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Techniques for accuracy assessment of tree locations extracted from remotely sensed imagery

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Abstract

Remotely sensed imagery is becoming a common source of environmental data. Consequently, there is an increasing need for tools to assess the accuracy and information content of such data. Particularly when the spatial resolution of imagery is fine, the accuracy of image processing is determined by comparisons with field data. However, the nature of error is more difficult to assess. In this paper we describe a set of tools intended for such an assessment when tree objects are extracted and field data are available for comparison. These techniques are demonstrated on individual tree locations extracted from an IKONOS image via local maximum filtering. The locations of the extracted trees are compared with field data to determine the number of found and missed trees. Aspatial and spatial (Voronoi) analysis methods are used to examine the nature of errors by searching for trends in characteristics of found and missed trees. As well, analysis is conducted to assess the information content of found trees.

Keywords: Feature extraction; Accuracy assessment; Voronoi polygon; Spatial autocorrelation

1. Introduction

Over the past decade, spatial, spectral, and temporal resolution of remotely sensed imagery has improved significantly. Finer spatial resolution has lead to particular improvements in environmental mapping. For example, high spatial resolution imagery has enabled the identification and mapping of individual trees, or groups of trees (Gougeon et al., 1999; Wulder et al., 2000a; Culvenor, 2002). Many issues impact the accuracy of feature extraction techniques. In forestry, these include trees located in close proximity, layering of multiple strata of trees, and the relationship between spatial resolution and tree crown size.

Although numerous procedures have been designed to extract environmental data from remotely sensed imagery, tools available for accuracy assessment are limited. By matching trees extracted from imagery to those found on the ground, we can determine the percentage of trees accurately located. However, this tells us nothing about the nature of the error. It may be useful, for example, to know if the errors are random or related to tree characteristics. Also, techniques to determine the information content of data would be valuable. For instance, in some cases researchers suspect trees identified through feature extraction may actually represent tree clumps (Gougeon et al., 1999).

In this paper we demonstrate a combination of spatial and aspatial methods (Table 1) useful for investigating both the nature of error and the actual information content of environmental data captured from remotely sensed imagery. We demonstrate our methods on individual tree data generated from high spatial resolution imagery (IKONOS) via local maximum (LM) filtering, which is described in the section that follows (Wulder et al., 2000a). However, our approach may also be used when examining the effectiveness of other feature extraction methods. To validate the efficacy of the tree identification

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Table 1
An overview of aspatial and spatial techniques for assessing the accuracy of environmental data extracted from remotely sensed imagery

Domain	Technique	Objective
Aspatial	Difference of means	Determine if summary characteristics of found and omitted objects differ significantly
Spatial	Voronoi	Convert point data to areal units
		Operationalize spatial relationships between objects
	Global measures of spatial association	Determine if the spatial pattern of feature extraction error is significantly different from a random expectation
	Local measures of spatial association	Detect if objects are significantly different from their immediate surroundings
Spatial/aspatial	Measures of association	Assess if local significance in object characteristics is related to the likelihood of an object being found or omitted during feature extraction

approach, we compare the individual tree characteristics of trees located and missed by the LM filter. Points representing individual tree locations are converted to Voronoi polygons (VPs) and spatial analysis (join counts) is conducted on the pattern of found and missed trees. We also search for spatial patterns in the aspatial characteristics of trees and VPs using local spatial autocorrelation measures and relate the patterns found to that of the missed trees. Then we assess the information content of trees located by the LM filter through a comparison of VP characteristics of trees found by the LM filter with those of the corresponding stem mapped trees.

2. Local maximum filtering

LM filtering automates the extraction of individual tree locations from high spatial resolution remotely sensed imagery (Wulder et al., 2000a). A kernel is moved over the image and trees are located when the central digital value in the kernel window is higher than all other values. The LM filter is based on the assumption that reflectance is highest at the tree apex and decreases towards the crown edge (Wulder et al., 2000a). The LM filter constrains the identification of trees to pixels that do not touch, thereby limiting the maximum number of trees that can be found in any remotely sensed image.

