Spatial Statistical Techniques for Aggregating Point Objects Extracted from High Spatial Resolution Imagery

by

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ABSTRACT

At present most forest management is based on stand units; however, detailed information on individual trees is increasingly required for accurate forest management and decision making. Developing methods to collect individual tree information for medium and large areas will improve the quality of forestry information. A further improvement may come from deriving forest stands based on individual tree characteristics. If stands are derived their composition is known.

In this thesis, research efforts focus on the development of a technique, which uses individual tree information to generate forests polygons which are homogenous in age. The goal of this research is to extract points from a 1m spatial resolution IKONOS image and apply spatial statistics to aggregate points into polygons based on forest structure.

Using an existing local maximum technique, on an IKONOS 1m panchromatic image covering a range of forest ages, points representing individual trees were extracted. Point based spatial statistics were applied to the local maximum points and metrics representing forest structure generated. The effectiveness of nearest neighbour distance statistics and Voronoi point pattern analysis techniques for generating forest structure attributes were examined. A metric generated using nearest neighbour distances was used to aggregate the points into polygons related to forest structure. The forest structure polygons show a meaningful association with a series of age classes used by the British Columbia Ministry of Forest. The metrics show potential for identifying forest areas

approximately homogenous in age, which may be used as a basis for polygon development.

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Table of Contents

Abstract ii
Table of Contents iv
List of Tables vii
List of Figures viii
Acknowledgments ix
Dedication x
1. 0 Introduction 1
1.1 Rational 1
1.2 Goal and Objectives 4
2.0 Literature Review 6
2.1 Forest Structure 6
2.1.1 Defining Forest Structure 6
2.1.2 Forest Structure Variables 7
2.2.1 Manual Tree Identification 9
2.2.2 User Assisted Tree Identification 9
2.2.2.1 Reducing Error 10
2.2.2.1.1 Remove Non-Forested Areas 12
2.2.2.1.2 Thresholds 12
2.2.2.1.3 Variable Window Size 13
1.4 Spatial Dependence 16
2.3 Spatial Statistics for Generating Attributes for Point Data 16
2.3.1 Spatial Statistical Terms 17
2.3.1.1 Spatial Scale 18
2.3.1.2 Sampled Vs Fully Mapped Data 18
2.3.1.3 Spatial Patterns in Point Data 19
2.3.2 Assigning Spatial Attributes 20
2.3.2.1 Nearest Neighbour Distances 20
2.3.2.2 Voronoi 25
2.3.3 Benefits and Issues of Spatial Attribute Generating Techniques 27
Benefit 28
Potential Issue 28
2.4 Aggregating Point Data Based on Spatial Attributes 28
2.4.1 Edge Detection 28
2.4.2 Region Growing 30
2.4.3 Clustering 31
2.4.3.1 Hierarchical 31
2.4.3.2 Optimization 32
2.4.3.3 Spatial Adjacency Constraints 32
2.4.4 Contouring 34
2.4.5.1 Polygon Properties 34
2.4.5.2 Area Based - Iterative 34
2.4.6 Thresholds 35
2.4.7 The Benefits and Issues of Aggregation Techniques 35
3.0 Study Sites and Data 37

3.1 Study Area 37
3.2 The Sooke Watershed 37
3.2.1 Sites 40
3.2.1.1 Sub-site 1 40
3.2.1.2 Sub-site 2 41
3.2.1.3 Sub-site 3 43
3.2.1.4 Site 4 44
3.3 Data Sources 46
3.3.1 Remotely Sensed Imagery 46
3.3.2 Field Data for Accuracy Assessment of Feature Extraction 47
3.3.3 Forest Inventory Map 47
4.0 Methods 49
4.1 Introduction 49
4.2 Feature Extraction 49
4.3 Accuracy Assessment of Feature Extraction 51
4.4 Forest Structure Metric Development 53
4.4.1 Nearest Neighbour Metric Development 56
4.4.2 Voronoi Metric Development 57
4.5 Generating Attributes 59
4.6 Aggregation and Object Creation 60
4.7 Preliminary Analysis 62
4.7.1 Metric Development with Field Data 63
4.7.2 Preliminary Metrics 64
5.0 Results and Discussion 65
5.1 Introduction 65
5.2 Feature Extraction 65
5.2.1 Non-smoothed IKONOS 67
5.2.2 Smoothed IKONOS 69
5.2.3 Effects of DBH 70
5.2.4 Effects of Crown Radius Size 70
5.2.5 Local Maxima Iteration used for Analysis 72
5.3 Forest Structure Metric Development 72
5.3.1 Nearest Neighbour Forest Structure Metrics 72
5.3.1.1 Average Distance to Neighbours within a Specified Distance 72
5.3.1.2 Average Number of Neighbours within a Specified Distance 74
5.3.1.3 Average Distance to the 20 Nearest Neighbours 75
5.3.2 Voronoi Forest Structure Metrics 76
5.3.3 Forest Metric Iteration Used for Analysis 77
5.3.4 Forest Metric Vs Attribute Results 78
Suggested by Metric 78
Suggested by Attributes 78
5.4 Aggregation and Object Creation 79
5.4.1 Results - Sub-site 1 79
5.4.2 Results - Sub-site 2 82
5.4.3 Results - Sub-site 3 84
5.4.4 Results - Sub-site 4 86

5.4.5 Discussion Sub-sites 1- 4 88
6.0 Conclusions 91
6.1 Feature Extraction 91
6.2 Metric Creation 92
6.3 Aggregation and Object Creation 93
References 95
Appendix 1 100
Appendix 2 101

List of Tables

Table 1. Selected benefits and potential issues of NND and Voronoi techniques for generating spatial attributes....28
Table 2. Selected benefits and possible issues of techniques for aggregating point data....36
Table 3. British Columbia Ministry of Forest's forest inventory age classes....38
Table 4. Summary of sub-site characteristics....40
Table 5. Wavelengths of IKONOS Bands....46
Table 6. The four tested variations of the local maxima filter....51
Table 7. An example the local maxima filtering data used for accuracy assessment....53
Table 8. The number of polygons located for each forest age class....55
Table 9. Variations of the nearest neighbour statistics used for metric generation....57
Table 10. New forest age classes correlate with Ministry of Forests inventory classes....61
Table 11. Age class attribute thresholds....62
Table 12. Results of the four iterations of the local maxima filter....68
Table 13. Accuracy assessment of feature extraction results - stratified by DBH....70
Table 14. Accuracy assessment of feature extraction results - stratified by crown radius....71
Table 15. Average distance to neighbours within a specified distance....73
Table 16. Result of constraining the calculation of the average distance between points by area....74
Table 17. Average number of neighbours within a distance....74
Table 18. Average distance to the 20 nearest neighbours....76
Table 19. Average area of contiguous Voronoi polygons....77
Table 20. Age classes and thresholds expected from metric development versus attribute generation....78

List of Figures

Figure 1. Digital surface showing theory used for local maxima filtering. 10
Figure 2. Local maxima filtering output...12
Figure 3. Digital values of forest and non-forest areas. 14
Figure 4. Breaks in slope occur at locations of minimum radiance. 15
Figure 5. Spatial point patterns. 19
Figure 6. Simulated NND distribution function.. 22
Figure 7. The point attribute equals the average distance of neighbours within a specified distance.. 23
Figure 8. The point attribute equals the average distance to *n* nearest neighbours......... 24
Figure 9. The point attribute equals the number of neighbours within a specified distance.. 24
Figure 10. Steps used to generate Voronoi polygons.. 26
Figure 11. Generating a surface to detect boundaries using lattice-wombling. 30
Figure 12. Computing spatial adjacency using NND.. 33
Figure 13. Location of the Sooke Watershed.. 39
Figure 14. Sub-site 1. 41
Figure 15. Sub-site 2. 42
Figure 16. Sub-site 3. 44
Figure 17. Sub-site 4. 45
Figure 18. Sample of stem plot field data collected for individual trees.. 48
Figure 19. An overview of project methodologies... 50
Figure 20. An overview of methods used to extract tree locations from high spatial resolution imagery.. 51
Figure 21. An overview of methods used to generate forest structure metrics. 54
Figure 22. Method for determining point contiguity. 58
Figure 23. Methods used to generate forest structure attributes. 59
Figure 24. Attributes used for generalization are equal to the number of neighbours within a 20m radius of each point. 60
Figure 25. Overview of methods used to aggregate points into polygons. 61
Figure 26. Non-smoothed IKONOS stem mapping and feature extraction results.......... 66
Figure 27. Smoothed IKONOS mapping and feature extraction results......................... 67
Figure 28. Objects created for sub-site 1... 81
Figure 29. Objects created for sub-site 2... 83
Figure 30. Objects created for sub-site 3... 85
Figure 31. Objects created for sub-site 4... 87

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Dedication

To Travis Ferbey

May we always be nearest neighbours.

1. 0 Introduction

Chapter Objective: To provide a context and the rationale for undertaking this research and to outline the goals and specific objectives of this project.

1.1 Rational

As concern over the Earth's environment grows, accurate and timely environmental information is needed at an accelerated rate for increasingly large areas. Environmental data are required at both fine and coarse scales. Fine scale data provide detailed information necessary for such purposes as assessing the effects of development on local environments; coarse scale data are required to study regional changes in land use and forest cover.

Traditionally fine scale environmental information has been obtained for *small* areas using manual interpretation of detailed aerial photography and intensive fieldwork. The need for detailed data on larger areas is growing; yet, few efficient techniques for collecting and analyzing fine scale data for *large* areas exist. New data sources, such as high spatial resolution IKONOS imagery, have added to the tools available for collection of detailed environmental information over large areas. Development of techniques for use with detailed data sources may allow fine scale data to be used operationally and more efficiently.

Coarse scale data are more easily collected for large areas and are often obtained using small to medium-scale aerial photographs and low spatial resolution satellite imagery. When data are collected at a coarse scale the landscape is generalized and detailed information potentially useful for research, decision-making, and management is often lost. One benefit of deriving coarse-scale data from fine data is that the detailed information is retained and the composition of generalized objects is known.

Forestry is an application area that would benefit from developments in the collection, analysis, and reformatting of detailed data. Detailed forestry data helps to increase our understanding of forests and improve information available for decision making. Forest stewards are increasingly seeing the value of detailed forestry information. For example, recently in British Columbia, the Ministry of Forests has expressed an interest in the use of individual tree information for forest inventories and management (Niemann, 2001). The difficulty in using individual tree information is that forest management practices are based on stands or groups of trees with similar properties. If one can reformat fine-scale individual tree information into coarser forest stand units it will allow comprehensive forestry data to be used in a standard way and may improve the consistency and accuracy of the stand units. Reformatting of fine data allows traditional forestry management practices to be used with more detailed data sources.

An increasing number of tools, existing and under development, aid in the acquisition and reformatting of detailed forestry information. High spatial resolution imagery is a data source, which allows the extraction of detailed information for ecological studies and management (Leckie et al., 1999a; St-Onge et al., 1999). Recent developments in satellites now provide high spatial resolution imagery from space, making detailed imagery more accessible than ever before. High spatial resolution imagery can be defined through the relationship between image elements and pixel size. Elements of interest in high spatial resolution imagery are larger than the image pixels;

several pixels equal one element (Strahler et al., 1986). The spatial arrangement of elements in high spatial resolution imagery allows for the collection of detailed information (Strahler et al., 1986).

Several techniques can be used to identify properties of individual trees from high spatial resolution imagery. Individual tree characteristics available from imagery include location information (Gougeon, 1995; Niemann et al., 1999), species (Gougeon et al., 1998), and disease or insect damage (Reich and Price, 1998; Leckie et al., 1999b). In this study tree locations extracted via user-assisted techniques and represented as points are of interest (Gougeon and Moore, 1989; Dralle and Rudemo, 1997; Niemann et al., 1999)

Generalization, which refers to the simplification or reduction of map information, can be used to reformat data obtained from high spatial resolution imagery (Bonham-Carter, 1994). For example, point data can be converted to polygons. Generalization of individual tree information into forest stands allows detailed data to be used in a unit common to forestry management. As well, forest stands generated with detailed tree information can be accurately characterized, as the individual tree properties are known.

At present few tools exist for generalization; most involve simple cartographic operations such as classification, simplification, and symbolization (Robinson et al., 1995). Cartographic generalization tools are often applied subjectively (Steward, 1974), and are difficult to use in conjunction with theoretical knowledge, such as the spatial pattern of an element. The development of generalization methods, which are based on spatial interactions may provide an objective and theoretically based technique for aggregating data.

The spatial patterns exhibited by trees change over a landscape reflecting such things as forest maturity, resource availability, and topography. If one can aggregate individual trees based on an existing understanding of spatial patterns, the likelihood that produced polygons are meaningful will increase. Research, development, and testing of user-assisted generalization techniques, which are based on the spatial relationship of objects, has the potential to improve forestry data and add to the tools available for generalization.

Full automation of individual tree generalization is not a realistic goal. If the process can be partially automated, allowing for heads-up digitizing, generalization will be more efficient. Heads-up digitizing refers to a process where the computer makes a suggestion and the analyst can choose to accept, reject, or modify the suggestion. Head-up digitizing is not yet common place and therefore the implications of such methods have not been determined.

1.2 Goal and Objectives

The goal of this research is:

1. to extract points (individual trees) from a 1m spatial resolution panchromatic IKONOS image, and apply spatial statistics to aggregate points into polygons (forest stands) based on forest structure.

The research objectives are:

1. to research, develop, and test a new technique for the generalization of objects extracted via local maxima filtering from high spatial resolution imagery;

2. to research, develop, and test a technology which improves the flexibility of information extracted from high spatial resolution imagery by allowing point information to be spatially organized and presented as areas.
3. to develop a method for generalization that can be packaged as part of a web based software for use with high spatial resolution imagery.

2.0 Literature Review

Chapter Objective: To provide background information necessary for understanding the theoretical basis and methodology of this thesis.

2.1 Forest Structure

The basic purpose for this project is to aggregate objects based on forest structure, as captured by local maximum filtering of high spatial resolution satellite data. Differences in forest structure can result from factors such as changes in stand maturity (Frazer et al., 1998), within and between species competition, environmental factors, and site disturbances (Oliver and Larson, 1996). Forest structure can be defined at different scales such as individual tree, landscape, or stand scales (Voller and Harrison, 1998). However, the difference between these scales can be subtle. The generalization procedure results in single tree forest structure being represented as stands units. The following chapter is a discussion of the factors impacting forest structure and the spatial patterns of individual trees.

2.1.1 Defining Forest Structure

Forest structure can be defined as the temporal and physical distribution of trees and other plants. The distribution of trees can be described by attributes such as species, vertical and horizontal spatial patterns, crown volume, leaf areas, stems, or age (Oliver and Larson, 1996). In this study it is the spatial distribution of tree patterns, manifest as a by-product of forest structure, which is of interest. When trees are represented as points, spatial patterns reflecting forest structure are a result of the distances between trees and the density of stems. Tree stem locations reveal patterns on the landscape which can be described as random, regular, or clustered (Oliver and Larson, 1996); (Frazer et al., 2000).

2.1.2 Forest Structure Variables

Many influences on forest structure are difficult to isolate. One of the easiest variables to isolate, relative to structure, is forest age. Biological theory suggests that in the coastal forests of British Columbia a relationship exists between forest structure and stand age (Frazer et al., 2000). The overstory of immature stands is characterized by small, evenly spaced canopy openings, with little spatial variation; these characteristics are the result of densely spaced, short trees, with uniform distribution of stems, and a monolayer canopy (Frazer et al., 2000). In contrast, the overstory of mature stands tend to exhibit larger, unevenly spaced canopy openings, with substantial variation in spatial distribution; these characteristics result from tall trees, with clumped stem distribution, and multilayer canopies (Frazer et al., 2000). In general, as stands mature, canopy openness increases and canopy gaps become more variable.

In the coastal forests of British Columbia it has been observed that forest structure of immature stands is typically represented by patterns which are more regularly spaced than mature trees which exhibit greater stem clustering (Frazer et al., 2000; He and Duncan, 2000). As well, the distances between mature trees are often larger than distances between trees in immature stands (Frazer et al., 2000).

Environmental factors also effect forest structure. For example, environmental gradients, such as soil, moisture, aspect, or elevation may produce stand edges. Forest structure usually varies when environmental conditions or disturbance patterns change (Oliver and Larson, 1996). As well, stand density may reflect environmental conditions, with high tree densities found in areas where nutrients are adequate and climatic conditions optimal (Oliver and Larson, 1996).

Variations in distances between trees are not only the consequence of age but can result from competition as trees differ in requirements for growing space and other resources such as light, moisture, and nutrients (Oliver and Larson, 1996). The inclusion or exclusion of new trees into stands depends partially on how the existing trees are using the resources (Oliver and Larson, 1996). Therefore, competition inherently affects the distribution of trees.

Finally, disturbances impact forest structure over large and small areas. Fire, insect damage, harvesting, and reforestation impact forest structure (Voller and Harrison, 1998). Modern harvesting and reforestation strategies can also influence forest structure at the individual tree level. For example, in the Sooke Watershed the younger stands were mostly planted whereas the older stands were the result of natural regeneration. Such activities increase the amount of spatial regularity in young stands.

2.2 Feature Extraction

The location of tree stems, and therefore spatial patterns of trees, can efficiently be obtained for large areas using high spatial resolution remotely sensed imagery. Many techniques have been developed and are available to extract trees from high spatial resolution imagery. Existing techniques include: human interpretation, local maxima or peak radiance filtering (Gougeon and Moore, 1988; Niemann et al., 1999); valley following (Gougeon, 1995); edge finding (Pinz, 1999); template matching (Pollock, 1999); morphology (Barbezat and Jacot, 1999); and clustering (Wulder, 1998; Culvenor et al., 1999). For this project representing individual trees as points which can later be linked to attributes is the focus. Therefore, the discussion will be limited to manual interpretation and the local maxima technique as both represent the location of individual trees as points.

2.2.1 Manual Tree Identification

The location of tree crowns can be identified manually and easily represented as point data. However, manual interpretations can be time consuming, expensive, and accuracy tends to vary with different interpreters (Gougeon, 1993). Individual tree information is needed for increasingly large areas making manual interpretation less practical to implement.

2.2.2 User Assisted Tree Identification

To optimize the consistency and efficiency of feature extraction from high spatial resolution digital remotely sensed imagery individual tree identification may be partially automated. The *local maxima* technique is a user-assisted approach to representing the location of trees with points.

The local maxima algorithm assumes the reflectance of individual trees is highest at or near the center of the tree and decreases towards the tree edge (Figure 1). At the center of the tree is the tree stem and thickest portions of the branches. Moving away from the tree center, branches become thinner and plant material less dense. A sensor is likely to capture the most reflected light from a tree's center where the plant material is dense. Therefore, theoretically the tree center should be represented by the brightest pixel in a tree. Illumination of trees is affected by the position of the sun. As the sun is rarely directly above a tree, the location of maximum illumination is often offset. In reality, it is not the center of a tree, but a pixel near the center of a tree that has the maximum reflectance value.

Using a roving window, the algorithm locates a tree apex by recording the pixels with the highest radiance values (Niemann et al., 1999). Trees are located by the local maxima filter and marked with a point (Figure 2). Local maxima filtering is able to locate trees using numerous types of high spatial resolution imagery including 1m resolution black and white orthophotos (Niemann et al., 1999) and MEIS imagery (Wulder et al., 2000a).

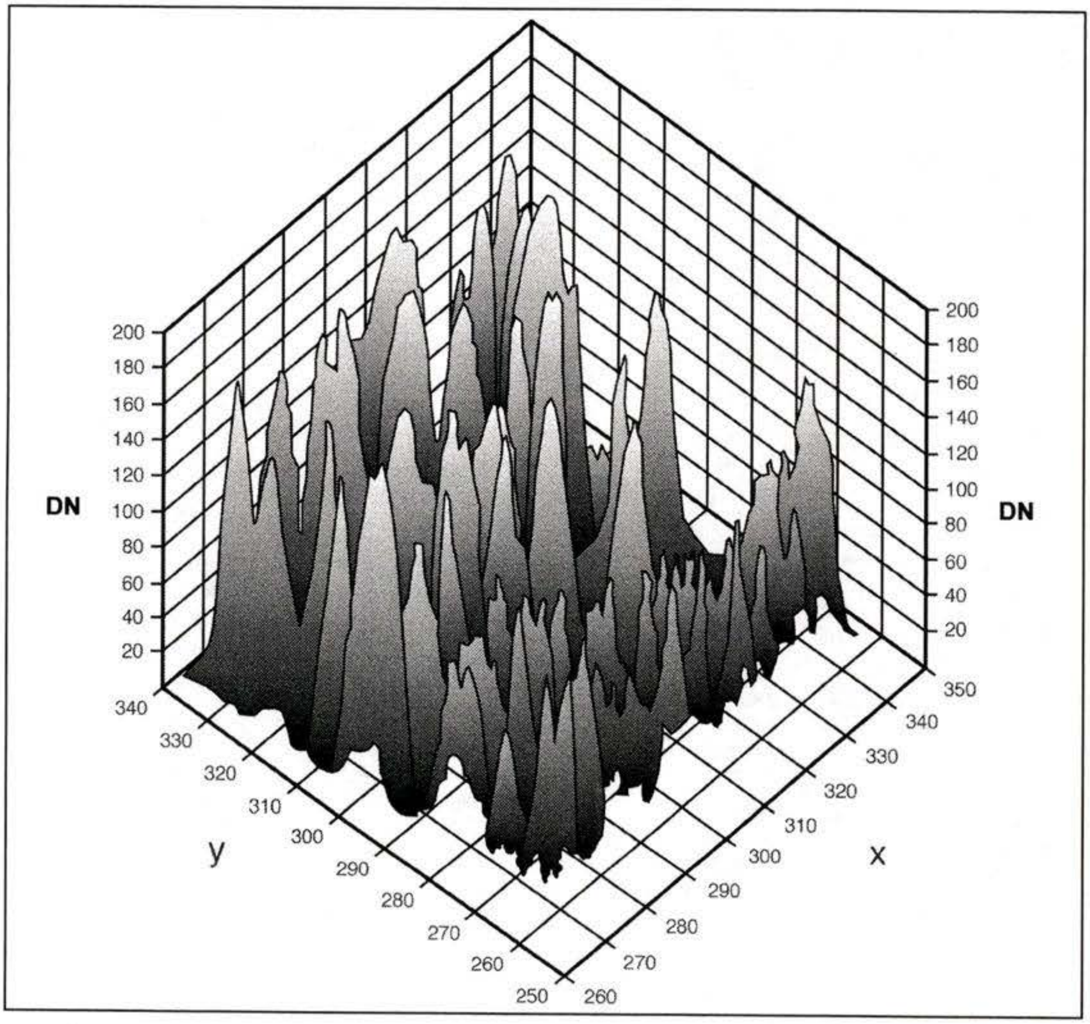

Figure 1. Digital surface showing theory used for local maxima filtering.

