre-disturbance crown volume. LAI change should also be normalized in order to make a comparison with damage more relevant and meaningful. Because pre-storm LAI data were unavailable, overstory and total LAI change were normalized by dividing the 2001 – 1999 LAI differences by the 2001 LAI data, which should most closely approximate pre-storm LAI due to an overall increase since the ice

storm. Understory LAI was normalized in a similar fashion with 1999 understory LAI data, which should most closely approximate pre-storm understory LAI, assuming that the understory was not severely damaged by the ice storm event. By normalizing LAI change in this manner, percent crown loss was compared to percent LAI change, both relative to an estimated pre-storm condition.

4.3.8. Statistical analyses

Pearson correlation analyses were used to evaluate relations between 1998 crown loss (damage) as the dependent variable and the following independent variables: single-date total LAI for 1999, 2000 and 2001, and absolute and relative change in overstory, understory and total LAI for the period of 1999 to 2001. The difference in measurement scales between damage estimated at the crown level, and single-date canopy LAI was not expected to produce strong (predictive) relations between the two measurements. Relations were evaluated instead for the ability of LAI to act as an indicator of damage for monitoring recovery. Therefore, all significant ($P < 0.05$) relations are reported, regardless of their strength.

Separate two-way analyses of variance (ANOVA) were used to determine if understory or overstory LAI change was related to plot treatment, with blocks as replicates in a randomized design (Snedecor and Cochran, 1980). Assumptions for ANOVA include normality of observations on the dependent variable within each group and homogeneity of variance (equal population variances) among groups. Because group sizes were

constant at 20 plots per treatment and 4 treatments per block, neither within group variance nor normality were considered to significantly affect the actual type I error rate (Stevens, 1992). Scheffe's post hoc test assuming equal variances was used to determine if any significant differences existed between individual treatment pairs.

4.4 Results and Discussion

4.4.1. LAI change

4.4.1.1 Aggregated results

Average total LAI increased from 4.54 in 1999 to 5.25 in 2000, and again to 5.52 in 2001 (Table 4.3). LAI increment was more than two and a half times as great between 1999 – 2000 (0.71) as it was between 2000 – 2001 (0.27). This indicates that LAI may be stabilizing to pre-ice storm levels four growing seasons after the event. Lower LAI increment between 2000 and 2001 was also due to a drought that affected Eastern Ontario in the summer of 2001 (Parker and Lautenschlager, submitted), causing many trees to shed leaves.

LAI increases were noted between 1999 and 2001 for both understory and overstory layers separately, contributing to a mean total LAI increase of nearly 1.0 (Table 4.3). Understory LAI increased by nearly 300%, while overstory increased by approximately 13%. Understory LAI contributed about 0.44 to the increase in total LAI and overstory

contributed the remaining 0.54.

Table 4.3. 1999 to 2001 average plot LAI by layer, N = 80. Understory vegetation survey was not conducted in 2000, thus only total LAI as measured with the TRAC is shown for that year.							
	Understory		Overstory		Total		
	1999	2001	1999	2001	1999	2000*	2001
Minimum	0	0.19	2.63	2.59	2.87	2.99	3.16
Maximum	0.8	1.4	6.49	6.98	6.67	7.06	7.89
Mean	0.23	0.67	4.31	4.85	4.54	5.25	5.52

*N = 76

These results indicate that average plot leaf area is recovering from damage suffered during the 1998 ice storm event. The dramatic increase in understory LAI was caused mainly by increased light levels reaching this layer (Parker and Lautenschlager, submitted), and is supported by the significant relation between damage and 2001 understory LAI (see below). It is suspected that much of the understory measured in 2001 was already established in 1999 but was too short to be detected by the TRAC. This is confirmed by a significant decrease in the 0.0 – 0.5m ground vegetation layer abundance from 1999 to 2001, which is likely caused by increased shading from the layers above. These results are similar to those of King et al. (2004), for an ice storm study in southern Quebec, which showed that established near ground vegetation took advantage of increased overstory openness, producing large increases in height and foliage in the 1998-2000 period, while germination and ground vegetation amounts decreased.

The contributions of understory and overstory to the overall increase in LAI correspond to light attenuation in forested canopies. Overstory layers receiving the most light have

exhibited greater absolute increases in LAI, while understory layers immediately below have increased slightly less. Both vertical layers respond to damage, with understory responding more than overstory in relative terms, while overstory has responded more in absolute terms.

4.4.1.2 Individual plot analysis of LAI change

Individual plot LAI response varied between 1999 and 2001 for both overstory and understory layers (Table 4.4). In twenty of 80 plots, overstory exhibited decreased LAI, while understory LAI decreased in only three plots. Although 25% of plots showed reduced overstory LAI, the observed decreases were beyond the 95% confidence level of measurement precision in only four cases. Relaxing this strict confidence definition to a lower but still reasonable level of 80%, the number of plots showing real decreased LAI was 10. If plot responses are considered to be replicates of block recovery, then block 15 appears to be declining, as three of four treatment plots have decreased LAI beyond 95% certainty, while the control plot has also declined, though not as significantly. At 80% certainty, blocks 25 and 44 displayed decreasing LAI in two of four plots.

Twenty-seven of 80 plots increased overstory LAI beyond the 95% certainty threshold. Blocks 9 and 21 improved by more than this threshold in all four plots, while blocks 12, 23, 26, 30, and 42 increased by at least this amount in three of four plots. At 80% certainty, the number

Table 4.4. Understory and overstory LAI change (1999 to 2001) by treatment. The significance level of measured overstory LAI change is also noted based on the precision analysis described in the text.

block	Treatment A			Treatment B			Treatment C			Treatment D		
	under.	over.	over. sign.	under.	over.	over. sign.	under.	over.	over. sign.	under.	over.	over. sign.
2	0.49	0.88	93%	0.84	0.39	74%	0.54	0.59	83%	0.61	0.53	81%
3	0.32	0.45	77%	0.89	1.00	>95%	0.60	-0.38	74%	0.19	-0.03	52%
9	0.49	1.49	>95%	0.13	1.17	>95%	0.56	2.34	>95%	0.86	1.60	>95%
12	0.45	0.92	94%	0.24	2.63	>95%	0.31	1.20	>95%	0.83	0.39	74%
15	0.41	-0.32	70%	0.96	-1.46	>95%	0.39	-1.52	>95%	0.69	-1.03	>95%
21	0.42	0.92	93%	0.13	1.30	>95%	0.09	1.04	>95%	0.57	2.32	>95%
23	0.52	0.85	92%	0.70	0.97	95%	0.79	0.54	81%	0.84	1.44	>95%
24	0.00	0.69	87%	0.17	0.94	94%	0.12	0.83	92%	0.52	0.42	76%
25	0.74	-0.63	85%	0.17	-0.64	85%	-0.18	0.06	54%	-0.03	-0.27	67%
26	0.39	1.14	>95%	0.84	0.74	89%	0.43	1.15	>95%	0.42	1.70	>95%
27	0.85	0.55	82%	0.18	0.84	92%	0.53	0.33	71%	0.46	-0.06	54%
28	0.22	-0.04	52%	0.25	2.25	>95%	0.30	0.09	56%	0.70	-0.88	93%
30	0.76	0.68	87%	0.23	1.48	>95%	0.55	0.98	>95%	0.43	1.20	>95%
31	0.06	0.53	81%	0.26	0.06	54%	0.31	0.32	70%	0.04	0.43	76%
32	0.28	-0.24	65%	-0.01	0.52	81%	0.26	0.48	78%	0.15	0.72	88%
39	0.54	0.52	81%	0.31	-0.69	87%	0.81	1.54	>95%	0.44	0.09	56%
40	0.11	0.51	80%	0.30	-0.67	86%	0.55	-0.07	54%	0.20	0.80	91%
42*	0.73	1.26	>95%	1.04	1.01	>95%	0.63	1.05	>95%	0.89	0.38	73%
43*	0.42	2.25	>95%	0.59	0.16	61%	0.20	0.60	84%	0.75	-0.08	56%
44*	0.25	-0.78	90%	0.48	-0.26	67%	0.48	-1.08	>95%	0.37	0.37	73%
mean	0.42	0.58	83%	0.43	0.59	83%	0.41	0.51	80%	0.50	0.50	79%

*herbicide blocks

of plots showing increased LAI was 36. All plots in blocks 9, 21, 23, 26, 30, and 42 were deemed to have increased in LAI beyond the 80% threshold, while three of four plots increased in blocks 2, 12, and 24.

4.4.2. Effects of drought on 2001 LAI

To examine the effect that drought may have had on LAI in the summer of 2001, LAI measured in 2001 was plotted against the measurement day since January 1, 2001 (Figure 4.6). A significant relation between LAI and measurement date ($R = -.361$, $N = 124$)

existed, indicating a trend of decreasing LAI later into the summer. This relation may simply have been due to bias in the measurement date of higher and lower LAI plots, or to changes in the sun's position over the course of the summer. However, when 1999 and 2000 LAI plot data were arranged in the order of the 2001 measurement date, the same decreasing trend was not observed. Therefore, no bias was introduced, suggesting that the trend of decreasing LAI late into the growing season must have been due to drought.

Figure 4.6. LAI measurement through the summer of 2001 shows decreasing LAI late into the growing season. Julian day and month are shown on the x-axis.

The effects of drought can also be assessed by examining Figure 4.7. The intercept of a best-fit line through the data on the LAI change axis indicates that for an undamaged stand, a LAI decrease of approximately one was expected. The effects of the drought on

LAI change were removed by regressing plot-level LAI change against damage, and adding the residual variation to a baseline LAI value obtained from the mean LAI of blocks 11, 39 and 41 ($LAI = 5.68$), which were measured in late June before the drought. Because the variation in LAI change is dependent on both damage (Figure 4.7) and date (Figure 4.6), residual variation in LAI change after regression includes variation due to date. Thus, residuals account for all factors that affect LAI change other than damage, including measurement precision, and it is assumed that the primary factor in this case, is drought. A drought factor was obtained by calculating the percent increase of total LAI after the correction, and this factor was applied to understory and overstory LAI separately, assuming that both layers were equally affected.

Figure 4.7. 1999 to 2001 percent total LAI change versus 1998 visual crown loss estimates (DAMAGE). Block numbers are noted on the right side, with the four plots per block represented by the associated symbols in the graph.

An examination of the descriptive statistics of 2001 LAI measurements obtained after the drought was accounted for (Table 4.5) revealed an increase in total LAI between 2000 and 2001 of 0.54, which was closer to the 0.71 increase observed between 1999 – 2000. The intercept of LAI change plotted against damage was close to zero after the application of the drought correction. However, given the noise in the data presented in Figure 4.6, the correction was not perfect and did not significantly improve 2001 LAI or LAI change relations with damage.

Table 4.5. 2001 average plot LAI data after drought correction, N = 80			
	Understory	Overstory	Total
Minimum	0.22	3.13	3.94
Maximum	1.45	7.07	8.18
Mean	0.70	5.09	5.79

Figure 4.6 shows mean LAI decreasing linearly from approximately six in late June to five in early September. To illustrate the effect of drought on LAI change, block 15 is considered as an example. This block was measured on July 31 in 2001 at almost the midpoint of the 2001 measurement period. Therefore, we could expect approximately half a unit of leaf area decrease to be accounted for by the drought. The removal of the effect of drought from LAI decrease by applying the drought correction to block 15 reduced the number of plots in significant decline beyond the 95% confidence interval from three to two.

4.4.3. LAI and LAI-change relations with damage

4.4.3.1 Annual LAI vs. damage

Table 4.6 shows significant relations between single year LAI measurements and damage. Overstory and total LAI of 1999, and total LAI of 2000 were significantly ($P < 0.01$) related to 1998 crown loss estimates. The 2001 overstory LAI and total LAI were not significantly related to damage. This demonstrates that in the second and third summers following the ice storm, LAI is a good indicator of damage estimated in the autumn immediately following the ice storm event. As the canopy responds by recovering, stabilizing, or declining further, LAI gradually explains less of the variation in the initial damage condition. By the fourth summer, LAI no longer accounts for a significant amount of variance in the 1998 damage estimate. The reduction in the amount of damage variance accounted for by LAI through time indicates progressive LAI change between seasons, so that by the fourth summer after the ice storm LAI is measuring a canopy condition that is different from the damaged condition immediately following the storm.

Table 4.6. Significant Pearson correlations (r) between damage and LAI, N = 72				
	1999		2000*	2001
	Overstory	Total	Total	Understory
Damage	-0.445	-0.448	-0.323	0.28
Sig. (2-tailed)	< 0.001	< 0.001	0.007	0.017

*N = 68

Understory LAI in 2001 was also significantly related to damage. This relation is caused by the response of understory vegetation to increased light levels caused by canopy damage. Thus, understory generally received more light (Parker and Lautenschlager, submitted) in highly damaged plots and responded by increasing in size and abundance.

4.4.4. 1999 – 2001 LAI change vs. damage

The significant relations between damage and 1999 - 2001 LAI change in understory, overstory and total canopy layers (Table 4.7) indicate a dependence of LAI change on the degree of damage sustained. These direct relations show that more heavily damaged plots are responding with greater increases in LAI than less damaged plots and are therefore recovering. Percent LAI change of overstory and total canopy layers was more significantly related to damage than absolute LAI change. For understory LAI, absolute change was significantly related to damage, percent LAI change was not. It is thought that the use of 1999 understory LAI as an approximation of pre-storm understory LAI might not be appropriate due to a time lapse of more than one full growing season between the storm and the 1999 understory vegetation survey, and the dramatic response of understory vegetation to overstory damage. Plots from block 15 appear below the best-fit line between damage and percent change in total LAI (Figure 4.7) and have decreased overstory LAI (Table 4.4). Overstory LAI of the four plots from block 15 does not appear to be recovering from moderate damage sustained, while understory vegetation is increasing as in most other plots.