There are three outcomes for a LM filter: correct identification of a tree, failure to find a tree that exists (omission error), or identification of a tree that does not exist (commission error). If the trees are small relative to the imagery pixel size, minimizing the kernel size will maximize accuracy; if trees are large relative to the image pixel, smoothing or use of a larger kernel may improve results. In reality, trees often vary in size throughout a study region and the LM filter should be optimized based on the acceptable type of error for a particular application. The LM filter is a well-documented feature extraction technique. Our goal is not to further develop this technique, but rather to provide a method for assessing the accuracy of LM filtering, and other feature extraction techniques that represent objects as points.

3. Data

Two data sets covering the same area were used for this analysis: (1) field data on the location and characteristics of individual trees, and (2) individual tree locations extracted from remotely sensed imagery using the LM filter.

3.1. Field data

Field data on the location and characteristics of individual trees were collected for a 0.72 ha area in the Sooke Watershed located near Victoria, BC. A ground survey was undertaken, over an area with little topographic variability, to produce a stem map where trees were located to the nearest 10 cm. In total, 199 trees were mapped of which 150 were classified as young and 49 mature (Fig. 1). The young stand was composed of a mixture of Douglas-fir (*Pseudotsuga menziesii*) and western red cedar (*Thuja plicata*), whereas the mature stand was dominated by Douglas-fir. Characteristics recorded for each tree include species, tree height, crown radius, and diameter at breast height (DBH). Diameter breast height is the circumference

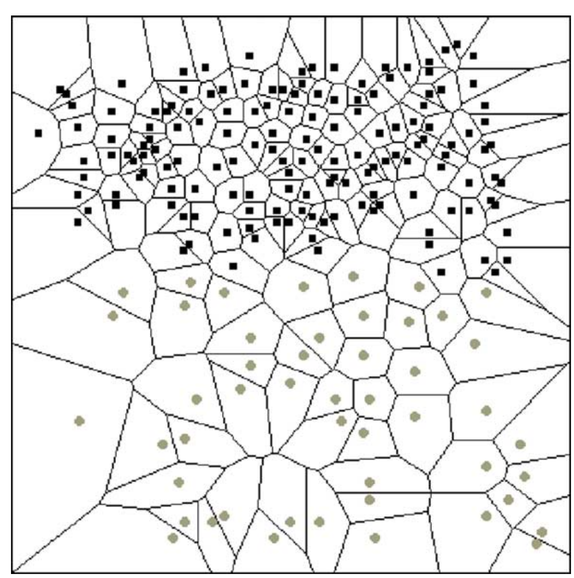

Fig. 1. Voronoi polygons generated from stem mapped trees. Grey circles represent the locations of mature trees and black squares represent the locations of young trees.

of a tree trunk at 1.3 m above the ground and is often correlated with tree height and crown radius (Avery, 1967, pp. 144–146). Crown radius was determined using standard forest measurements outlined in Avery, 1967 (pp 160–161), and a hypsometer was used to measure the height to an accuracy of 2–5% (see Avery, p. 154). For young trees, the average height, crown radius, and DBH were 19.2, 1.48, and 0.21 m, respectively. Average height, crown radius and DBH for mature trees were 47.52, 3.12, and 0.58 m, respectively. For details of the data collection procedure, we refer the reader the Hay and Niemann (1994).

3.2. Imagery data

LM filtering was performed on an orthocorrected IKONOS image captured at 19:05 h GMT June 3, 2000. The solar altitude and azimuth angles at the time of the satellite overpass were 60° and 146°, respectively. The image is panchromatic with a spectral range of 450–900 nm and a spatial resolution of 1 m, and trees appeared dark against the bright background.

Several variations of the LM filter were applied to the IKONOS imagery. For more information on LM filtering variations see Wulder et al. (2002a). The method that best-balanced accuracy with errors of omission and commission was a LM filter with a 3×3 window size, applied to a smoothed IKONOS image. The image was smoothed with a 3×3 averaging filter to reduce radiometric noise present in the imagery prior to LM filtering. While this variation missed several of the small trees, it had much lower commission error than other methods tried. While we demonstrate this method on a particular variation of the LM filter, it could be applied to other variations and point-based feature extraction techniques.

