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Spatial statistical techniques for aggregating point objects extracted from high spatial resolution remotely sensed imagery

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Abstract. Using a local maximum filter, individual trees were extracted from a 1 m spatial resolution IKONOS image and represented as points. The spatial pattern of individual trees was determined to represent forest age (a surrogate for forest structure). Point attributes, based on the spatial pattern of trees, were generated via nearest neighbour statistics and used as the basis for aggregating points into forest structure units. The forest structure units allowed for the mapping of a forested area into one of three age categories: young (1–20 years), intermediate (21–120 years), and mature (>120 years). This research indicates a new approach to image processing, where objects generated from the processing of image data (rather than pixels or spectral values) are subjected to spatial statistical analysis to estimate an attribute relating an aspect of forest structure.

Key words: Nearest neighbour statistics, aggregation, generalisation, feature extraction

JEL classification: Q23

1 Introduction

The spatial detail of remotely sensed data allows for the extraction of individual tree locations using automated techniques (Culvenor 2002; Niemann et al. 1999; Gougeon and Moore 1988). Individual tree data is manageable when applied to small areas; however, individual tree data can result in very large data sets and information unwieldy for large areas studies. When addressing large areas individual tree information may be generalized into homogenous units that describe characteristics of trees, similar to how trees are aggregated in management forest inventories (Leckie et al. 1999).

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The goal of this communication is to investigate the potential for aggregating objects, extracted from remotely sensed imagery, based on spatial pattern. We demonstrate our methods using individual trees, extracted via local maximum filtering. Using spatial statistical tools, the spatial patterns of individual tree locations may be used to generalise points into forest structure polygons.

2 Pattern, age, and forest structure

The link between pattern and process(es) is well established in ecology (Sokal 1998; Levin 1992). Studying the pattern of trees, for instance, can be used to better understand processes of forest structure. Forest structure is the physical or temporal distribution of trees and other plants and is impacted by a number of characteristics including species, crown volume, topography, and tree age (Voller 1998; Oliver 1996). Surrogates for forest structure may be measured *in situ* (e.g. Frazer et al. 2001), modeled (e.g. Landsberg and Waring 1997), or estimated from remotely sensed data (e.g. Cohen and Spies 1992; St-Onge and Cavayas 1995; Woodcock et al. 1997). Utilizing the spatial relationships between objects generated from remotely sensed data is a unique approach to the estimation of forest structure.

Clearly forest structure has many elements, one of the easiest to isolate is 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). Generally, as trees grow they require more space; therefore, distances between mature trees are larger than distances between young trees. Such trends can be seen in the spatial pattern of trees; the spatial patterns of individual tree allow us to infer age and therefore forest structure.

3 Study area

The study area is located in the Sooke Watershed, 40 km northwest of Victoria, British Columbia, Canada (48° 34′ N, 123° 42′ W) (Fig. 1). Due to management practices, the Sooke Watershed has a diverse age structure that is useful for studies on the relationship between forest structure and forest age. The Sooke Watershed, is dominated by coastal Douglas-fir (*Pseudotsuga menziesii*) with stand age ranging from 0 years to >250 years (GVWD 1991). The younger forests are managed plantations while the old growth stands are naturally occurring.

4 Data

Three types of data, on the Sooke Watershed, were used in this study: field data, a GIS forest inventory, and IKONOS imagery.

4.1 Field data

As discussed in Wulder et al. (2000), field data were collected to assess the quality of local maximum filtering. The location of all tree stems were