Table 4.7. Pearson correlations (r) between damage and 1999 to 2001 LAI change, N=72						
	Absolute LAI change			Percent LAI change*		
	Understory	Overstory	Total	Understory	Overstory	Total
Damage	0.351	0.422	0.518	0.159	0.445	0.561
Sig. (2-tailed)	0.003	< 0.001	< 0.001	0.188	< 0.001	< 0.001

*see text, Section 3.6.

Results outlined above suggest that percent change in total canopy LAI is a better indicator of ice storm canopy damage than any of the single date measures to which it was compared. However, LAI measurements were only initiated in the second growing season after the ice storm and progressive change in LAI was noted between successive summers. If LAI were measured in the first growing season following disturbance, it alone may have been a good indicator of damage, and changes in LAI in subsequent years may have provided stronger relations with damage than those found here.

When forest damage needs to be assessed, a baseline of pre-event data is rarely available to determine the magnitude of change caused by any particular disturbance. Instead, LAI response can be monitored as an indicator of post-disturbance recovery or decline, and to project back in time to estimate damage incurred. Such projections will not likely replace visual estimation of crown loss on an operational basis because the latter is easier to obtain. However, they will provide a means to study the cycle of LAI increase, stabilization, and decrease due to disturbance.

4.4.5. Treatment effects on LAI change

Plotting LAI response by treatment revealed slight differences among treatments for both overstory and understory layers (Table 4.4). Two-way analysis of variance revealed significant differences among blocks, but none among treatments. Scheffe's post hoc tests showed no significant differences between treatment pairs for any possible overstory or understory treatment combination. Therefore, no treatment effects on LAI response have been detected to date.

4.5 Conclusions

Optical measurement of LAI is a useful indicator for monitoring canopy response to structural damage suffered from a catastrophic disturbance, such as an ice storm. LAI measurement with the TRAC has been demonstrated to be sufficiently accurate as an indicator of damage, because it is significantly related to the initial damage condition in spite of discrepancies between the scales of crown and canopy measurements. Total LAI measured by the TRAC changed progressively through time, from the damaged condition following the event to one that is unrelated to the initial damage measurement four years later. Between-season LAI change suggests that measurement immediately after a disturbance may be a better indicator of damage than measurement one year later, as was tested here. It can also be concluded that LAI change is a better indicator of damage than any of the single-date LAI measurements to which it was compared. When all plots were combined, LAI increased in both understory and overstory layers through time, leading to

the conclusion that overall, forests are recovering from ice storm damage. By examining LAI change on a plot-by-plot basis in relation to LAI measurement precision, a confidence level was assigned to the observed changes for each plot. Seasonal weather variation such as drought can affect LAI and perhaps mask the longer-term trend towards recovery in certain cases. Therefore, a longer temporal series of measurements is required to fully evaluate recovery relative to pre-disturbance LAI. Finally, no treatment effects on LAI response were observed, although this might also require a longer time series of LAI measurements.

PART II : REGIONAL DAMAGE MAPPING

CH 5. SATELLITE REMOTE SENSING OF FOREST DAMAGE

5.1 Introduction

This chapter reviews the literature on methods to characterize and map regional forest damage. Forest structural and physiological symptoms of damage will be considered, as will the effects of their interaction on multispectral canopy reflectance.

Although many of the generalizations discussed in this chapter apply to a range of image scales greater than the areal extent of a single tree, satellite imagery from the Landsat TM sensor will be considered specifically covering a pixel spacing of 900m^2 on the ground. Previous reviews linking indicators of forest health and sustainability with measurements extracted from remotely sensed imagery focused on leaf spectral indicators (e.g. OMNR, 1997) without consideration of forest structural effects on reflectance. Spectral indicators will be reviewed briefly, particularly with respect to how these indicators interact with canopy reflectance changes caused by structural damage.

While many spectral indices have been derived from hyperspectral sensors that measure reflectance in very narrow ($\sim 2\text{nm}$) wavebands, data from the Landsat TM sensor used in this thesis have relatively broad wavebands. For example, the red band (TM 3) is 60nm wide from 630 to 690nm while the NIR band (TM 4) is 140nm wide from 760 to 900nm .

Hyperspectral remote sensing typically uses indices derived from many narrow wavebands that form a spectral reflectance curve. Broadband sensors such as TM do not acquire the large number of narrow wavebands necessary to calculate similar indices. Also, improperly selected bands can miss sensitive features altogether. For example, TM bands 3 and 4 miss the red edge completely (OMNR, 1997). In detection of forest damage, stress symptoms may not be detectable by broadband spectral indices, but structural changes may be if they are large enough to alter a pixel's radiance.

5.2 Canopy reflectance

A forest canopy is considered here to be a volume whose structure manifests itself as spatial variations in reflectance related to the arrangement, size and orientation of plant organs such as leaves, branches and stems. As such, forest structure has been shown to be the main determinant of above canopy reflectance over a wide range of conditions (Treitz and Howarth, 1996; Chen et al., 1999). However, certain conditions exist where leaf reflectance can dominate the above-canopy signal, such as deciduous chlorosis prior to leaf senescence in the fall, or similar changes in reflectance caused by insect damage and other stress agents (Ahern, 1986; Ahern, personal communication). Such severe symptoms usually change the reflectance property of leaves at extreme levels of stress prior to mortality. Other factors that affect canopy reflectance in more subtle ways include leaf properties such as chlorophyll content, nutrient concentrations, leaf age, species and development factors (Sampson et al., 2000). Some of these factors are physiological, and interact with structure to produce canopy reflectance.

5.2.1. Structural effects on canopy reflectance

The reflectance of a forest canopy includes a mixture of sunlit crown and different levels of within and between crown shadows. The intensity of the spectral response of the canopy is dependent on the areal fractions and brightness of sunlit crown and shadows within the imaged area. Analysis of these fractions has been conducted using airborne imagery where the pixel size is typically less than the individual crown and sunlit, thus shadow fractions can be visually detected and statistically related to canopy structure (Seed and King, 2003). The integrated shadow fraction (shaded crown and shaded background) is considered by some to provide the most useful information on canopy structure for the purpose of biophysical assessment (Peddle et al., 1999).

In airborne imagery at spatial resolutions less than the individual crown, gaps are visible and can be analyzed directly. At a pixel size larger than the individual crown, pixel brightness can be used to estimate structure since canopy reflectance varies with the area occupied by gaps within the pixel. Generally from low to moderate damage, a greater gap fraction occurring within a pixel will produce a lower canopy spectral response due to differences between view and illumination angles, which leads to the viewing of shaded understory and soil or rock on the ground except at the 'hot spot' where these angles coincide within the same canopy gap. Recent work by Seed and King (2003) has shown that shadow fraction and visible to NIR shadow brightness can offset each other in mixed boreal forest, i.e., that a larger shadow fraction will tend to be brighter than a smaller

shadow fraction and vice versa. The reason is that large shadow fractions are often caused by large gaps, which allow incident light to penetrate to the ground or understory layers and less interception of light reflected towards the sensor. Additionally, large gaps will tend to become occupied quickly by fast-growing vegetation, leading to understory that is relatively tall compared to the understory directly beneath the forest canopy. These understory layers with little leaf area above them have a high probability of becoming illuminated directly by the sun.

Where pixel spacing is larger than the individual crown, pixel reflectance represents the sum of the reflectances from sunlit crown, diffusely (sky) lit crown, background and shadow, weighted by their aerial fractions within the pixel. Included in the above are some contributions (mostly diffusely lit and shadowed) from the understory. Spectral unmixing (or spectral mixture analysis) of the pixel reflectance can be used to estimate the areal extent of different surfaces whose reflectances together contribute to the overall pixel level reflectance received by the sensor (Peddle et al., 1999). Unmixing requires knowledge of the reflectances of the individual surfaces, called end members, which together produce the overall reflectance of the pixel. Spectral mixture analysis has been used to estimate boreal forest biophysical structure (Peddle et al., 1999) and jack pine budworm defoliation (Radeloff et al., 1999).

5.2.2. Effects of structural damage on canopy reflectance

Some generalizations can be made about the image expression of forest structural damage. These generalizations assume that canopy closure is high prior to the disturbance event so that illuminated crowns and shadowed gaps, i.e. not understory or ground, produce the remote sensing signal. Where the canopy is relatively sparse and the ground illuminated, the effects of damage on image expression are subtler and these generalizations may not hold true.

Seen from above, an undamaged forest canopy consisting of several crowns and gaps in between will exhibit shadow related to the canopy gap fraction and distribution. With increasing levels of structural damage, the canopy becomes more irregular as branches break and trees topple. The irregular structural configuration that results from damage manifests itself as increased image shadow fraction due to a higher gap fraction and increased mutual shading, generally leading to lower canopy reflectance, especially in the green and NIR.

At the highest levels of damage, the canopy often becomes brighter in the visible and NIR as gap frequency and size increase and the understory or forest floor becomes illuminated. The composition of understory and ground cover that is illuminated determines the magnitude of reflectance increase. For example, ground and understory that are occupied mostly by healthy vegetation are expected to increase NIR reflectance more than ground cover composed of rock and soil.

The opposing effects of gap size and brightness on visible and NIR canopy reflectance may produce insensitive canopy reflectance to increasing gap fraction from damage. Increasing brightness at higher levels of damage may also be caused by greater direct scattering from damaged and irregular canopy surfaces. These two structural effects, in addition to stress factors causing increased reflectance at the leaf level, have led some authors to report increasing or non-linear visible and NIR reflectance with higher levels of canopy damage (e.g. Cosmopoulos and King, 2004). This trend has consistently been observed in conifers due their low undamaged reflectance and generally deciduous understory.

Figure 5.1. Typical canopy reflectance due to varying levels of structural damage, leaf and understory / forest floor reflectance

Radeloff et al. (1999) reported increasing NIR reflectance due to budworm defoliation of jack pine stands. Ardo et al. (1997) stated that reflectance increased in all bands, especially the mid IR with increasing Norway spruce damage in the Czech Republic. Both of these studies classified damage or defoliation of coniferous stands with varying amounts of hardwood understory. Radeloff et al. (1999) acknowledged the contribution of understory to increased reflectance at high levels of overstory jack pine defoliation. Increasing reflectance with increasing levels of conifer canopy damage in the visible bands may be largely due to physiological stress, and not structural damage itself.

The relative contribution of leaf reflectance and structure to the overall spectral response of a canopy will vary depending on canopy architecture and its effects on shadow.

Canopy spectral response is dominated by leaf reflectance where stands are relatively homogeneous in terms of species and height with small uniform spacing between trees. This condition is expected to produce a relatively flat canopy surface with little shadow, especially in deciduous stands with a high stem density. Where canopy surfaces are rough with large and irregular spacing between trees, or where crowns are conical, manifestation of canopy structure through changes in gap size and frequency tends to dominate the spectral response of the canopy.

5.2.3. Spectral indicators of damage and physiological stress

When leaf reflectance is plotted as a function of wavelength, healthy vegetation has a characteristic reflectance curve shown in Figure 5.2. The shape of this curve is explained

by low reflectance (high absorption) of vegetation in the blue and red bands (400-500nm and 600-700nm), greater reflectance in the green band (500-600nm) and the highest reflectance in the NIR portion of the spectrum (700-900nm) due to a lack of absorption by chlorophyll in this region (OMNR, 1997). Portions of the curve have been named to describe vegetation reflectance in that part of the spectrum. From lower to higher wavelengths, the curve goes from the *green peak* to the *chlorophyll well* in the red part of the spectrum followed by the *NIR plateau*. The region between the *chlorophyll well* and the *NIR plateau* has been termed the *red edge* (Curran, 1998).

Figure 5.2. Typical reflectance curves for "healthy" and "stressed" vegetation showing key descriptive features (from Rock et al. 1989).

While structure tends to dominate canopy reflectance over a broad range of conditions, spectral indices used to model structural damage are often similar to indicators of

physiological stress measured at the leaf level. Reflectance in the 400nm to 900nm wavelengths responds to the internal structure of leaves and may be sensitive to changes in vigour (Lillesand and Kiefer, 1994) and chlorophyll content (OMNR, 1997; Broge and Leblanc, 2001). Vegetation stress produces changes in the typical reflectance curve by decreasing total chlorophyll content and changing the proportion of light absorbing pigments, leading to less overall absorption in the visible bands (OMNR, 1997). Stress increases reflectance in the green peak centred at 550 - 570nm (Gates et al., 1965; Collins, 1978; Horler et al., 1980; Collins et al., 1983; Singhroy et al., 1986) and in the red chlorophyll absorption band (Lillesand and Kiefer, 1994). The result of an increase in both green and red reflectance is visible yellowing of stressed or damaged leaves. A shift in the red edge has also consistently been reported, though some authors have reported a shift towards shorter wavelengths, while others have reported a shift towards longer wavelengths (Singhroy, 1995). NIR reflectance is relatively insensitive to plant stress (Rock et al., 1989; Carter, 1993), but sensitivity increases in the Mid IR from 1400-2500 nm due to severe leaf dehydration and the accompanying decreased absorption by water. The mid infrared portion of the spectrum has been shown to be useful for discriminating between defoliation classes in needle leaf stands such as hemlock, spruce and fir (Leckie et al., 1988; Ahern et al., 1991; Hudak et al., 1992; Franklin et al., 1995).

Physiological stress or impairment reduces leaf chlorophyll content, moisture and other light absorbing pigments, producing changes in leaf reflectance. Canopy biomass removal symptomatic of damage produces a similar reduction in canopy chlorophyll, moisture and light absorbing pigments, resulting in a parallel change in canopy

reflectance. Therefore, physiological stress and structural damage may produce similar changes in reflectance at leaf to canopy scales over a range of damage, especially where shadow does not dominate the signal.