3.3. Relating the data sets

The stem map was overlain with the LM from the imagery to allow for a comparison of trees found on the ground with those extracted from the imagery. When many field-identified trees were located in close proximity, it was often difficult to link them with trees captured from the imagery. This was resolved by considering the found tree to be the field-identified tree with the largest DBH, while the others in the clump were omitted. Tree locations are measured to a nearest centimeter level of precision, whereas the LM trees are represented by a 1 m pixel, which can result in difficulties relating the points. Additionally, the LM generated from the image data are a function of factors such as sun angle, tree crown shape and size, and the relative height of a tree in comparison to its neighbors. Previous work has illustrated the link between accuracy and the relationship between tree and image pixel size (Wulder et al., 2000b).

The LM filter located 89 of the 199 trees identified in the field. Thirty-three of the 49 mature trees and 56 of the 150 immature trees were located. Four trees were located which did not exist on the ground (commission error). Commission errors were removed from the analysis as they had no corresponding tree on the ground for comparison.

4. Methods

4.1. Aspatial analysis of individual tree characteristics

Stem-mapped trees were partitioned into found and omitted classes and aspatial analysis conducted to determine if there were differences in the distribution of tree characteristics between the two classes. Data were also partitioned by age resulting in the following groups: (1) all found trees ($n=89$); (2) all omitted trees ($n=112$); (3) mature found trees ($n=33$); (4) mature omitted trees ($n=16$); (5) young found trees ($n=56$); and (6) young omitted trees ($n=94$). For each age class, the Mann–Whitney statistic was used to test for differences in the means of individual tree characteristics (DBH, crown radius, and tree height) when trees are captured or missed by the LM filter.

4.2. Spatial patterns of found and omitted trees

To further investigate the nature of feature extraction error, we use spatial analysis to determine if the omission error is random. Prior to spatial analysis, the points representing the location of individual trees were converted to VPs (Fig. 1). Given a set of points and continuous space, VPs partition a surface so that all locations are associated with the closest point (Okabe et al., 2000). VPs have the advantage of intrinsically defined spatial properties and additional attributes such as VP area, perimeter, shape, and the ratio of neighbors found and omitted (RNFO). Shape was determined using the simple index

$$S = \frac{4\pi A}{P^2} \tag{1}$$

where A and P are polygon area and perimeter, respectively. S ranges from 0 to 1. A VP is circular when $S=1$ and becomes more elongated as S approaches zero (Bogaert et al., 2000). The RNFO was computed for adjacent or first lag neighbors by dividing the number of adjacent located trees by the number of adjacent omitted trees. When RNFO$=1$, the same number of adjacent trees are located and omitted; RNFO<1 means more neighbors were omitted than found and RNFO>1 indicates more neighbors were found than omitted.

The VP surface was corrected for edge effects by excluding all VPs for which a circle centered at any vertex of a polygon and passing through the three points equidistance from the vertex, intersects the boundary of the study area (Okabe et al., 2000). The edge corrected surface included 150 polygons, of which 63 are found and 87 omitted by the LM filter. Of the correctly identified trees, 19 are mature and 44 are young. Of the omitted trees, nine are mature and 78 are young.

Although VPs were generated for the purpose of spatial analysis, the VP characteristics can be analyzed similarly to the individual tree characteristics discussed above. For each age class, the Mann–Whitney statistic was used to test for differences in the means of VP characteristics (VP area, VP perimeter, VP shape, and the RNFO) when trees are located or omitted.