2.2.2.1 Reducing Error

Accuracy of the local maxima filter is limited when trees grow close together. For example, the crowns of trees growing close together may merge making it difficult to determine where one tree begins and the other ends. Rather than indicating a single tree, a cluster of trees may be indicated by the local maxima filter. Similarly, trees growing underneath the canopy (i.e. shade tolerant trees) are not visible from above and therefore are unlikely to be located by the local maxima filter. To refer to the results of the local maxima filter as individual tree crown identification may be misleading (Culvenor et al., 1999); extraction of the brightest canopy pixels is a more correct description of the local maxima filter output. As well, if trees are too small or large relative to the size of the image pixel they are likely to be missed and are considered errors of *omission*. Generally, trees should be four to six times the size of the image pixel to be accurately located (Wulder et al., 2000a). Trees that are large relative to the pixel size may be represented by several local maximas. Another problem associated with using the local maxima filtering approach is that the algorithm reports the presence of local maximas, which exist on the imagery but may not represent trees (Niemann et al., 1999). Local maxima that do not represent a tree or several local maxima that represent a single tree are considered errors of *commission* or false positives.

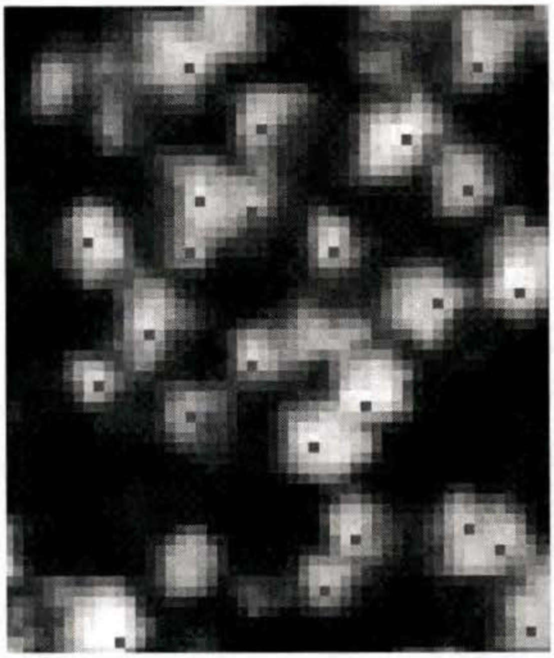

Figure 2. Local maxima filtering output. Points represent the apex of individual trees.

2.2.2.1.1 Remove Non-Forested Areas

Several existing techniques are useful for reducing local maxima filtering errors. By removing non-forest areas that may have local maxima, which do not represent trees, the number of trees erroneously located may be reduced. Forested and non-forested areas have unique spectral signatures, which can be differentiated with band ratios such as the normalized difference vegetation index (NDVI) (Loveland et al., 1991). When using panchromatic imagery it may not be possible to automatically remove the non-forested areas. However, thresholding image radiance may allow some non-forest areas, such as image shadow and water, to be extracted prior to analysis.

2.2.2.1.2 Thresholds

In Figure 3 the pixel values for forested and non-forested areas of an IKONOS image are shown. The amount of variation between the local maxima and the surrounding pixels is high in forested areas and lower in non-forest areas (Niemann et al., 1999). When the variance around a local maximum is lower there is a lower likelihood the identified pixel represents a tree. A variance threshold may be imposed to eliminate candidates, which are located but have low crown variance.

2.2.2.1.3 Variable Window Size

Varying the window size used by the local maxima filter may reduce the commission error. As the window size increases the algorithm considers a larger number of pixels when identifying the local maxima, and is therefore better able to identify large tree crowns. Applying a single window size to an entire image may not be the most effective technique as often tree crown size varies throughout the image. Semivariance and slope breaks of pixels are useful for determining when and how to vary the window size.

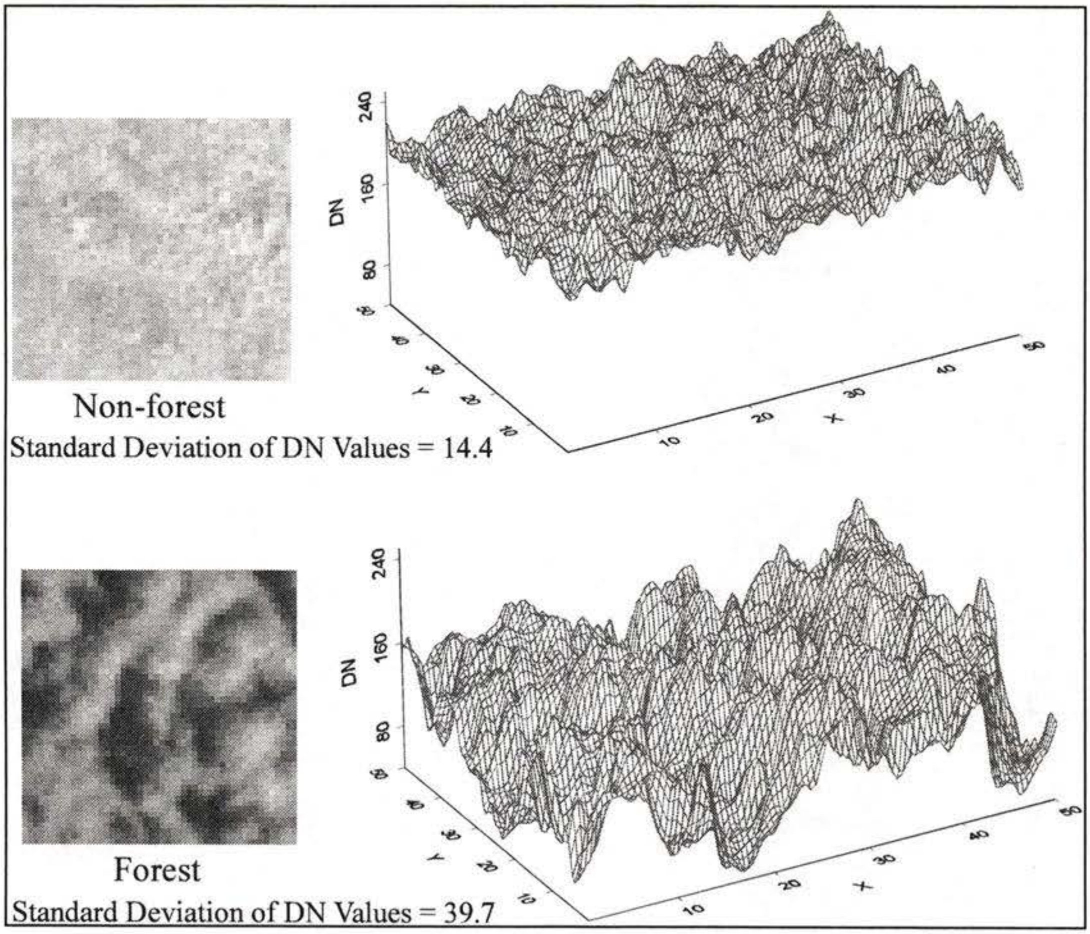

Figure 3. Digital values of forest and non-forest areas. On high spatial resolution imagery digital values for forest and non-forest areas differ in magnitude and variance.

Semivariograms are useful for measuring spatial dependency of continuous events and can be used to suggest appropriate window size for local maxima filtering. A semivariogram rises until reaching the *sill*, which indicates the maximum variability between pixels. The *range* is the distance to the sill (Curran and Atkinson, 1998). An average of the semivariance is computed in all directions for each image pixel inside a buffer, and is stored in the center cell. As the semivariance increases so does the local maxima window size (Wulder et al., 2000a). However, high spatial resolution imagery has limited inter-pixel variability and the semivariance becomes spatially dependent on stands, therefore user intervention is required to scale the values (Wulder et al., 2000a).

Slope breaks use information on the size of the region of dependence around a pixel to calculate variable window sizes for the local maxima filter. For each pixel the distance from the center pixel to the pixel of minimum radiance, in four or eight directions, is averaged (Figure 4). The point of minimum radiance is considered the tree edge; therefore, as the slope break distance increases so does the tree crown size. A larger window size will often improve the likelihood of locating a large tree. The slope break can be calculated for an entire image and automatically used to allow the system to appropriately scale the window size.

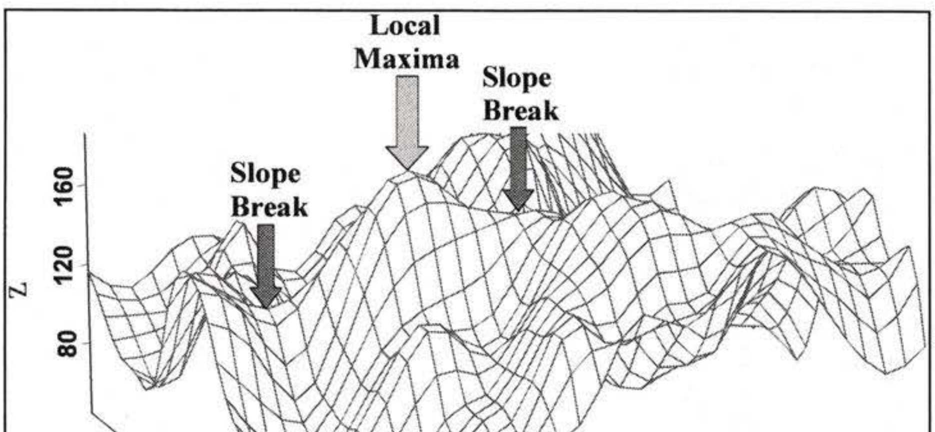

Figure 4. Breaks in slope occur at locations of minimum radiance. The greater the distance from the centroid pixel to the slope break the larger diameter of the crown and the larger the window size used by the local maxima filter.

1.4 Spatial Dependence

The Getis statistic (G_i^*), a measure of spatial dependence, can also be applied to remotely sensed imagery (Wulder and Boots, 1998). Unlike semivariance, G_i^* provides the strength of pixel association within a region of spatial dependence and is a standardized value. Large positive values of G_i^* indicate a cluster of high digital values and large negative values of G_i^* suggests a cluster of low digital values. On a panchromatic image high values suggest the likely presence of a tree object; whereas low values indicate non-tree features are probable. The Getis statistic can be used pre- or post-local maxima filtering to reduce the local maxima error. Post-filtering using the Getis statistics, is implemented similarly to the to the variance threshold discussed above. G_i^* is calculated for all candidate local maxima and if the value is less than zero the point removed (Wulder et al., 2000b). Prior to implementing the local maxima algorithm an image may be transformed to G_i^* values. Where G_i^* values are low the local maxima will not locate trees. The G_i^* statistic is likely sensitive to spatial resolution, as values form clusters of radiance values, and may only be appropriate when several pixels comprise an individual tree crown (Wulder et al., 2000b).

2.3 Spatial Statistics for Generating Attributes for Point Data

Once trees are represented as points, the goal is to aggregate the points based on captured forest structure. Spatial attributes generated for each tree point provide the basis for aggregation. In this section a literature review of spatial statistical tools, which show potential for generating meaningful point data attributes, is provided.

Statistics is the science of uncertainty, which attempts to find order in disorder (Cressie, 1993). A sub-discipline of statistics, spatial statistics, is used specifically to investigate the spatial arrangement of data (Bailey and Gatrell, 1995). One type of spatial statistics, point pattern analysis, provides a set of tools for investigating patterns of event locations (Cressie, 1993). Events are the result of an action or process. For example, the location of a tree is the result of processes, such as seed dispersal, and therefore, can be considered an event. In this study only techniques which can be used with events represented as points are of interest.

We are interested in generating spatial attributes, or labels, for each point reflecting the relationship between two or more trees. Point pattern analysis techniques, used to investigate and report on spatial relationships exhibited in point data sets, provide a means of generating point data spatial attributes. This chapter is a discussion of two point pattern analysis methods which may be used to generate spatial attributes for point data. First however, a few spatial statistical terms required to understand the principles of this thesis are provided.

2.3.1 Spatial Statistical Terms

Spatial analysis, is the quantitative study of phenomena located in space (Bailey and Gatrell, 1995). In contrast to non-spatial analysis, spatial analysis is concerned with event patterns and the location of one event in relation to other events. Therefore, information on the location of events must be available in order for spatial analysis to be performed. Often when performing spatial analysis one is attempting to determine if the events under study are spatially dependent. When the presence of one event is influenced by the presence of another event, the two events are said to have *spatial dependence*. Generally, ecological events are spatially dependent (Rossi et al., 1992). The difficulty however, can be determining the scale at which dependence occurs.

2.3.1.1 Spatial Scale

Spatial scale may be defined as the level of aggregation and the distance between objects at which measurements or analysis are occurring (Cressie, 1993). Spatial questions usually have a scale associated with them. For example, studying the spatial relationship between a queen bee and many worker bees will have a much different scale of analysis than studying the spatial relationship of two tree species. Determining the spatial scale at which analysis should take place is often difficult, as factors influencing an event may occur over several overlapping scales.

The two main scales of spatial analysis are *first order* and *second order*. First order trends, occur over large areas and relate to variation in the mean value of a process. Second order trends occur over smaller areas and result from spatial dependence within a process (Bailey and Gatrell, 1995). The scale of events under study and characteristics of the data influence the type of analysis that is appropriate. For example, when second order techniques are applied one generally assumes the mean and variance of an attribute do not change throughout a study region. Determining if a process should be studied at a first or second order scale can be difficult, as most natural processes result from interactions at both scales. This chapter includes a presentation of techniques available for aggregating points based on spatial dependence; all the methodologies discussed are based on second order analysis.

2.3.1.2 Sampled Vs Fully Mapped Data

Point data may be either *sampled* or *fully mapped*. Fully mapped point data exists when all observations or members of a population are enumerated, whereas a data subset considered a sample (Upton and Fingleton, 1985). Until recently, producing fully mapped data was resource intensive and often required extensive field programs therefore, sampled data was more commonly used. However, user-assisted techniques used with remotely sensed data, such as local maxima filtering (section 2.2), efficiently generate fully mapped data sets.

Different statistical assumptions can be made about fully mapped and sampled data sets. Some, but not all, statistical techniques can be used effectively with both fully mapped and sampled point data. The methods described below are for use with fully mapped data, although some are also suitable for use with sampled data.

2.3.1.3 Spatial Patterns in Point Data

There are three main types of patterns which are observed in point data: *random, clustered,* and *regular* (Figure 5). Randomly spaced points appear to have no interrelationship (Figure 5-A). *Real contagion* is a clustering pattern that results when there is a relationship of attraction between points, however clustering may also result from environmental inhomogeneity resulting in apparent contagion (Figure 5-B). *Apparent contagion* results from influences such as topography or soil moisture. Regularly spaced points likely have a relationship of repulsion (Figure 5-C).

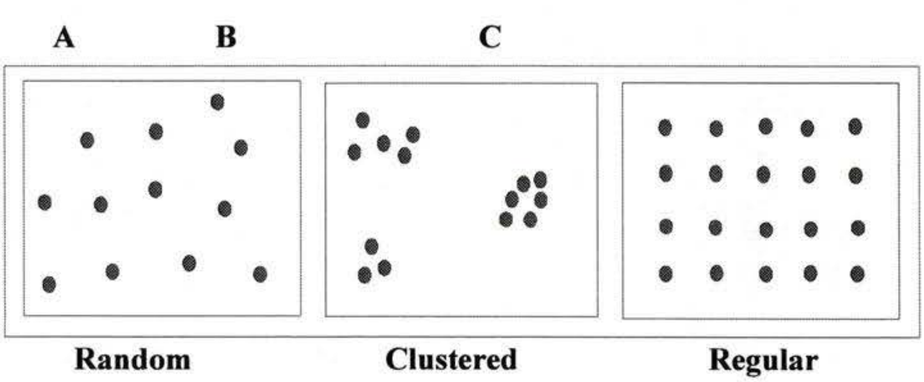

Figure 5. Spatial point patterns.

In a point data set the statistical significance of observed patterns can be tested by comparison with models representing complete spatial randomness (CSR) (Cressie, 1993). CSR is a data model used to simulate a random distribution of data. For the purpose of this study relative changes in patterns, not deviations from CSR, are of interest. Determining if the spatial point patterns surrounding point x are more or less clustered than the spatial point pattern surrounding point y is the focus. Comparisons with CSR will not be made.

2.3.2 Assigning Spatial Attributes

Two point pattern methods, which may be used to generate meaningful spatial attributes based on the spatial patterns of trees, are nearest neighbour distance and Voronoi techniques.

2.3.2.1 Nearest Neighbour Distances

Nearest neighbour distance (NND) techniques are one type of spatial statistical point pattern analysis. By analyzing the distances between observed neighbouring events NND techniques provide a means for both describing data and generating spatial attributes (Bailey and Gatrell, 1995). Nearest neighbour distance methods can be used to isolate information about second order interactions and therefore are useful when first order patterns are heterogeneous. The NND cumulative probability distribution is estimated by applying the following equation (Bailey and Gatrell, 1995):

$$\hat{G}(w) = \frac{\#(w_i \leq w)}{n} \tag{1}$$

where: $\hat{G}(w)$ = cumulative probability distribution
$\#$ = "the number of events where"
w_i = distance between events
w = stopping distance
n = number of events in the study area.

The stopping distance is a maximum distance between points, which can be considered nearest neighbours. If the $\hat{G}(w)$ values are low the distances between neighbours is small, as the value increases so does this distance between points.

As with all point pattern analysis, $\hat{G}(w)$ of points at the edge of the study region will be biased unless a correction is applied. To correct for edge bias a buffer or guard area can be constructed. Points within the guard area are allowed to be neighbours, but their $\hat{G}(w)$ is not calculated. The size of the guard area is relative to *w*; as *w* increases in size so should the buffer. Alternatively a NND algorithm which ignores points close to the boundary can be used (Bailey and Gatrell, 1995):

$$\hat{G}(w) = \frac{\#(b_i > wi \leq w)}{\#(b_i > w)} \qquad (2)$$

where: bi = the distance from an event *i* to the nearest point boundary.

Both the buffer and algorithmic edge corrections can be used for study regions regardless of shape (Bailey and Gatrell, 1995).

Information on the types of patterns found in second order trends of point data can be obtained by plotting the estimated NND distribution function against values of *w*. For example, if the distribution function has a steep slope initially and then flattens out, there is a high probability of short NNDs and therefore clustering (Figure 6-A). If the steep slope is in the latter portion of the graph there is a high probability of larger NNDs and therefore regularity or repulsion (Figure 6-B). If the NNDs are random, suggesting no interaction between data points the graph should be a straight line (Figure 6-C) (Bailey and Gatrell, 1995). The statistical significance of regular or clustered patterns cannot be determined without comparison to a data model such as CSR.

There are several ways in which the NND statistic can be used to generate spatial attributes for point data. A spatial attribute based on NND, could be the value equal to the average distance to neighbours within a specified distance (Figure 7). As well, attributes could equal the mean or median distance of *n* neighbours (Figure 8) or the total number of neighbours within a distance less than w_i from point *i* (Figure 9). Other descriptive statistics such as standard deviation and covariance may also be used to generate attributes. Using more than one NND to compute the spatial attribute may provide insight on the spatial relationships surrounding each point, not just the relationship between two points. However, if too many NNDs are used the statistic may be influenced by first order trends.