5.2.4. Vegetation indices

Vegetation indices derived from band ratios or band differences have been developed to make use of information contained in the vegetation spectral reflectance curve. Band ratios are less sensitive to variable illumination conditions due to atmosphere, slope, aspect and bi-directional reflectance than individual spectral bands because they measure the relative differences between discrete portions of the spectrum (Lillesand and Kiefer, 1994). The simple ratio of near infrared to red reflectance ($SR = NIR / Red$) has been shown to be highly related to LAI (Chen et al., 1999), vegetation cover (Lawrence and Ripple, 1998) and defoliation (Nelson, 1983). It has also been used to distinguish between damage classes in conifer-dominated sites in New England (Vogelmann, 1990) and damage caused by pest outbreaks using simple change detection techniques (Green and Cosentino, 1996).

5.2.4.1 NDVI

The Normalized Difference Vegetation Index ($NDVI = [NIR - Red] / [NIR + Red]$) is one of the most widely applied indices for vegetation assessment. By computing the

difference between NIR and red bands with respect to their sum, the NDVI effectively calculates a normalized red-edge slope, constrained to a range of -1.0 to $+1.0$.

NDVI has been found to be useful for distinguishing among three damage classes in deciduous sites, and less suitable for monitoring damage in coniferous sites by Vogelmann (1990). It has also been found to be related to forest productivity (Peddle et al., 1999; D'Arrigo et al., 2000), LAI across a range of vegetation types (Peddle et al., 1999; Chen et al., 1999), cover or crown transmittance of stratified forest classes (Gemmell and Varjo, 1999) and biomass (Peddle et al., 1999). Peddle et al. (1999), also noted that biophysical structure has been poorly and inconsistently estimated with traditional indices such as NDVI due to confounding factors such as background reflectance and canopy geometry.

Chen et al. (1999), noted a low sensitivity of red and NIR spectral indices, such as the NIR / red ratio and NDVI, to changes in LAI. The low sensitivity was caused by a small difference between the spectral signature of leaves and the background understory and ground vegetation. In a previous paper, Chen and Cihlar (1996) noted a simultaneous decrease in red and NIR reflectance with increasing LAI. It is generally assumed that red reflectance decreases with increasing LAI, but that NIR reflectance should increase due to greater reflectance of leaves than background in the NIR.

The behaviour of NIR reflectance with increasing LAI is explained by light absorbing shadow, whose areal extent and intensity tends to dominate the reflectance of the canopy

surface. Shadow was determined to control the spectral response more in coniferous than in deciduous stands, and more consistently in the red band than in the NIR. For deciduous stands, multiple scattering in the NIR was usually sufficient to overcome the shadow absorbing effect, but led to a low sensitivity of NIR reflectance to increasing LAI (Chen et al., 1999). These findings highlight the importance of the expression of canopy structure and shadow in remotely sensed imagery.

5.3 Damage modeling and mapping

5.3.1. Image data

Forest damage model development using remotely sensed data involves relating image reflectance to known levels of damage measured in the field. These models may then be extended to reflectance data outside of field plot areas to produce forest damage maps. Two approaches involving various statistical methods to relate image measures to damage have been applied in previous studies.

One approach involves relating damage to post-disturbance reflectance and assumes that the effects of damage on reflectance are greater than the natural variation in reflectance due to species and structural differences. This approach may be particularly effective where damage is modeled over a homogeneous forested surface, or where forest cover is stratified into homogeneous areas using other sources of data. Post disturbance reflectance data from the Landsat TM sensor has been used to map damage with some

success by Vogelmann and Rock, (1989); Ekstrand, (1994); Lambert et al., (1995) and Radeloff et al., (1999).

A second approach to damage modeling involves the application of pre/post disturbance change detection techniques. This approach is conceptually similar to damage measurement as a percentage of crown loss or mortality since the magnitude of change in canopy reflectance is related to the degree of damage sustained relative to a pre-disturbance condition. The data may be stratified prior to modeling if damage is expected to produce different changes in canopy reflectance according to forest type. Collins and Woodcock (1996) evaluated several change detection techniques for mapping forest mortality using multitemporal Landsat TM data. Ardo et al. (1997) used bi-temporal Landsat TM data to map forest damage in the Czech Republic. Singh (1989) provides an excellent review of some basic change detection techniques that may be applied to pre-post disturbance remotely-sensed data for damage mapping.

5.3.2. Modeling methods

Forest damage modeling and mapping studies have applied various methods, including linear regression (Franklin et al., 1995; Collins and Woodcock, 1996) and stepwise linear regression (Ekstrand, 1994), logit regression (Lambert et al., 1995), discriminant analysis (Franklin et al., 1995), supervised and unsupervised classification (Franklin et al., 1995), and neural networks (Ardo et al., 1997). Multi-temporal imagery has been used to establish a pre-disturbance baseline from which damage can be measured (Ekstrand,

1994; Franklin et al., 1995; Collins and Woodcock, 1996; Ardo et al., 1997; Radeloff et al., 1999). Collins and Woodcock (1996) assessed three linear change detection techniques for mapping forest mortality, including multi-temporal principal components analysis. Additional image processing techniques worth noting include the use of band ratios (e.g., Vogelmann, 1990) and spectral unmixing (Radeloff et al., 1999). Other studies have included topographic data to improve damage prediction (Ardo et al., 1997).

Most previous damage mapping studies have assessed defoliation in conifer forests (Vogelmann, 1990; Ardo et al., 1997; Lambert et al., 1995; Franklin et al., 1995; Collins and Woodcock, 1996; Radeloff et al., 1999). Deciduous forest damage has been modeled using high-resolution airborne imagery (Yuan et al., 1991; Lévesque and King, 1999, 2003; Olthof and King, 2000), and in a few studies, satellite imagery (Vogelmann and Rock, 1989; Vogelmann 1990; and Ekstrand 1994 for mixed forest damage assessment).

5.4 Conclusions

In remotely sensed imagery, the spectral reflectance of a forest canopy is a manifestation of leaf and background reflectance, as well as canopy structure. Structural alterations and changes in leaf level reflectance often co-occur due to the morphological effects of damage and the physiological stress that it causes. Damage alters canopy structure, generally producing lower visible canopy reflectance resulting from increased mutual shadowing due to an irregular residual canopy surface and a higher gap fraction. Extreme damage resulting in a high gap fraction and illumination of understory, rock or soil can

produce an increase in visible and NIR reflectance, depending on the mixture of cover types within the pixel. Physiological stress often manifests itself as an increase in visible leaf level reflectance. These two effects may offset one another, producing variable reflectance response or a low sensitivity of canopy reflectance to damage.

Vegetation indices developed from the spectral reflectance curve of individual leaves have been applied to remote sensing data of canopy reflectance for retrieval of numerous biophysical attributes (Nelson, 1983; Lawrence and Ripple, 1998; Chen, 1999). Some studies suggest that indices may be used to detect vegetation stress at the leaf level. However, many have found that spectral indices developed for leaf-level stress detection cannot be reliably upscaled to the canopy level due to confounding factors such as background reflectance and canopy architecture. In the case of damage detection, it is likely that reflectance simultaneously provides information on both physiological stress and canopy structure. In addition, while indices derived from narrow-band reflectance of high-resolution imagers may detect physiological stress of leaves or branches that can be resolved, broadband reflectance acquired at moderate (30m) TM resolution has shown little promise, except in extreme cases of stress approaching mortality.

In numerous studies, the mid IR provided more damage information than either the visible or NIR. This region of the spectrum is known to be sensitive to moisture content. Whether by insect defoliation or catastrophic disturbance, damage reduces leaf biomass and the moisture contained within. A more open canopy may also lead to increased soil evaporation, contributing to lower mid IR reflectance.

Finally, damage modeling and mapping with remotely-sensed imagery have been performed using one of two methods. Multi-temporal pre/post disturbance change detection has been applied to model damage by relating the magnitude of image change to damage. This approach is conceptually similar to field-based measurements that make reference to a pre-disturbance condition for damage characterization. A second approach involves the use of one-time post disturbance imagery, and assumes that the variation related to damage is greater than the variation due to differences in species and structure across the mapped area.

CH. 6. MAPPING DECIDUOUS FOREST ICE STORM DAMAGE USING LANDSAT AND ENVIRONMENTAL DATA

6.1 Introduction and objectives

This study was designed to evaluate the potential to map regional deciduous ice storm damage using pre-post ice storm Landsat imagery and environmental data. Research presented in this chapter was published in Olthof et al. (2004). An important contribution to this thesis and overall ice storm research conducted by the OMNR is the establishment of damage classes that can be mapped with an acceptable level of accuracy. In other words, we wish to answer the following question: ‘at what level of thematic detail can damage be mapped with a level of accuracy sufficient to make the product useful to decision makers?’.

To achieve this overall objective, modeling is conducted using both continuous damage measures and damage classes described below. Available plot data are stratified using various methods and accuracy is assessed for each method using multiple cross-validation trials. An examination of the variability in classification accuracy using these methods allows an assessment of errors related to common, but misused practices in remote sensing classification and accuracy assessment, and provides a robust estimate of the accuracy of the damage classification provided.

Specific objectives of this study were to:

1. compare the following four classification methods for ice storm forest damage mapping: linear stepwise regression, linear discriminant analysis, maximum likelihood, and neural networks.
2. determine remote sensing and environmental variables that can be effectively used to predict and map damage.
3. analyze and compare classification accuracies obtained using three reference data sets: the training data (calibration set), reference data samples located in close proximity to the training samples, and reference data that were spatially independent of the training data.

6.2 Data

6.2.1. Forest damage data

The OMNR provided plot-based visual damage estimates (mean percent crown loss for six representative focus trees per plot; 24 per block) acquired in the fall of 1998, described in Chapter 4. Individual tree estimates of crown loss were unavailable for some blocks, leaving 34 blocks, or 136 plots for this analysis. In this study, modelling is conducted using these continuous damage data and classification is conducted using pre-determined damage classes. The average percent crown loss of the six focus trees was assigned to low (0-25%), medium (26-50%) and high (51%+) damage classes for classification purposes. These class divisions were selected to be

able to assign a relative probability of survival based on existing literature. Both low and medium damage classes have a high to moderate chance of survival depending on tree vigour prior to the event, while the high damage class represents varying probabilities of survival from moderate to low with expected internal infection and / or growth suppression (Coons, 1999; QMNR, 2000). These classes were also selected because they were in common use in other ice storm studies (e.g. Kidon et al., 2001)

6.3 Geospatial data

6.3.1. Environmental Data

Elevation: Elevation data consist of a digital terrain model derived from the Ontario Base Mapping (OBM) Digital Topographic Data Base (DTDB) of Eastern Ontario. Spot heights were obtained for this database using photogrammetric compilation of 1:10000 airphotos and are positionally accurate to within 0.1m horizontally and 1.25m vertically. The elevation surface was created in ArcInfo and a 50m cell size. The interpolated elevation surface was provided by the OMNR.

Precipitation: Freezing rain measurements were made during the ice storm event at 284 stations located across Quebec, Southern Ontario and the Northeastern United States. Observations were made hourly at stations operated by Environment Canada and twice daily at stations operated jointly by Environment Canada and the Ministère de

l'Environnement et de la Faune du Québec (MEFQ). Both of these networks have manual and automated stations for recording weather data.

The type of precipitation varied considerably between locations and over the course of the ice storm. Precipitation was measured with a standard graduated cylinder rain gauge at manual stations at the prescribed measurement interval. They were heated to melt any precipitation that froze to the walls of the gauge and to obtain the water-equivalent of freezing rain.

Most automated stations contain antifreeze in their rain gauges, and measure the water equivalent of precipitation by the increase in weight of the liquid in the gauge. These gauges do not give a precise estimate of the different types of precipitation that have fallen. Freezing rain equivalents were inferred based on the temperature recorded at the station. If the hourly temperature recorded at the stations was above zero, then all precipitation was assumed to be rain. When temperatures were below zero, then methods described by Environment Canada (1997) were used to distinguish freezing rain from snow and ice pellets using assumed densities of each precipitation type. Other automated stations have sensors that can detect the type of precipitation from its intensity combined with external temperature information.

Total freezing rain equivalents for the ice storm at each of the 284 station locations were provided by Environment Canada. Station locations were in MTM coordinates, zone 8 with NAD 83 datum and had to be re-projected to a UTM coordinate system, zone 18,

WGS 84 datum. The freezing rain surface was generated with a 30m cell size through kriging interpolation of point estimates. A spherical variogram was used with a nugget value of zero, a sill value of 1 and the range set to the average distance between points. Blocks of data used to calculate variogram parameters were obtained using the r-tree mode in the PCI Inc. kriging program.

Wind: Wind became quite intense following ice deposition, and therefore would likely account for some of the spatial variation in forest damage. Ice accretion and susceptibility to wind damage after icing is likely controlled by the amount of precipitation received, the forest's susceptibility to damage and topographic variation governing exposure to wind. Unfortunately, reliable wind information was not available in the worst hit areas due to icing of anemometers; therefore, spatially explicit wind data could not be incorporated into the analysis. However, prevailing wind direction and intensity are given in Milton and Bourque, (1999), and help to explain some of the observed and mapped spatial patterns of ice and wind damage.

6.3.2. Remote Sensing Data

6.3.2.1 Kodak DCS 460 CIR

Image acquisition: Airborne imagery was acquired of 36 blocks by the OMNR Provincial Remote Sensing Office on August 31, 1999 between 9:41 and 11:45am using a Kodak DCS 460 CIR digital frame camera. The DCS acquires three spectral bands of

approximately 100nm bandwidth each in the near infrared, red and green. The camera has a total field of view of approximately 60 degrees along the long axis, and 42 degrees along the short axis. The resulting images are 3060 x 2036 pixels in size, with each pixel corresponding to an area of about 68cm x 68cm on the ground. Tests of known distances revealed that pixel size varies by ± 5 cm between images due to aircraft altitude variations. Total coverage for a single image frame is approximately 1.9-2.2km x 1.3-1.5km.