Join counts were used to analyze the spatial pattern of located and omitted trees for each age class. Join counts have been used in the analysis of remotely sensed data to investigate the nature of image classification error (Congalton, 1988), but to our knowledge have not been used to analyze feature extraction results. Join counts can be used to determine if polygons, with a binary attribute, exhibit significant clustering or dispersion of attribute values relative to a random expectation (Cliff and Ord, 1981). VPs were coded either 1 (black) if a tree was found or 0 (white) if it was omitted (Fig. 2). For 30 or more observations and proportions of B and W polygons greater than 0.2, the counts of BB and BW joins are approximately normally distributed (Cliff and Ord, 1981, Chapter 2; Upton and Fingleton, 1985, p. 163). Thus, a negative z-score indicates an under-representation of a particular join count while a positive value indicates an excess.

4.3. Spatial autocorrelation in attribute values

In Section 5, we show that certain individual tree and VP characteristics are significantly different for trees that are found and those that are omitted. We use global and local measures of spatial autocorrelation to examine if these differences in characteristics have a spatial component related to the pattern of omission error. Global measures of spatial autocorrelation summarize the overall pattern of spatial dependence in the entire data set, while local measures identify individual observations that show significant departures from this trend.

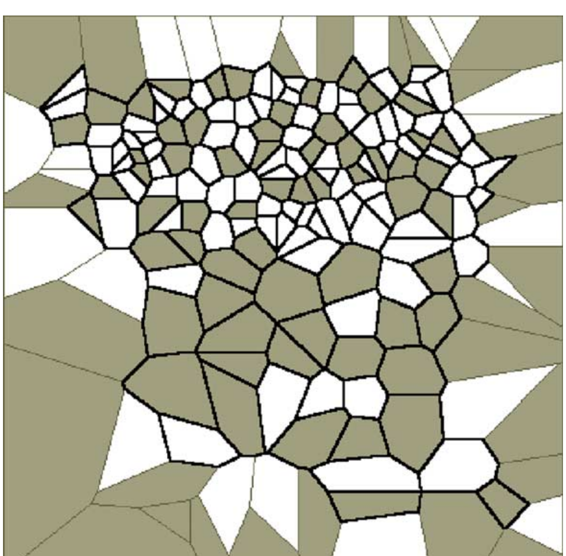

Fig. 2. VP surface for stem mapped (SM) trees (SM-VP). Gray equals found and white equals omitted by the LM filter. VPs with one or more sides represented by a thin line were removed during edge correction.

We use Moran's I to measure global spatial autocorrelation. I may be written as

$$I = \left(\frac{n}{W}\right)\left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2}\right) \tag{2}$$

where w_{ij} is a measure of the spatial relationship between observations i and j, $z_i = (x_i - \bar{x})$, n is the number of observations, and $W = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$, $i \neq j$ (Cliff and Ord, 1981, Chapter 2). Since I is asymptotically normally distributed, z-scores can be used to determine the extent to which the data exhibit positive (clustering of like values) or negative (dispersion of like values) spatial autocorrelation.

The local version of I, I_i, can be written as

$$I_i = \left(\frac{z_i}{\frac{\sum_i z_i^2}{n}}\right) \sum_j w_{ij} z_j \tag{3}$$

where w_{ij} and z_{ij} are as defined for I (Cliff and Ord, 1981, Chapter 2). Although I_i is not normally distributed (Boots and Tiefelsdorf, 2000; Gebhardt, 2001), z-scores can be used to give an approximate indication of significance when there is no global spatial autocorrelation in the data (Sokal et al., 1998). However, when there is significant global spatial autocorrelation, the number of locally significant observations will be overestimated. Thus, although our primary concern is with the results for local measures, it is necessary to measure global spatial autocorrelation in order to interpret the local measures appropriately.

The Getis statistics, G_i and G_i*, can be used to identify significant clustering of high or low values. G_i excludes observation i from the calculation while G_i* does not (Ord and Getis, 1995). The forms of these statistics are

$$G_i = \frac{\sum_{i \neq j\, j} w_{ij} x_j}{\sum_{i \neq j\, j} x_j}, \quad G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j} \tag{4}$$

when the number of neighbors (n_i) used in the calculation is at least eight, both G_i and G_i* are approximately normally distributed and therefore can be written in the form of a z-score. In this work, n_i averages six and so significance tests should be interpreted cautiously.