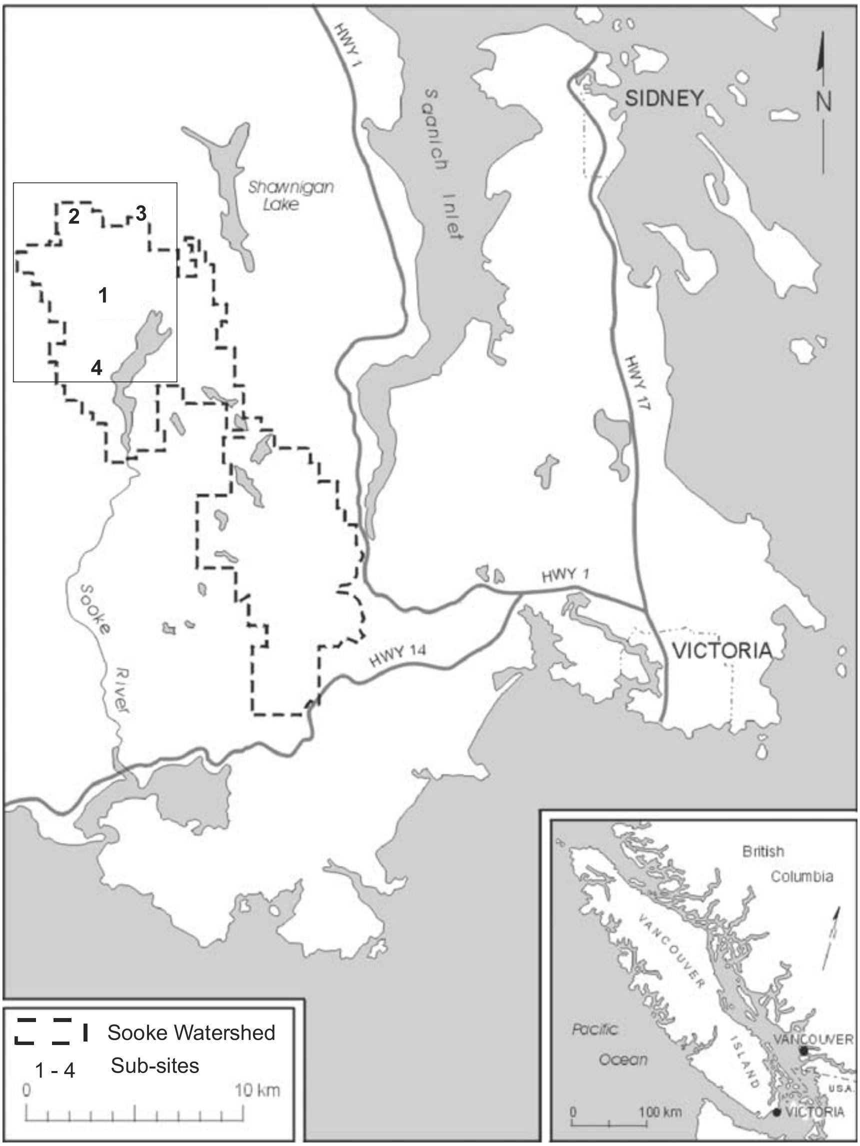

Fig. 1. Study location. Numbers 1–4 represent locations of the four small areas used for aggregation. The solid box indicates the extent of the IKONOS image

mapped for a 90×90 m area (NW Corner 446600E 5381884N) that straddles a boundary between young (approximately 40 years) and mature (approximately 150 years) trees. Plot corners were located via GPS, with the distance measurements used to map tree locations. In all, 199 trees were mapped and attributes including species, height, and diameter at breast height (trunk diameter) were collected.

4.2 Forest inventory map

Information on the age and species of forests, within the Sooke Watershed, were obtained from a GIS forest inventory (scale 1:15000) (GVWD 1991). Nine classes are used to represent tree age on the inventory map (1–20, 21–40, 41–60, 61–80, 81–100, 101–120, 121–140, 141–250, >250 years). As will be discussed in more detail below, in this study we use training areas from each of the nine age classes to test the sensitivity of different forest pattern attributes to tree age. All training areas were 50 × 50 m and the number of training areas ranged from 3 to 6, depending on the number of polygons of a particular age class in the forest inventory data. No areas were selected in the age class 121–140 years as there were no stands in this category. Training areas were selected to maximize homogeneity within each area. We also attempted to identify training areas throughout the full extent of the study area and to minimize the impacts of topography. It should be noted that the training areas do not overlap the 90 m^2 area where field data were collected.