The data were intended to be used for scaling plot damage to the landscape level for subsequent scaling to the regional level using Landsat TM data. Brightness variation due to bi-directional reflectance and vignetting were evident in the DCS imagery (Figure 6.1). A new correction methodology was developed for consistent extraction of image spectral and spatial measures related to damage (Olthof and King, 2003). While application of this methodology improved relations between field damage and image spatial measures, the relationships remained too low for accurate prediction of damage due to the lack of multispectral information. The camera uses a single CCD chip and performs interpolation between pixels to obtain a multispectral image. The resulting image has very high correlations among bands, producing a near grey-level image. Finally, due to saturation in the NIR band, data representing tree crowns were not usable. The images were therefore discarded from further analysis. They did, however, aid in georeferencing Landsat, in delineating plot boundaries and in separating deciduous forest from coniferous and mixed as described in subsequent sections.

Figure 6.1. Sample DCS NIR image, showing significant vignetting and BRDF effects

Block Ground Control Point (GCP) acquisition for image georeferencing: Between 4 and 5 ground control points per image frame were acquired with a real-time differential GPS unit with sub-metre accuracy. GPS coordinates of block centres and corners were acquired at the same time as the georeferencing coordinates to allow the location of blocks within the imagery. Image registration was done using a first-order (linear) transformation and bi-cubic convolution. Model-fit RMS errors ranged between 0.06 and 6.62 pixels (0.04-4.50m) in the x direction, and 0.17 and 10.78 pixels (0.11-7.33m) in the y direction. Higher errors are due to poor availability of identifiable points in the image and on the ground near a given block, or to steep topography at some block locations. Image subscenes corresponding to the block locations were cropped from the frames. A visual inspection of the block locations in relation to known features on the ground revealed a much higher accuracy than that which was reported by the model fit. For

example, block 20, which had the highest image geo-referencing RMS error (7.65m) is located atop a cliff, at the base of which lies a small lake. In spite of the high reported error, the imagery shows that the block location is within a few metres. Vector layers of the plot boundaries were overlaid on the image subscenes. Separate vector layers were created for each of the plots, which excluded a buffered area of 3m on all sides to account for registration errors.

6.3.2.2 Landsat TM

The TM sensor is a scanning optical sensor operating in the visible and infrared wavelengths. TM bands 1-5 and 7 measure reflected radiation from Earth's surface at a spatial resolution of 30-metres and band 6 measures the temperature of Earth's surface at a spatial resolution of 120-metres.

Eight scenes were provided by the Canada Centre for Remote Sensing and used to generate two separate mosaics – one pre and the other post ice storm. The best scenes available with the desired coverage were selected based on a report of scene quality and on visual assessment of cloud cover. Given the limitations of data availability (primarily due to cloud cover), images from several years were used. Pre-storm data consisted of scenes acquired in the summers of 1996 and 1997, while post-storm data scenes were captured in the summers of 1998 and 1999. Scenes and their imaging dates are listed in Table 6.1. The 1999 scene was generated by the Landsat 7 Enhanced Thematic Mapper (ETM+), which has somewhat different radiometric characteristics and calibration than

the TM sensor of the other scenes. There were only 3 maple blocks contained within it, therefore differences in radiometry among scenes should have had a minor effect on damage modeling with reflectance.

Table 6.1. Landsat scenes used for modeling and mapping forest ice storm damage.					
Path	Row	Sensor	Date and time of acquisition	UTM scene centre	
15	28	TM	July 30, 1997 15:15	529812 E	5098447 N
15	29	TM	July 30, 1997 15:15	489003 E	4959470 N
16	28	TM	July 18, 1996 15:04	416822 E	5099703 N
16	29	TM	July 18, 1996 15:05	380581 E	4962369 N
15	28	TM	August 2, 1998 15:22	529812 E	5098447 N
15	29	TM	August 2, 1998 15:23	489003 E	4959470 N
16	28	ETM+	July 3, 1999 15:43	416822 E	5099703 N
16	29	TM	September 10, 1998 15:29	380581 E	4962369 N

Geometric corrections: Georeferencing was accomplished in a series of steps using airborne digital frame camera imagery of the maple blocks as an intermediate data source between surveyed ground targets and Landsat imagery. Landsat scenes were registered individually to the airborne images using between 21 and 88 control points per Landsat scene. Plot centres for the maple experiment blocks were added to the database as a point vector layer, and the Landsat pixel closest to the plot centre location was used to represent the reflectance of the plot. Post-storm Landsat scenes were then individually registered to corresponding pre-storm scenes using between 16 and 72 control points per scene.

Radiometric calibration: Relative radiometric calibration was performed by plotting radiance in overlap areas between scenes to determine the function relating stable land

elements in adjacent or multi-temporal scene pairs. Scene 16/29, 1998 was selected as the master to which all other scenes were relatively calibrated. Absolute calibration to surface reflectance could then be performed by applying aerosol optical depth data, and sensor gains and offsets from the master scene to all other scenes in the mosaic.

Aerosol optical depth data were acquired from the Aerocan network of automatic sun tracking photometers. They were selected from three stations located nearest to Eastern Ontario and for the times closest to the satellite overpass. It was determined that the Egbert site (UTM 120609.5 N 4907956.4 E) was geographically closest to scene 16/29 and had acquired aerosol optical depth data 42 minutes prior to the satellite overpass on September 10, 1998. These data were selected to perform absolute calibration using gain and offset information from scene 16/29, 1998 and aerosol optical depth data acquired in 7 spectral bands. These parameters were entered into the calibration program 6S (Vermote et al., 1997), which calculates gains and offsets to convert scene radiance to surface reflectance for six individual TM bands (TM 1-5 and 7). The thermal band (TM 6) could not be calibrated due to a lack of surface temperature data required for calibration so it was excluded from further analysis. Geometrically registered and calibrated mosaics are shown in Figure 6.2. Surface reflectance variables are named as follows: TM 1-5 or 7_year (97 or 98).

Figure 6.2. Landsat composites – left: TM bands 4, 5, 3; right: TM bands 4, 3, 2 as R, G, B.

6.2.3.3 Forest classification

In the study region, forests are composed primarily of deciduous species with smaller areas of coniferous, or mixed species. For the purposes of this study, damage classification was conducted for deciduous forests only, as damage data for coniferous and mixed forests did not exist in the same format as described above, and the primary application of the map was for sugar maple damage assessment. Land cover information was obtained from two sources of data. The OMNR Ontario Base Map data layer ‘Woodarea’, which was derived from interpreted 1:10,000 aerial photography in 1991, consisted of a vector representation of woodland boundaries. In order to extract only deciduous forest areas, these woodland forest polygons were overlaid onto a thematic land cover map derived from clustering using Classification by Progressive Generalization (CPG) classification (Latifovic et al., 1999) of the mosaic of the four post-storm Landsat TM scenes (see below). The thematic map classification included separate deciduous and coniferous classes.

In the TM map, coniferous forest was originally classified with a 78.8% user's accuracy (100% - % errors of commission) using TM data only and independent reference areas that were visually interpreted from the 60 cm pixel airborne digital camera imagery. Once the TM classification was combined with the 'Woodarea' layer, confusion between conifer, water and agricultural crop classes was eliminated, increasing the conifer classification accuracy to 97.0%. Similarly, deciduous classification accuracy increased from 59.0% in the CPG map to 91.0% after intersection of the two spatial datasets. In addition to focusing damage classification on deciduous forests only, the map was also used to calculate proximity of forest pixels to other land cover classes to derive a measure of plot proximity to the forest edge for damage modeling.

Though it was desirable to further stratify forest cover to account for differential susceptibility of species to ice storm damage (Hopkin et al., 2003), no current reliable species cover data existed at the time of this study, nor were there accurately positioned field plots in all forest types. Since this study, the OMNR has been in the process of updating its Forest Resource Inventory (FRI) of Eastern Ontario, which should provide species composition and allow additional stratification of forest types for future mapping.

6.4 Methods

6.4.1. Classification of Ice Storm Damage and Stratification of Training and Reference Data

Forest damage was first modeled as a continuous variable using linear stepwise regression. Subsequently, using the three damage classes, four classifiers were implemented and compared: classification of the linear regression continuous function, linear discriminant analysis, maximum likelihood, and a neural network.

For the parametric methods (regression, discriminant analysis and maximum likelihood), histograms were visually checked for normality and transformations were applied to non-normal data in an attempt to normalize their distributions. The spectral bands, band ratios and NDVI, elevation, and precipitation were determined to be sufficiently normal for input into parametric models. Aspect could not be included as an independent variable in the parametric models due to its circular nature. Slope was significantly related to elevation in the study area ($r = 0.43$, $P < 0.01$) and could not be transformed to a normal distribution. A logarithmic transformation was applied to proximity to forest edge to normalize its distribution.

6.4.2. *Modeling and classification*

6.4.2.1 Linear regression

In modeling of damage as a continuous variable, forward stepwise linear regression was performed 100 different times (trials) using samples randomly drawn from the 104 plots as shown in Table 6.2. Probabilities to enter and remove were set at 0.05 and 0.10, respectively. The resulting models consisted of between two and six significant predictive variables. As models consisting of certain groups of variables were generated more frequently than others, a comparative analysis of prediction errors between these model groups was conducted. The identification of significant predictive variables from the regressions also allowed a reduction in the number of variables input into subsequent maximum likelihood and neural network classifications. A maximum of 16 input channels could be handled by the neural network algorithm, while maximum likelihood classifiers often perform best when trained with a limited number of discriminating channels (see below). Given the total number of available variables was 41, the regression results aided in reducing the number input to these classifiers.

In damage classification, for comparison with the other classifiers, ten training / reference sets were randomly selected from the original 100 trials and checked to ensure that they represented the full range of models in those trials.

Table 6.2. Samples used in different phases of damage modeling and classification error analyses					
Phase / Application		1 Examine regression errors and variable reduction	2* Comparison among classifiers	3* Assess NN accuracy distribution from set 2	4 Assess NN accuracy using block-based stratification
Damage variable		Continuous	Ordinal		
Stratification		Plot	Plot	Plot	Block
Method	Regress	x	x		
	Discrim		x		
	Max likelihood		x		
	NN		x	x	x
# cross-validation trials		100	10	10	20
# training plots / trial		80	80	80	84
# reference plots / trial		24	24	24	20

* subsets extracted from set 1

6.4.2.2 Linear discriminant analysis

Linear discriminant analysis seeks $k - 1$ discriminant functions, where k is the number of classes to differentiate. These functions are linear combinations of the predictor variables that give the greatest amount of squared difference between groups relative to the variance within groups. Each class mean (centroid) in $k - 1$ dimensional space is determined. Observations are assigned to the class whose discriminant function has the smallest Mahalanobis distance to the class mean (Lachenbruch, 1975). In two-dimensional space (where $k = 3$ classes), the Mahalanobis distance is identical to the Euclidean distance. Stepwise discriminant analysis was performed using the same probabilities for entry and removal as the stepwise regression analysis. All available normally distributed spectral and environmental data were entered as independent variables into the analysis.

6.4.2.3 Maximum likelihood

Before running the maximum likelihood classifier, variable selection was carried out to eliminate redundant information contained in multiple discriminating variables (Piper, 1992; Mather, 1999). Sixteen significant discriminating variables were identified in the stepwise regression analysis. Of these, the five variables that accounted for maximum variance in the original data, determined through principal components analysis, were selected for input to the maximum likelihood classification. These included post-storm spectral band 3, pre/post storm ratios of TM bands 3 and 5, and freezing precipitation. Transformed proximity to forest edge was also included based on results from the regression analysis. The number of discriminating variables (5) exceeded Piper's (1992) recommendation of one variable per 10-30 observations for the low damage class, which contained between 12 and 17 observations.

6.4.2.4 Neural network

A simple back propagation neural network (Pao, 1989; Atkinson and Tatnall, 1997) was used that consisted of an input layer, one hidden layer and an output layer. Separate neural networks were trained for 40 sets of training / reference data; 20 sets using plot-based, and 20 sets using block-based stratification (see below). The maximum number of channels that could be handled by the algorithm was used, consisting of 11 TM spectral bands and band transformations determined to be significantly predictive of damage from

the stepwise regression analysis, and all available environmental data. While neural networks can approximate any function type, selection of input variables was based on linear data reduction techniques for simplicity. For all trials, default parameters in the PCI algorithm were used: 1000 iterations, learning rate of 0.1 (controls the step size when weights are iteratively adjusted), momentum rate of 0.9 (refers to the size of the step at each iteration), maximum individual class error of 0.001, maximum total error of 0.01 (PCI Geomatics Group Inc., 2001).

6.4.3. Stratification

From the total set of 104 plots with complete coverage of all of the above-mentioned geospatial data types, mutually exclusive training and reference samples were randomly generated for classification and accuracy assessment using multiple cross-validation trials (Efron and Tibshirani, 1993). An approximate 80% / 20% ratio of training to reference data was used for stratification on both plot and block bases. In the case of plot-based stratification, 100 separate samples of training and reference data were generated with this ratio for treatment of damage as a continuous variable (per cent crown loss) in the stepwise regression analysis (Table 6.2). Following this analysis, ten of these samples were selected to compare among classification methods for treatment of damage as an ordinal variable (i.e. the three classes). In both of these analyses, randomly selected training and reference data plots could be in close proximity to each other since each block was comprised of four adjacent plots. Spatial proximity between plots was expected to produce artificially high classification accuracies due to the effects of spatial

autocorrelation, registration errors and the point spread function of the TM sensor, which integrates reflectance over a larger area than the pixel bounds. To evaluate spatially independent training and reference data, an additional twenty samples were generated using block-based stratification with five blocks (20 plots) set aside as reference data. From the above three data sets and analyses, the effects of spatial proximity on classification accuracy were assessed as described in the next section.