A 2×2 χ^2 test was used to compare the results of local spatial autocorrelation for trees found and omitted. In the χ^2 test, columns represent the frequency of trees found and omitted and rows represent significant or non-significant local spatial autocorrelation. The H_0 was that a significant value in G_i* or I_i is independent of whether a tree is found or omitted.

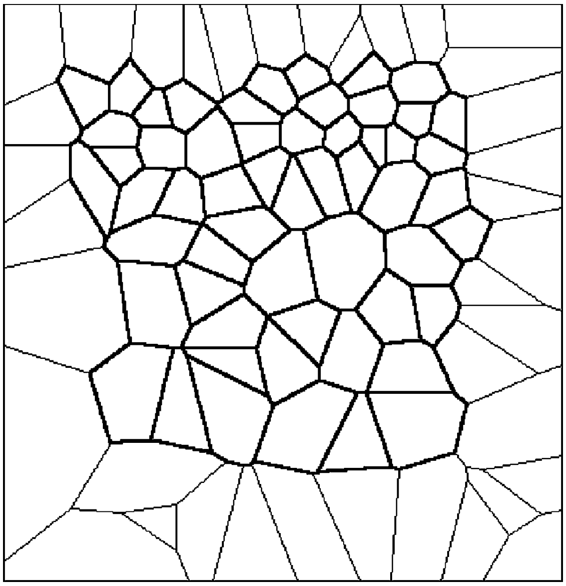

Fig. 3. VP surface for trees mapped with the local maximum (LM) filter (LM-VP). VPs with one or more sides represented by a thin line were removed during edge correction.

4.4. Analyzing the information content of trees correctly identified by the LM filter

The goal of LM filtering is to generate points representing single trees. However, some researchers suggest that when the spatial resolution of an image is not sufficient to resolve individual trees, LM points often represent clumps of trees (Gougeon et al., 1999). In this section, we analyze the information content of correctly located trees as a means of determining if LM trees represent individuals or groups of trees. We investigate the properties of found trees by overlaying the VPs generated from the stem mapped tree locations (SM-VPs) (Fig. 1) with VPs generated from the results of the LM filter (LM-VPs) (Figs. 3 and 4).

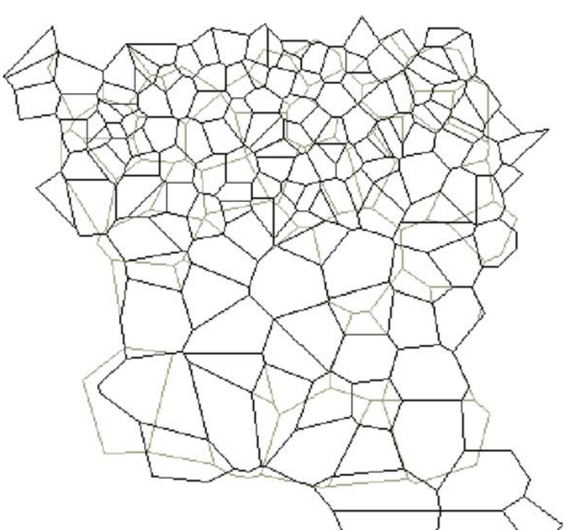

Fig. 4. Overlay of SM-VPs (black) and LM-VPs (grey). The overlay was used to generate two attributes: (1) the SM-VP area divided by LM-VP area; and (2) the number of times SM-VPs intersects a LM-VP.

The areas of SM-VPs were divided by the areas of corresponding LM-VPs. If the area ratio equals one, polygons are the same size, less than 1 indicates that the LM-VP is bigger than the SM-VP, while a ratio greater than 1 indicates the LM-VP is smaller than the SM-VP. A second attribute was generated based on the number of times a LM-VP was intersected by SM-VP when the two surfaces were overlain.