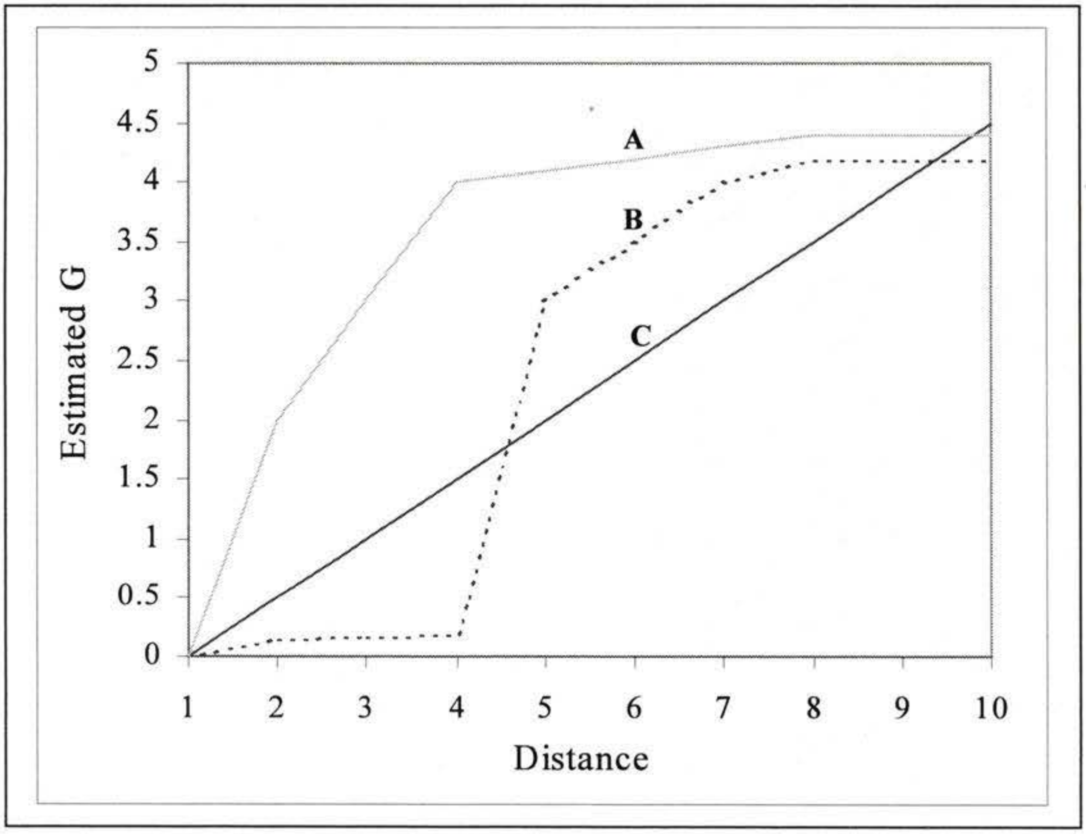

Figure 6. Simulated NND distribution function. A) shows a distribution with a high probability of few NNDs (clustering); B) shows a distribution with a high probability of many NNDs (regularity); C) shows no interaction between data.

The NND statistic is useful for generating spatial attributes for point data as: 1) NND can be used when the mean and variance of the process changes throughout a study region; 2) NND are mathematically simple and can be used with large data sets; and, 3) several permutations of the NND statistic may generate useful attributes.

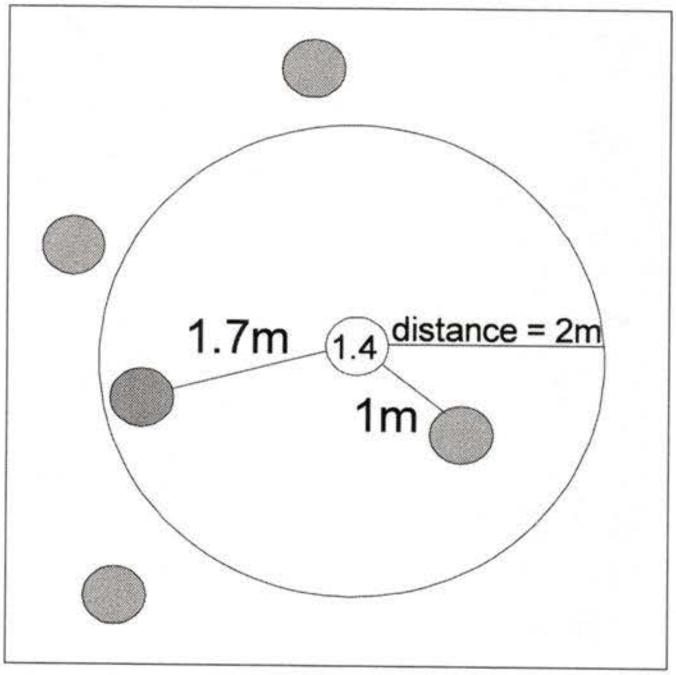

Figure 7. The point attribute equals the average distance of neighbours within a specified distance.

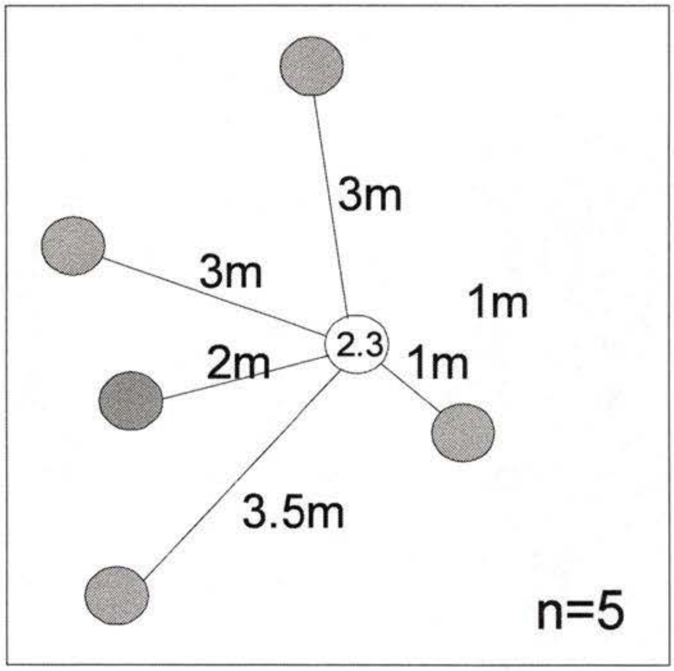

Figure 8. The point attribute equals the average distance to *n* nearest neighbours.

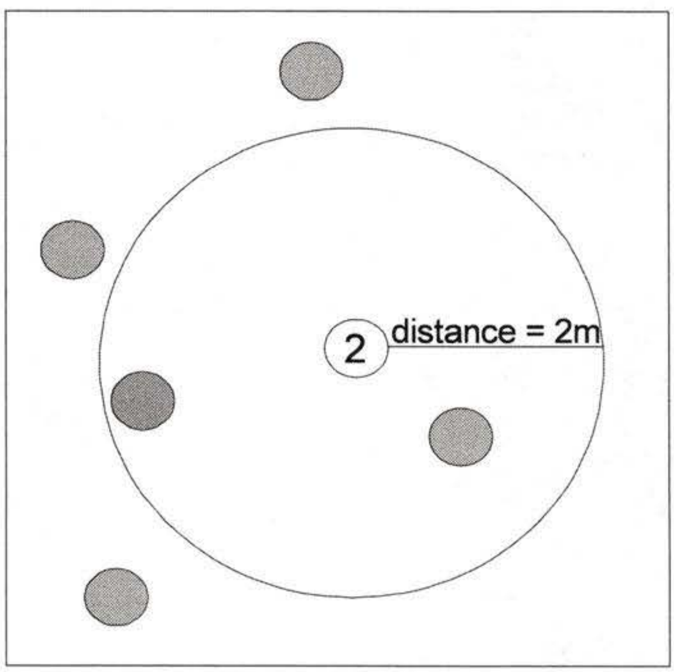

Figure 9. The point attribute equals the number of neighbours within a specified distance.

2.3.2.2 Voronoi

Techniques based on Voronoi polygons can also be used to describe the spatial nature of point data and generate point attributes. To generate Voronoi polygons, first draw Delauny Triangles by drawing lines connecting each point with all their nearest neighbouring points (Figuer 10-B). Next, bisect each line (Figure10-C), and finally, connect the bisectors of the lines (Figure10-D). The result is a series of polygons where all the space within in the polygon is closer to the point than all the space outside of the polygon. Characteristics of the Voronoi polygons, such as area, reflect the spatial nature of the point data.

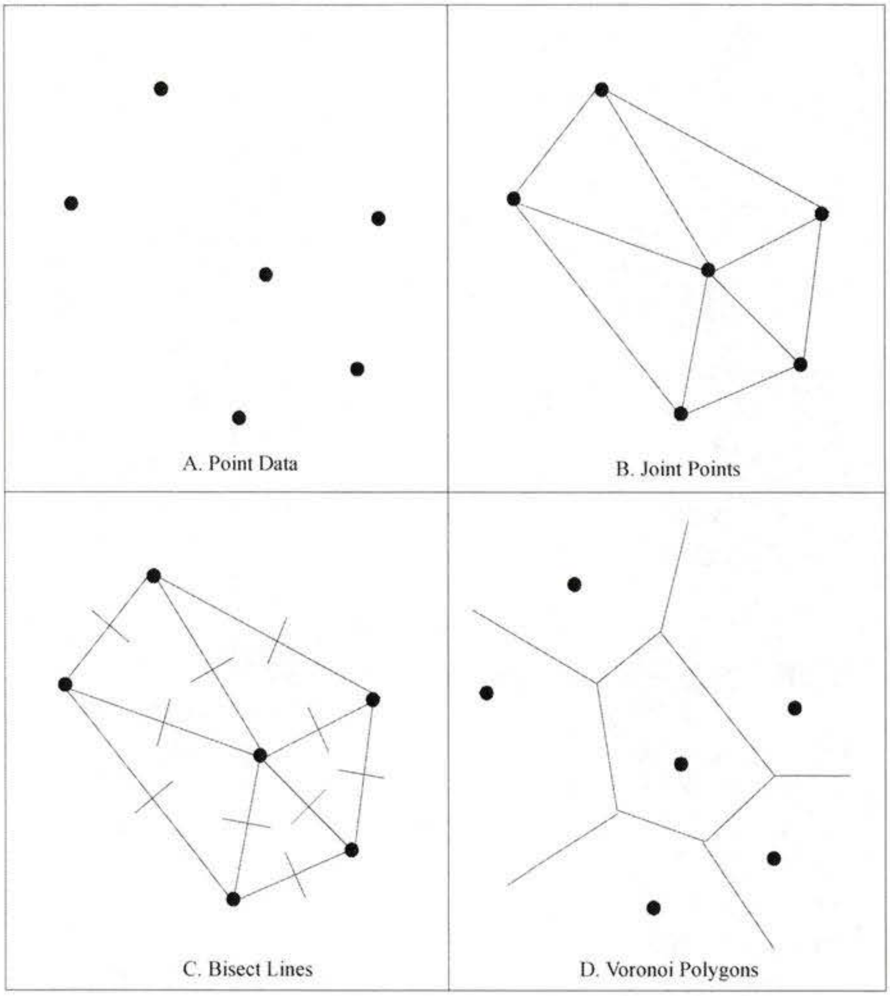

Figure 10. Steps used to generate Voronoi polygons.

Most Voroni polygons characteristics can be compared with complete spatial randomness (CSR) to determine if the pattern is significantly different than expected from a random pattern. Complete spatial randomness is data model which simulates a random data set. However, it is the relative change in spatial patterns between neighbouring points, not deviations from CSR, which are of interest.

Voronoi polygon attributes include the number of polygon sides, the length of the polygon perimeter, the polygon area, and the polygon shape (Okabe et al., 2000). Although the first three above-mentioned characteristics are self explanatory, the shape attribute is more complex. The shape of a point pattern is the geometric form produced by linking essential members of a point set. Whether a point is essential or not is determined by its spatial relationship to other members (Kirkpatrick and Radke, 1985). More than one shape can result from joining points; however, most have either linear or polygon shape (Okabe et al., 2000). Both internal and external shape properties can be computed (Okabe et al., 2000).

To generate point attributes from Voronoi polygon characteristics calculate the number of polygon sides, the length of the polygon perimeter, or the polygon area for each individual polygon and to store that value for each point. Using shape attributes is difficult requiring the analyst to develop an index of shapes types. Like the NND techniques, many variations of the Voronoi polygon methods exist. For example, one may compute statistics such as the mean, standard deviation, co-variance, median, or mode of all adjacent polygons or for the polygons of the nearest x points.

2.3.3 Benefits and Issues of Spatial Attribute Generating Techniques

An overview of the benefits and issues of using NND and Voronoi polygon techniques to generate spatial attributes for point data can be seen in Table 1. NND methods are useful when the mean and standard deviation of a study area are variable. As well, the simplicity of the NND techniques can be both a positive and negative aspect to their use depending on the application. Nearest neighbour statistics are relatively easy to use and are useful for initial investigations.

One of the difficulties with using Voronoi polygons is that they are computationally intensive; however, as technology advances Voronoi polygons are becoming easier to use. As well, Voronoi algorithms are increasingly included in software packages such as ArcInfo which are capable of working with large data sets.

Still, theoretically Voronoi polygons may be useful for developing many attributes, which cannot be investigated using existing commercial software packages. The computational requirements of the Voronoi techniques are not necessarily a negative, as it is the complexity, which results in a means to describe complicated phenomena.

Table 1. Selected benefits and potential issues of NND and Voronoi techniques for generating spatial attributes.

Techniques for assigning spatial attributes to points	Benefit	Potential Issue	**References**
NND	Computationally and theoretically simple; not influenced by variation in a study area's mean and standard deviation.	Potential for high variability in natural environments	Bailey and Gatrell, 1995
Voronoi Polygons	Many attributes may be generated; theoretically sound	More computationally complex than NND;	Okabe et al, 2000

2.4 Aggregating Point Data Based on Spatial Attributes

The attributes will be used as the basis for aggregation of points into polygons. Many existing techniques provide potential for aggregating point data into homogenous polygons. The methods presented in this section may be used with point data that has been assigned spatial attributes using the techniques described in the previous section. The aggregation methods described below may be used with regularly spaced point data, however some methods are flexible enough to also be used with irregular point data. Techniques appropriate for point aggregation include edge detection, region growing, clustering, contouring, Voronoi aggregation and thresholding.

2.4.1 Edge Detection

Edge detection is a means of segmenting data into areas by locating spatially contiguous regions representing high rates of change (Fortin and Drapeau, 1995). By locating boundaries, groups belonging to different spatial clusters are produced as a by-product. Edge detection provides information on the shape, size, and intensity of boundaries, (Fortin and Drapeau, 1995) which are important as boundaries are often areas where information is concentrated (Fu and Mui, 1981). Edge detection is a process which uses the following two steps. 1) Generate a surface representing the magnitude of change (*i.e.* the amount of difference between spatial attributes). 2) Locate regions where the maximum change is occurring (Wahl, 1987).

Several edge detection techniques, which could be used with point data exist. One technique appropriate for use with regularly spaced point data is lattice-wombling (Fortin and Drapeau, 1995). Lattice-wombling uses an algorithm that averages the absolute values of the derivations describing the variations of continuous variables in space (Womble, 1951).

In Figure 11 how the lattice-wombling algorithm generates a surface that reflects the magnitude of change is shown. The Womble algorithm calculates, over a four pixel kernel, the first partial derivative of the values of a given variable in the x and y directions. The rate of change is computed and stored in the centroid, the location where the four pixels meet. The steepness of the slope corresponds to the magnitude of the rate of change; where no change is occurring the slope is approximately zero (Fortin, 1994). Based on the magnitude of change surface, boundaries can be defined as the pixels where the magnitude of change is among the highest *k* percent (Fortin, 1994). The value for *k* is a threshold set by the analyst.

For lattice-wombling to be used on point data generated with remotely sensed imagery the input matrix must exclude non-local maxima pixels. Any pixel which does not include a point will have a zero value, therefore the surface representing the magnitude of change would show few, if any, areas with a high magnitude of change if background pixels are used.

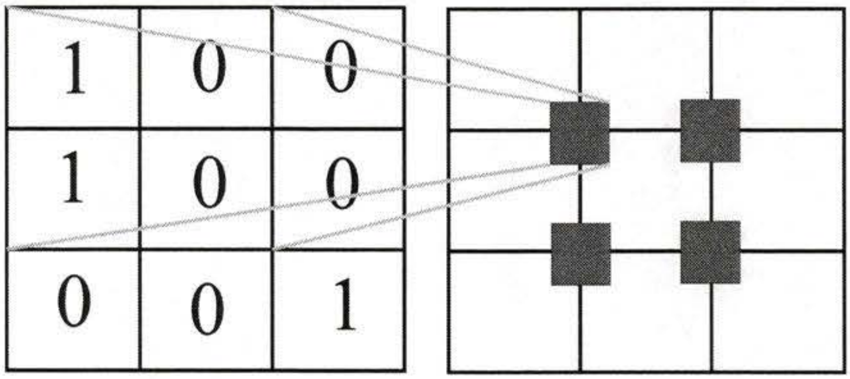

Figure 11. Generating a surface to detect boundaries using lattice-wombling.

Lattice wombling shows potential for defining boundaries around homogenous polygons, however there are some drawbacks to using edge detection methods for generating polygons. Edge detection techniques do not aim to form closed polygons, they are simply a first step in locating the boundaries of polygons (Fortin and Drapeau, 1995). Therefore, if using an edge detection technique further processing will be required to close meaningful polygon boundaries. As well, when using lattice-wombling, it may be difficult to determine the appropriate threshold to use for identifying boundaries.

2.4.2 Region Growing

Region growing is another technique potentially useful for aggregating points extracted from remotely sensed imagery. Starting with initial locations, region growing generates groups by assigning points with similar properties to sub-regions until all the data are classified (Wahl, 1987). The most difficult step in region growing is determining the locations of initial points. Region growing is most efficient if there is one initial point per homogenous group; if fewer initial points are used some groups will be missed and if too many initial points are used extra groups will be generated. One way to compensate for superfluous initial points is to merge similar groups once the regions have been determined (Wahl, 1987).

Initial points are iteratively assigned the remaining data as long as the generated groups do not meet the stopping criteria. Stopping criteria are generally determined by the analyst and may be the number of points in a group, a maximum difference between the mean of a group and a neighbouring cell, or the length of a common boundary (Wahl, 1987; Jau, 1989).

Region growing requires that all points are classified and is less sensitive to noise than boundary based segmentation procedures (Jau, 1989). However, region growing can be difficult to use if the number of regions and correct locations of initial points are not known *a priori* (Hall, 1979). Region growing tends to be computationally expensive, which may be a problem when working with large data sets.

2.4.3 Clustering

Cluster analysis attempts to place individuals into homogeneous groups based on variables or attributes, and may be used for segregation (top down) or aggregation (bottom up) of data. Cluster analysis is a two stepped process: 1) a matrix of dissimilarity (distance between observations) is generated; 2) each object is assigned to a group (Bailey and Gatrell, 1995).

2.4.3.1 Hierarchical

Hierarchical cluster analysis may start with each point in a separate group or all points in one group. Over a series of iterations either the more similar observations are grouped together or the least similar are separated based on the optimization of some criteria

(Lorr, 1983). For example, simple linkage or nearest neighbour clustering, groups observations based on minimizing the NNDs within a cluster. The stopping rule for simple linkage clustering is generally based on a maximum NND (Lorr, 1983).

2.4.3.2 Optimization

Unlike hierarchical clustering, optimization clustering requires a pre-specified number of groups (Lorr, 1983). Pre-specifying the number of groups allows the clusters to be optimized over all possible partitions with k number of groups. However, it also requires the user to have *a priori* knowledge of the number of expected clusters. The user will be required to perform several clusters with different numbers of groups to ensure that they have obtained the best possible results (Bailey and Gatrell, 1995).

One of the simplest and most common optimization techniques is the k-means clustering method. Given a predetermined value for k and a starting point, observations are grouped so that the within-group variance of the dissimilarity measure is minimized. Variance is minimized based on the sum of the squared distance between each sample and the centroid of the group to which it belongs (Fortin and Drapeau, 1995). The strength of the k-means clustering method is that for k groups within cluster heterogeneity is minimized (Legendre and Fortin, 1989).

2.4.3.3 Spatial Adjacency Constraints

Typically clustering algorithms do not require observations being grouped to be adjacent. Therefore, if using a clustering technique to aggregate adjacent points the algorithm must be spatially constrained, (Lefkovitch, 1978; Legendre and Fortin, 1989; Fortin and Drapeau, 1995). In order to spatially constrain clustering algorithms, the spatial adjacency of points must first be determined.

There are several techniques for determining spatial adjacency. The *Gabriel connection* considers observations adjacent if there is not another point within a circle formed by joining the two sites (*i.e.* the diameter of a circle is equal to the distance between the two sites) (Upton and Fingleton, 1985). *Delaunay triangulation* considers points spatially adjacent if three points can be joined without incorporating other observations. Finally, when point data are organized in a matrix the eight pixels surrounding a point (*i.e.* the eight NNDs) are the only observations adjacent to a particular point. For example, based on the relationship illustrated in Figure 12, the observations adjacent to point x,y are (x-1,y-1), (x-1,y), (x-1,y+1), (x,y-1), (x,y+1), (x+1,y-1), (x+1,y) and (x+1,y+1). Points along the edge of the matrix have fewer than eight adjacent points.

x-1,y+1	x, y+1	x+1, y+1
x-1, y	x, y	x+1, y
x-1, y-1	x, y-1	x+1, y-1

Figure 12. Computing spatial adjacency using NND.

Spatially constraining cluster analysis has two computational effects. First, the possible solutions are reduced as only adjacent pixels have the potential to be grouped (Fortin and Drapeau, 1995). Second, the within group variance will increase as the clustering algorithm's ability to minimize within group variance is constrained by the spatial requirements (Fortin and Drapeau, 1995). A computational drawback however, is that the spatial adjacency matrix must be constantly revised.

2.4.4 Contouring

Contouring uses isolines to join points of equal value. The only input required from the user is the interval at which isolines should be developed. Once the contour interval has been determined isolines can be drawn through straight-line segments which connect points. Straight-line segments are produced by Delaunay triangulation, which is also a technique for determining spatial adjacency (Bailey and Gatrell, 1995).

2.4.5 Voronoi Aggregation

Attributes developed with Voronoi polygon techniques may be aggregate based on Voronoi polygon characteristics.

2.4.5.1 Polygon Properties

Five types of Voronoi polygons have been identified: isolated points, members of curvilinear structure, members of a cluster with an empty interior, or members of either the boundary or the interior of a cluster with a non-empty interior (Ahuja, 1982). If the appropriate properties were used to generate attributes, ratio measures of adjacent polygons can be calculated and the edges used to determine which group a polygon belongs to. Polygon properties may be useful for aggregation if the classes required relate to the five polygon classes. However, if polygon type cannot be correlated to the classes required this aggregation technique may not be appropriate.