6.4.4. Accuracy assessment

Classification accuracy was determined using three reference data types. The first was a comparison of the classification to the training data used to develop it. This method overestimates true classification accuracy but is a useful means for comparison of multiple classification trials using different input data, parameters, or classifiers (as in this study). The second used plots randomly set aside as reference data in each trial. As these reference plots were almost always in close proximity to training plots taken from the same blocks, this method was expected to produce positively biased accuracy due to spatial proximity in the data. The third method used entire blocks as reference data. Blocks were generally spaced far apart from one another (typically more than 25 km) so these reference data were assumed to be spatially independent.

In regression modeling of percent crown loss, the root mean square error between the predicted and actual values was examined for both training, and reference sets for all 100 trials. For training data, this error is the standard error (SE) of regression, while for

independent reference data, it is reported as the root mean square error (RMSE).

Ordinal classification errors are reported as the user's accuracy (100% - % errors of commission), producer's accuracy (100% - % errors of omission), overall accuracy (total correct plots / total plots), and Kappa statistic (overall accuracy – accuracy achievable through random class assignment) (Lillesand and Kiefer, 1999). Overall accuracy within each classification and stratification method was calculated by summing the error matrices of all trials performed within each classification and stratification method. Differences among classification accuracies were assessed using pairwise t-tests, with each pair consisting of a reference set classification accuracy obtained using different classifiers. Difference distributions were visually assessed for normality.

6.5 Results

6.5.1. Damage as a continuous variable: linear regression models

All 100 regression models were significant at $P < 0.0005$ and had standard errors between 13.7 and 16.9% crown loss (Table 6.3). The range of RMSE of the reference data sets was greater than the range of standard errors, having both lower minimum and higher maximum errors. The mean error for the reference sets was 2.9% crown loss higher than the mean standard error. This difference was due to regression minimizing the residual sum of squares between actual and predicted values. The error generated from the

reference sets is a more realistic estimate of true model error when applied to the whole geospatial dataset.

Table 6.3. Regression model errors for 100 cross-validation trails. Units of SE and RMSE are percent crown loss.			
	R^2	SE	reference RMSE
Minimum	0.24	13.7	12.6
Maximum	0.52	16.9	25.0
Mean	0.39	15.3	18.2
Standard Dev	0.065	0.7	2.5

While the total error was relatively constant among the 100 trials, there was some variability due to the different significant predictors selected by the stepwise regressions (Table 6.4). Of the 100 models, 75 could be grouped according to one of four sets of significant predictors (model groups 1-4 in Table 6.4). These predictors were common to all regressions in the model group, while other variables not listed were either entered subsequently or were not common to all models of that group. Proximity to forest edge was automatically entered in all 100 models, suggesting that it is highly related to ice storm damage and complementary to spectral and other environmental data. Of the other environmental data, elevation was a significant predictor in only two models, while freezing precipitation was significant in four.

Table 6.4 Regression model errors grouped according to common predictor variables. Pre = pre-storm; Post = post-storm; Ratio = ratio of pre to post storm spectral band; Edgeprox = proximity of plot to nearest forest edge

model group	significant predictors	N	SE	reference RMSE
1	B1_pre, B5_pre, Edgeprox	33	14.9	18.0
2	B3_post, Edgeprox	19	15.1	16.4
3	B3_Ratio, Edgeprox	10	16.2	18.0
4	B7_post, Edgeprox	13	15.7	18.4
5	Other, Edgeprox	25	15.5	19.9

Pre-storm TM bands 1 and 5 were entered together 33 times, and were therefore related to the susceptibility of forest species and structure to subsequent ice storm damage. These bands have been shown to be useful for forest type mapping and vegetation moisture content, which may affect forest susceptibility to ice storm damage (Van Dyke, 1999; Hauer, 1994). The relation between pre-storm blue reflectance and ice storm damage may be explained by increasing canopy openness that predisposes a forest stand to damage, or may be accounted for by atmospheric conditions during image acquisition, as this band is particularly sensitive to Rayleigh scattering (Lillesand and Kiefer, 1999). Post-storm band 3 and a pre / post-storm band 3 ratio were significant predictors a combined total of 29 times. Thirteen models entered post storm TM band 7, while no more than 5 of the 25 remaining models could be grouped according to one or more common predictors.

Models that entered post-storm TM band 3 first had the lowest independent reference set errors, suggesting that perhaps this band is most useful for differentiating levels of damage. Post-disturbance TM band 3 has been found to be useful for discriminating different levels of deciduous damage in at least one other study (Vogelmann and Rock, 1989). In another study by Vogelmann (1990), NDVI was determined to be suitable for

distinguishing low, medium and high deciduous damage. This contrasts with results found here where none of the regression models entered the post-storm NDVI as the most significant predictor, but two models entered the pre-post storm NDVI ratio first.

Based on results from the regression analysis, the following spectral variables were retained for classification using neural networks: pre-storm TM bands 1-3, 5 and 7, post-storm TM bands 3 and 7 and NDVI, ratios of pre to post storm reflectance for TM band 1, 3 and 5, and all available environmental variables. The potential to identify non-linear patterns using neural networks justified the inclusion of environmental variables that were not linearly related to damage, while the selection of the spectral and edge proximity variables was based on linear variable reduction techniques.

6.5.2. Damage as an ordinal variable: classification comparison results

6.5.2.1. Training data accuracies

Table 6.5 presents the overall training data classification accuracies of three damage levels using the four methods described above.

The ten neural network classifications predicted the training dataset most accurately in all cases, achieving an overall accuracy of 94%. The maximum likelihood classifier did not perform nearly as well as the neural networks, with an overall accuracy of 72% for its ten classifications. However, it performed most consistently, with training set accuracies

ranging from 69% to 79%. Pairwise t-tests showed significantly different accuracies between all pairs of classifiers at $P < 0.01$. Both discriminant analysis and regression classifiers predicted training data poorly. Even with the typically inflated accuracies of training data over that expected from independent reference data, these results show that only the neural network and maximum likelihood classifiers are useful for such damage classification.

Table 6.5. Overall training data classification accuracies - the most accurate training data classification is shown in bold.				
Training set #	Regress	Discrim	Max likelihood	Neural Net
1	62%	70%	76%	96%
2	53%	60%	70%	99%
3	56%	64%	72%	97%
4	53%	66%	73%	98%
5	53%	62%	70%	100%
6	52%	51%	69%	99%
7	57%	65%	72%	91%
8	53%	58%	71%	92%
9	60%	59%	73%	75%
10	57%	65%	79%	94%
Average:	55%	62%	72%	94%
Range	10%	19%	10%	25%

6.5.2.2. Plot-based reference data accuracies

A direct comparison of the 10 plot-based reference data accuracies for the four classifiers again revealed the superiority of the neural network (Table 6.6). Its accuracies were highest seven out of ten times, while its performance was tied for first two of the remaining three times. Only one of the ten plot-based reference data sets had a lower overall accuracy than the other classifiers (trial #3). The range of classification accuracies was lowest for the maximum likelihood (17%) and highest for the neural network (35%)

(Table 6.6). Pairwise t-tests showed that all classifiers produced non-significantly different accuracies, except for the neural networks, which were significantly better than the others ($P < 0.01$).

Table 6.6. Overall plot-based reference data classification accuracies - the most accurate reference data classification is shown in bold.				
Reference set #	Regress	Discrim	Max likelihood	Neural Net
1	38%	38%	50%	50%
2	64%	64%	62%	85%
3	65%	62%	54%	54%
4	55%	45%	58%	63%
5	56%	44%	56%	69%
6	67%	61%	56%	67%
7	38%	52%	45%	67%
8	36%	64%	56%	67%
9	50%	45%	52%	60%
10	50%	41%	62%	76%
Average:	51%	52%	55%	65%
Range	31%	26%	17%	35%

The distribution of neural network accuracies shown in Table 6.6 is approximately normal, however, ten trials were insufficient to properly assess it. A second set of randomly split training and plot-based reference data sets were therefore generated and the classification results added to those of the first set to increase the number of trials to 20 (Table 6.2). The second set produced slightly higher accuracies than the first set, primarily due to two networks with accuracies greater than 90%. However, the difference between the two sets was determined to be insignificant using a t-test. Figure 6.3 shows the distribution of accuracies for the combined 20 neural network classifications.

6.5.3. NN reference data accuracies using block-based stratification

Comparison of the accuracies of the block-based stratifications of training and reference data (Figure 6.4) to the plot-based results of Figure 6.3 revealed the inflationary effects of the spatial proximity between training and reference data in the plot-based assessment. Overall block-based accuracy for 20 sets was 54.5% with a Kappa of 0.25 (Table 6.7), which was 14.2% lower than the overall accuracy obtained from the 20 neural networks using plot-based stratification. Because neural networks learn training data exceptionally well, and because the plot-based reference data were spatially-autocorrelated with the training data, these reference data were essentially pseudo-replicates of adjacent training data, thereby producing inflated accuracy estimates.

Figure 6.4. Distribution of Neural Network damage classification accuracies from 20 cross-validation trials and block-based stratification

Table 6.7. Combined error matrix for 20 Neural Network classifications, each assessed using 20 reference plots and block-based stratification

Classification	Reference damage class				User's
	1	2	3	Total	
1	15	16	8	39	38.5%
2	43	63	33	139	45.3%
3	19	63	140	222	63.1%
Total	77	142	181	400	
Producer's	19.5%	44.4%	77.3%		
Kappa:	0.25			Overall:	54.5%

Table 6.7 shows that while the overall classification accuracy was quite low, high damage areas were mapped relatively well. Indeed, 77.3% of spatially independent blocks having suffered high damage were correctly identified as such in the classifications. A 63.1% user's accuracy for the high damage class suggests that 63.1% of blocks classified as severe damage were actually severely damaged. The

low and moderate damage classes were subsequently merged into a single class to determine the accuracy with which high damage (significant probability of further decline) and low to moderate damage (low chance of further decline) could be classified. The overall accuracy increased to 69.3%, while the Kappa statistic improved to 0.39 with a standard deviation of 0.07, which was significantly different from chance agreement at $P < 0.0001$.

A map of the two deciduous forest ice storm damage classes was produced (Figure 6.5) using a voting strategy to select the most frequently occurring class for the twenty neural network classifications at each pixel location (Kanellopoulos and Wilkensen, 1997). The frequency of the most often occurring class (the mode) at each location provided a measure of confidence for the mapped output on a per pixel basis.

The resulting map suggests that greater damage occurred close to forest edges and at higher elevations found in the northwestern portion of Eastern Ontario. This area also coincides with the Canadian Shield, which is hillier than the Ottawa Valley and has poor and shallow soils. Damage does not appear to be directly related to precipitation, which was heaviest in the central to southeastern parts of Eastern Ontario. Factors that affect the magnitude of damage suffered from ice storm events are numerous, such as tree species, age and size, ice accretion and stand position, among others (Proulx and Greene, 2001), but complete discussion of them is beyond the scope of this thesis.

Figure 6.5. Deciduous forest damage in Eastern Ontario resulting from the January 4 – 10, 1998 ice storm.

6.6 Discussion

Due to the relatively small number of deciduous damage mapping studies in the literature and the absence of published deciduous damage classification accuracies, comparison of results found here must be made primarily to studies of coniferous forest damage.

Deciduous defoliation mapping studies were performed during extensive gypsy moth outbreaks that occurred in North America in the 1980s, but few carried out rigorous,

quantitative accuracy assessments that can be compared to the current study. Hall et al. (1984) used pre-post defoliation Landsat MSS red and NIR bands to discriminate healthy from defoliated aspen in northwestern Alberta, but did not perform an accuracy assessment due to a lack of reference data. During a more recent gypsy moth outbreak in Michigan, Joria and Ahearn (1991) compared Landsat TM and SPOT data for differentiating two levels of defoliation from non-defoliated deciduous forest. They noted the better discriminating ability of TM over SPOT data, primarily due to the presence of mid-infrared TM bands 5 and 7. TM data produced a best accuracy of 82 percent when assessed against manually interpreted high altitude aerial photography. The photography was assessed using 17 ground plots as a reference, achieving an overall accuracy of 70.6 percent for the photo interpretation. The Landsat classification accuracy was not reported using ground plot data as a reference (Joria and Ahearn, 1991).

In modelling conifer damage as a continuous variable, Ekstrand (1994) obtained a correlation (r) of -0.75 ($P < 0.001$) between TM band 4 reflectance and percent needle loss for 30 sites. The correlation coefficient improved to $r = 0.81$ for 39 sites when field and air photo determined stand characteristics were included in the model. In another study, Collins and Woodcock (1996) used orthogonal transformations of multitemporal and multispectral TM data. The best correlation coefficient obtained was $r = 0.89$ ($P < 0.0001$) for 25 mixed conifer sites using Kauth-Thomas change components. While all regression models in this study had an equal or lower correlation coefficient than $r = 0.72$ (Table 6.3), the significance level of all models was similar due to the larger sample sizes used in this study.

Damage classification typically requires assignment of a continuous damage measure into discrete damage classes. A limitation of the classification approach is that the boundaries between damage classes are artificial and subjective. For example, in this study, while a distinction is made between 24% crown loss and 26% crown loss in terms of damage classes, the difference between them is insignificant, especially in relation to the precision of visual crown loss estimation. Damage classes in this study were chosen to be consistent with those employed by other ice storm research groups, and to be able to assign a probability level of further decline from the literature based on the amount of crown loss suffered.