4.3 IKONOS imagery

As will be examined in the methods section, features were extracted from a panchromatic, 1 m spatial resolution IKONOS satellite image that was collected on June 3, 2000 at 11:05 PST. The upper left corner of the image is 441962E, 5386346N and the lower right corner is 451162E, 5377371N, covering an area approximately 9200 m by 8975 m. Geometric corrections were based on a 20 m digital elevation model derived from British Columbia's Terrain Resource Information Management data. Due to processing constraints, aggregation was only performed on four sub-areas of the image (Fig. 2). It should be noted that sub-areas used for aggregation are separate from the training areas. Coincidentally the field data does overlap with sub-area 1, however, this has no implication for the study.

5 Methods

5.1 Feature extraction

Trees were isolated from a satellite image using a feature extraction technique known as local maximum filtering. Our goal is not to revisit this well documented technique, but rather to develop an approach for use with a variety of different objects extracted via feature extraction. For details on the theories and issues related to local maximum feature extraction we refer the reader to Wulder et al. (2000). In brief, the local maximum filtering approach is based upon the geometry of trees resulting in the apex being approximately located where image radiance values are highest. Using a roving window, the local maximum finding algorithm identifies the high radiance pixels (e.g. the central pixel in a 3 × 3 window is greater than all other pixels in the window). The result is a surface of points representing tree locations. It is the inter-relationships between points that we use to generate objects related to forest structure.

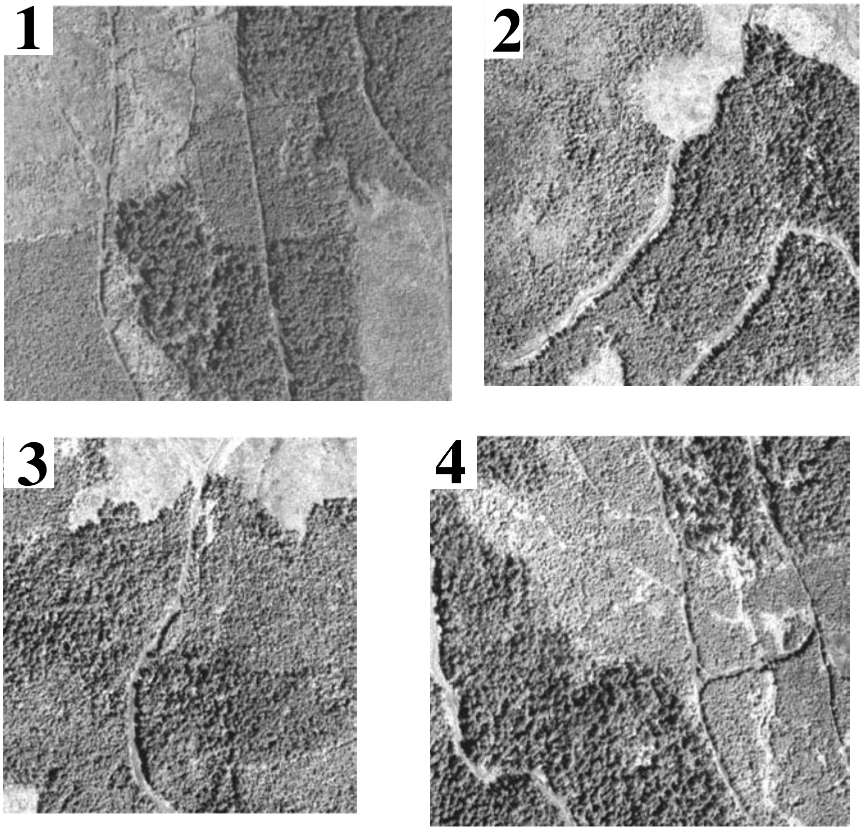

Fig. 2. Areas of the panchromatic 1 m spatial resolution IKONOS image used for aggregation. The forest ages in these areas are representative of the large IKONOS image

Individual tree extraction from the IKONOS image was achieved through the use of a 3×3 local maximum filter. Prior to feature extraction the image was smoothed using a 3×3 averaging filter to remove image noise, thereby reducing the potential for trees to be falsely identified. The drawback to smoothing an image is some "real" information is lost reducing the likelihood of finding trees with small crowns. The 199 stem mapped tree locations were mapped on the IKONOS image and used to assess the accuracy of the local maximum filter.