2.4.5.2 Area Based - Iterative

Duyckaerts et al (1994) developed an iterative technique to aggregate points based on the area of Voronoi polygons. The technique is a three stepped process. First, the smallest Voronoi polygon is located. Second, contiguous polygons are examined and combined with the reference polygons if the size of the new polygon does not exceed a predefined threshold. Step two is repeated until the threshold is reached. Finally, the new polygon is removed from analysis. Steps one to three are repeated until all the polygons have been aggregated. Duyckaerts' process is only effective if the analyst knows the maximum area of the final polygons.

2.4.6 Thresholds

The simplest means of aggregating point data is to apply thresholds to the attributes. The thresholds can be determined using cartographic methods used for generating class intervals on choropleth maps (Robinson et al., 1995) (Dent, 1996). When aggregating environmental phenomenon the most useful method of determining class intervals is the natural break technique. Inspecting graphed data to determine where numerical breaks occur is one means of determining the natural breaks (Dent, 1996). However, to ensure the groups produced by thresholding are meaningful, it may be wise to use a training data set to establish breaks or threshold values. Although thresholds are simple to use they are not useful if points have multiple attributes. As well, thresholding does not consider spatial contiguity information, making polygon generation potentially difficult. It may be necessary to use decision rules to spatially constrain groups generated by thresholding.

2.4.7 The Benefits and Issues of Aggregation Techniques

The benefits and drawbacks of using different aggregation techniques are presented in Table 2. Thresholding may be effective due to relative simplicity in implementation, however is unlikely to work well in complex scenarios. Generally, edge detection is not designed to generate closed polygons. Cluster analysis and region growing may produce similar results depending on the type of stopping rule used for region growing. Contouring may be an appropriate technique for aggregating point data, but tends to produce clusters that are approximately shaped like concentric circles. Voronoi polygons are only useful for aggregation if the classes produced by the aggregation relate to the polygon types, area, or other Voronoi polygon characters.

Table 2. Selected benefits and possible issues of techniques for aggregating point data.

Techniques for aggregating points into polygons based on spatial attributes	Benefit	Possible Issues	References
Edge Detection	Provides information on edges; locates regions of maximum change	Does not output closed polygons; threshold for determining edge is arbitrary	Fortin and Drapeau, 1995
Region Growing	Classifies all data; user specified stopping rule	Computationally intensive; arbitrary location of initial points	Wahl, 1987; Jau, 1989
Spatially Constrained Cluster Analysis	Classifies all data; software available for working with large data sets; works on irregularly spaced data	May require user to input the number of classes; arbitrary location of start location	Lorr, 1983; Bailey and Gatrell, 1995
Contouring	Works with irregularly spaced data	Computationally intensive; theoretically simplistic	Bailey and Gatrell, 1995
Voronoi Polygon	Works with irregularly spaced data, theoretically sound; computationally simple if attributes generated with Voronoi polygons	Computationally intensive; data dependent and outcome dependent	Okabe et al., 2000
Thresholding	Theoretically and computationally simple	Not for use with multiple attributes; not spatially constrained	Robinson, 1995; Dent, 1996

3.0 Study Sites and Data

Chapter Objective: To describe the study site and the sub-sites used to test the spatial aggregation method and overview data types used throughout this project.

3.1 Study Area

An IKONOS image of the Sooke watershed was the key data used in this thesis. Due to operational constraints some methodological steps used only sub-sites of the image. The entire image was used for feature extraction and selection of training areas for metric creation. Four sub-sites were selected from the full IKONOS image. Accuracy assessment of feature extraction was preformed for a small area in one of the sub-sites, and the aggregation was preformed on all four sub-sites of the IKONOS image. The general area of the Sooke Watershed, as well, the specific characteristics of the sub-sties are described below.

3.2 The Sooke Watershed

The Sooke Watershed is located 40 km northwest of Victoria, British Columbia, Canada (48° 34' N, 123° 42' W) (Figure 13), and is part of the Capital Regional District's water supply. The Sooke Watershed, is dominated by coastal Douglas-fir (*Pseudotsuga menziesii)*, however western red cedar (*Thuja plicata)* and western hemlock (*Tsuga heterophylla*) are also prevalent. The Sooke Watershed is well suited to a study of age related forest structure as anthropogenic influence has lead to a variety of stand ages in a relatively small distance. Stand age ranges from 0 years to >250 years and can be represented using the British Columbia Ministry of Forest's forest inventory age classes (Table 3). Age class 7 is not represented in the watershed and relatively few stands between 41 years and 140 years exist. Different management strategies have been used throughout the watershed. Many stands approximately 100 years in age have not been thinned; most stands approximately 20 years old have been thinned.

Table 3. British Columbia Ministry of Forest's forest inventory age classes.

Class	Age
1	1-20
2	21-40
3	41-60
4	61-80
5	81-100
6	101-120
7	121-140
8	141-250
9	251+

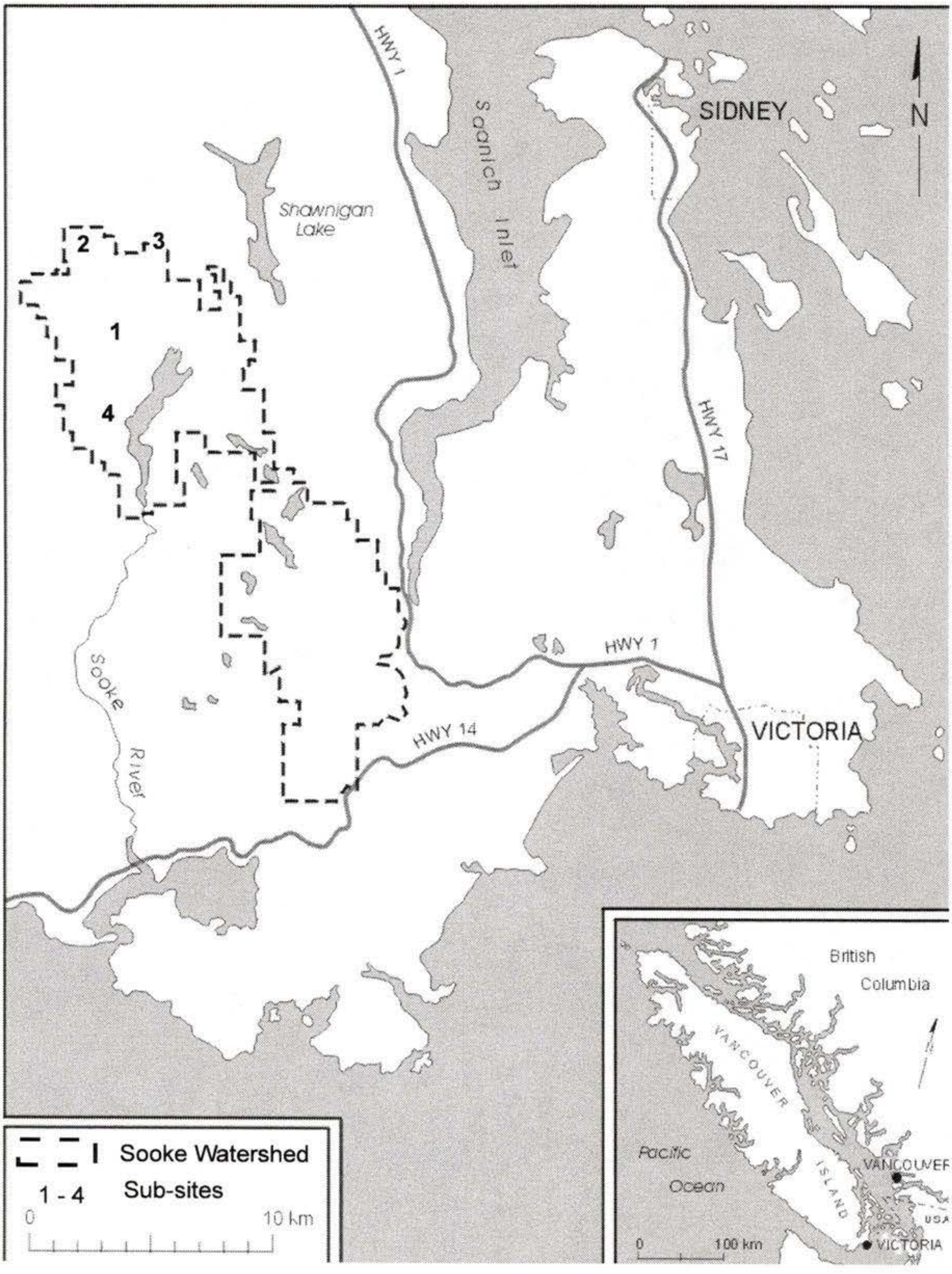

Figure 13. Location of the Sooke Watershed.

3.2.1 Sites

Use of the entire IKONOS image of the Sooke Watershed for development and testing of thesis techiques was impractical. Local maxima filtering located 1,214,277 trees on the IKONOS image. Using 1.2 million tree locations for the development of a generalization procedure would be more time consuming than necessary. To make analysis manageable, four sub-sites within the Sooke Watershed were selected for analysis (Figure 13). In Table 4 a summary of the characteristics for each site is provided. The sub-sites had between 7,817 – 11,872 trees. An effort was made to select sub-sites which: represented all available forest ages classes, were distributed over the entire study area, were composed of pure Douglas-fir stands, and had sufficient auxiliary data available. Sampling the entire Sooke watershed was limited particularly by the need to have stands representing as many age classes as possible. In the following detailed descriptions of each site, forest age will be based on the British Columbia Ministry of Forests' forest inventory age classes (Table 3).

Table 4. Summary of sub-site characteristics.

Site	Area (sq m)	NW Corner (UTM)	SE Corner (UTM)	Dominant Age Class*	Dominant Species Class
1	720	446162E, 5382346N	447062E, 5381546N	1, 2, 8, 9	Douglas-fir
2	578	445112E, 5385516N	445862E, 5384746N	2, 6, 8	Douglas-fir
3	525	448412E, 5384796N	447462E, 5379296N	1, 3, 6, 8	Douglas-fir/Hemlock
4	600	441962E, 5386346N	451162E, 5377371N	1, 2, 8, 9	Douglas-fir

* Age classes based on the B.C. Ministry of Forests' forest inventory age classes (see Table 3).

3.2.1.1 Sub-site 1

Sub-site 1 is located in the northwest portion of the Sooke Watershed and is centered on Rithet Creek (Figure 14). The northwest corner of site 1 is located at 446162E, 5382346N and the southwest corner is located at 447062E, 5381546N. Sub-site 1 is

800m by 900m equaling an area of 720 000m^2. Stands are dominated by Douglas-fir, however stands of mixed Douglas-fir and Cedar, and mixed Douglas-fir and Hemlock also exist. Age classes represented in Sub-site 1 include classes 1, 2, 8, and 9. Several roads run through sub-site 1.

Figure 14. Sub-site 1. 800m by 900m subset of an IKONOS image of the Sooke Watershed.

3.2.1.2 Sub-site 2

Sub-site 2 is located in the northern Sooke Watershed slightly east of Grant Lake (Figure 15). The northwest corner of the site is located at 445112E, 5385516N and the southeast corner is located at 445862E, 5384746N. Sub-site 2 is 750m by 770m and has an area of 577 500m^2. With the exception of a small stand of mixed Douglas-fir and Cedar, sub-site 2 is almost entirely composed of pure Douglas-fir. The small Douglas-fir and Cedar stand is age class 5, however age classes 2, 6, and 8 dominate the site. There are two roads that run through sub-site 2.

Figure 15. Sub-site 2. 750m by 770m subset of an IKONOS image of the Sooke Watershed.

3.2.1.3 Sub-site 3

Sub-site 3 is located near the edge of the northern extent of the Sooke Watershed management area, directly above the western coastline of the upper portion of Sooke Lake (Figure 16). The northwest corner of the site is located at 448412E, 5384796N and the southeast corner is located at 447462E, 5379296N. Sub-site 3 is 700m by 750m and has an area of 525 000m^2. Sub-site 3 has many mixed species stands, but was selected due to the presence of age class 3 stands. The species composition of stands include: pure Douglas-fir; Hemlock and Douglas-fir; Douglas-fir, Cedar, and Hemlock; Douglas-fir and Cedar; Douglas-fir, Cedar, and White Pine. Age classes include 1, 3, 6, 8, as well as a small portion of age 4. One road runs through the center of sub-site 3.

Figure 16. Sub-site 3. 700m by 750m subset of an IKONOS image of the Sooke Watershed.

3.2.1.4 Site 4

Located near the junction of Rithet Creek and Sooke Lake, sub-site 4 is the most southerly site in this study (Figure 17). The northwest corner of the site is located at

441962E, 5386346N and the southeast corner is located at 451162E, 5377371N. Sub-site 4 is 800m by 750m and has an area of 600 000m^2. Aside from a small pocket of Cedar of age class 8, this area is almost entirely pure Douglas-fir and composed of age classes 1, 2, 8, and 9. Like all the other sites, there is a road running through sub-site 4.

Figure 17. Sub-site 4. 800m by 750m subset of an IKONOS image of the Sooke Watershed.

3.3 Data Sources

Several types of data were used throughout this thesis. IKONOS imagery was used as input for local maxima filtering. Field data, in the form of a stem plot, was used to assess the accuracy of the local maxima filtering results. A forest inventory map was used to help select training areas used for metric creation and to interpret aggregation results. The following is a description of each data type used in this thesis. Details of *how* the data were used will be provided in the methodology section.

3.3.1 Remotely Sensed Imagery

In 1999 Space Imaging launched the high spatial resolution IKONOS-2 satellite. The IKONOS satellite produces panchromatic images with a spatial resolution of 1m and multispectral images with 4m resolution. The multispectral images are composed of four bands, one in each of the blue, green, red, and near infrared portions of the electromagnetic spectrum (Table 5). IKONOS images are up to 10x10km and ground areas are re-imaged every one to three days.

Table 5. Wavelengths of IKONOS Bands.

Band	nm
Pan	450-900
Blue	445-516
Green	506-595
Red	632-698
NIR	757-853

The IKONOS image used in this study was collected on June 3, 2000 at 11:05 PST and is a single panchromatic image. The solar elevation was 60.7° and the solar azimuth was 146.5°. The upper left corner of the image is 441962E, 5386346N and the lower right corner is 451162E, 5377371N. The image is 9200m by 8975m, and covers approximately two thirds of the Sooke watershed management area and also extends beyond the western extent of the management area (Appendix 1).

3.3.2 Field Data for Accuracy Assessment of Feature Extraction

The first phase in this project is to extract tree locations from the remotely sensed imagery. Once objects have been extracted, it is important to consider how accurately they represent the locations of existing trees. In the summer of 1992 a 90 by 90m field stem plot, centered in sub-site 1, was collected (Hay, 1994). The stem plot straddled a boundary between young trees (approximately 40 years) and older trees (approximately 150 years). In all, 208 trees were located and attributes including species, height, diameter breast height, crown radius, and crown height were collected for each tree (Figure 18). A revisit to the stem plot site in the summer of 2000 revealed blow down of nine trees in the southwestern corner of the plot. 150 immature and 49 mature trees remained (Wulder et al., 2001). The updated stem plot trees were mapped on the IKONOS image and used to assess the accuracy of several different variations of the local maximum finding technique.

3.3.3 Forest Inventory Map

Information on forest stands within the Sooke Watershed was obtained from the Capital Regional District (CRD) Water Department Watershed Management Operations Sooke Watershed map. The forest ages on this map are projected to 1998 and the map scale is 1:15000 (GVWD 1991). Forest ages are listed using the Ministry of Forest's nine inventory age classes (Table 3). There are concerns regarding the quality of this map, therefore it was only used in areas where comparisons with imagery and aerial photography confirmed the map attributes. Throughout the remaining document this map will be referred to as the forest inventory map.

Tree ID	X	Y	Species	DBH (m)	Crown Radius (m)	Crown Height (m)	Tree Height (m)	Regen/ Mature
1	1.4	6.7	h	0.13	1.3	7.3	11.2	r
2	2.8	4.0	h	0.18	1.4	7.2	18.8	r
3	1.0	2.9	f	0.15	1.0	12.4	15.8	r
4	5.1	5.1	h	0.15	1.0	11.1	13.2	r
5	6.6	8.6	f	0.33	1.8	17.5	21.6	r
6	9.9	2.5	h	0.22	1.5	10.4	17.9	r
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
209	86.0	87.0	c	0.8	3.9	50.0	60.0	m

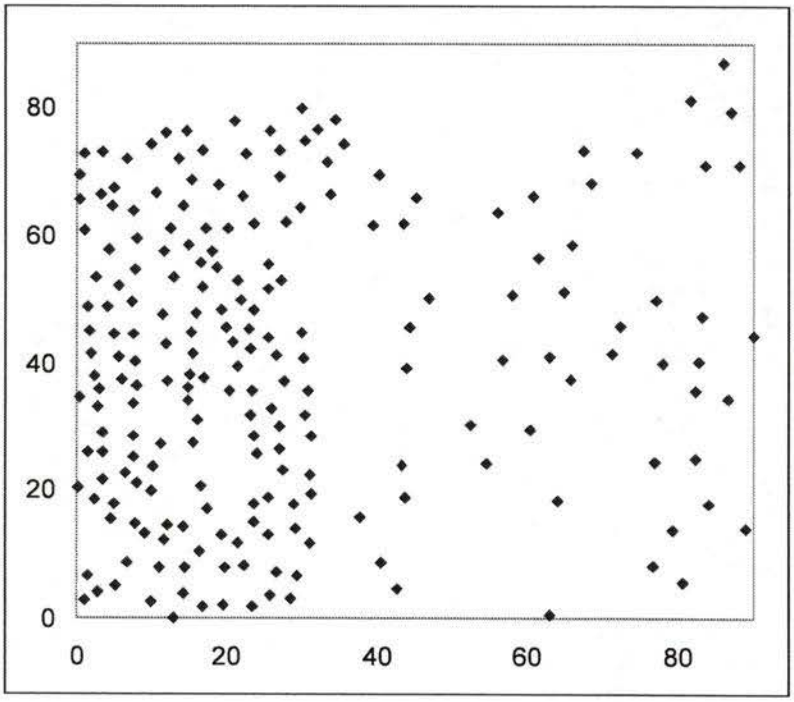

Figure 18. Sample of stem plot field data collected for individual trees. For each tree the location, species, DBH, crown radius, crown high, tree height, and forest maturity were collected.

4.0 Methods

Chapter Objective: To provide a description of the methods used to carry out this project.

4.1 Introduction

In this section details will be provided on methods used for: 1) the extraction of features, tree locations, from high spatial resolution imagery; 2) the accuracy assessment of feature extraction; 3) the development of forest structure metrics; 4) the generation of point attributes; and 5) the aggregation of trees into objects representing forest structure. An overview of the methods implemented in this project can be seen in Figure 19.

4.2 Feature Extraction

Prior to feature extraction the IKONOS image was orthocorrected. To orthocorrect the IKONOS image a rasterized DEM, which had 25m spacing and was derived from a Terrain Resource Information Management (TRIM) map was used. TRIM maps have a scale 1:20000 and are generated from 1:40000 black and white aerial photographs. Control points were identified on road and hydrologic TRIM vectors. The orthocorrected IKONOS image had a RMS of approximately 2.4 meters.

An overview of the methods for feature extraction and accuracy assessment can be seen in Figure 20. Features, representing tree locations, were extracted from the orthocorrected IKONOS image via local maxima filtering. Variations of the local maxima filter have previously been tested on high spatial resolution imagery by Wulder et al (2000a). Based on this work four variations of local maxima filtering were chosen for testing with the IKONOS image (Table 6). Three variations were tested on the orthocorrected IKONOS image: 1) a local maxima filter with a non-variable 3x3 window;

2) a local maxima filter with a window size varied based on slope breaks; and 3) a non-variable 3x3 window with a variance threshold of 15%. The orthocorrected IKONOS image was also smoothed with an averaging filter with a 3x3 window and a local maxima filter with a non-variable 3x3 window. From this point on the orthocorrected image will be referred to as the IKONOS image and the filtered image will be known as the smoothed IKONOS image.

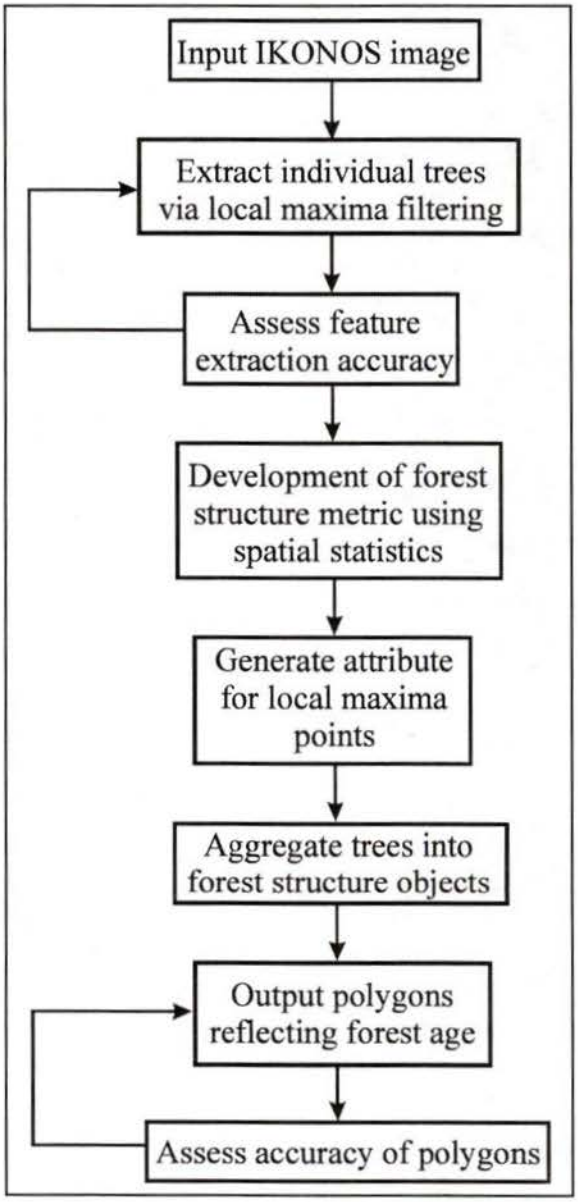

Figure 19. An overview of project methodologies.