Lambert et al. (1995) provided an overview of nine previous satellite-based damage studies in coniferous forests that demonstrated the variability of methods and results obtained from nine different studies. TM bands 1, 3, 4, 5 and 7 have all been used to map conifer damage, as well as various ratios of these bands. However, most of the studies had inadequate sample size (8-22) to allow direct comparison to this study with two exceptions. Rosengren and Ekstrand (1988) used 92 stands to obtain an accuracy of 76% for four damage classes, while Lambert et al. (1995), used 243 stands and logit regression to map even-aged stand damage with an accuracy of 71-75% for three classes.

Franklin et al. (1995) achieved a best overall accuracy of 86% using discriminant functions to classify 21 coniferous plots into three defoliation classes. Multi-temporal TM indices were used to obtain this result, consisting of pre and post-disturbance Tasseled

Cap (Kauth-Thomas) brightness, greenness, and wetness. The same plot data that were used to produce the discriminant functions were also used to assess the classification accuracy. Thus, the accuracy obtained in Franklin et al. (1995) is optimistic, and a similar accuracy would not be achieved with an independent reference set, as was shown in this study. Average training set accuracy for the discriminant analysis in this study (Table 6.5) was not found to be as high as those obtained in Franklin et al. (1995). However, they assessed defoliation in pure conifer stands and a relatively small sample size was used. Additionally, the range of accuracies of 48-86% was wider than the range found here and the minimum accuracy was less than that of this study.

Franklin et al. (1995) also evaluated supervised and modified unsupervised k-means classifications using the 21 sites mentioned above, producing an overall training data accuracy of 67% for both methods. In this study, an average training set accuracy of 72% was achieved using a maximum likelihood classification (Table 6.5). This dropped to 55% when assessed using the 10 independent plot-based reference sets, with a best overall accuracy of 62% for a single classification (Table 6.6).

The overall accuracy obtained using neural networks and plot-based stratification in this study was similar to those obtained by Ardo et al. (1997) when using single date TM and topographic data to classify three conifer damage classes (62-68% overall classification accuracy). However, their results improved when using bi-temporal TM and topographic data (77-78% accuracy). The block-based stratification of data produced lower overall accuracies than the plot-based stratification for the neural network classifier. This was

due to the high accuracy with which neural networks classify training data, and the effect of spatial proximity between training and reference plots. Block-based stratification was not performed with the other classifiers as none performed well enough in the plot-based stratification to consider further. However, the inflationary effects of spatial autocorrelation on accuracy of other classifiers will depend on how well the classifier predicts training data. Poorer classification of training data will likely result in less inflated accuracy of spatially proximal reference data. These results demonstrate the importance of spatial independence between training and reference data for proper validation. Few studies report distance between training and reference data or consider its effects on model accuracy.

Better overall classification accuracy may have been achievable had several neural network architectures been tested (e.g., different momentum and learning rates, number of hidden layers, number of iterations). A lack of consistent guidelines on network configuration led to the selection of a basic architecture for evaluation. In addition, other input variables could be included depending on availability. For example, forest species and structure or forest management methods may be linked to damage. Inclusion of these was intended for this study but such data had not been collected for the OMNR plots and forest inventory for Eastern Ontario was too out of date.

Although neural networks performed better than other classifiers in this study, they have not been commonly applied in operational mapping due to perceived difficulties in extension of well learned training data over regional areas and in the time required

to train the network and test different configurations. In this research, rigorous assessment of a high and low damage classification using spatially independent test data has shown that accuracy is reasonable for the whole Eastern Ontario region. A set of ten networks required only two days to train and use of neural networks enabled testing of more variable types than was possible with the parametric classifiers. Thus, for the purpose of this study, to produce a more precise and objective damage map than was obtained immediately following the storm using aerial sketch mapping, the methods have proven to be moderately successful.

The final map produced from the research is not intended to replace sketch mapping as a means for near real-time assessment, as Landsat data must be acquired in the growing season following such a storm and the environmental data require a certain period of time to integrate into the database. It can, however, in conjunction with the knowledge gained from the study, be used over the longer term in policy development for improved forest and landscape management to reduce susceptibility to future storms. After future storms, the methods can be applied to provide damage maps in the medium term (by the end of the summer following the storm) to supplement sketch maps and be used for insurance and salvage/restoration needs.

6.7 Conclusions

Modelling and classification of forest ice storm damage was conducted using Landsat and environmental data. This study sought to examine some of the variation in damage

mapping error associated with: 1) modeling or classification methods; and 2) stratification methods of available plot data into training and reference sets. In comparison of classifiers, a simple neural network outperformed three parametric classifiers and compared favourably to results reported in other studies. Among the other classification methods selected for comparison, the range of accuracies obtained generally agreed with results from other studies where similar methods were used. The neural networks had difficulty discriminating low and moderate damage, but produced reasonable accuracies for high damage areas. The map that was produced using voting strategies could therefore be considered useful for targeting areas for cleanup and compensation to maple syrup producers where high damage was most likely to have occurred.

In data stratification for training and validation, the distance between training and reference data must be considered when assessing classification accuracy to ensure spatial independence. Single training and reference sets can produce significantly biased classification accuracy, with the magnitude of bias being dependent on the classification method used. In order to obtain robust and representative classification accuracies, multiple trials should be performed and assessed using random subsets of data.

CH. 7. FOREST DAMAGE MAPPING USING INTERPOLATION OF TEMPORARY SAMPLE POINT (TSP) DAMAGE ESTIMATES

7.1 Introduction

Immediately following the 1998 ice storm, the OMNR produced a preliminary map of the extent and severity of forest damage across Eastern Ontario using aerial sketch mapping (Scarr et al., 2003). Damage was visually assessed on a 5km grid from a helicopter hovering between 60 and 100m above the canopy and was defined as loss of fine to large branches or broken tops measured by 11 categories to describe the impact to individual stands (e.g. trees flattened, trees severely bent, clumps of conifers flattened, broken stems, missing branches, missing main branches, uprooted stems). The damage map was interpolated from point samples, improved by the removal of non-susceptible land cover types and further stratified by conifer and hardwood forest type.

In order for the interpolation to be effective at capturing the local to landscape scale spatial variation and distribution of damage, the distance between sample points must be less than or equal to the maximum distance at which the mapped phenomenon is spatially dependent. This distance may be obtained through spatial autocorrelation or semivariance analysis of damage. If the sampling interval is greater than the range of the semivariogram, then interpolated damage values cannot be predicted accurately using common interpolation methods that assume a constant directional change between adjacent sample points.

Damage can vary considerably over short distances because of numerous factors that affect tree susceptibility to damage. It has been previously described as patchy, due to the dynamics that affect the distribution of precipitation and trees across the landscape (Van Dyke, 1999). Disease, decay and prior damage also contribute, and often co-vary with tree age or size. Scarr et al. (2003) acknowledge the dependence of damage on such factors as tree size, location within a stand, species, and whether stand openings had recently been created. Because of the spatially variable nature of damage, a damage interpolation that accurately describes local to landscape scale variation will require a very dense network of points.

Sampling size, spatial density and distribution are inter-related factors that control the accuracy of an interpolation. A larger sampling unit will vary less than a smaller sampling unit over the same sampling distance because of stand-level averaging, which removes individual tree and microclimatic factors that account for damage variation among trees. These broader-scale changes in damage are more dependent on climatological factors than on individual tree characteristics. The aerial-based survey done on a 5 km grid was too coarse to accurately capture the changes in local to landscape level damage across the region. From one sample point on the 5km grid, tree or plot-level actual damage may increase and decrease several times before reaching an adjacent point, while the interpolator assumes a constant directional change. Broader-scale damage variation controlled by macroclimate may be adequately captured by assessing a number of stands within the field of view of the helicopter, in which case a 5 km grid may be appropriate.

In Scarr et al. (2003), the sampling unit was not precisely defined. Observers could generally assess significant damage to a distance of approximately 1 km on either side of the aircraft. More variable or less severe damage was more difficult to detect and assess (Scarr et al., 2003). It was not stated whether one damage measure was assigned based on what could be visually detected at each point on the 5 km grid, or if an attempt was made to map damage at each point.

Due to differences in damage assessment scales between the maple plots and the aerial survey, the quantitative comparison among maps conducted in Chapter 8 does not include the aerial sketch map. Instead, interpolated maps were generated using 2000 temporary sample plots (TSPs) for comparison with other regional maps. TSP damage assessment methods were more similar to the maple plot measurement methods than to the aerial assessment methods, making the comparison of TSP interpolations to maps derived using maple plot data more valid.

This chapter describes the development and evaluation of interpolation-based damage maps using TSP data to determine if such an approach can provide a useful map for short-term regional assessment of damage. A comparative analysis of maps produced in this Chapter with maps produced from chapter 6 is presented in Chapter 8.

7.2 Temporary Sample Plots (TSPs)

7.2.1. *Layout*

Approximately 2000 Temporary Sample Plots (TSPs) were established by the OMNR according to their compartments; with each compartment having at least one TSP. Plots were located on a map or airphoto or within the forested area of the compartment when airphotos or maps were not available. Positional accuracy of TSPs was inconsistent and unknown. TSPs were variable radius plots in which a minimum of 10 trees per plot were assessed.

7.2.2. *Damage measurement*

Trees located within the plot were recorded for species and assigned to one of four size classes by a basal area prism sweep. They were then classified into one of four damage classes based on percent crown loss for deciduous trees or the number of years growth remaining for conifers. Each tree was assigned to a bent class based on the number of degrees from vertical that the tree was leaning. Trees that were leaning more than 60 degrees were re-assigned to the highest damage class based on their probability of survival.

Plot damage was calculated as the average damage class weighted by basal area. This was done to transform plot damage from simple crown loss to a measure that would

relate more to overall canopy biomass lost to damage. The reasoning is that larger trees having a certain percentage of their crown missing from ice storm damage will have lost more total biomass than smaller trees with the same percent crown loss. In most plots, weighted and unweighted plot damage scores agree well with each other, except for cases where a strong relation exists between tree size and damage.

7.3 Methods

Various interpolation methods were evaluated using a subset of TSP data to determine which method was most accurate for application to the entire TSP set. Three interpolation methods were compared using the tolerant hardwood dataset because this stratum had the greatest number of plots (Table 7.1), and the best method was applied to the other strata to produce the final interpolated damage surfaces. The three interpolation methods tested were Natural Neighbour, Inverse Distance Weighting (IDW) and Kriging. Interpolation methods were evaluated using methods described below under Accuracy Assessment.

7.3.1. Interpolation methods

7.3.1.1. Natural neighbour

Points located on the circumference of a circle are natural neighbors. They are found by laying down the least number of the largest possible circles that cover the data

completely, with no data lying inside any circle. It has been found that this can be achieved by constructing each circle with exactly three data points forming a triangle.

For any location inside a circle, its interpolated value is influenced by the three data points of the triangle weighted by the coordinates of the Natural Neighbours. The interpolated value of a location will be generated based on the influence from all the circles that it intercepts. It equals the summation of the product of the Natural Neighbour's coordinate and the grey level of each data point (PCI, 2001).

7.3.1.2. Inverse Distance Weighting

Inverse distance weighting calculates an interpolated value based on weights that are inversely proportional to the power of the distance from the center of a search radius. For each point, the interpolated value is calculated from the sample values of known surrounding points within a specified radius and weighted by their distances elevated to a specified power. Default values were used in PCI Inc. for all parameters, including minimum and maximum search radii of 300m and 1500m respectively, and a weighting of the inverse square of the distance.

7.3.1.3. Kriging

Kriging is a statistical interpolation method that generates a surface through minimization of the error of interpolated values. Interpolated values are calculated from the weighted

sum of known neighbouring points. Weights are determined by evaluating the co-variation between pairs of neighbouring points as well as between neighbouring points and each interpolated value. Co-variation is derived from a semivariogram generated by considering the semivariance between pairs of points at distances between those points. All pairs of points within a fixed sampling area are considered, so that various distance increments called the lag are included when building the semivariogram. The semivariogram is fitted using either a spherical, exponential or Gaussian function that levels out asymptotically at a distance where points are no longer co-dependent. This distance is referred to as the range, and the variance that is reached at the range is called the sill. The nugget refers to the fitted variance at a lag of zero, and represents inherent noise in the data. Default values were used in PCI Inc. to generate the Kriging surface. These include a spherical variogram with a nugget value of 0, a sill value of 1 and the range calculated by the program as the average distance between points.

7.3.2. TSP stratification

TSPs were stratified by forest type in Table 7.1, producing separate damage surfaces that were later combined in the final damage map. Stratification was performed to account for differential susceptibilities of various forest types to ice storm damage. For example, intolerant hardwoods are generally considered to be more susceptible to damage than conifers, therefore, damage of an intolerant site would be underestimated if all of its immediate neighbours were conifer. However, by stratifying by forest type, each interpolated surface is generated by fewer points, which should adversely affect

interpolation accuracy. Thus, different stratifications were tested to determine which combination would produce the best accuracy for the greatest number of forest types. Interpolations were performed on all hardwood plots and on tolerant and intolerant hardwood plots separately to determine if greater stratification would reduce the error of the damage surface. Conifer plots were also interpolated separately.

TSPs were stratified to one of four woodlot type classes plus one plantation class. The four woodlot classes are shown in Table 7.1, along with the number of TSPs in each. Tolerant hardwood generally refers to upland species such as maple, beech and oak, while intolerant hardwood refers to lowland species such as birch and poplar. The terms hardwood and deciduous are used interchangeably to describe these strata. Conifer stands are dominated by species such as cedar, pine, spruce or fir. Separate damage surfaces were not produced for plantations or mixed woodlots, since composition was unknown for these forest types and their coverages were not available for Eastern Ontario. Coverages of conifer and deciduous forest types were determined from the forest cover map derived from TM and OBM data for Eastern Ontario described in Chapter 6.