5.2 Developing a NND based attribute

As trees are represented as points, a subset of spatial statistics, point pattern analysis, is useful for describing forest age and generating attributes to be used for aggregating data into forest structure units. For each of the 50×50 m areas, nearest neighbour distance (NND) statistics were calculated and assessed for sensitivity to changes in forest age. The first NND statistic used was the distance from a point to each neighbour within 5, 10, 15, and

20 m radius. Five meters was the minimum radius used for analysis as smaller distances may not include enough data to provide a meaningful interpretation of the relationship between points when trees are mature. Twenty metres was the maximum radius investigated as young trees further than 20 m apart are unlikely to have a significant impact on one another. Radii of 10 m and 15 m were also analysed in order to search for spatial trends in the relationship between trees. The second NND statistic investigated was the average distance to the nearest 20 neighbours. For each local maximum point in the age stratified sample area the nearest neighbour statistics were calculated. The average and standard deviation of the attributes for age class sample areas were averaged to determine the attribute's sensitivity to forest age.

5.3 Aggregation

So far, attributes have only been generated for training areas, in order to test their sensitivity to forest age. Once the attribute most sensitive to forest age was determined (the number of neighbours within 20 m of each tree), attributes were generated for large areas and aggregations preformed. Generating attributes for all trees extracted from the IKONOS image, would have been unnecessarily cumbersome. Therefore, four sub-areas were selected and an attribute, the number of neighbours within 20 m of each tree, was generated for all trees in the four sub-areas. The current approach is based upon thresholds developed from visual inspection of attributes generated for the sub-areas (rather than thresholds based on some form of sensitivity analysis). In future analysis, we suggest adding a buffer to training areas prior to assessment of attribute sensitivity. Trees were assigned to (aggregated) one of three classes: Young (1–20 years), Intermediate (21–120 years), and Mature (>120 years). Trees with more than 25 neighbours within a 20 m radius were considered part of the Young class, the Intermediate class had 17–25 trees, and the Mature class had less than 17 neighbours. Non-forest areas such as roads were removed prior to analysis.

An accuracy assessment was performed by comparing the aggregation results with the forest inventory polygons on a pixel by pixel basis. Inventory polygons were overlain on the aggregation results and accuracy reported in a confusion matrix.

6 Results and discussion

6.1 Feature extraction

The local maximum filter located 44% of the trees accurately (Table 1), finding most of the mature trees (70%) and falsely identifying few (<1%). When working with a local maximum filter the error must be optimised; one must choose between few falsely identified trees or few missed trees. We optimised the filter to minimise the number of falsely identified trees. Falsely identified trees would have made it difficult to distinguish between forest age classes. Mature trees surrounded by falsely identified trees would appear to have a similar density to younger trees. As well, if many trees are falsely

Table 1. Results of the 3 × 3 local maximum filter on smoothed the IKONOS image. Results are stratified by age and determined based on a stem map generated in the field

	Smoothed 3×3
All (n = 199)	
Correct	0.44
False positive	0.04
Missed	0.56
Young (n = 150)	
Correct	0.37
False positive	0.01
Missed	0.64
Mature (n = 49)	
Correct	0.70
False positive	0.11
Missed	0.34

identified the spatial pattern could reflect non-tree vegetation or image noise. Due to our optimisation technique, many of the small trees were not identified; however we could determine that the pattern provided by the local maximum filter represented the spatial pattern of the larger trees. Both types of error (missed and falsely identified trees) negatively impact the ability to determine tree age based on spatial pattern, however the loss of small trees will impact analysis less than the inclusion of non-trees. When small trees are lost, the spatial pattern is incomplete, whereas false trees represent noise.