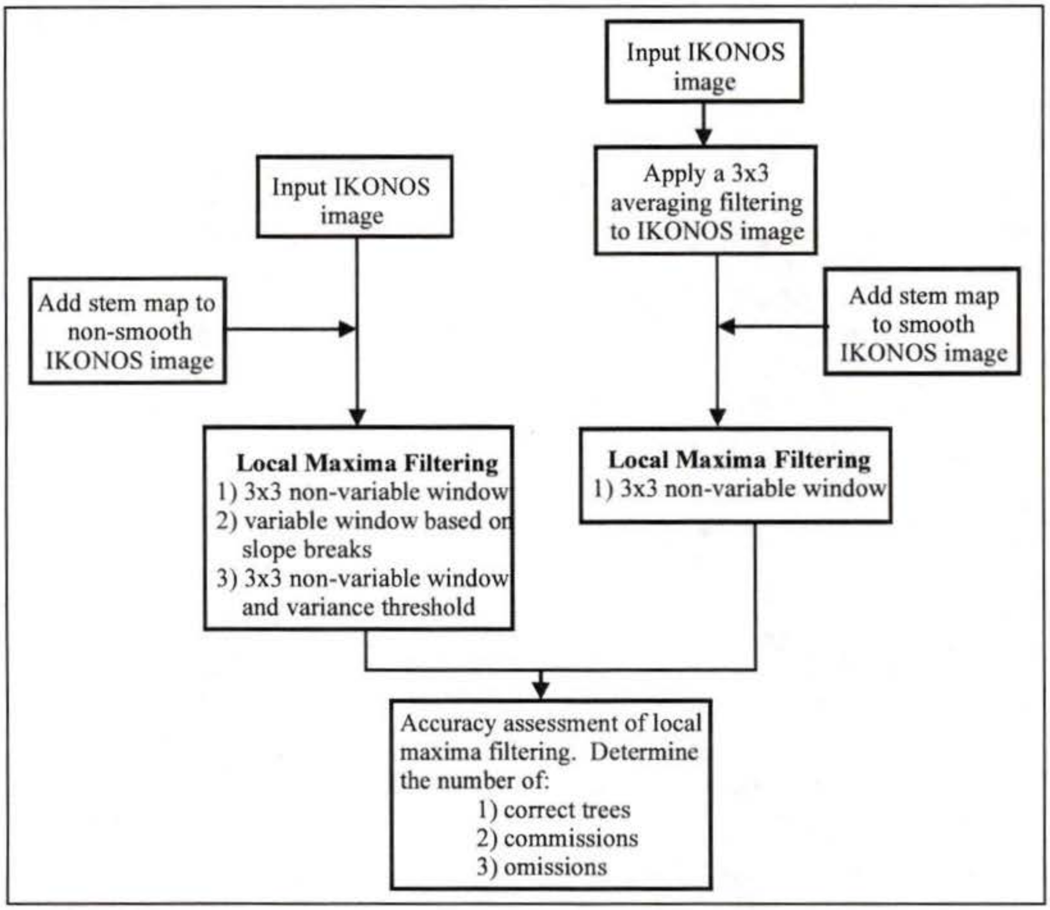

Figure 20. An overview of methods used to extract tree locations from high spatial resolution imagery.

Table 6. The four tested variations of the local maxima filter.

IKONOS Image	*Smoothed* IKONOS Image*
3x3 Window	3x3 Window
Variable Window (Slope Breaks)	
3x3 Window Size with Variance Threshold	

* Image smoothed with a 3x3 mean filter

4.3 Accuracy Assessment of Feature Extraction

A stem map was used to assess the accuracy of feature extraction. Stem locations were mapped on the IKONOS image. The stem map was produced by a field survey at the center of sub-site 1. Tree attributes collected in the field, particularly DBH, were useful for mapping trees on the IKONOS image. As well, stem locations previously mapped on a Multispectral Electroptical Imaging Scanner (MEIS) image of the same area, were useful to help locate trees on the IKONOS image (Wulder et al., 2000a). In order to ensure that the field data could be compared with the feature extraction results the local maxima results were used as the starting point for stem mapping. When existing trees were mapped on the IKONOS image there were several pixels that could be considered the precise tree location. Where possible, ground truth trees were mapped to the same pixel as the local maxima point, allowing the accuracy assessment to be automated. Stem mapped trees missed, or falsely located, by the local maxima filter were added or removed as necessary.

Smoothing the IKONOS image resulted in a slight shifting of the bright pixels. As a result the local maxima positions were one to two pixels different when extracted from the smoothed versus the unsmoothed image. In order to automate the accuracy assessment process the field data were mapped separately on both the IKONOS image and once on the smoothed IKONOS image. All the same ground truth trees were located in both versions of the imagery.

The mature and immature areas of the stem map were analyzed separately in order to allow the relationship between forest maturity and local maxima filtering accuracy to be assessed. In Table 7 an example of how the ground truth and two local maxima results were compared is shown. Each pixel had a unique identifier; for example, in the first row the Pixel ID is 17. In pixel 17 ground truthed tree 150, which has a DBH of 0.3m and a crown radius of 1.6m was located. The first local maxima iteration located a tree in pixel 17; the second iteration did not. Therefore, pixel 17 represents a tree that was correctly found by the first local maxima iteration and omitted by the second.

Table 7. An example the local maxima filtering data used for accuracy assessment.

Pixel ID	Tree ID	DBH (m)	Crown Radius (m)	LM-1	LM-2	LM-1 correct	LM-1 omis	LM-1 comm	LM-2 correct	LM-2 omis	LM-2 comm
17	150	0.3	1.6	1	0	1	0	0	0	1	0
39	0	-	-	1	0	0	0	1	0	0	0
47	133	0.2	1.5	1	1	1	0	0	1	0	0
75	151	0.4	1.6	1	0	1	0	0	0	1	0
107	92	0.2	1.2	0	0	0	1	0	0	1	0
112	0	-	-	0	1	0	0	0	0	0	1
121	0	-	-	1	1	0	0	1	0	0	1

Note: each row represents a pixel

In order to compare results from the iterations of the local maxima filtering, the number of local maxima trees correctly located, omitted, and committed were averaged using the total number of ground truth trees as the denominator. Stratifying the field data allowed for analysis of the relationship between feature extraction accuracy and changes in forest maturity, DBH, and crown radius.

4.4 Forest Structure Metric Development

The forest structure component of interest for this project was tree age. An overview of the methods used to develop the forest structure metric can be seen in Figure 21. In order to develop metrics representing forest age, training areas were selected and stratified by age. Age stratification was based on the nine forest inventory classes use by the British Columbia Ministry of Forests (Table 3). Areas representing each of the nine forest age classes were located on the forest inventory map, and digitized on the IKONOS image.

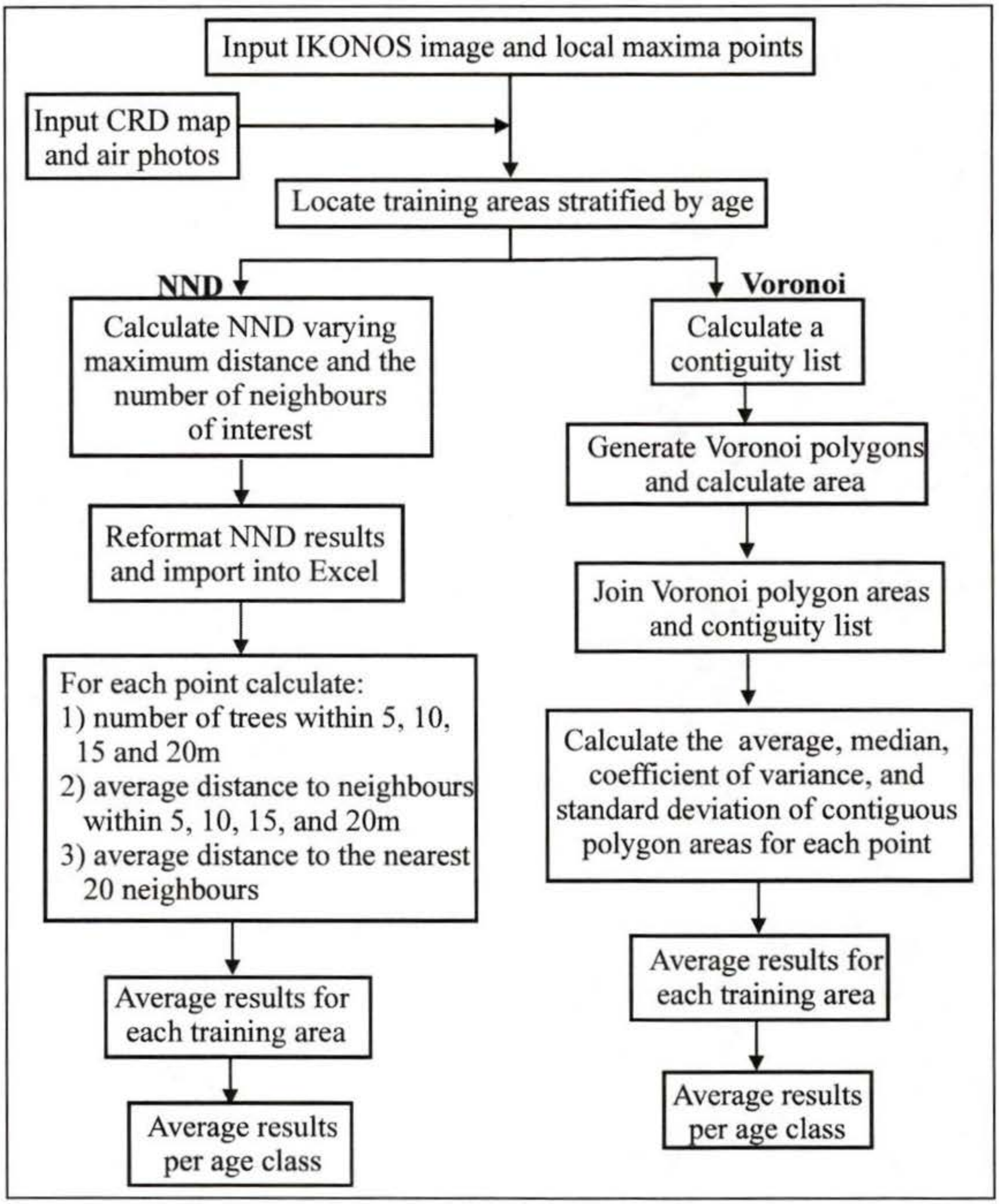

Figure 21. An overview of methods used to generate forest structure metrics.

Up to eleven training areas were located for each forest age class and an attempt was made to ensure training areas were distributed over the *full* IKONOS image. Wherever possible the training areas were digitized as 50x50m squares. For each training area the species composition, confidence in the location and forest age, and shape (square or irregular) were recorded.

The training areas were separated into two classes. Type 1 training areas were areas that I was confident of both the age and location of the forest stand; although I was still confident of the accuracy of type 2 training areas, they were less optimal. Some type 2 training areas were not 100% pure Douglas-fir while other were not exactly 50x50m areas. The goal was to ensure there were at least five type 1 training areas for each age class, however, some forest ages were not well represented on the IKONOS image. In Table 8 the number of polygons located for each of the forest age classes is shown.

Table 8. The number of polygons located for each forest age class.

Age	*Type 1*	*Type 2*	*Total*
1	6	5	11
2	4	4	8
3	5	0	5
4	3	0	3
5	4	2	6
6	5	5	10
7	0	0	0
8	5	4	9
9	4	3	7

Once training areas were mapped on the IKONOS image the locations of local maxima points, for each training area, were extracted into text files. Text files were used as input for developing forest structure metrics. Two spatial statistical approaches, nearest neighbour distances and Voronoi Polygons, were used in developing forest metrics.

4.4.1 Nearest Neighbour Metric Development

Three nearest neighbour statistics were calculated for each training area (Table 9). The first nearest neighbour statistics used a roving window centered at each point and calculated the total number of neighbours within distances of 5, 10, 15, and 20m radius were calculated. The second nearest neighbour statistics was calculated based on the distance from a point to each neighbour, within 5, 10, 15, and 20m radius. The third nearest neighbour statistic calculated was the average distance to the nearest 20 neighbours.

Five meters was the minimum radius used for analysis as it was hypothesized that smaller distances would not reveal significant spatial patterns in the data. Especially in the mature stands, a limited number of neighbours would be found within 5m. Twenty meters was the maximum radius investigated, as it was possible the spatial patterns resulting from trees further than 20m apart may not be significant. The maximum distance for analysis was also constrained by the desire to analyze homogenous areas. As larger areas are investigated the likelihood of heterogeneous areas increases. Radii of 10 and 15m were also analyzed in order to search for trends in the nearest neighbour statistics and determine if an optimal radius for generating a forest structure metric existed. When calculating the final nearest neighbour statistic the distance to any number of neighbours could have been calculated. In preliminary tests 20 neighbours appeared to provide appropriate information to differentiate between the spatial patterns of age classes, within a small enough area to ensure the patterns were meaningful.

Table 9. Variations of the nearest neighbour statistics used for metric generation.

Average Neighbour Distance within	*Number of Neighbours within*	*Average Distance to k Nearest Neighbours*
5m	5m	k = 20
10m	10m	
15m	15m	
20m	20m	

For each local maxima point in the training areas the nearest neighbour statistics were calculated. The average and standard deviation of the statistics were then calculated for each training area. Finally, the average and standard deviation for all training areas within an age class were averaged to calculate a single attribute value for each Ministry of Forests' inventory age class.

4.4.2 Voronoi Metric Development

Several programs were developed to calculated attributes based on Voronoi and are listed in Appendix 2. Only one Voronoi based metric was examined. Preliminary analysis along with previous studies suggested that Voronoi Polygon area would be the most useful indicator of the spatial patterns of points. Generating the Voronoi metric was a three stepped process, which will be described below. The three steps are: 1) For each point a list of contiguous neighbours was created; 2) Voronoi polygon was generated and the areas for each polygon calculated; and 3) an attribute was created for each point by averaging areas for all Voronoi polygons in which a point was contiguous to the point of interest.

To generate a list of contiguous neighbours, triangulated networks were generated for all training areas. Points were considered contiguous if joined by a line of a triangulated network. For example, in Figure 22 the contiguous neighbours of point *A* are points *B*, *C*, *D*, *E*, and *F*. Existing ArcView functions were used to generate the Voronoi polygons, calculate polygon area, and link the area and contiguity information. Once the polygons area and point contiguity information were linked the average, standard deviation, coefficient of variation, and median of areas for contiguous Voronoi polygons were calculated for each point. The Voronoi statistics values were averaged and reported for each training area. Statistics for training areas of the same age class were averaged to produce a Voronoi area metric based on forest age.

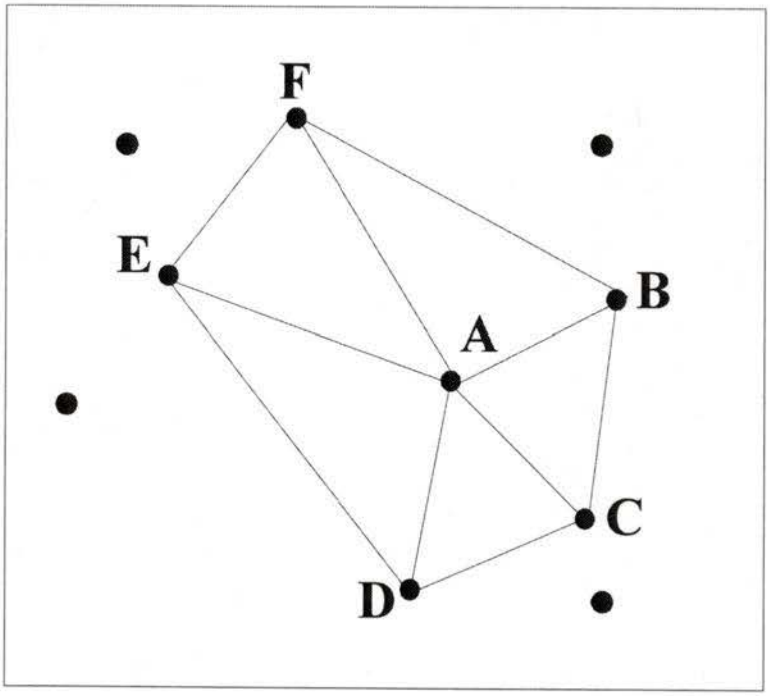

Figure 22. Method for determining point contiguity. Contiguous points are linked by a line in an triangulated network. For example, contiguous to point A are points C, B, D, E, and F.

In both the nearest neighbour and Voronoi Polygon metrics development, statistics for each age class were calculate by weighting each training area equally. A more accurate method for calculating the attributes may have been to weight each tree the same. If all trees were weighted equally, the maximum amount of information would have been used in the final calculation. However, the trees are weighted approximately the same as the number of trees in each 50x50m plot are similar.

4.5 Generating Attributes

The goal of developing metrics was to determine a suitable method for generating forest structure attributes. An overview of methods used to generate attributes is shown in Figure 23. A metric appropriate for generating attributes must change relative to forest age. Based on forest structure metric results (section 5.3) it was decided to generate point attributes using the average number of neighbours within 20m from each point (NND20) (Figure 24).

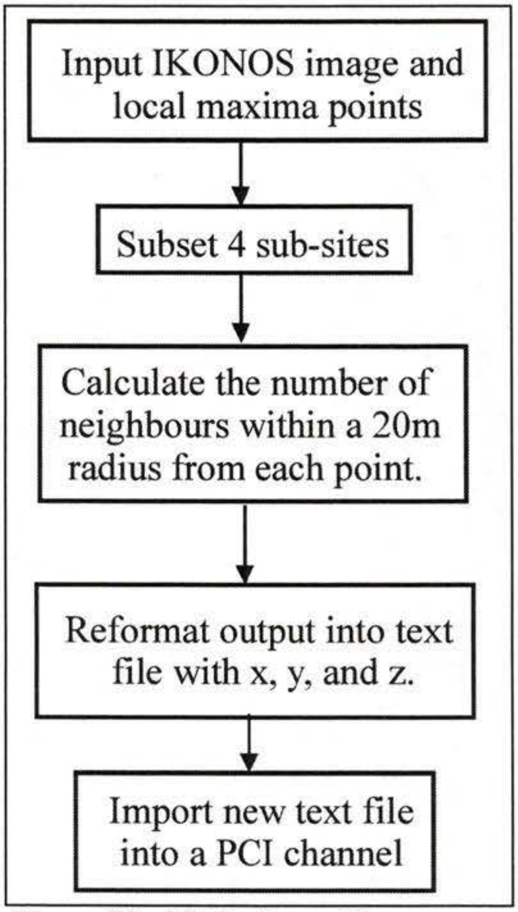

Figure 23. Methods used to generate forest structure attributes.

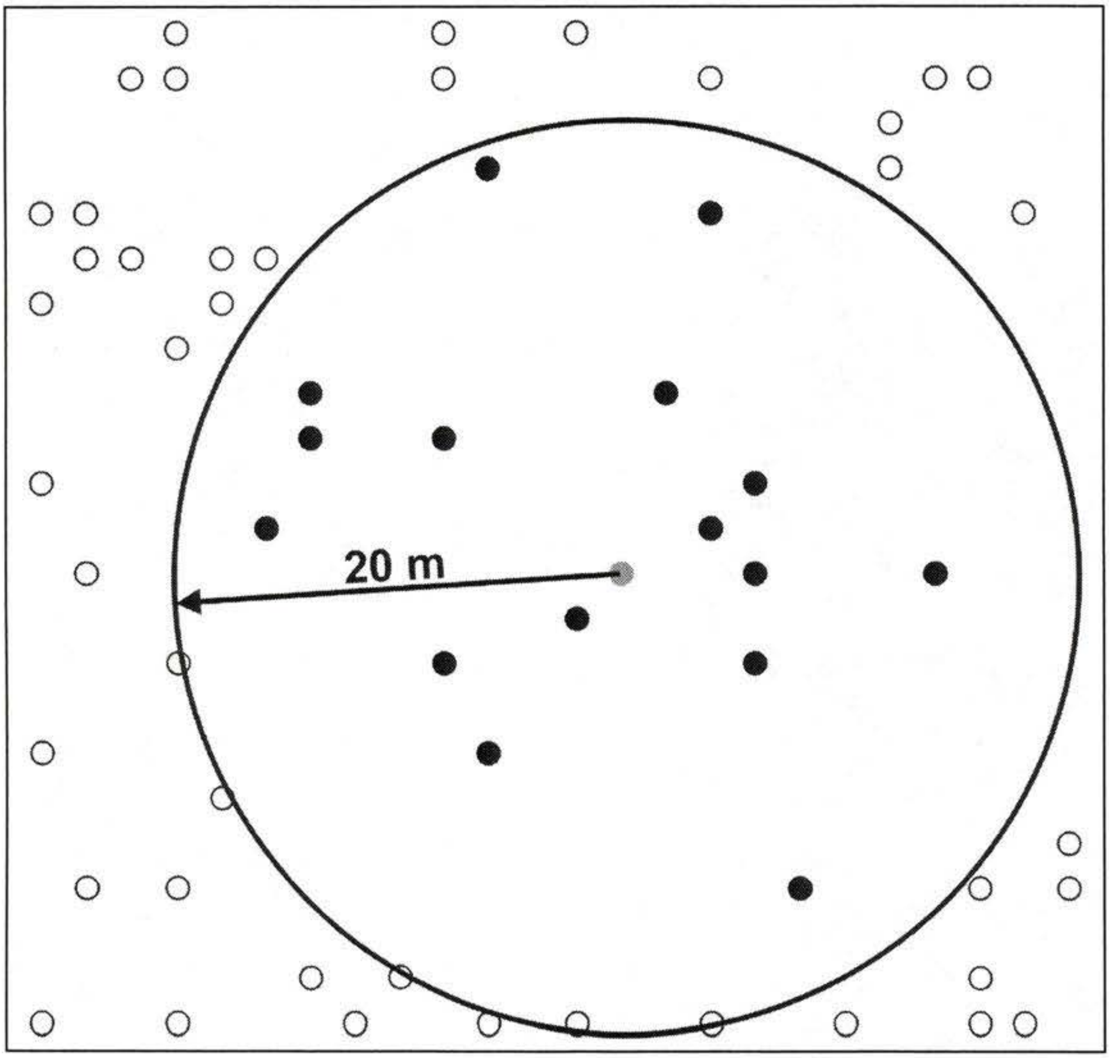

Figure 24. Attributes used for generalization are equal to the number of neighbours within a 20m radius of each point.