5. Results and discussion

5.1. Aspatial analysis of individual tree and VP characteristics

The results of aspatial (Mann–Whitney) analysis for the individual tree and VP characteristics can be seen in Table 2. For every age class, DBH, crown radius, tree height, VP area, and VP perimeter are larger for found trees than for omitted trees. However, the significance of these relationships varies. When all trees are analyzed, differences in DBH, crown radius, and tree height are statistically significantly different between found and omitted trees. Mature trees show significant differences in DBH and tree height. For young trees, DBH, crown radius, VP area, and VP perimeter show significant differences. Regardless of age, trends in VP shape are not statistically significant. In every class the RNFO is lower for located trees; if a tree is located fewer of its neighbors are found than if a tree is omitted. The trend in the RNFO is only statistically significant for young trees.

Differences in the DBH of found and omitted trees should be interpreted cautiously. Recall that the procedure for matching stem mapped trees to those found by the LM filter favored locating trees with a large DBH. Most of the mature trees are large enough to be fully imaged by the sensor and captured by the LM filter. Young trees often have a crown radius size that is similar to the spatial resolution of the imagery. When an object size is similar to the image spatial resolution, the object (tree) is imaged within few pixels, reducing the effectiveness of the LM approach and resulting in higher omission error during feature extraction. Therefore, matching young stem mapped trees to those found by the LM filter relied more heavily on DBH size. Still, the mean DBH for found and omitted trees is only slightly more different for young trees than for mature trees, perhaps suggesting that the trend in DBH is only partially explained by the relationship between tree crown and pixel size.

With the exception of tree height, mature trees have less significant disparity in the mean of characteristics for found and omitted trees. As mentioned above, most of the mature trees were big enough to be imaged by the sensor and therefore the error may be more random than for young trees

Table 2
Aspatial comparison of the distribution of characteristics for trees found and omitted

Variable	All			Mature			Young		
	Found	Omit	*Z*	Found	Omit	*Z*	Found	Omit	*Z*
DBH (cm)	49.34	28.11	5.13	92.03	70.81	3.02	23.73	20.92	3.11
Crown radius (m)	2.13	1.60	4.88	3.11	2.88	1.24	1.54	1.38	3.09
Tree height (m)	31.47	22.02	4.07	51.00	39.71	2.99	19.75	19.04	1.33
VP area (m^2)	40.05	24.24	1.83	79.45	72.79	0.57	23.03	18.64	2.61
VP perimeter (m)	24.15	19.30	1.61	35.87	34.77	0.57	19.10	17.52	2.34
VP shape	0.76	0.73	1.08	0.76	0.75	0.27	0.76	0.73	1.42
RNFO	1.02	1.04	0.50	2.20	3.17	1.59	0.50	0.80	4.13

Values in the found and omit columns are the mean for each characteristic. The *Z* columns are *z*-scores calculated using a Mann–Whitney test.

where size seems important. VP area and perimeter, as well as the RNFO, seem to be the most important factors in the correct identification of young trees.

5.2. Spatial patterns of found and missed trees

The results of the join counts for each age class can be seen in Table 3. For every class, join count statistics reveal a non-significant under-representation of BB adjacencies; all and mature trees have a non-significant over-representation of BW joins. For young trees, the *z*-score for the BW joins is significantly positive, suggesting the omission error is spatially disperse. Dispersion in the omission error of young trees is most likely an artefact of the LM filter, which prohibits the locating of trees in adjacent pixels. This implies that the area for each tree covers a minimum of 9 pixels (center plus the 8 adjacent), resulting in a minimum diameter of 3 m. Therefore, at the pixel scale, the filter imposes a certain level of dispersion. Since many young trees have a crown radius smaller than 3 m, the filter causes identified trees, and therefore omission error, to be dispersed. Mature trees on the other hand, typically have a crown radius much larger than the size of a pixel, so the spatial pattern of the error is not strongly impacted by the adjacency constraint of the filter. The spatial nature of commission error also explains why aspatial analysis shows the RNFO is significantly different for young trees omitted and located but not for mature trees.