6.2 Attribute development

In general, the average number of neighbours within a window reflects forest density. Regardless of the analysis distance considered, the number of neighbours decreases as the forest age increases (Table 2). As the window size used to generate the attribute increases, the attributes sensitivity to changes in age also increases. The standard deviation for the number of neighbours within a radius from each tree does not reflect changes in forest age. Although the oldest trees have a lower variance in the number of neighbours than the youngest trees, no clear trend exists for the intermediate age classes. Larger areas tend to have greater variation; therefore it is not surprising that the magnitude of the standard deviation increases as the analysis area expands.

The standard deviation and average distance to the nearest 20 neighbours increases with forests age (Table 3). The use of 20 neighbours was determined based on experience in the field. Twenty neighbours incorporates enough area to allow analysis of matures trees to be meaningful, while maintaining sufficient homogeneity areas where trees are younger. However, depending on factors such as forest type, tree size, and topography the appropriate number of neighbours for analysis may vary. To attributes (1) number of neighbours within 20 m from each point, and (2) the average number of neighbours within 20 m distance of each point, have a similar

Table 2. Results of sensitivity analysis for the average number of neighbors within some distance of each point. This table shows how the attribute values varies with forest age. Using this table the sensitive of attributes based on the number of neighbors within a distance of each point was assessed. Average standard deviations are reported in brackets, and *n* equals the number of neighbors in each class

Age (years)	*n*	5 m	10 m	15 m	20 m
1–20	283	1.6 (0.7)	5.1 (2.1)	11.6 (4.3)	17 (6.1)
21–40	149	1.4 (0.5)	4.6 (2.0)	10.7 (3.4)	15.4 (4.6)
41–60	166	1.3 (1.6)	4.2 (1.7)	10.2 (3.5)	15.3 (5.0)
61–80	102	1 (0.6)	4 (1.9)	9.6 (3.8)	14.1 (4.7)
81–100	107	1 (0.0)	3.2 (1.5)	7.9 (2.7)	11.6 (3.9)
101–120	147	1.1 (0.2)	3.2 (1.3)	7.4 (2.6)	11 (3.5)
141–250	94	1 (0.1)	2.2 (1.1)	5.3 (2.1)	8.1 (3.0)
250+	70	1.1 (0.0)	2.8 (1.3)	6.6 (2.5)	9.1 (3.2)

Table 3. Results of sensitivity analysis for the average distance to neighbors within 20 m of each point. This table shows how the attribute value varies with forest age. Using this table the sensitive of the attribute based on the average distance to neighbors within 20 m was assessed. *n* equals the number of neighbors in each class. Average standard deviations are reported in brackets

Age (years)	*n*	
1–20	283	13.8 (2.7)
21–40	149	15.1 (3.0)
41–60	166	15.5 (3.1)
61–80	102	16.7 (3.9)
81–100	107	18.0 (3.5)
101–120	147	18.7 (3.5)
141–250	94	22.6 (4.1)
250+	70	21.0 (4.1)

sensitivity to forest age. However, we feel that the number of neighbours within 20 m from each point is less subjective and therefore will be used in this analysis.

6.3 Aggregation

The objects created by the aggregation are shown in Fig. 3 and the accuracies of aggregation is summarized in Table 4. For all four areas, the average overall accuracy of the objects is 65.1%. Average accuracy for the young, intermediate, and mature classes are: 41.0%, 61.3%, and 76.8%. The confusion matrix shows the young and intermediate classes, and intermediate and mature classes are often confused; there is little confusion between the young and old classes.

Forest inventory polygons are designed to be homogenous based on several characteristics including tree species, age, and height. Comparing the forest age objects produced in this work with forest inventory polygons generated from several tree characteristics may lead to an artificially low

Table 4. Average confusion matrix for all aggregated areas. Accuracy determined by comparisons with forest inventory polygons. The number of 1 m^2 pixels in each of the age classes is as follows: Young – 297985; Intermediate – 1172372; Mature – 952143

	Young	Intermediate	Mature
Young	41.0%	55.8%	3.2%
Intermediate	14.4%	61.3%	24.3%
Mature	0.4%	22.9%	76.8%