4.6 Aggregation and Object Creation

An overview of the methods used to aggregate local maxima points is shown in Figure 25. Using attributes generated from NND20 aggregating trees into the Ministry of Forests nine age classes was not possible. Spatial attribute values are similar between classes reflecting the gradual transition in the spatial pattern of forests with changing age. Using the NND20 metric three forest age classes were separable (Table 10). The metric also suggested the age range that each aggregated class should represent and the threshold required when aggregating the trees into three classes. Once attributes were generated for the sub-sites the thresholds suggested by the metric did not produce meaningful classes. The discrepancy between the metric and the attributes is the result of edge effects and will be further explained in the following section.

Table 10. New forest age classes correlate with Ministry of Forests inventory classes.

Class Name	*Age (years)*	*MOF Inventory Classes*
Young	1-20	1
Intermediate	21-120	2, 3, 4, 5, 6
Mature	>120	8, 9

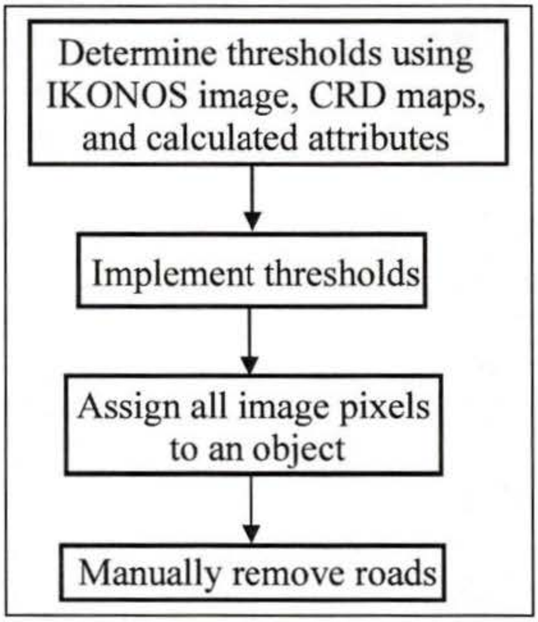

Figure 25. Overview of methods used to aggregate points into polygons.

Since the thresholds suggested by the metrics could not be used, new thresholds were developed. Using the forest inventory map as an indicator of forest age, I visually compared age with the generated attribute values. This exploratory investigation revealed three age classes Young (1-20 years), Intermediate (21-120 years), and Mature (>120 years) (Table 10). With tree locations and attributes overlaying the IKONOS image I applied thresholds determined during the visual investigation. Thresholds were then adjusted slightly in order to achieve optimal aggregations. Thresholds used can be seen in Table 11. All trees with greater than 25 neighbours in a 20m radius were considered part of the Young class, the Intermediate class had 17-25 trees within a 20m radius, and the Mature class had less than 17 neighbours in a 20m radius.

Table 11. Age class attribute thresholds.

Class Name	*Attribute Values*
Young	> 25
Intermediate	17-25
Mature	< 17

Applying thresholds did not produce polygons; pixels surrounding the local maxima points were not classified. In order to produce polygons the non-local maxima pixels were assigned to an age class. First, the nine pixels surrounding each point were given the same attribute as the point. Then pixels surrounding each group of 3x3 pixels, which had a value of zero were iteratively assigned the nearest point attribute. Between 13 and 16 iterations were required to classify every pixel within each of the sub-sites. Roads, which should not be classified into any forest group were removed manually and subtracted from the final objects.

4.7 Preliminary Analysis

For others doing work in this area it is worth noting methods tested which were not useful for this work The following is a discussion of a field data set used for testing preliminary methods. Also, metrics tested preliminarily, which were not used in the final analysis are outline.

4.7.1 Metric Development with Field Data

Initially, field data consisting of four one hectare stem mapped sites was used as input for metric development. The field data used was four stem mapped sites, each one hectare in size. Two sites had trees approximately 200 years old, one site had trees 80 years, and one site had trees 40 years old. Several NND statistics were run on the field data set to generate metrics. Metrics produced were meaningful, in that changes in metric values correlated with changes in age. It became clear that developing metrics with field data would not be effective for three reasons. First, stem maps as large as one hectare are uncommon. Still, it was not possible to extract enough sample from the data to allow for metric development. If only one area was used when developing metrics for different age classes, impacts such as topography, management practices, and soil quality may have had a large affect on the metric value. It was important to develop metrics based on several areas with a similar age of forest.

The second reason the field stem maps were not used for analysis is that they only covered a small portion of the age classes found in the Sooke Watershed. It was preferable to develop metrics for all nine of the forest inventory age classes, not just three. Although, no metric was developed for age class 7, the other eight age classes were represented in the metric development.

Finally, metric development was one step to aggregating information extracted from high spatial resolution imagery. As clear from the feature extraction accuracy assessment, the local maxima filter does not map all the trees. It became clear it would be difficult to apply metrics developed on a field stem mapped data set to local maxima filter results. Using the local maxima filter results for the entire IKONOS image allowed several samples of each age class to be used for metric development.

4.7.2 Preliminary Metrics

Prior to detailed investigation several metrics were tested preliminarily. Preliminary analysis began with simple NND analysis such as, the distance to the nearest neighbour or the distance to the fifth closest neighbour. It became clear that to aggregate tree locations, based on forest structure, attributes would need to be based on the relationship between several points.

For all the NND metrics developed the median values were calculated. In the results section only the mean values are reported. The metrics based on median calculations generally produced the same trend as the mean, however median values were more similar throughout age classes.

Along with the Voronoi polygon area of contiguous points, the average, standard deviation, median, minimum, and maximum of the distance to contiguous points were determined. All of these metrics, except of the standard deviation, changed with forest age, however the change was not as pronounced as with other metrics. The number of vertices for each Voronoi polygon was also calculated. The average number vertices was six and therefore did not change with forest age.

5.0 Results and Discussion

Chapter Objective: To present and discuss project results and related issues in order to provide a background for conclusions.

5.1 Introduction

This section includes a presentation and discussion of the results from, 1) local maxima filtering , 2) forest structure metric development , and 3) point aggregation.

5.2 Feature Extraction

The number of trees omitted (missed), committed (falsely identified), and correctly identified, for each of the four variations of the local maxima filter, can be seen in Table 12. In this document a tree is *correctly* identified if the local maxima filter found a tree where a manual tree existed. The number of correct trees may be a misleading measure as it does not consider the number of manual trees which may have two or more associated local maxima. The results of the local maxima filter from the IKONOS and smoothed IKONOS images will be presented and discussed in separate sections, followed by a comparison between feature extraction accuracy and changes in DBH, and crown radius. Local maxima and stem mapping results may be seen in Figures 26 and 27.

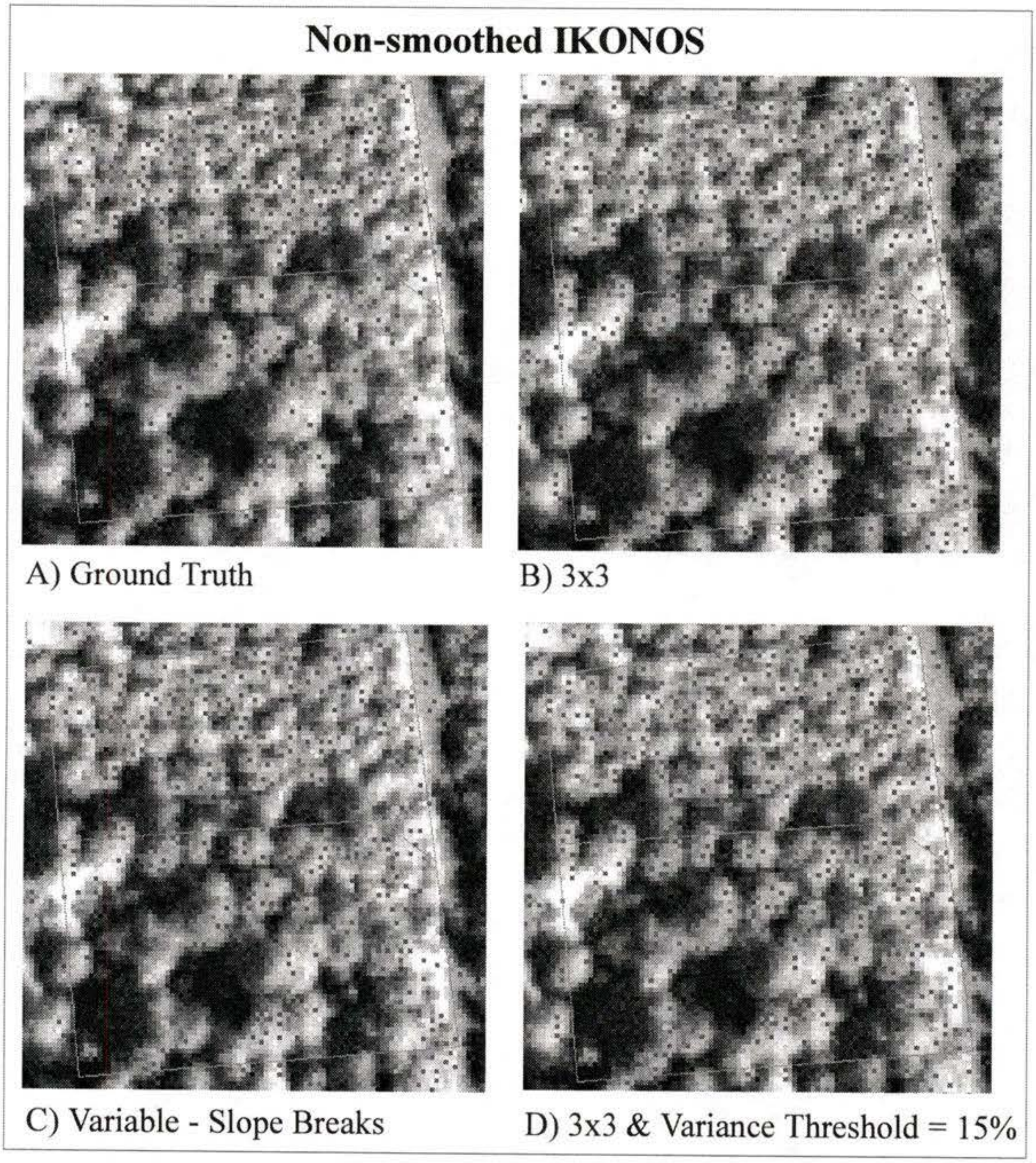

Figure 26. Non-smoothed IKONOS stem mapping and feature extraction results.

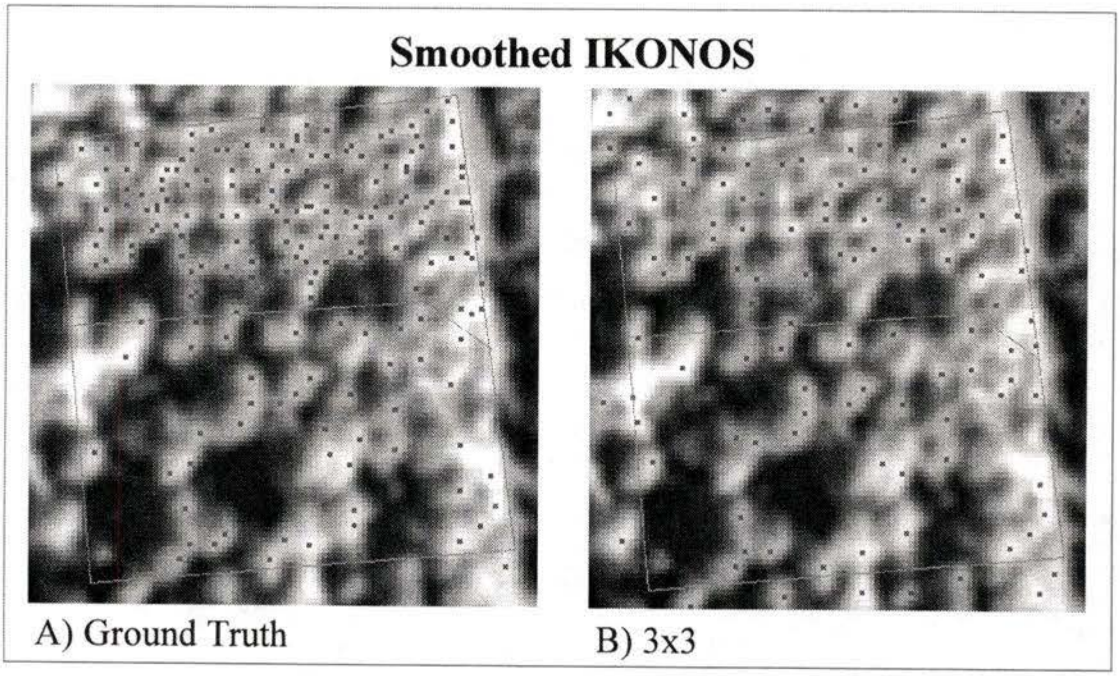

Figure 27. Smoothed IKONOS mapping and feature extraction results.

5.2.1 Non-smoothed IKONOS

Using the IKONOS image and a 3x3 local maxima filter 85% of the trees were located correctly, but the commission error was high (51%). Stratifying the ground truth by age shows that most of the commission error occurred in the older trees. Post local maxima filtering, a variance threshold was applied to remove some spurious local maxima pixels and reduce commission error. A variance threshold of 15% reduced commission error by 5% overall and 19% in the mature trees. Although 19% reduction in commission errors in mature forests seemed significant only 9 trees were impacted.

Table 12. Results of the four iterations of the local maxima filter. 3x3 – a non-variable 3x3; SB – window size varied based on slope breaks; 303VAR-THR - a 3x3 window used and local maxima with less than 15% variance removed.

	Non- Smoothed			Smoothed
	3x3	SB	3x3 VAR-THR = 15%	3x3
All (n=199)				
Correct	0.85	0.61	0.85	0.44
False positive	0.51	0.48	0.46	0.04
Missed	0.15	0.39	0.15	0.56
Young (n=150)				
Correct	0.81	0.63	0.81	0.37
False positive	0.11	0.13	0.10	0.01
Missed	0.19	0.37	0.19	0.64
Mature (n=49)				
Correct	1.00	0.55	1.00	0.70
False positive	1.76	1.55	1.55	0.11
Missed	0.00	0.45	0.00	0.34

Use of a variable window size, determined by slope breaks, reduced commission error only by 3%. The number of trees correctly found decreased to 61% and the number of omitted trees more than doubled. Use of the variable window and variance threshold were not effective; the small reduction in commissions came at the expense of a 24% reduction in the number of trees correctly located and a doubling of the missed trees.

In all cases local maxima results from the IKONOS image had relatively low commission error in the immature forest compared with the mature forest. Although commission error may result from image noise, the majority of commission error is found in the mature stands suggesting that due to a high sun angle image vegetation under the forest canopy or in openings is located by the local maxima filter. In the mature stand the vegetation below the canopy is dense, which likely accounts for the increased commission error.

5.2.2 Smoothed IKONOS

Commission error was greatly reduced by smoothing the IKONOS image with a 3x3 averaging filter. Using a 3x3 local maxima filter on the smoothed IKONOS image reduces the number of correctly located trees to half, the commission error becomes negligible, and the number of missed trees is increased by four times. It is difficult to determine if it is more accurate to use the non-smoothed or smoothed IKONOS image. Reduction in commission error from smoothing comes at a loss of accurately identified trees. Depending on the application local maxima results from a smoothed or non-smoothed image may be preferable. For example, in work by Nelson (1998) classification of individual trees was based on signatures generated from local maxima. When generating signatures erroneously located local maxima cannot be tolerated, and therefore trees should be extracted from smoothed imagery.

The behavior of local maxima filter on the smoothed IKONOS image further corroborates the notion that the commission error in the non-smoothed image may represent understory. Relative to the mature trees, understory and young trees are represented by few pixels. When the image is smoothed objects represented by a few pixels are more likely to be lost than if represented by many pixels. Smoothing has only a moderate impact on the percentage of mature trees correctly identified, whereas the correctly identified younger trees and commission error are reduced significantly. If commission error was related to image noise, one might expect smoothing to have the same effect on all the local maxima filter's ability to locate all sizes of trees. However, smoothing has a larger impact of the accurate locating of smaller objects, suggesting that commission error is actually representing small understory objects.

5.2.3 Effects of DBH

Additional investigations were performed to assess the impact of smoothing on the ability of local maxima filtering to locate small and large trees. Comparisons were made between feature extraction accuracy, and both DBH and crown radius size which were collected during field work.

The relationship between DBH and the local maxima filtering accuracy can be seen in Table 13. In all cases the non-smoothed IKONOS image allows the local maxima filter to correctly locate more trees than the smoothed image. The non-smoothed IKONOS image is less sensitive to DBH than the smoothed image. As the DBH decreases the disparity between the number of trees found in the smoothed and non-smoothed IKONOS image increases. It stands to reason that the reduction of image information caused by smoothing has a larger impact on the small trees than on the larger trees, which are composed of a greater number of image pixels.

Table 13. Accuracy assessment of feature extraction results - stratified by DBH.

	All (n=*199*)			*Young* (n=*150*)			*Mature* (n=*49*)		
DBH range (cm)	<35 (n=149)	35-70 (n=14)	>70 (n=36)	<35 (n=148)	35-70 (n=2)	>70 (n=0)	<35 (n=1)	35-70 (n=12)	>70 (n=36)
Non-smooth (3x3)	0.81	1.00	1.00	0.80	1.00	0.00	1.00	1.00	1.00
Smooth (3x3)	0.36	0.43	0.78	0.36	0.50	0.00	0.00	0.42	0.78

Smooth – the image smoothed with a 3x3 mean filter.

5.2.4 Effects of Crown Radius Size

Perhaps a more meaningful way to stratify forestry field data, when working with remotely sensed imagery, is by crown radius (Table 14); although crown radius and DBH are correlated, crown radius is actually represented on an image, as remotely sensed imagery is an aerial view. Stratifying the local maxima results based on crown radius shows a similar pattern to stratification based on DBH, and better demonstrates trends between tree size and local maxima filtering accuracy. Using smoothed and non-smoothed imagery, as the crown radius of trees increase so does the accuracy with which they are extracted from the imagery. Using the non-smoothed image all trees with a radius greater than 3m are located, where a crown radius of 4m appears to be required to ensure tree extraction using the smoothed image.

Using a smoothed image the local maxima filter is more sensitive to changes in crown radius size than is the non-smoothed image. When using the smoothed image the percentage of correctly located trees ranges from 0-100%, and only ranges from 74-100% using the non-smoothed image. As with the relationship between feature extraction accuracy and DBH, smaller trees, represented by fewer pixels, are more impacted by the loss of image information due to smoothing. The fact that smaller trees are more affected by smoothing, explains why the disparity in the percentage of trees found between images increases as the crown radius decreases. In the crown radius class 1-1.4m the difference in the percentage of trees found between images is 47% and decreases to 33% when the crown radius is between 3-3.9m.

Also, it should be noted that in the non-smoothed image the accuracy is higher for trees with 1m crown radius than for trees with a crown radius between 1-1.4m. The above trend is unexpected and likely an artifact of the difference in the number of trees, or sample size, in each class rather than a real trend.

Table 14. Accuracy assessment of feature extraction results - stratified by crown radius.

	0m to 0.9m (n=*5*)	*1m to 1.4m* (n=*73*)	*1.5m to 1.9m* (n=*67*)	*2m to 2.9m* (n=*26*)	*3m to 3.9m* (n=*24*)	*>4m* (n=*4*)
Non-smooth	0.80	0.74	0.90	0.92	1.00	1.00
Smooth	0.00	0.27	0.48	0.62	0.67	1.00

Smooth – the image smoothed with a 3x3 mean filter.

5.2.5 Local Maxima Iteration used for Analysis

For the rest of this project the local maxima results created using a 3x3 window on the smoothed image were used for analysis. In order to develop a forest structure metric and aggregate trees into age groups it is important that the commission error is relatively low, as high commission error in the mature forests may make isolating differences in the spatial pattern of young and mature trees difficult. The young trees, which are not located, will reduce the difference in spatial patterns between the two forest types, but at least 67% of trees with a crown radius greater than 3m will be isolated. The resulting pattern of the local maxima filter at least represents the forest structure of larger trees. When commission error is high the emerging point pattern may not be related to forest structure and may suggest the imagery being analyzed is the wrong spatial resolution.