Table 7.1. Number of temporary sample plots by forest type	
TSP forest type	N
Tolerant hardwood	606
Intolerant hardwood	189
Conifer	187
Mixed*	293
Plantations*	723
Total	1998

*separate interpolated surfaces were not created for these forest types

7.3.3. Accuracy assessment

In order to evaluate the accuracy of the interpolations, three sets of randomly selected TSPs were set aside as reference data, while the sets of remaining TSPs were used in three separate interpolations. The number of TSPs set aside for validation of interpolations for each forest type depended on the total number of TSPs available for that type. For intolerant hardwood and conifer types, each reference set consisted of 20 plots, while for tolerant hardwoods, each set consisted of 30 plots.

Accuracies of percent crown loss predicted for each stratum were computed as the Root Mean Square error (RMSE) between actual and interpolated damage for each of the three reference sets. For the combined tolerant and intolerant hardwood damage surface, the RMSE of each of the two forest types was computed separately, and an overall RMSE for combined forest types was also determined. Additionally, percent crown loss was assigned to low, medium and high damage classes as described in Chapter 6, and the accuracies were determined from the confusion matrices for direct comparison to other methods of damage classification.

7.4 Results

7.4.1. Comparison of interpolation methods

In evaluation of the accuracy of each interpolation technique, average RMS error as a

percentage of tolerant hardwood crown loss was similar among test sets and among interpolation methods (Table 7.2). IDW performed slightly better than the other methods, but took several days to generate the surface. Kriging, which took only a half-hour to complete, was therefore chosen as the method for all remaining interpolations.

Table 7.2. RMS errors for tolerant hardwood % crown loss interpolations				
	Test1	Test2	Test3	Mean RMS
Kriging	14.18	17.26	15.06	15.50%
IDW	14.20	16.79	15.36	15.45%
Natural Neigh.	14.09	17.03	15.81	15.64%

7.4.2. Hardwood interpolation

The TSPs were first stratified according to the forest types that could be mapped using the TM and OBM Woodarea data in Eastern Ontario. Three sets of 30 randomly selected hardwood TSPs were set aside for accuracy assessment, while three sets of 765 remaining TSPs were used to perform three separate interpolations. Of the 30 TSPs that were set aside, 25, 21 and 23 were tolerant hardwood TSPs for the three test sets, while the remaining TSPs in each set were intolerant hardwood. Average RMSE as percentage crown loss of the three test sets and two forest types are shown in Table 7.3, as well as an overall RMSE for the two forest types combined.

Table 7.3. RMS errors in % crown loss by TSP hardwood type of combined tolerant / intolerant hardwood interpolations							
	Test1	N	Test2	N	Test3	N	Average RMSE
Tolerant	14.70	25	18.85	21	11.80	23	15.12%
Intolerant	26.21	5	25.99	9	18.10	7	23.43%
Overall	16.54	30	20.77	30	13.17	30	16.83%

Separate interpolations were also performed for each of the two hardwood forest types. Of the 606 tolerant hardwood TSPs, three separate sets of 30 were set aside for accuracy assessment, leaving 576 TSPs for the tolerant hardwood interpolations. Twenty of 189 intolerant hardwood TSPs were set aside for accuracy assessment, leaving three different sets of 169 TSPs for the intolerant hardwood interpolations.

By performing separate interpolations for the different hardwood types, the RMS error of the intolerant hardwood map was reduced from 23.43% to 19.06%. However, the RMS error was slightly higher for the tolerant hardwoods when interpolated separately from the intolerant hardwoods, and overall RMSE increased slightly as well (Table 7.4).

Overall RMSE simply combines the RMS errors of tolerant and intolerant hardwoods for test sets 1 – 3. The interpolations and the test sets are from separate forest types, and therefore the combination of errors producing an overall RMSE is somewhat arbitrary. For example, errors from Test 1 from the tolerant interpolation could have been combined with the errors of Test 2 from the intolerant interpolation, producing slightly different overall RMS errors.

Table 7.4. RMS errors in % crown loss by TSP hardwood type of separate tolerant / intolerant hardwood interpolators					
	N	Test1	Test2	Test3	Average RMSE
Tolerant	30	14.18	17.26	15.06	15.50%
Intolerant	20	19.84	18.08	19.25	19.06%
Overall	50	16.48	17.41	16.67	16.85%

These results indicate that the combined tolerant-intolerant hardwood interpolation performs adequately for the tolerant hardwoods, but that intolerant hardwood damage is better predicted by interpolating an intolerant damage surface separately. In order to use a separate intolerant hardwood interpolated damage surface in a final forest damage map for Eastern Ontario, intolerant hardwood stands need to be mapped. Since no data exist to separate hardwood types in Eastern Ontario, the final map presented in Figure 7.1 will show hardwood damage from the combined intolerant / tolerant hardwood interpolation.

Binning continuous damage estimates into damage classes as described earlier enabled an assessment of interpolation accuracy that could be directly compared to the accuracies obtained for classifications generated in Chapter 6. An overall accuracy of 54.4% was achieved for the hardwood interpolation (Table 7.5) with a Kappa statistic of 0.20, indicating slightly better than chance agreement.

Table 7.5. Error matrix for the hardwood interpolation					User's
	Reference damage class				
Kriging	1	2	3	Total	
1	8	11	2	21	
2	9	34	12	55	
3		7	7	14	
Total	17	52	21	90	
Producer's	47.1%	65.4%	33.3%		
Kappa:	0.20			Overall:	54.4%

7.4.3. Conifer interpolation

Three sets of 20 randomly selected TSPs were set aside for accuracy assessment, while the remaining 167 TSPs were used in the interpolations. An average RMS error of 19.41% was achieved for the three test sets (Table 7.6).

Table 7.6. RMS error in % crown loss of TSP conifer interpolation					
	N	Test1	Test2	Test3	Average RMS
Conifer	20	17.72	19.73	20.77	19.41%

Assigning continuous damage measures to damage classes and assessment of their accuracy revealed an overall accuracy of 55.0% and a Kappa of 0.26 (Table 7.7).

Table 7.7. Error matrix for the conifer interpolation					User's 68.2% 47.1% 50.0%
	Reference damage class				
Kriging	1	2	3	Total	
1	15	5	2	22	
2	13	16	5	34	
3	1	1	2	4	
Total	29	22	9	60	
Producer's	51.7%	72.7%	22.2%		
Kappa:	0.26			Overall:	55.0%

The map (Figure 7.1) generated by combining separate hardwood and conifer interpolations according to their occurrence in Eastern Ontario generally revealed pockets of severe damage of varying size spread across the region surrounded by a large area of medium damage with low damage occurring along the perimeter.

Figure 7.1. Damage map of combined interpolated hardwood and conifer damage surfaces.

Table 7.8 shows differences between the severity of damage sustained by deciduous and conifer forests. Medium damage accounts for more than three times as much area as low damage in deciduous forests, while in conifer forests, medium damage accounts for slightly less area than low damage. Similarly, there is a greater proportion of area in the high damage class for deciduous than for conifer forests. These results are likely accounted for by differences in the susceptibilities of coniferous and deciduous trees to ice storm damage.

Table 7.8 Area by forest type and damage class of combined hardwood / conifer interpolated TSP map				
		Area (ha)		
Class	Damage - crown loss	Hardwood	Conifer	Total
Low	0 - 25%	102884	76580	179464
Medium	26 - 50%	348490	50499	398989
High	> 50%	42978	6645	49623
Total		494352	133724	628076

7.5 Conclusions

This chapter has described the development of an interpolated damage map from nearly 2000 plot observations. Various stratification methods were tested and assessed using multiple cross validation trials to produce the most accurate damage map possible. In the following chapter, the final map produced in this chapter will be compared to the damage map produced in Chapter 6 from Landsat and environmental data, and sources of error will be discussed.

CH. 8 COMPARATIVE EVALUATION OF DAMAGE MAPPING RESULTS

8.1 Introduction

This chapter compares forest ice storm damage distributions among maps produced in Chapters 6 and 7, with modeled reflectance and environmental data and interpolation, respectively, and the aerial sketch map produced by the OMNR and described by Scarr et al. (2003) (Figure 8.1). There is little agreement among damage maps produced from different data and methods. However, based on accuracy assessments and meteorological data, certain conclusions can be made about the likelihood of true representativeness of the mapped damage distributions.

A summary of the assessment methods and accuracies of the 20NN and kriging maps is presented in Table 8.1. Accuracies are similar between methods for the three damage class maps, but kriging predicts two damage classes better than neural networks when assessed with overall accuracy. When taking into account the number of reference plots used for accuracy assessment, the Kappa statistic shows that the 20NN map predicts two and three damage classes better than the kriging map. A quantitative accuracy assessment was not performed for the aerial sketch map, and therefore its accuracy could not be compared to the other two maps.

Figure 8.1. Top left: 20NN map, top right: interpolated map, bottom left: freezing precipitation, bottom right: aerial sketch map.

Table 8.1. Summary of methods and accuracies of damage mapping				
	20NN		Kriging	
assessment method	20 trails x 20 plots / trial		3 trials x 30 plots / trial	
# reference plots	400		90	
# damage classes	3	2	3	2
overall accuracy	54.5%	69.3%	54.4%	76.7%
Kappa	0.25	0.39	0.20	0.26

The freezing rain map produced by Environment Canada (Figure 8.1) and the report by Milton and Bourque (1999) both show that freezing precipitation in Eastern Ontario was greatest along the shore of the St-Lawrence. The report by Milton and Bourque (1999) also stated that tree damage was greatest in these areas of highest freezing precipitation accumulation. Understanding of the mechanisms responsible for tree damage due to

freezing ice storms would also suggest that trees in these areas should have been severely damaged by the ice storm. The north shore of the St-Lawrence is highly exposed, offering few obstructions or shelter for trees against wind and rain. Surprisingly, neither interpolated data nor the areal sketch map show high forest damage in these areas. In fact, both maps suggest that these areas suffered mainly low damage, with some moderate damage along a short stretch of the north shore in the center of Eastern Ontario.

Although it is known that forest ice storm damage is dependent on numerous forest structural and meteorological factors, it remains somewhat surprising that there is such poor agreement between freezing precipitation and forest damage. This suggests that other factors responsible for damage vary at a coarse spatial scale across Eastern Ontario. For example, the 20NN map appears to suggest that higher elevation may have been a contributing factor to greater damage, as higher elevation areas on the Canadian Shield in the northwest are overall more heavily damaged than other parts of Eastern Ontario (Figure 8.1) where the terrain is hillier and soils are poorer and thinner. Landscape fragmentation may have influenced damage in the central part of Eastern Ontario where it is predicted greatest in the aerial sketch and interpolated maps.

Numerous and different factors that may have controlled sub-regional levels of damage across Eastern Ontario cannot easily explain the regional distribution of damage. Another factor not already discussed may help to explain distribution of damage in the interpolated and aerial sketch maps. Both of these maps rely heavily on human interpretation of damage from the ground and the air. It is curious to note that both of

these maps depict the highest levels of damage in the central part of Eastern Ontario, and lowest levels of damage on the perimeter, in spite of meteorological data that could have suggested the opposite. It is possible that the subjective nature of human interpretation would lead interpreters to think that their region was hardest hit by the storm, and therefore depict the storm's impacts as such.

Though subjectivity could have also led to errors in the 20NN map, it is less likely that biases were spatially dependent as they might have been in the other maps. In fact, methods used to produce the 20NN map practically remove any subjective spatial bias from the map production process. In order to remove spatial bias from the interpolated maps, sampling should have been done randomly with no knowledge of location by the interpreter. This type of sampling would be difficult to perform from the air or ground, as it precludes the use of any systematic sampling pattern and would therefore require traveling great distances if performed in real time. A better approach may have been to take airphotos and have the interpreter classify them with no knowledge of their location. This would ensure that knowledge of location or spatial bias would not have been present in these maps.

Another possible source of error that may account for the discrepancies between the aerial sketch map, 20NN map and the interpolation is the difference between the timing of the surveys. Aerial sketch mapping was performed in the winter immediately after the ice storm. Severe ice loading of conifers and intolerant hardwoods made damage appear to be much greater than after spring melt. Many trees that were completely flattened from

ice loading and appeared to be severely damaged sprang back to vertical after snow melt and actually suffered light to nil damage (Bragg et al., 2003).

Difference among assessment scales may be the largest source of disagreement among maps. As was mentioned in Chapter 3, damage can be assessed at a range of scales, and its magnitude at a given location may be dependent upon the scale at which damage is assessed. In Chapter 2, factors that control the level of damage suffered by a tree, stand or forest were discussed and these were linked to possible tree, environmental and meteorological characteristics that occur at a range of scales, each one controlling damage variation at a particular scale. Briefly, it is probable that individual tree characteristics control damage variation at the sub-crown to crown level, environmental characteristics discussed in Chapter 2 control stand level damage and meteorological characteristics of the event control regional variation in damage. In other words, damage variation at a given scale is affected by factors and processes that control damage susceptibility at that scale. The relationship between factors that control damage susceptibility and scale were discussed in section 3.3.

While damage assessment performed at different scales may contribute to some of the discrepancies observed among maps, one would expect that there should be some level of agreement at a very broad scale. In order to test this assumption, the interpolation and 20NN maps were divided into three, almost equal sub-regions, corresponding to the east, center and west of Eastern Ontario, and damage distributions were compared between maps for these three sub-regions (Figure 8.2). The 20NN map depicted higher levels of

damage across all sub-regions, indicating possible biases in one of the maps relative to the other. Even if substantial bias exists in one of the maps, sub-regional damage distributions should be similar between maps. However, they do not appear to be, indicating a significant random error component, whose possible sources have been discussed.