5.3. Spatial autocorrelation in attribute values

When young and mature trees were analyzed together, all characteristics have significant positive global spatial autocorrelation (Table 4). When only the mature trees were analyzed, significant positive global spatial autocorrelation occurred only for VP perimeter and shape. In the young trees, significant positive global spatial autocorrelation occurred in all characteristics except DBH and the RNFO. For the characteristics where global spatial autocorrelation is found, local measures are more prone to type I errors and the associated tests of significance should be interpreted cautiously.

Table 3
Join count results for all trees, mature trees, and young trees

Z-value	All	Mature	Young
BB	−1.05	−0.53	−1.67
BW	1.27	0.99	2.00

B represents trees found by the LM filter and W represents trees omitted. Values are *z*-scores

In almost all cases, using the χ^2 test we were unable to reject the H_0 that a significant value of G_i* or I_i is independent of whether a tree is found or omitted ($\alpha = 0.05$). Therefore, a tree's likelihood of having significant local spatial autocorrelation in a particular characteristic seems independent of whether or not the tree is found by the LM filter. The only exception is tree height among young trees, which had a χ^2 value of 3.95. When $\alpha = 0.05$ the expected value of $\chi^2 = 3.84$. This suggests that a tree in a group of tall young trees may be more likely to be extracted from remotely sensed imagery than a tree in other situations. However, local tree height results should be interpreted carefully due to the presence of significant global spatial autocorrelation in this variable.

5.4. Analyzing the information content of trees correctly identified by the LM filter

The average ratio of SM-VP area divided by LM-VP area is 0.52, 0.42, and 0.79 for all, young, and mature trees, respectively. For the number of intersections, the average values for all, young, and mature trees are 5.53, 6.43, and 3.58, respectively. These values demonstrate that LM-VP

Table 4
Global Moran's *I*, *z*-scores for individual tree and VP characteristics

Variable	All	Mature	Young
DBH	14.81	−0.66	0.89
Crown Radius	13.67	1.22	2.21
Tree Height	14.04	−1.61	2.98
VP Area	15.62	0.86	8.11
VP Perimeter	16.71	2.66	9.54
VP Shape	3.40	3.50	2.51
RNFO	5.73	−1.56	−0.46

is on average twice the size of the SM-VP and are intersected by an average of about 6 SM-VP. Even when a LM point represents the location of an individual tree and not a tree clump, the area of a point seems to be associated with a clump of trees. Thus, one should exercise caution when converting LM trees to area based forestry measures (i.e. forest density). Misrepresentation of area may be severe in young stands where trees are split between an average of more than six trees.

6. Conclusions

We have demonstrated a set of tools for assessing the accuracy of feature extraction techniques. If features are represented as points, and a comparable surface representing reality exists, these methods can be used to analyze both the nature of error and information content of data. As environmental data are increasingly acquired from remotely sensed imagery, it is important that we have means of assessing the quality of these data.

The LM filter's constraint, prohibiting trees from being located in adjacent pixels, seems to result in the dispersion of errors for young trees, but not for mature trees. When the object size is similar to the pixel size adjacent trees are automatically missed. However, when the object size is much larger than the pixel size this constraint is not problematic and the error is random.

Although LM points often represent the location of individual trees, this is not always the case. This is especially so in young forests when more than one tree, or at least portions of more than one tree, may fall within a single pixel. This problem is exacerbated by the LM constraint of locating trees in pixels that do not touch other pixels with trees. Even when LM points do represent a single tree, it is likely that the area associated with the point is related to multiple trees or a tree clump. Image preprocessing also intensifies this problem. While image smoothing reduces commission error, it also results in a loss of information that may help in the identification younger, and, therefore, smaller trees.

Although the tree and VP characteristics appear important in determining if trees are found or not, the spatial nature of these characteristics is not related to that of omission error. It is most likely the relationship between the object and pixel size that impacts error. When a tree is small relative to the size of a pixel, it is less likely to be fully imaged by the sensor and therefore less likely to be extracted from the imagery. Relating image content to the effectiveness of the LM filtering explains why young trees are more sensitive to differences in individual tree and VP characteristics than are mature trees. In this study, most mature trees are large enough to be imaged by the sensor.

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