5.3 Forest Structure Metric Development

Literature review and exploratory analysis of the feature extraction data suggested that both nearest neighbour and Voronoi based statistics had the potential to create meaningful forest structure attributes. A presentation and discussion of the results from metric development using nearest neighbour statistics will be followed by Voronoi based metric results.

5.3.1 Nearest Neighbour Forest Structure Metrics

The results of forest structure metric development, using variation of the nearest neighbour statistic are shown in Table 15, 17, and 18.

5.3.1.1 Average Distance to Neighbours within a Specified Distance

In Table 15 the results of developing metrics using the average *distance* to neighbours within a radius of 5, 10, 15, and 20m are shown. There is no significant change in the distance to neighbours as forest age increases. Change in the average and stand deviation of distance to neighbours did not follow any meaningful trend related to forest age.

Table 15. Average distance to neighbours within a specified distance.

Age	*5m*		*10m*		*15m*		*20m*	
1	3.4	(0.7)	6.8	(0.2)	10.6	(0.1)	12.8	(0.2)
2	3.6	(0.6)	6.9	(0.9)	10.3	(1.0)	12.6	(1.2)
3	3.7	(0.6)	6.9	(1.0)	10.4	(1.0)	12.9	(1.1)
4	2.8	(1.7)	6.9	(1.0)	10.3	(1.0)	12.7	(1.1)
5	3.8	(0.8)	6.9	(1.2)	10.6	(1.1)	12.9	(1.1)
6	3.6	(0.8)	6.9	(1.3)	10.5	(1.2)	12.7	(1.4)
8	3.5	(0.8)	6.8	(1.3)	10.8	(1.6)	13.1	(1.5)
9	3.1	(0.6)	7.3	(1.1)	10.7	(1.4)	12.8	(1.4)

() – standard deviation

Biological theory, as well as visual inspection of the local maxima points extracted for training areas, suggests that the distance between neighbouring trees should increase as forests age. The homogeneity in the statistics, presented in Table 15, is likely an artifact of the window size used for analysis, which constrains the maximum distance between points to the diameter of the window. The diameter of the window, and maximum distance between points, is double the distance considered (Figure 9). The average distance between the points is approximately 1/3 of the window diameter (Table 16). Calculating a metric based on distance within a specified window does not report point density. The number of points within the area is partially predetermined by the fact that no point can be outside the specified area, and due to constraints of local maxima filtering no two points can be less than 1m apart.

Table 16. Result of constraining the calculation of the average distance between points by area.

Distance of Analysis From Point	*Analysis Area Diameter*	*Average Distance Between Points*
5	10	3.4
10	20	6.9
15	30	10.5
20	40	12.8

5.3.1.2 Average Number of Neighbours within a Specified Distance

The results of forest structure metrics developed, based on the average *number* of neighbours within a specified distance, are shown in Table 17. Regardless of the distance considered in the analysis, the number of neighbours decreases as forest age increases. When a 5m radius from each point is analyzed the average change in the metric values between age classes is 0.1, however the average difference in the metric values increases to 1.4 when a 20m radius is considered. Using an analysis area of 15 or 20m seems to provide enough information to aggregate point data, representing trees, in three age classes.

Table 17. Average number of neighbours within a distance.

Age	*5m*	*10m*	*15m*	*20m*
1	1.6 (0.7)	5.1 (2.1)	11.6 (4.3)	17.0 (6.1)
2	1.4 (0.5)	4.6 (2.0)	10.7 (3.4)	15.4 (4.6)
3	1.3 (1.6)	4.2 (1.7)	10.2 (3.5)	15.3 (5.0)
4	1.0 (0.6)	4.0 (1.9)	9.6 (3.8)	14.1 (4.7)
5	1.0 (0.0)	3.2 (1.5)	7.9 (2.7)	11.6 (3.9)
6	1.1 (0.2)	3.2 (1.3)	7.4 (2.6)	11.0 (3.5)
8	1.0 (0.1)	2.2 (1.1)	5.3 (2.1)	8.1 (3.0)
9	1.1 (0.0)	2.8 (1.3)	6.6 (2.5)	9.1 (3.2)

() – standard deviation

Compared with the forest structure metric based on between neighbour distance, calculating the number of neighbours within a specified distance better represents changes in forest age. The average number of neighbours within a window reflects forest density. There is a maximum number of points that can be found within an area, resulting from the local maxima filter constraint which does not allow trees to be identified in pixels which touch the location of an existing tree. This local maxima constraint on the maximum number of trees does not seem to negatively effect the usefulness of the metric.

When the number of trees within a 5m radius from each point is considered, the standard deviation does not correlate with changing forest age. Although the oldest trees have lower values than the youngest trees, the standard deviation for the intermediate aged trees (classes 3-8) do not follow any pattern. When a 10m or larger radius from each point is considered, the standard deviation begins to follow a more linear pattern. Except for age classes 2, 3, and 4, there is an inverse relationship between standard deviation and the age of the forest. The magnitude of the standard deviation increased as the areas of analysis increased, which is sensible as larger areas have greater variation.

5.3.1.3 Average Distance to the 20 Nearest Neighbours

The results of the final iteration of the nearest neighbour statistic used to generate a forest structure metric can be seen in Table 18. Both the standard deviation and the average distance to the nearest 20 neighbours increases as forest age increases. The average difference in the average distance to the nearest 20 neighbours is 1.5.

Table 18. Average distance to the 20 nearest neighbours.

Age		
1	13.8	(2.7)
2	15.1	(3.0)
3	15.5	(3.1)
4	16.7	(3.9)
5	18	(3.5)
6	18.7	(3.5)
8	22.6	(4.1)
9	21	(4.1)

() – standard deviation

The metric developed, using the average distance to the nearest 20 neighbours, differentiates forest age structure based on the average number of neighbours within 20m of each tree. Calculating the statistics based on the nearest 20 neighbours worked in this example, however 20 neighbours was chosen only after preliminary analysis suggested 20 neighbours may produce meaningful results. If trees grew far apart the nearest 20 neighbours could include trees too far from the tree of interest to be meaningful. Although the average distance to the nearest 20 neighbours showed potential for use as an attribute, a theoretical basis for selecting the number of neighbours requires development.

5.3.2 Voronoi Forest Structure Metrics

Preliminary analysis and previous work suggested that Voronoi Polygon area would provide a meaningful forest metric. The average, standard deviation, coefficient of variation, and median of contiguous Voronoi Polygon area was computed (Table 19). In age classes 1 to 8 the average and median polygon area increases with forest age; in age class 9 polygon area decreases. The mean difference between age classes for the average area of contiguous polygons is 6.2 and 5.9 for the median area.

Table 19. Average area of contiguous Voronoi polygons.

Age	*Avg*	*Stdev*	*CoVar*	*Med*
1	50.7	15.4	30.7	49.6
2	60.5	19.3	32.4	58.8
3	61.5	19.9	32.5	59.6
4	64.8	20.4	30.5	61.4
5	67.1	18.2	26.9	66.1
6	70.6	21.0	28.3	67.9
8	101.1	32.0	30.9	99.1
9	94.0	32.4	34.8	91.1

As with the metric created using the number of neighbours within a specified distance, the average or median area of contiguous Voronoi polygons provided the potential to aggregate forests into three age classes: Young (age class 1); Intermediate (age classes 2-6); and Mature (age classes 8 and 9). The standard deviation and coefficient of variation also seem to provide a reasonable metric based on forest structure.

5.3.3 Forest Metric Iteration Used for Analysis

The number of neighbours within 20m from each point (NND20) was chosen for generating forest structure attributes. The NND20 was used for attribute generation for three main reasons. First, the metric developed on the NND20 allowed the forest to be aggregated into three meaningful classes. Although using the average or median area of contiguous Voronoi polygons also allows three age classes to be aggregated, the Intermediate age class is quite large and the young age class only includes age class 1. Secondly, attributes based on the NND20 are relatively quick to produce. Finally, compared with Voronoi polygons statistics based on nearest neighbour distances are conceptually simple. If these methods are to be used in a web based software, it is best to keep the methods clear so that all users can fully and quickly understand the processes they are using. Voronoi polygons is not necessarily inferior for developing forest structure attributes and may well be the focus of future work.

5.3.4 Forest Metric Vs Attribute Results

Based on NND20 it was expected that the Young, Intermediate, and Mature forest classes would represent Ministry of Forests classes 1-4, 5-7, and 8-9. Once the attributes were generated for the entire image three classes could be generated, however the forest ages represented by each class were different (Table 20). Also, thresholds required to meaningfully aggregate the three classes were different (Table 20).

Table 20. Age classes and thresholds expected from metric development versus attribute generation.

	Suggested by Metric		Suggested by Attributes	
	MOF Age Classes	NND20 value	MOF Age Classes	NND20 value
Young	1-4	> 14	1	> 25
Intermediate	4-7	10-14	2-6	17-25
Mature	8-9	< 10	7-9	< 17

The main reason for the difference in the thresholds and age classes represented by the Young, Intermediate, and Mature forest categories, is that the training areas used for metric development were small and strongly influenced by edge effects. Training areas were first extracted from the image, and then attributes used for metric development were generated. Consistency between the metrics developed and the final aggregation would have improved if the attributes were generated first for the entire image and then the training areas extracted, as edge effects would have been negligible. However, there were computational difficulties using available software to produce attributes for all 1.2 million trees.

One reason Voronoi polygon area was not used to generate attributes was the age classes which could be generalized using the nearest neighbour distance metric *seemed* more meaningful. The Voronoi area metric suggested forest could be grouped into three classes: 1-20 years, 21-120 years, and >120 years, whereas the NND20 metic suggested trees could be grouped into: 1-80 years, 81-140 years, and >140 years. The NND20 Young and Intermediate classes had a better balance of ages in each class. As mentioned, once attributes were generated it became clear that the grouping age classes suggested by the NND20 metric could not actually be applied to the point data. The age class groupings represented by Voronoi area metric reflected the groups that were actually formed using attributes generated with NND20. Further investigation into the feasibility of using Voronoi based attributes to aggregate trees into forest structure polygons is suggested.

5.4 Aggregation and Object Creation

Once attributes were generated for all points in the sub-images (based on the NND20), thresholds were applied to group the points into Young, Intermediate, and Mature forest age groups. Objects created from the aggregated points can be seen in Figures 28-31. The results of thresholding for each sub-site will be presented separately, results are consistent between images and will be discussed in a single section.

5.4.1 Results - Sub-site 1

In Sub-site 1 all three forest age classes (Young, Intermediate, and Mature) were identified relatively well (Figure 28). There are two main areas of Mature forest in sub-site 1, at the bottom center and upper right corners of the image. The Mature stands at the bottom center of the image are located more consistently a the Mature stands in the upper right corner of the image. The Intermediate aged stands, confused with the Young and Mature forest, were the least accurately located. In the lower left corner of the sub-site the stands are Mature, however are primarily classified as Young. The Young stands, are located most accurately in areas where a grid-like pattern can be seen on the IKONOS image. An example of the grid-like pattern is the lower right corner of the sub-site. Forest is least accurately aggregated near roads and the image edge. Except for the Mature areas, stands near roads are generally grouped in an older age class.

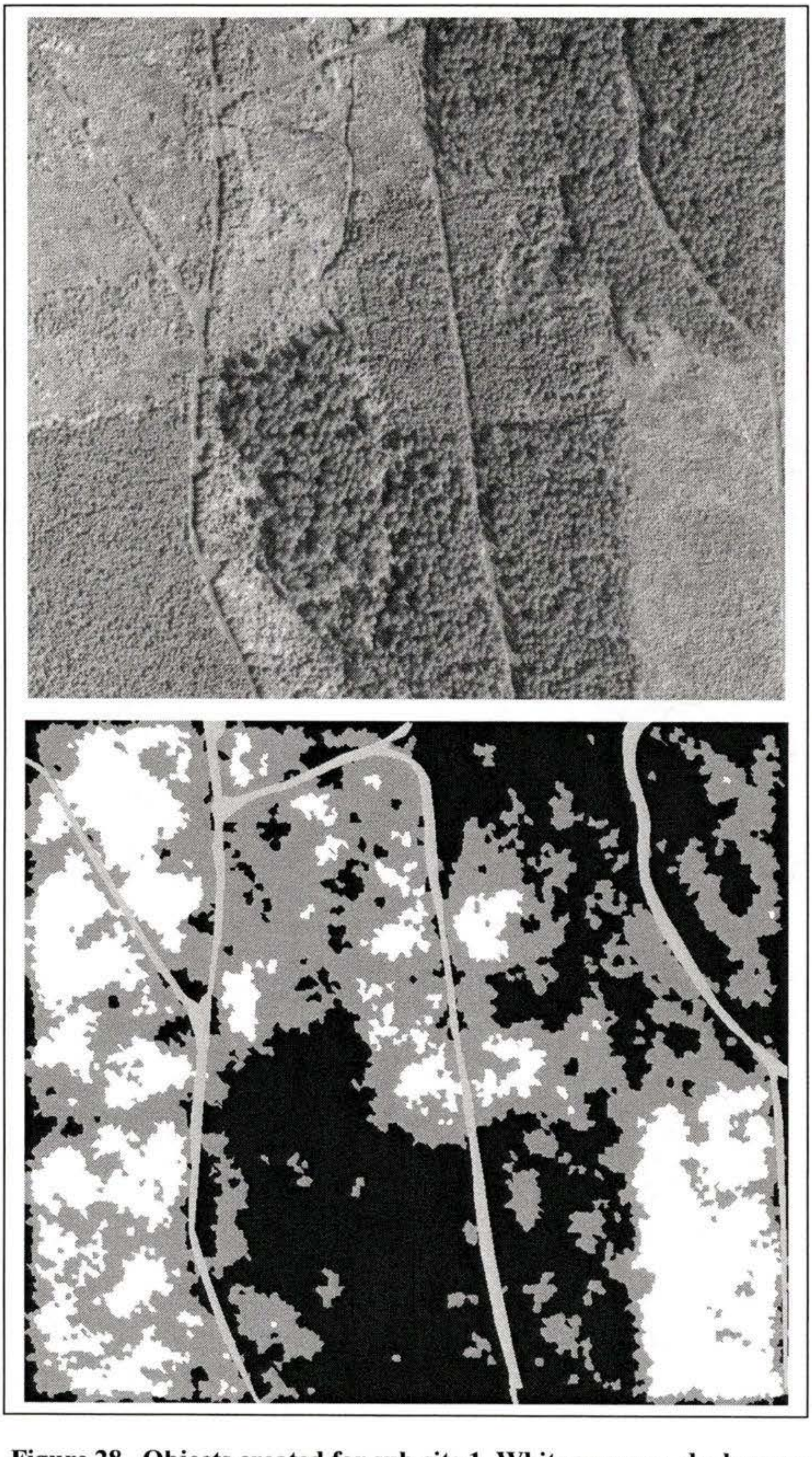

Figure 28. Objects created for sub-site 1. White = young, dark grey = intermediate, black = mature, light grey = road.

5.4.2 Results - Sub-site 2

The results of sub-site 2 are the most difficult to interpret (Figure 29). Overall the Mature forest areas are well identified. However, there is a large portion of Intermediate age forest and Age class 6 is prominent. The majority of the forest in the upper left portion of the image should be considered Intermediate, however the aggregation classified it as both Mature and Young.

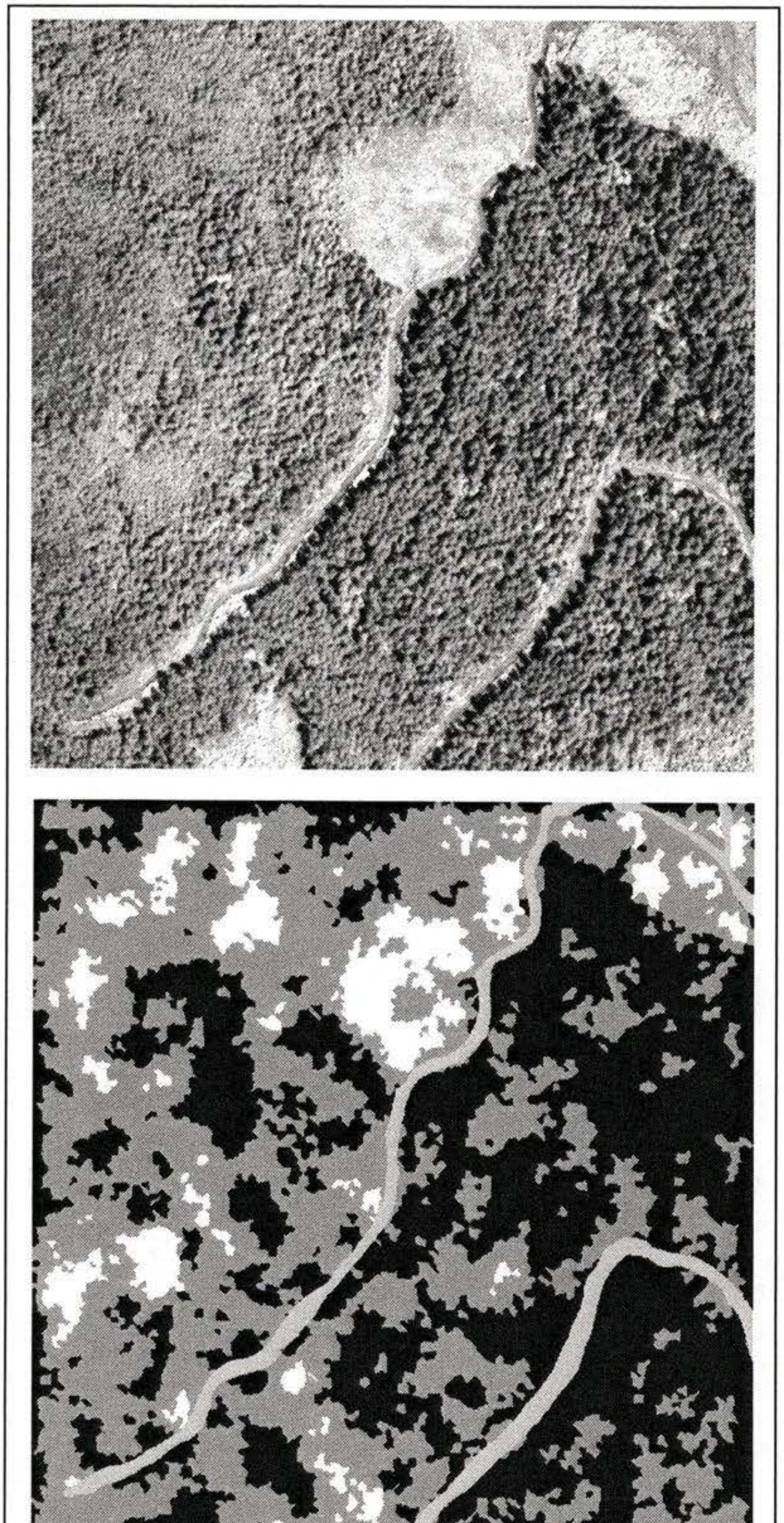

Figure 29. Objects created for sub-site 2. White = young, dark grey = intermediate, black = mature, light grey = road.

5.4.3 Results - Sub-site 3

The object creation results for sub-site 3 can be seen in Figure 30. As with all other sub-sites the Mature forests were located accurately. Sub-site 3 has a large portion of Intermediate aged forest. The Intermediate forest was more commonly confused with the Mature class than the Young class. A few Young forest polygons are erroneously located in forest from age classes 3 and 4. The Young forest, which is in the upper center portion of the image was classified as both Young and Intermediate.

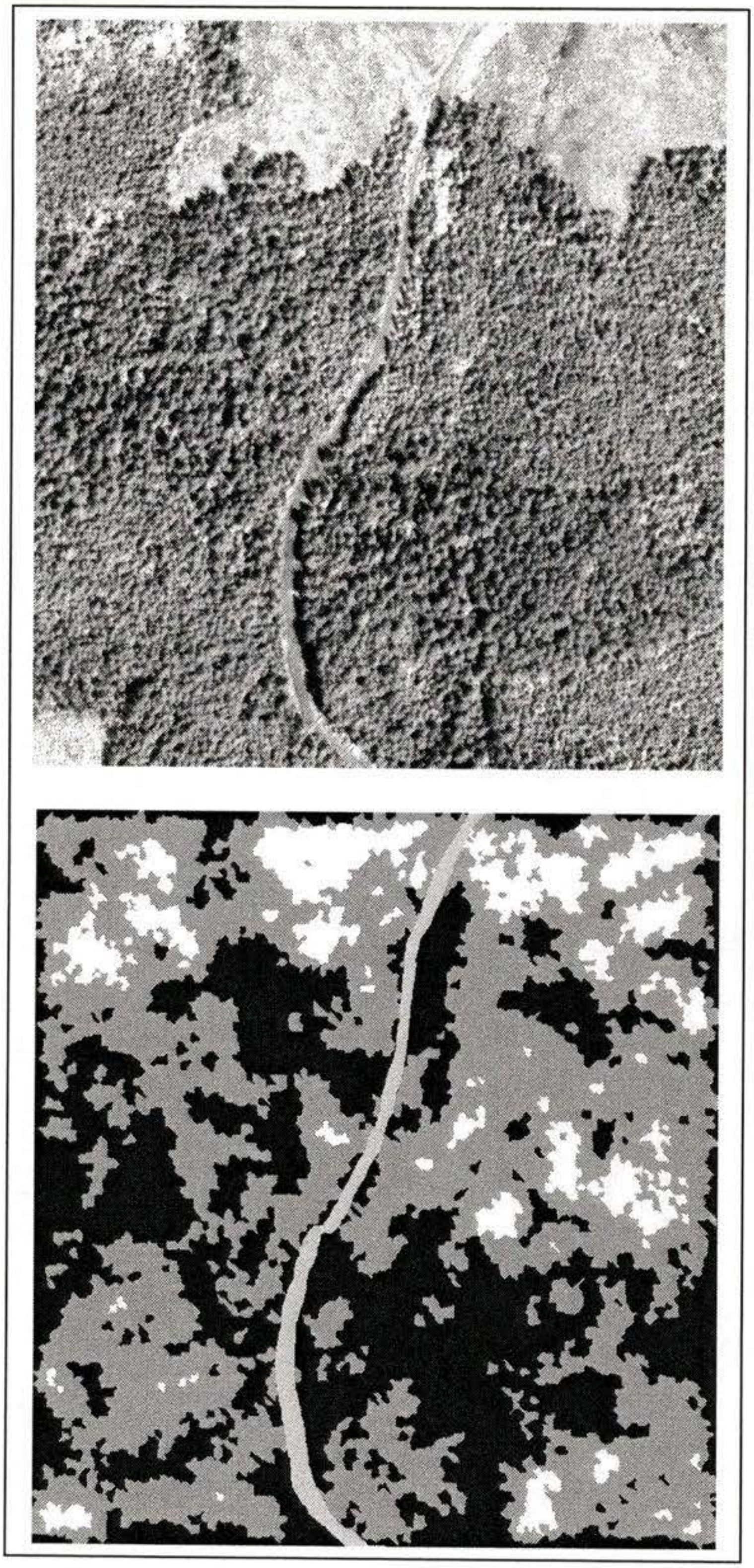

Figure 30. Objects created for sub-site 3. White = young, dark grey = intermediate, black = mature, light grey = road.