Figure 8.2. Distributions of damage for the 20NN map (left) and the interpolated map (right) by sub-region.

8.2. Limitations, implications and recommendations

The primary limitation of this thesis is the reliance on a reference field-based damage measurement from visual estimation of percent crown loss caused by the ice storm event. The precision of this measurement cannot be determined from the data that were collected. Ideally, repeat estimates should have been made by different assessors to be able to assign a level of precision to damage measurement. By assigning a confidence interval to damage, modeling could have been performed using damage measure

distributions on individual plots that account for measurement precision, rather than absolute damage values.

While visual estimation of percent crown loss was used as a reference damage measure, its accuracy relative to real damage sustained from the event cannot be known. It is likely that in most cases, damage occurs primarily to the tops of crowns due to increased exposure to wind and rain, and is therefore not easily seen from the ground. Maple decline studies have shown that dieback, including chlorosis, begins at the top of crowns and works its way down (Dessurault, 1986). This can sometimes produce a discrepancy between what an assessor sees from the ground, and what a remote sensor sees from above. This discrepancy will produce a bias towards lower damage assessed from the ground, and the magnitude of this bias will likely depend on the amount of damage suffered. In low damage, visibility of crown tops is obscured more than in the case of severe damage, producing a systematic bias toward lower damage in low damage plots.

Confidence in the visual damage estimation was built through relating these measurements to other, independently acquired crown and canopy measurements. A significant relation between two independently acquired visual estimates of damage measured at different scales, based on crown and canopy loss for OMNR and AgCan respectively, helped build confidence. Other, significant relations between damage and TRAC measures of LAI, LAI change and clumping also helped build confidence. However, absence of significant relations between modeled and interpolated regional damage reduced confidence somewhat. The absence of such relations can be explained by:

1. Differences in scales of damage assessment between TSP and maple plot data.
2. The inaccuracy of TSP geolocation.
3. The coarse scale of interpolation of TSP plot damages relative to the scale at which damage varies. Since damage is dependent on many factors, and each factor may vary significantly over distances that are much less than the average distance between TSPs, then interpolation cannot capture the true and fine scale spatial variation of regional damage. For example, unmanaged maple stands are generally known to be of uneven age structure due to the nature of the disturbance regime and shade tolerance of maple saplings. The magnitude of damage suffered by a maple tree has been shown to be dependent on tree age (Van Dyke, 1999). Therefore, variation in damage is expected to occur at the stand level due to these two factors. Disease, prior damage, species, height and crown diameter are also factors that have been shown to vary at the stand level and affect tree susceptibility to damage.
4. Inaccuracy and imprecision of either TSP or maple plot damage measurement.

A second limitation was that all data were acquired at slightly different spatial scales. Visual, field-based estimation in the maple study was performed on six focus trees, judged to be representative of the average crown loss in the plot. True representation of plot damage in the six focus trees makes this measurement scalable from the six crowns of the focus trees to the entire canopy within the plot boundaries, occupied by approximately 80-160 crowns whose diameter at breast height (DBH) exceed 9.5cm.

True representativeness cannot be ensured, especially since only between 3.75 and 7.5% of the crowns were sampled in the plot. Inaccuracy in the visual estimation of crown loss and inaccuracy in the representativeness of the selected focus trees both contributed to inaccuracy of damage scaled to the plot level, and therefore lead to errors when relating to measurements acquired at different scales. Similar errors exist in canopy reflectance and TRAC measurements, due to scale differences between sampling methods.

In addition to differences in spatial scales among assessment methods, there are also intrinsic differences in the way in which the canopy is sampled. Visual assessment of focus trees representative of canopy damage is loosely based on canopy-scale assessment, as discussed above. Errors in visual estimation of percent crown loss, and errors in the representativeness of canopy damage of selected focus trees will both contribute to random errors in scaling damage to the plot level.

Specific criteria for selection of focus trees were not explicitly stated, except to say that they were representative of canopy damage. However, other criteria also needed to be met for a tree to be selected as a focus tree. For example, focus trees were always tapped and therefore had to meet a minimum size criterion. Depending on the tree size distribution of the stand, meeting this criterion might have made focus trees representative of stand damage difficult. Tree size, age, stand level species composition and prior disturbance are all factors that affect stand level damage. Focus trees should be representative of the range of these factors to be truly representative of the distribution of damage at the stand or plot level.

There are also differences in the way in which optical measurements sample the canopy. Radiative transfer is directional, while above and below canopy optical measurements are made in different directions. Above-canopy measurements are taken within the field of view of the Landsat TM sensor, which is approximately ± 7.5 degrees from directly below the spacecraft (nadir). Below-canopy measurements with the TRAC are made at approximately 40 degrees zenith. The radiative transfer budget dictates that at all directional angles, the sum of incident, absorbed and reflected or radiated energy should equal zero. Reflected and radiated energy from a surface integrated over all angles is surface albedo. At a specific angle, this budget does not hold true due to the directional dependence of non-lambertian canopy reflectance. However, at a very generalized level, the budget should nearly balance as the amount of radiation reflected is inversely related to the amount transmitted for a similar surface type and across all angles. Differences between the directional measurements of above and below canopy sampling will lead to random errors when relating these two measurements.

While the method used to compute LAI from TRAC measurements should remove any dependence of LAI on solar zenith angle (SZA), some dependence still exists. This is confirmed in Chapter 5, as within day measurements acquired at different times exhibited greater variance than between day measurements acquired at a similar time of day. Above-canopy reflectance exhibits a similar dependence on SZA due to bidirectional reflectance.

Limitations related to differences among sampling scales are compounded by limitations outlined in Chapter 4 on the use of canopy reflectance for damage assessment. These limitations will not be discussed here as before, but can be summarized as follows:

- Structure has been shown to be the main determinant of above canopy reflectance across a broad range of leaf reflectance (Treitz and Howarth, 1996)
- The integrated shadow fraction (shaded crown and shaded background) provides the most useful information on canopy structure for the purpose of biophysical assessment (Peddle et al., 1999).
- LAI and LAI change have been shown to be significantly related to percentage crown loss as a measure of ice storm damage (Olthof et al., 2001; Olthof et al., 2003 and in this thesis)
- NIR reflectance and derived indices are insensitive to LAI change due to light absorbing shadow whose intensity and areal extent dominate canopy reflectance (Chen et al., 1999).
- Remotely-sensed spectral indices used to measure LAI tend to saturate above LAI levels of 3-4 (Sellers, 1985).
- Physiological and structural effects of damage can produce opposite canopy reflectance response, especially in visible bands.
- Shadow fraction and shadow brightness are inversely related, producing a flat response of canopy reflectance to changes in the shadow fraction (Seed and King, 2003).

8.2.1. Innovative aspects and significant findings of the research

LAI has been shown to be a key biophysical variable that controls mass and energy exchanges with the earth's surface (Bonan, 1995). LAI has also been linked to forest habitat, diversity and growth characteristics via net primary productivity (NPP) and using ecosystem models (Franklin et al., 1997). Its measurement using direct and indirect methods has been a preoccupation of environmental researchers for more than 50 years. However, its use in operational forest assessment has been limited. An important contribution of this thesis is LAI measurement using a commercially available instrument to address information needs that arise following disturbance. To meet the need of consistent damage appraisal through time, optical LAI and LAI change are used as local, medium to long-term damage indicators shown to be useful for damage assessment and monitoring recovery.

A key component of this research that demonstrates the appropriateness and usefulness of LAI as a damage indicator has been its agreement with percent crown loss as a reference damage measurement. Optical LAI measurement offers three main advantages over visual estimation of damage: 1) potential for a greater sampling intensity; 2) assessment of measurement precision (repeatability); and 3) evaluation of LAI change in relation to precision. Post-disturbance LAI change coupled with understory LAI measurement has been shown to be most useful, indicating the potential for further improvement using multiple height LAI measurement and pre-post disturbance LAI change. This last point

emphasizes the need to establish a network of permanent LAI sampling plots to enable pre-post disturbance assessment for future events.

A second significant contribution of this thesis is the identification of damage mapping limitations from a theoretical structural / reflectance perspective, as well as modeling and interpolation applications. Other studies have revealed similar limitations for mapping LAI (e.g. Sellers, 1985; Chen et al., 1999), but none have been so explicit in attempting to map damage. A robust methodology for mapping damage and error analysis was included in this thesis that incorporates some innovative aspects, and was performed to identify limitations and to extract the most information possible related to damage from the data. Error analysis including multiple cross validation showed the range of possible accuracies that could be reported had a single validation been performed. Unfortunately, most studies still rely on single validation, and therefore reported accuracies are often high, in my opinion, since only high accuracies are worthy of publication.

A final important contribution of this thesis is the multidisciplinary approach to the description of the current status of the maple syrup industry within a changing economic and demographic environment of Eastern Ontario. The thesis on a whole includes aspects of social and environmental science, forestry and remote sensing.

CH 9. CONCLUSIONS

Ice storms are the major recurring regional-scale natural disturbance responsible for tree mortality in many temperate forests around the world. Ice storms produce forest damage that is variable across space and can be measured at a range of scales from individual leaves to entire forest ecosystems. Factors that control damage may be different at each of these scales, and include individual tree characteristics such as species, age and condition prior to disturbance at the tree level, environmental aspects such as slope, aspect and proximity to forest edge at the stand level, and meteorological factors of the storm event at the forest ecosystem or regional level.

Information needs that arose from the 1998 ice storm were identified at short, medium and long-term temporal scales. These were designed to assist in short-term cleanup and compensation, medium-term impact management and long-term refinement of damage estimates and mitigation evaluation through monitoring. While the OMNR had addressed many short-term information needs, their reference damage measure was based on visual percent crown loss relative to pre-storm crown volume, which is of limited use when addressing long-term needs. This study was designed primarily to evaluate methods for measuring and monitoring damage in the medium to long-term. At each temporal scale, local, landscape and regional spatial scales were considered.

At a local scale defined as the extents of a single plot, field-based optical analysis of canopy structure was conducted in maple plots using the TRAC instrument designed to

measure LAI and clumping from the canopy gap fraction and gap size distribution for initial assessment and monitoring of canopy condition. Results indicate that optical measurements of LAI are useful for monitoring canopy response to structural damage from disturbance, such as an ice storm. TRAC LAI measurements were shown to be accurate indicators of damage, because they are significantly related to initial damage in spite of discrepancies between scales. Total LAI measured by the TRAC changed progressively from the damaged condition following the event to one that was not significantly related to the initial damage estimate four years later. Between-season LAI change suggested that measurement immediately after a disturbance might be a better indicator of damage than measurement one year later, as was tested here. It could also be concluded that LAI change is a better indicator of damage than single-date LAI measurements to which it was compared. When all plots were combined, LAI increased in both understory and overstory layers through time, leading to the conclusion that forests are recovering LAI in the medium term. By examining LAI change on a plot-by-plot basis in relation to LAI measurement precision, a confidence level was assigned to the observed changes for each plot. Seasonal weather variation such as drought can affect LAI and perhaps mask the longer-term trend towards recovery in certain cases. Therefore, a longer temporal series of measurements may be needed to fully evaluate recovery. Finally, no treatment effects on LAI response were observed, although this might also require a longer time series of LAI measurements.

At the regional level, two maps were produced; one to meet short-term information needs arising immediately following the storm and the other to establish a more accurate

baseline to address longer-term recovery information needs. Interpolation maps were produced and assessed by stratifying 1998 temporary sample plots by forest type, applying three different interpolation methods and evaluating each method using three separate interpolations with 30 reference plots held out each time. For three damage classes based on percent crown loss, overall accuracy varied between 52 and 57% for the 90 reference plots per method. Interpolation accuracies did not vary significantly but the best method was inverse distance weighting (IDW), then kriging and finally, natural neighbour. Final interpolation maps were produced using kriging, since its accuracy was nearly as high as IDW, but was more computationally efficient.

The regional damage map created to address long-term information needs was derived using Landsat and environmental data in neural network modeling. Previous damage mapping studies using Landsat imagery have produced varied results due to methods employed, including: 1) the nature and scale of damage measurement; 2) modeling or classification methods; and 3) single stratification of plot data into training and reference sets without consideration of the effects of spatial autocorrelation. This thesis sought to examine some of the variation in damage mapping error associated with the second and third factors above. Damage mapping accuracy was compared among four classification methods and within each method by randomly splitting the data into multiple training and reference sets on plot and block bases. Several conclusions and recommendations could be drawn from the results obtained. First, as has been reported previously, classification accuracies from the prediction of training data significantly overestimate true map accuracy from an independent test set. Neural networks ‘learn’ training data extremely

well, with training data accuracies consistently above 90%, while reference data of adjacent plots produced accuracies that were approximately two-thirds that value. When plots were stratified on a block basis to ensure independence between training and reference data, classification accuracies dropped again by 14.2%. Second, data stratification into single training and reference sets can produce biased damage classification accuracy, depending on the classification method employed. Maximum likelihood produced the most consistent damage classification accuracies of the four methods tested. Therefore, if a single classification were to be performed and if the assumption of data normality is met, then maximum likelihood should be the best method for obtaining an unbiased estimate of map error. Finally, while neural networks produced the highest classification accuracies, they were also the most variable and therefore most prone to bias. Thus, neural networks should be trained and assessed using multiple random training and reference sets to avoid such bias.

In comparison to visual field damage estimates, neural networks had difficulty discriminating low and moderate damage, but were accurate for high damage, producing a 69.3% overall accuracy in discriminating low-to-medium from high damage using spatially independent validation samples. The map that was produced using voting strategies could therefore be considered useful for identifying areas where high damage was likely to have occurred. These areas can subsequently be targeted for careful monitoring and application of management strategies to mitigate the effects of damage.

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