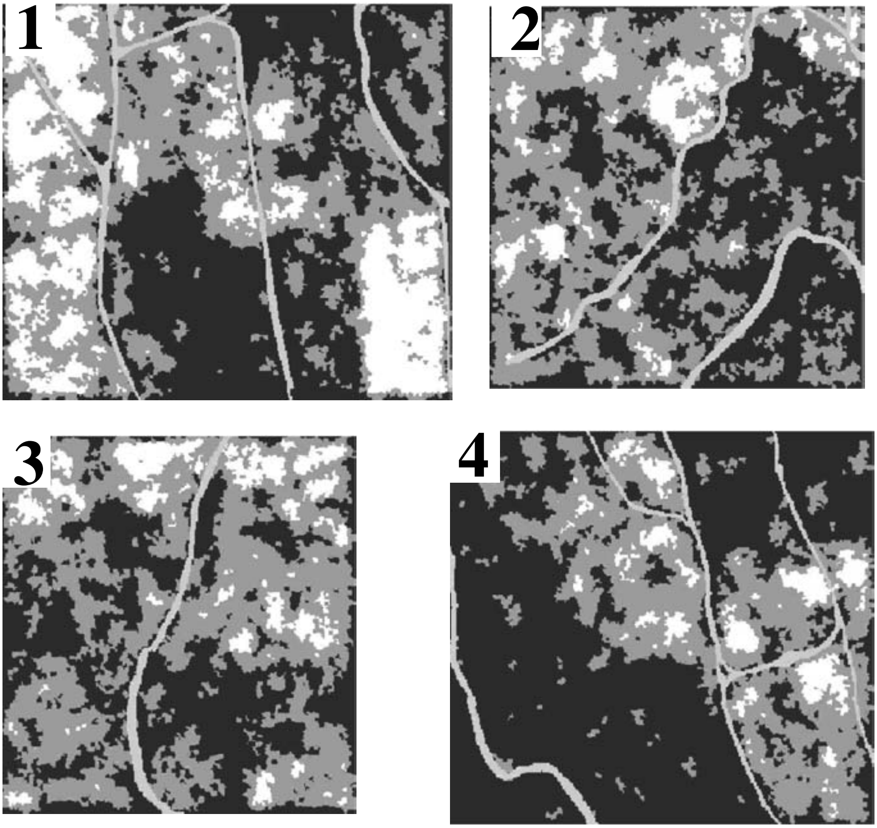

Fig. 3. Objects aggregated based on attributes equal to the number of neighbours within 20 m or each point or tree. (Where, *White* = Young Forest; *Dark Gray* = Indermediate Aged Forest; *Black* = Mature Forest; and *Light Gray* = Road)

accuracy report. Visual inspection suggests that the accuracy may be higher and that the method appears to identify subtle differences of age within forest inventory polygons. More detailed field investigations are required to quantitatively address this issue.

As a result of edge effects, forest surrounding roads and image edges were often classified incorrectly. Through the masking, no trees are located in the road; therefore, trees near the road had fewer neighbours than they would if surrounded by forest. As trees with few neighbours are generally mature, points near roads were often aggregated into an older class. Forests near non-forested areas will likely require user assistance to ensure aggregation into the correct class.

In the Sooke Watershed forest age was an adequate indicator of forest structure. In other areas factors such as topography, species competition, and management practices may have significant influences. When applying these techniques users must determine which factors (i.e. age, topography) can be linked to forest structure.

7 Conclusions

The interrelationship between tree locations, extracted from the remotely sensed imagery, appears to capture changes in forest structure related to age. As well, attributes based on the relationship between points are useful for aggregating trees into forest structure objects. The use of spatial statistics to aggregate objects generated from remotely sensed data into meaningful units indicates a new approach for the estimation of attributes of indicative of forest structure.

The resolution of the aggregation was likely limited by the accuracy of the feature extraction. Improved accuracy in feature extraction from satellite imagery may allow finer classes to be aggregated. Although NND statistics allowed us to develop attributes useful for generating forest structure objects other spatial statistical methods, such as Voronoi Polygons, better retain spatial information and may be even more sensitive to changes in forest structure. As well, more sophisticated aggregation techniques, such as clustering, may be useful for generalising points based on several attributes.

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