5.4.4 Results - Sub-site 4

Sub-site 4 is an excellent example of how well the Mature class can be located (Figure 31). In both the top right corner of the image, and the lower right portion of the image the Mature class is located with high accuracy. Most of the remaining image is Intermediate age with a small amount of Young forest, also well isolated. The forest surrounding roads is generally considered Mature, even if it is located in Intermediate aged forest.

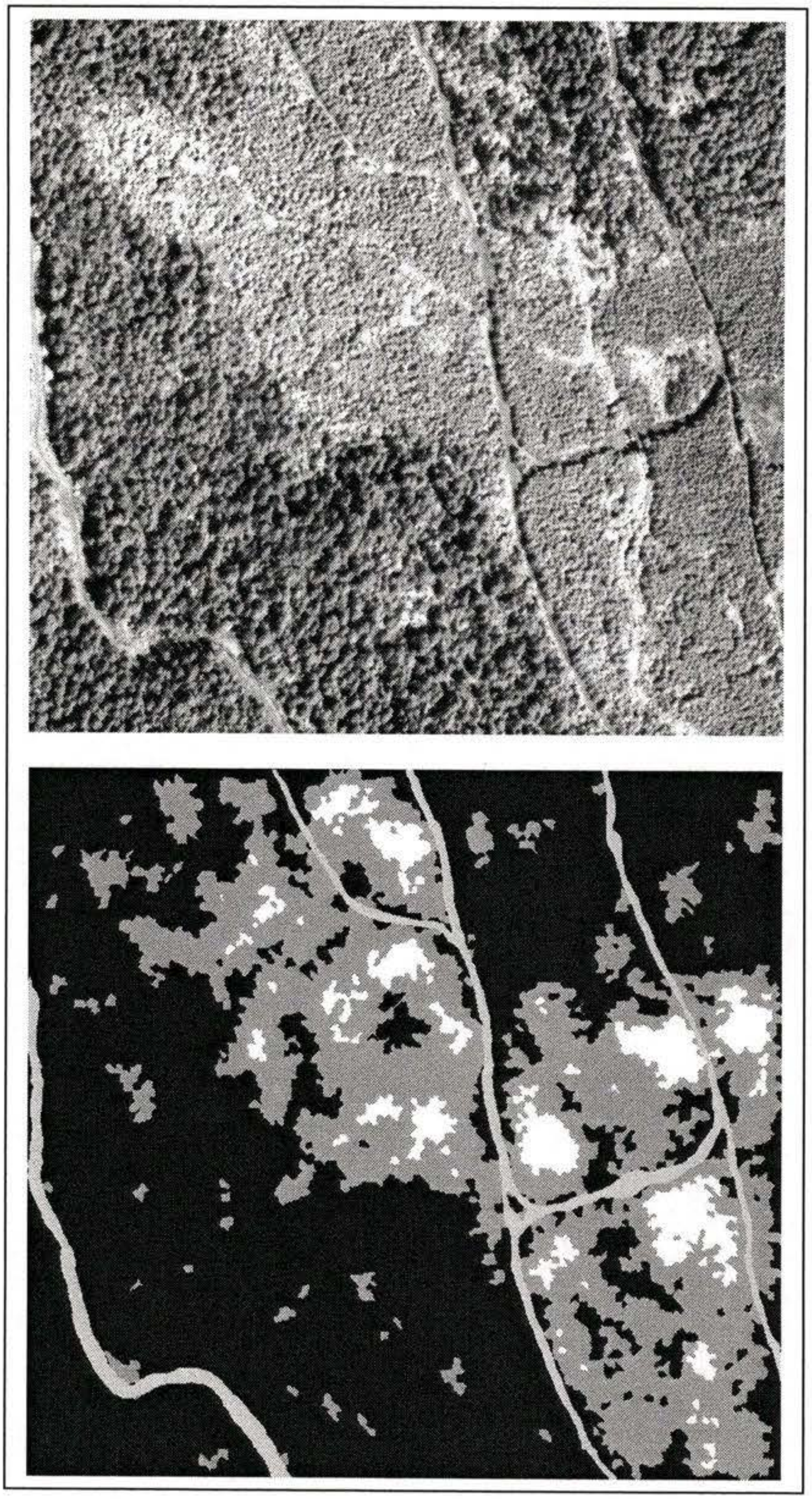

Figure 31. Objects created for sub-site 4. White = young, dark grey = intermediate, black = mature, light grey = road.

5.4.5 Discussion Sub-sites 1- 4

The methods used in this paper are relatively successful at producing polygons reflecting forest age. Overall the youngest forest is classified in the Young class and the oldest forest in the Mature class. Forest belonging to the Intermediate age class was the least accurately classified, and equally confused with the Young and Mature classes. It is not surprising that it is the two extreme age classes that are the easiest to classify.

As a result of edge effects, forest surrounding roads and image edges was sometimes classified incorrectly. The forest surrounding roads was often grouped into an older class. No trees should be located on the road, therefore when NND20 was calculated for local maxima points located near the road the values were artificially low. Errors surrounding image edges are not of major concern as buffer areas can be used to correct this error; inaccuracies near roads are of greater concern. It should also be noted that while there are no urban areas or water bodies within the analyzed images, such areas would have a similar effect to roads on the aggregation. Forests near non-forested areas will likely need user assistance to ensure correct classification. Even so, on many forested landscapes the number of roads and urban areas are small relative to the total area in need of classification.

The methods developed in this thesis provide a means to aggregate individual trees based on forest age, however when forests are a single age it is also useful for identifying areas subject to different management or harvesting practices. Sub-site 2 provides an example of how these methods may be applied to locate changes in forest management. All stands west of the upper road and the open area in the north are part of age class 6, but are grouped into all three of the age classes. Looking at the IKONOS image for sub-site 2 (Figure 29) shows that the size of crowns and spacing of trees changes throughout the area. The heterogeneity of the spatial patterns of the trees reflect changes in forest management; some areas were thinned while others were not. When management strategies are inconsistent throughout an area these methods are not sensitve to age.

That tree spatial patterns can be related to forest management strategies, shows it is unrealistic to assume that these methods be used on their own to determine forest age classes. In this study harvesting strategies influenced the spatial pattern of trees. Interpreting the cause for changes in spatial patterns requires additional information and user input. Other factors such as topography, moisture, and species composition could have a similar impact in different forested areas. These methods are just one tool that under the correct conditions aid in determining forest age classes. In the Sooke Watershed, there is a relationship between forest age and the spatial pattern of trees. In other areas spatial patterns may be related to different forest structure elements. This thesis is an investigation into some of the techniques useful for describing the spatial pattern of trees. In this case, the spatial pattern correlates with age. Even still, these methods should not be used on their own to identify forest age.

The spatial pattern of trees examined in this thesis are not real; the patterns are a representation of reality provided by local maxima filtering. Just as harvesting strategies affect the spatial pattern of trees, different local maxima results would affect the metric development, attribute generation, and aggregation phases of this project. It would be interesting to re-test these methods on different local maxima results in order to determine the sensitivity of this analysis on the accuracy of the local maxima filtering.

The majority of trees in the Sooke Watershed are Douglas-fir. Using the techniques developed in this thesis, aggregation by forest age may be difficult when species composition is heterogeneous. Species homogeneity was one criteria used to select training areas for metric development. Heterogeneous species composition will likely impact the spatial relationship of the individual trees, as interspecies composition is considered an important factor in forest structure (Oliver and Larson, 1996; He and Duncan, 2000). Therefore, further testing of these methods is required before application to areas where species composition is heterogeneous or dominated by non-coniferous tree species.

6.0 Conclusions

Chapter Objective: to synthesize results and draw conclusions based on the discussion and to suggest areas of future research. A second objective is to note problems with this research that should be addressed in future work.

Tools to utilize information from remotely sensed data will enable increased amounts of environmental information to be collected and studied. User-assisted techniques for the extraction and aggregation of individual tree locations, from remotely sensed imagery, may allow more detailed forestry information for management and decision making. Through this project, techniques allowing trees to be aggregated based on forest structure, specifically tree age, using spatial statistics have been developed. It has been shown that, via user-assistance, it is possible to aggregate individual trees extracted from 1m IKONOS imagery into polygons representing forest age. Depending on the characteristics of a forest, the spatial patterns of trees may be related to non-age forest structure elements. Specific conclusions relating to the individual steps in the methodology are presented below.

6.1 Feature Extraction

The first step in this project was to extract trees from the IKONOS image via local maxima filtering. Although the local maxima filter is well researched, to the authors knowledge the filter has not previously been applied to IKONOS imagery. Several conclusions regarding the application of the local maxima filter to IKONOS imagery can be made.

1. When extracting individual trees via local maxima filtering using IKONOS imagery, users must choose between a high number of correctly located trees and a large commission error, or fewer correctly located trees and lower commission error.

2. The accuracy of the local maxima filter is more correlated with DBH and crown size when used with a smoothed panchromatic IKONOS image than with a non-smoothed panchromatic image.

3. Depending on the type of information required, smoothing of the IKONOS image might improve the results of the local maxima filtering. If the interest is primarily in older trees, then a smoothed IKONOS image may be used, whereas, if focusing on younger trees a non-smoothed IKONOS image is more appropriate.

It may be possible to reduce commission error while maintaining the accurately located trees by using the multispectral IKONOS imagery to remove non-treed areas prior to applying the local maxima filter.

6.2 Metric Creation

Based on the iterations tested for metric development several conclusions can be made.

1. Both nearest neighbour distance and Voronoi methods have the potential to be used to generate point attributes based on forest structure.

2. Of the potential metrics developed the average NND20 *appeared* to be the most useful information for aggregation of trees based on age related forest structure.

3. Edge effects have a significant impact on the metric results and small areas should not be used for metric development.

Only a few of the metrics that could be developed to represent forest structure using spatial statistics have been investigated. It is suggested that the use of Voronoi polygons to develop attributes for the aggregation of trees into forest structure polygons be investigated further. Several Voronoi properties, such as shape and perimeter, may improve the classification of the Intermediate age class.

The developed metrics were only tested on forests having homogenous species composition. Further research is required to determine if the methods outlined may be applied to forests when the species composition is heterogeneous. As well, subsequent studies may include investigations on how to generate forest age polygons in areas where management practices vary throughout the region. Also, in subsequent efforts, attributes should be generated prior to extracting training data used for metric development in order to reduce edge effects.

6.3 Aggregation and Object Creation

The final product of this work is the objects, or polygons representing forest age. Based on a visual examination of the polygons several conclusions can be made regarding the overall effectiveness of the methods presented throughout this work.

1. In the Sooke Watershed using attributes representing the NND20, trees can be aggregated into three forest age groups: Young (1-20 years), Intermediate (21-120 years), and Mature (> 120 years).

2. Forests belonging to the Young and Mature classes are more accurately located than forest in the Intermediate aged group. Intermediate aged forests are often classified as both Young or Mature.

3. Due to edge effects areas adjacent to roads are often classified incorrectly. Trees surrounding non-forest areas are generally grouped into older forest classes.

4. The spatial pattern of individual trees may be related to non-age forest structure elements such as harvesting strategies.

In the Sooke Watershed the aggregation of tree into polygons reflecting age was successful. Under different forest conditions the patterns in a forest may relate to other forest structure elements; it would be naive to assume that these methods may be used as a stand-alone technique to determine forest age. Future work may help to improve results by investigating techniques to reduce the edge effects of non-forested areas. As well, more sophisticated aggregation techniques may be used to cluster several attributes. Generating more than one attribute may provide more information useful to further stratify the Intermediate age class. Existing remote sensing techniques and auxiliary data sources may help to improve the results of this work. For example, using existing road and water boundary vectors to remove non-forest areas would be useful.

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Appendix 1

Complete IKONOS image used in study. The IKONOS image used in this study was collected on June 3, 2000 at 11:05 PST and is a single panchromatic image. The solar elevation was 60.7° and the solar azimuth was 146.5°. The upper left corner of the image is 441962E, 5386346N and the lower right corner is 451162E, 5377371N. The image is 9200m by 8975m, and covers approximately two thirds of the Sooke watershed management area and also extends beyond the western extent of the management area.

Appendix 2

A) Contiguous

```
#Trisalyn Nelson and M. Fortin
#November, 2000
#This program is based on the triangulate function in the spatial statistics
   package of SPLUS.
#Given a file with x & y locations for several points this program will compute
   the distances of all line
#segments which are part of triangles.  I.e. for each triangle it will give the
   distance between point 1-2
#1-3, and 2-3.
contiguous_function(x, y, plot.it = T, shrink = 0.1)
{
   if(missing(y)) {
      if(!is.null(x$y)) {
         y <- x$y
         x <- x$x
      }
      else if(is.matrix(x) && ncol(x) > 1) {
         y <- x[, 2]
         x <- x[, 1]
      }
   }
   x <- as.single(x)
   y <- as.single(y)
   n <- length(x)
   if(length(y) != n)
      stop("x and y must have same lengths")
   out <- .Fortran("idtang",
      n,
      x,
      y,
      nt = integer(1),
# ipt = integer(6 * n - 15),
      ipt = integer(6 * n),
      nl = integer(1),
      ipl = integer(6 * n),
      integer(18 * n),
      integer(n),
      single(n))[c("nt", "ipt", "nl", "ipl")]
   #cat("nt=", out$nt, "nl=", out$nl, "\n")
   out$ipt <- matrix(out$ipt[1:(3 * out$nt)], nrow = 3, ncol = out$nt)
   out$ipl <- matrix(out$ipl[1:(3 * out$nl)], nrow = 3, ncol = out$nl)
   out1 <- matrix(0, 0, 3)
   if(plot.it) {
      plot(x, y)
      for(i in seq(length = out$nt)) {
         xx <- x[out$ipt(in progress)]
         xx <- mean(xx) + (xx - mean(xx)) * (1 - shrink)
         yy <- y[out$ipt(in progress)]
         yy <- mean(yy) + (yy - mean(yy)) * (1 - shrink)
         polygon(xx, yy, col = i, density = 0)
      }
   }#In the following section distances of each of the triangles line segments
   are computed.
   for(i in seq(length = out$nt)) {
   dis1 <- euclidean(x[out$ipt[1, i]], y[out$ipt[1, i]], x[out$ipt[2, i]],
      y[out$ipt[2, i]])
```

```
dis2 <- euclidean(x[out$ipt[2, i]], y[out$ipt[2, i]], x[out$ipt[3, i]],
   y[out$ipt[3, i]])
dis3 <- euclidean(x[out$ipt[1, i]], y[out$ipt[1, i]], x[out$ipt[3, i]],
   y[out$ipt[3, i]])
#In the following section the program outputs the distances.  i = triangle,
out$ipt[1,i] = point 1,
#out$ipt[2,i]= point 2, and dis1 = the distance.  rbind is used to write to
the matrix, it is
#useful as it appends several lines.
       out1 <- rbind(out1, c(out$ipt[1, i], out$ipt[2, i], dis1))
       out1 <- rbind(out1, c(out$ipt[2, i], out$ipt[3, i], dis2))
       out1 <- rbind(out1, c(out$ipt[1, i], out$ipt[3, i], dis3))
   }
dimnames(out1) <- list(NULL, c("pt1", "pt2", "dist")) #lables the output
columns (note i is not output)
out1 <- sort.col(out1, ("@ALL"), c("pt1", "pt2"), T) #sorts the output based
on column 1
out1 <- as.data.frame(out1)
return(out1)
   }
```

B) Avg

```
#Trisalyn Nelson
#November 2000
#In SPLUS, this function takes input from contiguous and calculates the average
   distances to the neighbours
#identified using triangulate.  Does not include Zero or NA values in the
   averaging calculations
#at the end of the program.  This was used to average the Voronoi areas.
   Remember compile with <F10>
#NOTE only searches the first column (not both) when calculating the average
   area of all contiguous
#neighbours for each point.  To use this accurately the doubles (resulting from
   contiguous) must be removed
#manually.

avg_function(x) # x = the name of the input file
{
   nrows <- length(unique(c(unique(x[,1]),unique(x[,2])))) #determines the
   number of points which need an average
   #distance reported.  unique is a command which tells how many unique numbers
   exist.  In this case
   #the unique numbers are determined based on the columns 1 and 2 of file x.
   co <- matrix(0,nrows, 1) # a matrix full of zeros, with the number of rows =
   to the unique values and one column.
   sd <- matrix(0,nrows,1)
   cv <- matrix(0,nrows,1)
   ptavg <- matrix(0,nrows, 1)
   med <- matrix(0,nrows, 1)
            for(i in 1:nrows) {
         ptavg[i,] <- mean(x[x[,1]==i,3])
         #mean = a SPLUS command, (in progress) = a column, [i,] = a row. For
   file x it looks in columns 1 and 2.  If
         #the values equal i then it averages the distances in column 3.
         co[i,] <- length(x[x[,1]==i,3])#same as above only now counting the
   number of neighbours for each point
         sd[i,] <- stdev(x[x[,1]==i,3])#same as above only now computing the
   standard deviation
         med[i,] <- median(x[x[,1]==i,3])#

      for(i in 1:nrows) {
         cv[i,] <- (sd[i,]/ptavg[i,])*100#calculates the coefficient of
   variation
      }

                  avgavg <- colMeans(ptavg, na.rm=T, dim=1)# mean of the
   column, ptavg = file, na.rm=T =if
                  #there is a value which equals "NA" ignore when calculating
   the mean.  dim=1 = there is one column.
                  sd<-sd[sd[,1] !=0,]  #remove zero value in column 1 from
   file sd.
                  avgstdev <- colMeans(sd, na.rm=T, dim=1)
                  avgcv <- colMeans(cv, na.rm=T, dim=1)
                  med<-med[med[,1] !=0,]
                  avgmed <- colMeans(med, na.rm=T, dim=1)
                  outfile <- c(avgavg, avgstdev, avgcv, avgmed)
   return(outfile)
```

C) Ptlength

```
#Trisalyn Nelson
#Dec 2000
#In SPLUS this calculates averages the number of neighbours for each point.
   Used in combination
# with output from find.neighbor to generate spatial point attributes.
ptlength_function(x)
{
   nrows <- length(unique(c(unique(x[,1])))) #determines the number of points
   which need an average
   ptlength <- matrix(0,nrows,1)
             for(i in 1:nrows) {
         ptlength[i,] <- length(x[x[,1]==i,1])
      }

                    outfile <- (ptlength)
return(outfile)
}
```

D) Fillopen

```
! Trisalyn Nelson
! Jan 11, 2001
! In PCI, this program iteratively grows points into objects so that every
pixel
! within the image is eventually part of an object.
!
! Assigns values to pixels with DN = 0.
! Rules
! 1.   If pixel = 0 and an adjacent pixel has a value, assign the pixel the
!      adjacent value.
! 2.   If the pixel =0 and adjacent pixels are all 0 the pixel remains 0 until
!      a later iteration
! 3.   If the pixel >0 remains the same.

input "Input the channel number to be processed: " %lm;
input "Input the channel number to receive the LM output: " %temp;
if (%lm = 0) and
(%lm[-1,-1]>0) then
%temp = (%lm[-1,-1]);
   extrif (%lm =0) and
   (%lm[-1,0]>0) then
   %temp = (%lm[-1,0]);
      extrif (%lm =0) and
      (%lm[-1,1]>0) then
      %temp = (%lm[-1,1]);
         extrif (%lm =0) and
         (%lm[0,-1]>0) then
         %temp = (%lm[0,-1]);
            extrif (%lm =0) and
            (%lm[0,1]>0)then
            %temp = (%lm[0,1]);
               extrif (%lm =0) and
               (%lm[1,-1]>0) then
               %temp = (%lm[1,-1]);
                  extrif (%lm =0) and
                  (%lm[1,0]>0) then
                  %temp =(%lm[1,0]);
                     extrif (%lm =0) and
                     (%lm[1,1]>0) then
                     %temp =(%lm[1,1]);
else  %temp = %lm;

endif;
```

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Spatial Statistical Techniques for Aggregating Point Objects Extracted form High Spatial Resolution Imagery

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August 10, 2001